A Macro Econometric Model for Forecasting the Hotel-Room Night Demand: The Case of Switzerland.

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Abstract

This article proposes a macroeconomic-oriented method to forecast hotel room demand in Switzerland for the period stretching from the third quarter of 1974 to the fourth quarter of 2013. The method increases accuracy by weighting characteristics of the inbound tourists' economies for their relative contribution. It adopts the VECM technique, which produces reliable forecasts in both the short and long run without making ex ante assumptions regarding the causality of the explanatory variables. The results indicate that the method outperforms alternative forecasting methods in both the short and long run. The analysis shows that in the short run hotel room demand depends on income in visiting countries but not on the real GDP of Switzerland while in the long run demand depends on the real exchange rate and the real GDP of Switzerland.

Keywords
Forecasting hotel room demand; Switzerland, econometric models; accuracy comparisons; macroeconomics

Focus of Paper Theoretical/Academic

Introduction

Generating and having access to accurate forecasts of tourist arrivals and hotel room demand is crucial for companies operating in the hospitality and tourism industry (Pan et al., 2012; Rajopadhye et al., 2001; Song et al., 2008) since many goods and services supplied in this industry are perishable and cannot be inventoried (Archer, 1987; Dharmaratne, 1995; Jackman and Greenidge, 2010; Song and Witt, 2006). Specifically, companies such as airlines, tour operators, hotels and recreational facilities are interested not only in meeting but also in anticipating the demand as empty restaurants tables, unsold hotel rooms or unreserved tour packages cannot be stored and resold (Song and Witt, 2006). Forecasts also provide valuable budgeting information to the public sector (Greenidge, 2010) for planning infrastructure investments such as highways, rail-links and airports (Song and Witt, 2006), and governments use forecasts to plan long-term strategies (Song and Witt, 2006).

However, the academic literature struggles to reach a consensus on a universal forecasting method (Dharmaratne, 1995; Song and Li, 2008; Witt and Witt, 1995) mainly due to the fact that the available econometric models perform differently under different conditions (Dharmaratne, 2010; Song et al., 2003) and the same econometric models can produce contradictory results if the data were collected at different frequencies or cover different time periods or if the same econometric model uses a different method (Song et al., 2003). The only point of agreement amongst academics seems to be that advanced (i.e. more complex and detailed) methods, such as VAR, ECM or ADLM, tend to outperform simpler methods (Dharmaratne, 1995) by producing more reliable forecasts while avoiding spurious regressions (Song and Li, 2008). The forecasting method introduced and tested in this study is the so-called vector error correction model

(VECM), which generates more reliable forecasts compare to similar models, because it considers both the long- and short-run relationships among the variables and does not rely on *ex ante* restrictions on the causality of variables. VECM can therefore be used to fit the vector autoregressive model (VAR) when the variables are non-stationary.

The method is tested in the context of Switzerland for the period from Q3 1974 to Q4 2013. Only a small number of studies (e.g. Ferro Luzzi and Flückiger, 2003) have empirically investigated the impact of macroeconomic variables on Swiss tourism despite the fact that tourism is considered a strategic sector in Switzerland and a major contributor to Swiss GDP, accounting for CHF 32.6 billion (3% of the GDP) in 2005 (Swiss Federal Statistical Office, 2008; State Secretariat for Economic Affairs, 2008). Switzerland is a small, diversified open economy and, unlike many other European countries, maintains its own currency and monetary policy. These characteristics make it easier to recognize the effects the global economy has on the Swiss economy and, therefore, helps to avoid strong reverse causality.

The contribution of this article is a new and more accurate method to forecast hotel room demand. The forecasting model is derived from the review of the recent studies in the area. The proposed and tested method is novel, because it weighs the characteristics of the inbound tourists' economies for their relative contribution. More precisely, the method takes into account the inflation rate, exchange rate, real GDP of the inbound countries and assigns a weighting to each macroeconomic variable for the tourists' countries of origin.

