Effect of Demand Volatility on Productivity in the European Hotel Industry

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Abstract

This article empirically tests whether the productivity of an industry with high adjustment costs is affected by an external factor such as changes in the demand. Using the capacity utilization (occupation) of the quasi fixed factor (capital) as the measure of productivity, I find that at the metro area-segment-year level, the productivity of European hotels which face high adjustment costs of capacity, in some cases, is negatively affected by demand volatility, and in other cases, it is not affected.

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1 Introduction

Since the second half of the 20th century, tourism has become a stable and steady trigger of economic development of many countries and Europe has become a very important destination, attracting 51% of the global tourist arrivals and 36% of the international tourism receipts in 2018. By the same year, the influence of tourism business in Europe was close to 3.5% of the GDP and created about 3.7% of the total employment (World Travel and Tourism Council, 2018, as cited by Mitra, Chattopadhyay and Jana, 2019).

Economic growth is what primarily drives the development of countries. To improve productivity of firms is the first step to increase the welfare of societies, and understanding the factors that drive the productivity of a business is crucial to improve the performance of a firm. At a micro level, there are different strategies at the disposal of managers to plan the best mix of inputs to generate as much output as possible. But what about other circumstances that are out of the control of managers? There exist external factors that are not being accounted for in the scheduling done by managers that could be affecting their performance without them being aware of it. As will be described in the next chapter, Syverson (2011) mentions that productivity spillovers, intra-market competition, trade competition, flexible input markets and deregulation or proper regulation are part of these external factors.

This paper will follow the theoretical model of production and the empirical approach of Butters (2020). The premise of this model is based on three main components: the demand volatility that firms face, the adjustment costs and their subsequent productivity. The level of adjustment costs is crucial for the effect of demand volatility on productivity: having low adjustment costs would imply no effect of demand volatility on productivity, whereas having high adjustment costs would translate into a drop in productivity.

One of the first theories that relate some of these components was developed by Pindyck (1982). The author created a dynamic model of the firm that combines the uncertainty of demand with input factors. In response to the uncertainty from the demand side, some of these input factors can be easily adjusted and some cannot. An example of inputs that are easy to adjust is the case of labor. On the other hand, one of the input factors that are costly to adjust, and therefore, are quasi-fixed, is capital. In the hospitality context, capital is presented in the form of capacity.

If firms were able to adjust capacity freely, then the uncertainty of demand would not influence the performance of the firms. Further, if firms could use inventories, the need for short-term adjustments in capacity would be smaller, but to build these reserves is also costly. The main result of the theoretical model of Pindyck (1982) is that if the marginal adjustment costs are rising at an increasing rate, the shifts in demand will increase (1) the desired capital stock (capacity) and (2) the output level of firms.

Similarly, the model of production of Butters (2020) explains that when two firms have identical technical productivities, but face different levels of demand volatilities, they will perform differently. Even in the case where both firms use inputs in an efficient way, they will have different unit costs. This will be reflected in the utilization rates of the inputs that have high adjustment costs (such as capital). Empirically, the author tests the model by using the hotel industry and the airline industry as examples of firms with high adjustment costs and firms with low adjustment cost, respectively.

Butters (2020) predicts that in hotels, the effect of demand volatility on productivity should be negative and different from zero, whereas in airlines, the effect of demand volatility should be zero. The author uses the hotel and airline industries to test the effects of demand volatility on productivity because it is composed of firms with volatility of sales. Furthermore, they "produce" perishable goods, which means it is not possible to have inventories. The study of Butters focuses on the American market and it is used as inspiration for the present article to investigate the European market, specifically the hotel industry.

The research question of this article is: What is the effect of predictable demand volatility on the measured productivity of the hotel industry in Europe? The main analysis will evaluate panel observations between the years 2006 and 2009, allowing me to see the differences between the European and American contexts (the American results are those of Butters, 2020). Following this, I will test the research methodology in a longer time period, from 2006 until 2020 to see whether the effects are consistent through time. My main hypothesis is that, given that the hotel industry has very high fixed and adjustment costs, to deal with volatile changes in the demand will negatively affect its productivity.

To answer the research question, I run several regressions in which the dependent variable is the occupation levels as a measure of productivity, and the independent variable is the demand volatility that hotels face. I use monthly data on the quantity of room nights sold in hotels located in 17 touristic cities around Europe to calculate the yearly demand volatility. As a source of exogeneity, I use an instrumental variable that will hopefully capture the pure effect of *shifts* in the demand that hotels face. This instrument will be abstracting from possible effects deriving from the supply side of hotels such as management decisions on pricing strategies that could likely generate movements *along* the demand curve.

Having two measurements of the demand volatility, I obtain different results with each of them. (1) With the first measurement, estimating the volatility of demand with a coefficient of variation, in a short sample between 2006 and 2009 I find that by having more demand volatility, the productivity of hotels in Europe defined as levels of occupation could be negatively affected. However, the coefficients in the regression are not statistically significant. Whereas in a longer sample from 2006 to 2020, the effect is most likely null. (2) When using the second measurement of demand volatility, the instrumental variable, in the shorter sample it is clear that the effect of demand volatility is negative, decreasing the occupation by 41.2%. Whilst in the longer sample, the instrument is not statistically significant but suggests a relatively small negative effect: at most -12.5% change in productivity, although in some robustness checks, it suggests a null effect.

This study sheds light on external factors that can be affecting the productivity of hotels in Europe. Currently, in the management literature there are studies on internal factors and the drivers of technical productivity (the optimal mix of inputs). However, there is not enough research in economics related to the effects of environmental factors affecting the performance of businesses, and even less research in the European context. This study is between the first ones testing empirically the effect of external factors in productivity at the microeconomic level in Europe. This article is showing the first evidence that there are negative fluctuations in productivity derived from predictable changes in the demand in the European hotel industry. These changes in demand are predictable since they are actually known by the industry, occur on a monthly basis, and are generally driven by well studied seasonal fluctuations. Consequently, even though managers can do demand forecasting and plan accordingly, the volatility itself can still be having a negative impact on performance of hotels. Therefore, this study opens the door to keep exploring other environmental elements that could also have undesirable effects on industries within the continent.

With the contemporary rapid development of technology, it is mandatory to investigate, for example, how regulations would affect the productivity of start-ups, or how productivity spill-overs are helping some inefficient firms to survive, rather than these firms staying in the competition due their own innovations and optimal utilization of resources. Furthermore, this study helps to realize that there is not enough economic research being done in the industry in the aggregate European context. Most of the available articles are related to management practices but economical components are not being investigated.

The paper proceeds as follows. In section 2 I will show some of the relevant work that has been done related to the important variables of the model that will help me to answer the research question, afterwards, the theoretical model from which the analysis is rooted will be presented. In section 3 the research design is explained, the motivation behinds it and the data used in this analysis. In section 4 I present the results of the main analysis and in section 5 I show some robustness checks with different ways of calculating the main variables. Furthermore, I show the results for a different time sample in section 6. In section 7 I present my conclusion and offer some discussion where I present opportunities for future research that could further explain my results.

2 Theoretical Background

2.1 Related literature

A starting point when discussing the important elements related to the findings of this article is to understand what drives the productivity of a firm. The first step is to look at the total factor productivity (TFP). Diewert & Nakamura (2007) define the TFP as the rate of transformation of total input into total output, while Comin (2006) defines it as the portion of output not explained by the amount of inputs used in production.

From the point of view of Syverson (2011) it is even a complex task to define the output and the input. The author describes that the classical models explain that to achieve long-run growth in the income per capita of a country, there must be a significant growth in the TFP. In order for the growth in the TFP to happen, there must be innovation and this is incorporated in the models when monopolistic rights are given as an incentive to the innovator to make up for the innovation costs. The endogenous growth models started to clarify what the influences are behind the improvement of the TFP, among which it is possible to mention research and development subsidies, plenty of skilled labor and the increase in the size of the markets that leads to more revenues.

Aguirregabiria (2019) explains that there are two types of differences between the TFP across firms: those that are large and those that are persistent.

– The large differences come from empirical studies that show that the most productive firms within an industry are 1.92 times more productive than those firms in the 10th percentile of the distribution of the productivity, and even in the case of developing countries, this ratio can go up to 5 times.

– On the other hand, the persistent differences are measured with the slope parameter calculated with a regression of the log(TFP) of a firm on the log(TFP) of the previous year of the same firm, and the empirical studies show that the resulting coefficient goes between 0.6 and 0.8.

It is still uncertain which mechanisms are behind the differences between the productivity of firms, whether firms can actually take part and influence these factors or whether these factors are merely exogenous. Nevertheless, the mechanisms impacting the productivity could be classified as internal and external factors.

Aguirregabiria (2019) mentions the endogenous factors which are the ways that firms can affect their TFP and have been empirically tested: the human resources and managerial practices, learning by doing, organizational decisions (such as outsourcing or vertical integrations), adoption of new technologies, investment in research and development, and innovation.

In contrast, Syverson (2011) discusses how the environment can have an effect on the productivity levels and growth of the firms. There are external elements can have an indirect effect by altering the incentives of the firms to utilize the endogenous factors that improve their TFPs. In general, the external factors can happen within the firms by improving the productivity of each producer, and between firms (Darwinian selection), where the more efficient producer will grow faster and can eventually replace the less efficient businesses in the competition. Between these factors, it is possible to find the productivity spillovers, intra-market competition, trade competition, flexible input markets and deregulation or proper regulation.

In the following part of this subsection I will introduce how other researchers have studied productivity, in some of the cases only by considering internal factors and in others, only external factors. I mention the drivers that they considered important for productivity in the contexts of their investigations, the different measurements that they have implemented to analyze their data, and their findings.

Freeman et al. (2011) study the impact of an internal factor such as innovation in the productivity of one of the more efficient firms in the United States: Wal-Mart. They review the results found by the McKinsey Global Institute (2001) over the contribution of information technology relative to other input factors in the performance of Wal-Mart. An important insight of this case is that even though the technology that this company applied was not recently created, the way in which it was mixed with managerial and organizational innovations resulted in an enormous impact in the productivity growth in the U.S. in 2001.

To investigate the productivity of Wal-Mart, McKinsey Global Institute (2001) uses the labor productivity as a proxy, and measures it as the output divided by a measure of labor input. Freeman et al. (2011) point out that the interactions between the retail and wholesale industries are important. In the case of Wal-Mart, the company took the decision of doing its own distribution and has reduced the participation of wholesalers taking them out of the competition. Between they key factors that positioned Wal-Mart as retail leader were: collecting big data to improve operations, sharing the data with business partners to help them reduce costs, developing bar codes labels, using radio frequency identification (RFID) tags to scan multiple products at once and hiring centralization.

The hiring innovation was key because it allows Wal-Mart to have a steady supply of skilled candidates, giving the firm a stronger position when fighting unions. The unions have tried to organize workers to deter the Wal-Mart expansion and the company has responded by closing down the stores where workers unionized. Nevertheless, the study of Devicienti et al. (2018) found that the effect of workplace unionization makes firms use more temporary contracts when there are low levels of demand volatility, and less temporary contracts when there are high levels of demand volatility. This helps unionized firms to lessen the impact of volatility compared to firms that do not have unions. In conclusion, the case of Wal-Mart is an example of how the factors that the firm can control affect its productivity and in the case of such a strong company, then the spillover effects of its technological changes also affect its partners.

Another study related to the internal factors affecting productivity was done by Brown and Dev (2000). In this case two large hotel chains in the United States were analyzed to investigate the drivers of their productivity. In the model used, the output is explained by inputs including capital, labor and managerial decisions. They abstracted from environmental factors such as competitive intensity, market size, growth, labor quality and availability, and capital costs and availability, because they did not have data to assess their impact. Consequently, this is a good example where studies on the hotel industries are ignoring the external factors that can be affecting the productivity of the firms, as those mentioned above, from Syverson (2011). The way in which Brown and Dev (2000) measured the components of their model of production is as follows:

– The output was measured similarly to the way in which McKinsey (2001) measured the output of Wal-Mart: the value added. In this case, it was the firm's sales revenues of the last year minus the fees remitted to the chain to which they belong

– The inputs were measured using the number of full time and part time workers, the number of rooms available for sale, intangible assets, the price positioning (to which segment they serve, from economy to luxury), the business strategy, and whether the hotel is owned by a chain.

The results found by Brown and Dev (2000) after studying the 247 hotels in their sample were that the changes in productivity varies depending on the size of the hotels. Nevertheless, for all sizes the increase in the number of employees significantly raises the value added of the firms. Lastly, when the management is executed by an external party, large hotels seem to improve their efficiency. In general, the marginal product of labor increased as the size of the hotel increased, whereas the marginal product of capital varied depending on the size of hotels. This study completely abstracts from environmental elements that could affect the productivity of hotels, therefore, it shows that to study external factors is an important issue to truly understand the drivers of productivity.

In contrast, Park et al. (2016) study both endogenous and exogenous factors that influence productivity. In this case, a monthly series of disaggregated panel data from 43 hotels in the U.K. is used to see the effect of demand variation on service productivity. The authors explain that the demand variation shows up in the form of business cycles and seasonal fluctuations:

– The demand variation from business cycles happens in a long term horizon. It occurs when, for example, higher levels of unemployment translate into lower disposable incomes, and when drops in asset prices and capital push firms away from debt, and hence, decreasing investment in innovation, which will have implications for productivity levels.

– The demand variation from seasonal fluctuations is shaped by two factors: (1) the institutional factors, which are customary behavioral patterns driven by public holidays, school schedules, and cultural and religious events such as Christmas; and (2) the natural factors, for example, climatic changes.

In the case of the sample of Park et al. (2016) in the U.K. between 2005 and 2013, it was clear that the occupancy of hotels every year was at its minimum in late winter, while the peak was between May and September. The seasonal fluctuations can affect the hotels both in the off-peak and peak seasons. When demand is very low, there are dramatic drops in revenue due to underutilized capacity and the constant fixed costs of operation. This means that during peak seasons, the firms must generate sufficient money to sustain the business the whole year. However, a low demand season also allows the hotels to do maintenance, to create new structures and to develop new markets, which will increase the long term productivity. Nonetheless, given the adjusting costs of managing staff, the seasonality is still a challenge, and the way to work through it is with labor flexibility.

The point of view of the analysis of Perk et al. (2016) is focused on the chase demand strategies (such as flexible working) rather than demand management (revenue management and dynamic pricing strategies). The mechanism proposed is as follows:

– When demand is low, the capacity is underutilized, becoming an inhibitor of labour productivity, and together with the high fixed costs that hotels face, there will be a decrease in productivity.

– When the demand is high, there will be a negative effect on the quality of the service, and this potentially will also translate into a decrease in productivity.

These changes in demand represent high adjustment costs, and the way to respond to them is through flexibility of labor: with numerical flexibility (varying the amount of labor) and functional flexibility (internal transfer of workers between departments or tasks). This means that a *key issue* for managers is the scheduling of the right number of employees with the skills needed at the appropriate time each day based on the demand forecasting. Therefore, Park et al. (2016) proxied productivity of the hotels with the level of labor productivity measured as the gross revenue per hour of labor input. The main explanatory variables are (1) numerical flexibility, based on the variation of worked hours per employee relative to his average monthly hours; and (2) functional flexibility, measured with the share of hours of interdepartmental employee transfers of the total employee hours.

Contrary to the results of Brown and Dev. (2000), Park et al. (2016) found that having more employees decreases productivity. This implies that there are enough employees and there is no room for improvement in productivity with additional workforce, which could be related to increasing fixed costs when dealing with variable demand. An example of this is keeping bars and restaurants open even though the demand was forecasted to be low, just to meet the requirements of a brand. In general, it is found in this sample from the U.K. that labor is directly affected by demand variations and that effective use of labor inputs is related with a variation of 6% to 13% of productivity in hotels.

