Artificial Intelligence and Dynamic Pricing Technology Adoption: Evidence from the Hospitality Property Sector

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Abstract

We present large-scale evidence on the impact of the adoption of a new dynamic pricing technology by the largest hostel group worldwide. The new technology replaces the previous human-based backward-looking grid pricing model by incorporating Artificial Intelligence and machine learning techniques to estimate future customers' willingness to pay and set prices. We extend the Difference-in-Differences estimator by exploiting variation in the timing of technology adoption by different units. We find statistically significant and economically sizable positive effects of adopting the new technology on revenue and occupancy, and an increased price dispersion at the tails of the occupancy distribution.

Keywords: dynamic pricing technology adoption, grid human-based pricing, artificial intelligence and machine learning, quasi-experiment, hospitality property industry.

JEL Classification: G14, L85, R32, Z33.

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1 Introduction

Dynamic pricing is a set of pricing strategies aimed at maximizing revenue while balancing demand and supply. Early applications of dynamic pricing methods have been mainly present in the service industries where managing demand is particularly important because capacity (supply) is fixed in the short-term and perishable (Baker and Collier, 2009). Once the sales period ends, the lost revenue from an empty airline seat or hotel room is lost forever. In the hospitality real estate industry, dynamic pricing systems allow to increase prices at peak days and decrease prices when demand is low, thus enabling a larger occupancy at all times and maximizing the value of the asset.

In recent years, the great developments of artificial intelligence (AI) and machine learning algorithms have created unique opportunities for real estate companies. In the property industry these technologies are predominantly used in predictive analytics, with the aim to produce increasingly accurate algorithms and create value from the newly-available swarms of big data (see Baum et al., 2020). One application of this is the development of automated and continuous pricing systems based not only on past performance, but also on real-time pick-up.

In this paper, we investigate the adoption of a new artificial intelligence and dynamic pricing technology in the property industry. In particular, we examine the impact on hostel performance of a new pricing algorithm (called Pace Revenue) that features two distinctive elements that are new to the literature on dynamic pricing. First, using artificial intelligence and machine learning techniques, the new technology combines historical data with future booking data, relying heavily on real-time pick-up to set prices, and picking up much faster unusual booking activity on future dates. Second, prices are updated continuously based on the estimated market's willingness to pay, regardless of house level occupancy, day of week, or category.

We compare the performance of this new technology that leverages data to drive decision-making in pricing with that of an alternative human-based pricing algorithm (the Grid pricing model), which made prices vary only based on achieved asset occupancy, according to a fixed grid specifying a fixed price hierarchy among different categories, and fixed increments between the grid cells. Contrary to the new Pace pricing algorithm, the Grid pricing model is human-based, in the sense that in the grid the occupancy intervals as well as the rate are set up by a human upfront.

We present large-scale evidence on the effects of the adoption of this new technology using daily data by the largest and leading hostel group worldwide, A&O Hostels, which runs 28,031 beds located across 23 cities in eight European countries, with an estimated market share of 23% across all the cities where it is present.

Our empirical strategy connects key dates of the adoption of the new pricing technology to subsequent changes in the pricing strategy, thus allowing us to quantify the impact

of technology adoption on revenue and occupancy rates, while dealing with unobserved heterogeneity across different units. In particular, we use a Difference-in-Differences estimator, which exploits the differences in timing of technology adoption across hostels by comparing performance of those that adopted the new technology at an earlier stage with those that adopted it later. In fact, starting from December 20th 2019, the adoption of Pace Revenue was gradually rolled out in all the hostels over a period of about eight months. In each day, we identify two groups of beds, the treated and the control. Treated beds are located in hostels whose prices were set using the new Pace algorithm. Control beds belong to hostels that were still using the old Grid pricing algorithm. We then compare our outcomes of interest for treated units that adopted Pace before and after technology adoption, while using control units that did not receive the treatment to absorb other possible confounding factors that are correlated with treatment and affect the outcome of interest.

Specifically, since treated units receive treatment at different times, we extend the standard Difference-in-Differences model by including time and group fixed effects. On the one hand, the inclusion of day fixed effects allows us to absorb daily fluctuations in price and/or occupancy due to unobserved factors that would otherwise bias the estimated treatment effects. On the other hand, we also include group fixed effects at the bed level to control for unobserved (and time invariant) differences across beds. Finally, since group level fixed effects do not allow us to control for hostel-level characteristics, we investigate how results change when we include a rich set of control variables. Specifically, we control for hostel-specific characteristics, as well as for a number of characteristics of the neighborhood/city where hostels are located. Indeed, our data set contains additional information on properties, such as ownership status and market share. Additionally, we query Google Maps API's in order to gather information about amenities around each property. Finally, we also collect city-level data from Eurostat and OECD in order to control for the business activity.

Overall, our estimates suggest that the new pricing algorithm positively affected both revenue and occupancy. We find that the adoption of the new technology is associated with an increase in revenue between 0.30 and almost 0.90 Euros. As for occupancy, the estimated treatment effect ranges from about 1.6 to 4.2 percentage points. The estimated treatment effect on performance is the highest in our preferred specification including all controls, together with date fixed effects. The magnitude of this effect is not only statistically significant, but also economically relevant. In fact, our estimates represent about 10% and 12% of the respective mean outcomes in the control group.

We also study how the effect of adopting the new pricing algorithm changes by the amount of time that the technology has been adopted, by estimating the so-called dynamic treatment effects. To this end, we implement the doubly-robust estimator introduced in the recent paper by Callaway and Sant'Anna (2020), where the authors specifically

focus on estimating treatment effects with variation in treatment timing. While the estimated effects on occupancy are somewhat mixed, our estimates confirm that the effect on revenue of adopting the new pricing algorithm is positive, suggesting a pattern where the magnitude of the effect increases with length of adoption, up to an estimated effect of about 2.26 Euros per bed for the longest adoption period.

When treatment timing varies, the general identifying assumption is that "interventions must be as good as random, conditional on time and group fixed effects" (Bertrand et al., 2004). If this is not the case, then units that did not adopt the new technology in our sample period are not a good control group for those that did. Although this assumption is clearly not testable directly, we provide evidence supporting it. First of all, we know that the management board did not follow any particular criterion to choose which hostels should have adopted the new Pace Revenue technology earlier or later in time. On the contrary, the selection order of the hostels was random. Additionally, we formally check whether our estimates are robust to pre-trend analysis. Quite reassuringly, we find that hostels that adopted the new Pace system do not exhibit significantly higher revenue or occupancy rates in the pre-treatment period.

Finally, we dig deeper into the mechanisms that are more likely to explain the success of this new property technology. The previously used Grid model made prices vary only based on overall asset occupancy, day of week and season, with a fixed price hierarchy among different categories, and fixed increments between the grids. Therefore, under the Grid, higher house occupancy leads to higher average rates mechanically. We verify that this holds true also under Pace. At the same time, however, we show that, under the new Pace model, price dispersion increases. Indeed, while under Grid the average daily rate is limited to the fixed grid intervals, under Pace it can realize bigger jumps (both upwards or downwards). We also highlight how this difference is particularly evident in nights where occupancy takes on "extreme" values (high or low). In fact, we study how the two algorithms differ in their tail pricing strategies. In other words, we study differences in price patterns at the tails of the occupancy distribution and show that, especially in the so-called compression nights where occupancy is particularly high, the average price charged is much higher under the new Pace price model. This suggests that the new technology is better able to capture part of the consumer surplus that would be otherwise left to the consumer.

Our main limitation is that the post-treatment period is rather limited. Indeed, the Covid pandemic erupted around mid-March 2020 – only few weeks after the first A&O hostels had adopted the new technology – bringing dramatically both daily occupancy and revenue down close to zero. For this reason, we limit our main analysis to the pre-Covid period, up to February 13th 2020, which corresponds to the Covid disruption date of financial markets. Since the earliest treatment date by the hostel that first adopted the new Pace system is December 20th 2019, the post-treatment period includes less than

two months. Thus, we choose to consider a three-month pre-treatment period, starting from October 1st 2019. To sum up, we consider the time period spanning from October 1st 2019 to February 13th 2020, which results in a final sample of 3,702,056 observations (which are defined as bed-day combinations), for a total of 27,233 beds located in 37 hostels, representing a 23% market share in the cities where A&O is present. Hostels in the treatment group – those that adopted the new technology within our sample period – amount to 13, while those in the control group – those that adopted it only afterwards – are 24.

Our work adds and brings together three strands of literature. First, we add to the vast literature investigating the impact of adopting dynamic pricing systems. From the theoretical standpoint, the firm's objective is to dynamically price the product to maximize expected revenues, given an initial inventory of items, an unknown stochastic demand, and a finite selling horizon (Gallego and van Ryzin, 1994, 1997).[1] While dynamic pricing systems have been adopted across different industries – e.g., airlines (Belobaba, 1987; Talluri and van Ryzin, 2004; Williams (forthcoming)), hotels (Baker and Collier, 2009; Cho et al., 2018), cruise-lines (Ayvaz-Cavdaroglu et al., 2019), and sporting events (Sweeting, 2012) –, the hostel industry is somewhat neglected in the literature and has so far been largely understudied, despite experiencing strong growth in recent years.[2] Yet, the hostel sector features some characteristics that crucially differentiate it from the widely studied hotel sector, for example that hostels sell beds instead of rooms and the fact that in a hostel two guests that do not know each other might share a room. These dynamics have an impact on revenue management and occupancy strategies, as hostel operators will be focused on maximizing bed occupancy instead of room occupancy.

We contribute to this strand of literature by investigating the impact on hostel performance of replacing a previous human-based backward-looking grid pricing model by a new technology which employs a continuous pricing model based on innovative AI and machine learning techniques that estimate future customers' willingness to pay and set optimal prices to maximize revenue. Our paper complements the dynamic pricing structural estimation models in Williams (forthcoming) and Cho et al. (2018) by quantifying the impact on performance of a pricing algorithm featuring such distinctive features using a quasi-experimental method.[3]

In a recent paper, Ban and Keskin (2020) study how a seller can dynamically adjust the price at the individual customer level, by exploiting the newly available information

[1] Dana (1999) shows how setting different prices on flights at different times can shift demand from pick hours flights to alternative ones. He also shows how both low- and high-fare customers may benefit from price dispersion.

[2] According to Savills, a global real estate services provider listed on the London Stock Exchange, the hostel sector was expected to produce about $5 billion in bed revenue in 2020, and is forecasted to continue to grow and gain more importance as institutional sector (The Savills Blog, 2018).

[3] Cho et al. (2018) extends Williams's (forthcoming) dynamic pricing model of a monopolist airline to a competitive environment for the hotel industry.

about customers' characteristics thanks to machine learning techniques. In our setting, prices are not personalized. Yet, the new Pace pricing algorithm uses machine learning techniques to estimate future customers' willingness to pay using future booking data and continuously reevaluate every price point in the next 365 days every 60 minutes.

Second, we contribute to a recent and growing literature on corporate value creation through big data. The digital transformation enabled by business intelligence solutions presents a large opportunity to drive performance, as data-driven organizations embrace the vision of quicker and better-informed business decisions to compete and create value. Davenport et al. (2012) argue how companies capitalizing on big data depart from traditional data analysis as they exploit data flows as opposed to stocks. Rather than using the data to examine the past, companies must think in terms of continuous flows and processes (forward looking decision making). Today, thanks to the increasing availability of big data, firms are becoming increasingly able to capture the willingness to pay for their products. Dynamic pricing enables a company to engage in flexible pricing strategies based on changing consumer demand (Erevelles et al., 2016). In this perspective, our work provides direct evidence about how the availability of big data creates value for the firm, by making its pricing strategy more effective to boost performance. In particular, we argue that innovative pricing strategies benefit from big data. As compared to more outdated occupancy human-based pricing models, the Pace pricing algorithm is better able to predict consumers' willingness to pay in every time point in the future, continuously adjusting the price as new information gets collected.

Finally, we also add additional evidence about the relative diffusion of price dispersion. Already at the beginning of the 1990s, Borenstein and Rose (1994) document substantial dispersion in the prices in the airline industry, finding that the expected difference in fares between two passengers on a route was as high as 36 percent of the airline's average ticket price. Abrate et al. (2012) and Melis and Piga (2017) study the inter-temporal pricing structures in the hospitality sector and document significant heterogeneity in the adoption of dynamic pricing across hotels, depending on characteristics like the booking date or the star rating. By contrast, Gibbs et al. (2017) show that Airbnb hosts make limited use of dynamic pricing strategies, especially as compared to hotels. To the best of our knowledge, no paper has so far addressed the adoption of dynamic pricing techniques in the hostels industry. We fill this gap by analyzing the extent to which the largest and leading hostel group worldwide with a 23% market share, A&O Hostels, actually makes use of dynamic pricing techniques. We show how the new pricing technology increases price dispersion, in particular with regards to pricing at the tails of the occupancy distribution, suggesting how the recent advancements in AI and machine learning will likely affect the way in which assets are priced. Firms are now better able to estimate customers' willingness to pay and, thanks to the increased automation in price setting, they can also dynamically and continuously update their prices accordingly. This results in

an increased incidence of price dispersion.

The rest of the paper is structured as follows. Section 2 describes the setting, with a focus on the company A&O, the hostel industry, as well as the new Pace pricing system. Section 3 introduces the data. Section 4 describes the identification strategies used to estimate the static and dynamic average treatment effects of adopting the new pricing algorithm Pace on firm performance and presents the results. In Section 5, we show that our strategy is robust to pre-existing trend analysis. Section 6 digs deeper into the mechanisms behind the estimated effects. Section 7 concludes.

2 The setting

A&O Hostels is the largest and leading hostel group worldwide, with 28,031 beds across 23 cities located in eight European countries. It has a market share of 23% across all the cities where it is present, and can therefore serve as a proxy and be a good representative of its industry.[4]

A&O has been working on a Business Intelligence system for several years and has added accretive elements over time. There is a data warehouse and they also work with Tableau where they can use custom mapping tables and join data from multiple databases (data warehouse environment), which allows them to generate interactive dashboards (business analytics) and detailed reports (business performance measurement) either for finance, accounting, operations or revenue management. All eligible users have access to their reports via an online portal (user interface).

Starting from December 2019, A&O adopted a new technology called Pace Revenue[5], to improve business decisions and profitability. The decision to invest into technology for the overall group had been decided the previous year by the management board. The technology adoption was gradually rolled out in all 38 hostels over a period of about eight months. The selection order of the hostels was random and was not based on any pattern or criteria. As we will see later in Section 4, this is particularly important for the validity of our identification strategy, as it supports the assumption that units that adopted the new technology later in time are comparable to those that did it at an earlier stage, and may thus serve as a good control group for the latter ones.

