

Competitive Survival in a Devastated Industry: Evidence from Hotels during COVID-19

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Abstract

In the face of COVID-19, the federal government scrambled to provide emergency funding to businesses, but did not always take into account the heterogeneous nature of firms, especially within industries. Using the lodging industry as the application, this article shows that businesses' failure risk in a pandemic depends on a business' native ability to adapt to changing safety needs, in particular its ability to provide a socially-distanced environment. Hotels not well suited to social distancing – e.g. destination-type hotels with large gathering spaces and many personalized services – offered deeper price discounts or closed down altogether during the pandemic. Simpler hotels with fewer ancillary services were more likely to remain open, with a substantial proportion actually increasing prices. Area infection rates mattered little. Effects are identified by comparing pre-pandemic expectations of outcomes to updated within-pandemic expectations of outcomes, all while holding the place and the time of consumption fixed.

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1 Introduction

The collapse of the U.S. economy triggered by the COVID-19 coronavirus in March 2020 was less of an economic meltdown and more of an economic flash fire. In the eight week period from mid-March to mid-May, 36.2 million Americans applied for unemployment benefits and the U6 underemployment rate briefly skyrocketed to 22.8%, approaching Great Depression era numbers (DOL (2020), BLS (2020)). Stay-at-home orders were issued, non-essential businesses were shuttered, and even essential businesses remaining open saw a collapse in demand of a scale and speed not previously

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imagined. In March and April especially, federal and state governments scrambled to provide emergency financial support to businesses and citizens through a variety of programs, including liquidity loans for banks, loans to large businesses in selected industries, loans to small businesses such as Paycheck Protection Program loans (PPP) and Economic Injury Disaster Loans (EIDL), stimulus checks to persons below certain income cutoffs, and enhanced employment benefits to the recently laid off.

Not surprisingly given the speed at which programs were drawn up, the relief did not always go to where it was most needed. Consider the PPP program. The initial window to apply for loans closed quickly and many small businesses were shut out of assistance altogether (Humphries et al. (2020)). Rules changed by the day, making repayment risks difficult to gauge, and even a slight hesitation by a small business owner could leave him or her behind. Meanwhile, news reports began to surface about large corporations and other large entities receiving hundreds of millions of dollars under the program, arguably without the same need, and only by virtue of getting in line first (Bartik et al. (2020)). Distribution of funds and vetting of recipients was arguably less than ideal as the government rushed to attack a very large problem with very large amounts of money very quickly.

In this article, I examine how a more carefully planned federal pandemic response could better target emergency funds to those businesses with the greatest actual need. Obviously, smaller businesses often have a greater insolvency risk and larger businesses often have larger numbers of employees at risk, and these are important, but there is much more to it. And it is this "much more" that has not always been taken into account. Businesses will generally be hurt, but not always uniformly, and not always in strict proportion to their size, even within the same industry.

I focus on one important and often-overlooked factor that affects relative failure risk – "native adaptability". Native adaptability is a business' ability, or inability, to easily and quickly adapt to safer health practices in a pandemic – mostly notably, its ability to create or maintain an environment conducive to social distancing among their customers. I use the term "native" because businesses were generally not set up with a pandemic in mind, and were faced with a set of largely pre-determined product and service characteristics that may or may not align very well with changing public safety needs in a pandemic. Greater native adaptability means that it is easier

for a business to implement pandemic-safe health practices, such as requiring masks or ensuring greater social distancing between consumers, and lower native adaptability means it is inherently less easy to do so. Online businesses, for example, have a high degree of native adaptability because in-person interaction tends to be minimal in these businesses. Conference centers and nightclubs have a much lower degree of native adaptability because their business model relies on patrons being in close contact with one another, and this is harder to change. Restaurants and gyms have lower native adaptability because they are not as amenable to mask-wearing, whereas retail shops have more native adaptability because mask-wearing is easier to implement. While small changes can be made around the edges to improve safety, the fundamental nature of a business limits how much they can ultimately adapt, and this inherent degree of native adaptability directly affects relative failure risk in a pandemic.

Native adaptability to changing safety needs in a pandemic has received little attention in the federal response, so it makes sense to have a dialogue here. Federal programs often distinguish between industries as a whole, but rarely distinguish between similarly-sized businesses within the same industry. The latter omission is important because businesses within the same industry tend to be heterogeneous and will generally experience different degrees of failure risk. For example, a hotel with small rooms but large communal spaces (fancy lobbies, a conference center, or resort-style pool areas where patrons would normally gather) would fare differently in a pandemic than a similarly-priced hotel focused on large and fancy rooms but minimal common spaces. The former is more set up for group interaction, the latter is more set up for individual privacy. Since the native adaptability of these businesses differ, their demand losses should differ and their failure risks should differ as well. If federal programs fail to distinguish among firms with different degrees of native adaptability and failure risk in targeting funds, the marginal value of the last dollar spent on each business would not be equal, leading to an obvious deadweight loss. The overall outcome could be improved by redistributing emergency funds from lower risk to higher risk businesses and increasing the "bang for the buck" on public dollars. Said another way, taking into account native adaptability, a necessarily microeconomic exercise, has important macroeconomic consequences for recovery.

To highlight the issues, I explore native adaptability in the context of one particularly hard-hit

industry, the hotel and lodging industry. The industry is an excellent laboratory for studying native adaptability for a variety of reasons. First, businesses can differ significantly in native adaptability. Hotels are highly heterogeneous, from simple roadside motels to luxury vacation resorts and all varieties of accommodations in between. While some are highly amenable to social distancing (such as simple hotels that largely cater to pass-through highway traffic), others are not (such as hotels with resort-style pools, restaurants, and conference centers that may be destinations in their own right). Second, the hotel industry was deemed an essential industry and individual hotels were not required to close by health authorities.¹ Hotels were able to compete for whatever residual consumers remained during the pandemic, and closure decisions were made by the individual hotel franchisees and not the health authority. Third, and as is well known, hotels were among the hardest hit of businesses not otherwise forced to close. Hotel occupancy rates collapsed to an all-time record low of 21.6% in mid-April 2020 (STR (2020)), before rebounding in early May when state economies began to reopen (Fairlie (2020)).

Another advantage of using the hotel industry as the application is practical. The industry allows for an exceptionally clean identification of effects because it offers a control for what would have happened after the start of the pandemic but in the absence of the pandemic. This is rare for most consumer product industries. The industry operates on an advance purchase model, where one can reserve a hotel room for a future stay (assuming the hotel is to be open) at a current price that fluctuates over time leading up to the stay, based on then-current demand expectations. It is akin to a futures market, but for heterogeneous consumer goods rather than commodities. It makes it possible to peer into the future to see whether a hotel expected to be open, and what prices it expected to get, for a stay occurring after the start of the pandemic, but as those expectations were formed before there was any thought of a pandemic. I can then compare those pre-pandemic expectations to the hotel's updated expectations on closures and prices, all for the same stay date, but this time after the pandemic arrived and after travel demand had collapsed. In other words, I can compare pre-pandemic and within-pandemic expectations of closures and prices, holding both the product (hotel and room) and the exact timing of consumption (the date of stay) all fixed. It

¹In very few cases, hotels were limited to housing essential travelers only, but the definition of essential travel tended to be broad and proof of essential travel was neither checked nor required.

is unusually well identified.

A review of the COVID-19 literature shows that empirical analyses are often of the before-and-after variety, comparing observed outcomes from before the start of the pandemic to observed outcomes after. While it may be hard to argue that the pandemic was not a major cause of economic woes starting in late March 2020, simple before-and-after exercises can be infected by unobserved time-varying correlates. Unobserved time-variant factors correlated with the timing of the pandemic can get mixed up in the estimates of interest and bias results. In general, it is difficult to find a control for what would have happened in the post-pandemic world in the absence of a pandemic (such is the nature of pandemics), but the advance purchase model in hotel industry offers such a peek.

Using operations data from a large dataset of over five thousand hotel franchisees, I explore how heterogeneous degrees of native adaptability differentially affect relative demand outcomes. I examine two important outcomes in particular – the decision of whether to remain open or close, and the decision of what price to charge if remaining open.² I pay special attention to a hotel’s native adaptability – in particular, its amenability to social distancing – both inside the hotel and in the surrounding areas where guests would typically go (and why guests might choose the hotel in the first place). One such external factor is local area COVID-19 infection and death rates.

The analysis focuses on stays in April 2020 in the immediate aftermath of the demand collapse. It is an ideal time frame to study the heterogeneous effects of native adaptability. States had largely shut down their economies by late March, and unemployment rates peaked in mid-April.³ Hotel demand was at its lowest in April with occupancy rates bottoming out at record levels. Consumers had less compassion fatigue at that time and were likely to be more particular and wary when choosing activities and businesses. Come May, things began to improve from an economics point of view, if not from a public health point of view. The vast majority of states lifted stay-at-home orders in the final days of April and the first two weeks of May, and began reopening their economies

²A third and related outcome variable would be hotel occupancy rates, conditional on a hotel remaining open. Unfortunately, occupancy rates at the hotel level, necessary for the types of comparisons made here, are not publically available. I do, however, use aggregate-level hotel occupancy data to bound the overall impacts of the pandemic on hotel profits.