Lastly, the study of Chen and Lin (2013) evaluates a similar research question to that from my analysis, but instead of looking at changes in *occupation* levels, they look at the effect of uncertain demand on the *capacity* of hotels in Taiwan, using the operational data of 71 international hotels from 1996 to 2008. They measure the uncertain demand as the *residuals* of a demand model which is estimated with a first order auto-regressive process. To measure the effect on capacity, they regress the number of rooms on the uncertain demand, hotel characteristics and market variables. Between these market variables, they are able to control for strategic interactions, such as the level of competition, by measuring the market concentration as the market share of each of the hotels. They also control for market diversification, by creating an index with the proportion of revenues coming from food and beverages, from room nights sold and from miscellaneous.

The findings on the effect of uncertain demand is that this factor increases the hotel capacity, and there are more chances that independent hotels that face demand uncertainty increase their capacity. The effect has an inverse U shape for different sizes of hotels, which means that the implications of uncertain demand are higher for medium-sized hotels, so this size of hotels are more sensitive to demand uncertainty by adjusting capacities than other small or large hotels, which implies that medium-sized hotels might be subjected to more costs related to capacity adjustments, negatively affecting their performance.

In the following section of this chapter, I will introduce the theoretical model behind the research design that is used to shine light on the effect of demand volatility on the productivity of hotels in Europe.

2.2 Theoretical Framework

For the research design of my study, I will follow the theoretical background developed by Butters (2020). He presented a model of production to see the effect of demand volatility on measured productivity when there are two firms with identical constant elasticity of substitution production functions. The firms face the same price for capital (rent) and labor (wage) with inputs supplied by competitive markets. They produce only for two periods and storage is impossible, and because of adjustment costs in capital, the level of capital is fixed during these two periods, but labor is perfectly flexible. The only difference between the firms will be the demand volatility that they face: firm A faces constant demand and always produces the same amount of quantity Q_A, and firm B faces lower demand in period 1 than in period 2, thus producing $Q_B - D$ in period 1, and $Q_B + D$ in period 2.

Because of this difference in demand, firm A as a business only needs to minimize costs, coordinating the best mix between labor and capital, and in both periods, produces at a point where the short-run cost curve is the same as the long-run cost curve. Firm B instead, faces the constraint of the costs of adjusting capital. It needs to choose a level of capital that reaches an equilibrium between in period 1, having an excess of capital, and in period 2, having the right amount of capital needed to face a higher demand ($Q_B + D$).

Butters uses as an example for firm A the airline industry, given that airlines can easily adjust the number of flights and size of planes to meet the demand, and for firm B the hotel industry, because hotels face high costs when adjusting the available number of rooms. Eventually, firm B will need more capital and more labor than Firm A, and both firms will produce the same level of output. Given that the measured productivity is different, regardless of the technical productivity of both firms being identical, this would be seen as firm B (that faces more demand volatility) being less productive than firm A.

The elasticity of substitution between factors has an important role. When the elasticity of substitution is close to one, so the inputs behave more as substitutes, firm B would just use more labor inputs but would keep the capital constant, in the same level as firm A. But when the elasticity of substitution is close to zero, so they are complements, firm B responds by using more of the input that has adjustment costs (capital), while the flexible input (labor) is equal to the level that firm A uses. Being the capital quasi-fixed, then the effect of demand volatility will be reflected on capacity utilization rates.

To be able to empirically measure the effect of adjusting costs and demand volatility on productivity, it is important to not have temporal aggregation because according to Butters, the differences in the volatility of quantity demanded across firms would not be disclosed, in for example, annual data. The same would happen for changes in the productivity of firms: given that the adjustment costs are significantly high, the temporal aggregation would not really show changes in performance. Therefore, it is important to use monthly observations of demand to be able to capture the effect of high adjustment costs. On the other hand, low adjustment costs would have a trivial effect on productivity.

To estimate the measured productivity, Butters uses the capacity utilization considering that it is an accurate estimate that is capturing the effect of demand volatility and adjustment costs on the productivity differences across firms, even when it is not taking other inputs such as labor, materials and energy into account. However, this measure of productivity is different from those in the previous articles presented in this section. The reason for this is, as Butters (2020) writes:

> To the extent that firms minimize costs and these other inputs (labor, materials and energy) are flexible, achieve constant returns to scale, and have no technical substitution with capital, the difference between the capacity utilization measure given above (occupation) and a more traditional measure of productivity that includes all inputs would only be a constant. Given that the goal of this paper is to explain productivity differences, this constant shift would have no impact on the results presented here. (p. 10, footnote 10)

What this means is that there is a difference between *measured* productivity and *technical* productivity. The former is the type of measurement used in some of the articles presented in the related literature subsection, considering input factors such as the skills of employees or managerial strategies. On the other hand, an example of measured productivity would be the levels of occupation. Butter explains that when firms are facing different changes in demand and have different levels of adjustment costs, the variation occurring in the measured productivity could not necessarily be mirrored by variations in technical productivity. Thus, it could be the case that the changes in the measured productivity are not reflecting changes in the input factors of firms, such as the competitive advantages or the capabilities of producers, but instead, the *measured* productivity could expose differences that exist in the demand *environment* of these firms. Therefore, the measured productivity is used for the empirical analysis.

Regarding the demand volatility, the foundation of its measurement is that "variations in the state of demand that affect the capacity utilization are those that *ultimately* move the quantity demanded" (Butters, 2020, p. 10). There are several sources from which the changes in demand occur. However, it can be the case that there are changes in the demand conditions that at the end, do not move the quantity demanded. This could happen when, holding supply conditions constant, the level and price elasticity of demand fluctuate in a way that precisely leads to a *constant* quantity demanded. In such a case, the demand conditions will not have a consequence on the productivity by way of capacity utilization driven by demand volatility and adjustment costs.

Because of the possibility of no changes in quantities while there are changes in the demand conditions, Butters then concludes that to address the influence of fluctuations in the demand conditions on productivity, specifically through capacity utilization (occupation), it is sufficient to measure the demand volatility. By measuring the demand volatility as the coefficient of variation of rooms demanded, as will be explained in the Research Design chapter, the variations that directly (when there are no changes in price) and indirectly (through the pricing strategy of hotels) cause movements in the quantity demanded (thus, making it *not* constant), will be captured.

The demand volatility will be measured within a year and this requires monthly observations. As demonstrated by Park et al. (2016), in the U.K. there are seasonal fluctuations in the demand. Butters maintains that these variations are understood by the hotels, and therefore, are predictable. This would not be the case of weekly or yearly frequencies, because other incalculable factors could be leading these variations (such as the weather and recessions). This predictability allows firms to plan operation schedules and, in the case of hotels, the adjustment costs represented by this planning are higher compared to other industries with lower adjusting costs, such as airlines, and this will be reflected in their capacity utilization.

2.3 The Performance of Capacity in the Hotel Industry

As a first glance of the nature of quasi-fixed capital in the hotel industry, in figure 1 the performance of the demand and the capacity of rooms is shown. The ranking of the twelve months of each of the four years of the sample is on the X axis. The peak month is month 1, with the maximum number of rooms that were sold in that year (quantity demanded, in orange) and the maximum number of rooms that were available in that year (capacity, in blue). The subsequent months in the ranking show in the Y axis the quantity demanded and capacity as a share of the maximum number of these variables in that year, as defined by the leading month in the ranking (month 1). The dotted top lines are the 90th percentile and the bottom lines the 10th percentile of a given month in the ranking across the years from 2006 until 2009.

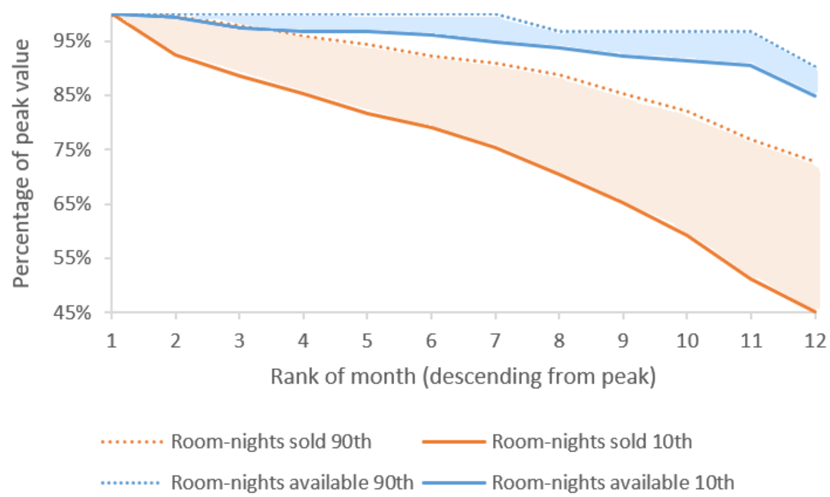

Figure 1: Annual Peak to Trough Demand and Capacity

In figure 1 the stationary nature of the capacity is noticeable, and this is evidence of the large adjustment costs that hotels deal with when planning the supply of rooms. Along the ranking, it is possible to observe that the capacity varies very little and even in the month in the last place of the ranking, the lowest number of rooms available is still 85% of the peak. On the other hand, the quantity demanded drops drastically to a minimum of 45% of the peak number in the 12th month of the ranking. The highest spread between the 90th and 10th percentiles of the capacity is of only 6 percentage points, while for the demand the spread can go up to 28 percentage points.

To check the association of the supply and demand of rooms, table 14 in the appendix shows descriptive regressions of the relationship between the monthly rooms demanded and the monthly rooms available and with the active hotels in the city. The results of table 14 confirm the intuition behind the figure 1: 1% increase in the rooms demanded in a month is associated with a 7.3% increase in the room nights available and only a 2.3% increase in the active hotels. This helps to conclude that hotels do not really adapt to the demand fluctuations that occur within a year. To emphasize the implication of this finding, in the study of Butters (2020) the same regression in the hotel industry gives almost identical results in the American context, but in the airline industry, 1% increase in the quantity demanded is related to an increase of 73.4% in the quantity supplied (in the form of number of flights), ten times of the effect found for hotels in my sample. This validates the contrast of the reactions and subsequent adjustment of supply between a firm that faces very high adjustment costs and a firm that does not.

Digging more into the supply of rooms, as part of the data of STR that I was granted access to (described in the following chapter), there is information on the supply of rooms and new hotel projects for some specific cities of the Netherlands, one of the countries that is used in the main analysis on this paper. With this information, it is possible to see at country scale using some representative cities that the supply of rooms tends to be still and only after 3 to 4 years of planning is when the number of rooms available could drastically change.

Table 15 in the appendix shows the total of hotels and available rooms per city from 2016 to 2021 and the change across years. This data is part of the market pipeline report that Smith Travel Research (STR) does for the areas where it recollects information of the hotel industry. In this table it is shown that for some cities such as Amsterdam and The Hague, the increase in the supply of rooms was relatively small from 2016 until 2020. However, it is evident that there was a huge increase in the rooms available since the Covid-19 pandemic started. The highest growth by April 2020 is in The Hague, where the current available rooms is almost double of the previous year.

In the pipeline market report there is information of future projects in each of the cities. On table 16 in the appendix, the planning for the increase of rooms supply is reported. Most of the projects that are in construction, final planning and planning show a projected opening date. For example, in Rotterdam and Amsterdam the projects have a forecasted opening for the end of 2021, 2022 and 2023. It is observable that given the situation that the world faced during the years 2020 and 2021, the projected plans for expanding the room supply, at least in the Netherlands, seem to have evaporated compared to the years preceding the pandemic. While for 2021 there was a 41% increase in rooms available in Amsterdam, which probably belonged to projects from at least three years in advance, in the coming two to three years the planned increase in rooms would only be of around 7%.

The STR's market pipeline report provides a sample of the changes in the supply by brand for each of the cities or metro areas. Between April 2016 and April 2021, the majority of changes in the supply seems driven by the creation of new hotels or the closing down of hotels, given that the changes of rooms occur in high quantities, for example between 100 and 500 rooms. Only in a few cases the changes give the impression that the hotels of a specific brand build or close down a small quantity of rooms, because the changes of supply is only between 2 and 20 rooms. This is evidence that hotels are not adjusting capacity and it is basically fixed since the moment that they are opened to the public, thus, the calculation of capacity is done before the construction and probably it is not changed once the building is completed.

3 Research Design

In order to answer the research question, the research design is based on the analysis of monthly observations of quantity demanded. In the following table I show an example of the data to make it easier for the reader to understand the observations used to calculate the equations that will be described in this chapter.

i	m	t	s	Q	Supply	*Price*
Metro area	Segment	Year	Month	Rooms Demand	Rooms Supply	RevPAR
Amsterdam	Luxury Class	2006	1	13076	25327	145.24
		2006	2	13782	22876	166.24
		2006	3	18356	25327	217.85
		2006	4	21073	24510	298.85
		2006	5	22202	25327	333.89
		2006	6	22086	24510	376
		2006	7	19959	25327	261.73
		2006	8	19170	25327	237.63
		2006	9	21728	24510	349.04
		2006	10	20148	25327	283.07
		2006	11	20077	24510	289.05
		2006	12	16388	25327	215.71
		2007	1	13797	25327	176.23
		...	...	...	...	...
		2021	4	3139	40170	26.25
	Upper upscale class	2006	1	104864	164889	96.55
		...	...	...	...	...
		2021	4	18902	201510	11.16

Table 1: Example of the Data

The i is referring to the metro areas or cities, in this example Amsterdam is used. In the sample there are in total 17 cities. The m is the class or segment that groups the hotels that follow this pricing strategy. In the table, the Luxury and the Upper upscale segments are shown, in total there are 6 segments. For each of these segments, data is reported for each month s within each year t. The column Q in this case is showing the demand for rooms, namely, between all the hotels that belong to that Luxury segment in Amsterdam, they sold a total of 13076 room nights in January 2006. In a similar way, the column Supply is showing that, by the same date, there were 25327 room nights available to sell, this means that in January 2006, the rate of occupation when counting all the luxury hotels in Amsterdam was 51.6% (13076/25327). Whereas the occupation ($Capacity\ Utilization_{imt}$) for the whole year 2006 of the same segment was 76.4% (sum of Q from month 1 to 12 divided by the sum of supply from month 1 to 12 = 228045/298205).

The data contains, as well, the total revenue generated (sales) and the number of active hotels and built rooms in that segment, among others. The last column is showing the revenue per available room, which is the monthly average of money that hotels in that segment received for selling one room night. By comparing the prices, it is possible to see that a luxury hotel in Amsterdam received on average 145.24 for selling a room night in January of 2006, whereas a hotel from the upper upscale class in the same month received on average 96.55 euros.

3.1 Demand Volatility

In order to test whether the volatility of demand has an effect on the productivity in the hotel industry, I will follow the methodology that Butters (2020) developed. The idea is to disentangle the pure effect of the volatility of the demand that occurs within a year (analyzing monthly data), by measuring the coefficient of variation of the demand at the metro area-segment-year level and see its effect on the capacity utilization of hotels. In my case, the metro areas are European cities, the segments are the class of the hotels (economy, luxury, mid-scale, upper mid-scale, upper upscale, upscale) and the years go from 2006 until 2009, and for robustness check I test longer time periods.