Pace is a good example of technology adoption. Based on an AI and machine learning dynamic pricing model, it leverages data to drive decision-making. Next we describe the distinctive features of Pace Revenue. The goal here is to shed light on the mechanisms

[4]Specifically, A&O has 21% and 23% of, respectively, the total active and available capacity across all the cities where it is present. The market share is estimated by dividing the total number of A&O's beds by the total number of active/available beds across Online Travel Agents (OTAs) platforms in the cities where A&O is present. Note that, as a result, A&O estimated market share is weighted by the total number of beds that are active/available in each of the cities.

[5]See https://www.pacerevenue.com.

explaining the success of this new technology.

Figure 1: Pace optimization cycle

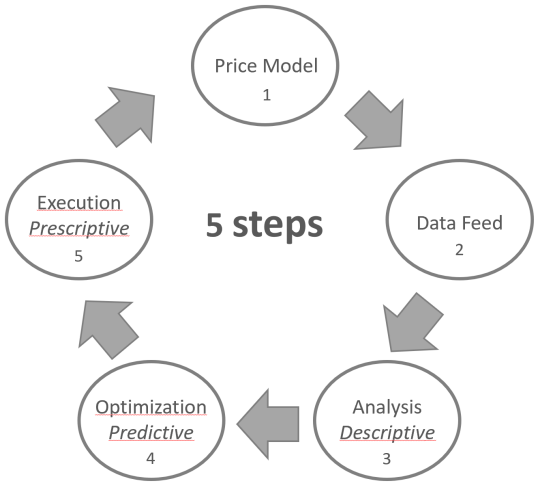


Figure 1 depicts the Pace Optimization Cycle, which is based on the following five steps. First, the Pace technology is based on a pricing model with distinctive features. Before the introduction of the new Pace system, the A&O pricing strategy was based on the so-called "Grid" pricing model, which required significant human input. According to this model, the price was set based on the occupancy level of the respective hostel, according to a fixed grid of price intervals. By contrast, the Pace Price Model is a continuous pricing model which reevaluates every price point in the next 365 days every 60 minutes. Thanks to AI and machine learning techniques, it combines historical data with future booking data. Pace is based on primary data which is directly collected through its own system, and disregards third party data.[6] As shown in Section 4, using only primary data in its model has proved successful for A&O. The quality of competitive data can be questioned, especially in the hostel and budget sector. Although we do not observe Pace's pricing algorithm, in Section 6 we will further describe and discuss the main distinctive features of its pricing strategy, comparing it with the previously used Grid pricing model.

Second, the Data Feed is powered by a tailor-made web service, which extracts every ten minutes new reservation data from the ASSD[7] database, to provide Pace with a real-time image of the secured business reflected in the accounts.[8] Using all relevant data available, Pace continuously refreshes its demand forecast by category for any night in the future booking window. Leveraging historical performance data, the model generates numerous what-if scenarios to model the optimal booking curve.

[6] A&O has the option to observe competitive market prices via a third-party provider. It however stopped doing that in 2019 as it provided limited value at a notable cost.
[7] ASSD stands for Andreas Stolz Software Development.
[8] A frequency of less than 10 minutes does not add any benefit considering the number of reservations per minute.

Third, Analytics (*descriptive analysis*) is a powerful Business Intelligence tool with a range of interactive dashboards and multi-dimensional reports, enabling users to create their customized scorecards subject to their business needs. Recently Pace extended their Application Programming Interface (API) to enable bottom line performance analysis, for example analysing gross operating profit per square meter. During each cycle, Pace compares latest booking data *versus* its forecast model and anticipated booking curves.

Fourth, the Optimisation procedure (*predictive analysis*) runs every 60 minutes for the next 365 days, reevaluating past and future data of each category, segment, night and their performance *versus* forecast and expected booking curve. Price changes occur either as anticipated price updates (e.g., demand picking up as expected, price increases gradually as expected), or corrective price updates (e.g., demand higher than expected, strong price push). Logically, same applies in negative scenarios.

Finally, the Execution part (*prescriptive*) is fully automated with no human interaction required. Pace is set up to push all price changes to its channel manager *Autoupdate* fully automatically. Subject to *Autoupdate* responsiveness, this takes on average 3 seconds. Only strategic controls set by A&O for each property determine the minimum and maximum price bounds for Pace, and implicitly the maximum price change in each optimisation step. Within the chosen upper and lower price bounds, the Pace Price Model can freely move any price within the next 365 days. Human interference is only required to manage exceptions for which automated alerts are generated in Pace Analytics.

3 The data

In our empirical analysis, we study the effect of adopting the new Pace technology on firm performance. Our identification strategy exploits the differences in technology adoption across different hostels by comparing the performance of hostels that adopted the new technology at an earlier stage with those that adopted it later.

For our empirical analysis, we rely on data provided by A&O Hostels. Our data set includes 28,031 beds located in 37 hostels for the time period spanning from January 1st 2017 to February 15th 2021. The large majority of hostels are located in Germany (25 out of 37), while the rest of the hostels are located in other European countries (Austria, Czech Republic, Italy, Hungary, the Netherlands, Denmark and Poland). Appendix Table 11 provides a detailed description of the hostels' main characteristics.

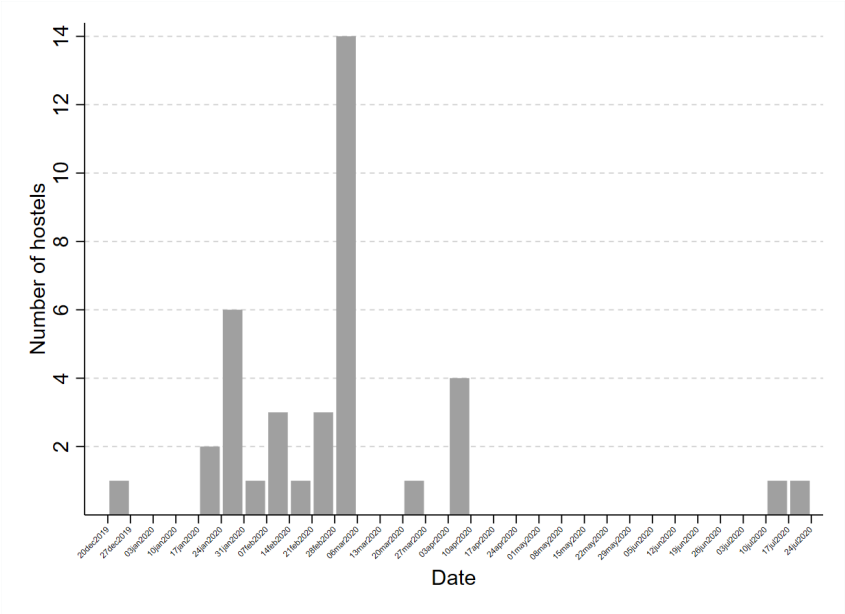
Our data set contains daily information about the bed occupancy and average rate. We obtain the bed average daily revenue by multiplying occupancy and average daily rate. Our data set is therefore a balanced panel where the cross-sectional unit is a bed and the longitudinal unit is a day, for a total of 42,242,717 observations (bed-day combinations).

Additionally, the data set contains information about the exact location of each hostel and the date when Pace was adopted. This allows us to define our treatment variable by

using the exact dates of the new technology adoption.

As previously highlighted, the new property technology was adopted by different hostels at different points in time. Figure 2 shows a timeline of the technology adoption per week. As shown, the first hostel adopted the new technology at the end of December 20th 2019, while the last adoption dates correspond to the second half of July 2020. Most hostels adopted Pace between mid-January 2020 and mid-March 2020.

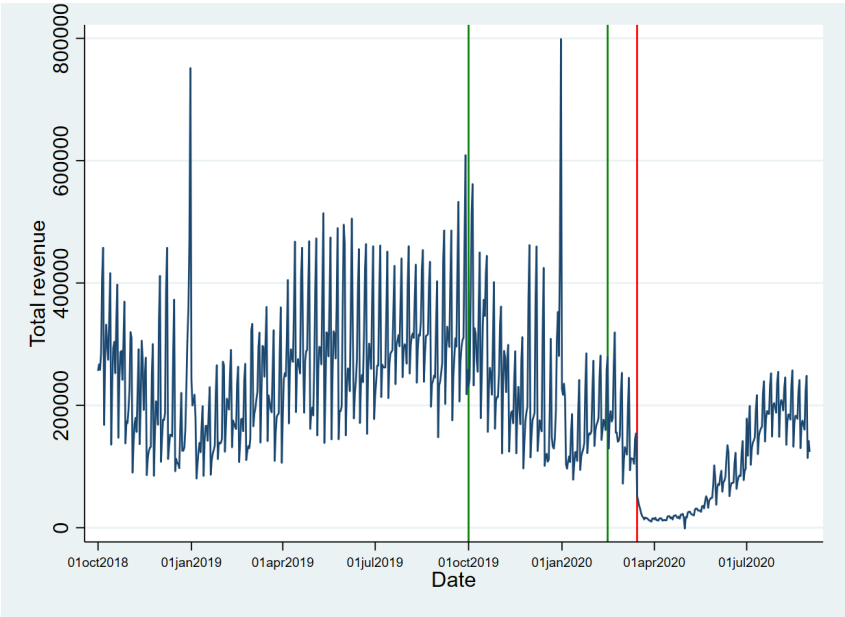
Figure 2: Timeline of property technology adoption



Notes. The graph shows the number of hostels that adopted the new technology in each week.

Because of the Covid outbreak in mid-March 2020, daily occupancy (and, in turn, revenue) dropped close to zero temporarily. Figure 3 shows that the drop in total daily revenue occurred precisely from March 15th 2020 (red line in the figure). For this reason, we choose to limit our main analysis to the pre-Covid period. Since the Pace algorithm is a forward looking pricing algorithm, which picks up future booking data, we limit our analysis to February 13th 2020, based on the fact that this is the date when the S&P500 started plummeting. This allows us to be fairly confident that the Pace pricing algorithm is not capturing a drop in future occupancy. At the same time, however, this reduces the post-treatment period, which includes approximately two months. In fact, as can be seen in Appendix Table 11, the earliest adoption date is that of Hamburg City hostel, which introduced Pace on December 20th 2019. In total, only thirteen hostels adopted the new technology before the end of our sample period, February 13th 2020. We then consider a three-month pre-treatment period.

Figure 3: Total daily revenue



Notes. The graph displays total daily revenue for the time period between October 1st 2018 and September 1st 2020. All hostels are included in the sample. The red vertical line indicates the March 15th 2020 date, which corresponds to the major drop in occupancy and revenue due to the Covid outbreak. The green vertical lines correspond to the period between October 1st 2019 and February 13th 2020, which is the period considered in our main analysis.

Hence, our sample period spans from October 1st 2019 to February 13th 2020, which results in a final sample of 3,702,056 observations, for a total of 27,233 beds located in 37 hostels[9].

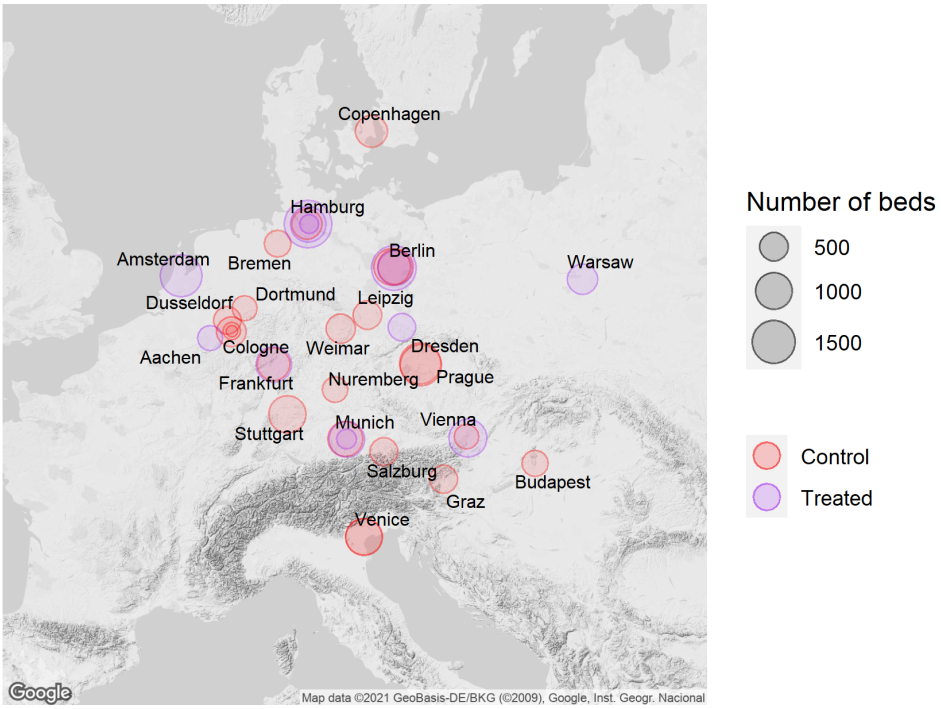
Figure 4 displays the geographical distribution of hostels in the treatment (purple) and control (red) groups. Hostels in the treatment group adopted the new technology before the end of our sample period (February 13th 2020). Hostels in the control group adopted it only afterwards. In total, the treatment and control groups are composed of 13 and 24 hostels, respectively. In terms of beds, treated beds amount to 11,544, while control beds are 15,689. In terms of observations, our control group includes 3,427,579 bed-day combinations, while the treatment group counts 276,109.

In our analysis below, we control for the bed's room size (i.e., the total number of beds in the room where the bed is located), as well as for several hostel level characteristics that may potentially affect technology adoption, or the hostel's occupancy and revenue. First, we will control for the hostel's ownership status. In fact, whether a hostel is owned or leased by A&O may impact both the firm's decision to adopt the new technology at a relatively early stage, as well as the performance, as A&O has generally more control over the hostels that are owned rather than leased.

Second, we will control for each hostel's market share, both active or only available, es-

[9]Currently, A&O runs an additional hostel in Copenhagen. However, this hostel was opened on April 2020. Since our analysis focuses on the pre-Covid period, we cannot use it in our analysis.

Figure 4: Treatment and control hostels



Notes. The figure displays the 37 hostels in the treatment (purple) and control (red) groups. Hostels in the treatment group adopted the new technology before the end of our sample period (February 13th 2020). Hostels in the control group adopted it only afterwards.

timated using information from Hostelworld.com, which is considered the world's leading hostel-focused online booking platform. The active market share measures the hostel's share of estimated stock, which is given by the hostel's number of beds divided by the estimated total number of active beds from hostels in the city. The available market share, instead, measures the estimated available capacity, which compares the hostel's number of beds to the available beds (thus including hostels having availability which can be potentially loaded at any future date).