³Record unemployment numbers released by the Bureau of Labor Statistics and officially attributed to May 2020, are based on a workplace survey conducted the week of April 12-18, 2020.

again. Travel picked up and occupancy rates rebounded some. By August, hotels had reversed more than half of their occupancy rate losses.⁴

To preview results, I find that the native adaptability of a business matters for relative demand loss and failure risk. The likelihood of closure and the extent of price discounting was highest for hotels where social distancing was inherently more difficult, and lowest for hotels where social distancing was inherently easier. A meaningful percentage of the latter group were even able to raise prices during the pandemic. This interesting result can be attributed to the better native adaptability of these hotels causing a shift in the elasticity of the residual consumer. Area characteristics, including COVID-19 infection and death rates, show surprisingly little effect.

The remainder of this article is organized as follows. Section 2 discusses the ever-growing COVID-19 literature and provides some additional background. Section 3 describes the data. Section 4 outlines the methodology and Section 5 presents the empirical results. Section 6 concludes.

2 Background and Literature

The novel coronavirus COVID-19 caused a sudden and historic shutdown of the U.S. economy starting in late March 2020. Chinese officials first reported a contagious flu-like illness in Wuhan, China, to the Chinese office of the World Health Organization, on December 31st, 2019 (WHO (2020)). The U.S. was notified on January 3, 2020, and news of the illness began to slowly spread over the next few weeks. WHO reported the first known case outside of China on January 15th, and the U.S. Centers for Disease Control and Prevention reported the first known case in the U.S. on January 20th (WHO (2020), Holshue et al. (2020)). At the end of February, there were nineteen known cases in the U.S.. By the end of May, there were more than 1.5 million U.S. cases and over 100,000 deaths. By the end of September, over 7 million cases and 200,000 deaths. By the following March, over 30 million cases and 550,000 deaths.

The first tangible indication of stress on the U.S. economy came the week of February 24th, when the stock market began a significant period of volatility (Baker et al. (2020a)). It was triggered in part by news of community spread and a prediction from the director of the National

⁴August occupancy rates were 49%, approximately 22 percentage points below typical August rates, compared with April occupancy rates of 21%, approximately 45 percentage points below typical April rates.

Center for Immunization and Respiratory Diseases that it would not be a question of ‘if’ the virus would spread, but how many Americans would be severely affected when it did (CNN (2020)). The virus spread quickly and, by mid-March, state governments began closing down large parts of the economy. By the end of May, forty million Americans had applied for unemployment benefits (DOL (2020)).

There is an ever-growing economic literature that examines the economic impacts of COVID-19 on a wide variety of outcomes. Macroeconomic efforts include studies of economic uncertainty (Baker et al. (2020a), Altig et al. (2020)), aggregate consumption and GDP (Chen et al. (2020), del Rio-Chanona (2020), Auray et al. (2020)), stock prices (Baker et al. (2020b), Alfaro et al. (2020)) and recovery scenarios with and without government intervention (Eichenbaum et al. (2020), Stock (2020), Atkeson (2020), Barro et al. (2020), McKibbin & Fernando (2020)), Guerrieri et al. (2020)). Labor studies examine a variety of COVID-induced labor market outcomes (Coibion et al. (2020), Baek et al. (2020), Forsythe et al. (2020)), including side effects from working from home (Hsu & Henke (2021)), increased togetherness (Hamermesh (2020)), effects on race (Kantamneni (2020)), and effects across countries (Adams-Prassl et al. (2020)). School closure effects is a common theme, with researchers evaluating both the effects of the pandemic on students and their parents (Croda & Grossbard (2021), Bansak & Starr (2021)). Policy papers examine the effect of specific government policies to curb the spread of COVID-19, from lockdown orders (Song et al. (2021)) to targeted closures (Spiegel & Tookes (2020)) to mask requirements (Chernozhukov et al. (2021)).

Numerous studies examine the effects of the pandemic on industries as a whole. Bloom et al. (2021), Fairlie & Fossen (2021) and Alekseev (2020), like many others, show that businesses were hurt by the pandemic overall, and that it varied substantially across industries, with off-line industries hurting the most. Davis et al. (2020) use stock market returns to show that businesses related to travel, retail, and energy had the largest demand drops, and Gourinchas (2020) finds a similar set of highly affected industries across countries. Barrero et al. (2020) argue that the pandemic is also a reallocation shock, changing long-run demand for certain types of businesses, e.g. online businesses.

The hotel industry, the subject of this study, was hit particularly hard by the pandemic (Fairlie & Fossen (2021), Campos-Vazquez & Esquivel (2021)). While hotels themselves were not forced

to close, many of the complementary services offered within the hotel (e.g. dine-in restaurants, conference meeting spaces, casino floor, etc.) and area attractions that consumers might want to travel for in the first place (e.g. beaches, theme parks, theatre) were. These closures, combined with increased safety risks of travel, led consumers to travel less and to avoid less safe travel situations when they did (Lagos (2020)).⁵

In this article, I want to examine the role that native adaptability plays within an industry, within the hotel industry in particular, rather than just across industries as a whole. In other words, I am not interested in how overall demand changed in the hotel industry (it fell a lot), but rather in how *relative* demand changed across hotels, i.e. how residual demand got redistributed during the pandemic, and why.

Since governments did not pick and choose which hotels could stay open and which must close (hotels were allowed to remain open), government restrictions did not directly determine which hotels would and would not be available to the now-fewer consumers still able to travel. But government restrictions did affect *relative* demand through its closures of complementary services and attractions, inside and outside the hotel. Complementary services and nearby area attractions are important factors for hotel demand in normal times, at least for many hotels. For example, a hotel with a nice dine-in restaurant and located close to Disneyland, popular in normal times, will become much less attractive to a traveler when the restaurant and Disneyland itself are closed by government restriction (or if consumers just did not feel safe using them). In contrast, a hotel without a restaurant and not near a major attraction is unlikely to be adversely affected in the same way. Demand may still be down overall, but relative demand loss should be higher in the former case.

For the purposes of this study, it does not actually matter whether government, consumers, or consumers under the advice of government are the ones picking and choosing which hotels consumers will stay at, conditional on traveling. I am interested in *why* certain hotels are picked and chosen over other hotels, and this is necessarily a question about hotel and area characteristics. My hypothesis is that a hotel's native adaptability to changing safety needs in the pandemic is

⁵Sharma et al. (2021) discuss some of the simpler safety protocols hotels were able to put in place, such as plexiglass protectors, increased cleaning schedules, and mobile check-in kiosks.

important for whether or not they are picked or chosen, and thus important for their idiosyncratic failure risk.

Understanding native adaptability can help policymakers identify the most vulnerable firms in a pandemic and improve the targeting of emergency funds. Bartik et al. (2020a) show that targeting to date has been less than perfect – the businesses most likely to have received PPP funding are simply those with stronger pre-existing bank relationships and not necessarily those with the greatest need for assistance. Other factors matter for failure risk as well, such as firm size and solvency, but native adaptability may be among the most overlooked. This article contributes to the literature by showing that failure risks depend on native adaptability in an important way, and that native adaptability differs substantially not just across industries but within industries as well.

Given that the application is the hotel industry, my study naturally shares a common thread with other hotel industry studies in the Industrial Organization and Management literatures, albeit for more normal times. These include studies of hotel entry and exit (Mazzeo 2002, Enz et al. (2008)) and hotel pricing (Abrate et al. (2012), Hung et al. (2010), Tappata & Cossa (2014), Guo et al (2013), Koulayev (2014)) in particular. The study also has interesting parallels with the pharmaceuticals literature and the crime literature, as discussed later.

3 Data

The relevant data falls into three categories, 1) hotel operations data, 2) hotel characteristics data, and 3) area characteristics data. The hotel operations data and hotel characteristics data all derive from a major international hotel franchisor that has approximately thirty hotel brands and over five thousand hotels in its network in the United States. I collect detailed information on 5,253 hotels in total, representing a sizeable sample of 10% of all hotels operating in the U.S. As with most major hotel companies, the company itself does not own or operate its branded hotels, but simply leases its brand names and use of its central reservation system to individual franchisees. It is the individual franchisees that own and operate the individual hotels. They pay a franchise fee as a percentage of revenues and must meet brand quality standards, otherwise the franchisees are

independent and solely responsible for their own daily operations, including pricing and opening decisions.

The fact that the data derives from a single franchisor can give rise to representation concerns, but it is important to keep in mind three caveats. First, the same franchisees often own multiple hotels and contract with multiple franchisors, sometimes even switching hotels between franchisors at contract expiry, so the franchisees within the dataset and those outside the dataset are often one and the same. There is no reason to suspect franchisees would respond to the pandemic differently with one particular franchisor than another. The physical hotels themselves are also generally very similar, conditional on quality level, from one major franchisor to the next. Second, hotels affiliated with the franchisor span essentially the entire quality spectrum in the industry, with the only exception being at the very low end – the often single-story unbranded roadside motels, which have been disappearing from the U.S. Aside from this, there are no gaps in quality coverage. Keep in mind that the sample includes one in every ten hotels in the country, a substantial fraction of the total. Third, and anecdotally, we see similar patterns in closures across hotels from franchisees under all major hotel franchisors. There is no reason to suspect that native adaptability would be very important for relative demand for one franchisor, such as a Hyatt, but not for another, such as a Hilton, in producing patterns of response. Representation issues are unlikely to be a problem in the context, but the potential concern is noted.