The remainder of the article is organized as follows. In next section the literature on forecasting and econometric methodology is discussed in order to locate the scope and relevance of the proposed method. Section three describes the data and establishes how the variables were constructed. Section four introduces and explains the model and summarizes the results. Section five elaborates on the consistency of hotel room demand forecasts and compares the method proposed with alternative ones. Finally, section six concludes the study and provides future research avenues.

Literature background

There is a wealth of tourism literature documenting the importance of forecasting (Archer, 1987; Yang et al., 2014; Witt and Witt, 1995) and there is also a growing interest in the econometric methodology behind it (Li et al., 2005). However, the literature fails to reach a consensus on which model is the most accurate and reliable as Li et al. (2005) concluded after conducting an extensive survey to establish the "state of the art" methods in the tourist demand forecasting literature. After revising 84 studies from 1960 to 2004, the authors concluded that prediction accuracy depends on the frequency at which data are collected, the forecasted horizon and the specific aspects of each region studied but that no particular forecasting model performs better than the others. More recently, Song and Li (2008) conducted a similar exercise confirming that no one model tends to outperform the others. However, dynamic methods such as ECM, VAR or the autoregressive distributed lag model (ADLM) were found to be the most popular in the tourism literature currently. This might be due to the fact that those models avoid spurious regression and they manage to produce reliable forecasts (Song and Li, 2008). In this regard, analogous conclusions were reached by Witt and Song (2000) who argue the superiority of dynamic models compared to static models and by Song et al. (2003) who compare the reliability of the main econometric models in predicting international tourism in Denmark. In particular, Song et al. (2003) find that the TVP (time varying parameter) model outperforms alternative models in the short run, while the ARIMA model tends to produce the least accurate forecasts.

Tourist arrivals is the most common measure of tourist demand (Li et al., 2005; Song and Li, 2008) ahead of tourist expenditure (Li et al., 2005). However, Ferro Luzzi and Flückiger (2003) argue that the number of overnight stays is a better measure of tourist demand as it takes into account the length of stay, the consumption pattern, and it removes tourists who stay with their friends. Moreover, the number of nights spent in tourist accommodations allows researchers to interpret the results better, especially in terms of elasticity (Ferro Luzzi and Flückiger, 2003).

Relative price of tourism (including both travel expenditure and the cost of living at the destination) and income were found to be the main determinants of tourism demand (Li et al., 2005). The price of tourism services and products can be measured through the Consumer Price Index and the exchange rate (Song and Witt, 2006). Other variables that have been found to play an important role are substitute prices in alternative destinations, the previous year tourist demand, the time trend, and marketing (Song and Witt, 2006). Ayeh and Lin (2011) find that "word of mouth" and behavioral persistence are the most important variables affecting tourist demand in China, followed by the price of tourism and the income level of the tourist's country of origin. Ladesma-Rodríguez et al. (2001) include public spending on promotion in their analysis and they show that it positively and significantly affects tourist demand.

Using the National Bureau of Economic Research's (NBER) turning point criteria as well as the statistical correlation method Choi (2003) proposes 70 economic indicators (such as price index, unemployment, GDP, different stock price indexes, money supply, etc.) to predict U.S. hotel room demand and shows that the latter ones help predicting the cyclical fluctuations of the hotel industry. Likewise, Choi et al. (1999) study the U.S. hotel industry business cycle and they find that on average the peak-to-peak industry cycle is 7.3 years. The authors show how the study of the business cycle provides insight into forecasting hotel demand. Slattery (2009) proposes the Otus theory to explain "developments in the size and structure of the hotel business and its medium- to long-term prospects" (Slattery, 2009, 113). The theory posits that hotel demand is positively linked with the size of the service sector in an economy (Slattery, 2009).

Another variable the literature has considered is the opinion of experts. For instance, Yüksel (2007) proposes a forecasting methodology for predicting hotel demand in Ankara based on the Analytical Hierarchy Process (AHP) that incorporates expert opinions. Specifically, the author asked a pool of experts to identify which variables should be used to implement the AHP model. The experts came up with a list of 40 variables divided into 7 categories[1], which include (at the international and national level) in order: global economic crisis, wars, international events, exchange rate, inflation rate, national economic recession or crisis and political mobility (Yüksel, 2007). The importance of experts' opinion in forecasting tourist demand is also emphasized by Archer (1980). Finally, Pan et al. (2012) and Yang et al. (2014) show that Google search volume data reliably predict hotel room demand.