Third, we also control for a number of characteristics of the neighborhoods and cities where hostels are located. Specifically, we search for variables with the aim to measure the touristic and business activities in the hostel's area. In fact, different kinds of amenities attract different kinds of customers, thus affecting performance. For instance, group travelers *versus* free individual travelers (FITs) lead to different occupancy patterns (e.g., higher occupancy during weekdays *versus* weekends, respectively) and pricing patterns (e.g., due to relatively low *versus* high price elasticity, respectively).

In order to gather data on the hostels' neighborhoods, we query Google Maps API's (specifically, Places API's) to collect information on amenities in the neighborhood. In particular, we search for the number of restaurants within a radius of 400 meters (i.e., five minutes walking), as well as the number of tourist attractions, bus stations and subway stations within a radius of 1 kilometer. We select these control variables with the aim to

measure the touristic activity within the hostel's neighborhood. Furthermore, we collect data from Eurostat and OECD on the hostel's city population, GDP, and number of companies in order to proxy also for the business activity. For each city, we use the last year available data. Further details about how we build our control variables can be found in Appendix Table 12.

4 Empirical strategy

Let us now describe our empirical strategy, which aims to empirically estimate the average treatment effect (ATE) of adopting the new pricing algorithm Pace on firm performance. Since only some of the hostels in our sample adopted Pace in our period of study, we can estimate the effect of adopting the new technology using a Difference-in-Differences estimator. This allows us to compare our outcomes of interest for treated units that adopted Pace before and after technology adoption, while using control units that did not receive treatment to control for other possible confounding factors that are correlated with treatment and affect the outcome of interest.

The standard difference-in-differences model contains two time periods – pre and post – and two groups of observations – treated and control units. In our case, however, treatment occurs at different times, since the new technology was adopted by hostels on different dates between December 2019 and July 2020. Since treated units receive treatment at different times, we rely on an empirical strategy that is sometimes referred to as staggered difference-in-differences.

Specifically, we generalize the standard Difference-in-Differences model by including time and group fixed effects. As for time, all our specifications include day fixed effects. These allow us to absorb daily fluctuations in price and/or occupancy due to unobserved factors that would otherwise bias the estimated treatment effects. As for group fixed effects, we consider bed fixed effects in order to control for (unobserved) differences across beds. In fact, unobserved differences may exist not only across hostels, but also across beds. For instance, even within the same hostel, a bed in a double room may systematically perform better than one in a ten-people room because that city attracts predominantly free individual travelers (FITs), but not many groups. At the same time, we wish to control also for unobserved heterogeneity across different hostels. Yet, the inclusion of bed fixed effects does not allow us to include hostel-level characteristics, due to multicollinearity problems.[10] For this reason, we then estimate a different specification where different sets of hostel-level controls are used.

When several time periods are available, before and after treatment, one can identify not only a "static" treatment effect, as described so far, but also "dynamic" treatment

[10]These arise because of the relatively small number of hostels (37) included in our data set. This is also the reason why we cluster standard errors at the bed, rather than at the hostel level.

effects. While the first one is an aggregated summary measure of the treatment effect, the "dynamic" treatment effects measure the effect of being treated at different lengths of exposure to the treatment. In other words, dynamic treatment effects refer to treatment effects by length of exposure to treatment – in the spirit of an "event study".

For this reason, in a second step, we estimate the dynamic treatment effects of the new technology on revenue and occupancy using the methods introduced in the recent paper by Callaway and Sant'Anna (2020). In this paper, the authors specifically focus on identification and estimation methods for treatment effect parameters using Difference-in-Differences with variation in treatment timing. First, we estimate the *group-time average treatment effect*, i.e., the average treatment effect for a given treatment group (where a "group" is defined by the time period when units are first treated) and date. Then, we average the estimated group-time average treatment effects across different lengths of exposure to the treatment.

Descriptive statistics. The descriptive statistics for our main outcomes and covariates of interest are reported in Table 1. We can see that a bed's average daily revenue is about 8 Euros[11]. Daily occupancy is on average 34 percent. The standard deviation is given by almost 15 Euros and 50 percent for revenue and occupancy, respectively. Additionally, we can see that the *Treatment* indicator has an average of 0.075, which means that only 7.5 percent of our observations (bed-day combinations) are treated. Indeed, as previously noticed, because of the pandemic, the post-treatment period is relatively short.

In what follows, we first estimate the static treatment effect of the new technology on performance using a generalized version of the Difference-in-Differences estimator (Section 4.1). Afterwards, in Section 4.2, we estimate the dynamic treatment effects for different lengths of exposure to the treatment, following the methods introduced by Callaway and Sant'Anna (2020).

4.1 Static treatment effect

We now focus on the estimation of the static treatment effect of technology adoption on our performance measures of interest, namely revenue and occupancy. Our identification strategy exploits variation in the adoption of the new technology by different hostels. Because of the different timing of adoption, we can compare performance of hostels that adopted the new technology with those that did not adopt it within our sample.

[11] We highlight that 8 Euros is the bed's average daily revenue considering also beds for which the occupancy and, in turn, revenue, is zero. In fact, the average daily revenue of *occupied* beds is much higher, and given by 24.26 Euros.

Table 1: Descriptive statistics

Variable	**Mean**	**Median**	**Std. Deviation**	**N**
Revenue	8.278	0.000	14.482	3,702,056
Occupancy	0.341	0.000	0.474	3,702,056
Average daily rate (ADR)	8.278	0.000	14.482	3,702,056
Room size (# beds)	4.189	4.000	1.727	3,702,056
Treatment	0.075	0.000	0.263	3,702,056
GDP per capita (USD)	49,615.97	49,722	10,421.05	3,702,056
# companies	120,309.100	97,300.000	95,801.653	3,286,394
Owned	0.425	0.000	0.494	3,702,056
Market share (active)	0.247	0.200	0.152	3,702,056
Market share (available)	0.286	0.250	0.157	3,702,056
# restaurants	24.741	16.000	19.109	3,702,056
# tourist attractions	12.739	8.000	13.437	3,702,056
# bus stations	6.274	5.000	5.696	3,702,056
# subway stations	2.221	2.000	2.439	3,702,056

Notes: This table displays the descriptive statistics for the time period spanning from October 1st 2019 to February 13th 2020. Only beds with non-missing revenue are considered.

4.1.1 Specification with bed fixed effects

Formally, let $i = 1, ..., I$ denote a bed located in hostel $j = 1, ..., J$ at day $t = 1, ..., T$. We estimate the following fixed-effect model specification:

$$Outcome_{ijt} = \alpha + \beta Treatment_{jt} + \gamma_i + \delta_t + \varepsilon_{ijt} \tag{1}$$

where $Outcome_{ijt}$ is the outcome of interest for bed i in hostel j at time t and $Treatment_{ijt}$ is an indicator which takes on value one if the hostel j of bed i used the new technology in period t and zero otherwise. The coefficient of interest is thus β, which captures the effect of technology adoption on the considered outcome. γ_i and δ_t are bed and day fixed effects, respectively. Finally, in our specification, standard errors are clustered at the bed level.

A possible concern with this specification is that beds might experience differential shocks to revenue and occupancy because of specific events or fairs in the hostel or city where they are located. A second and related concern is that different beds might be on differential (possibly growth) trends because of other changes in the hostel, such as a renovation intervention, or in the city economy, such as increased tourism or business activity. The inclusion of bed level fixed effects prevents us from including fixed effects defined at a more aggregate level, such as hostel or city level fixed effects. To address these concerns, we augment equation 1 by city fixed effects interacted with date fixed effects.[12] Hence, this allows us to mitigate our concerns about a possible bias arising from other changes or trends experienced by hostels or cities where beds are located.

Table 2 shows the results of estimating equation 1 when the outcome is revenue (columns 1 and 2) or occupancy (columns 3 and 4). Columns (1) and (3) display estimates from the baseline specification when only day fixed effects are included. The estimated effect is positive and statistically significant for both revenue and occupancy. Specifically, the estimated coefficients of the treatment dummy indicate that treated beds experienced an increase in revenue and occupancy relative to the control group by 0.194 Euros ($p < 0.10$) and 1.6 percentage points ($p < 0.01$), respectively. Columns (2) and (4) add bed fixed effects, together with day fixed effects interacted with city fixed effects. When revenue is the outcome of interest, the point estimate of β slightly decreases in magnitude to 0.179, but becomes highly statistically significant ($p < 0.01$). However, the estimated effect on occupancy becomes negative. At the same time, despite being highly statistically significant, the coefficient estimate is given by -0.010, and therefore it is quite small in magnitude.

[12] Note that we cannot interact date with hostel fixed effects because they would absorb the impact of treatment.

Table 2: The effect of technology adoption on revenue and occupancy

Dependent Variable:	*Revenue*		*Occupancy*	
	(1)	(2)	(3)	(4)
Treatment	0.194*	0.179***	0.016***	-0.010***
	(0.108)	(0.059)	(0.005)	(0.002)
Fixed effects				
Day	Yes	Yes	Yes	Yes
Bed	No	Yes	No	Yes
City × day	No	Yes	No	Yes
Observations	3,702,056	3,702,056	3,810,584	3,810,584
R-squared	0.079	0.672	0.061	0.670
Hostels	All			
Period	1oct19-13feb20			

Notes: This table displays results from fixed effects regressions of the treatment indicator on the daily revenue (columns 1-2) and occupancy (columns 3-4). The treatment indicator takes on value 1 after the Pace technology had been adopted in that bed's hostel, and zero otherwise. The data set is a balanced panel where the cross-sectional unit is a bed and the longitudinal unit is a day. Each observation thus represents a bed-day combination. The time interval spans between October 1st 2019 to February 13th 2020 (i.e., one month prior to the major drop in revenue due to the Covid outbreak). Columns (1) and (3) display estimates when only day fixed effects are included. Columns (2) and (4) add bed fixed effects, together with date fixed effects interacted with city fixed effects. Standard errors clustered at the bed level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Importantly, specification 1 does not allow us to include bed- nor hostel-level control variables. Bed-level controls cannot be included because bed-level fixed effects absorb their impact. Besides, also hostel-level control variables, when included, are omitted due to multicollinearity with bed fixed effects. However, while bed fixed effects absorb unobserved time-invariant differences between beds, most of this variation is likely due to differences across hostels. In other words, the major source of unobserved heterogeneity is likely across hostels, rather than across beds. For instance, managerial decisions – including the treatment of adopting the new technology – are implemented at the hostel level. For this reason, we choose to estimate a different specification where we control for bed- and hostel-level variables.

4.1.2 Specification with bed- and hostel-specific controls

We now test whether results are robust to substituting group-fixed effects with a rich set of bed, hostel, and neighborhood controls. In all specifications, we include day fixed effects.

More precisely, we now estimate the following model:

$$Outcome_{ijt} = \alpha + \beta Treatment_{jt} + \lambda_1 X_i + \lambda_2 W_j + \delta_t + \varepsilon_{ijt} \tag{2}$$

where $Outcome_{ijt}$ is the outcome of interest for bed i in hostel j at time t and $Treatment_{jt}$ is an indicator which takes on value one if the hostel j of bed i used the new technology in period t and zero otherwise. The coefficient of interest is still denoted by β, which measures the effect of technology adoption. X_i and W_j are the vectors of bed- and hostel-level controls. These include the characteristics of the bed, as well as the hostel and hostel's neighborhood characteristics that are reported in Appendix Table 12. δ_t are date fixed effects. Finally, in our specification, we cluster standard errors at the bed level.

Results are displayed in Tables 3 and 4 for revenue and occupancy, respectively. In columns (1) to (3) we include bed, hostel and neighborhood controls, respectively. Finally, column (4) includes all these controls. Analyzing the treatment effect on revenue in Table 3, the point estimates for the estimated coefficient on the treatment dummy range between 0.320 in column (1) to 0.867 in column (4), when all covariates are included. The estimated effects are always statistically significant (at the 1 percent level). Similarly, the estimates of the average treatment effect on occupancy from Table 4 are always positive and statistically significant ($p < 0.01$). Also in this case, the estimated coefficient is the largest when all covariates are included (column (4)) and given by 0.042.

Furthermore, the estimated effects are not only statistically significant, but also economically sizable. In fact, in order to get a sense of the economic magnitude of our estimated coefficients, we interpret them in terms of the mean outcomes among control beds. From Table 1, we can see that bed daily revenue and occupancy are on average

Table 3: The effect of technology adoption on revenue

	Dependent variable: *Revenue*			
	(1)	(2)	(3)	(4)
Treatment	0.320***	0.390***	0.416***	0.867***
	(0.096)	(0.114)	(0.109)	(0.100)
Additional controls:				
Bed controls	Yes	No	No	Yes
Hostel controls	No	Yes	No	Yes
Neighborhood controls	No	No	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,702,056	3,286,394	3,702,056	3,286,394
R-squared	0.186	0.119	0.095	0.230
Hostels	All			
Period	1oct19-13feb20			

Notes: This table displays results from OLS regressions of the treatment indicator on the average daily revenue. The treatment indicator takes on value 1 after the Pace technology had been adopted in that bed's hostel, and zero otherwise. The data set is a balanced panel where the cross-sectional unit is a bed and the longitudinal unit is a day. Each observation thus represent a bed-day combination. The time interval spans between October 1st 2019 to February 13th 2020 (i.e., one month prior to the major drop in revenue due to the Covid outbreak). Column (1) displays estimates when only bed level controls (room size) are included. Column (2) includes only hostel level controls. These are the hostel city's population and the number of companies, as well as the hostel's market shares (both available and active) in the city, and an indicator for whether the hostel is owned by A&O. Column (3) includes neighborhood level controls. These are the number of restaurants within a 400m radius, as well as the number of tourist attractions, bus stations and subway stations in a 1km radius. Column (4) includes bed, hostel, and neighborhood level controls. All specifications include day fixed effects. Further details on the variables used can be found in Appendix Table 12. Standard errors clustered at the bed level are displayed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 4: The effect of technology adoption on occupancy

	Dependent variable: *Occupancy*			
	(1)	(2)	(3)	(4)
Treatment	0.019***	0.034***	0.019***	0.042***
	(0.004)	(0.005)	(0.005)	(0.004)
Additional controls:				
Bed controls	Yes	No	No	Yes
Hostel controls	No	Yes	No	Yes
Neighborhood controls	No	No	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,703,688	3,286,576	3,703,688	3,286,576
R-squared	0.137	0.091	0.066	0.168
Hostels	All			
Period	1oct19-13feb20			

Notes: This table displays results from OLS regressions of the treatment indicator on the daily occupancy. The treatment indicator takes on value 1 after the Pace technology had been adopted in that bed's hostel, and zero otherwise. The data set is a balanced panel where the cross-sectional unit is a bed and the longitudinal unit is a day. Each observation thus represent a bed-day combination. The time interval spans between October 1st 2019 to February 13th 2020 (i.e., one month prior to the major drop in revenue due to the Covid outbreak). Column (1) displays estimates when only bed level controls (room size) are included. Column (2) includes only hostel level controls. These are the hostel city's population and the number of companies, as well as the hostel's market shares (both available and active) in the city, and an indicator for whether the hostel is owned by A&O. Column (3) includes neighborhood level controls. These are the number of restaurants within a 400m radius, as well as the number of tourist attractions, bus stations and subway stations in a 1km radius. Column (4) includes bed, hostel, and neighborhood level controls. All specifications include day fixed effects. Further details on the variables used can be found in Appendix Table 12. Standard errors clustered at the bed level are displayed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

8.28 Euros and 34%, respectively. When the sample is restricted to control beds, the mean daily revenue slightly increases to 8.38 Euros (with a standard deviation of 14.66), while the mean occupancy remains essentially stable at 34% (with a standard deviation of 0.475). In our preferred specification where all controls are included, we found that treatment increases the predicted revenue by 0.867 Euros. This estimate represents about 10% of the outcome mean in the control group. Similarly, if the bed is treated, the likelihood of occupancy rises by about 4 percentage points, which represents about 12% of average occupancy.

