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Abstract

The purpose of this study is to investigate the causal effects of governments' social distancing measures to curb the spread of the ongoing SARS-COV-2 outbreak on the hotel industry of major tourist destinations (France, Greece, Italy, Spain, Portugal, and Turkey). The empirical analysis employs a static threshold model developed in Hansen (1999; 2020) using a daily dataset over the six months from the first confirmed European COVID-19 case (25.01.2020). The results indicate that the investigated relationship is non-monotonic ("*U-shaped*") depending on the intensity of the lockdown measures proxied by the Coronavirus Government Response Tracker Index (CGR). The empirical findings corroborate that the effect of lockdown measures on the hotel industry can be positive and statistically significant if and only if sample tourist destinations surpass a certain threshold of lockdown effectiveness (high regime). However, if sample countries adopt social distancing measures below a given threshold level, the effect is negative though significant (low regime). The threshold analysis suggests that COVID-19 increases hotel room revenues even at 12,7% and subsequently the level of hotel performance, only for already "*lock downed stringent"* countries, supporting the effectiveness of social distancing measures. Finally, the "*U-shaped*" (convex) curvature does not drastically change when alternative indicators of hotel performance and non-parametric techniques are employed.

Keywords: Hotel industry; COVID-19; Coronavirus Government Response Tracker Index; Social distancing; Threshold model
JEL Codes: Z31; C24; C23

1. Introduction

At the onset of the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-COV-2), humanity must cope with unprecedented health and financial conditions. The novel coronavirus disease has jeopardized the international markets, posing significant financial restrains even to the most prosperous economies. Amid the pandemic (from 11.03.2020), numerous countries all over the world have steered to adopt social distancing and isolation efforts to mitigate the negative effects of the COVID-19 in all the socioeconomic aspects.

The hotel industry constitutes one of the four main travel and tourism pillars (airlines, cruise lines, and car rentals) that has been hit by the SARS-COV-2 (Sharma and Nicolau, 2020). On the supply side, the COVID-19 has hit hotels especially hard, as travel has decreased during the peak and off-peak season as a result of the adoption of stringent restrictive measures (e.g. lockdowns, the closing of the national borders, closure of airports and ports, etc) to prevent its spread. On the demand side, customers have followed staying stay-at-home orders to reduce the spread of the virus and minimize health risk exposure (Cook et al, 2020). As a result, COVID-19 has caused significant disruptions to the international hotel industry.

It is argued that the COVID-19 pandemic crisis will incur several consequences not only for the hotel industry and international tourism (inbound and outbound) but also for the economic growth and prosperity of several economies (see among others Farzanegan et al, 2020; Gössling, et al. 2020; Yang et al. 2020). To give an example of its tremendous impact on the tourism sector, it is estimated that over 75 million jobs in tourism are at immediate risk and the industry losses are exceeding 2.1 trillion US dollars for the first quarter of 2020 (see Zenker and Kock, 2020).

The hotel industry has already overshadowed from COVID-19 since hotel companies must deal with a dual crisis; declining demand and increased prices for their services jeopardizing the profitability level in the industry (Polemis 2020). Although the long-term consequences of this pandemic crisis are difficult to estimate, some studies are attempting to trace the short-term consequences of the pandemic (see for example Assaf and Scuderi, 2020; Mariolis et al, 2020; Sharma and Nicolau, 2020; Tsionas, 2020).

In a recent study Sharma and Nicolau, (2020), adopt a market-based model to quantify the impact of COVID-19 on several global travel and tourism industries including the hotel sector. They argue that each of the investigated industries has experienced a substantial fall in valuation because of the pandemic crisis though not precisely estimated.

In another study, Tsionas (2020) examines the problem of post-COVID-19 gradual reopening in the hotel industry under three limited capacity scenarios. He argues that reopening requiring the same level of profit as in the pre-COVID-19 period is considerably more difficult and requires capacity near 33% diminishing the risk of adopting state aid measures (e.g. subsidies, tax exemptions, etc). Similarly, Assaf and Scuderi (2020) propose strategies that the tourism industry can adopt to adjust to the post-COVID-19 era, while they critically discuss the role of policy measures to accelerate the hotel industry performance. Based on their evaluation, "*governments should move quickly from the first stage of subsidizing for liquidity to incentivizing sustainable recovery and innovation*".

In a different strand of literature, Qiu et al., (2020), estimate residents' willingness to pay (WTP) to reduce the risk associated with tourism activities in three Chinese cities amid the COVID-19 pandemic crisis. The empirical findings reveal that most respondents were willing to pay for risk reduction and action in responding to the COVID-19, although younger residents were willing to pay more for risk reduction.

They also argue that residents' WTP is significantly driven by demographic and economic characteristics such as age, income, and tourism employment.

While most of the existing studies have tried to focus on the economic consequences of COVID-19 on the tourism sector emphasizing the hotel industry, scarce attention has been paid to the investigation of the effectiveness of the underlying restrictive measures on the performance of the industry.

This study contributes to the current knowledge of quantifying the effects of social distancing measures on the performance of the hotel industry at the outbreak of COVID-19. For this reason, we rely on linear and non-linear parametric econometric techniques to uncover the shape of the investigated relationship to better understand the effectiveness of the adopted restrictive measures on the hotel industry.

Contrary to the conventional wisdom that dictates a negative (linear) relationship between a pandemic crisis (e.g. similar to a shock or a natural disaster) and tourism activity, the empirical findings postulate that the effect of lockdown measures on the hotel industry can be positive and statistically significant on the condition that the sample countries must exceed a high regime threshold. In other words, this study argues that the level of total hotel room revenues is linked with the lockdown stringency index in a non-linear way ("*U-shaped*" curvature).

The rest of the paper is organized as follows. Section 2 discusses the data set and the methodology applied. Section 3 provides the empirical results, while Section 4 reports the findings from the robustness analysis. Finally, Section 5 concludes the paper and offers some policy implications.

2. Data and Methodology

2.1 Data and sample selection

The sample consists of a balanced daily panel data set comprising of six international tourist destinations (France, Greece, Italy, Spain, Portugal, and Turkey) over a six month period starting from 25.01.2020 to 25.07.2020 yielding 1,098 observations (N = 6 and T = 83). The starting date (25.01.2020) refers to the first confirmed case of the novel coronavirus disease reported in France.

The hotel variables (e.g. room revenues, occupancy rate, room supply, etc) are obtained by the Smith Travel Research hotel database. The sample reports mean variables from all the available hotel categories (luxury, midscale, upper midscale, upper-upscale, upscale). The Coronavirus Government Response Tracker index is obtained from Hale et. al, (2020). [1] The values of this index range from 0 (no lockdown measures in place) to 100 (total lockdown). We must bear in mind that the relevant index simply records the number and strictness of government policies and cannot be interpreted as '*scoring'* the appropriateness or effectiveness of a country's response. In other words, a higher position in an index does not necessarily mean that a country's response is 'better' than others lower on the index. The rest of the covariates are extracted from Roser et al, (2020). Finally, since we use a high-frequency dataset over a short period, we do not control for other global factors and macroeconomic fundamentals (Eleftheriou and Patsoulis, 2020).