This study aims to expand the existing literature by proposing a macroeconomic-based method to predict hotel room demand in Switzerland. My study differs from previous studies in two main aspects. First of all, it explores the case of Switzerland for which there is little evidence. As argued, Switzerland is a European inland country with a small open economy and its own currency. Those characteristics make Switzerland a suitable study case. Secondly, the method proposed differs from others because it includes the main macroeconomic variables and proposes a strategy to increase the precision of the esteems weighting the data according to the country of origin of guests. I show that the macroeconomic variables affect hotel room demand, identify a causal link, and provide a theoretical framework. Finally, I give evidence that the proposed method outperforms alternative methodologies.

Data

Data

I retrieve from the Swiss Federal Office of Statistics detailed information on nights spent in Swiss hotels by both domestic and international guests. The Swiss Federal Office of Statistics reports detailed information on the number of nights spent in Swiss hotels on a quarterly basis. I collect such information for the period ranging from 1960 (first quarter) to 2013 (fourth quarter). Data are missing for 2014, but I use TRAMO[2] to seasonally adjust and fill the missing values. The Swiss Federal Office of Statistics also provides data regarding the country of origin of guests on an annual basis. I use a linear interpolation method to fill the missing value of 2004. From the database, I identify the percentage of domestic guests and non-resident guests for each year and compute the inbound market for Switzerland. In particular, I isolate the countries providing the largest number of tourists for Switzerland each year.

Table 1 shows the decade-by-decade trend in hotel nights sold in Switzerland from 1960 to 2013. Domestic guests account for approximately 40% of total guests. Among non-resident guests, Germans are

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[1] International criteria, national criteria, social criteria, hotel criteria, natural criteria, competition criteria and customer criteria.

[2] Tramo stands for Time series Regression with ARIMA noise, Missing values and Outliers. It is a free software program developed by Gomez and Maravell (1996) and available on the Banco de Espana website (http://www.bde.es).

the most represented, followed by the British and, in the more recent decades, by Americans. The percentage of inbound tourism from neighboring countries such as France and Italy has declined in the most recent decades.

Table 1. ***Domestic and inbound tourism to Switzerland***

	Domestic and inbound tourism		Inbound tourism form:					
	Resident (%)	Non-resident (%)	Germany (%)	UK (%)	France (%)	Italy (%)	US (%)	Rest of the world (%)
1960	41.14	58.86	26.5	18.74	16.89	6.29	9.61	21.97
1970	38.19	61.81	26.95	11	13.26	6.55	12.77	29.47
1980	41.49	58.51	37.74	6.92	8.92	3.93	8.65	33.84
1990	41.19	58.81	30.49	9.8	7.3	6.49	11.93	33.99
2000	41.3	58.7	32.36	9.94	6.2	4.81	10.91	35.78
2010	43	57	28.42	9.43	7.09	5.26	7.38	42.42
2013	44.11	55.89	23.16	8.67	6.85	4.96	8.04	48.32

I retrieve national accounts data from the OECD iLibrary for Switzerland, Germany, United Kingdom and the United States of America. In particular, from the OECD national accounts statistics database, I collect quarterly data on real gross domestic product (GDP) (in millions of national currency, reference year 2005, annual levels, seasonally adjusted), nominal GDP (in millions of national currency, annual levels, seasonally adjusted), the deflator (seasonally adjusted) and the growth rate compared to the previous quarter (seasonally adjusted).

I obtain data on the nominal exchange rate from the Eurostat database. Specifically, I retain the nominal exchange rate between one euro and the Swiss Franc, the pound sterling and the US dollar from the third quarter of 1974 to the fourth quarter of 2013.