Overall, although our treatment period is relatively short due to the Covid outbreak just after technology adoption, the data suggests that the new pricing algorithm positively affected both occupancy and revenue. Moreover, our findings show that the magnitude of the effects is economically significant. The adoption of the new technology is in fact associated with an increase in bed daily revenue between 0.32 and 0.87 Euros. As for occupancy, the estimated treatment effect ranges from about 1.6 to 4.2 percentage points. These estimates suggest that technology adoption may boost performance, up to a point where adopting the new technology for an additional bed increases the likelihood of having it occupied by 12%, as well as its predicted revenue by 10%.

4.2 Dynamic treatment effects

We now estimate the dynamic treatment effects of the new technology on revenue and occupancy using the methods introduced in the recent paper by Callaway and Sant'Anna (2020). In this paper, the authors specifically focus on identification and estimation methods for treatment effect parameters using Difference-in-Differences with variation in treatment timing. First, we use the doubly-robust estimator to estimate what they refer to as the *group-time average treatment effect*, i.e., the average treatment effect for group $g = 1, ..., G$ at time $t = 1, ..., T$, where a "group" is defined by the time period when units are first treated. Then, we aggregate the estimated group-time average treatment effects computing average effects across different lengths of exposure to the treatment. This is similar to an "event study" where the overall effect averages the effect of the treatment across all positive lengths of exposure.

Section 4.2.1 describes the estimation framework and Section 4.2.2 presents the results.

4.2.1 The framework

Let $i = 1, ...n$ denote a unit (a bed), $t = 1, ..., T$ denote the time period (a day) and G_i the time period when unit i first becomes treated. Thus, for units that get treated within our sample period, G_i identifies the "group" they belong to. In our setup, we have nine groups, i.e., nine groups of hostels that adopted treatment (the Pace algorithm) on a given date, prior to the end date of our sample period, February 13th 2020. Let $G_{i,g}$

be a dummy variable equal to one if unit i first becomes treated in period g. That is, $G_{i,g} \equiv \mathbb{1}\{G_i = g\}$, $g = 1, ..., T$, where $\mathbb{1}$ is an indicator function which takes value 1 when unit i's group, G_i, corresponds to period g, and 0 otherwise. Next, consider the potential outcome framework generalized to a setup with multiple treatment groups and multiple time periods. Define $Y_{i,t}(0)$ as the untreated potential outcome that unit i would experience at time t if it never got treated throughout the whole time period, and $Y_{i,t}(g)$ as the potential outcome that unit i would experience at time t if it first became treated in time period g.

In the standard Difference-in-Differences setup, with two time periods and one treatment group, the main causal effect of interest is the average treatment effect on the treated, defined as $ATT = E[Y_2(2) - Y_2(0)|G_2 = 1]$. In a setup with multiple time periods and multiple treatment groups, this is naturally generalized to the *group-time average treatment effect*, which represents the key building block of this estimation strategy and is defined as the average effect of participating in the treatment for units in group g at time t, that is:

$$ATT(g,t) = E[Y_{i,t}(g) - Y_{i,t}(0)|G_{i,g} = 1]. \tag{3}$$

where $Y_{i,t}$ is the outcome of interest (revenue or occupancy) of unit i at date t, $Y_{i,t}(0)$ is the untreated potential outcome of unit i had it never received treatment, and $G_{i,g}$ is a dummy variable equal to 1 if unit i belongs to group g. Importantly, focusing on this causal parameter does not impose any restrictions on the heterogeneity of the treatment effect across treatment groups or across time periods. Thus, the identification of these group-time treatment effects allows us to analyze how average treatment effects vary across groups of units or time.

In order to estimate the group-time average treatment effects, $ATT(g,t)$'s, we implement the doubly robust estimator introduced in Callaway and Sant'Anna (2020), and consider the case where the comparison group includes never-treated units. Then, in order to study how the effect of participating in the treatment varies with length of exposure to the treatment, we aggregate the group-time treatment effects by averaging effects across different lengths of exposure. Note that, for the clarity of exposition, in the analysis of the dynamic treatment effects, we use weekly (instead of daily) data, obtained by averaging the bed $\times$ day observations at the bed $\times$ week level. In this case, t denotes the week (instead of the day) and g indexes the group, i.e., the week when a unit is first treated. This reduces the number of groups from nine to six, i.e., there are six groups of hostels that started adopting the Pace algorithm on a given week, prior to February 13th 2020.

4.2.2 Results

Figures 5 and 6 display the dynamic treatment effects on respectively revenue and occupancy, along with simultaneous 95% level confidence intervals. They show how the effect of adopting the new Pace pricing algorithm changes by length of adoption, i.e., by the number of weeks that Pace has been adopted (as indicated on the x-axis). In both figures, the left-hand panel depicts the unconditional estimated treatment effects when no covariates are included, while the right-hand panel displays the conditional estimates obtained when including all of our covariates, as listed in the Appendix Table 12. The plots display treatment effect estimates (in blue) and also pre-treatment estimates (in red). We show the point estimates of the dynamic treatment effects in Table 5, where columns 1 and 2 report, respectively, the unconditional and conditional estimates of the treatment effects on revenue, and columns 3 and 4 those on occupancy.

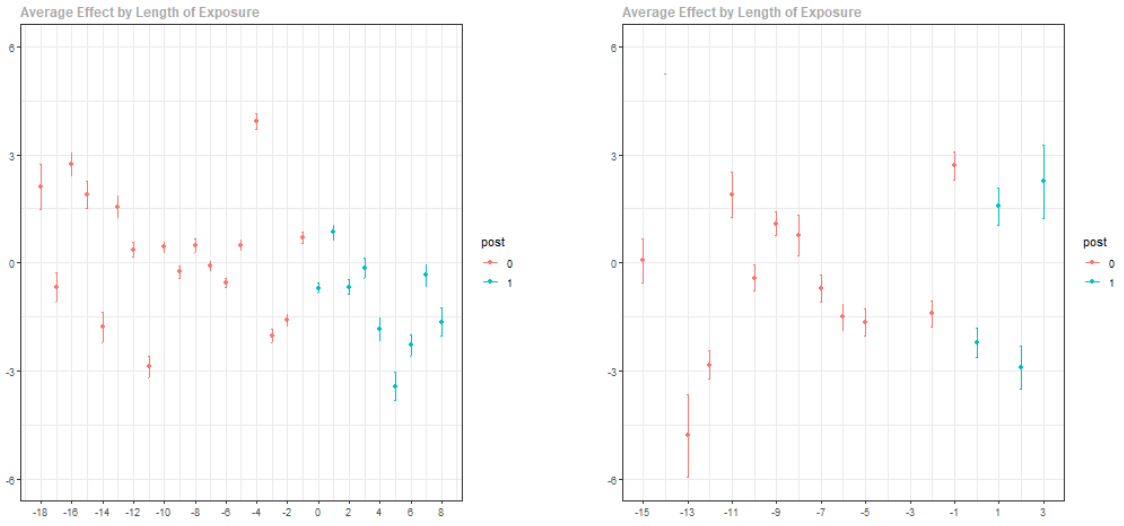
We first analyze the dynamic treatment effects on revenue. Looking at the unconditional estimates (see panel (a) of Figure 5 and column (1) of Table 5), we can see that, at the beginning, the effect on revenue of adopting the new technology appears to be positive. After one week from technology adoption, revenue is estimated to increase by about 0.85 Euros per bed. Afterwards, however, the estimated effect on revenue decreases and becomes negative, until the fifth week from technology adoption (-3.42 Euros), when it starts to increase again. Even if it does not switch back to a positive sign, this reversed tendency suggests that the effect of technology adoption on revenue tends to increase with the length of adoption. Indeed, this is confirmed from analyzing the estimates when covariates are included (see panel (b) of Figure 5 and column (2) of Table 5).[13] In this case, the estimated treatment effects on revenue are mostly positive and the magnitude of the effect of adopting the new technology increases with length of adoption, up to an estimated effect of about 2.26 Euros per bed.

Let us now examine the dynamic treatment effects on occupancy, as displayed in Figure 6 as well as in columns (3) and (4) of Table 5. When covariates are not included, the effect of adopting the new technology on the occupancy rate appears to be negative at first, before starting to increase and becoming positive for longer periods of technology adoption. In particular, in the seventh week that the new pricing algorithm has been adopted, a bed's occupancy rate is estimated to increase by 5.4 percentage points, and in the eight week by 3.2 percentage points. When covariates are included, however, the estimated treatment effects appear to be negative and relatively stable around -5 percentage points for all lengths of adoption.

Finally, we point out that some of the estimates of the dynamic treatment effects in pre-treatment periods (displayed in red in Figures 5 and 6) are significantly different from zero, which appears to be against the parallel trends assumption. At the same time,

[13] Note that the inclusion of covariates reduces the number of estimated effects. We get the estimated treatment effects only up to three weeks since adoption.

Figure 5: The effect of technology adoption on revenue by length of adoption (in weeks)

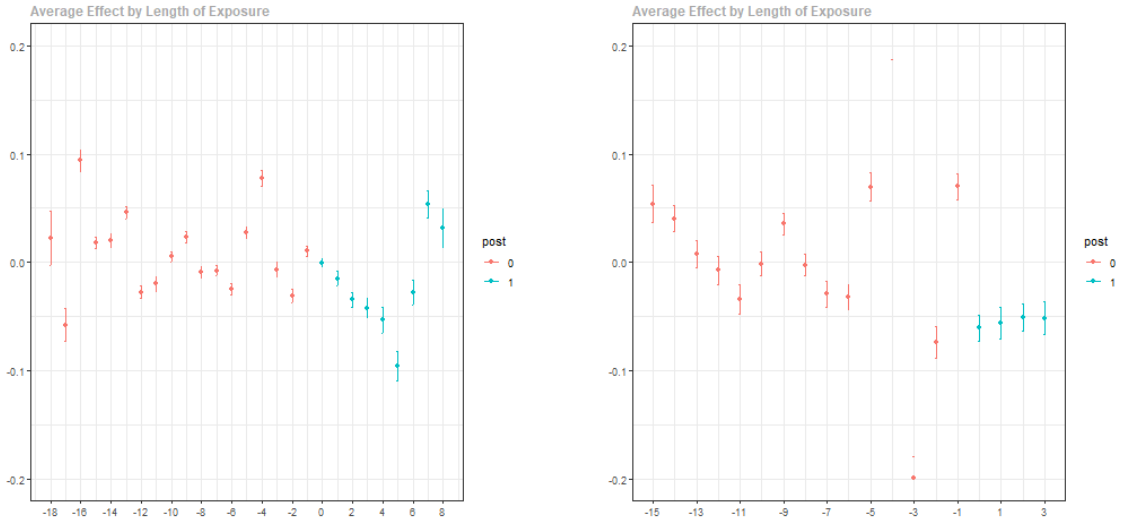


(a) No covariates

(b) W/ covariates

Notes. The figure displays the dynamic average treatment effect on revenue by length of exposure to treatment (number of weeks), as indicated on the x-axis. The time period spans from October 1st, 2019 to February 13th, 2020. Red lines give point estimates and 95% confidence bands for pre-treatment periods allowing for clustering at the bed level. Blue lines provide point estimates and 95% confidence bands for the treatment effect of adopting the Pace technology allowing for clustering at the bed level. In panel (a), no covariates are included. In panel (b), the specification includes all bed-, hostel-, city-, and neighborhood level controls. Covariates include bed level controls (room size), hostel level controls (the hostel city's GDP per capita and the hostel's market shares, both available and active, in the city, and an indicator for whether the hostel is owned by A&O), neighborhood level controls (the number of restaurants within a 400m radius, as well as the number of tourist attractions, bus stations and subway stations in a 1km radius). The description of the control variables used can be found in Appendix Table 12. The estimates use the doubly robust estimator discussed in Callaway and Sant'Anna (2020). Notice that we are not able to provide estimates of the coefficient estimates of covariates, since the *did* package used to implement the methods developed in Callaway and Sant'Anna (2020) does not report them.

Figure 6: The effect of technology adoption on occupancy by length of adoption (in weeks)



(a) No covariates

(b) W/ covariates

Notes. The figure displays the dynamic average treatment effect on occupancy by length of exposure to treatment (number of weeks), as indicated on the x-axis. The time period spans from October 1st, 2019 to February 13th, 2020. Red lines give point estimates and 95% confidence bands for pre-treatment periods allowing for clustering at the bed level. Blue lines provide point estimates and 95% confidence bands for the treatment effect of adopting the Pace technology allowing for clustering at the bed level. In panel (a), no covariates are included. In panel (b), the specification includes all bed-, hostel-, city-, and neighborhood level controls. Covariates include bed level controls (room size), hostel level controls (the hostel city's GDP per capita and the hostel's market shares, both available and active, in the city, and an indicator for whether the hostel is owned by A&O), neighborhood level controls (the number of restaurants within a 400m radius, as well as the number of tourist attractions, bus stations and subway stations in a 1km radius). The description of the control variables used can be found in Appendix Table 12. The estimates use the doubly robust estimator discussed in Callaway and Sant'Anna (2020). Notice that we are not able to provide estimates of the coefficient estimates of covariates, since the *did* package used to implement the methods developed in Callaway and Sant'Anna (2020) does not report them.