Table 1 presents the summary statistics. It appears that the logged room supply exhibits the lowest standard deviation among the sample variables equal to 0.579, while, the GDP per capita the highest. The relevant variable is positively skewed

[1] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

(0.0831) and the (excess) kurtosis value suggests a leptokurtic distribution (<3). Similarly, most of the rest sample variables are heavy-tailed revealing a leptokurtic distribution either positively or negatively skewed.

<Table 1 about here>

2.2. Econometric methodology

To examine the potential non-linear relationship between the COVID-19 pandemic and hotel performance, we employ a static panel threshold regression model, which is expressed as follows:

$$y_t = x_t^T \beta_1 + u_t, q_t \leq \gamma \tag{1}$$

$$y_t = x_t^T \beta_2 + u_t, q_t > \gamma \tag{2}$$

These equations describe the relationship between the variables of interest in each of the two regimes (high and low deregulation), while q_t stands for the threshold variable with γ being the unknown sample split (threshold) value that needs to be estimated. The threshold variable could be an element of x_t^T, the k-dimensional vector of exogenous regressors (Hansen, 1999; Bick, 2010).

We assume for simplicity that the error term u_t is independent and identically distributed (i.i.d) with mean zero and finite varianceσ_v^2, although one can also allow for a conditional heteroskedastic error structure and weak dependence.

The approach that we employ here does not rely on a known γ. This means that the parameter γ needs to be estimated along-side the other unknown parameters of the model. However, the method is based on the first testing for the presence of a threshold effect. Once we reject the null of no threshold, we proceed in the estimation of the model that includes the estimation of the threshold and allows for the sample split. The method is based on a Concentrated Least Squares (CLS) technique that splits the model into the two regimes, whereby there is a full interaction of all the variables with the (estimated) threshold (Hansen, 1999).

By introducing a dummy variable $d_t(\gamma) = I(q_t \leq \gamma)$, we can write the model above in a single expression (see also Hansen, 1999, Savvides and Stengos, 2000; Polemis and Stengos, 2019):

$$y_t = x_t^T\beta \quad + x_t^T(\gamma)K + u_t \tag{3}$$

where$\beta = \beta_2$and$K = \beta_1 - \beta_2$. For testing that there is no threshold, the null hypothesis is simply that H_0: K=0 or H_0:$\beta_1 = \beta_2$. Based on the above, our threshold model takes the following algebraic form:

$$ln(REV)it = \mu_i + \theta_t + \beta_1^{'}x_{it}I(CGR_{it} \leq \gamma) + \beta_2^{'}x_{it}I(CGR_{it} > \gamma) + u_{it} \tag{4}$$

The subscripts i = 1, . . ., 6 represent the country included in our sample, while t = 1, . . . , 183 indexes the time (number of days). The vector x_{it} includes the exogenous control variables (lnADR, lnSupply, GDP, and POP) with regime independent slope coefficients. *I (·)* is the indicator function taking the value one when the condition in the parenthesis is satisfied and zero otherwise. The latter also represents the regime defined by the threshold variable (CGI) and the threshold value γ that needs to be estimated within the model. μ_i is the unit-specific residual that differs between countries but remains constant for any particular country (unobserved country-level effect) and θ_t captures the time effect and therefore differs across days but is constant for all countries in a particular day. Finally, u_{it} denotes the error term which allows for conditional heteroskedasticity and weak dependence (i.i.d).

We complement the above threshold model with a benchmark linear analysis. In this way, we will be able to draw the differences between these results and the traditional benchmark specifications to focus on issues that were depicted in the threshold model and are different from the linear one (Polemis and Stengos, 2017). We provide below the general exposition of the three linear benchmark models:

$$ln(REV)it = \mu_i + \theta_t + \mu_i X\theta_t + \beta 0 + \beta 1 \ln(ADR)\, it + \beta 2 \ln(Supply) it + \beta 3 CGR_{it} + u_{it} \quad (5)$$

$$ln(REV)it = \mu_i + \theta_t + \mu_i X\theta_t + \beta 0 + \beta 1 \ln(ADR)\, it + \beta 2 \ln(Supply) it + \beta 3 CGR_{it} + \beta 4 GDPit + \beta 5 POPit + u_{it} \quad (6)$$

$$ln(REV)it = \mu_i + \theta_t + \mu_i X\theta_t + \beta 0 + \beta 1 \ln(ADR)\, it + \beta 2 \ln(Supply) it + \beta 3 CGR_{it} + \beta 4 \ln(GDP) it + \beta 5 \ln(POP) it + u_{it} \quad (7)$$

Compared to the threshold model (see Eq. 4), we have added the interaction of country and day fixed effects ($\mu_i\ X\ \theta_t$) to capture the daily room revenue cycle for each sample country.

3. Results and discussion

Ignoring cross-sectional dependence may have serious consequences in terms of size distortions and low power for tests that assume cross-section independence (see Pesaran, 2015). This is especially the case when neighboring countries or countries with similar developments are considered as this study does. However, in macro panel data modeling where T>N as in this case, the problem of cross-section dependence is not so severe as in the case of micro panels (e.g longitudinal panels, where T<N is fixed).[2] Therefore, we proceed to the estimation of the benchmark model under various specifications along with the threshold model.

[2] We have checked though the existence of cross-section dependence, and the relevant tests suggest that we must reject the null hypothesis (e.g. cross-section independence) at the 1% level of significance. However, this is not a problem since the panel cointegration tests reveal the existence of a structural relationship between the sample variables securing the validity and consistency of the estimates. In other words, we argue that there exists a long-run cointegration between the variables considered in the model. To preserve space, the results are available from the authors upon request.

3.1. Results with the benchmark model

Table 2 presents the results from the baseline parametric (linear and quadratic) regressions. The linear specification estimates confirm the existence of a negative and statistically significant correlation between the lockdown stringency index and the (logged) level of hotel room revenues. The magnitude of the estimates between the two models (see Column 1 and 2) converges to -0.0244, denoting that, a one-unit increase in the lockdown stringency index will decrease the room revenues and subsequently the performance of the hotel industry by about 2.4%. This finding is expected since, during the lockdown period, there is a negative performance of hotels. The rest of the covariates (lnADR, lnSupply, GDP, and POP) when significant are properly signed (e.g. positive impact on hotel performance).