Variables

The purpose of this article is to construct an empirical macroeconomic model to forecast hotel room demand in Switzerland. Following the recent literature, the macroeconomic variables I examine are the real exchange rate, real GDP of the inbound countries and real GDP of Switzerland. I follow a similar - but not identical - method to that of Ferro Luzi and Flückiger (2003) in constructing the database. In particular, I construct an index for the GDP of the inbound countries as follows. Firstly, I identify the countries providing the largest number of guests for Switzerland, which are Germany and the United Kingdom. From these two countries, I retain annual real GDP, on a quarterly basis, and the percentage of the total nights spent (weights). All remaining non-resident tourists are allocated to a third category designated as "all other countries visiting Switzerland". As a proxy for the real GDP of "all other countries visiting Switzerland", I use the real GDP of the United States. I then compute the weighted real GDP using the percentage of inbound tourists as weights. Specifically, I convert the GDP of Germany, the UK and the USA into Swiss Francs. Then, for each quarter, I compute weighted GDP using the following formula:

$$weighted\ GDP_t = \sum_{i=1}^{3} w_i GDP_{i,t}$$

where w_i stands for the percentage of guests visiting Switzerland from one of the three countries *i* (Germany, the United Kingdom and all other countries visiting Switzerland) at the year-quarter *t*.

In a similar manner, I compute the weighted real exchange rate. Firstly, I obtain the real exchange rate for Germany, the U.K. and the U.S.. To do so, I take the nominal exchange rate (defined as the amount of foreign currency that can be bought with one Swiss Franc), multiply the nominal exchange rate by the Swiss deflator, and divide by the deflator for Germany, the U.K. and the U.S. This procedure allows the model to account for the inflation rate and monetary policy. I then use the same method that had been used to construct the weighted exchange rate to compute the weighted real exchange rate. This method allows to weight the characteristics of the main Swiss trading partners for the hospitality industry and by doing so, accuracy is increased.

To summarize, I was able to collect a time series of quarterly data from 1973 (third quarter) to 2013 (fourth quarter) - a total of 158 quarters - for each of the four variables. I log-transform the four variables. Figure 1 plots the evolution through time of the log-transformed hotel room purchases of both domestic and non-resident guests in Switzerland, the real GDP of Switzerland, the weighted real GDP, and the weighted real exchange rate of the Swiss Franc.

Figure 1. ***Time series***

The model

The methodology

To forecast hotel room demand, I use a vector autoregressive model (VAR). One of the biggest advantages of the VAR methodology is that it does not rely on *ex ante* identification assumptions, which makes it particularly well suited for forecasting. In other words, VAR does not require assumptions regarding causality among the four endogenous variables (real GDP, weighted real GDP, weighted real exchange rate and the number of nights spent in Switzerland). Indeed, if, on the one hand, one can expect an increase in real GDP to lead to higher demand for hotel rooms; on the other hand, one can argue that an expansion in demand leads to higher income. Similarly, the relationship between hotel room demand and the real exchange rate might not be unidirectional. Finally, Swiss GDP and demand for hotel rooms depend on the overall economic situation of Switzerland's primary trading partner, and similarly, the economy of Switzerland might affect the economic situation of its trading partner. The VAR methodology also includes post-estimation tests of the VAR model, which allows us to establish causality among the variables and test the effects of a shock to all variables (impulse-response analysis).

To implement the VAR model, I proceed as follows. First, I test the null hypothesis that the four time series contain a unit root using the modified Dickey-Fuller test. I fail to reject the null hypothesis at the 1% confidence level for all four variables (results omitted).

Following what the econometrics literature prescribes in presence of non-stationary integrated variables of the same order, I look for cointegrating relationships. Intuitively, variables are said to be cointegrated if they move together in the long run, which means that, despite the fact single variables are non-stationary and thus tend to deviate from their own mean, the long-run relationship between them is stationary. This method is better known as the Vector Error Correction Model (VECM), and it is used to fit the VAR in presence of non-stationary variables. To fit the VECM, I use four main criteria to identify the lags-order to include in the VECM: the Schwarz's Bayesian information criterion (SBIC), the Akaike's information criterion (AIK), the Akaike's final predictor error (FPE) and the Hannan and Quinn's information criteria (HQIC). All criteria unanimously point to two lags. Table 2 reports the results.