The hotel operations data contains two key dependent variables of interest - a hotel's open/closed status for each day in April 2020 and, if open, the hotel's lowest available price on that day (for a standard room through direct booking on the company's website or phone reservations system). Operations data was collected for January 2020 and July 2020 as well, in addition to April 2020, for ancillary analyses discussed below.

Importantly, the operations data for each hotel for each stay date in the month of April 2020 was collected twice. It was first collected in the last week of December 2019 before the start of the pandemic and before there was any inkling that a pandemic would soon be coming. It was collected again in the last week of March 2020 after the pandemic hit U.S. shores and had collapsed hotel demand in a dramatic fashion. The first snapshot shows which hotels were expecting to be open in April 2020, and what prices they were expecting to get, as these expectations were formed in

late December 2019. The second snapshot shows which hotels were still expecting to be open in April 2020 and what prices they were now expecting to get, as these expectations were updated in late March 2020. The difference in the snapshots represents the effect of the pandemic on hotel closures and prices, holding both the product (the hotel) and the time of consumption (the April date of the stay) fixed. Being able to hold fixed the time of consumption is unusual and leads to an exceptionally well identified set of effects.

The data forms a three dimensional panel instead of the usual two - the first dimension being the identity of the hotel, the second dimension being the date on which the given hotel stay in April is to occur, and the third dimension being the pre-awareness-of-pandemic date or post-start-of-pandemic date on which the open/closed status and price for a given hotel stay in April 2020 was recorded.

The hotel characteristics data contains the key independent variable of interest - a hotel's category rating. Category ratings are set by the franchisor (not the franchisee) and are used to determine the redemption price, as measured in reward points, at which members of the franchisor's loyalty program can redeem reward points for free nights at the hotel. In more normal times, the category rating reflects the overall popularity of a hotel, which is based on factors including destination value and the level of services and personal attention it provides. During a pandemic, however, it measures something potentially more problematic - decreased native adaptability, and most notably a lower native adaptability to social distancing practices.

Higher category hotels tend to have larger and fancier lobbies, more ancillary on-site services (e.g. pools, bars, restaurants and shops), and more personalized services (e.g. bellmen, valets, and spa services) than lower category ones do. They tend to be busier, and are more likely to be located in more popular business and tourist areas where crowds are common. They are often larger and taller buildings that require elevators to access rooms. Generally considered higher quality hotels for all these reasons in more normal times, the characteristics of higher category hotels are a liability in a pandemic. They are less amenable to social distancing and, because of their full-service model, rarely scale down well.

In contrast, lower category hotels tend to be simpler hotels, with fewer personal services and fewer on-site staff, and fewer areas where guests congregate. They tend to be shorter buildings

that offer ground floor rooms making elevators less necessary. They are less likely to be located in a destination area and more likely to cater to pass-through traffic along highways and interstates. In fact, it is often possible to come and go from a low-category hotel, from vehicle to room to vehicle, with minimal human contact. These features make lower category hotels more amenable to social distancing than their higher category counterparts, and that can matter to consumers still travelling in a pandemic.

There are eight categories in all. Category 1 and 2 hotels are simple hotels with small lobbies and few services, usually located along highways outside of major cities and providing basic accommodations to largely drive-through overnight traffic. Category 3 and 4 hotels are hotels with larger lobbies and a wider array of services, often located in major cities and popular destination areas. Category 5 and 6 hotels are large full-service hotels with upscale lobbies and numerous personalized services, generally located in the most popular business and tourist destinations. Category 7 and 8 are the elite luxury resort hotels in the system, few in number, and located in the heart of major metropolitan business districts and the most prestigious tourist vacation destinations around the country.

In addition to the category rating, I collect brand and location information for each hotel, and map each hotel to the county in which it is located, for later matching with area characteristics.

The area characteristics data includes county-level demographic information on population, as reported by the Census Bureau using 2015 estimates, and daily county-level information on COVID-19 infections and deaths as assembled by the New York Times from state health authorities. These variables serve as area demand controls. Higher COVID-19 infections and deaths in a local area measure exposure risk and are expected to depress hotel demand generally across area hotels. Population serves as a proxy for higher infection potential even conditional on actual infections, since these are busier areas in general, and this should similarly depress demand. Area characteristics are matched by county FIPS code to the hotels located in each county.

Because two of the three dimensions in the panel are time-based, it is important to consider the appropriate time dimension for aligning time-varying COVID-19 infection and death rate data to time-varying hotel operating data. I align infection and death rates to be contemporaneous with the dates on which expectations of future open/closed status and future prices were then current

(the third dimension of the data) rather than the dates the future stay would actually occur (the second dimension of the data). The reason is that expectations about future open/closed status and future prices should be based on information known at the time and not on ex-post realizations of what ultimately occurs. In alternative specifications, I explore other types of infections forecasts, including perfect foresight, and results do not meaningfully change.

4 Methodology

The methodology is based on the three-dimensional panel. With two snapshots of each hotel's April 2020 price calendar taken at different times, once before the start of the pandemic and once after the start of the pandemic, I can compare outcomes for a given hotel - not across different stay dates - but for the exact same date in April 2020, once as price and closure expectations for April were formed in late December 2019 prior to the start of the pandemic, and again as price and closure expectations for April were updated in late March 2020 after the pandemic hit.

To avoid the double use of the word "expectations", I hereafter refer to late December 2019 expectations of April outcomes as "expectations" and late March 2020 expectations of April 2020 outcomes as "realizations". It is purely nomenclature and has no effect on results. The name derives from the fact that April closure decisions were largely set in stone by late March, and even April prices changed relatively little following the initial collapse in expectations in mid-March. I do not mean to suggest that late March expectations of April closures and prices and "day-of" April realizations of closures and prices are one and the same and they do they need to be. It is the former (March expectations of April prices) that is the relevant outcome here, enabling me to compare two identically-collected apples-to-apples snapshots of expected closures and prices for upcoming April stays. The new nomenclature is only to simplify the discussion in the text.

The main analysis proceeds in two stages. I first estimate a series of closure regressions that compare each hotel's "expected" closure status for the month of April 2020 (as expected in December 2019) with its "realized" closure status for the month of April 2020 (as expected in late March 2020). Then I do the same for expected and realized prices.

With two time dimensions, the empirical strategy takes the familiar form of a natural experiment

with treatment and controls, but with a twist. Specifically, it calculates 1) the difference between realized April outcomes and realized January outcomes for a given hotel (i.e. the treatment group receiving the pandemic treatment), and 2) the difference between expected April outcomes and realized January outcomes for that same hotel (i.e. the control group receiving no pandemic treatment). Because realized January outcomes appear on both sides and cancel out, this trivially reduces to the difference between realized April outcomes (from the second snapshot) and expected April outcomes (from the first snapshot), all for the same hotel and stay date. Interestingly, it is no longer necessary to look for a separate group of hotels unaffected by the pandemic, as would be the case in a typical natural experiment, because hotels' expectations of April 2020 demand, as recorded in late December 2019, were all unaffected by the then-unknown COVID-19 pandemic. In other words, each hotel is both in the treatment group and in the control group. It is like applying a treatment to a subject and checking the response, then reversing back in time and giving a placebo to the same subject and checking the response a second time. The advance purchase model in the industry allows for this uniquely well-identified estimation framework, and it is a key advantage over the usual kind of natural experiment involving separate subjects in the treatment and control groups. There is no concern that the two groups may differ from each other in unobserved ways, as they are one and the same. The identifying assumption is simply that hotels' seasonal demand expectations based on current information are not systematically biased. I develop a test for this later.

I estimate overall closure rates, and how these rates vary across a set of hotel and area characteristics, including category ratings and local infection rates, with the following equation:

$$\begin{aligned}
E(CLOSED_{ijrt} \mid H, D, V, R, \Theta) &= G(\alpha^c + \beta^c H_{ijr} + \gamma^c D_{ijr} + \delta^c V_{ijr} + \rho^c R_r \\
&\quad + \phi^c(R_r * H_{ijr}) + \psi^c(R_r * D_{ijr}) + \lambda^c(R_r * V_{ijr}))
\end{aligned}$$

where $CLOSED_{ijrt}$ is a dichotomous variable equal to one if hotel i located in county j will be closed at time t according to the hotel's expectation at time $r < t$, where r is either late December 2019 or late March 2020, and time t is a date in April. The matrix H consists of hotel characteristics

(in particular its category rating), the matrix D consists of area characteristics unrelated to the pandemic (population), and the matrix V consists of local infection and death rates due to the pandemic. The variable R is an indicator function equal to one for information current as of late March 2020, and zero for information current as of December 2019. I call this variable *REALIZED* in the tables for better readability. The Θ is shorthand for all model parameters. The data is collapsed to the monthly level since all right side variables are month-of-stay-invariant except R .⁶ For partial month closures, I set $CLOSED = 1$ if a hotel reported to be closed on a majority of days.⁷

The key variables of interest are the interaction terms, which show the effect of each explanatory variable on the change in expected April closures from late December expectations ("expectations") to late March expectations ("realizations"). As I am most interested in the effect of the pandemic on closure rates across the different hotel category ratings, a complete set of hotel category rating indicator variables are included in the H , except for the omitted category, Category 1. The interaction of a given hotel category rating variable h and the snapshot R measures the excess increase in new April closures (from late December expectations to late March realizations) for hotels in Category h , up and above the corresponding increase for Category 1.