Similar findings are reported when we add in the model the quadratic term of the lockdown stringency index (see Column 3). The linear term of the index (CGR) is also negative and statistically significant and its magnitude almost equal to the previous finding (-0.0233). However, the quadratic term though negative is not statistically significant, supporting the linearity hypothesis.

As it is evident, the estimates are drawn from the augmented Model II (see Column 4) unveil a different picture, since they provide strong evidence for the existence of a non-monotonic "*U-shaped*" curvature between lockdown stringency and hotel performance across the sample countries. Specifically, both the linear influence of the lockdown stringency index (CGR) on hotel performance and its squared coefficient estimate (CGR^2) are statistically significant, alternating their signs starting from negative to positive.

3.2. Results with a threshold model

Before proceeding with the threshold estimates, we should first test the null hypothesis of no threshold against the alternative of threshold allowing heteroskedastic errors (White corrected). The LM-statistics, along with their bootstrap p-values, are presented in Table 3. We observe that the null hypothesis of no single threshold is rejected in all the three models (see Columns 1-3) since the bootstrap p-values are equal to zero. Consequently, we infer that there is only one threshold in all the regression relationships. This means that we reject the linearity hypothesis even at the 1% level of statistical significance for the included countries.

<Table 3 about here>

The sharp threshold point estimates ($\hat{\gamma}$) for the three models along with their 95% confidence intervals (CI) are also reported in the relevant table. The threshold estimates equal to 83.33 for models I and II (see Columns 1-2) and appears to be lower (52.78) when we use the log-log augmented specification of Model III (see Column 3).

More information about the threshold estimates can be obtained from plots of the confidence interval using likelihood ratio (LR) statistics (see Figures 1a and b). Specifically, the point estimates are the value of γ at which the LR equals zero (Hansen, 1999). From the inspection of the relevant figures, we observe that the (first-step) threshold estimate is the point where the LR (γ) equals zero, which occurs at $\hat{\gamma}$ = 83.33. Since there is not a statistically significant second major dip in the LR function, we argue that there is only one threshold in both specifications (Model I and II). The existence of a single threshold splits the sample into two regimes (low and high regime). The (high) regime above the threshold ($\hat{\gamma}$ >83.33) captures the upper higher levels of lockdown stringency since it includes the sample countries where the CGR exceeds the estimated value of 83.33. On the opposite, the (low) regime below the threshold

($\hat{\gamma}$ $\leq$83.33) includes the sample countries with a moderate or low lockdown stringency level.

<Figures 1a&b here>

It should be noted though, that testing a non-monotonic relationship between lockdown stringency and hotel performance using country-level data raises important empirical difficulties described as follows.

First, one significant issue is the sharp estimation of the turning point of this relationship. One simpler, but not accurate, way is to resort either to non-linear terms (i.e. quadratic terms of the CGR index) or to a non/semi-parametric specification using local smoothers or splines. However, such methods involve bandwidth choices, and they do not lend themselves to estimating sharp turning points/thresholds as it is the case in the threshold model (Polemis and Stengos, 2019). To solve this difficulty, we rely on the estimation of a static panel threshold model with FE firstly introduced by Hansen (1999) and later developed by Hansen, (2000), Bick, (2010), and Kourtellos et al., (2016). The adopted threshold model avoids the ad hoc, subjective pre-selection of threshold values, since it uses LM tests for the presence of such a threshold and then estimates it (Hansen, 2000; Kourtellos et al., 2016).

Second, we need to deal with the endogeneity of the lockdown stringency index in our empirical setting. As mentioned before endogeneity may arise from omitted variable bias or reverse causality and prevents us from arguing in favour of a causal effect. Similarly to other studies (Polemis and Stengos, 2017), we attempted to address the presence of a possible endogeneity of the regulatory variable (lnTRI) by using the lagged (CGR) as the regime-dependent (threshold) variable. It is noteworthy that our empirical results remained relatively robust. Therefore, we argue that the issue of endogeneity is not as severe in our case.[3]

Having properly addressed the above estimation problems, and after rejecting the linearity hypothesis (e.g. existence of one threshold), we proceed to the discussion of results generated by the single threshold model that will be contrasted with the baseline (benchmark) parametric estimates.

Table 4 presents the results for the threshold model under various specifications (Model I and II). As it is evident the lockdown stringency negatively and significantly affects the hotel performance if countries fall below the threshold level (CGR < 83.33). Specifically, the relevant estimate for both models equals to -0.024. This means that a one-unit change of the lockdown stringency index (CGR) incurs a decrease in the (logged) total room revenues by 2.4% for both log-level models. The relevant finding which is also traced in other studies (see for example Tsionas, 2020; Polemis, 2020) can be explained by the fact that the hotel industry has been hit hard by the pandemic crisis, therefore its total level of room revenues will follow a downward trend.

<Table 4 about here>

On the other hand, the impact of social distancing measures (e.g. lockdowns) on hotel performance is positive and statistically significant if and only if countries adopt such measures above the threshold level (CGR > 83.33). The relevant magnitude of the estimates ranges from 0,046 (Model II) to 0,127 (Model I), signifying that a one-unit change of the Coronavirus index will surprisingly increase the (logged) total room revenues even by 12.7%. From the magnitude of the estimated threshold coefficients, we argue that the impact of the lockdown stringency is more important in the sample above the threshold (high regime) than below it (low regime). This finding concurs that

[3] The results are available upon request.

for highly lockdown stringent tourism countries the adoption of "*austere*" social distancing measures does positively affect the hotel performance. Taken together, this study reveals that there is a non-monotonic "*U shaped*" (convex) relationship between hotel performance (proxied by the logged total room revenues) and lockdown stringency.

The relevant finding contrast some studies of the related literature who argue that there is a negative (linear) correlation between the pandemic crisis and the level of hotel performance for some tourism destinations (see for example Polemis, 2020; Sharma and Nicolau, 2020). The "*U-shaped*" curvature can be explained as follows. If tourism countries adopt restrictive measures below the threshold level (e.g. downward part of the curve), they experience lower hotel room revenues due to high up-front investment costs that need to undertake (e.g. hygiene measures, contactless technology, voice-based guest engagement solutions, mobile check-in programs, etc) to ensure cleanliness and health safety.

However, if tourism countries reach a threshold of lockdown stringency (high regime), then they start to benefit from economies of scale and decreased costs of the adopted social distancing measures, while the effect of the lockdown on hotel performance becomes positive and significant (e.g. upward part of the curve). On the demand side, hotel customers are more confident towards tourist destinations and countries that undertake severe restrictive social distancing measures since they believe that they will be more safe and secure. Moreover, during the ongoing pandemic crisis, many hotels offer multiple discounts to attract customers and increase their revenue levels. Lastly, regarding the rest of the covariates, we argue that they exhibit a positive and statistically significant correlation with the hotel performance. Overall, these findings are in alignment with previous studies (Yeon et al, 2020; Polemis, 2020).