Table 2. ***Lag order selection criteria***

lag	FPE	AIC	HQIC	SBIC
0	0.00	-7.66	-7.63	-7.59
1	0.00	-19.49	-19.33	-19.09
2	0.00*	-19.9388*	-19.6505*	-19.2289*
3	0.00	-19.90	-19.48	-18.88
4	0.00	-19.79	-19.24	-18.45

I then look at the number of cointegrating relationships among the variables using the maximum eigenvalue tests and the trace tests. Table 3 reports the results. Both statistics suggest one cointegrating relationship.

Table 3. ***Tests for cointegration***

Maximum rank	eigenvalue	trace statistic	5% critical value	max statistic	5% critical value
0		55.9179	47.21	37.1821	27.07
1	0.21207	18.7358*	29.68	12.6652	20.97
2	0.07798	6.0706	15.41	6.0666	14.07
3	0.03814	0.0041	3.76	0.0041	3.76

Finally, I estimate the four VECM equations (including a time trend). I adopt the following specification:

$$\Delta y_t = a + \partial trend + \Theta\Delta y_{t-1} + \alpha\beta \mathrm{y}_{t-1} + \varepsilon_t$$

where y_t is a 4x1 vector defined as follows:

$$y_t = \begin{pmatrix} \Delta GDP\_W_t \\ \Delta GDP\_CH_t \\ \Delta E_t \\ \Delta \mathrm{NIGHTS}_t \end{pmatrix}$$

and where,

- GDP_W_t is the log-transformed weighted real GDP at time *t*,
- GDP_CH_t stands for the log-transformed real GDP of Switzerland at time *t*,

- E_t represents the weighted real exchange rate at time *t* (log transformed),
- NIGHTS_t stands for the hotel room nights (log-transformed),
- and $trend$ represents the time trend term.

I report the results in table 4.

Table 4. ***Estimated coefficients for VECM. The t-statistics are reported in parentheses.***

	ΔGDP_W_t	ΔGDP_CH_t	ΔE_t	ΔNIGHTS_t
Cointegrating Equation (t-1)	0.023679	0.0030948	0.0124531	-0.1958238
	[0.85]	[0.88]	[0.56]	[-8.18]
ΔGDP_W_{t-1}	-0.1873264	0.0504682	0.2490656	0.5051359
	[-0.75]	[1.6]	[1.26]	[2.35]
ΔGDP_CH_{t-1}	0.1933346	0.516023	0.079968	0.1561172
	[0.39]	[8.14]	[0.2]	[0.36]
ΔE_{t-1}	-0.5739214	0.05881	0.5473479	0.5293979
	[-1.83]	[1.48]	[2.19]	[1.96]
$\Delta \text{NIGHTS}_{t-1}$	0.0026604	-0.0001229	-0.090459	-0.1506576
	[0.03]	[-0.01]	[-1.33]	[-2.05]
trend	0.0000193	0.00000136	-0.00000848	0.00000182
	[0.23]	[0.13]	[-0.13]	[0.02]
constant	0.0006415	0.0018125	0.0024213	-0.0052244
	[0.08]	[1.85]	[0.39]	[-0.78]
R^2	0.0909	0.4987	0.1055	0.4994
N	156	156	156	156

Cointegrating equation	
GDP_W_t	1
GDP_CH_t	-8.054214
	[-8.86]
E_t	1.508037
	[11]
NIGHTS_t	3.932557
	[10.48]
trend	0.0274879
constant	51.13801

The short-run Granger Causality can be inferred immediately from Table 4, as the VECM model includes only one lagged delta of all endogenous variables. However, for completeness, I report the short-run Granger causality in Table 5 (including the test that none of the other variables of y_t Granger-cause $y_{i,t}$). In the short run, hotel room demand depends on income in the visiting countries but not on the real GDP of Switzerland. In the short run, the real exchange rate is positively associated with hotel room demand.