In principle, the estimation framework begins as a difference-in-differences-in-differences specification – where I compare 1) the increase in closures between "realized" April outcomes (based on the March snapshot) and "realized" January outcomes (based on the December snapshot), for hotels in a given category, i.e. the with-pandemic treatment group, and 2) the increase in closures between "expected" April outcomes (based on the December snapshot) and "realized" January outcomes (again based on the December snapshot) for hotels in that same category, i.e. the without-pandemic control group. I then compare this difference-in-differences estimate with the corresponding difference-in-differences estimate for Category 1 hotels.

Since the "realized January outcomes" cancel out, in practice the analysis reduces to a more typical difference-in-differences. Ultimately, I compare posted closures and prices for the same

⁶There will be two datapoints per hotel for the month of April, one for expected April closure ($R = 0$) and one for realized April closure ($R = 1$).

⁷The vast majority of hotels either expected to remain open or remain closed for the entire month of April. Using a percentage closure measure instead of a dichotomous one produces very similar results.

category h hotel for the same room for a stay on the exact same day in April, first without any knowledge of an upcoming pandemic, and then, fully in the midst of it, then I do the same thing for a category 1 hotel, and estimate relative effects from one category to the next.

Two forms of the G function are used - the main specifications use $G(\delta) = \exp(\delta)/(1 + \exp(\delta))$ to produce a logit model, and the alternate specifications use the identity $G(\delta) = \delta$ to produce a linear probability model (LPM). The logit model produces odds ratios and the LPM produces marginal effects. The LPM is sometimes disfavored, but is a useful alternate lens for viewing results since pre-pandemic expected closures were rare and odds ratios can grow very large with small denominators. While t-statistics in an LPM are often viewed with caution, I note that statistical significance patterns across logit and LPM models turn out to be very similar, errors are all adjusted for heteroskedasticity using the Huber-White sandwich estimator, and 99.7% of all LPM predicted values lies within the unit line. Standard errors are clustered at the hotel level in all models.

In the second stage, I estimate a series of conditional price regressions, conditional on a hotel remaining open during the pandemic, at the daily level. I compare each hotel's expected price for a given night stay in the month of April (as expected in late December before the start of the pandemic) with its realized price for that same night stay in the month of April (as realized in late March after the start of the pandemic). I estimate overall price changes and how they vary across hotel and area characteristics including category ratings and local infection rates, with the following equation:

$$\begin{aligned}
 f(PRICE_{ijrt}) &= \alpha^p + \beta^p H_{ijr} + \gamma^p D_{ijr} + \delta^p V_{ijr} + \rho^p R_r \\
 &\quad + \phi^p (R_r * H_{ijr}) + \psi^p (R_r * D_{ijr}) \\
 &\quad + \lambda^p (R_r * V_{ijr}) + \varepsilon_{ijrt}^p
 \end{aligned}$$

where $PRICE_{ijrt}$ is a continuous variable representing the best available price for a standard room in hotel i in county j for a stay occurring at time t according to the hotel's expectations of demand at time $r < t$. Two forms of the f function is used, the identify $f(\delta) = \delta$ for a constant linear

effects model and the log function $f(\delta) = \ln(\delta)$ for a constant percentage effects model. Matrices are as defined above, and the ε_{ijrt} is an i.i.d. normally distributed error term. Standard errors are clustered at the hotel level in all models.

The key variables are again the interaction terms between the snapshot time R and the hotel category rating H . These show by much how price decreases for a Category h hotel (from late December expectations to late March realizations) exceeded the corresponding price decreases for a Category 1 hotel over the same period. All price regressions use pairwise-complete data only, to eliminate the potential for composition bias. In other words, hotels must be open and publishing prices at both $r = 0$ (late December) and $r = 1$ (late March) for stays at time t (in April) to be included in the price regressions.

The price effects measured here are conditional price effects, conditional on a hotel remaining open. This is distinct from unconditional price effects, which measure the price changes that hotels either implemented or, for closed hotels, would have implemented had they remained open. I am primarily interested in conditional price effects, which represent the actual prices consumers paid among their still available choices, but later I estimate a selection model that estimates unconditional price effects as well. Ex ante, I expect conditional and unconditional estimates to be similar, since most hotels remained open even during the pandemic.

Of special interest is how the pandemic differentially affected hotels with different degrees of native adaptability. Higher category hotels are generally the least adaptable, given their larger scale, higher levels of personal services, and normally busier locations. Lower category hotels are generally the most adaptable, given their quieter environments, limited services, and less-frills approach. Table 1 shows that over 90% of hotels fall in the midrange Categories 2 through 5, with the most common categories being Category 3, accounting for 36.7% of all hotels, and Category 4, accounting for 26.3% of all hotels. There are roughly equal numbers of Category 2 (13.3%) and Category 5 hotels (14.0%), with relatively fewer Category 6 hotels (6.4%), and very few Category 1 (0.7%), Category 7 (1.9%), and Category 8 hotels (0.6%).

5 Results

5.1 Closures

I begin by examining the overall impact of the pandemic on hotel closures, and report the results in Table 2. I regress a hotel’s closure status *CLOSED* on the *REALIZED* variable and a constant. Specification (1) is based on a logit model and displays odds ratios, Specification (2) is based on a linear probability model and displays probability point changes.

Specification (1) shows that a hotel was 5.2 times more likely to report being closed in April, from its pre-pandemic expectation to its within-pandemic realization.⁸ Specification (2) translates this into probability point changes, and shows that April closures increased by 11.3 percentage points from pre-pandemic expectations to within-pandemic realizations. These are hotels that had expected to be open in April but reversed course and closed its doors once the pandemic hit. All coefficients are statistically significant (different from one in the logit specification and different from zero in the LPM) at better than the 1% level. Both specifications agree that the impact of the pandemic on hotel closures was large.

Since the odds ratio in Specification (1) is less than infinity, one might ask why there were any hotels at all planning to be closed in April as of the previous December. The constant term in the LPM regression of Specification (2) shows that 3.2% of hotels fall in this category, and a quick investigation reveals that the vast majority were new buildings under construction or buildings undergoing renovations before becoming active. It is worth a quick side trip to ask whether existing and new hotels differed in their rates of unexpected closure. On one hand, new hotels may find it easier to postpone openings, since they need not lay off as many permanent staff or cancel as many upcoming reservations, but on the other hand, new hotels often have higher debt obligations and may be more eager to start generating revenue.

To investigate, I define existing hotels as those that were open and operating in January and new hotels as those that were not. Specification (3) and (4) consider existing hotels. The logit Specification (3) shows that an existing hotel open in January was 54.6 times more likely to unexpectedly close in April. It is statistically significant at the 1% level. The LPM Specification

⁸More accurately, the odds of April closing versus April opening, according to the late March realization, was 5.2 times larger the odds of April closing versus April opening, according to the late December expectation.

(4) provides an alternative look, and yields a coefficient on *REALIZED* of 11.3, statistically significantly different from zero, and showing a 11.3 percentage point increase in unexpected April closures of existing hotels. The constant coefficient is small, at 0.002, confirming that few hotels were originally expected to be closed in April, partly accounting for the very high odds ratio.

Specification (5) and (6) consider new hotels instead. The logit Specification (5) shows that a new hotel was only twice as likely to unexpectedly close in April, with "only" being a relative term. But in probability point terms, the LPM Specification (6) shows a coefficient on *REALIZED* is 11.6, statistically indistinguishable from that of existing hotels (11.3) and all hotels overall (11.3). Basically, the same percentage of existing and new hotels unexpectedly closed (or delayed openings), but from very different baseline levels.⁹

Table 3 presents the full model regressions that examine the relationship between closures and hotel and area characteristics, including a hotel's native adaptability, as captured by the hotel's category rating, and area infection and death rates. I would expect hotels with higher category ratings to experience higher closure rates. One might expect virus hot spot areas to be associated with higher closures rates as well.

In Specifications (1) and (2), I regress closure status on *REALIZED*, a set of dichotomous indicator variables for the category rating of a hotel (*CATEGORY 2* – *CATEGORY 8*), with *CATEGORY 1* being the omitted variable, and all interactions between the two. Specification (1) of Table 3 reports results from a logit model and Specification (2) reports results from an LPM. To preserve space, I report only the category interaction terms plus the *REALIZED* coefficient (relevant to the omitted Category 1) in the table.

Specification (1) shows that the pandemic had significantly heterogeneous effects across hotels with different degrees of native adaptability. Impacts were severe across the board but especially severe on higher-category hotels, where social distancing is most difficult. Category 1 hotels, basic limited-service hotels in mostly drive-through areas, had the fewest unexpected closures. The

⁹The concern that unexpected delays in the construction schedule - unrelated to the pandemic - might cause a few additional unexpected April closures, is easily dismissed. Because it is problematic to have to contact customers and cancel existing reservations, hotels often set opening dates conservatively into the future and move them forward in stages as uncertainty over the construction time frame decreases. Any bias thus goes the other way - working towards a small number of unexpected April *openings* rather than April closures. The construction industry itself was not affected by stay-at-home orders and was generally able to proceed with building projects as usual.

coefficient on *REALIZED* shows that a Category 1 hotel was "only" 20% more likely to unexpectedly close in April, relative to late December expectations. The point estimate is large but not statistically significant given the small number of Category 1 hotels in the network.