4. Sensitivity analysis

To test the robustness of our findings, we conduct sensitivity analysis by using two alternative hotel performance indicators, as suggested by the existing literature (see for example Yeon et al, 2020; Polemis, 2020; Viglia et al., 2016; Xie and Kwok, 2017). Moreover, since, we uncover a non-monotonic relationship between hotel performance and lockdown government stringency measures, we employ the semi-parametric fixed effects model (SPFEM) developed in Baltagi and Li (2002) which is a flexible model not driven by the functional form and suitable for the presence of non-linearities (see Pesaran, 2015; Baltagi and Li, 2020).

4.1 Robustness tests: Alternative definitions of hotel performance

This section makes use of alternative definitions of hotel performance. Specifically, there is a literature that supports other hotel performance indicators, namely occupancy rate and revenue per available room (see among others Yeon et al, 2020; Xie and Kwok, 2017; Haywood et al., 2016; Viglia et al., 2016; Neves and Lourenço, 2009). Specifically, the occupancy rate directly denotes consumers' demand, which can be a consequent outcome of the regulation effect (Yeon et al, 2020). Similar to other related studies (see Yeon et al, 2020; Li and Srinivasan, 2019; Manson, 2006) we employ the (logged) revenue per available room, that addresses competition concerns, to provide robust estimates of the impact of coronavirus government regulation on hotel performance.

Table 5 reports the new empirical results along with the corresponding estimations. As it is evident, the results indicate that, once again, lockdown stringency exerts a statistically significant non-linear effect on hotel performance of a "*U-shaped*" type in all the specifications.

<Table 5 about here>

4.2. Robustness tests: A non-linear approach

This part of the empirical analysis makes use of the SPFEM, proposed by Baltagi and Li (2002) to properly test the robustness of the (non-linear) findings. This approach presents two main advantages. First, a SPFEM specification allows the hotel performance-lockdown index coefficient to vary not only across countries but also over time. Second, the relevant model allows for a smooth change in country-specific correlation, depending upon the threshold variable. Besides, semi-parametric modeling does not impose a specific functional form just like parametric techniques and is superior to the threshold analysis since it is not sensitive to the threshold variable chosen (see Polemis et al, 2019, Tran and Tsionas, 2010). The former implies that our model is not subject to misspecification error arising from potentially wrong functional forms, while the latter reflects the overall and true relationship between the sample variables.

Figures 2a and b, portray the relevant curvatures drawn from the estimation of the alternative semi-parametric fixed effects model (SPFEM) without including the extra covariates of GDP and POP (see Eq. 5/Model I).[4] As it is evident, from Figure 2a the convexity between lockdown stringency (CGR) and hotel performance (lnREV) is statistically significant and well preserved when B-splines are used to perform the nonparametric fit. It is evident from the shape of the curvature that there is a minimum "*threshold*" where beyond this turning point the effect of lockdown measures on total hotel room revenues becomes positive ("*U-shaped*"). Also, it becomes evident, that the turning point ("*threshold*") appears at a high level (around 80 units), which fully confirms our previous threshold model findings.

<Insert Figure 2a>

[4] The other two models provide similar curvatures. To preserve space the relevant results are available from the authors on request.

Similar findings are confirmed, when the SPFEM is estimated by employing the Epanechnikov kernel-weighted local polynomial smoothing. As it is observed from Figure 2b, the non-monotonic convex relationship between the lockdown stringency index and hotel performance remains intact and the turning point of the curve approaches the estimated threshold value reported before (83.33).

<Insert Figures 2b here>

5. Conclusions and policy implications

The scope of this paper is to assess the impact of restrictive social distancing measures -as in the case of national lockdowns- on the hotel industry of six international tourist destinations. Based on the empirical findings, we argue that the statistical significance of the single threshold statistic leads to the rejection of the linear "*hotel performance-lockdown stringency*" relationship.

In line with this, the empirical results indicate that the single threshold splitting the sample into two regimes concerning the CGR index appears at significantly high levels of lockdown stringency. The lockdown effect below this level is negative and statistically significant, while above this level, it turns out to be positive and statistically significant. Based on the threshold model results, under the (high) regime of strong increases in lockdown stringency (>83.33), other things being equal, a one-unit increase in lockdown stringency index will lead even to a 12,7% increase of the total room revenues. Whereas in the other (low) regime (<=83.33), the effect of the CGR index turns out to be negative and statistically significant, reducing the hotel performance by 2,4% on average in case of a one-unit increase in the related social distancing index.

The empirical findings postulate tourism countries with a lockdown stringency index below this threshold, experience a moderate decrease in their hotel performance industry as a result of the novel coronavirus outbreak, whereas in countries with a CGR index above this threshold, any relaxation in the lockdown measures adopted to mitigate the pandemic spread, will negatively affect the performance of the hotel industry. Taken together, the anti-pandemic social distancing measures exhibit a non-linear convex pattern on the performance of the hotel industry.

This finding could be important for policy modeling considering the gradual reopening of the hotel industry in the aftermath of the pandemic crisis. Specifically, if policymakers would have relied only on linear (parametric) models, then they would have concluded that social distancing measures are negatively correlated with hotel performance. However, our findings with the threshold model unveil a different story. In all the underlying specifications, the governments' social distancing measures to curb the spread of the ongoing SARS-COV-2 outbreak are positively and significantly associated with hotel performance for the whole sample of countries as long as these countries adopt lockdown measures above a given threshold.

One of the most important strategies the hotel industry should implement to reach the upward part of the curve is to undertake some necessary infrastructure investments (e.g. cleaning and sanitizing systems, hard flooring, air handling systems, etc) to maintain a safe and secure environment for its guests and personnel. Moreover, contactless technologies, including robots and artificial intelligence (AI) may help hotel facilities to decrease their fixed costs, improve liquidity and resilience and help to maintain social distance (Assaf and Scuderi, 2020). Another crucial issue assisting the hotel industry to increase room revenues is related to pricing strategies. Many hotels must come up with multiple offers and discounts to appeal to customers, including inter alia lower rates for midweek bookings, shorter minimum night stays, long-term discounts, and vouchers for their restaurants. Besides flexible prices, terms, and conditions can reduce risks and increase financial liquidity.

Lastly, this study is not free from research limitations. One of the most prominent ones is related to the small sample size. Future research may rely on more tourist countries or regions to test the validity of the current findings across larger cross-section units (N). Moreover, this study investigates the threshold level of lockdown measures when a panel data framework is used, and thus a future study may use time series threshold models to examine potential thresholds for a given country (region). Another shortcoming is the absence of the investigation of spatial characteristics on the hotel industry as suggested by Cook et al, (2020), who argue that social distancing is affected by the policies set in neighboring counties, even after controlling for confirmed COVID cases.