The main dependent variable is the productivity which is measured as the capacity utilization or occupancy rates of hotels. For this measure of productivity, Butters assumes that first, there is no technical substitution between capital and other production inputs (labor, energy, materials), and second, the returns to scale in the long run (so, at the point in time in which capital is not fixed or quasi-fixed anymore) are constant. These assumptions make that the production function of hotels uses inputs in fixed proportions, in other words, it follows a Leontief functional form. Assuming that all the inputs besides capital are completely flexible, in the short run, the production suggests that the marginal costs are constant until the point where the capacity constraint is reached, namely, the marginal costs are constant until the moment when all the available rooms are occupied. The capacity utilization or occupation is measured as follows:

$$Capacity\ Utilization_{\,i\,m\,t} = \frac{Rooms\ Nights\ Sold_{\,imt}}{Rooms\ Night\ Available_{\,imt}} \tag{1}$$

The main explanatory variable is the demand volatility. In this case, it is measured with the coefficient of variation (CV) defined by the following equation:

$$Demand\ Volatility_{\,i\,m\,t} = \sqrt{e^{\,std\,(ln(Q_{\,i\,m\,t\,s}))^2} - 1} \tag{2}$$

Where Q_{imts} are the quantity of room nights sold in a metro area i, segment m, year t and month s, with a log-normal transformation to fix the skewness of Q_{imts}. The coefficient of variation is measuring the standard deviation of these monthly observations, Butters (2020) expresses that it is key to study monthly observations because it is naturally giving more information than just annual studies, but also because at a monthly frequency the volatility of the demand can be predicted, as explained in the previous chapter, and as will be confirmed in the beginning of the Empirical Results chapter.

It is important to grasp that the variation in the demand volatility is within segments, so the calculation is done on the monthly changes in the demand that each segment faces throughout a year. From the example of table 1, the first observation of the analysis will be the coefficient of variation that measures the demand volatility that the luxury hotels (segment m) in Amsterdam (metro area i) faced during 2006 (year t), thus, using the data of the twelve months (s) from 2006 we obtain one observation: $Demand\ Volatility_{\ Amsterdam,\, Luxury,\, 2006}$. By doing the same for all the segments (6 in total) that are within the metro areas (17 cities), during 4 years (2006-2009) the resulting observations are approximately 408 ($6 \times 17 \times 4$), in the specific case of the main results, 348 observations.

3.2 Instrumental Variable for the Demand Volatility

The aim of the strategy is to only capture the volatility in the quantity demanded that is not related to changes in productivity or in capacity conditions of the hotels within a segment. In a hypothetical case where there exist only demand shocks (shifts in the demand) and therefore, other factors that can affect the demand or the productivity (such as factors derived from the supply side) do not occur, then the coefficient of variation of equation 2 could effectively measure the demand volatility. But because there could be confounding factors from the supply side that are affecting the variations in productivity, for example, the own decisions of the firms with respect to the number of rooms available due to maintenance or pricing strategies during peak seasons, and these examples themselves could be affecting the volatility of quantity demanded, there is a risk of simultaneous causality bias. Thus, it is important to isolate the *shifts* in the demand curve from movements *along* the demand curve (those derived from the supply side) so as to identify the effect of demand volatility on productivity.

In order to only capture shifts in the demand, there are two assumptions that the instrument is doing:

1. The volatility of the quantity of rooms demanded in a *whole city* is going to be correlated

with the volatility of demand that *individual firms* face.

2. This volatility at *city level* is uncorrelated with changes in the supply conditions made by *individual firms*. So, the decisions made by a specific hotel should not have repercussions on the aggregate demand volatility of the city where this hotel is located.

Hence, the instrument captures the demand volatility for a specific segment in a metro area in a given year (*imt*) that can be explained by the demand volatility occurring at the city level (equation 5), as well as the share that *that specific segment* maintains over the rest of the other markets in the sample (equation 4. The instrument interacts two components and is as follows:

$$Instrument_{\,i\,m\,t} = Share_{\,i\,m} \times Demand\ Volatility_{\,i\,t} \tag{3}$$

$$Share_{\,i\,m} = \frac{1}{\#\,market(m) - \#\,Market(m)_i} \sum_t \sum_{j \neq i} \frac{Q_{j\,m\,t}}{\sum_l Q_{j\,l\,t}} \tag{4}$$

$$Demand\ Volatility_{\,i\,t} = \sqrt{e^{std(ln(Q_{i\,t\,s}))^2} - 1} \tag{5}$$

Where the $Share_{im}$ is the average market share that segment m experiences in all other markets j and years t. The first part of equation 4 is a ratio that takes into account how many times the segment m shows up in the whole data set (# Markets (m)) except for the number of observations of the same segment m in the metro area i for which the instrument is being built (- # Markets (m)i). As an example, $Share_{im}$ could be the share of the metro area Rome and the luxury segment: $Share_{Rome,\,Luxury}$. The first part of the share would be 1 divided by the number of times that the luxury segment shows up in my data set (across all the 17 cities and across the 4 years, from 2006 until 2009) minus all the observations of the luxury segment in Rome from 2006 to 2009.

The second part of equation 4, to the right hand side, starts with the share of room nights sold at the metro area-segment-level by the same segment m out of the total of room nights sold by the all the segments ($\sum_l$ = sum of segments 1, 2, 3, 4, 5 and 6). For example, the room nights sold by the luxury segment in Amsterdam in 2006, divided by the sum of all the room nights sold by the hotels in the economy class, luxury class, mid-scale class, upper mid-scale class, upper upscale class, and upscale class in Amsterdam in 2006. Even though the instrument is being built for the metro area i = *Rome*, because exogeneity is the aim, this second part of equation 4 is capturing what is happening with the segment m = *luxury* in the rest of the data set besides the metro area $i = \textit{Rome}$. Continuing the explanation, this share of room nights sold by segment $m = \textit{luxury}$ is going to be calculated for all the metro areas $j \neq i$ of the sample (so, $\frac{Q_{j\,m\,t}}{\sum_l Q_{j\,l\,t}}$ for the other 16 cities of my sample) and all of them will be added, without including the metro area i (thus, $\sum_{j \neq i}$ adds the 16 cities and excludes Rome). Afterwards, the summation of the shares of room nights sold of all the metro areas excluding Rome ($\sum_{j \neq i} \frac{Q_{j\,m\,t}}{\sum_l Q_{j\,l\,t}}$) will be added from the years 2006 until 2009 ($\sum_t$), generating $\sum_t \sum_{j \neq i} \frac{Q_{j\,m\,t}}{\sum_l Q_{j\,l\,t}}$.

The $Demand\ Volatility_{\ it}$ is calculated using the coefficient of variation of equation 2 but at an aggregate level. Thus, instead of calculating the standard deviation of the natural logarithm of the monthly room nights sold at the *imt* level (metro area-segment-year), the standard deviation is calculated over a broader level *it* (metro area-year). The standard variation is calculated after adding the monthly sales of all the segments within an area, generating the observations Q_{its}, the overall market size, which is the monthly room nights sold in Rome in 2006, and then calculating the standard deviation at the metro-area level. To make it easier to understand the calculations of the instrumental variable, the Python code is available in the appendix.

The credibility of the instrument relies on the fact that the demand volatility faced by a specific segment must relate to the demand volatility of a whole city (as seen on Figure 6, in the results chapter, where indeed there is a significant correlation between equation 2 and the instrument), and that the instrument should not be capturing effects from the supply side of that specific segment in that city. Given the large size of the European cities of my sample I will show in the descriptive statistics at the end of this chapter that the share of sales per segment are on average 19.48%, hence, it is improbable that supply side changes in the productivity of a specific segment could be driving the aggregate demand volatility of the city.

As a final step, I present the main estimation equation. Equation 6 shows the main regression that I use for the analysis:

$$\log(Capacity\ \ Utilization_{\,i\,m\,t}) = \varrho\ \text{ Demand } \text{ Volatility}_{\,i\,m\,t} + \beta\, X_{i\,t} + \lambda_t + \Psi_m + \varepsilon_{imt} \qquad (6)$$

Where the dependent variable is the logarithm annual level of occupation for a specific segment of hotels, as calculated with equation 1, and will allow to interpret the coefficient of interest as a semi-elasticity. Where ϱ is the coefficient of the main explanatory variable, the Demand Volatility at the metro area-segment-year level. This coefficient will demonstrate the effect that changes in the demand produce in the productivity of the hotels as measured by the capacity utilization, assuming that there are no supply side factors affecting the demand or the productivity, otherwise, equation 3 will be used as instrument. The X is a set of control variables that I will explain in detail in the following part of this section. λ_t and Ψ_m are fixed effects to control for invariant characteristics over time and across the hotels' segments, and ε_{imt} is the error term which is clustered at the metro area level.

3.3 The Data

The data over the hotel industry in Europe that is used for this analysis was provided by Smith Travel Research (STR), an American company that gathers data of the lodging industry to serve clients in the hotel, tourism, independent accommodations and commercial real estate industries providing market insights.

To investigate the demand volatility in the European context, the data granted by STR had a maximum of 24 metro areas, which is almost a fifth of the total metro areas that Butters (2020) used in the analysis of the American hotel industry (a total of 92 areas). Unfortunately, the data that STR manages in the European continent is not as exhaustive and complete as the case of the United States. After inquiring for the data of 24 European metro areas of a large size, that are touristic and generally included on European holiday's tours, reasons that could make them more likely to have enough market information collected, only 17 cities had the complete data needed for the analysis. These 17 metro areas have at least six segments or classes of hotels, while the leftover cities (Oslo, Nice, Eindhoven, The Hague, Rotterdam, Maastricht and Zurich) are considered by STR as a sub-market, instead of as a market, and had the segments combined to 3 categories ("collapsed classes"), which made it impossible to take them into account in my analysis of the demand volatility effect per metro area-segment-year.

The final sample consists of the monthly data of the hotel industry from Amsterdam, Athens, Barcelona, Berlin, Brussels, Budapest, Copenhagen, Lake Geneva, Lisbon, London, Madrid, Milan, Munich, Paris, Prague, Rome and Vienna. The data covers the monthly information of the hotels in these 17 cities, which are classified by the segments where they belong, going from economy to luxury types, a total of 6 segments: economy, midscale, upper midscale, upscale, upper upscale and luxury. In my case, an independent segment for hotels that are independently affiliated, that is, that do not belong to a chain, does not exist.

For each of the segments that exist in each of the cities, the data contains monthly information on the rooms demand, rooms supply, rooms revenue, rooms revenue per available room, a census of the existing built rooms and a census of the active hotels. In total, I have 18769 observations, given that the monthly information is available from January 2006 until April 2021. For the main analysis, to make the results comparable to the United States' case, I use a total of 4897 observations from January 2006 until December 2009. In this sample, when reducing the observations to yearly data (after calculating the demand volatility at metro area-segment-year level). The histogram of figure 2 shows the share of rooms from which STR has collected information, out of the total number of rooms that exist within those segments in those metro areas (as measured by the census).

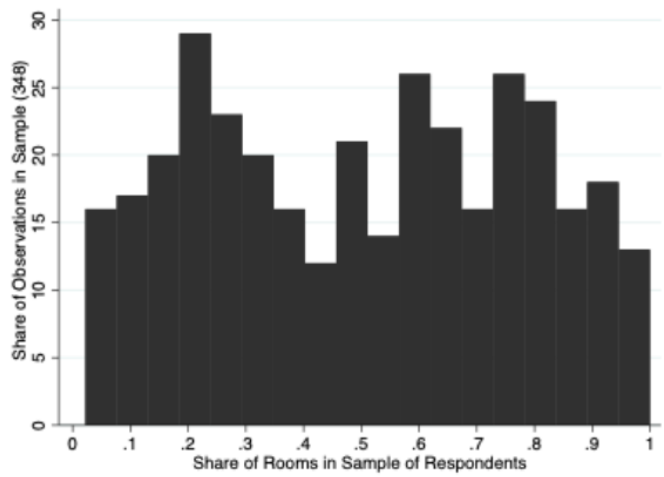

Figure 2: Histogram of Share of rooms Covered by STR Respondents for all Metro area-segment-years, for Europe

In figure 2 it is evident that the power of recovering information of the cities in the European Union is diverse. In this histogram it is possible to see that approximately only 13 observations of metro area-segment-year show information that covers the 100% of the total existent rooms, while, for example, around 15 observations are presenting the data of only 10% of the census (total existent rooms). This is different from the American case as explored by Butters (2020). In the figure 7 in the appendix, from his own article, I present the coverage that STR has over the American metro areas.

Comparing the two histograms, it is possible to see that the collected data from Europe is less representative than that of the United States, perhaps it is more difficult to collect data from different countries. This is a start point of possible differences in the results between the two economic areas. Perhaps the lower degree of integration of the European labor market, compared to the American one, can be a key issue when collecting the data, and could not only be affecting this, but could also have repercussions in the performance of the European hotel industry, if thought from the point of view of less labor mobility and the costs of hiring, which could translate into a less flexible labor input. When taking into account that the European Union, at least as an economic bloc, groups 27 countries with 24 official languages, with local laws in each of the countries, own ways of collecting disaggregated data and different macroeconomic conditions, I argue that this state of affairs could affect the productivity of the hotel industry and these elements are more difficult to capture than in the case of United States, a economic bloc with high integration, with one language and where all the information is mainly situated under one umbrella.

In an attempt to control for some conditions that can be affecting the results and following the methodology of Butters (2020), several control variables are used that can be classified in three categories: those related to marginal costs and price of capacity, the overall level of demand in the metro areas and long term movements.

Related to marginal costs, the mechanism that Butters (2020) explains is that as the marginal cost of a room increases, and there are chances that it is not sold and therefore it stays being costly, there will be less motivation to expand the capacity of a hotel, eventually increasing the occupation. The log of the salaries of employees in the hotel industry is used as the price of labor. In the European context, I was able to find annual average personnel costs (personnel costs per employee) in thousands of euros. To control for the price of energy, I use the electricity prices for industrial consumers including all taxes and levies, measured as the euros per kilowatt-hour. As the price of capacity, I use the rent per square meter of a one-bedroom apartment in the city center, which unfortunately was not available for the years between 2006 and 2009.

For the overall state of the demand, the reason behind is that a good state of the economy should generate more shifts in the demand and influence the capacity utilization. I use the gross domestic product (GDP) per capita, the total number of employees working in the hotels and restaurants, the unemployment rate and the share of workers in the hotels and restaurants (out of the total number of employees in the economy). Since Syverson (2004) showed that the quantity of employees per square mile increased productivity in the concrete industry, Butters includes a similar control for the hotel industry by using the number of employees in the hospitality industry per square mile. In my case, given that in Europe the employment is not reported at the metro area level, I was only able to use the level of employment at the country level. In an attempt to capture the same factor, I divided the employees in hotels and restaurants by the size of the country. To capture long term trends, I use the 5-year difference of the log GDP and the 5-year difference of the log number of employees in hotels and restaurants.

Ideally, all the controls should be at metro area level, unfortunately, in most of the cases it was not possible. Most of the data is available in different files from Eurostat, otherwise, I collected it from the websites of the statistics institutions of each of the countries. In the case of the UK and Switzerland, I used the average annual exchange rate in order to transform the data from the national currencies to Euros when some of their data was not available in Eurostat, but on their own national statistics institutions' websites.

Control	Level	Source
log(personnel cost)	Country	Eurostat, UK Office for National Statistics
log(electricity price)	City	Eurostat, Swiss Federal Statistical Office
log(rent)	City	Numbeo, Swiss Federal Statistical Office
log(GDP per capita)	Country	Eurostat
log(employment in hospitality)	Country	Eurostat
Unemployment rate	Country	Eurostat
log(share of hosp. employment)	Country	Eurostat
log(density hosp. employment)	Country	Eurostat
5-year difference log(GDP)	Country	Eurostat
5 year difference log(hosp. empl.)	Country	Eurostat

Table 2: Levels and Sources of Control Variables

Table 2 shows the control variables, the level at which I was able to find the data and their source. The only data that is at the metro area level are the average electricity price and the rent of an apartment. Eurostat does have some of the data for these control variables available at the metro area under the "statistics per metropolitan region", however, a big majority of the cities in my sample does not have the data available. To illustrate this issue, the file from Eurostat that contains the unemployment rates by sex, age and metropolitan regions does not even have data on such a large an important city as Paris, and for the rest of the metro areas that it covers, it only starts to become more complete from 2017 onward. In the case of employment per metro area, the data is too broad. It is not possible to only filter workers in the hotels and restaurants, as in the case of country level, but the data would include workers of the wholesale and retail trade, transport, accommodation and food service activities. Finally, there is no available data for the control variables for 2021, so it is not possible to include the most recent data from 2021 in the analysis.