The impact of the pandemic grew substantially larger with higher category hotels and lower native adaptability. Category 2 hotels, simple hotels with limited services and usually located along highways, were 77% more likely to close in April, relative to late December expectations. Category 3 and 4 hotels, more likely to be multi-service hotels, with restaurants, fitness centers, and pools, and located in relatively higher demand areas, were 3.7 times (274%) and 3.6 times (260%) as likely to close. Category 5 and 6 hotels, large full-service hotels located in popular tourist and business destinations, were 5.3 times (427%) and 12.5 times (1154%) more likely to close. Category 7 and 8 hotels, the elite luxury hotels in the network located in the most prestigious locations, were 94.6 times (8461%) more likely and 27.01 times (1706%) more likely to close in April, relative to December expectations. Coefficients are very large and statistically significantly different from one in each case.

Specification (2) confirms the heterogeneity of effects in percentage point terms. The coefficient on *REALIZED* shows that 2.4% of all Category 1 hotels unexpectedly closed in April, relative to late December expectations. An additional 1.1% and 3.3% of Category 2 and 3 hotels unexpectedly closed in April, up and above that of Category 1, for a total increase in closures of 3.5% and 5.7%, relative to late December expectations. The individual coefficients are not statistically significantly different from zero, but the total increases are. The remaining interaction coefficients show an additional 6.8% of Category 4 hotels, 14.6% of Category 5 hotels, 35.9% of Category 6 hotels, 49.5% of Category 7 hotels, and 67.6% of Category 8 hotels, unexpectedly closed in April, up and above that for Category 1, relative to late December expectations. The results agree and show that native adaptability to the pandemic matters significantly for closure rates. The hotels least amenable to social distancing are the most likely to close.

Next I add area characteristics to the model. Since higher category hotels are often located in more populous areas, where the risk of infections is often larger, area characteristics rather than internal hotel characteristics may play a role in hotel outcomes. To test for independent effects of area characteristics, Specifications (3) (logit) and (4) (LPM) add county level population data to

the model. Specification (3) shows that, conditional on the category of hotel, population has no additional effect on hotel closures. The odds ratio is very close to one, and insignificantly different from it. Specification (4) confirms this in probability point terms, with a marginal effect close to and insignificantly different from zero. Meanwhile, the category interactions continue to be as large and as statistically significant as before.

Specifications (5) and (6) present the full model that includes virus-related infections and deaths as well. I regress April closure status on county-level COVID-19 cases, COVID-19 deaths, county-level population, a complete set of hotel category indicator variables, plus interactions between all of the above and the *REALIZED* variable. Cases are measured in cases per thousand and deaths are measured in deaths per million to avoid very small coefficients in the table. If demand decreased disproportionately more in those areas where the rate of transmission was also high, we should expect to see more closures in those areas. If instead demand decreased more uniformly across the country, consistent with widespread stay-at-home orders, we should not see as much of a difference. I report only the interaction coefficients and the *REALIZED* coefficient in the table to preserve space.

Specification (6), based on the LPM, shows a positive coefficient on infection rates, but it is surprisingly small. The coefficient implies that for every five hundred new cases in a county of five hundred thousand people (every 0.1% increase in the infection rate), the probability of closure would increase by just 1.3%. In April, a 0.1% infection rate was well above the national county average, so little variation in closure rates can be explained by infection rates. The coefficient is statistically significant at the 10% level only. The corresponding coefficient in the logit model of Specification (5) is positive but not statistically significant. I find no effect of local death rates on closures in either case.¹⁰

Albeit small, the relatively larger impact of infection rates over death rates has an interesting parallel with the crime literature. That literature finds that crime is generally more responsive to the probability of being caught rather than the severity of the punishment after being caught (Chalfin & McCrary (2017)). Here, demand is more responsive to the probability of catching the virus rather than the severity of the illness after catching it.

¹⁰The result is consistent with Kim et al. (2020) who find little impact of local area infections on revenue losses.

In both specifications, the hotel category interaction coefficients continue to be high and statistically significant. The result is robust across specifications and it shows that hotels that are less natively adaptable to the pandemic fared relatively worse, and those that are more natively adaptable fared relatively less worse. It is the intra-industry counterpart to the inter-industry findings in the literature. The recent COVID-19 literature identifies a set of industries that have particularly high failure risks and losses, and these are also the industries where one would expect native adaptability to be especially low, e.g. retail, travel, and other non-essential offline industries (Bloom et al. (2021), Fairlie & Fossen (2021), Alekseev (2020), Davis et al. (2020), Gourinchas (2020)). The results here show that native adaptability matters not just across industries but within industries. Within-industry heterogeneity can and should be taken into account, as well as other factors, in understanding failure risk. Recall that Bartik et al. (2020a) show that PPP funds were distributed largely to those with good pre-existing banking relationships, and not necessarily to those in the greatest need. The results of this study show one way to measure need and improve upon that outcome.

5.2 Price Effects

The pandemic is felt not only in the businesses that close their doors but in those that stay open. I examine price impacts in a series of conditional price regressions, i.e. conditional on a hotel remaining open, and report the results in Table 4. Specification (1) uses price levels as the dependent variable and yields constant dollar estimates, and Specification (2) uses the log of price and yields constant percentage estimates. These are always pairwise price comparisons - for the same room in the same hotel for the same night in April, once based on late December expectations and once based on late March realizations.

Both specifications find that the conditional price effects are large. Specification (1) shows that hotel operators lowered prices for April stays by an average of \$39.24, from late December expectations to late March realizations. Specification (2) translates this into constant percentages and shows that hotels lowered prices by an average of 23.0%.¹¹

But not all hotels lowered prices. Price decreases far outnumbered price increases, but a mean-

¹¹The average percentage effect is given by $\exp(-0.261) - 1 = 0.23$.

ingful percentage of hotels actually raised prices for April dates after the pandemic hit. A simple ordered logit model shows that the probability that a price would fall was 0.83 (s.e. 0.004), the probability that a price would remain stable was 0.03 (s.e. 0.001) and the probability that a price would rise was 0.13 (s.e. 0.003). I return to which hotels increased prices and why later.

Specifications (3) through (6) revisit differences between existing and new hotels. Specifications (3) and (4) limit the data to only existing hotels, and show that April prices fell an average of \$39.09, or 22.9%, relative to late December expectations. Specification (5) and (6) limit the data to only new hotels and show that April prices fell an average of \$61.53, or 30.4%, relative to late December expectations. All coefficients are statistically significant at the 1% level and statistically significantly different from each other in cross-equation tests. If higher capital expenditures following a new build or renovation applies greater pressure on a new hotel to generate positive revenue flow, it can incentivize such hotels to price more aggressively. The effect persists even controlling for other factors.

Table 5 presents the full model regressions that examine the relationship between conditional price effects and hotel and area characteristics, including native adaptability as captured by hotel category ratings, and infection and death rates. In Specifications (1) and (2), I regress price (or log price) on *REALIZED*, a set of dichotomous indicator variables for the category rating (*CATEGORY 2 – CATEGORY 8*), with *CATEGORY 1* being the omitted variable, and all interactions between the two. Specification (1) uses a linear-linear functional form and the Specification (2) uses a log-linear functional form. The results show that the impact of the pandemic on prices was severe, especially on higher-category hotels where social distancing is more difficult. The coefficients on *REALIZED* show that a Category 1 hotel discounted its April prices, from late December expectations to late March realizations, an average of \$8.29, or 8.7%. Summing relevant coefficients, Category 2 hotels discounted April prices an average of \$18.93 or 15.9%, Category 3 hotels discounted April prices an average of \$30.29, or 20.9%, and Category 4 hotels discounted April prices an average of \$45.15, or 25.5%.¹² At the higher end of the spectrum, Category 5 hotels discounted prices an average of \$64.72 (29.8%), Category 6 hotels discounted prices an average of

¹²For example, the Category 2 absolute discount is $\$8.29 + \$10.64 = \$18.93$, and its percentage discount is $\exp(-0.091 - 0.083) - 1 = 0.159$.

\$83.26 (31.8%), and Category 7 hotels discounted prices an average of \$94.97 (28.3%). Category 8 hotels discounted prices an average of \$119.18, or 23.4%. All estimates are statistically significantly different from zero.

Specifications (3) and (4) add county population to the model. The point estimates on population are negative as expected, but small, and statistically significant only in Specification (3). The coefficient implies that every additional one million people in a county results in only an additional one dollar discount. The hotel category interaction coefficients continue to be large and statistically significant in every case.