References

Assaf, A., and Scuderi, R. (2020) COVID-19 and the recovery of the tourism industry, *Tourism Economics*, vol 26 (5): 731-733.

Baltagi, B., and Pesaran. H. (2007). Heterogeneity and cross section dependence in panel data models: theory and applications introduction. *Journal of Applied Econometrics* 22 (2): 229-232.

Baltagi, B.H., and Li, D. (2002). Series estimation of partially linear panel data models with fixed effects. *Annals of Economics and Finance*, 3(1), 103–116.

Bick, A. (2010). Threshold effects of inflation on economic growth in developing countries. *Economics Letters,* 108: 126–129.

Cook, J., Newberger, N., and Smalling, S. (2020). The spread of social distancing, *Economics Letters*, 196, https://doi.org/10.1016/j.econlet.2020.109511.

Eleftheriou, K., and Patsoulis, P. (2020). COVID-19 Lockdown Intensity and Stock Market Returns: A Spatial Econometrics Approach, MPRA Paper 100662, University Library of Munich, Germany.

Farzanegan, M.R., Gholipour, H.F., Feizi, M., Nunkoo, R., and Andargoli, A.E (2020). International Tourism and Outbreak of Coronavirus (COVID-19): A Cross-Country Analysis, *Journal of Travel Research*, https://doi.org/10.1177/0047287520931593

Gössling, S., Scott, D., Hall, C. M. 2020. Pandemics, Tourism and Global Change: A Rapid Assessment of COVID-19. *Journal of Sustainable Tourism* 1-20.

Hale, T., Webster, S. Petherick, A., Phillips, T., Kira, B. (2020). Oxford COVID-19

Government Response Tracker, Blavatnik School of Government. Data use policy: Creative Commons Attribution CC BY standard.

Hansen, B.E., (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica* 64, 413–430.

Hansen, B.E., (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. *Journal of Econometrics*. 93, 345–368.

Hansen, B.E., (2000). Sample splitting and threshold estimation. *Econometrica* 68, 575–603.

Haywood, J., Hoyt, A., Wilson, C., Hennis, S., and Alvarado, C. (2016). STR: Airbnb's impact minor on Manhattan hotels. http://www.hotelnewsnow.com/Articles/29639/STR-Airbnbs-impact-minor-on-Manhattan-hotels,

Kourtellos, A., Stengos, T., and Chih, T. M. (2016). Structural Threshold Regression. *Econometric Theory*, 32(4), 827–860.

Li, H., and Srinivasan, K. (2019). Competitive dynamics in the sharing economy: An analysis in the context of Airbnb and hotels. *Marketing Science*, 38(3), 365–391.

Manson, E. (2006). RevPar needs an overhaul. *Caterer and Hotelkeeper*, 196, 16.

Mariolis, T., Rodousakis, N., and Soklis, G. (2020). The COVID-19 multiplier effects of tourism on the Greek economy, *Tourism Economics* https://doi.org/10.1177/1354816620946547.

Neves, J. C., and Lourenço, S. (2009). Using data envelopment analysis to select strategies that improve the performance of hotel companies. *International Journal of Contemporary Hospitality Management,* 21(6): 698-712.

Pesaran, M.H. (2015). *Time series and panel data econometrics*. Oxford University Press.

Polemis, M. (2020). The impact of COVID-19 on hotel performance: Evidence from a Difference-in-Differences approach, *MPRA Paper 102053*, posted June 2020

Polemis, M., Stengos, T., and Tzeremes, N. (2019) Revisiting the impact of financial depth on growth: A semi-parametric approach, *Finance Research Letters*, 2019, https://doi.org/10.1016/j.frl.2019.101322.

Polemis, M., and Stengos, T., (2019). Does competition prevent industrial pollution? Evidence from a panel threshold model, *Business Strategy and the Environment*, 28(1): 98-110.

Polemis, M., and Stengos, T., (2017). Electricity Sector Performance: A Panel Threshold Analysis, *The Energy Journal*, 0 (Number 3).

Qiu, R., Park, J., Li, S and Song, H. (2020). Social costs of tourism during the COVID-19 pandemic, *Annals of Tourism Research*, 84, https://doi.org/10.1016/j.annals.2020.102994

Roser, M., Ritchie, H., Ortiz-Ospina, E,, and Hasell, J. (2020). Coronavirus Pandemic (COVID-19). Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/coronavirus.

Savvides, A., and Stengos, T. (2000). Income inequality and economic development: evidence from the threshold regression model, *Economics Letters*, 69(2): 207-212.

Sharma, A., and Nicolau, J.L. (2020). An open market valuation of the effects of COVID-19 on the travel and tourism industry, *Annals of Tourism Research*, https://doi.org/10.1016/j.annals.2020.102990.

Tran, K., and Tsionas, M. (2010). Local GMM Estimation of Semiparametric Panel Data with Smooth Coefficient Models, *Econometric Reviews*, 29(1): 39-61.

Tsionas M. (2020). COVID-19 and gradual adjustment in the tourism, hospitality, and related industries, *Tourism Economics*, DOI: 10.1177/1354816620933039.

Viglia, G., Minazzi, R., and Buhalis, D. (2016). The influence of e-word-of-mouth on hotel occupancy rate. *International Journal of Contemporary Hospitality Management*, 28(9), 2035–2051.

Villa, J.M. (2016) diff: Simplifying the estimation of difference-in-differences treatment effects, *The Stata Journal* 16 (1): 52‑71.

Xie, K. L., and Kwok, L. (2017). The effects of Airbnb's price positioning on hotel performance. *International Journal of Hospitality Management*, 67, 174–184.

Yang, Y., Zhang, H., Chen, X. (2020). Coronavirus pandemic and tourism: Dynamic stochastic general equilibrium modeling of infectious disease outbreak. *Annals of Tourism Research*.

Yeon, J., Song, H.J., Lee, S. (2020). Impact of short-term rental regulation on hotel industry: a difference-in-differences approach, *Annals of Tourism Research*, 83, https://doi.org/10.1016/j.annals.2020.102939.

Zenker, S., and Kock, F. (2020). The coronavirus pandemic – A critical discussion of a tourism research agenda, *Tourism Management*, 81, https://doi.org/10.1016/j.tourman.2020.104164.