Now, the descriptive statistics of the 2006-2009 sample are shown. In the appendix, table 17 presents the summary statistics of the control variables for the same period.

	Mean	Std	Min	Max
Observations N = 349				
Occupancy	68%	8%	40%	83%
log(Occupancy) (log(%))	-0.17	0.05	-0.40	-0.08
Demand Volatility (CV_{imt}), in units)	0.18	0.06	0.07	0.38
Number of hotels (per metro area-segment)	89	89	5	388
Number of rooms (per metro area-segment)	7062	5227	373	24630
Number of rooms volatility (CV_{imt}) , in units)	0.01	0.02	0.00	0.20
Market share (room nights sold, per segment)	19.48%	10.42%	0.34%	64.28%

Table 3: Descriptive Statistic, 2006-2009

In Table 3 it is possible to see the descriptive statistics of the sample between 2006 and 2009. There are in total 349 observations, which are the approximately 6 segments per each of the 17 cities along the 4 years of the time period (6x17x4 = 408   349). Even though it is not used in the analysis, I provide the descriptive statistics of the occupancy rates to illustrate in a more tangible way the performance of the hotel industry's productivity around Europe, given the available information of the cities in the sample. On average, at a metro area-segment-year level, the occupancy or capacity utilization of the hotels is 68%. When looking at the logarithm of the occupancy, it is possible to see that its standard deviation is in absolute terms a 30% of the average of -0.17, indicating that there is variation in the productivity. In each of the segments per city, there are on average 89 hotels and 7062 rooms available to be rented, and the biggest segment has three times the average, with a total room supply of 24630.

The following figure shows the market shares that the segments hold at the metro area-segment-year level. These shares are calculated in the same way that the share of room nights sold used in the last part of equation 4 that constitutes the instrument ($\frac{Q_{j\,m\,t}}{\sum_l Q_{j\,l\,t}}$) room nights sold by all t, over the sum of the room nights sold by the hotels of the segments 1, 2, 3, 4, 5, 6 or $\sum_l$ in that same metro area j in the same year t.

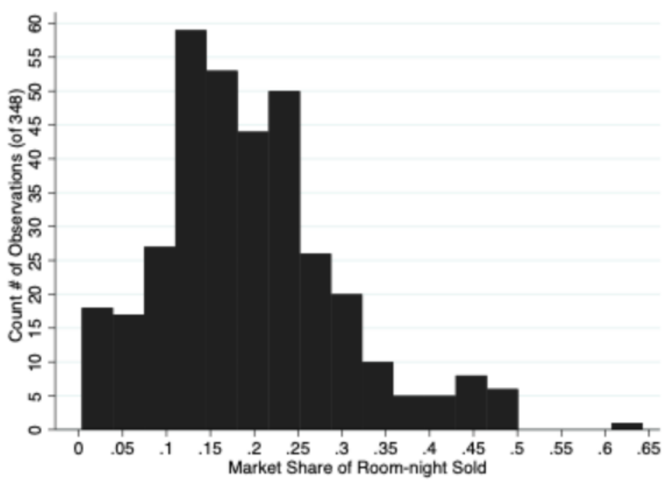

Figure 3: Histogram of Market Shares (Room-nights Sold) for all Metro area-segment-years

On average, the share of the market that a segment holds is approximately 20%, and at most, 64%. Given that on average there are 89 hotels per segment, it is possible to infer that one hotel sells around 0.2% (89 hotels x share of 20%) of the annual total of room nights in the city where it belongs.

The volatility of the available rooms which was calculated with the coefficient of variation equation is only 0.01. This can be interpreted as a corroboration of the capital intensive nature of the hotel industry, where the supply of rooms is quite stationary, especially on a short period of time.

4 Results

As described by Butters (2020), the reason behind choosing the monthly frequency of room nights sold is because it is more predictable than, say, weekly or daily frequencies. The changes in demand at such a high frequency could be mainly driven by random elements, for instance, the weather conditions, rather than situations that are possibly predictable to the hotels. As designed by Butters (2020), the monthly frequency or with-in year variation allows the analysis "to focus on the portion of demand variation that is likely to be predictable to the firms and persistent".

The monthly frequency gives some slack to make it possible for the firms to predict the sales and subsequently adapt to meet the demand, by for example, adjusting the personnel needed at a certain month or season, being commonly known that the quantity of guests at that time is similar year after year. In figure 4 it is possible to see the volatility of the room nights sold in the cities of my sample. In the horizontal axis I show all the months of the 2006-2009 period, month 1 corresponding to January 2006 and month 48 to December 2009.

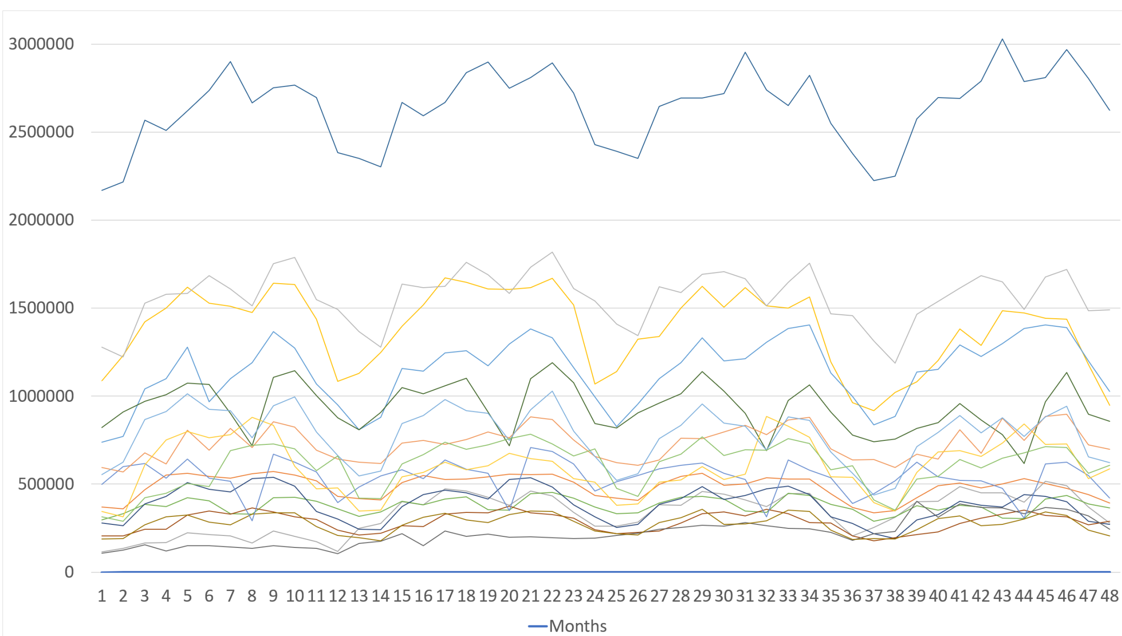

Figure 4: Room Nights Sold Per Month Across Metro Areas, Europe 2006-2009
Y axis: number of room nights sold per month, X axis: number of months (48 in total)

To describe one of the cities' lines, it is easier to spot the highest blue line, which is far from the rest of the trend lines: this is the trend line for London. Just by a graphical analysis it is possible to observe that there is a pattern in which the sales rise and drop every month similarly across years, but the levels are not exactly identical. This is a confirmation that monthly sales, to a certain extent, are very likely to be predictable to the hotels. This gives validity to the inference that the within year variation in the room nights sold in my sample should be strong enough to be captured in the statistical analysis.

4.1 Preliminary Analysis

To do the data analysis, given the complexity of equations 2 and 3, and the length of the data set, I used the Python programming language to clean and process the data (the code can be made available upon request) to build the CV and the instruments, and for the econometric analysis and the majority of the figures, I used Stata.

Figure 5 shows a first approach of describing the relationship between the productivity of hotels in my sample, measured as occupancy rates (thus, as a percentage) from equation 1, and the demand volatility within years, equation 2 (in units). In the plot it is possible to observe a negative relationship of 0.3692 between these two variables (with a t-statistic of 7.4), being the Pearson correlation coefficient statistically significant with a p-value of 0.00. This relationship is very similar to the one found by Butters in the sample of American hotels, nevertheless, the relationship here seems to be slightly less strong than the one from the United States' sample. Then, it is plausible to expect that the coefficient of the equation in my case is going to be different from the results of Butters (2020).

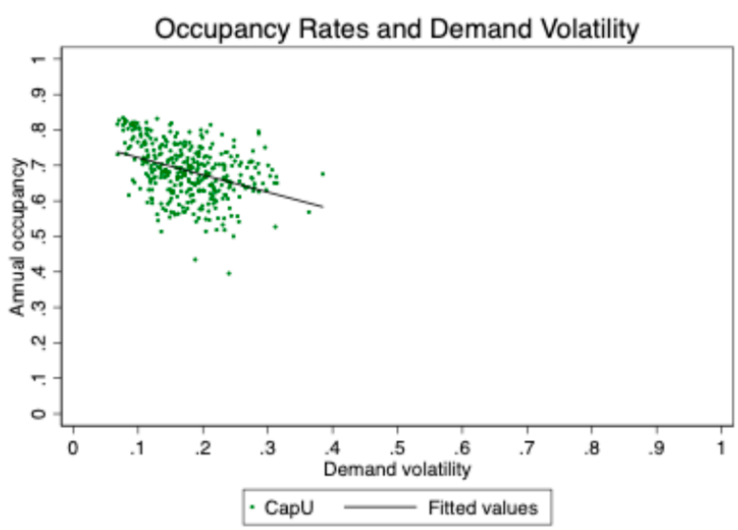

Figure 5: Relationship Between Occupancy Rates (in percentage) and Demand Volatility (in units)

In a similar way, figure 6 shows the relationship between the demand volatility measured by the coefficient of variation and the instrument based on equations 2 and 3. The correlation between these two variables is 0.4831 with a t-statistic of 10.29 and the Pearson correlation coefficient is significant with a p-value of 0.00. This figure shows part of the credibility of the instrument, where it is confirmed that the instrument, even though it is measuring the demand volatility at an aggregate level, is related to the individual demand volatility that a segment alone faces.

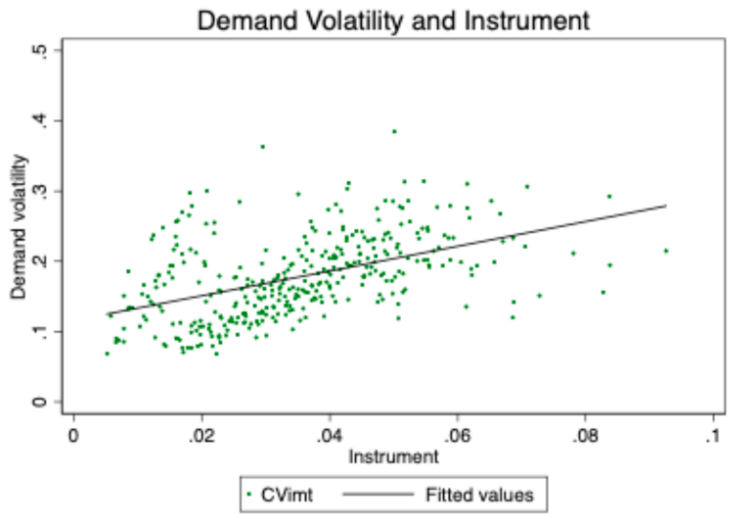

Figure 6: Relationship between the Demand Volatility and the Instrument

4.2 Main Results

In Table 4 I provide the results of the main regression for the sample from 2006 until 2009. The dependent variable is the logarithm of the capacity utilization and the main independent variable varies across columns. In columns 1 and 2 the coefficient of variation (CV) at the metro area-segment-year level as demand volatility is the independent variable, in column 3 and 4 I use the instrument built with equation 3.

In column (1), when using the CV as the demand volatility, its coefficient is establishing a negative relationship with the productivity of the hotels, however, it is not statistically significant. Nevertheless, when looking at the overall R2 it is possible to interpret it as the demand volatility could be explaining 12% of the change in the occupation rates.

In column (2), once more with the CV as a main explanatory variable, the regression is run together with the controls and also with year and segment fixed effects. The coefficient is negative, but it is approximately half of its simile from column (1), meaning that the effect that the demand volatility has on the capacity utilization is not as strong now

	(1) CV	(2) CV	(3) IV	(4) IV
Demand Volatility	-0.114	-0.0620	-0.532***	-0.465***
	(0.0934)	(0.0501)	(0.157)	(0.175)
Dependent variable mean	-0.17	-0.17	-0.17	-0.18
Year / segment fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Drop 2008				Yes
First stage F statistic			12.04	11.18
Hausman test			0.12	0.24
Adjusted R2 first stage			0.53	0.51
R2 (overall)	0.12	0.46	0.50	0.52
Observations	349	349	349	261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Main Regression, 2006-2009

Results based on equation 6. Explanatory variables: in columns 1 and 2 the coefficient of variation (CV) as calculated by equation 2, in columns 3 and 4 the instrumental variable as calculated by equation 3. Dependent variable: log(Occupancy)

that controls and fixed effects are included in the model. Once more, the coefficient is not statistically significant, but its interpretation is as follows: given that the dependent variable is a logarithm, to have one extra unit of demand volatility would imply that the capacity utilization of hotels will change by approximately $(e^{-0.062} - 1)$*100 = -6.01%. When looking at the descriptive statistics of the sample (Table 3), there is not a single observation over the four years in which the demand volatility was more than 1 unit. The mean of the CV_{imt} of quantities demanded was 0.18 and the standard deviation was 0.06. Therefore, I will now resize the results to accommodate them to the reality of the sample. Given that the demand volatility increases by a standard deviation (0.06 units), the productivity would change by -0.371% $(e^{0.06*-0.062} - 1)$*100).

For the first two columns, next to the fact that the coefficients are not statistically significant, there could be a chance of simultaneity causality bias in the case that the firms that belong to a specific segment are themselves affecting the changes in the available capacity as Butters (2020) mentions, for example, the closing downs of rooms for maintenance. Therefore, the instrumental variable is used in columns (3) and (4) and the models are calculated using two-stages least squares (2SLS),but in column 4 the observations from the year 2008 were dropped to see the difference when not taking into account the within year variations in demand and productivity during the Great Recession.

In both of these models the coefficients are still negative and are now statistically significant, but their magnitude changed by a large amount. In column 3, an additional unit of demand volatility would imply a decrease of 41.26% (($e^{-0.532}$-1)*100) in the productivity of hotels. When resizing the results by using the standard deviation, an extra standard deviation of demand volatility (0.06) would imply a more moderate drop of 3.4% (($e^{-0.532*0.0.6}$-1)*100) in the occupancy, which is approximately half of a standard deviation of hotel occupation in my sample (8%). The coefficient of column 4 is very close to that of column 3. An extra standard deviation of demand volatility in this specification suggests a decrease in occupation of 2.75% (($e^{-0.465*0.0.6}$-1)*100), in this case, almost a third of a standard deviation of the occupation in the sample, a very close result to that of column 3. In consequence, it is possible to conclude that the effect of the demand volatility is not being driven by the situation caused by economic cycles in 2008.