Specifications (5) and (6) present the full model that includes virus-related infections and deaths in the surrounding area. I regress April prices on county-level COVID-19 cases, COVID-19 deaths, county-level population, a complete set of hotel category indicator variables, plus interactions between all of the above and the *REALIZED* variable. The results show that local area infection and death rates have little effect on pricing. Specification (5) shows a statistically significant but economically small impact of infections on price discounts, with each additional five hundred infections in a county of five hundred thousand people resulting in an only a \$1.32 discount. The corresponding coefficient in Specification (6) is not statistically significant. Death counts are not statistically significant in either case, conditional on the number of infections.

Consistent with the closures analysis, the primary factor driving heterogeneity in the price change distribution is a hotel's native adaptability. Small, limited-service hotels along highways catering to drive-through traffic responded with the smallest average price discounts overall, while large full-service hotels that are destinations unto themselves responded with the largest average price discounts, in absolute and percentage terms. There is some evidence that infection hotspots matter, but the estimates are small and statistical significance is mixed.

I noted earlier that there was a meaningfully large number of April price increases, rather than price decreases, from late December expectations to late March realizations, in spite of occupancy losses across the board. If native adaptability were an underlying cause, I would expect lower category hotels to raise April prices the most often. These hotels are the most natively adaptable to the pandemic, smaller with fewer public spaces and fewer ancillary services, easier ingress and egress (generally in a private vehicle), and more amenable to social distancing.

A breakdown of the direction of price changes by hotel category confirms that this is the case. Category 1 hotels increased instead of decreased prices the most, 26.7% of the time, in spite of lower demand. Category 2 hotels increased prices the second most, 18.8% of the time and Category 3 hotels increased them the third most, 13.8% of the time. Percentages fall monotonically as category rating increases, up to Category 8 hotels which increased them just 1.2% of the time. It is an interesting demonstration of how the pandemic inverted long-standing notions of "high" and "low" quality, with lower-category hotels becoming a relatively better option in the pandemic for its normally less notable non-price features.

There is an interesting overlap here with the branded pharmaceutical pricing literature. That literature shows that when low-cost generic manufacturers begin producing a drug after the branded drug manufacturer loses patent protection, the branded firm sometimes responds by increasing, rather than decreasing, its branded price (Frank & Salkever (2004), Berndt & Conti (2018)). It is more profitable for the branded firm to do so because consumers who still insist on a purchasing the branded version of the drug even when much cheaper generic alternatives are available tend to be more inelastic and care more about non-price characteristics. I find a similar effect here - consumers who still insist on staying at hotels in a pandemic are likely to be more inelastic and care more about non-price characteristics, which in this context includes a greater ability to social distance throughout a stay. A more inelastic residual consumer still traveling in a pandemic can enable a significant number of lower category hotels to raise prices.

5.3 Alternate Specifications

Table 6 reports results from a set of alternate regressions to check the robustness of the main results. Specifications (1) and (2) revisit the main model using infection and death *growth* rates instead of infection and death rates themselves (i.e. the rate of change in infection and death rates). It addresses the concern that consumers may care more about quickly emerging hotspots rather than steady rates of infection. Specification (1) is a closure regression based on the logit model and Specification (2) is the corresponding price regression based on a linear model.¹³ The dependent

¹³A challenge in measuring growth rates is that, as of late March, many areas had few or no infections or deaths, leading to either zero or undefined growth rates. Another is that growth rates up to late March are generally highly correlated with the usual rates because rates largely started close to zero in March. I thus assume a perfect foresight

variables are not the same across specifications so the point estimates are not comparable, but the overall patterns in the coefficients are.

The specifications confirm the main results. The pandemic had a severe impact on closures and prices overall, and the heterogeneity in effects is largely driven by native adaptability. The coefficient on the infection growth rate is statistically significant in the price regression, but economically small, and the other COVID-19 coefficients are not statistically significant.

Specification (3) addresses another concern, specific to the price regressions, that prices for some April stays could mechanically rise from late December to late March simply because of expiring advance purchase discounts. This would potentially violate the unbiased expectations assumption, and ultimately bias price effects downwards towards zero. The concern is unlikely to be a problem for several reasons. First, advance purchase discounts are limited across the network and, second, they are often exchanged with an equivalent discount under a different name or by a newly-lowered regular rate upon expiration. Third, the size of the discount (generally 5%) is dwarfed by the magnitude of price effects estimated here, and fourth, the bias actually goes the wrong way and would only make the results more conservative.

It is possible nonetheless to test for the effect of advance purchase discounts. The vast majority of discounts, where offered, expire within fourteen days of the stay, which suggests a simple test. I define the indicator variable *ADVANCE* to be equal to one if a stay takes place in the last half of April, and zero if it takes place in the first half of April. I add both it and its interaction with *REALIZED* to the full model. Advance purchase discounts cannot be a factor in late April stays since a discount available in late December will still be available in late March. It can only be an issue for early April stays, where a late December discount may have expired. If expiring discounts are materially affecting estimates, the interaction term should be negative and large, showing that late April prices fell significantly more than early April prices from the first to the second snapshot (because early April prices include this potential offset). If so, the estimated price effects would be understated.

model in which hotel operators can predict infection and death rates in their respective counties as of the end of April, from current information. If infection and death rates are expected to increase at a steady or proportional rate, then the original model applies. I calculate the infection growth rate as the monthly change in infections per thousand people and the death growth rate as the monthly change in deaths per million people over April.

I find this not to be the case. Specification (3) shows that the coefficient on the *ADVANCE* interaction is very small and statistically insignificant. The point estimate corresponds to only a 37 cent additional price decrease for late April stays than for early April stays, from the first to the second snapshot. Compare this to the overall estimated price decrease for April stays from the first to the second snapshot of \$39.24. Advance purchase discounts do not meaningfully affect results.

Specification (4) addresses another potential concern, also specific to the price regressions, that serial correlation in prices could lead to downward-biased standard errors and overrejection bias. Bertrand et al. (2004) show in Monte Carlo simulations that standard OLS implementation in the presence of serially correlated data without standard error corrections can reject the null hypothesis of no effect (at the 5% level) almost 50% of the time when the null is true.

To address this, I implement the two corrections that Bertrand et al. find work best. First, I use an arbitrary variance-covariance matrix to estimate standard errors, i.e. clustering, to account for serial correlation in the error term. This correction is already embedded into all the specifications contained in this study and all the standard errors in the tables already include it. Bertrand et al. show that this adjustment largely cures overrejection bias when there are many clusters. With fifty clusters, the rejection rate falls to 6% (instead of 50%) when the null is true and the 5% significance level is used. The dataset in this study has over five thousand clusters, so overrejection bias using the corrected standard errors is largely a non-issue.

I can confirm the absence of overrejection bias another way as well, by implementing the second suggested method. I aggregate the data up to a coarser unit of time, essentially collapsing serially correlated observations into a single observation, and removing much of the time dimension from the analysis. This approach reduces Type I error to the correct level, even with few clusters, but at the cost of increasing Type II error. I report results of the aggregated model in Specification (4). Even though the number of observations is reduced from over a quarter of a million to less than ten thousand (a total of two per open hotel), point estimates and statistical significance levels are similar to that from the full data and all conclusions carry through.¹⁴

¹⁴The closure regressions already natively include this correction, since the data in those regressions are aggregated to the monthly level (with two datapoints per hotel based on $R = 0$ and $R = 1$). I do not duplicate those specifications here.

5.4 Conditional and Unconditional Price Effects

A remaining question surrounds the difference between *conditional* price effects, i.e. average price changes conditional on a hotel actually remaining open, and *unconditional* price effects, i.e. average price changes in a hypothetical world in which all hotels would have remained open during the pandemic, even those that decided to close. I am primarily interested in conditional price effects, but it would be interesting to see how the two sets compare. Unconditional effects are of prime interest in other settings, such as in studies of gender wage inequality.

Estimating unconditional effects requires a selection equation that includes variables determining whether a hotel is likely to remain open (observed) or to close (unobserved), but that does not affect the price discount they would offer if open. The challenge is that the pandemic shocked hotel demand, and demand factors that affect hotel closures are likely to also affect hotel prices.

One promising idea relates to the length of commitment between a hotel and its customers. Most hotels cater to very short visits, (e.g. overnight, weekend, a vacation week), but three brands in the hotel company's portfolio are distinct in that they cater to longer term stays instead. These long-stay hotels make up 25% of all hotels in the network. They provide kitchenettes in all rooms, appliances and dishware, and a small living and dining area in each room. They are open to all consumers, but are actively marketed as temporary or semi-permanent living quarters for contract workers, businesspeople, and other residents. The average length of stay in these hotels is much longer. Approximately half of long-stay hotel guests stay for more than a week and half of those for more than a month.

This suggests a potentially useful selection variable. The longer time commitment between a long-stay hotel and its existing long term guests means that these hotels should be less likely to close than their non-long-stay counterparts, even as occupancy rates falls, because they have made a commitment to provide long term accommodations to remaining long-stay residents. At the same time, conditional on remaining open, their price discounts should be similar to those of non-long-stay hotels because they still compete for the same residual short-stay consumers. Their pricing decisions continue to be interdependent.

I first test for the requisite relationship between long-stay hotels and closure rates. I define the

dichotomous variable *STAY* to be equal to one if a hotel is part of the one of these long-term-stay brands, and zero otherwise. I add both it and its interaction with *REALIZED* to the main logit model for hotel closures and re-estimate the model in Specification (5). The coefficient on the *STAY* interaction variable is 0.288, less than one, and statistically significantly so, showing that long-stay hotels were indeed less likely to close compared with non-long-stay hotels. Other coefficients in the model are not meaningfully affected.