Table 5: Dynamic treatment effects

Dependent variable:	*Revenue*		*Occupancy*	
	No covariates (1)	W/ covariates (2)	No covariates (3)	W/ covariates (4)
e=0	-0.694*	-2.200*	-0.000	-0.061*
	(0.042)	(0.138)	(0.001)	(0.004)
e=1	0.851*	1.565*	-0.015*	-0.056*
	(0.066)	(0.174)	(0.002)	(0.005)
e=2	-0.677*	-2.891*	-0.034*	-0.051*
	(0.066)	(0.204)	(0.002)	(0.004)
e=3	-0.148	2.258*	-0.042*	-0.051*
	(0.089)	(0.343)	(0.003)	(0.005)
e=4	-1.839*	-	-0.053*	-
	(0.096)	-	(0.004)	-
e=5	-3.415*	-	-0.095*	-
	(0.117)	-	(0.004)	-
e=6	-2.285*	-	-0.028*	-
	(0.010)	-	(0.004)	-
e=7	-0.336*	-	0.054*	-
	(0.091)	-	(0.004)	-
e=8	-1.635*	-	0.032*	-
	(0.120)	-	(0.005)	-
Observations	354,020	354,020	354,020	354,020
Hostels	All			
Period	1oct19-13feb20			

Notes: This table reports the dynamic average treatment effect on revenue (columns 1 and 2) and occupancy (columns 3 and 4) by length of exposure to treatment (number of weeks). Here, e indexes the length of exposure to treatment (that is, technology adoption) as measured in weeks. Estimates in columns 1 and 3 are based on the specification when no control is included. Estimates in columns 2 and 4 are based on the specification with control variables. These include bed level controls (room size), hostel level controls (the hostel city's GDP per capita and the hostel's market shares, both available and active, in the city, and an indicator for whether the hostel is owned by A&O), neighborhood level controls (the number of restaurants within a 400m radius, as well as the number of tourist attractions, bus stations and subway stations in a 1km radius). The description of the control variables used can be found in Appendix Table 12. Standard errors clustered at the bed level are displayed in parentheses. The estimates use the doubly robust estimator discussed in Callaway and Sant'Anna (2020). Notice that we are not able to provide estimates of the coefficient estimates of covariates, since the *did* package used to implement the methods developed in Callaway and Sant'Anna (2020) does not report them. The symbol * denotes estimates significant at the 95% level.

however, in most of these cases, the pre-treatment estimated effects are negative. This suggests that, if anything, before being treated, treatment units were performing worse than control units. Thus, quite reassuringly, we can exclude that the positive treatment effects reflect a pre-treatment trend by which treated units were performing better than control units, already in the absence of treatment.

Overall, although the estimated treatment effects are sometimes negative for occupancy, our results suggest that the adoption of the new pricing algorithm increases the revenue of treatment units, relative to what it would have been without technology adoption. Not only the static average treatment effect is positive and significant in magnitude, but estimates of the dynamic treatment effects (both conditional and unconditional ones) also suggest a pattern of the dynamic treatment effects where the magnitude of the effect of adopting the new technology tends to increase with length of adoption, up to an estimated effect of about 2.26 Euros per bed. We can therefore conclude that the new technology improves firm performance. In Section 6, we will go further into analysis of the mechanisms underlying the estimated performance effects, with a special focus on the role of prices.

5 Robustness

In this section, we provide evidence with regards to the validity of our identification assumption. Our setting differs from the standard framework where the treatment is introduced at a specific point in time for a subgroup of units. In our case, instead, different groups of hostels get treated in different dates. Our difference-in-differences strategy thus identifies the change in the performance gap between treated and non-treated groups of hostels after treatment adoption, as compared to the gap between treated and non-treated groups of hostels in the pre-treatment period. Thus, our empirical strategy assumes that, *ceteris paribus*, this difference would have remained stable in the absence of treatment. Of course, we cannot directly test whether this assumption holds or not. In what follows, we provide suggestive evidence that hostels that did not adopt the new technology during our sample period can serve as a good control group for the treated ones.

First of all, the decision to invest into the new technology for the overall group had been decided the previous year by the management board. The technology adoption was gradually rolled out in all the hostels over a period of about eight months (spanning from December 2019 to July 2020). Importantly, the selection order of the hostels was random and was not based on any pattern or criteria, as already explained in Section 2. Hence, each hostel had the same probability of adopting the new technology in a given date.

Next, we show that treated and control units experienced similar pre-existing trends in both outcomes of interest in the period prior to the earliest treatment adoption date. To this end, we consider the indicator variables identifying different groups of hostels

according to their treatment (Pace) adoption date. A "group" is defined by the date when units are first treated (i.e., adopt the new Pace technology). Recall that in our setup, we have nine groups, i.e., nine groups of hostels that adopted the Pace algorithm prior to the sample end date of February 13th 2020. This can be easily seen in the Appendix Table 11, where hostels are listed according to the Pace adoption date.

We then test whether hostels that adopted Pace were already performing better as compared to control hostels before the earliest treatment adoption date. More specifically, we restrict the sample to the period prior to the earliest treatment adoption date (December 20th 2019) and test whether treatment group indicator variables have an explanatory power on revenue and occupancy.

Results on pre-existing trends are displayed in Table 6. Reassuringly enough, we can see that most of the effects are not statistically significant from zero. Specifically, in column (1), the dependent variable is revenue. The treatment effect is statistically significant only for groups of beds that adopted Pace on January 23rd, January 29th, January 31st, and February 13th (corresponding to 4 hostels with 1,704, 914, 167, and 461 beds, respectively). However, in the first case, the effect is negative. Thus, if anything, this should bias downwards our estimates of the treatment effect. As for the last three groups, the effect is positive. However, the contribution of these beds to the estimated treatment effect is relatively limited, since their adoption dates are at most about two weeks before the end date of our sample.

Similar considerations can be made when the outcome variable is occupancy (column (2)). In most cases, the estimates of the treatment adoption group dummy are either not statically different from zero, or negative. Then, the estimates are significantly positive for the same three groups of beds that delivered positive effects on revenue (i.e., those that adopted Pace on January 29th, January 31st, and February 13th). However, the estimated effect is significantly positive for one additional group of beds, namely the one that adopted Pace on December 20th 2019. This is the Hamburg City hostel, which is the largest hostel with its 1,942 beds. The fact that such a large hostel was registering an occupancy level significantly higher than that of the control group might bias our estimates of the treatment effect on occupancy. At the same time, we are partly reassured by the fact that this holds solely for occupancy, and not for revenue.

Table 6: Pre-treatment trends

Dependent variable:	*Revenue*	*Occupancy*
	(1)	(2)
Treated 20dec19	0.209	0.031***
	(0.232)	(0.008)
Treated 20jan20	0.170	-0.016
	(0.384)	(0.013)
Treated 23jan20	-1.340***	-0.023**
	(0.240)	(0.009)
Treated 24jan20	0.188	-0.017**
	(0.220)	(0.007)
Treated 28jan20	-0.390	0.018
	(0.300)	(0.012)
Treated 29jan20	5.262***	0.096***
	(0.463)	(0.013)
Treated 31jan20	6.871***	0.273***
	(0.896)	(0.027)
Treated 10feb20	-0.447	0.011
	(0.316)	(0.011)
Treated 13feb20	2.134***	0.085***
	(0.538)	(0.018)
Day FE	Yes	Yes
Observations	2,177,592	2,178,640
R-squared	0.066	0.060
Hostels	All	
Period	1oct19-19dec19	

Notes: This table displays results from OLS regressions of treatment group indicator variables on daily revenue (column 1) and occupancy (column 2). The sample is restricted to the period prior to the earliest treatment adoption date (thus spanning from October 1st to December 20th 2019). The data set is a balanced panel where the cross-sectional unit is a bed and the longitudinal unit is a day. Each observation thus represents a bed-day combination. The regressors of interest are treatment group indicator variables, which take on value 1 depending on the treatment (Pace) adoption date, and zero otherwise. Specifically, *Treated 20dec19* takes on value 1 for hostels that adopted Pace on December 20th 2019; *Treated 20jan20* takes on value 1 for hostels that adopted Pace on January 20th 2020; and so on. See Table 11 for Pace adoption dates of each hostel. All specifications include day fixed effects. Standard errors clustered at the bed level are displayed in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

6 Mechanisms

In this section, we dig deeper into the mechanisms behind the estimated effects of the adoption of the new technology on performance, discussing potential channels that differentiate the new pricing algorithm from the previously used Grid pricing model.

First, Section 6.1 provides a detailed description of the two pricing models. Then, in order to further infer the behavior of prices under the two alternative schemes, we compare, under the two algorithms, the relationship between the average daily rate (ADR) and property occupancy (Section 6.2), the ADR paths over the considered time period (Section 6.3), the ADR at the tails of the occupancy distribution (Section 6.4), and the degree of price dispersion (Section 6.5).

6.1 The two pricing models

As already mentioned, the Grid pricing model is occupancy- and human-based. First, it is occupancy-based since it considers house level occupancy, and applies a corresponding fixed rate grid for all categories. With the Grid, changes in the rate are a consequence of changes in house occupancy. In addition, the Grid is human-based, in the sense that the grid specifying the occupancy intervals, together with the corresponding rates, is set up by a human upfront. As an illustrative example, the Table in Appendix 8.1 provides the Grid prices for one of the A&O hostels.

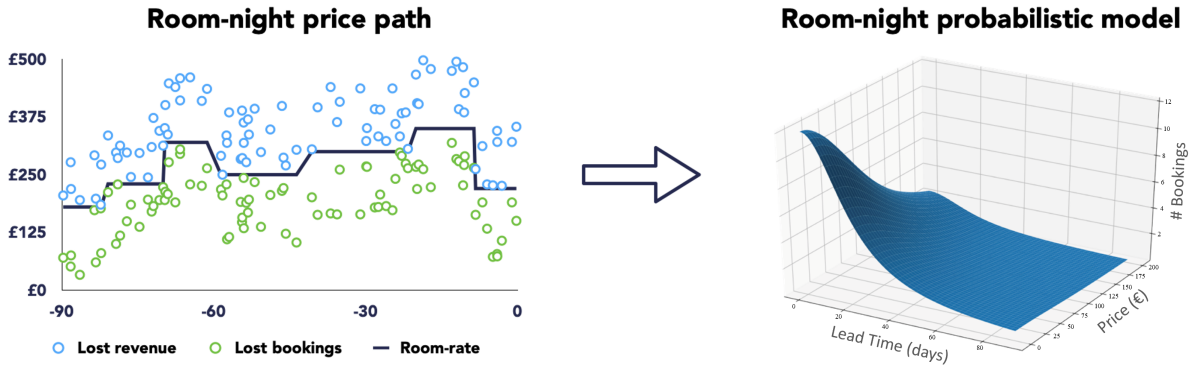
By contrast, the Pace pricing model is a continuous pricing model which capitalizes on real-time data. Thanks to AI and machine learning techniques, it reevaluates every price point in the next 365 days every 60 minutes. The model combines historical data with future booking data and therefore does not rely on having past patterns to set optimal prices. Contrary to the occupancy-based Grid pricing model, which will always charge a higher price at higher occupancy levels, the Pace model is three-dimensional, as it analyzes the lead time, price and number of bookings for any given category or date within the active window. In order to find the optimal balance between volume and price within the remaining lead days, the price continuously floats within a strategic min/max price bandwidth.

Figure 7 considers a hypothetical scenario with the aim to illustrate how Pace adapts its continuous pricing strategy for every night with the main objective to maximize revenue.[14] Consider the price charged for a room for a given booking date over a 90-days lead time window (where zero lead time corresponds to the date of the booking). The left-hand panel shows how Pace continuously updates the room price depending on the estimated market's willingness to pay. The black line represents the price charged for a room as a function of the lead time (on the horizontal axis), while the dots represent

[14] Figure 7 considers a hypothetical scenario for illustrative purposes, without referring to a specific time period.

some hypothetical consumers' willingness to pay. On each date, the blue dots, those lying above the line, represent the lost revenue because the ADR charged on that day was relatively too low. At the same time, there is likely some demand (the green dots, those lying below the line) that is not satisfied because the ADR was relatively too high. The right-hand panel visually depicts how this translates into a three-dimensional pricing model. The lead time is still represented on the x-axis, while the y- and z-axes represent the price charged and the number of bookings, respectively. Mechanically, at the top-left corner, corresponding to zero lead time, the number of bookings is the highest (as it is cumulative). As the lead time increases, on the one hand the number of bookings (mechanically) decreases; on the other hand, the price does not show such a monotonic behavior. In fact, since Pace continuously explores the market's willingness to pay based on past performance and real-time pick-up, it adapts its pricing strategy for every night, with no fixed constraints on the direction. In other words, on each date, the price can either increase or decrease, depending on the estimated market's willingness to pay (the dots of the left-hand panel).

Figure 7: The Pace pricing algorithm



Source. Pace Revenue.

On the one hand, the Pace system picks up much faster on any unusual booking activity on future dates – for example when a major event is announced and demand is expected to dramatically increase accordingly – and will aggressively push the price before the house fills up. By contrast, traditional systems would require human input to set up a special event in advance which potentially causes selling out at low rates. On the other hand, even in periods with extremely low demand, the Pace pricing algorithm will continuously test the price sensitivity in order to find any extra euro to increase the RevPAR. While a human revenue manager likely sets their crisis-prices once and does not change much until demand fully returns, the algorithm ignores the traditional human understanding that the price must increase in line with occupancy booked in the accounts. In reality, higher occupancy does not necessarily mean we are able sell at higher prices if the markets are not compressed. For instance, this was the case in summer 2020: there

was plenty of availability in the markets but due to A&O's aggressive pricing strategy, A&O was able to generate record high volumes of free independent traveler (FIT). A traditional pricing approach would have increased A&O's prices along with occupancy, while A&O would actually outprice themselves from the market. With the machine learning in Pace, the model quickly realized that the number of reservations it received at higher prices was too low, therefore prices (intensive margins) were kept competitive even despite high volume (extensive margin).