Overall in table 4 , when applicable, the Hausman test goes from 0.12 to 0.24 making it insignificant, this means that the null hypothesis stating that the main independent variable is exogenous cannot be rejected. Under this result there should be no need to use an instrumental variable, but as shown in the first two columns, the demand volatility was not statistically significant and its coefficient in both columns seems to be economically insignificant suggesting only a fifth of the drop in occupancy inferred by the instruments from columns (3) and (4) which do show statistical significance. Further, even though the R2 are not particularly close to 1, because I am using only one instrument per regression, the f-statistic is the square of the t-statistic of the correlation between the instrument and the demand volatility (f = t^2), and as indicated by Wooldridge (2015), the t-statistic should not be lower than about 3.3 so the f-statistic should be at least 10.89, which is the case of all the f-statistics that are shown in table 4. When focusing directly on the f-statistic as a test over the validity of the first-stage of the 2SLS, the threshold for a valid instrument published by Stock and Yogo (2002) is an f-statistic that should be no less than 10, and that is the case for all the f-statistic on table 4.

In the following table, I present the results of the control variables of the main regression presented in table 4. In this sample for 2006-2009 it was not possible to include the control for the rent of an apartment in the free market, nevertheless, I can still test the effect of the marginal cost of a hotel room with the commercial electricity price and the personnel costs in the hospitality industry. In general, the magnitude of the control variables are pretty small compared to that of the main explanatory variable.

In this sample, the marginal costs of a room seem to have a negative effect on the occupation of hotels, having log(personnel cost) and log(electricity price) a negative coefficient in all of the models and being statistically significant in all cases, except for the one of column (6). These negative results are the opposite to those found in the USA by Butters (2020).

	(2) CV	(3) IV	(4) IV
log(personnel cost)	-0.0797*	-0.0596**	-0.0565*
	(0.0411)	(0.0275)	(0.0316)
log(electricity price)	-0.0387*	-0.0833***	-0.0827***
	(0.0222)	(0.0280)	(0.0247)
log(GDP per capita)	0.131**	0.107**	0.0820*
	(0.0606)	(0.0486)	(0.0464)
log(employment in hospitality)	0.0290**	0.0288***	0.0205*
	(0.0144)	(0.00934)	(0.0108)
Unemployment rate	-0.00153	-0.00226	-0.00286**
	(0.00104)	(0.00146)	(0.00141)
log(share of hosp. employment)	0.0375	0.0534	0.0752**
	(0.0411)	(0.0335)	(0.0358)
log(density hosp. employment)	-0.0199	-0.0338	-0.0459
	(0.0478)	(0.0296)	(0.0302)
5-year difference log(GDP p. c.)	0.161	0.128	0.186
	(0.170)	(0.212)	(0.197)
5 year difference log(hosp. empl.)	0.0685	0.0422	0.0265
	(0.0786)	(0.0832)	(0.0774)

Table 5: Estimated Coefficients for Control Variables, 2006-2009

In the American case, Butters argues that as the marginal costs of a room -that could be productive by selling room nights or could be unproductive because it was not sold- rise, then there are no incentives as a firm to expand the supply of rooms and therefore the capacity utilization will tend to increase.

In the European case, it seems that rather than affecting the incentives of expanding the supply, the rise of marginal costs are directly decreasing the occupancy and this could be motivated by the strategic decision of just rising the price per night, passing the burden of extra costs directly to the client, naturally decreasing the demand and subsequent capacity utilization. This could be specially driven by the stricter laws related to labor in the European Union where companies have less freedom to fire employees. With respect to modifications of capacity, given that most of the cities are antique, there are urban laws that can severely control the expansion and development of buildings in these metro areas which also tend to be smaller compared to American cities, where new developments could be easier to execute.

From controls that have to do with a more general state of the economy, only the GDP per capita is statistically significant across all the specifications, and it is overall positively related to occupancy, so a bullying state of the economy as signalized by a higher GDP implies a better situation for the productivity of the hotel industry. The employment in the hospitality industry is significant only in the first three specifications, without and with an IV, all with a very similar magnitude. Only in the specifications with the IV from columns

(4) to (6) the unemployment rate and the share of hospitality employment have a statistically significant coefficient. Unemployment shows both a negative and a positive relationship with occupancy, however, it is really close to zero, while a higher share of hospitality employment which could imply a better economic state of the tourism industry is indeed related to a higher capacity utilization.

The control for density, approximated as the quantity of employees per square kilometer, is only significant when using the aggregated sales IV, and has a negative effect on productivity. This result is contrary to that of the American results and also to the results of the ready-mix concrete industry, where the hypothesis and results reveal that dense markets have higher productivity levels (Syverson, 2004 as cited by Butter, 2020). My negative results could be driven by the fact that the density is being measured at a national level given that there is no available data on hospitality employment at metro area level, thus, it is not possible to make sure that indeed the density in the European hotel industry is reducing the productivity levels.

Lastly, I report the 5 year differences of GDP per capita and hospitality employment to test the effect of important economic variables on a longer time frame that could affect the demand. Surprisingly, in none of the cases they have statistically significant coefficients nor all of the signs are the same as the original variables for only the current years of the sample.

When comparing the main results of the effect of demand volatility in Europe to its effect on the American market, the coefficients of the CV are very distant. In the US the CV implies a drop in productivity of 34.2% (($e^{-0.42}$-1)*100), while in Europe only 6% (($e^{-0.06}$-1)*100), but the latter is not statistically significant. Nevertheless, the resulting coefficients of the instrumental variable are closer than the results when using the coefficient of variation CV_{imt}. Butters (2020) found that an extra unit of demand volatility would decrease the occupation by 27.4% (($e^{-0.32}$-1)*100) when using the instrument, whereas my results on the European context suggest a drop in productivity of 41.26% (($e^{-0.532}$-1)*100).

An important difference between the results of Europe and the results of USA is that the occupancy rates in the American sample are relatively low. The mean of occupancy rates in the USA is 31%, whereas in my sample, the mean is 68%. This hints to the possibility that the productivity of the European sample could be more sensitive to the effects of demand volatility, thereby decreasing in larger magnitudes.

A additional explanation could be that several factors that characterize the European continent are driving this difference. For example, because of the more protective employment laws within the European continent, it can be the case that the labor input is not as flexible as in the USA (Gill, Koettl and Packard, 2013), generating more adjustment costs to the firms. Furthermore, even though the European Union (EU) is an economic and monetary union, the wide diversity represented by the differences between each of the countries that belong to it, could imply that its integration is uneven (Epstein and Johnson, 2010) compared to that of the states constituting the USA.

This reality can lead to different consequences, one of them could be personnel shortages for construction and hospitality industries in countries consisting of more highly educated populations, as is the situation of the Netherlands (Buijs, 2020), given that the labor mobility between countries is somewhat low. On the other hand, stricter construction product regulations (CPR) to preserve the antique architecture of European cities and the space constraints that most of these cities face could also be limiting the capacity of hotels and subsequent performance.

5 Robustness Checks

In this chapter, the methodology of Butters (2020) is followed to test alternative measurements of the instrument, and of the dependent and independent variables of the main regression in equation 6.

5.1 Alternative Instrumental Variable

Butters (2020) also presents another possibility of the main instrument from equation 3, which is using the coefficient of variation at the metro area-year level of the monthly quantity of employees in the leisure and hospitality industry, instead of the rooms nights sold. In my case, it was not possible to test this alternative instrument since in the European Union the monthly number of employees is available only annually, as opposed to the Bureau of Labor Statistics of the United States, which publishes this type of data on a monthly basis. The only country from those of my sample that reports the employees in tourism at a higher frequency is Spain (on its own national statistics' website) but the reports are only per trimester.

With respect to the original instrument of equation 3, since it still has (low) chances of capturing *aggregate* market-level shifts in supply, Butters (2020) implements an alternative instrument that I was able to replicate. Instead of using the aggregate *demand* volatility at the metro area-year level as in equation 5 where the room nights sold $Q_{i\,m\,t\,s}$ are the demand, in the *altInstrument* the volatility of the aggregate *sales* per metro area at a given year is used.

The measure of sales is the total revenues (number of room nights sold multiplied by prices) that all the hotels within a specific segment or class (as luxury or economy) made during a month *s*. As explained by Butters (2020), this second version of the instrument is used with the aim of abstracting from possible shifts in the supply at a more aggregated level. An example of these shifts in supply could be if there were staff shortages in the city that could induce the managers of hotels to make the decision of not offering all the available rooms, limiting the effective capacity and changing prices accordingly. This could be generating movements *along* the demand curve, instead of *shifts* in the demand curve, and confounding the results of the original instrument.

$$altInstrument_{\,i\,m\,t} = Share_{\,i\,m} \times Sales\ Volatility_{\,i\,t} \tag{7}$$

$$Sales\ Volatility_{\,i\,t} = \sqrt{e^{\,std\,(ln(Sales_{i\,t\,s}))^2} - 1} \tag{8}$$

With the alternative instrument of equation 7 it is possible to capture *shifts* in the demand curve thanks to the aggregate market level information coming from the prices. Given that the sales are the $Q_{its} \times \text{Prices}_{its}$, the room nights' market price in a city is being taken into account when calculating the coefficient of variation of *sales* in equation 8, instead of only capturing changes in quantities demanded, as in equation 2.

	(5) alternative IV	(6) alternative IV
Demand Volatility	-0.649***	-0.632**
	(0.220)	(0.255)
Dependent variable mean	-0.17	-0.18
Year / segment fixed effects	Yes	Yes
Controls	Yes	Yes
Drop 2008		Yes
First stage F statistic	18.02	15.38
Hausman test	0.13	0.18
Adjusted R2 first stage	0.52	0.5
R2 (overall)	0.44	0.46
Observations	349	261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression using the alternative instrument 2006-2009
Results based on equation 6. Explanatory variables: in columns 5 and 6 the alternative instrumental variable as calculated by equation 7. Dependent variable: log(Occupancy)

This table is the same as the table of the main regression (Table 6), using the same dependent variable: the level of occupation of hotels. Therefore, I present the results as a continuation of the main results: in columns 5 and 6 I use the alternative instrument of equation 7.

In columns (5) and (6) with the alternative instrument, once again, the coefficients of the demand volatility are negative, but now slightly larger than when using the original instrument (from table 6, the coefficient is -0.532***). Both coefficients are statistically significant but the one from column (6), when dropping the 2008 observations, is significant only at a 5% level and relatively smaller. When taking into account all the observations, an extra standard deviation of demand volatility, proxied with the aggregate sales in a city, would generate a drop of 3.8% (($e^{-0.649*0.06}$-1)*100) or half standard deviation in the productivity of hotels, almost exactly the same result when the specification uses the main instrument of equation 3, implying that the main results from the previous chapter are likely to be driven by shifts in the demand curve and are not contaminated by changes in the supply that affect the capacity of the hotels.

5.2 Alternative Measure of Productivity

An alternative measure of productivity is the revenue per available room in euros (RevPAR) for a given year, so instead of looking at the occupation of the hotel, I use the income that each room generates. I calculated the RevPAR by dividing the total revenue per metro area-segment-year by the total supply of rooms at the same level.

Financial measures, instead of physical measures, are a theoretically pertinent way to estimate the productivity in services because, in a competitive market, prices reflect the perceived quality of a service (Gronroos and Ojasalo, 2004, as cited in Park et al., 2016). Additionally, in the article of Park et al. (2016) cited in the related literature chapter, RevPAR was the most important predictor of productivity, making it a good option for a robustness check. In short, by using RevPAR, the extra information coming from the prices is being taken into account. The following table shows the results of the main analysis when using the log(RevPAR) as the dependent variable, instead of using occupation levels.

In table 7, the dependent variable mean is 2, so it is approximately 100 euros what a room sold generates. At first glance, it is possible to see that all the coefficients of Demand Volatility are negative. In the first column, the coefficient of variation does not seem to explain much of the variations in productivity, given that the R2 is only 0.03. When using the control variables, the explanatory power improves and the coefficient of demand volatility becomes statistically significant. Given that the there is an additional unit of demand volatility, the revenue per available room would decrease by 10.4% (($e^{-0.11}$-1)*100), which could imply a drop in the revenue per available room of around 10 euros.

When using the instrument for demand volatility of equation 3, the revenue decrease would be approximately by 72.5% (($e^{-1.292}$-1)*100). Even though the coefficients are sta-

	(1) CV	(2) CV	(3) IV	(4) IV
Demand Volatility	-0.161	-0.110*	-1.292***	-1.267***
	(0.174)	(0.0614)	(0.455)	(0.535)
Dependent variable mean	2	2	2	2
Year / segment fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Drop 2008				Yes
First stage F statistic			12.04	11.18
Hausman test			0.05	0.068
Adjusted R2 first stage			0.53	0.52
R-squared (overall)	0.03	0.86	0.85	0.85
Observations	349	349	349	261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regression Revenue Per Available Room Night, 2006-2009
Results based on equation 6. Explanatory variables: in columns 1 and 2 the coefficient of variation (CV) as calculated by equation 2, in columns 3 and 4 the instrumental variable as calculated by equation 3.
Dependent variable: log(RevPAR)

tistically significant, they differ by a large amount when using the instrumental variable. Nevertheless, it seems that the instrument is appropriate, given that the F-statistic is high enough to pass the 10 units threshold. What it is possible to conclude is that, indeed, the demand volatility negatively affects the productivity of hotels when measured as the revenue per available room.

5.3 Alternative Measure of Demand

Butters mentions that the measure of demand volatility of the room nights sold could suffer from two problems: (1) censoring from above and (2) capturing movements along the demand curve. The first problem could arise from the constraint of available capacity at the aggregate city level, that is, that perhaps there are not more room nights demanded because the supply of rooms has a limit. Nevertheless, in my sample the occupation levels in none of the months reaches 100%. The second problem comes from using only the quantity demanded as a measure of demand, which could be capturing a mixed effect coming from shifts in the demand as well as movements along the demand curve. To test these issues, Butters (2020) adds the price information to the measure of demand.

Consequently, an alternative to measure the demand is to include the price information under the assumption that the demand that hotels at the metro area-segment-year-month level face is specified by the constant elasticity functional form of the following equation:

$$Q_{\,i\,m\,t\,s} = D_{\,i\,m\,t\,s} \times Prices_{i\,m\,t\,s}^{-\eta} \tag{9}$$

Where $Q_{i\,m\,t\,s}$ is the quantity of rooms demanded per metro area i, segment m, year t and month s. $D_{\,i\,m\,t\,s}$ is the measure of demand at the same level. $Prices_{i\,m\,t\,s}$ is the measure of prices, in this case I use the monthly average of the revenue per available room, for example, the number that I used as a price for a room night in a luxury hotel in Amsterdam in January 2006 was 145.24 euros, which is the RevPAR (from the first row of table 1). The $\eta > 1$ is the constant price elasticity of demand. After applying logarithms, equation 9 becomes:

$$log(D_{\,i\,m\,t\,s}) = log(Q_{\,i\,m\,t\,s}) \times \eta\, log(Prices_{i\,m\,t\,s}) \tag{10}$$

Then, $D_{\,i\,m\,t\,s}$ is cleared and used as demand. As Butters highlights, by controlling for changes in prices, $D_{\,i\,m\,t\,s}$ corresponds to shifts in the demand curve. Further, in the case that occupancy is reaching the maximum capacity, "shifts in the demand curve are reflected in movements in price given the binding capacity constraint." (Butters, 2020, p. 39). The η should ideally be available in the literature. In the case of the United States, Butters (2020) uses two options: the constant price elasticity of demand equal to 1.85 and equal to 4. The number 1.85 "is the average of the price elasticity of demands that rationalize the average of the Lerner indices implied by the average marginal costs reported by Kalnins (2006) for economy and luxury hotels" whereas 4 is the "price elasticity of demand used in Bloom (2009) to model the aggregate economy" (Butters, 2020, p. 40, footnote 54).

To use this new measure of demand, $D_{i\,m\,t\,s}$ is implemented as the quantity $Q_{i\,m\,t\,s}$ in the equation 2 for the coefficient of variation and in the equations 4 and 5 that make up the instrument. In the following table, equation 6 is executed, but using $D_{i\,m\,t\,s}$ from equation 10 as the quantity of rooms demanded. In columns 1-4 it is assumed that the constant price elasticity of demand is 1.85 and in columns 5-8 that this elasticity is 4.