Tables & Figures

Table 1: Descriptive statistics

Variables	Observations	Mean	Median	Min	Max	SD	Skewness	Kurtosis
ln(REV)	1,098	15.54	15.61	12.33	18.35	1.592	-0.293	2.342
ln(ADR)	1,098	4.852	4.682	3.736	6.783	0.661	0.895	2.950
ln(Supply)	1,098	12.52	12.59	11.47	13.37	0.579	-0.250	1.842
GDP	1,098	30,96	31,10	24,57	38,61	5,349	0.0831	1.381
POP	1,098	120.4	108.6	83.48	205.9	40.27	1.405	3.546
CGR	1,098	54.82	63.89	0	93.52	29.57	-0.666	2.140
CGR^2	1,098	3,879	4,082	0	8,746	2,758	0.0036	1.782
ln(PAR)	1,098	3.029	3.277	0.694	5.773	1.337	-0.090	2.159
ln(OCC)	1,098	2.782	2.826	0.241	4.371	1.064	-0.778	3.191

Notes: lnREV denotes the logged total daily room revenue. lnADR denotes the logged average daily room rate, lnSupply is the logged room availability, GDP denotes the Gross Domestic Product per, POP is the population density, CGR and CGR^2 denote the Coronavirus Government Response Tracker Index in levels and in its quadratic form, lnPAR is the logged revenue per available room and lnOCC denotes the logged room occupancy rate.

Table 2: Baseline Regression Results

	Linear estimates **Dependent variable ln(REV)**		*Non-linear estimates* **Dependent variable ln(REV)**	
Variable	**(1) Model I**	**(2) Model II**	**(3) Model I**	**(4) Model II**
ln(ADR)	0.798^{*} (0.348)	1.417^{***} (0.035)	0.787^{*} (0.371)	1.420^{***} (0.0344)
ln(SUPPLY)	0.0268 (0.641)	0.515^{***} (0.056)	0.00027 (0.516)	0.547^{***} (0.0553)
GDP	-	0.000165^{***} (1.05e-05)	-	0.000162^{***} (1.02e-05)
POP	-	-0.000301 (0.00035)	-	-0.000135 (0.000339)
CGR	-0.0244^{***} (0.00492)	-0.0244^{***} (0.0009)	-0.0223^{*} (0.0115)	-0.0357^{***} (0.00316)
CGR^2	-	-	-2.11e-05 (0.000102)	0.000116^{***} (3.03e-05)
Constant	12.62 (7.751)	-1.604^{***} (0.368)	13.00^{*} (6.138)	-1.953^{***} (0.369)
Diagnostics				
Observations	1,098	1,098	1,098	1,098
Country FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Day X Country FE	Yes	Yes	Yes	Yes
R-squared	0.866	0.914	0.867	0.915
Shape of the curve	Negative (linear)	Negative (linear)	Negative (linear)	U-shaped (Non-linear)

Note: Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6. The dependent variable in all the models is the logged total daily room revenue (lnREV). The independent variables are the logged average daily room rate denoted by lnADR, the logged room availability denoted by lnSupply, the GDP per capita denoted by GDP, the population density (POP) and the Coronavirus Government Response Tracker Index in levels and in its quadratic form, denoted by CGR. Time and country fixed effects (FE) are included but not reported. Robust standard errors in parentheses. Significant at ***1%, **5% and *10% respectively.

Table 3: Test for single threshold

	Model I	Model II	Model III
Threshold estimate γ	83.33^{***} [83.33, 83.33]	83.33^{***} [77.78, 83.33]	52.78^{***} [49.54, 83.33]
LM	141.221	243.764	254.97
Bootstrap P-value	0.000	0.000	0.000

Note: Test of null hypothesis of no threshold against alternative of threshold allowing heteroskedastic errors (White Corrected). The trimming percentage is set to 0.15 and the Bootstrap replications are set to 2,000. The numbers in brackets denote the 95% robust confidence intervals. Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6, while Model III is simply the log-log augmented specification expressed in Eq. 7. Significant at ***1%

Table 4: Panel Threshold Regression Results

	Model I Dependent variable ln(REV)		Model II Dependent variable ln(REV)	
Variables	**(1) Low regime**	**(2) High regime**	**(3) Low regime**	**(4) High regime**
ln(ADR)	1.089^{***} (0.0204)	0.329^{***} (0.074)	1.344^{***} (0.0324)	0.390^{***} (0.047)
ln(SUPPLY)	1.527^{***} (0.0204)	1.691^{***} (0.066)	1.135^{***} (0.0479)	0.898^{***} (0.052)
GDP	-	-	0.000061^{***} (6.2532e-06)	0.00012^{***} (5.0236e-06)
POP	-	-	0.0013^{**} (0.00044)	-0.0012^{**} (0.00032)
CGR	-0.024^{***} (0.0005)	0.127^{***} (0.006)	-0.0241^{***} (0.00052)	0.046^{***} (0.0062)
Constant	-7.503^{***} (0.415)	-19.802^{***} (1.251)	-5.858 (0.430)	-6.819^{***} (0.950)
Observations	904	194	904	194
Countries	6	6	6	6
R-squared	0.848	0.920	0.864	0.978
Residual variance	0.363	0.081	0.327	0.0205
Shape of the curve	U-shaped		U-shaped	

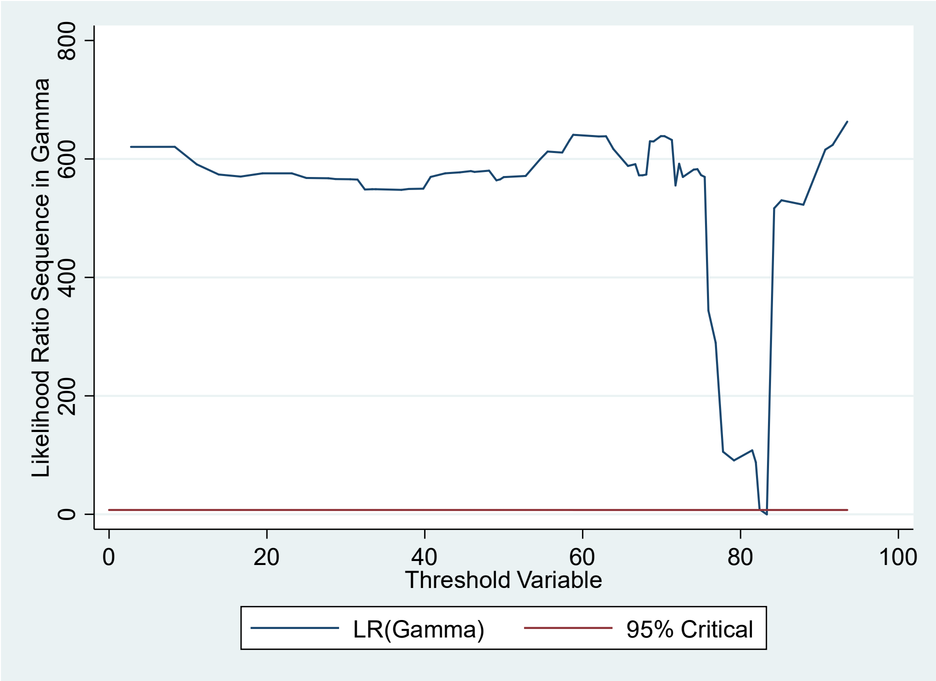
Note: Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6. The dependent variable in all the models is the logged total daily room revenue (lnREV). The independent variables are the logged average daily room rate denoted by lnADR, the logged room availability denoted by lnSupply, the GDP per capita denoted by GDP, the population density (POP) and the Coronavirus Government Response Tracker Index in levels and in its quadratic form, denoted by CGR. White heteroscedasticity corrected standard errors in parentheses. Significant at ***1%, and **5% respectively.