6.2 Relationship between ADR and property occupancy

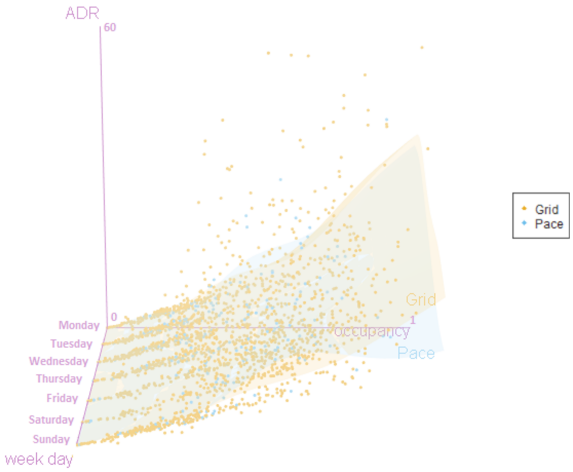
First of all, we expect that the relationship between average daily rates (ADRs) and property occupancy may differ substantially under the two alternative pricing algorithms. In fact, under the Grid algorithm prices are set based on property occupancy, so that the relationship between average rates and occupancy is fixed. By contrast, the new Pace algorithm adapts its pricing strategy for every night based on past performance and real-time pick-up. As a consequence, while the relationship between average rates and occupancy is fixed *a priori* under Grid, the same does not necessarily hold true under Pace.

Figure 8 shows the average daily rate (on the y-axis), as a function of occupancy (on the x-axis) and week day (on the z-axis). Each dot represents the average daily rate charged by a given hostel on a given date. Yellow (blue) dots correspond to average rates charged under the Grid (Pace) pricing algorithm. Smooth regression surfaces are fit separately for the two groups. The figure shows that under both systems, the higher the occupancy is, the higher the price charged will be. At the same time, since the surface fitted on observations priced with the Pace system (the blue one) lies below the surface fitted on Grid observations (yellow), we deduce that for higher occupancy levels, the Pace system charges on average lower prices.

This is in line with our expectations. In fact, the Grid pricing system is occupancy driven. Since the grid prices are set depending on occupancy of the property (as well as day of the week), under the Grid pricing the positive relationship between prices and occupancy obtains mechanically. When the considered hostel is almost full, the price will be high. Under the Pace system, however, this is not necessarily true. Pace recognizes that higher price does not necessarily result in a higher revenue, even when occupancy is relatively high. In fact, there can be situations where a relatively lower price will increase occupancy even more, thus leading to a higher revenue.

While the smooth regression surfaces are indicative of average price patterns, they are not informative about prices set for particularly high or low values of occupancy. As a matter of fact, these are the scenarios where Pace differentiates from the Grid. First of all, one important advantage of the new Pace algorithm is to recognize situations where there

Figure 8: Average daily rate against occupancy and week day by pricing algorithm



Notes. The Figure shows the average daily rate (on the y-axis), as a function of occupancy (on the x-axis) and week day (on the z-axis). The average daily rate is computed by hostel. Thus, each dot represents the average daily rate charged by a given hostel on a given date. Yellow (blue) dots correspond to average rates charged under the Grid (Pace) pricing algorithm. Smooth regression surfaces are fit separately for the two groups. The time interval spans between December 20th 2019 (i.e., the earliest treatment adoption date) to February 13th 2020.

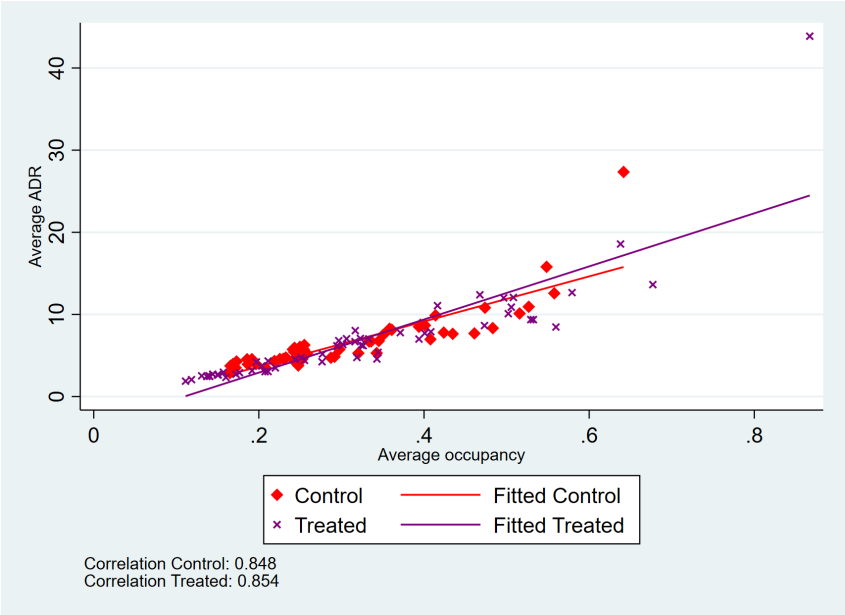
is so much volume that the price can be increased not only by, say, 1%, as would happen under the Grid, but even by 1000%. This is the case during "compression nights", which are defined as nights where occupancy is higher than 95%, such as the best-selling nights of the year (e.g., the 31st of December) or when the city hosts important fares (e.g., the Oktoberfest in Munich). On these occasions, Pace outperforms the Grid because the Grid will never exceed the pre-defined price range. For instance, the Grid does not recognize that during the Oktoberfest in Munich, it can charge suddenly on certain nights 500% or 1000% more per night. In other words, when there are compression nights, having a limitation or a cap on the price that can be charged can lead to important losses in the form of foregone revenue.

At the same time, Pace also recognizes the opposite scenario. When demand is particularly low, Pace will drastically reduce the price in order to attract as many customers as possible. As noted above, there are periods when additional customers can be attracted only if the price is kept sufficiently low. This is the case when markets are not compressed and additional bookings do not necessarily imply that we are able to sell at higher prices. As a result, the range of the ADR under Pace is larger than under the Grid because there are no limitations in both directions: Pace will charge very high prices during compression nights and drastically reduce the price during nights where occupancy is low.

This is exactly what we see in Figure 9 where the ADR is plotted against occupancy.[15]

[15]We also check whether the observed positive relationship between the ADR and occupancy is robust to the exclusion of the observations for December 31st 2019, which represent an outlier for both the treatment and control groups. As shown in Appendix Figure 12, this is indeed confirmed.

Figure 9: Graph of average daily rate (ADR) against occupancy



Notes. The figure displays the correlation between the average daily rate and average daily occupancy for the period starting from the earliest Pace adoption date (20dec2019-14feb2020). Each point represents a day. Red diamonds (purple crosses) depict averages for all observations that were not using (were using) Pace on that day.

Again, both under the Grid and the Pace algorithms, as occupancy increases, the ADR increases, as indicated by the positive slopes of both the red and purple fitted regression lines, respectively. The correlation between ADR and occupancy is particularly strong and given by 0.848 and 0.854 under Grid and Pace, respectively. Although the two correlation coefficients are not statistically different, the positive correlation between price and occupancy is slightly higher under Pace. In fact, with Pace, the price can increase more than proportionally with occupancy, as compared to what would be allowed with the Grid. In other words, the ADR can realize bigger jumps (both upwards or downwards), as it is not just limited to the grid intervals. For instance, in Figure 9, we can see the two outliers under Pace (purple cross in the top-right corner) and under Grid (red diamond at the top-right). These represent the average daily rate on the compression night of December 31st 2019 for treated and control hostels, respectively. Specifically, on December 31st 2019, while the average rate across treated hostels is almost 45 Euros (purple cross at the top-right corner), that for control hostels is lower than 30 Euros (red diamond in the top-right).[16] Thus, already from this simple comparison, it is evident that prices under Pace are much more volatile at high occupancy levels.

[16]Similarly, on another compression night, January 1st 2020, when the average occupancy of treated and control hostels is given by 51% and 42%, the average rate across treated hostels is above 12 Euros, while it is just above 7 Euros among for control hostels. A similar discrepancy is registered also on December 30th, when the average daily rate was about 19 and 15 Euros for treated and control hostels, respectively.

6.3 The price paths

Next, we ask whether the two algorithms give rise to differences in the price paths across time.

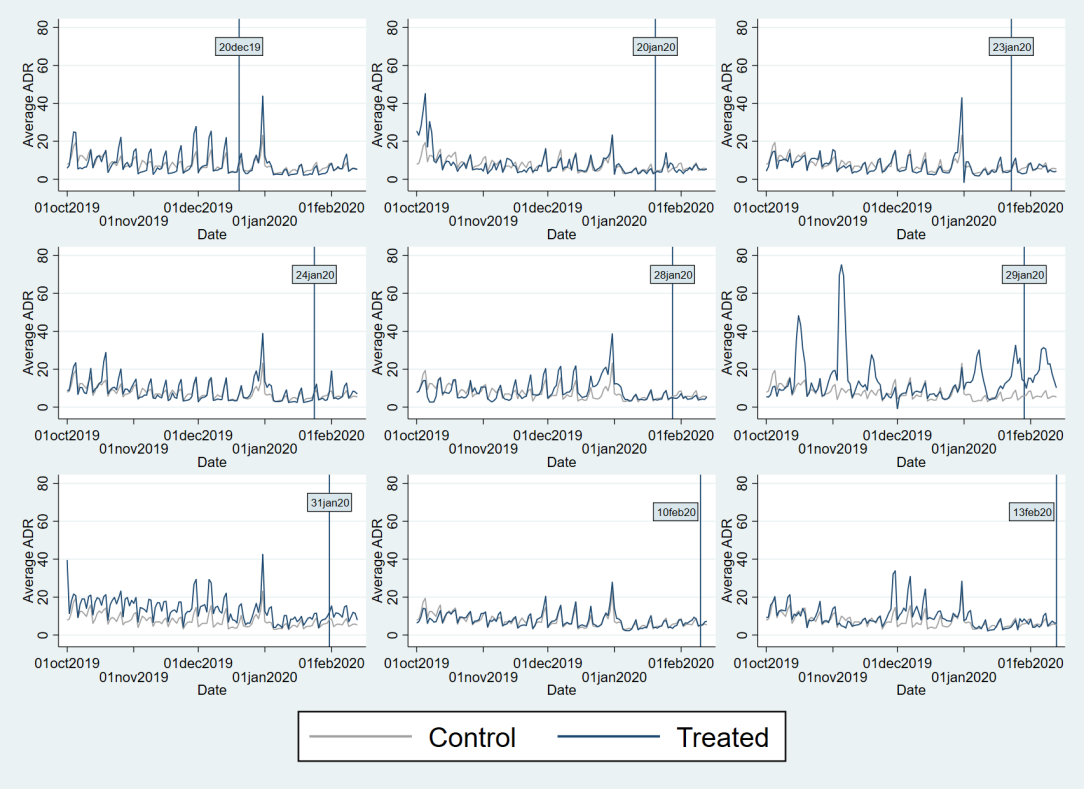
Figure 10 plots the price paths by Pace adoption group, where a group is defined by the date when units are first treated. Specifically, it depicts the average daily price.[17] The gray lines represent price paths of the hostels in the control group, that are all the hostels that always adopted the Grid system in our sample period, as Pace adoption happened at a later date for them. Instead, the blue lines depict price paths of the hostels in the treatment group, where the treatment group is identified by the hostels' Pace adoption date of the considered panel. In other words, while the control group is always the same across all panels, each panel considers a different treatment group, which includes all the hostels that adopted Pace on a particular date (indicated by the vertical line in each panel). So, for instance, take the upper-left panel in Figure 10. The gray line depicts the average daily rate of all the hostels that were adopting the Grid price system. The blue line depicts the average daily rate of all the hostels that adopted Pace since December 20th 2019.

We can see that, indeed, the raw comparison of the average weekly rate of treated and control hostels, shows no clear pattern or break. In fact, there may be several confounding factors that may make this comparison not that meaningful. First, hostels differ markedly in their room composition. In other words, we are comparing prices of beds that are located in rooms for one or two people, to those of others in rooms for four, six, eight or even ten people. On the one hand, the hostels' composition in terms of bed categories is fixed over our considered time span. Thus, like all the other characteristics that vary across hostels but are fixed over time, it will not affect the comparison of average prices over a relatively short time span. On the other hand, however, the hostels' composition of *occupied* beds – those for which we observe prices – likely varies over time. To see this, suppose for example that, on a certain pre-treatment date when all hostels are using the old Grid algorithm, occupied beds in treated hostels are all located in twin rooms, while occupied beds in control hostels are all located only in ten-people rooms. Then, suppose that, on a given post-treatment date when treated hostels are now using the new Pace algorithm, the reverse was true. If this is the case, it is very likely that, on the first (second) date, we will observe a much higher (lower) average rate for treated hostels, as compared to control hostels. Yet, it is pretty straightforward to see that, this difference is due to the category of occupied beds, rather than to the different pricing algorithm used by treated hostels in the two considered dates.

In fact, while hostels differ in many characteristics, such as ownership status, market share, amenities, etc., most of these characteristics are fixed over our considered time

[17] In Appendix 8.4, Figure 13 depicts the average weekly price.

Figure 10: Price paths by Pace adoption group (daily average)



Notes. The figure displays the evolution of the average daily rate by Pace adoption group. The gray lines depict the price paths of control hostels (i.e., those that adopted Pace after the end of our sample period – after February 13th 2020). The dark blue lines depict the price paths of treated hostels (i.e., those that adopted Pace within our sample period – before February 13th 2020). In the upper-left panel, these include hostels that adopted Pace on 20dec2019; in the upper-center panel, those that adopted Pace on 20jan2020; and so on, with Pace adoption dates given by 23jan2020, 24jan2020, 28jan2020, 29jan2020, 31jan2020, 10feb2020, 13feb2020, respectively.

span. As such, they do not alter the comparison of price paths across treatment and control groups of hostels. By contrast, characteristics that change over time, such as the bed category composition of *occupied* beds, do affect such a comparison. As a consequence, we may be comparing, say, the price of beds in single *versus* ten-people rooms on a certain date, and the price of beds in eight-people *versus* twin rooms on another date.

Second, as previously noticed, the new Pace algorithm likely improves the pricing strategy especially in "extreme nights", namely those nights with "extreme" (high or low) values of occupancy. In these nights, we expect to observe the price going up or declining, respectively, more markedly with Pace than what would be observed under the Grid pricing algorithm. In the first case, hypothesizing a relatively low demand elasticity, Pace will set particularly high prices, while in the second case, it will reduce the prize, in order to attract as many customers as possible. As a result, we expect the Pace pricing algorithm to differentiate from the previous Grid, especially with regards to these particular dates.

6.4 Tail pricing

In what follows, we compare the pricing behavior under Grid *versus* Pace algorithms focusing on "extreme nights", namely those where occupancy takes on "extreme" values (high or low). In other words, we will now focus on the "tail pricing" strategies of the two price algorithms by comparing average rates under Grid and Pace at the two tails of the occupancy distribution.