When using the new measure of demand, the strength of the explanatory power of the coefficient of variation is very similar to that of one from main regression (0.12, table 4). However, none of the coefficients are statistically significant in the columns where the coefficient of variation of demand volatility is used as explanatory variable (columns 1, 2, 5 and 6).

Contrarily, the instrument is pretty robust with a very high f-statistics compared to the main results and it is statistically significant in almost all of the specifications where it is

	(1) CV	(2) CV	(3) IV	(4) IV	(5) CV	(6) CV	(7) IV	(8) IV
Demand Volatility	-0.0364	-0.0186	-0.101***	-0.0946**	-0.00341	-0.00133	-0.0114*	-0.00814
	(0.0240)	(0.0137)	(0.0303)	(0.0373)	(0.00407)	(0.00210)	(0.00651)	(0.00882)
Dep. variable mean	-0.17	-0.17	-0.17	-0.18	-0.17	-0.17	-0.17	-0.18
Year / segment F.E.		Yes	Yes	Yes		Yes	Yes	Yes
Controls		Yes	Yes	Yes		Yes	Yes	Yes
Drop 2008				Yes				Yes
First stage F statistic			91.04	104.47			33.34	28.93
Hausman test			0.10	0.18			0.70	0.24
Adjusted R2 first stage			0.58	0.57			0.39	0.38
R-squared (overall)	0.14	0.47	0.53	0.54	0.10	0.45	0.53	0.53
Observations	349	349	349	261	349	349	349	261

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Alternative Measure of Demand, 2006-2009

Results based on equation 6. Explanatory variables: in columns 1, 2, 5 and 6 the coefficient of variation (CV) as calculated by equation 2, in columns 3, 4, 7 and 8 the instrumental variable as calculated by equation 3. Dependent variable: log(Occupancy).

used. Nonetheless, the magnitude of the coefficients differs a lot depending on the price elasticity used, therefore, it is crucial what estimate to use for η. Assuming that the demand for rooms is relatively less elastic (with a price elasticity of demand of 1.85), then an extra unit of demand volatility would imply a decrease of approximately 10% (($e^{-0.101}$-1)*100) in the occupation of hotels. When assuming that the demand is very elastic (with a price elasticity of demand of 4), more demand volatility implies a very small decrease in occupation of only 1.1% (($e^{-0.0114}$-1)*100), and this is the upper bound, assuming a whole extra unit of demand volatility. Thus, the results are associating the fact that having clients who are extremely sensitive to changes in the price of room nights spent in a hotel with a smaller negative impact of demand volatility on the productivity of hotels.

Given the very different results obtained when using different elasticities, it would be ideal to be able to use an estimate of the for each of the cities in the specific years used in my sample, however, there is not enough literature regarding these elasticities in the European context. Konovalova and Vidishcheva (2013) present the average price elasticity of demand for tourism for some of the European countries, they mention that for France it is 0.53, for Germany 0.33, Spain 1.38, the Netherlands 0.61 and for Italy 0.49.

Further, the range of possibilities to improve the results does not stop there, given that Alrawabdeh (2021) found that between 2017 and 2020 the price elasticity of demand in local and international hotels in Dubai presents different magnitudes throughout the year: in low seasons, the demand is more elastic (up to 4.5) because of high supply, whereas in high seasons, the elasticity is very low (to a minimum of 0.1). Another example of different elasticities that appear within the year, in the case of a hotel in Mallorca, Vives et al. (2019) found that between 2014 and 2015 during the period closest to the stay date the elasticity is at its highest level, and the periods where most of the bookings are done, the elasticity is smaller. Thus, perhaps an annual elasticity of demand could even be inaccurate and it would be better to have the elasticity per metro area per season.

When comparing the robustness checks with the main results (table 4), it is always the case that when using the instrument or the alternative instrument, the effect of the demand volatility is larger than when using the coefficient of variation as explanatory variable. When using the alternative demand, only the coefficients of the instrument are statistically significant and robust, but these coefficients imply almost a quarter of the drop in capacity that the main regression results suggested (10% vs 41.26%). Perhaps having the true data over the prices and price elasticity of demand could allow for more similar results.

When taking the revenue per available room as a dependent variable, the negative impact of the instrument is dramatic. If seen as a drop in productivity it is twice the drop found in the main results (a drop of 72.5% vs. a drop of 41.26%). This could be driven by the fact that pricing strategies are crucial in the hotel industry, and that the revenues are very sensitive to these strategies. Therefore, negative effects from the demand side could be more visible in the revenue per available room than in the occupancy rates.

Nevertheless, when still using the alternative productivity as dependent variable, the impact measured with the coefficient of variation (CV) in table 7 implies a drop of productivity similar to that of the results when using an alternative demand in table 8 (10.4% vs 10%), and hence, also a quarter of the effect calculated with the instrument in the main regression of table 4.

6 A Longer Time Period

To see whether the coefficients of the main results are consistent, given the available data, I follow the same methodology of chapters 4 and 5 analyzing samples of different time periods. In the subsection 9.4.1 of the appendix, I show the results of a sample of the same length as the main results, from 2017 until 2020. The main findings from that short and recent period is that when using the alternative demand, the instrument seems to be very strong, and the effect of demand volatility on occupation is null. In this chapter, I focus on a longer time period and discuss the changes that could be driving the results.

To test for a longer period, I use the monthly demand of room nights from 2006 until 2020. Given that for the first years the information about the rent of an apartment is not available, that control is not included. However, after testing an alternative specification from 2010-2020 it is important to know that the log(Rent) was always positive and statistically significant, and the coefficients of the explanatory variable, though not statistically significant, were different but close to the resulting coefficients in the 2006-2020 period. This could imply that log(Rent) is in part affecting the explanation of the changes in productivity, therefore, when ignoring this control for the 2006-2020 period, it is possible that the coefficients of the demand volatility are, to some small extent, under or overestimated.

The descriptive statistics (Table 19, in the appendix) of this period are pretty similar to that of the period 2006-2009. However, the mean of demand volatility as measured by the coefficient of variation is larger: 0.24 (the numbers for the first sample 2006-2009 are shown between parentheses: 0.18), the standard deviations is now 0.27 (whereas in 2006-2009 it was only 0.06), the minimum is 0.04 (0.07) and the maximum is 5.40 (whereas in the 2006-2009 the maximum was only 0.38), which is coming from the demand volatility that one of the hotel segments in Prague faced during 2020.

6.1 Main Results

The following table shows the results when running equation 6 for the main analysis. In this case, for column (4) the observations of both 2008 and 2020 were dropped.

	(1) CV	(2) CV	(3) IV	(4) IV
Demand Volatility	-0.0366***	9.67e-05	-0.134	-0.228
	(0.0130)	(0.00330)	(0.0999)	(0.157)
Dependent variable mean	-0.21	-0.21	-0.21	-0.21
Year / segment fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Drop 2008 & 2020				Yes
First stage F statistic			29.95	7.58
Hausman test			0.21	0.11
Adjusted R2 first stage			0.13	0.11
R2 (overall)	0.0082	0.85	0.78	.
Observations	1,364	1,364	1,364	1,179

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Main Regression, 2006-2020

Results based on equation 6. Explanatory variables: in columns 1 and 2 the coefficient of variation (CV) as calculated by equation 2, in columns 3 and 4 the instrumental variable as calculated by equation 3.
Dependent variable: log(Occupancy)

The estimates are only statistically significant in column 1, where the coefficient of variation is used as a measure of demand volatility. Nevertheless, when not dropping the 2008 and 2020 observations, the instrument should be robust enough given its high f-statistic. From column 1, it could be inferred that an extra unit of demand volatility is associated to a decrease of 3.92% (($e^{-0.04}$-1)*100) in the occupancy.

6.2 Alternative Instrument

Using the alternative instrument based on the sales at a metro area-segment-year level, the results are as follows:

	(5) alternative IV	(6) alternative IV
Demand Volatility	-0.0443	-0.197
	(0.118)	(0.172)
Dependent variable mean	-0.18	-0.18
Year / segment fixed effects	Yes	Yes
Controls	Yes	Yes
Drop 2008 & 2020		Yes
First stage F statistic	18.6	9.98
Hausman test	0.76	0.28
Adjusted R2 first stage	0.13	0.11
R2 (overall)	0.85	.
Observations	1,364	1,179

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Regression using the Alternative Instrument, 2006-2020
Results based on equation 6. Explanatory variables: in columns 5 and 6 the alternative instrumental variable as calculated by equation 3. Dependent variable: log(Occupancy)

In the specification of column 5 it is possible to see again that the instrumental variable should be robust enough given its high f-statistic. Even though it is not statistically significant, when using an instrument based on the sales instead of the quantity of rooms demanded, the coefficient is very close to that of column 1 from the previous table, where the demand volatility was measured as the coefficient of variation of equation 2 (without controls): -0.0443 and -0.0366***.

6.3 Alternative Measure of Productivity

When doing the analysis with an alternative measure of productivity, using the RevPAR as the dependent variable, the results seem to be more statistically consistent, making Columns 1 and 3 more interesting for the discussion. Nevertheless, even though it is not statistically

	(1) CV	(2) CV	(3) IV	(4) IV
Demand Volatility	-0.0494***	-0.00256	-0.443**	-0.593
	(0.0166)	(0.00372)	(0.2201)	(0.368)
Dependent variable mean	1.95	1.95	1.95	1.98
Year / segment fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Drop 2008 & 2020				Yes
First stage F statistic			29.95	7.58
Hausman test			0.095	0.15
Adjusted R2 first stage			0.13	0.11
R-squared (overall)	0.02	0.86	0.73	0.5
Observations	1364	1364	1364	1179

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: Regression Revenue Per Available Room, 2006-2020
Results based on equation 6. Explanatory variables: in columns 1 and 2 the coefficient of variation (CV) as calculated by equation 2, in columns 3 and 4 the instrumental variable as calculated by equation 3.
Dependent variable: log(RevPAR)

significant, the coefficient of the CV in the specification that uses the control variables (column 2) is for the first time very close to zero, implying that the effect of demand volatility could be null.

In these columns, the coefficients are statistically significant. But their magnitudes are very different. An extra unit of demand volatility according to the coefficient of variation implies a decrease in the revenue per available room of 4% (($e^{-0.0494}$-1)*100), while the instrument implies a decrease of 36% (((($e^{-0.443}$-1)*100), which is actually very close to the drop in capacity that the same instrument in the main regression results from 2006-2009 suggested (41.26%, in table 4). Being the mean of the dependent variable approximately 89 euros, these drops would imply 3.5 and 32 euros, respectively, less in revenues per available room, which are pretty different results. But seeing the drop as a decrease in productivity, then the 4% is very close to the result of column 1 of the previous table.

When using the alternative measure of demand of equation 10, the results do not have much explanatory power. Only the coefficient of variation (CV) as a measure of demand volatility is statistically significant, and using a price elasticity of demand of 1.85 or 4, does not change the result: more demand volatility has no effect on the occupation of hotels. For completeness, this table is reported in the appendix (Table 20).

6.4 Changes within the Industry

Testing over a longer time period can be problematic because there could be many changes happening within the industry along this time frame that could impact the applicability of the instrument. For example, technological changes and globalization that can affect the way of doing business and also improve the availability of information, which help managers to make better decisions and also helps to partially solve the asymmetric information problem from the point of view of customers. Next, I will present some of the changes that could influence how the industry works.

- Spillovers

There could be spillovers between the hotels that belong to different segment or even between hotels of different metro areas. Mitra et al. (2019) found that there are high spillover effects in tourism between European countries. The spillovers could be driven by different elements such as various supply and demand related factors, socioeconomic and cultural relations, and the attractiveness of the places. For example, the spillover from the demand side surges when tourists visit many countries in a single tour.

Based on Mitra et al. (2019), for occupancy rates in hotels in the nine most visited countries in Europe, the spillover index value (that goes from 0 to 100) is at its highest for a medium horizon of four to twelve months, being 63.08. This indicates that the transmission of shocks from one market to others happens over a medium horizon, rather than a short (1-3 months) or a long one (+12 months). An explanation for this is that international visits are planned in advance, and a shock in one country could not damage a visit to another country in the short term, contrary to a medium term, when customers have the flexibility to change their travels.

- The Sharing Economy

Another factor that can influence the industry is the sharing economy. The sharing type of businesses are those where economic activities such as sharing access to goods and services happen between peers. The sharing economy can influence the business profitability, the structure of industries, and challenge legal institutions when regulating these activities (Hamari, Sjöklint and Ukkonen, 2015, as cited in Aznar et al., 2017). In 2008, one of the biggest players of the sharing economy, Airbnb, was founded. By 2012, it announced its 5 millionth booking (Bloomberg. 2012). Given its rapid expansion, there have been several studies on its impact on the hotel industry around the world.

Aznar et al. (2017) explain that because of the high fixed cost of hotels, they are vulnerable to negative shocks in demand, implying that drops in revenue greatly affect their profit, whereas Airbnb hosts offer a similar but cheaper service and have no significant fixed costs. Studying the case of Barcelona, the authors found that location is crucial: if hotels are located close to several Airbnb, what generally happens in the city centers, the drop in revenues for hotels is smaller than when the hotels are located in the outskirts of the city.

Dogru, et al. (2019) using data from 10 major cities in the U.S. between 2008 and 2017, found that in general, more Airbnb supply negatively affects the performance measures of hotels. Given the rapid growth of Airbnb, a 100% increase of its supply decreases hotel sales (RevPAR) by 2%, the average daily rate (ADR) by up to 1 % and occupancy levels by between 0.5% and 1%, depending on the segment (class) of hotels. They conclude that the additional capacity provided by Airbnb is accommodating the high demand of peak seasons that would otherwise be served by hotels. Dogru et al. (2019) emphasize that this extra capacity coming from Airbnb is a reality due to the lack of regulations, giving Airbnb an unfair advantage because, for hotels, expanding capacity would take years and implies significantly high costs.

- Online Presence: OTAs and Crowd-voting

The hotel industry is being impacted by the online presence of hotels. Smithson et al. (2011) explain that the online visibility helps firms to capture new clients and increase the occupancy rate, generating a better organisational performance. Further, the internet distribution costs are cheaper than the traditional ways. The authors explain that given the condition of the capital intensive nature of hotels, it is indispensable for these firms to maximise the use of capacity, therefore, they use the return on assets (ROA) as a measure of organisational performance that is related to occupancy rates. From a database of 105 hotels in Spain between 2008 and 2009, they found that online visibility is significant in explaining the ROA of the firms, thus, more online visibility would imply better organizational performance through higher occupation rates.

The online presence also comes with third party websites. These websites generally act as an online travel agency (OTA), and between the most common are Hotels.com, Travelocity, Expedia, Priceline.com, Booking.com, Orbitz, and Hotwire (Cho et al., 2018). A crucial feature of these websites is the crowd-voting -when a website shows a large amount of opinions and ratings over a topic or establishment-. The influence of platforms such as Booking.com has been well studied in the literature. Booking.com was launched in 2010 as the first mobile application for lodging which is nowadays a reference for publishing the supply of rooms and for making reservations.

Garrigos-Simon et al. (2017) studied crowd-voting and maintain that the votes over all the aspects of hotels that are published in the OTAs affect the sales and subsequent performance of hotels. Better reviews in Booking.com would imply higher sales through virtual media, including not only through the OTA but also through the main websites of hotels, and also would imply higher sales to direct customers. The crowd-voting influences the behavior of hotels because the reviews of more exposed firms force them to increase the quality and focus more on consumer requirements, which influences the reputation, pricing strategies and ultimately, the performance. On the other hand, the use of OTAs are part of the influence of information technology (IT), which affects costs, efficiency, service quality and customer satisfaction (Kucukusta et al., 2015 as cited in Garrigos-Simon et al., 2016, p. 424).