Table 5: Robust Panel Threshold Regression Results

	Model I Dependent variable ln(OCC)		**Model II Dependent variable ln(OCC)**		**Model I Dependent variable ln(PAR)**		**Model II Dependent variable ln(PAR)**	
Threshold	83.33^{***} [83.33, 83.33]		83.33^{***} [77.78, 83.33]		83.33^{***} [83.33, 83.33]		83.33^{***} [77.78, 83.33]	
Variables	**(1) Low regime**	**(2) High regime**	**(3) Low regime**	**(4) High regime**	**(5) Low regime**	**(6) High regime**	**(7) Low regime**	**(8) High regime**
ln(ADR)	0.088^{***} (0.0205)	-0.671^{***} (0.074)	0.344^{***} (0.032)	-0.610^{***} (0.047)	1.088^{***} (0.0204)	0.329^{***} (0.074)	1.345^{***} (0.0324)	0.3909^{***} (0.047)
ln(SUPPLY)	0.527^{***} (0.034)	0.691^{***} (0.066)	0.135^{***} (0.048)	-0.102^{***} (0.053)	0.527^{***} (0.034)	0.691^{***} (0.066)	0.135^{***} (0.0479)	-0.1021^{***} (0.0527)
GDP	-	-	0.00006^{***} (6.2581e-06)	0.0001^{***} (5.0236e-06)	-	-	0.00006^{***} (6.2521e-06)	0.00012^{***} (5.0236e-06)
POP	-	-	0.0013^{***} (0.0004)	-0.0012^{***} (0.0003)	-	-	0.0013^{***} (0.0004)	-0.0012^{***} (0.0003)
CGR	-0.0236^{***} (0.0005)	0.127^{***} (0.006)	-0.024^{***} (0.0005)	0.046^{***} (0.0062)	-0.024^{***} (0.0005)	0.127^{***} (0.006)	-0.0241^{***} (0.0005)	0.046^{***} (0.0062)
Constant	-2.899^{***} (0.415)	-15.197^{***} (1.251)	-1.257^{***} (0.429)	-2.214^{***} (0.950)	-7.503^{***} (0.415)	-19.802^{***} (1.251)	-5.857^{***} (0.429)	-6.819^{***} (0.950)
Observations	904	194	904	194	904	194	904	194
Countries	6	6	6	6	6	6	6	6
R-squared	0.620	0.894	0.658	0.973	0.768	0.791	0.791	0.948
Residual variance	0.363	0.081	0.328	0.0205	0.363	0.081	0.327	0.0205
Shape of the curve	U-shaped		U-shaped		U-shaped		U-shaped	

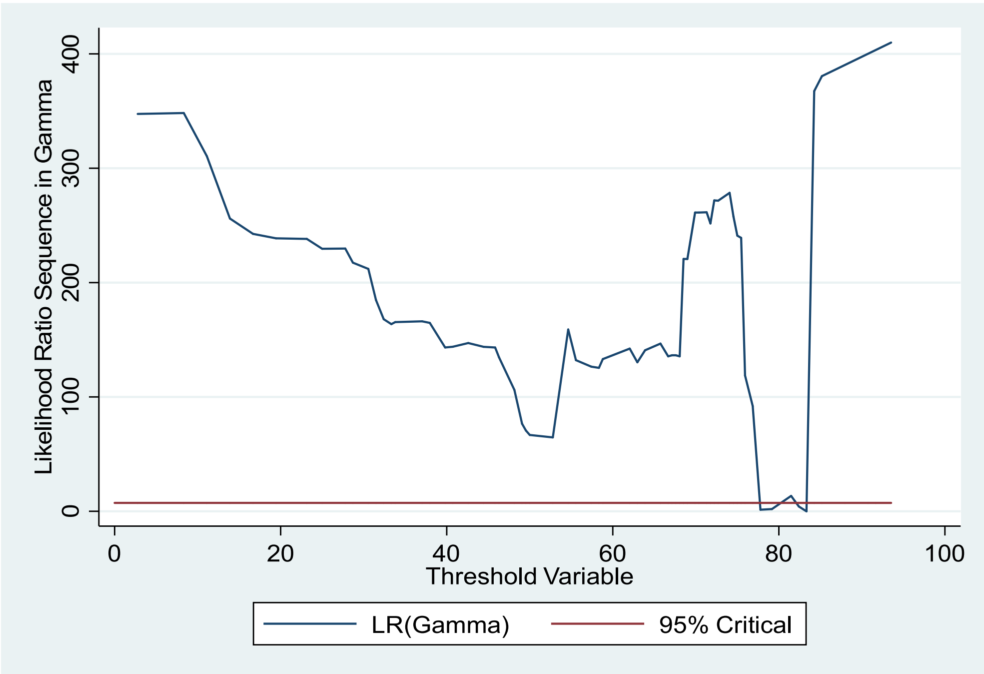
Note: Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6. The independent variables are the logged average daily room rate denoted by lnADR, the logged room availability denoted by lnSupply, the GDP per capita denoted by GDP, the population density (POP) and the Coronavirus Government Response Tracker Index in levels and in its quadratic form, denoted by CGR. White heteroscedasticity corrected standard errors in parentheses. The numbers in brackets denote the 95% robust confidence intervals. Significant at ***1%.

Figure 1a: Confidence interval construction when CGR is used as a threshold variable (Model I)