Table 5. ***Granger causality Wald tests.***

	Equation			
Excluded	ΔGDP_W_t	ΔGDP_CH_t	ΔE_t	ΔNIGHTS_t
ΔGDP_W_{t-1}	-	0.1096	0.2094	0.0188
ΔGDP_CH_{t-1}	0.6999	-	0.841	0.7177
ΔE_{t-1}	0.0679	0.1387	-	0.0505

$\Delta\text{NIGHTS}_{t-1}$	0.9751	0.9909	0.1823	-
All	0.2768	0	0.2066	0.084

The long-run relationship between the four variables can be immediately inferred from table 4 (cointegrating equation). The equilibrium relationship can be rearranged as follows:

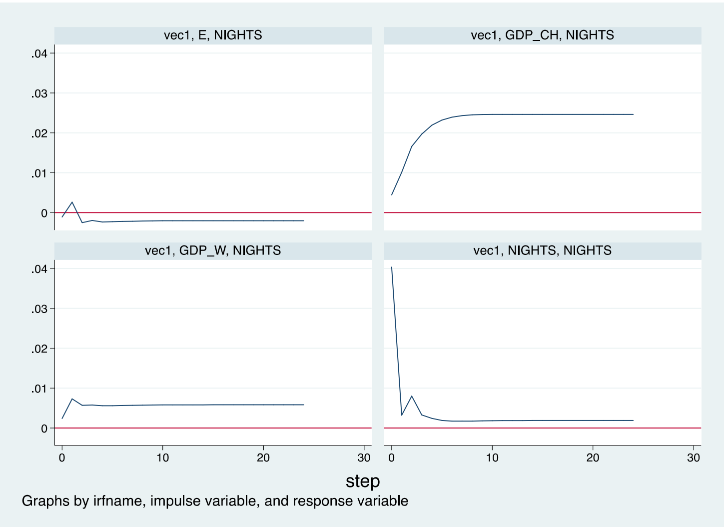
$$\text{NIGHTS}_t = -0.25(GDP\_W_t) + 2.05(GDP\_CH_t) - 0.38(E_t) + 0.01trend + 13.00$$

The long-run relationship plays a crucial role only for explaining hotel room demand. The long-run relationship shows that the income elasticity of hotel room demand from non-residents is negative, while the income elasticity of demand from resident guests (i.e. Swiss residents visiting Switzerland) is positive.

To study the impact of an orthogonalized shock to any of the four variables to hotel room demand through time, I conduct the impulse-response analysis. Figure 2 displays the 24-step orthogonalized impulse-response function. I assume the following order: a shock to the real GDP of Switzerland’s trading partners leads to a change in the real GDP of Switzerland, which affects the exchange rate and, in the end, hotel room demand.

As expected, an appreciation of the real exchange rate leads to a permanent decline in the demand for hotel rooms. On the other hand, a sharp rise in both the real GDP of Switzerland and weighted real GDP leads to a permanent increase in demand for hotel rooms.

Figure 2. *Impulse-response analysis.*



Forecasting

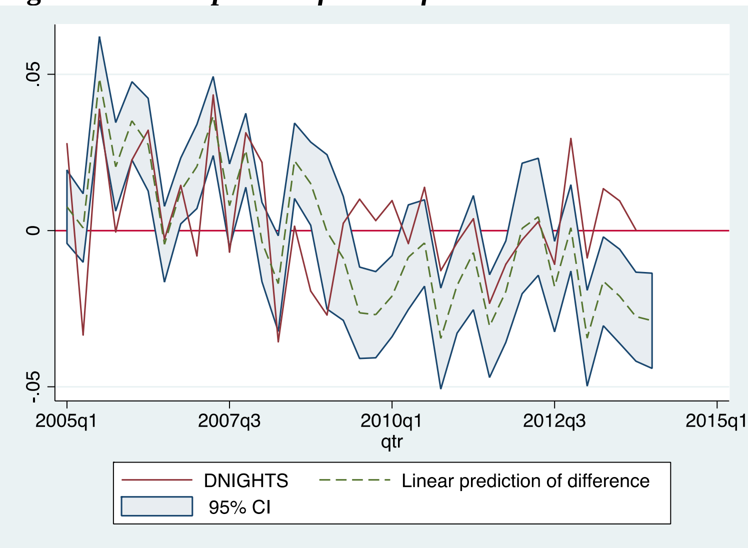
In this section, I explore the forecasting accuracy of the proposed model. In the first part, I test how well the method forecasts the percentage change in hotel room demand. In the second part, I compare the VECM model proposed with other forecasting methods and give evidence that the VECM produces the most accurate forecasts.