I then estimate a full two-stage Heckman selection model. The first stage selection equation is based on a probit model, as is standard, and includes the complete set of right hand side variables plus *STAY* and its interaction term as selection variables. The dependent variable in the first stage is *OPEN* rather than *CLOSED* since complete prices are observed only for hotels that remained open. The second-stage price regression equation is based on a linear functional form and contains the complete set of right hand side variables except for *STAY* and its interaction.

Specification (6) presents the second-stage results and shows that the unconditional price effects are similar to the conditional price effects estimated earlier.¹⁵ It is not surprising given that 85% of hotels were still open. The point estimates are only marginally smaller, consistent with the idea that hotels that choose to close down are also those that cannot profitably lower prices to the necessary degree to compete. All other conclusions carry through. The main driver of heterogeneity continues to be native adaptability. Higher category hotels offer the largest discounts as they try to attract residual consumers who see them less favorably in a pandemic, and lower category hotels offer the smallest, both in absolute and percentage terms. Coefficients on population and infection rates continue to be statistically significant, but small.

5.5 Expectation Dynamics

Finally, it would be interesting to take a quick look at expectation dynamics and ask whether hotels expected the collapse in demand to persist beyond just a few months, at least as of late March. I test this using additional closures and price data for the month July 2020, based on the same two snapshots from late December 2019 and late March 2020. Since it is presumably

¹⁵Coefficients in the first-stage probit model are not shown, but have similar significance patterns to the corresponding logit model. The *STAY* interaction is statistically significant and positive, and the inverse mills ratio is statistically significant and negative.

costly to prematurely announce a July closure only to recant it later, or prematurely offer July discounts only to regret it later, I would expect firms to be relatively conservative in their approach to distant stays, as of late March. Any effect I find should reflect a reasonably strong downturn in expectations about July prospects.

I present results in Table 7. Specifications (1) and (2) examine the change in July closures, from late December expectations to late March expectations. Specification (1) is a high-level closure regression and Specification (2) is the full model including hotel and area characteristics. Specification (1) yields a coefficient on the *REALIZED* variable of 0.006, statistically significant but very small, and showing that very few hotels had changed course and committed to a longer term closure by late March. Specification (2) shows, of those that did, higher category hotels were most likely to close. The interaction coefficients may appear large at first glance, but they are only large to offset the imprecisely estimated and negative *REALIZED* main effect, applicable to the few Category 1 hotels in the data. Adding the relevant category interaction coefficient to the *REALIZED* main effect, the estimated closure rates are less than 1% and statistically insignificant for Categories 2, 3, 7, and 8. Estimated closure rates are statistically significant for the most common higher categories, 1.3% for Category 4, 1.5% for Category 5, and 2.6% for Category 6.

Specifications (3) and (4) are the corresponding price regressions for July 2020. Specification (3) shows a coefficient on *REALIZED* of -1.074 , statistically significant but very small, and implying only a one dollar price discount built into July prices as of late March. Specification (4) presents the full model and shows *positive* point estimates on the lower three category interactions (with one significant), and negative point estimates on the upper five (with four significant). The highest average price increase for July stays was \$3.14, for Category 3 hotels (summing the relevant coefficients), and the highest average price discount for July stays was \$24.81, for Category 8 hotels. The price discounts are higher with higher category hotels, consistent with the fact that consumers often begin planning vacations and other destination travel further in advance than they do for other trips.

The results are generally consistent with those of Bartik et al. (2020b) who find significant heterogeneity in firms' expectations about when demand would rebound, and Fairlie (2020) who

find that demand was modestly rebounding already beginning in May.

6 Conclusion

The COVID-19 pandemic caused an economic collapse of a size and speed not before seen. The virus began spreading rapidly in mid-March 2020 and, within a few weeks, state governments began shutting down large portions of the economy to slow it down. Federal and state governments scrambled to provide emergency financial support to businesses through a series of hastily assembled programs, but a lack of advance planning and vetting of recipients meant that the relief did not always go to where it was most needed (Bartik et al. (2020a)).

To target emergency funds more efficiently in a pandemic, it is necessary to step back and ask which individual businesses are likely to have the greatest failure risk in a pandemic. Much is known about heterogeneous failure risk at the industry level (e.g. Davis et al. (2020), Gourinchas (2020)) but less is known about heterogeneous failure risk at the intra-industry level. Firm size and solvency are important factors (e.g. Alekseev et al. (2020)), but another is relative demand loss - how losses are spread among businesses in an industry during a pandemic. Most industries are made up of heterogeneous businesses selling heterogeneous goods to heterogeneous consumers, and demand loss is rarely equal across businesses. It is easy to see how demand losses can differ across businesses in the same industry - Amazon versus brick-and-mortar retailers, drive-in movie theatres versus indoor movie theatres, fast-food drive-thrus versus table-service restaurants with a view, roadside motels with drive-up rooms versus downtown hotels with congested elevators, and so on.

In this article, I focused on one of the many industries hit hard by the pandemic, the hotel and lodging industry. I utilized a new microdataset of hotel closures and prices for over five thousand hotels in a three dimensional panel, that included two time dimensions. I found that the impact of the pandemic on closures was severe. It was most severe for higher category hotels where native adaptability to the pandemic is most difficult. Closure odds ratios approached triple digits and closure rates exceeded 50% in percentage point terms at the higher end of the category scale. Price discounts averaged 23% but topped out at over 30% in the higher categories. A meaningful number

of hotels at the lower end of the category scale were actually able to increase prices, because their product and service characteristics are amenable to travellers in a pandemic.

In absolute terms, there were likely no winners in the hotel industry. April occupancy rates were 68.7% lower than the previous April (STR (2020)), and with average prices down 23.0% for those hotels that remained open, simple calculations show that average revenues fell by an incredible 75.8%. In terms of profitability, note that a common estimate of net profit margins in normal times is about 8% and a common estimate of the ratio of fixed costs to all costs in normal times is about 70%. If variable costs are proportional to occupancy rates and fixed costs are not, simple calculations show that total costs would fall by only 20.6%, next to a 75.8% drop in revenues. This corresponds to a 766% drop in profits on average overall, basically in a month.

The results of this study show that all or almost all hotels suffered demand losses and that higher category hotels did relatively worse than lower category ones due to differences in native adaptability, all else equal. Size and solvency are important as well, but these are altogether different from native adaptability which drives relative demand loss. The point of this article is that the latter should be taken into account as well, wherever possible. It would be a significant exercise given its microeconomic nature, but with an important efficiency purpose.

With the need for economic assistance in a pandemic so great, and public funds insufficient to support an economic shutdown for even a short while, it is important to start thinking about native adaptability when looking to distribute emergency funds in the most efficient manner possible. This article starts a conversation along these lines.

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Table 1. Summary Statistics

	<u>Num. Obs.</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min.</u>	<u>Max.</u>
Price per Night	35024	171.17	91.60	23.7	2253.2
Closures	42104	0.168	0.374	0.0	1.0
Category 1	42024	0.007	0.088	0.0	1.0
Category 2	42024	0.133	0.339	0.0	1.0
Category 3	42024	0.367	0.482	0.0	1.0
Category 4	42024	0.263	0.440	0.0	1.0
Category 5	42024	0.140	0.348	0.0	1.0
Category 6	42024	0.064	0.244	0.0	1.0
Category 7	42024	0.019	0.138	0.0	1.0
Category 8	42024	0.006	0.075	0.0	1.0
County Population	42104	1136.70	1612.710	5.5	10170.3
County Infections	42104	902.61	2541.84	0.0	25271.0
County Deaths	42104	35.41	109.16	0.0	1226.1

Population in thousands. Infections and deaths in cases. Price per Night in dollars.

Table 2. High-Level Closure Regressions

<i>Dep. Var.: Closed</i>	(1)	(2)	(3)	(4)	(5)	(6)
Realized	5.158** (22.757)	0.113** (25.395)	54.585** (13.855)	0.113** (25.122)	1.968** (4.190)	0.116** (4.266)
Constant	0.033** (-43.462)	0.032** (13.131)	0.002** (-20.894)	0.002** (3.468)	2.541** (6.156)	0.718** (23.346)
Model	Logit	LPM	Logit	LPM	Logit	LPM
Jan. 2020 Status	All	All	Open	Open	Closed	Closed
Num. Obs.	10526	10526	10094	10094	432	432
Adj/Psuedo R-squared	0.071	0.040	0.164	0.057	0.018	0.017

Logit estimates expressed as odds ratios. t-statistics (LPMs) or z-scores (logit) in parentheses.