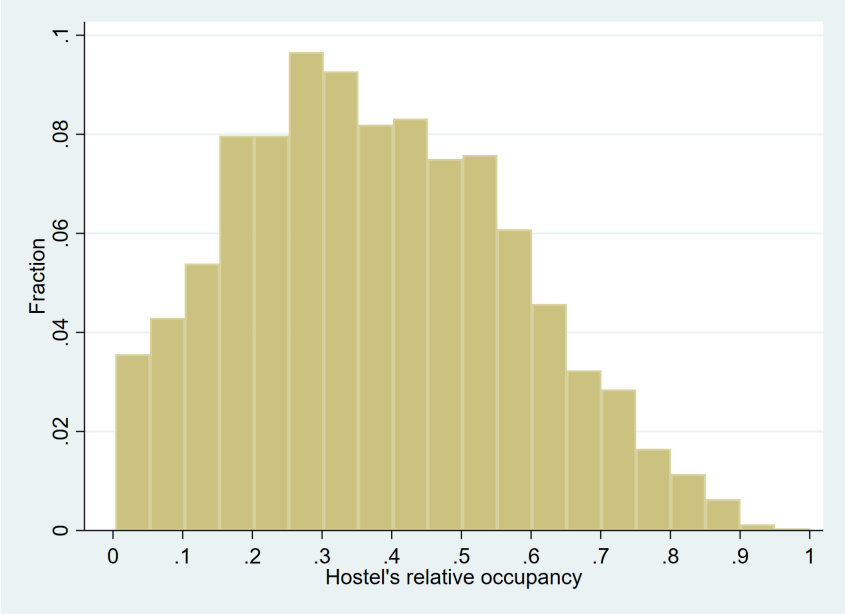
In order to study differences in tail pricing between the Pace and Grid algorithms, for each date we need to consider only beds that are located in hostels whose relative occupancy is *particularly* low/high. To this end, we first compute relative occupancy for each hostel and date as the ratio between the number of occupied beds in the considered night and the total number of beds. Figure 11 shows the distribution of the hostels' relative occupancy in each date of our sample period. We can see that the vast majority of hostels (73%) has a daily occupancy between 15% and 60%, while the remaining hostel-date combinations are almost equally split at the sides of these two thresholds.[18] However, only few of the data points in the left tail are from treated hostels in the post-treatment period. For this reason, for each date we choose to select only hostels with less than 30% and more than 60% of occupied beds.[19] Therefore, we compare pre- to post-treatment

[18] As for the upperbound threshold of 60% occupancy, note that, even if it cannot be classified as a compression night, it represents in fact a quite high occupancy level. Indeed, occupancy is measured at the bed level. As such, an observed relative occupancy of 60% would translate into an approximately 15-20 percentage points higher room occupancy. For instance, in 2019 the bed occupancy was 52.3% which translated into 68.8% room occupancy, i.e., 16.5 percentage points higher.

[19] In fact, we thus face a trade-off between our desire to study pricing behavior at the two tails of the occupancy distribution, while keeping enough data points. If we considered only hostel-date combinations with occupancy lower than 15%, we would observe post-treatment average daily rates only for two (out of nine) treatment groups. For this reason, in order to study pricing at the left tail of the

differences in average daily rates set in treated *versus* control hostels in "extreme nights".

Figure 11: Distribution of hostels' daily relative occupancy



Notes. The figure displays the fraction of hostels in each relative occupancy bin. Observations are identified by a hostel and date. The sample is restricted to hostels with positive occupancy.

Tables 7 and 8 report differences in average daily rates for high and low occupancy nights, respectively. In each table, price differences are shown by bed category.[20] In particular, we distinguish two main types of rooms, that are *(i)* private rooms (including single or double rooms) and *(ii)* shared rooms (with three-, four-, five-, six-, eight-, or ten-people rooms). Considering only occupied beds, single and double beds represent 2% and 40% of the sample, respectively, while the shared rooms categories represent 0.5%, 36%, 0.02%, 15%, and 3% of the sample, respectively.

More specifically, for each date, we first restrict the sample to beds that are located in hostels with occupancy higher than 60% (in Table 7) or lower than 30% (in Table 8). We further restrict the sample to beds in private (columns 1 and 2, in both tables) or shared (columns 3 and 4) rooms. For each treatment group, we compute the treatment-control difference in the average daily rate in the pre-treatment period (columns 1 and 3, in both tables) and in the post-treatment period (columns 2 and 4).[21] The treatment group changes across rows, and is defined depending on the treatment adoption date (indicated in the first column). The control group, instead, is the same across all rows, and includes

occupancy distribution, we set the threshold at 30% occupancy (instead of 15%).

[20] Since we have discrete points that are not continuous in time, we do not show price paths, but rather report treated-control average price differences before and after treatment for different bed categories using tables.

[21] Note that we do not report the statistics for the last two treatment groups (i.e., those that adopted Pace on February 10th or 13th 2020). In this way, the post-treatment period includes at least two weeks for all treatment groups.

Table 7: Differences in Average Daily Rates (Treated - Control) for high occupancy nights

	Private rooms		Shared rooms	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
	(1)	(2)	(3)	(4)
Treated 20dec2019	-1.31	10.25	-0.30	9.25
Treated 20jan2020	-5.62	12.24	-6.69	-1.58
Treated 23jan2020	-1.91	-5.34	0.72	-5.36
Treated 24jan2020	2.88	15.41	6.13	9.48
Treated 28jan2020	-6.07	–	0.73	–
Treated 29jan2020	-4.19	0.46	-3.32	0.18
Treated 31jan2020	-5.08	-2.36	-6.40	-3.11

Notes: This table displays the average difference in Average Daily Rates between the treatment and control groups in the pre-treatment (columns 1 and 3) and post-treatment (columns 2 and 4) periods. In each row, the treatment group is identified by the treatment (Pace) adoption date indicated in the first column. The control group, instead, is the same across all rows, and includes hostels that never got treated in our considered sample period (spanning from October 1st 2019 to February 13th 2020). Average prices are computed only across occupied beds. The sample is restricted to beds located in hostel's with daily relative occupancy at least as high as 60 percent. In columns (1) and (2), the sample is further restricted to beds located in private rooms. In columns (3) and (4), the sample is restricted to beds located in shared rooms. The missing data is due to the lack of post-treatment dates where the considered treated hostels had at least 60% of occupied beds.

Table 8: Differences in Average Daily Rates (Treated - Control) for low occupancy nights

	Private rooms		Shared rooms	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
	(1)	(2)	(3)	(4)
Treated 20dec2019	3.53	2.49	-1.81	-1.91
Treated 20jan2020	11.08	8.02	-1.44	-2.18
Treated 23jan2020	1.85	4.78	0.040	1.07
Treated 24jan2020	0.29	4.89	-0.60	2.71
Treated 28jan2020	1.69	0.84	-0.54	0.33
Treated 29jan2020	4.63	–	0.34	–
Treated 31jan2020	0.53	–	-4.37	–

Notes: This table displays the average difference in Average Daily Rates between the treatment and control groups in the pre-treatment (columns 1 and 3) and post-treatment (columns 2 and 4) periods. In each row, the treatment group is identified by the treatment (Pace) adoption date indicated in the first column. The control group, instead, is the same across all rows, and includes hostels that never got treated in our considered sample period (spanning from October 1st 2019 to February 13th 2020). Average prices are computed only across occupied beds. The sample is restricted to beds located in hostel's with daily relative occupancy at most as low as 30 percent. In columns (1) and (2), the sample is further restricted to beds located in private rooms. In columns (3) and (4), the sample is restricted to beds located in shared rooms. The missing data is due to the lack of post-treatment dates where the considered treated hostels had at most 30% of occupied beds.

hostels that never got treated.

Let us first analyze Table 7 on high occupancy nights. As an example, consider columns 1 and 2, where the sample is further restricted to beds in private rooms. The first row refers to the first treatment group (*Treated on 20dec2019*). In the pre-treatment period (i.e., before 20dec2019), treated hostels have an average daily rate of 34.24, while for control hostels it is 35.55. The treatment-control difference is thus given by -1.31, as indicated in column 1 (the pre-treatment column for beds in private rooms). The same figures in the post-treatment period are given by 43.78 and 33.53, respectively, which gives a post-treatment difference of 10.25 (as indicated in the post-treatment column). This means that with Pace the average price charged in high-occupancy nights increased considerably, contrary to what happened in hostels in the control group.

As a matter of fact, this pattern is confirmed for all treatment groups. As expected, treatment-control price differences are always higher in the post- than in the pre-treatment period. This is true both for beds in private rooms (as the price difference in column 2 is always larger than the corresponding figure in column 1) and in shared rooms (as the price difference in column 4 is always larger than the corresponding figure in column 3).[22] With Pace, in high occupancy nights rates are larger. Indeed, this suggests that Pace is better able to capture part of the consumer surplus that, under the lower Grid prices, would be otherwise left to the consumer.

Similarly, Table 8 reports price differences in low occupancy nights for beds in private rooms (columns 1 and 2) and in shared rooms (columns 3 and 4). Since we expect that prices under Pace realize bigger jumps in both directions, we expect that in low occupancy nights, Pace may charge lower prices than what would have happened under Grid. In other words, we expect the post-treatment treated-control price difference (figures in columns 2 and 4 for private and shared rooms, respectively) to be lower than the pre-treatment counterpart (in columns 1 and 3). Indeed, this is exactly what we see for some treatment groups (in five out of ten cases). The evidence, however, is less clear-cut than in Table 7 on high occupancy nights. There can be different reasons for this. First, the 30% threshold does not represent such a low occupancy, especially if we consider that it is measured at the bed level (and would translate into about 15-20 percentage points higher room occupancy). Then, while Pace has more flexibility than Grid to charge lower prices to try to deliver higher occupancy, Pace profitability does not imply that, *ex-post*, we need to observe lower prices for the same realized low occupancy levels.

[22] There is only one exception: the treatment-control price difference post-treatment is actually smaller than the pre-treatment counterpart for beds located in shared rooms that got treated on January 23rd 2020. Moreover, the post-treatment price difference cannot be calculated for the 28jan2020 treatment group, since none of the hostels that got treated on that date ever reached an occupancy level of at least 60% between the treatment date (January 28) and the end of the sample period (February 13).

6.5 Price dispersion

Finally, we provide further evidence that Pace increases price dispersion, as compared to the previously used Grid pricing algorithm. To this end, in this section we focus our analysis on specific clusters of hostels that are located in the same city. Comparing treated and control groups of hostels located in the same city clearly helps us to control for city-specific factors affecting prices, such as the presence of exceptional events like fares, as well as level and type of tourism activity. In particular, we now zoom into hostels located in four German cities, that are Berlin, Frankfurt, Hamburg and Munich. These cities all share a feature that is particularly desirable to our purpose of comparing pricing strategies under the Pace and Grid algorithms. That is, these cities have both treated and control hostels. For instance, in Berlin, A&O has four hostels and these adopted Pace on January 23rd 2020, February 10th 2020, March 5th 2020, and March 25th 2020. Thus, the first two hostels belong to the treatment group, while the last two are included in the control group.

Table 9 reports some descriptive statistics for the ADR and occupancy rate separately for the hostels that were using the Grid or Pace. For each city, the sample is restricted to dates starting from the earliest Pace adoption date for that city. We report the mean, standard deviation, number of observations, the minimum, the maximum, and the coefficient of variation (CV). With regards to the latter, the coefficient of variation represents the standard deviation divided by the mean, and is commonly used as a measure of price dispersion (Kaplan and Menzio, 2015). It is generally better than simply using the standard deviation because it accounts for differences in the means. Comparing the statistics on the ADR and occupancy under Grid and Pace within each city, we confirm our prediction that the adoption of Pace increases the volatility of the ADR. With few exceptions (in Munich for occupancy and in Frankfurt), from Table 9, we can see that the coefficient of variation is always higher under Pace, both for revenue and occupancy. Similarly (with the exception of Berlin), the range of the ADR is much higher with Pace. For instance, while in Frankfurt the highest price charged under the Grid is about €70, the maximum price almost doubles under Pace, reaching about €130.

Table 9: Price and occupancy descriptive statistics by pricing algorithm used

		mean	sd	count	min	max	CV
				Hamburg			
With Grid	ADR	9.042	13.265	72,261	0.000	98.592	1.467
	Occupancy	0.387	0.487	72,261	0.000	1.000	1.258
With Pace	ADR	6.623	11.315	130,347	0.000	107.110	1.708
	Occupancy	0.321	0.467	130,347	0.000	1.000	1.455
				Munich			
With Grid	ADR	6.383	10.175	23,082	0.000	49.828	1.594
	Occupancy	0.350	0.477	23,082	0.000	1.000	1.363
With Pace	ADR	7.048	11.939	27,243	0.000	76.880	1.694
	Occupancy	0.354	0.478	27,243	0.000	1.000	1.350
				Berlin			
With Grid	ADR	6.184	10.346	57,252	0.000	44.048	1.673
	Occupancy	0.296	0.457	57,252	0.000	1.000	1.544
With Pace	ADR	5.529	9.285	40,824	0.000	39.311	1.679
	Occupancy	0.290	0.454	40,824	0.000	1.000	1.566
				Frankfurt			
With Grid	ADR	14.878	16.384	11,648	0.000	70.763	1.101
	Occupancy	0.586	0.492	11,648	0.000	1.000	0.840
With Pace	ADR	18.769	20.211	14,624	0.000	129.926	1.077
	Occupancy	0.651	0.477	14,624	0.000	1.000	0.733

7 Conclusion

In this paper, we evaluate the impact of a dynamic pricing technology adoption, driven by AI and machine learning, on hotel performance in the hospitality property sector. To this end, we exploit data from the largest and leading hostel company worldwide, A&O Hostels, with 28,031 beds across 23 cities located in 8 European countries, representing 23% market share, which can therefore serve as a proxy and as a credible representative of its sector.

The new dynamic pricing system was adopted starting from December 2019 and features two distinctive elements that are new to the literature on dynamic pricing. First, historical data is combined with real-time future booking data, without heavily relying on past patterns or human input to set prices, and is picking up much faster unusual booking activity on future dates. Second, prices depend on the customers' willingness to pay, regardless of occupancy, day of week, or category. We compare the pricing behavior under this new property technology with that of the previous human-based pricing algorithm (the Grid Pricing Model), which made prices vary only based on overall asset occupancy, day of week and season, with a fixed price hierarchy among different categories, and fixed increments between the grids.