5.1. Forecasts

Firstly, I compute the one-step-ahead forecast for the rate of change in hotel room demand. I report the results for the last decade in Figure 3. Figure 3 reveals that, most of the time, the one-step prediction is inside the 95% confidence interval, as is usually the case for the one-step-ahead-prediction because it is continuously updated with the true value (Becketti, 2013). This result implies that the proposed model manages to produce reliable predictions. However, the confidence interval increases after the financial meltdown of 2008. That is, the financial crisis increased volatility and thus uncertainty about demand.

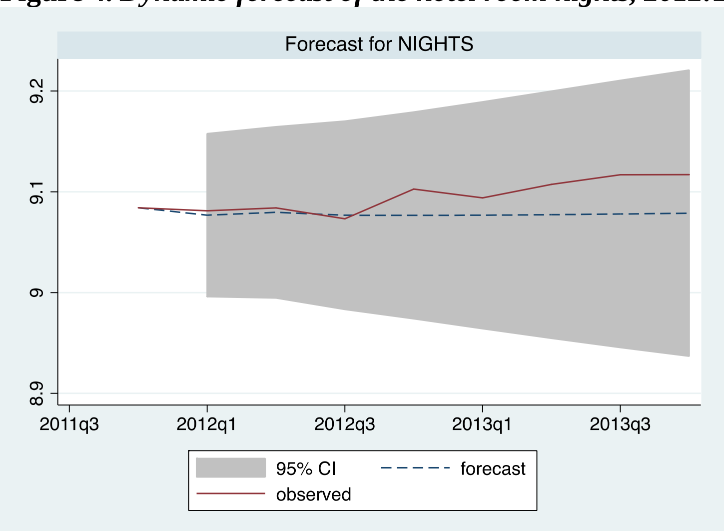
Moreover, the largest gaps between the true value and the prediction occurred during the global recession of 2008.

Figure 3. ***One-step-ahead forecast for hotel room demand.***



Secondly, I compute the dynamic forecasts for hotel room demand (in log) to test the model's ability to produce reliable predictions, not only in the short run. I again run the VECM model, but exclude the last 2 years of observations (I omit the results). Then, I use the estimated model to forecast the remaining two years (8 quarters) and compare the results with the true value. I report the predictions and the true value in Figure 4. From Figure 4, it can be inferred that the adopted method is accurate.

Figure 4. ***Dynamic forecast of the hotel room nights, 2012:1-2013:4.***



Comparison

The next question is whether the VECM model proposed outperforms other methods in forecasting future hotel room demand. I compare the VECM model with three other forecasting methods and test the ability of forecasting both the short period (one-step-ahead) and the long period (one-year-ahead).

The first model is a simple moving average predictor (MA) on the last four quarters. The second method is a random walk that retains the current information as a predictor of one-step-ahead and four-steps-ahead hotel demand. The third method is a more elaborate autoregressive integrated moving average (ARIMA) model. To fit the ARIMA, I firstly select the number of lags to include in the specification using both the

Akaike information criterion (AIC) and the Bayesian information criterion (BIC). I report in Table 6 the AIC and the BIC esteems for each specification. Both criteria unanimously suggest modelizing hotel room demand using an ARIMA (2,1,1). Finally, I produce one-step-ahead and four-steps-ahead forecasts.