** Significant at the 5% level. * Significant at the 10% level.

Table 3. Main Closure Regressions

<i>Dep. Var.: Closed</i>	(1)	(2)	(3)	(4)	(5)	(6)
Realized	1.201 (1.011)	0.024 (1.012)	1.247 (1.196)	0.026 (1.076)	1.207 (1.005)	0.024 (1.009)
Category 2 * Realized	1.765** (2.261)	0.011 (0.449)	1.766** (2.266)	0.011 (0.450)	1.723** (2.165)	0.011 (0.424)
Category 3 * Realized	3.744** (5.528)	0.033 (1.321)	3.738** (5.532)	0.033 (1.320)	3.619** (5.342)	0.031 (1.254)
Category 4 * Realized	3.600** (5.607)	0.068** (2.686)	3.669** (5.706)	0.069** (2.720)	3.492** (5.377)	0.066** (2.602)
Category 5 * Realized	5.267** (6.655)	0.146** (5.262)	5.484** (6.660)	0.148** (5.320)	5.185** (6.309)	0.145** (5.217)
Category 6 * Realized	12.542** (8.159)	0.359** (9.990)	12.940** (8.205)	0.360** (10.028)	12.346** (8.019)	0.357** (9.944)
Category 7 * Realized	94.610** (4.451)	0.495** (8.993)	97.280** (4.488)	0.496** (9.021)	91.425** (4.416)	0.491** (8.937)
Category 8 * Realized	27.061** (4.816)	0.676** (7.754)	27.973** (4.843)	0.677** (7.771)	25.727** (4.670)	0.669** (7.702)
Population * Realized			1.000 (-1.084)	0.000 (-0.735)	1.000 (-1.009)	0.000 (-0.720)
Infections/1KPop * Realized					1.041 (0.364)	0.013* (1.835)
Deaths/1KPop * Realized					1.006 (0.964)	0.000 (-1.106)
Model	Logit	LPM	Logit	LPM	Logit	LPM
Num. Obs.	10506	10506	10506	10506	10506	10506
Adj/Pseudo R-squared	0.155	0.130	0.155	0.129	0.156	0.130

Logit estimates expressed as odds ratios. t-statistics (LPMs) or z-scores (Logit) in parentheses.

** Significant at the 5% level. * Significant at the 10% level.

Table 4. High-Level Price Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Realized	-39.236** (-75.377)	-0.261** (-83.737)	-39.088** (-75.174)	-0.261** (-83.366)	-61.527** (-6.849)	-0.363** (-8.459)
Constant	161.786** (196.547)	5.020** (1135.593)	161.634** (196.242)	5.019** (1134.137)	184.609** (14.029)	5.140** (76.064)
<i>Dependent Variable:</i>	<i>PRICE</i>	<i>ln(PRICE)</i>	<i>PRICE</i>	<i>ln(PRICE)</i>	<i>PRICE</i>	<i>ln(PRICE)</i>
Num. Obs.	258792	258792	257084	257084	1708	1708
Adj R-squared	0.108	0.138	0.107	0.137	0.213	0.229

t-statistics in parentheses. ** Significant at the 5% level. * Significant at the 10% level.

Table 5. Main Price Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Realized	-8.290** (-3.770)	-0.091** (-3.788)	-7.553** (-3.411)	-0.089** (-3.715)	-7.290** (-3.289)	-0.088** (-3.670)
Category 2 * Realized	-10.639** (-4.583)	-0.083** (-3.308)	-10.630** (-4.581)	-0.083** (-3.310)	-10.486** (-4.516)	-0.082** (-3.281)
Category 3 * Realized	-21.998** (-9.659)	-0.144** (-5.888)	-22.026** (-9.677)	-0.144** (-5.899)	-21.761** (-9.546)	-0.143** (-5.851)
Category 4 * Realized	-36.863** (-15.327)	-0.203** (-8.190)	-36.456** (-15.140)	-0.202** (-8.145)	-35.997** (-14.887)	-0.200** (-8.061)
Category 5 * Realized	-56.429** (-19.783)	-0.262** (-10.146)	-55.594** (-19.326)	-0.260** (-10.025)	-55.117** (-19.134)	-0.258** (-9.944)
Category 6 * Realized	-74.971** (-17.311)	-0.292** (-9.422)	-74.352** (-17.169)	-0.291** (-9.372)	-73.940** (-17.015)	-0.289** (-9.299)
Category 7 * Realized	-86.682** (-11.178)	-0.242** (-6.089)	-85.762** (-11.128)	-0.239** (-6.013)	-85.284** (-11.140)	-0.238** (-5.968)
Category 8 * Realized	-110.887** (-17.329)	-0.175** (-6.264)	-108.593** (-16.921)	-0.170** (-5.599)	-108.287** (-16.907)	-0.168** (-5.560)
Population * Realized			-0.001** (-2.430)	0.000 (-1.038)	-0.001** (-2.453)	0.000 (-1.062)
Infections * Realized					-1.323* (-1.854)	-0.003 (-0.709)
Deaths * Realized					0.005 (0.219)	0.000 (-0.328)
<i>Dependent Variable:</i>	<i>PRICE</i>	<i>ln(PRICE)</i>	<i>PRICE</i>	<i>ln(PRICE)</i>	<i>PRICE</i>	<i>ln(PRICE)</i>
Num. Obs.	258792	258792	258792	258792	258792	258792
Adj/Pseudo R-squared	0.434	0.426	0.440	0.432	0.441	0.434

Logit estimates expressed as odds ratios. t-statistics (LPMs) or z-scores (Logit) in parentheses.

** Significant at the 5% level. * Significant at the 10% level.

Table 6. Alternate Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Realized	1.201 (0.961)	-6.834** (-3.027)	-7.094** (-3.195)	-7.309** (-3.304)	1.540** (2.106)	-6.492** (-3.233)
Category 2 * Realized	1.695** (2.097)	-10.404** (-4.413)	-10.487** (-4.516)	-10.453** (-4.509)	1.720** (2.100)	-10.013** (-4.867)
Category 3 * Realized	3.536** (5.231)	-21.605** (-9.330)	-21.761** (-9.547)	-21.796** (-9.580)	3.640** (5.197)	-20.430** (-10.072)
Category 4 * Realized	3.445** (5.362)	-35.962** (-14.681)	-35.997** (-14.887)	-36.255** (-15.004)	3.532** (5.326)	-33.621** (-16.401)
Category 5 * Realized	5.133** (6.311)	-55.006** (-18.978)	-55.116** (-19.134)	-56.828** (-19.404)	4.686** (5.857)	-50.409** (-23.683)
Category 6 * Realized	12.373** (8.023)	-73.898** (-16.965)	-73.944** (-17.015)	-77.183** (-17.517)	10.666** (7.455)	-63.404** (-25.752)
Category 7 * Realized	94.826** (4.459)	-85.427** (-11.197)	-85.289** (-11.140)	-94.551** (-11.800)	74.577** (4.215)	-67.628** (-20.211)
Category 8 * Realized	27.760** (4.837)	-108.452** (-16.862)	-108.254** (-16.878)	-107.900** (-16.445)	21.264** (4.428)	-93.921** (-12.825)
Population * Realized	1.000 (-1.075)	-0.001** (-2.420)	-0.001** (-2.453)	-0.001** (-2.306)	1.000 (-0.982)	-0.001** (-8.540)
Infections * Realized			-1.323* (-1.854)	-1.449** (-1.970)	0.989 (-0.239)	-1.005** (-3.533)
Deaths * Realized			0.005 (0.219)	0.005 (0.186)	1.001 (1.323)	0.002 (0.238)
Infection Rate*Realized	0.983 (-0.385)	-0.721** (-2.673)				
Death Rate*Realized	1.001 (1.388)	0.003 (0.837)				
Advance*Realized			-0.367 (-1.209)			
Stay*Realized					0.288** (-8.620)	
Model:	Logit	Linear	Linear	Linear	Logit	Selection
Dependent Variable:	CLOSED	PRICE	PRICE	PRICE	CLOSED	PRICE
Collapsed Data	Y	N	N	Y	Y	N
Num. Obs.	10506	258792	258792	8976	10506	286092
Adj R-squared	0.156	0.443	0.442	0.560	0.167	

Logit estimates expressed as odds ratios. t-statistics (price) or z-scores (logit) in parentheses.

** Significant at the 5% level. * Significant at the 10% level.

Table 7. Closure and Price Regressions, July

	(1)	(2)	(3)	(4)
Realized	0.006** (2.835)	-0.049 (-1.468)	-1.074** (-3.193)	1.176 (1.174)
Category 2 * Realized		0.042 (1.226)		1.679 (1.539)
Category 3 * Realized		0.050 (1.476)		1.960* (1.871)
Category 4 * Realized		0.063* (1.846)		-0.430 (-0.355)
Category 5 * Realized		0.065* (1.871)		-7.506** (-4.803)
Category 6 * Realized		0.076** (2.110)		-11.540** (-4.701)
Category 7 * Realized		0.049 (1.434)		-21.747** (-5.099)
Category 8 * Realized		0.048 (0.830)		-25.982** (-3.871)
Population * Realized		0.000 (0.543)		-0.001** (-2.860)
Infections * Realized		0.001 (0.196)		0.069 (0.127)
Deaths * Realized		0.000 (-0.905)		-0.005 (-0.240)
Model:	LPM	LPM	Linear	Linear
Dependent Variable:	CLOSED	CLOSED	PRICE	PRICE
Num. Obs.	10526	10506	300602	300602
Adj/Psuedo R-squared	0.000	0.008	0.000	0.453

t-statistics in parentheses. ** Significant at the 5% level. * Significant at the 10% level.