Based on the measure of hotel performance from Garrigos et al. (2005) that covers: (1) profitability; (2) growth; (3) competitive position; and (4) stakeholder satisfaction, Garrigos et al. (2017) investigated the effect of crowd-voting. Specifically using reviews from Booking.com and data from those hotels that were reviewed on the website. They found that crowd-voting has a positive and significant impact on virtual and direct sales, which in turn has a direct and positive effect on hotel performance. An important insight from their study is that the use of OTAs and the crowd-voting tool that comes with them is especially convenient for small firms, giving them more power and enhancing their competitiveness by avoiding traditional tour operators and travel agencies, which improves their margins.

Another important feature of the OTAs is that they attenuate the problem of information asymmetry between the hotels and potential guests through the customer ratings, and as a by-product, these ratings allow for a price premium for making the online transactions less risky (Ba and Pavlo, 2020 as cited in Öğüt and Onur Taş, 2012, p. 200). Given the fixed capacities and the seasonality, the underpricing and overpricing on the OTAs can lead to important revenue losses, making the fair pricing of room nights a critical task in the management of hotels.

Öğüt and Onur Taş (2012) found that 1% increase in prices decreases the RevPAR from 0.91% up to 1.32% in Paris and London, while 1% increase in the online ratings written by customers, translates into around 2.6% increase in the RevPAR in the same cities. From their results, they were able to conclude as well, that customers find online reviews more reliable than the traditional star ratings. Given the transparency of prices provided by the OTAs, even though managers have the possibility of comparing the room prices of hotels they run with the prices of competitors, the firms can differentiate themselves through online reviews and location. The authors stress the importance of online reviews (a signal for quality) as a new way of competing besides price competition and the traditional star ratings, particularly for small hotels that do not belong to big hotel chains.

- Pricing Strategies

Lastly, I will mention the pricing strategy of hotels as a factor that has evolved over the last years and has important repercussions on the industry. The pricing has become very important especially when talking about revenue management (RM). "RM is the application of information system control and pricing that allows for revenue maximization via the allocation of the right capacity at the right time in the right place". (Ivanov and Zhechev, 2012, as cited in Vives and Jacon, 2020, p. 268). RM allows to identify different classes of customers and sell them the same product at a different price, that is, firms can implement dynamic pricing (DP). As Melis and Piga (2017) mention, DP is already known by the industry: from a survey done by the Global Business Travel Association (GBTA) in 2014, 75% of hotels reported to be aware of DP, but only 22% were actively using it.

It is with RM when OTAs enter the discussion once more. Melis and Piga (2017) explain that hotels can use websites such as Booking.com and Expedia not only as a platform to gain more exposure, but also as a RM tool. These platforms intensify price transparency and decrease menu costs (those incurred when changing prices), reducing frictions in the market (Bryniolfsson and Smith, 2000, as cited in Melis and Piga, 2017 p. 163). Still, the use of OTAs is becoming more costly for hotels, implying high commission costs and wholesale room discounts (King, 2016, as cited in Cho et al., 2018, p. 11). However, according to Cho et al. (2018), OTAs argue that these high costs are justified by the additional demand that they bring during periods of low occupancy thanks to their marketing exposure to an extensive range of market segments.

By testing models to investigate the pricing strategies of hotels, different authors have found diverse results. Vives and Jacob (2020) tested two types of models:

- A deterministic model: studying prices across the booking horizon, thus, the prices are a variable that depends on the number of days prior to the stay.
- A stochastic model: a consumer choice framework that studies types of consumer and their price elasticities.

Vives and Jacob (2020) found that in the maximization process of a specific hotel in Majorca, setting a price between 3% and 6% higher than the competitors resulted in up to 73% more revenue than in similar hotels.

Cho et al. (2018), found that a hotel in a major US city was apparently doing "price following" and "price undercutting" strategy, because the strong co-movement of the prices of seven important hotels in the city had the appearance of tacit collusion "that could be sustained by commercial price shopping services that inform the hotels of each others' prices in real time, combined with the hotels' use of revenue management systems (RMS) that provide recommended prices". However, the authors realized that the revenue manager (in charge of making the last decision) most of the time ignored the rate recommended by the hotel's RM system. They also found that the price setting behaviour was not necessarily collusive, but a best response to the pricing of competitors, making the dynamic a Bertrand price competition between these hotels "which are subject to aggregate demand shocks that cause their occupancy rates and prices to move together".

Finally, from four touristic areas of Italy, Melis and Piga (2017) found that hotels with more stars tend to use more DP, and that this tendency does not correlate to the size of hotels. This implies that the costs of setting-up a RM system does not seem to be a constraint given that the scale of the hotels does not interfere in the propensity of using DP. Nevertheless, in their sample, the majority of hotels with 3 stars or less tend to use uniform pricing. Overall, in the Italian case was found that the DP was not so common by 2015, and even though due to the online presence the menu costs are low, changing prices still implies higher managerial costs, which "may enhance price stickiness" (Melis and Piga, 2017, p. 173). However, the DP was seen more often during high demand periods, which suggests that to incur in managerial costs to *dynamically* change prices was profitable as long as the hotels are close to reach their capacity constraints.

- Price Volatility in the European Context

When looking at the data used in this article, a possible option to see the variability of prices is to calculate the coefficient of variation at the metro area-segment-year level using the equation 2 with the monthly prices (instead of the monthly room nights demanded). As a measure of prices I use the revenue per available room.

Prices volatility (CVimt)	Observations	Mean	Std	Min	Max
2006-2009	349	0.282	0.07	0.126	0.482
2017-2020	381	0.440	0.332	0.063	2.077
2017-2019	284	0.273	0.078	0.063	0.606
2006-2020	1364	0.328	0.200	0.063	2.077
2006-2019	1267	0.28	0.078	0.063	0.778

Table 12: Price Volatility

In table 12 it is possible to see that the mean of the volatility of prices of the more recent years 2017-2020 is 0.44, whereas the one from the years of the main results 2006-2009 is only 0.28. This could suggest that in more recent years, prices are moving more dynamically allowing hotels to profit more from the willingness to pay of customers, hence, being more efficient. However, in the last column, the higher price volatility in the sample is coming from the hotel segment 5 in Prague during 2020, suggesting that the additional price volatility comes from the observations of the year 2020. This is indeed the case: when dropping the year 2020, the mean of the price volatility is the same for almost all time periods shown on table 12. Perhaps to investigate the volatility with data of a higher frequency could give a better idea of the current situation of the pricing strategies of hotels in my sample.

From my perspective, the factors previously mentioned could imply that the instrumental variable is not applicable for the more recent years of the sample. It could be possible that changes in technology and subsequent availability of information are allowing some individual firms in a segment of hotels to have repercussions on the aggregate demand volatility of the metro area where these individual firms are located.

I suspect that with new types of competitors in the industry and the current ease with which hotels can implement pricing strategies through the use of revenue management tools and online travel agents, some firms could be influencing competitors from the same segment or competitors from other segments from the same city or even other cities, ultimately affecting the exogeneity. It could be the case that between those hotels that are being influenced, there are firms of a smaller scale or more limited resources. From my point of view, this situation is more likely to happen in cities of smaller size, which is the case of European cities such as Amsterdam or Geneva which are in my sample. On the other hand, it could also be the case that as shown by some of the results, in recent years the industry has become more efficient and the null effects of demand volatility on productivity could be a reality.

7 Conclusion

To conclude, I summarize the resulting coefficients in the following table including only the specifications with all the observations, that is, when I am not dropping observations from 2008 or from 2020. For the instruments, the f-statistic is shown between parentheses.

In the main analysis using observations from 2006 until 2009, the first measure of demand volatility is negative but not statistically significant, although the instrument is, and it implies that a whole extra unit of demand volatility would negatively impact productivity, reducing the capacity utilization by 41.3%. (-0.532***). The same occurs when using an alternative measure of demand that assumes a constant price elasticity of 1.85 (equation 10), but the instrument suggests, at most, a drop of only 9.6% (-0.101***) in productivity.

When testing the methodology on different time frames, the coefficient of variation becomes statistically significant, but the effect is zero when using an alternative measure of demand, and very small and negative, both when estimating the main regression of equation (8) and when using the alternative measure of productivity (RevPAR): between 1.3% (0.0133**) and 9.7%(-0.0962***) decrease in productivity, respectively. When using the instrument in the alternative time frames, the drop in productivity is also 0% in many cases, and at most, 36% when using RevPAR as a measure of productivity.

With the analysis that I have carried out, I cannot completely argue that, as stated in

Time period	Y: Occupation			
	CV	CV with controls	Instrument	Alt instrument
2006-2009	-0.114	-0.062	-0.532*** (11.18)	-0.649*** (15.38)
2017-2020	-0.0962***	-0.0133**	0.142 (3.2)	0.0545 (4.9)
2006-2020	-0.0366***	0	-0.134 (29.95)	-0.0443 (18.6)
	Y: Occupation, X: Alternative demand			
	n =1		n = 4	
	CV with controls	Instrument	CV with controls	Instrument
2006-2009	-0.0186	-0.101*** (91.04)	-0.00133	-0.0114* (33.34)
2017-2020	0***	0*** (559.57)	0***	0*** (4586.34)
2006-2020	0***	0.00997 (0.28)	0***	0 (1.91)
	Y: RevPAR			
	CV	CV with controls	Instrument	
2006-2009	-0.161	-0.110*	- 1.292*** (12.04)	
2017-2020	-0.0756***	-0.0110*	-0.258*** (3.19)	
2006-2020	-0.0494***	-0.00256	-0.443** (29.95)	

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Summary of Results

the hypothesis, there are negative effects of demand volatility on productivity because of the following reasons: (1) some of the results imply that this effect could be zero; (2) some of the coefficients are not statistically significant; (3) sometimes the instrument is not strong enough; and (4) the magnitudes of the coefficients differ by a large amount. Nevertheless, in the majority of the cases the effect seems to be negative, suggesting that for hotels that have high adjusting costs, facing demand volatility will negatively impact their measured productivity.

This is the first study looking at the effect of environmental factors affecting the productivity of the hotel industry in the European context. This enlightens the fact that there is a lack of research on empirical microeconomics studies in this industry in the continent. In the case of accepting my results as being negative, this implies that firms must take into account this effect in their strategic planning. As mentioned by Butters (2020), this negative effect coming from the environment must be taken into account on welfare calculations and studies on aggregate productivity that use the measure productivity.

When looking at similar studies, it is possible to find only the American case done by Butters (2020), where he found more consistent estimates that throughout the analyses had almost the same magnitudes implying that more demand volatility is associated with a drop in productivity of around 34%. Perhaps these results are more consistent given the size of the data: the American sample has 92 cities, which could give more strength to the econometric analysis. Which brings me to the limitations of this paper, between which I can mention the size of the data, that is perhaps not allowing for more strong instruments. Even though I have a long number of observations, the results are based on only 17 cities. It will be ideal to have more cities included in the sample to see whether the results could be more conclusive when covering more markets within Europe. Moreover it would also be desirable to have accurate estimates of the price elasticity of demand of the hotel industry in each of the cities included in the sample to have more precise results of the alternative demand measure.

In other studies such as that one from Brown and Dev (2000) it was demonstrated that the size of the hotels are an important factor when explaining the productivity, thus, it would be good to add to my analysis a control variable for the average size of the hotels that constitute the segments observed in the data. Furthermore, given the diversity of the European context as an economic bloc, it would be interesting to control for relative income of countries and the share of employees that have emigrated to work in cities where hospitality workers are paid higher salaries, such as Zurich and Geneva.

Since the instrument was not robust in some of the specifications in the more recent years, it is pertinent to test whether spillover effects are occurring between segments of hotels located in the same city. When thinking from another point of view related to the relationships between the hotels, it is also important to realize that the analysis is abstracting from strategic interactions, and ideally it should be accounted for.

As a suggestion for further research, given that in my sample the occupancy never reached 100%, it would be useful to study whether there are overcapacity issues. Alemayehu and Kumbhakar (2021) found in Norway that excess capacity in hotels considerably increases the costs and increases inefficiency. Moreover, given the small size of the majority of cities in Europe, it would be interesting to study another external factor such as the land use regulations. Suzuki (2013) studied the land use regulation as a barrier to entry in the lodging industry of Texas, he shows that an increase in regulatory stringency is associated with an increase of 8% in operating costs and 6% on entry costs.

Accounting for external factors such as the demand volatility could in the short term improve the performance of hotels and the mid to long-term help enterprises and independent firms that choose the capacity of new hotels to make better informed decisions. Consequently, in the future it is key to keep studying other external factors that are affecting different industries so those who make decisions can achieve better results, that will eventually contribute to economic growth and the improvement of the welfare of the society.

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9 Appendix

9.1 From Theoretical Background

(Go back to section 2)

- Regression Performance of Capacity

	(1) log(Room nights available)	(2) log(Active hotels)
log(monthly rooms demanded)	0.0733***	0.0230***
	(0.0110)	(0.00335)
Dependent variable mean	5.22	1.74
Metro-segment-year fixed effects	Yes	Yes
R2 (overall)	0.95	0.81
Within R2	0.12	0.08
Observations	4,134	4,134

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Behaviour of Capacity in the Hotel Industry

This table presents the regression between the number of rooms sold and number of rooms available in a month at a metro area-segment level, from January 2006 until December 2009. For example, one of the 4134 observations is the total rooms demanded (sold) in January (a month) of 2006 (a year) by the group of hotels that make up the "economy" class (a segment) in London (a metro area).