Table 6. ***Lags selection.***

		AIC		
AR/MA	0	1	2	3
0	-455.2954	-504.7512	-503.8268	-503.1549
1	-499.0471	-504.1754	-502.205	-500.2175
2	-503.89	**-507.8739**	-500.7474	-504.2273
3	-501.9506	-506.981	-505.2899	-505.4974
		BIC		
AR/MA	0	1	2	3
0	-449.1829	-495.5824	-491.6018	-487.8737
1	-489.8784	-491.9504	-486.9237	-481.8801
2	-491.6651	**-495.6489**	-482.41	-482.8336
3	-486.6694	-488.6436	-483.8962	-484.1037

For each of the three models and each timeframe, I compute the root-mean-square error (RMSE) and compare it to the RMSE obtained from the VECM. Table 7 summarizes the results. The first row shows the RMSE obtained using as a random walk forecasting method for both the short run and the long run. The columns "% improvement" compare the result with the VECM model and report the improvement deriving from the adoption of the proposed VECM. The second row reports the results for the moving average method, the third column displays the RMSEs obtained forecasting demand with an ARIMA and the last column reports the RMSEs from the proposed VECM model. The results show that the proposed VECM performs better than all of the other methods and that the RMSE of the VECM is between 17% and 42% less than that of the other methods. Moreover, the relative performance of the VECM increases as the forecast horizon increases. Specifically, the improvement deriving from the VECM is almost double that of all the other alternatives as the horizon increases from one-step-ahead to four-steps-ahead. Finally, for the VECM forecast, the RMSE for the 4-steps-ahead forecast is only 0.96% less than the RMSE of the 1-step-ahead forecast. These results suggest that the VECM tends to maintain its accuracy as the horizon increases and that the decrease in accuracy is less marked than that of all the other methods considered.

Table 7. ***RMSEs from the VECM model and three alternative methods.***

	one-step ahead prediction	% improvement	one-year ahead	% improvement
RMSE RW	0.05604532	29.095846	0.06753264	41.71677577
RMSE MA	0.04911685	19.09403799	0.06148478	35.9838321
RMSE ARIMA	0.04765436	16.61107189	0.0588761	33.14740616
RMSE_VECM	0.03973846		0.0393602	

Conclusions

This paper proposes an effective macro-econometric model that analyzes both the short run and the long run to predict hotel room demand. The forecasting model is derived from the revision of the most recent literature in the area. It analyses the specific case of Switzerland but the method can be easily applied to other economies.

The added value of this study is the fact that it treats the case of Switzerland, for which, to the best of my knowledge, no previous studies had been conducted. In addition, this study increases forecast accuracy proposing a method that weights the characteristics of the inbound tourists' economies for their relative contribution. The forecasting method used for this study is the vector error correction model (VECM). The VECM has two main advantages. Firstly, it does not impose *ex ante* causality on variables. Secondly, the VECM make a distinction between short-run relationships and long-run relationships among the variables. Thanks to these characteristics, the VECM is particularly effective as a forecasting model. In addition, the methodology includes post-estimation tests, which make it possible to test the causality of the variables ex post and to conduct policy simulations.

The analysis shows that the suggested method generates accurate predictions. Additionally, the analysis compares the forecasts generated by the proposed method to other methods. It demonstrates that the method tends to outperform other alternative forecasting methods, both in the short run and in the long run.

The article demonstrates that hotel room demand in Switzerland depends on income in the visiting countries in the short run, but not on the real GDP of Switzerland. In the long run, however, demand depends on the real exchange rate and the real GDP of Switzerland. The impulse-response analysis reveals that an appreciation of the real exchange rate causes a permanent decrease in demand, whereas the real GDP of Switzerland and the GDP of Switzerland's top-trading partners causes sustained growth in demand.
The results have strong policy implications for the Swiss hospitality industry because they help to predict the long-run demand for overnight stays under different macroeconomic conditions.

Future research should incorporate expert opinions on upcoming trends in the hospitality industry and thus refine the present model using a Bayesian approach. In general, experts and professionals in the hospitality industry are found to provide accurate predictions of future trends (Rajopadhye et al., 2001). These opinions, therefore, will further increase the accuracy of the model.

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