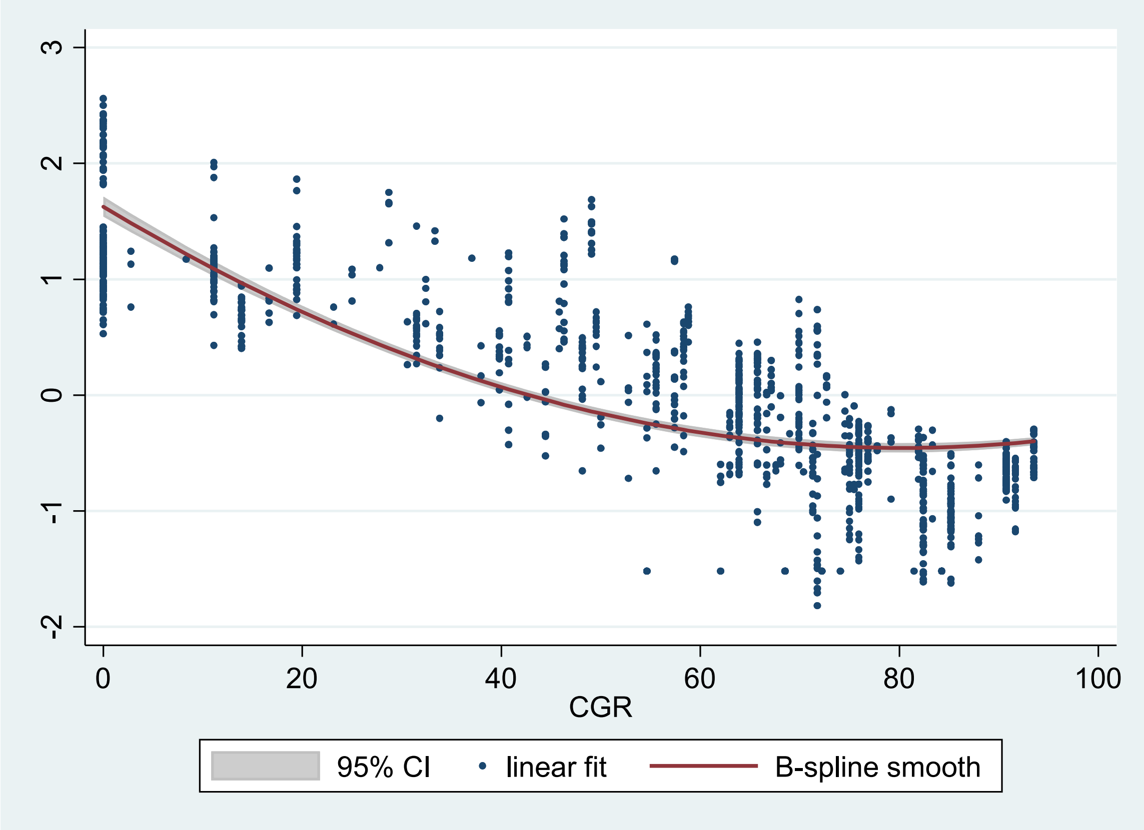
Notes: Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6. The figure shows the Likelihood Ratio confidence interval in the single threshold model (Model I). The red line denotes the critical value at the 95% confidence level.

Figure 1b: Confidence interval construction when CGR is used as a threshold variable (Model II)



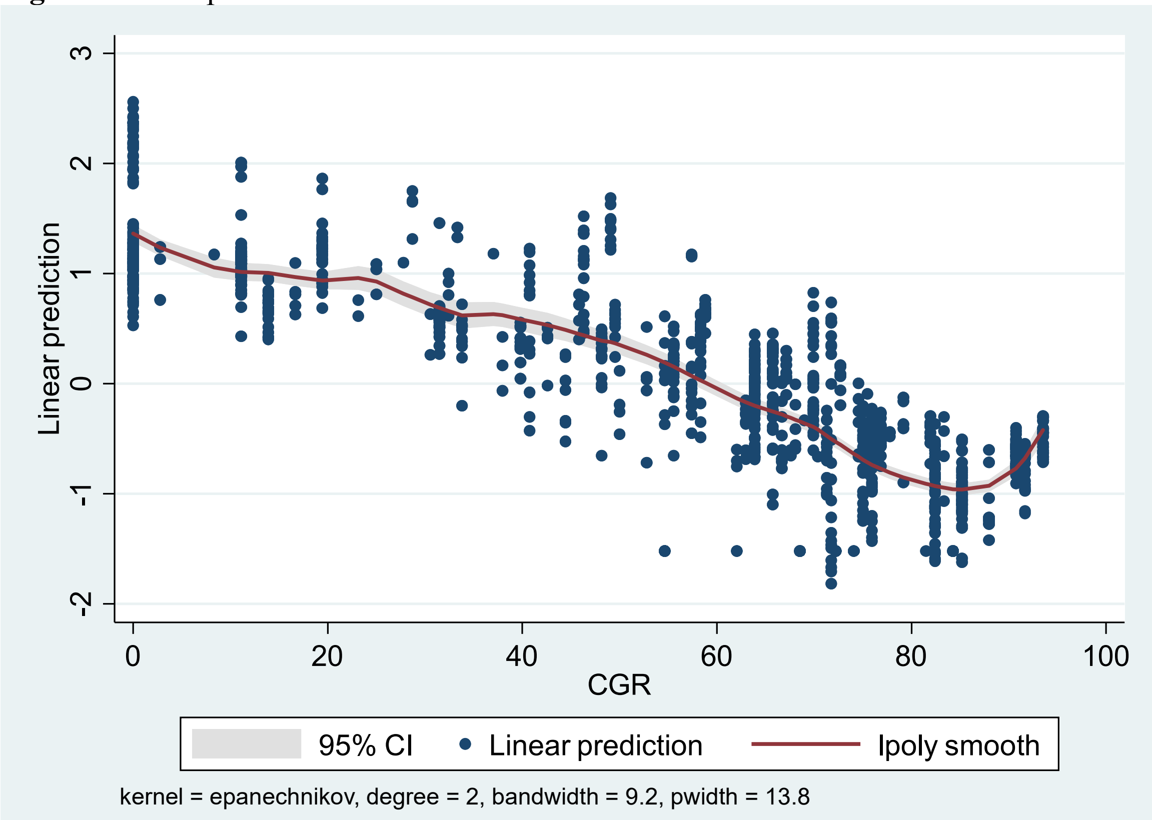
Notes: Model I refers to the primary baseline specification reported in Eq. 5. Model II stands for the augmented baseline specification with the two extra covariates (GDP and POP) reported in Eq. 6. The figure shows the Likelihood Ratio confidence interval in the single threshold model with the extra covariates (GDP and POP). The red line denotes the critical value at the 95% confidence level.

Figure 2a: Nonparametric estimates of CGR for Model I



Notes: The dots in the graph represent the estimated partial residuals for hotel performance in the semi-parametric specification of Model I. The maroon curve illustrates the semi-parametric estimation of f(CGR). The B-splines of power (degree) two were used to perform the nonparametric fit. The gray shaded area denotes the 95% confidence bands. The type of standard errors reported is corrected using the Huber/White/sandwich estimator.

Figure 2b: Nonparametric estimates of CGR for Model I



Notes: The dots in the graph represent the estimated partial residuals for hotel performance in the semi-parametric specification of Model I. The maroon curve illustrates the semi-parametric estimation of f(CGR). The Epanechnikov kernel-weighted local polynomial smoothing of power (degree) two was used to perform the nonparametric fit. A rule-of-thumb kernel bandwidth estimator is calculated and used. A half-width of 13.8 of the smoothing window around each point was used. The gray shaded area denotes the 95% confidence bands. The type of standard errors reported is corrected using the Huber/White/sandwich estimator.