- Changes in Hotel and Room supply in the Netherlands

City		Year					
		2016	2017	2018	2019	2020	2021
Rotterdam	Total Rooms	62	62	72	74	78	146
	Change		0%	16%	3%	5%	87%
	Total Hotels	6554	6554	7728	8172	8406	14288
	Change		0%	18%	6%	3%	70%
Amsterdam	Total Rooms	167	173	183	194	203	438
	Change		4%	6%	6%	5%	116%
	Total Hotels	25725	26754	27953	30863	32639	45991
	Change		4%	4%	10%	6%	41%
Eindhoven	Total Rooms	40	42	46	48	52	78
	Change		5%	10%	4%	8%	50%
	Total Hotels	5326	6114	6690	6864	7384	8500
	Change		15%	9%	3%	8%	15%
Maastricht	Total Rooms	40	40	42	44	46	88
	Change		0%	5%	5%	5%	91%
	Total Hotels	3270	3270	4026	4182	4322	5978
	Change		0%	23%	4%	3%	38%
The Hague	Total Rooms	48	50	54	60	60	140
	Change		4%	8%	11%	0%	133%
	Total Hotels	5638	6326	6462	7004	7018	12316
	Change		12%	2%	8%	0%	75%

Table 15: Pipeline Market Report, changes in rooms and hotels

- Pipeline Report from the Netherlands

(Go back to section 2)

City	In Construction	Final Planning	Planning	Unconfirmed	Total
Rotterdam	768	974	1432	0	3174
Amsterdam	1749	945	530	280	3494
Eindhoven	330	0	250	0	580
Maastricht	32	300	144	0	476
The Hague	408	764	0	288	1460

Table 16: Pipeline Report for New Supply

9.2 From Research Design

(Go back to section 3)

- Code developed to calculate the instrumental variable
  - Equation 4, first part on the right hand side

```
    #building equation 4, Share
Qimt_firstsample = firstsample.groupby(['metroarea', 'segment','year']).agg({'Rooms Demand':sum})
Qimt_firstsample['division']= Qimt_firstsample['Rooms Demand']/Qimt_firstsample.groupby(['year','metroarea'])['Rooms Demand'].transform('sum')
```

  - Equation 4, first part on the left hand side

```
    #equation 4 [1/(# Market (m) - # Market(m)i)]
Sim_firstsample = firstsample.groupby(['metroarea', 'segment','year'], as_index=False).sum()
Sim_firstsample['instances'] = Sim_firstsample['segment'].map(Sim_firstsample['segment'].value_counts())
occur_firstsample = Sim_firstsample.groupby(['metroarea', 'segment']).size().to_frame('size')
occur_firstsample = occur_firstsample.reset_index()
Sim_firstsample_first = occur_firstsample.merge(Sim_firstsample)
Sim_firstsample_first ['firstratio'] = (1/(Sim_firstsample_first ['instances']-Sim_firstsample_first['size']))
    # equation 4. Summations
#sum of market share of all areas and years (summation t, summation j including i)
Sumallsegments_firstsample = Qimt_firstsample.groupby(['segment']).agg({'division':sum})
Sumallsegments_firstsample.rename(columns={'division':'sumseg'}, inplace=True)
#sum of martket share in each area (i)
Sumsegmentarea_firstsample = Qimt_firstsample.groupby(['metroarea','segment']).agg({'division':sum})
Sumsegmentarea_firstsample.rename(columns={'division':'sumsegarea'}, inplace=True)
#merge the two summations
Sumsegmentarea_firstsample = Sumsegmentarea_firstsample.reset_index()
Sumallsegments_firstsample = Sumallsegments_firstsample.reset_index()
zum_firstsample = Sumallsegments_firstsample.merge(Sumsegmentarea_firstsample)
#merge to have all the observations
Simsecond_firstsample = zum_firstsample.merge(Sim_firstsample)
#creating the summation j≠i, to exclude the area i of the final summation
Simsecond_firstsample['summ'] = Simsecond_firstsample['sumseg']-Simsecond_firstsample['sumsegarea']
```

  - Equation 5

```
    #equation 4 [1/(# Market (m) - # Market(m)i)]
Sim_firstsample = firstsample.groupby(['metroarea', 'segment','year'], as_index=False).sum()
Sim_firstsample['instances'] = Sim_firstsample['segment'].map(Sim_firstsample['segment'].value_counts())
occur_firstsample = Sim_firstsample.groupby(['metroarea', 'segment']).size().to_frame('size')
occur_firstsample = occur_firstsample.reset_index()
Sim_firstsample_first = occur_firstsample.merge(Sim_firstsample)
Sim_firstsample_first ['firstratio'] = (1/(Sim_firstsample_first ['instances']-Sim_firstsample_first['size']))
```

To build the instrument, the data frame 'Sim firstsample first' (left hand side of equation 4) is multiplied with the data 'frameSimsecond firstsaple' (right hand side of equation 4) and also multiplied with 'STDit firstsample' (equation 5).

- Share of rooms from which STR has collected information in the USA, 2006-2009

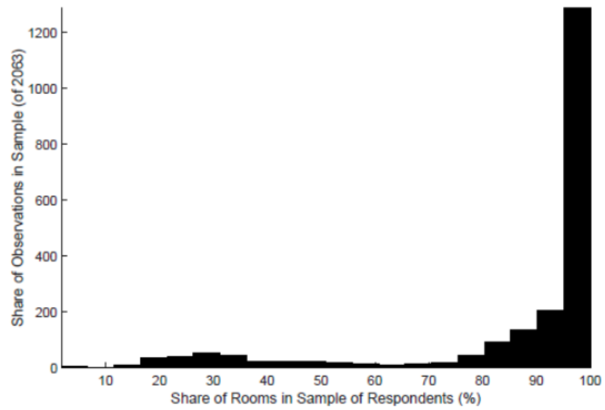

Figure 7: Histogram of Share of rooms Covered by STR Respondents for all Metro area-Segment-Years, For United States

Note: Recovered from "Demand Volatility, Adjustment Costs, and Productivity: An Examination of Capacity Utilization in Hotels and Airlines, Online Appendix". Butters (2020).

(Go back to section 3)

- Summary of control variables, 2006-2009

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
log(personnel cost)	349	1.204	0.226	0.724	1.883
log(electricity price)	349	-0.883	0.196	-1.238	-0.0953
log(GDP per capita)	349	4.433	0.168	3.992	4.768
log(employment in hospitality)	349	2.596	0.425	1.827	3.084
unemployment rate	349	7.451	2.767	3.400	17.90
log(density hosp. employment)	349	0.390	0.180	0.106	0.840
log(share of hosp. employment)	349	-1.366	0.124	-1.625	-1.166
5-year difference log(GDP p. c.)	349	0.0330	0.0271	-0.0229	0.110
5 year difference log(hosp. empl.)	349	0.0825	0.0470	0.00247	0.190

Table 17: Summary of Controls, sample 2006-2009

9.3 From Robustness Checks

(Go back to section 5)

- Results of control variables using the Alternative Instrument, 2006-2009

	(5) altIV	(6) altIV
log(personnel cost)	-0.0620*	-0.0700
	(0.0353)	(0.0498)
log(electricity price)	-0.0429***	-0.0459***
	(0.0121)	(0.0150)
log(GDP per capita)	0.0961**	0.114*
	(0.0461)	(0.0637)
log(employment in hospitality)	0.00311	0.00211
	(0.0161)	(0.0185)
Unemployment rate	0.00605***	0.00577***
	(0.00210)	(0.00211)
log(share of hosp. employment)	0.110**	0.117**
	(0.0472)	(0.0520)
log(density hosp. employment)	-0.0785***	-0.0727*
	(0.0295)	(0.0424)
5-year difference log(GDP p. c.)	-0.0330	0.00678
	(0.170)	(0.180)
5 year difference log(hosp. empl.)	-0.0249	0.0239
	(0.0757)	(0.0965)

Table 18: Results of control variables using Alternative Instrument, sample 2006-2009

9.4 From a Longer Time Period

(Go back to section 6)

- Descriptive statistics from the sample period 2006-2020

	Mean	Std	Min	Max
Observations N = 1366				
Occupancy	68%	13%	16%	91%
log(Occupancy) (log(%))	-0.21	0.20	-2.19	-0.01
Demand Volatility (CV_{imt}) , in units)	0.24	0.27	0.04	5.40
Number of hotels (per metro area-segment)	91	90	5	423
Number of rooms (per metro area-segment)	7486	5747	330	32599
Number of rooms volatility (CV_{imt}) , in units)	0.02	0.06	0.00	0.75
Market share (room nights sold, per segment)	18.67%	10.10%	0.34%	64.28%

Table 19: Descriptive Statistics, 2006-2020

- Regression using the alternative measure of demand volatility for the period 2006-2020

	(1) CV	(2) CV	(3) IV	(4) IV	(5) CV	(6) CV	(7) IV	(8) IV
Demand Volatility	1.08e-05*	6.59e-06***	0.00997	-0.00181	0***	0***	1.17e-09	-2.63e-10
	(6.43e-06)	(1.71e-06)	(0.0187)	(0.00172)	(0)	(0)	(8.74e-10)	(2.78e-10)
Dependent variable mean	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18	-0.18
Year / segment fixed effects		Yes	Yes	Yes		Yes	Yes	Yes
Controls		Yes	Yes	Yes		Yes	Yes	Yes
Drop 2020				Yes				Yes
First stage F statistic			0.28	1.71			1.91	1.82
Hausman test			0	0.17			0	0
Adjusted R2 first stage			0.00	0.00			-0.00	-0.00
R-squared (overall)	0.00	0.89	.	.	0.00	0.89	.	.
Observations	1,364	1,364	1,364	1,179	1364	1364	1364	1179

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Alternative Measure of Demand Volatility, 2006-2020

Results based on equation 6. Explanatory variables: in columns 1, 2, 5 and 6 the coefficient of variation (CV) as calculated by equation 2, in columns 3, 4, 7 and 8 the instrumental variable as calculated by equation 3. Dependent variable: log(Occupancy).

Columns 1 to 4 assume a price elasticity of demand of 1.85, and columns 5 to 8, a price elasticity of demand of 4.

9.4.1 A more recent time period: 2017-2020

(Go back to section 6)

Given the availability of the data, I now turn to replicate the main results but using a sample from 2017 until 2020. The descriptive statistics for this period of time (Table 21) are very similar to those of 2006-2009. However, the mean of demand volatility as measured by the coefficient of variation is larger: 0.39 (the numbers for the first sample 2006-2009 are shown between parentheses: 0.18), the standard deviations is now 0.5 (whereas in 2006-2009 it was only 0.06), the minimum is 0.04 (0.07) and the maximum is 5.40 (whereas in the 2006-2009 the maximum was only 0.38), which is coming from the demand volatility that one of the hotel segments in Prague faced during 2020.

In this time period, the data for the rent of an apartment in each of the cities is available, thus, the control log(Rent) is used and it is significant across all the specifications as shown in the coefficient of the control variables in table 22.

	Mean	Std	Min	Max
Observations N = 381				
Occupancy	64%	22%	16%	91%
log(Occupancy) (log(%))	-0.23	0.20	-0.81	-0.04
Demand Volatility (CV_{imt}) ,in units)	0.39	0.5	0.04	5.40
Number of hotels (per metro area-segment)	94	90	6	423
Number of rooms (per metro area-segment)	7988	6289	467	32599
Number of rooms volatility (CV_{imt}) , in units)	0.06	0.10	0.00	0.75
Market share (room nights sold, per segment)	17.80%	9.76%	1.02%	55.84%

Table 21: Descriptive Statistics, sample 2017-2020

In table 23 it is possible to see that, contrary to the main results (table 4), when using more recent data, the coefficient of variation is statistically significant, but the instruments are not, and only when dropping the observations of the covid-19 pandemic (columns 5 and 6), the instruments have a f-statistic larger than 10. Based on the Hausman test, the null hypothesis that the variables are exogenous cannot be rejected. In the case that it could be possible to assure that the coefficient of variation is exogenous, then the impact that demand volatility has on productivity (from column 1: 9.7% (($e^{-0.0962}$-1)*100) in this time frame would be closer to the lower bound of the impact found for the 2006-2009 period when using the coefficient of variation as demand volatility (6.01%).

Additionally, when using the RevPAR as a dependent variable, all the coefficients seem to be statistically significant, but the instrument (column 3) is not robust, being the f-statistic only 3.19, which also implies that the first stage is not significant. When dropping the 2020 observations, the instrument becomes robust and its magnitude is close (but a half) to that of the coefficient of variation as a measure of demand volatility (column1), -0.039 vs -0.0756.

	(2) CV	(3) IV	(4) IV	(5) altIV	(6) altIV
log(personnel cost)	-0.152***	-0.181***	-0.0889***	-0.155**	-0.0890***
	(0.0538)	(0.0613)	(0.0229)	(0.0741)	(0.0229)
log(Rent)	0.173***	0.198***	0.0906***	0.173**	0.0907***
	(0.0529)	(0.0599)	(0.0268)	(0.0695)	(0.0250)
log(electricity price)	-0.0903***	-0.0211	-0.0701***	-0.0474	-0.0699***
	(0.0306)	(0.0607)	(0.0240)	(0.0715)	(0.0219)
log(GDP per capita)	0.0446	0.0997	0.0507	0.0706	0.0508
	(0.0808)	(0.0932)	(0.0341)	(0.101)	(0.0345)
log(employment in hospitality)	0.00582	-0.00198	0.00959	0.00327	0.00955
	(0.0129)	(0.0134)	(0.00747)	(0.0154)	(0.00678)
Unemployment rate	0.000115	0.00282	-0.00357***	0.00113	-0.00356***
	(0.00251)	(0.00268)	(0.00124)	(0.00398)	(0.00108)
log(share of hosp. employment)	-0.0112	-0.00851	0.0423*	-0.00622	0.0422*
	(0.0477)	(0.0542)	(0.0245)	(0.0457)	(0.0235)
log(density hosp. employment)	-0.106***	-0.0981**	-0.0724***	-0.0976***	-0.0723***
	(0.0356)	(0.0428)	(0.0163)	(0.0353)	(0.0157)
5-year difference log(GDP p. c.)	-0.737***	-0.532*	0.0581	-0.557**	0.0583
	(0.280)	(0.308)	(0.140)	(0.277)	(0.138)
5 year difference log(hosp. empl.)	0.0257	-0.0894	0.240***	-0.00426	0.239***
	(0.217)	(0.216)	(0.0769)	(0.262)	(0.262)

Table 22: Estimated Coefficients for Control Variables, 2017-2020

	(1) CV	(2) CV	(3) IV	(4) IV	(5) alt IV	(6) alt IV
Demand Volatility	-0.0962***	-0.0133**	0.142	-0.0269	0.0545	-0.0262
	(0.00587)	(0.00556)	(0.119)	(0.0697)	(0.163)	(0.0579)
Dependent variable mean	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23
Year / segment fixed effects		Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes
Drop 2020				Yes		Yes
First stage F statistic			3.20	11.78	4.90	16.29
Hausman test			0.28	0.70	0.72	0.65
Adjusted R2 first stage			0.23	0.18		
R2 (overall)	0.06	0.93	0.83	0.47	0.92	0.47
Observations	381	381	381	284	381	284

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Main Regression, 2017-2020

	(1) CV	(2) CV	(3) IV	(4) IV
Demand Volatility	-0.0756***	-0.0110*	-0.258***	-0.039***
	(0.0124)	(0.0071)	(0.1775)	(0.253)
Dependent variable mean	1.88	1.88	1.88	2
Year / segment fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Drop 2020				Yes
First stage F statistic			3.19	11.76
Hausman test			0.29	0.068
Adjusted R2 first stage			0.23	0.18
R-squared (overall)	0.00	0.94	0.83	0.93
Observations	381	381	381	284

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Regression Revenue Per Available Room Night, 2017-2020

In table 24 it is possible to see that with the coefficient of variation, the impact of demand volatility of productivity could be, once again, close to -7% (($e^{-0.0728}$-1)*100) when using the coefficient of variation and -4% (($e^{-0.039}$-1)*100) when using the instrument. Being the mean of the dependent variable close to 76 euros, this translates to a drop in revenue per available room between 5 (101.88 x 7%) and 3 (101.88 x 4%) euros.

When testing with the alternative measure of demand of equation 10, the results are significant only when is assumed to be 1.85. Table 25 in the appendix shows the results: from column 1 to 4, the coefficient of demand volatility is negative but practically zero. In this case the instrument of equation 3 is very robust with a f-statistic of 560, but once the observations of 2020 are dropped, its power vanishes. The same happens with the alternative instrument. In conclusion, when using an alternative measure of demand volatility, there is no relationship between volatility of demand and the productivity of the hotels in the more recent years.

	(1) CV	(2) CV	(3) IV	(4) IV	(5) CV	(6) CV	(7) IV	(8) IV
Demand Volatility	-9.89e-05***	-2.7e-05***	-6.64e-05***	0.00449	0***	0***	0***	1.28e-08
	(6.60e-06)	(3.52e-06)	(9.50e-06)	(0.00923)	(0)	(0)	(0)	(1.33e-08)
Dependent variable mean	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23
Year / segment fixed effects		Yes	Yes	Yes		Yes	Yes	Yes
Controls		Yes	Yes	Yes		Yes	Yes	Yes
Drop 2020				Yes				Yes
First stage F statistic			559.57	0.23			4586.34	.860135
Hausman test			0.00	0.09			0	0.2879
Adjusted R2 first stage			0.36	0.06			0.86	-0.02
R-squared (overall)	0.024	0.94	0.94	.	0.02	0.94	0.94	0.19
Observations	381	381	381	284	381	381	381	284

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 25: Alternative Measure of Demand Volatility, 2017-2020

Results based on equation 6. Explanatory variables: in columns 1, 2, 5 and 6 the coefficient of variation (CV) as calculated by equation 2, in columns 3, 4, 7 and 8 the instrumental variable as calculated by equation 3. Dependent variable: log(Occupancy).

Columns 1 to 4 assume a price elasticity of demand of 1.85, and columns 5 to 8, a price elasticity of demand of 4.

(Go back to section 6)