In order to quantify the revenue and occupancy increase due to technology adoption, while dealing with unobserved heterogeneity across different units, we implement a quasi-experimental methodology, an extended version of the Difference-in-Differences estimator with time and group fixed effects. We show that the adoption of this innovative pricing system can improve business decisions and respective financial performance in an organization. We document how units that adopted the new technology experience an increase in bed daily revenue and occupancy by up to about 0.90 Euros and 4 percentage points per bed, respectively. This is a sizable upper bound to the impact on revenue and occupancy, since it implies that adopting the new technology for an additional bed increases the likelihood of having it occupied by 12%, as well as its predicted revenue by 10%, as compared to the outcome means in the control group. We also estimate dynamic treatment effects to study how the effect of adopting the new technology changes by length of adoption, following the methods proposed in Callaway and Sant'Anna (2020). Our estimates confirm that the adoption of the new technology positively affects the revenue of the treated units, suggesting a pattern where the magnitude of the effect increases with length of adoption, up to an estimated effect of about 2.26 Euros per bed for the longest adoption length.

Finally, we dig deeper into the mechanisms that can explain the success of the new pricing algorithm. We provide evidence of the increased price dispersion under the new pricing model. In fact, the average daily rate can realize bigger jumps (both upwards or downwards), as it is not limited to the fixed grid intervals. In particular, the key difference

between the two models emerges with regards to tail pricing, that is, price patterns at the tails of the occupancy distribution. Especially in the so-called compression nights, where occupancy is particularly high, the average price charged increases considerably under the new price model. This suggests that the new technology is better able to capture part of the consumer surplus that would be otherwise left to the consumer.

We conclude that our results provide new evidence on how an AI driven system capitalizing on real-time data to dynamically adjust prices represents not only a powerful source of value creation for a business, but it also outperforms the human driven system, and represents therefore the next potential step in the evolution of dynamic pricing algorithms from "Human" to "Artificial Intelligence". And from a practical perspective, as the large majority of the market participants still use human based systems, the roll out of this property technology across the sector could have a significant impact on individual and sector performance, and in particular a competitive advantage for early movers.

8 Online Appendix

8.1 Grid pricing strategic settings: An example

Table 10: Grid pricing based on property occupancy

Occupancy Intervals		<60%	60to70%	70to80%	80to90%	>90%
Single room	Mon	€30	€32	€34	€36	€40
	Tue	€30	€32	€34	€36	€40
	Wed	€30	€32	€34	€36	€40
	Thu	€30	€32	€34	€36	€40
	Fri	€30	€32	€35	€38	€44
	Sat	€30	€32	€35	€38	€44
	Sun	€28	€30	€32	€35	€39
Twin room	Mon	€38	€40	€42	€44	€48
	Tue	€38	€40	€42	€44	€48
	Wed	€38	€40	€42	€44	€48
	Thu	€38	€40	€42	€44	€48
	Fri	€38	€40	€43	€46	€52
	Sat	€38	€40	€43	€46	€52
	Sun	€36	€38	€40	€43	€47
4-people room						
Price per bed	Mon	€13	€14	€15	€16	€18
	Tue	€13	€14	€15	€16	€18
	Wed	€13	€14	€15	€16	€18
	Thu	€13	€14	€15	€16	€18
	Fri	€15	€16	€17	€18	€20
	Sat	€15	€16	€17	€18	€20
	Sun	€13	€14	€15	€16	€18
6/8-people room						
Price per bed	Mon	€10	€11	€12	€13	€15
	Tue	€10	€11	€12	€13	€15
	Wed	€10	€11	€12	€13	€15
	Thu	€10	€11	€12	€13	€15
	Fri	€12	€13	€14	€15	€17
	Sat	€12	€13	€14	€15	€17
	Sun	€10	€11	€12	€13	€15

Notes: This table displays the occupancy based Grid pricing settings for one A&O property. The price setting rule is displayed for each room category. Prices for single and twin rooms refer to the price for the whole room. Prices for 4-, 6- and 8-people rooms refer to a single bed. Occupancy intervals refer to the percent occupancy of the whole property.

8.2 Property characteristics

Table 11 describes the main property characteristics of the hostels used in the empirical analysis.

Table 11: Property characteristics

Name	**Country**	**City**	**Class**	**Pace Adoption Date**	**# beds**
a&o Hamburg City	Germany	Hamburg	LFL	20dec2019	1,942
a&o Munich Hackerbrücke	Germany	Munich	LFL	20jan2020	936
a&o Berlin Mitte	Germany	Berlin	LFL	23jan2020	1,704
a&o Munich Central Station	Germany	Munich	LFL	24jan2020	183
a&o Hamburg Central Station	Germany	Hamburg	LFL	24jan2020	917
a&o Amsterdam Zuidoost	Netherlands	Amsterdam	LFL	24jan2020	1,420
a&o Warsaw Wola	Poland	Warsaw	Opening 01oct2019	24jan2020	600
a&o Vienna Central Station	Austria	Vienna	LFL	28jan2020	1,102
a&o Frankfurt Galluswarte	Germany	Frankfurt	LFL	29jan2020	914
a&o Hamburg Hammer Kirche	Germany	Hamburg	LFL	31jan2020	167
a&o Berlin Friedrichshain	Germany	Berlin	LFL	10feb2020	834
a&o Aachen Central Station	Germany	Aachen	LFL	10feb2020	364
a&o Dresden Central Station	Germany	Dresden	LFL	13feb2020	461
a&o Weimar	Germany	Weimar	LFL	17feb2020	541
a&o Dusseldorf Central Station	Germany	Dusseldorf	LFL	21feb2020	464
a&o Stuttgart City	Germany	Stuttgart	LFL	21feb2020	1,028
a&o Munich Laim	Germany	Munich	LFL	26feb2020	894
a&o Dortmund Central Station	Germany	Dortmund	LFL	28feb2020	363
a&o Frankfurt Ostend	Germany	Frankfurt	LFL	28feb2020	728
a&o Graz Central Station	Austria	Graz	LFL	05mar2020	472
a&o Prague Rhea	Czech Republic	Prague	LFL	05mar2020	1,380
a&o Copenhagen	Denmark	Copenhagen	LFL	05mar2020	684
a&o Berlin Central Station	Germany	Berlin	LFL	05mar2020	1,012
a&o Leipzig Central Station	Germany	Leipzig	LFL	05mar2020	508
a&o Cologne Neumarkt	Germany	Cologne	LFL	05mar2020	567
a&o Nuremberg Central Station	Germany	Nuremberg	LFL	05mar2020	372
a&o Cologne Dom	Germany	Cologne	LFL	05mar2020	84
a&o Hamburg Reeperbahn	Germany	Hamburg	LFL	05mar2020	592
a&o Cologne Central Station	Germany	Cologne	LFL	05mar2020	134
a&o Bremen Central Station	Germany	Bremen	LFL	05mar2020	420
a&o Venice Mestre	Italy	Venice	LFL	05mar2020	988
a&o Berlin Kolumbus	Germany	Berli n	LFL	25mar2020	908
a&o Vienna Stadthalle	Austria	Vienna	LFL	09apr2020	335
a&o Salzburg Central Station	Austria	Salzburg	LFL	09apr2020	474
a&o Prague Metro Strizkov	Czech Republic	Prague	LFL	09apr2020	1,353
a&o Venice Mestre 2	Italy	Venice	Opening 20feb2019	09apr2020	980
a&o Budapest	Hungary	Budapest	Opening 01oct2019	10jul2020	408

Notes: This table displays the property characteristics for each hostel. Properties are ordered according to the Pace adoption date. Only hostels that opened before the Covid outbreak are included.

8.3 List and description of variables

Table 12 describes the variables used in the empirical analysis.

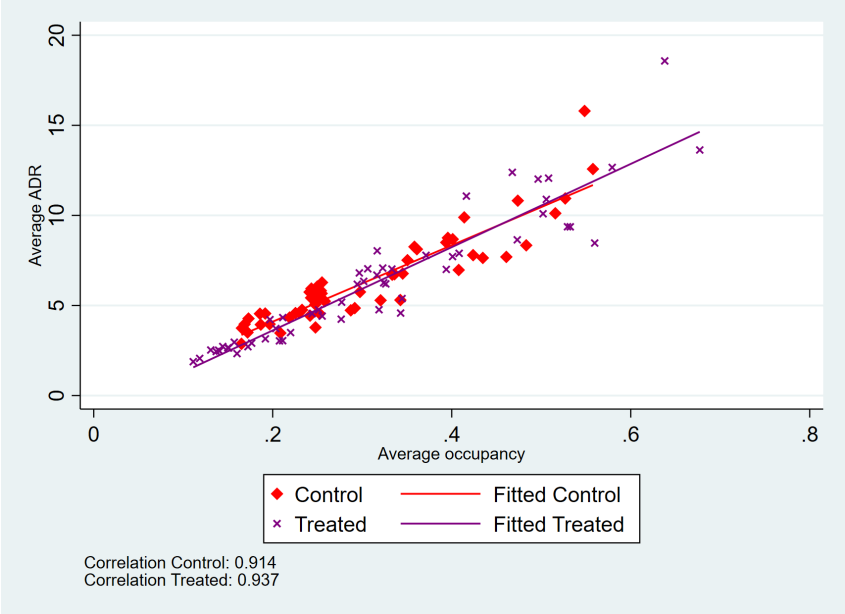
Table 12: Variables description

Variable	Definition
	Outcomes of interest:
Revenue	Numerical variable defined as the product of occupancy and average daily rate
Occupancy	Dummy variable indicating whether the bed was occupied in a given date
Average daily rate	Numerical variable measuring the average price charged for a given bed in a given date
	Bed controls:
Room size	Total number of beds in the bed's room (Possible values: 1, 2, 3, 4, 5, 6, 8, 10)
	Hostel controls:
Market share (active)	Numerical variable measuring the hostel's share of estimated stock, which is given by the hostel's number of beds divided by the estimated total number of active beds from hostels in the city
Market share (available)	Numerical variable measuring the hostel's share of estimated available capacity, which is given by the hostel's number of beds divided by the estimated total number of available beds for Hostel World hostels in the city[a]
Owned	Dummy variable indicating whether the hostel is owned by A&O (rather than leased)
GDP per capita	Ratio between the GDP of the hostel's metropolitan area in 2018 (USD) (OECD, base year 2015) and the hostel's city population (Eurostat, last data available)
ncompanies	Numerical variable measuring the total number of companies in the hostel's city (Eurostat, last data available)
	Neighborhood controls:
nrestaurants	Number of restaurants within radius of 400m
ntattractions	Number of tourist attractions within radius of 1km
nbusstations	Number of bus stations within radius of 1km
nsubwaystations	Number of subway stations within radius of 1km

[a] Available hostels are classified as hostels that have availability loaded for any future date.

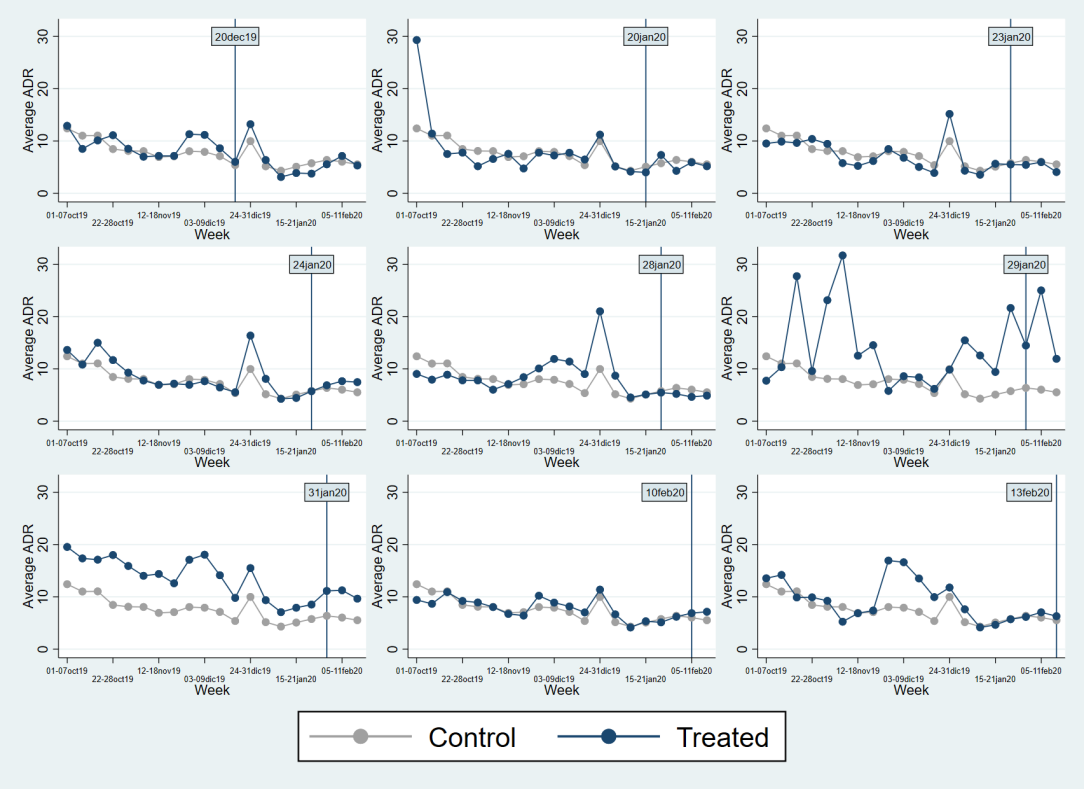
8.4 Other figures

Figure 12: Graph of average daily rate (ADR) against occupancy



Notes. The figure displays the correlation between the average daily rate and average daily occupancy for the period starting from the earliest Pace adoption date (20dec2019-13feb2020). Each point represents a day. Red diamonds (purple crosses) depict averages for all observations that were not using (were using) Pace on that day. The observation for December 31st 2019 is dropped for both the treatment and control groups.

Figure 13: Price paths by Pace adoption group (weekly average)



Notes. The figure displays the evolution of the average weekly rate by Pace adoption group. The gray lines depict the price paths of control hostels (i.e., those that adopted Pace after the end of our sample period – after February 13th 2020). The dark blue lines depict the price paths of treated hostels (i.e., those that adopted Pace within our sample period – before February 13th 2020). In the upper-left panel, these include hostels that adopted Pace on 20dec2019; in the upper-center panel, those that adopted Pace on 20jan2020; and so on, with Pace adoption dates given by 23jan2020, 24jan2020, 28jan2020, 29jan2020, 31jan2020, 10feb2020, 13feb2020, respectively.

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