Real Effects of Rollover Risk:
Evidence from Hotels in Crisis[*]

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Abstract

We show how firms scheduled to roll over debt in a crisis strategically reduce operations, regardless of their liquidity constraints. Our research design utilizes contractual features of commercial mortgages that generate as-good-as-random variation in whether debt is scheduled to mature during a crisis or just before. Once the crisis begins, borrowers cut labor expenses and produce less output at properties collateralizing loans coming due during the crisis, especially high-leverage loans. These effects hold with owner fixed-effects, consistent with strategic default and not liquidity constraints as the dominant mechanism. A parsimonious model of debt overhang with rollover risk rationalizes these results.

I INTRODUCTION

How do firms modify their operations when their debt comes due during a crisis? A common view is that firms in such a circumstance face liquidity constraints, so they redirect internal cash flows away from operations or investment to pay off the debt (e.g., Almeida et al., 2011; Benmelech, Frydman and Papanikolau, 2019; Costello, 2020). However, that strategy becomes infeasible when the amount of maturing debt exceeds the amount of resources a firm could plausibly raise by scaling back operations or investment. In such cases, creditor takeover is a realistic outcome, so the need to roll over debt affects not only the borrower's *ability* to operate the firm but also the *incentive* to maintain it. It is not obvious whether the need to roll over large amounts of debt in a crisis incentivizes borrowers to scale their operations up or down. Distressed borrowers might scale up operations to convince creditors to forbear the loan, or they may scale down operations if they believe that creditors will capture most of the firm's future cash flows.

In this paper, we build a novel dataset to provide direct empirical evidence on the real effects of large debt rollovers during an economic crisis. We focus on the commercial real estate sector, which accounts for 20% of investable U.S. assets and commonly features leverage ratios of at least two-for-one (Ghent, Torous and Valkanov, 2019; Glancy et al., 2022). Commercial mortgages are unique not only for their high leverage ratios but also because they typically feature large balloon payments at maturity, implying that borrowers must pay off far more debt relative to pledged assets at a given time than a standard corporate entity.[1] These balloon payments are rarely prepayable without substantial penalties, which enables a research design that is robust to endogenous early refinancing (e.g., Mian and Santos, 2018; Xu, 2018). Specifically, we compare hotels collateralizing mortgages scheduled to mature around the abrupt onset of the COVID-19 pandemic. Studying hotels lets us exploit detailed, high-frequency microdata on hotel operations, enabling granularity that is typically not possible in other studies of debt rollover. The COVID shock provides us with a sudden and unexpected source of variation that is ideal for identifying the effect of debt rollover in a crisis.

Our core empirical analysis is a difference-in-differences regression that compares outcomes across hotels with balloon mortgages scheduled to mature just after the pandemic's onset ("treatment group") to those whose mortgages were scheduled to mature just before ("control group"). The difference in outcomes between these hotels gives an unbiased estimate of the treatment effect of a crisis debt maturity, under the realistic assumption that hotel owners did not choose the

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[1]Bank and CMBS mortgages amortize over much longer schedules than their loan terms (Glancy et al., 2022), implying a substantial balloon payment at maturity (e.g., 70% of the initial loan balance in the CMBS sample in Titman and Tsyplakov, 2010). Compustat data from 2015–2019 indicate that, among firms with debt coming due in a given year, the median ratio of maturing debt to assets is 2%. The sample consists of domestically headquartered firms excluding financials, utilities, and multinationals.

month of their loan maturity in anticipation of the COVID shock.

Implementing this analysis, we find that having a debt maturity scheduled during the early months of the pandemic significantly amplifies the negative effects of the pandemic on hotel performance. Relative to control group hotels, hotels in the treatment group exhibit much sharper drops across various measures of operating performance starting from the onset of the pandemic and persisting up to two years. For example, between February and April of 2020, revenue declines 40 log points more in the treatment group than the control group, and about a third of this gap persists into 2022. This drop in revenue is driven almost entirely by lower occupancy and is accompanied by similarly sized relative declines in expenses, indicating that owners and managers of these hotels choose not to maintain operations at the same level as they would if they were not facing a looming balloon payment.

As in any difference-in-differences setting, our key identifying assumption is that outcomes for treatment and control group hotels would have evolved in parallel throughout the pandemic were it not for the fact that treatment group hotels faced the need to rollover their debt. Consistent with this assumption, outcomes for both groups of hotels move in lock-step for the three years preceding the pandemic and only begin to diverge afterward. Furthermore, our results are robust to allowing for fully-flexible interactions between month fixed effects and an extensive list of hotel characteristics, including hotel chain-by-geographic market (e.g., Hilton DoubleTree in Boston), year of origination, operation type, size, and purpose of stay (e.g., airport versus resort). These tests help rule out the concern that treated hotels are more sensitive to the COVID shock for reasons unrelated to their scheduled debt maturity. Finally, we also show that the results are robust to alternate ways of assigning hotels to the treatment and control groups.

Interestingly, the dominant explanation for our results does not appear to be liquidity constraints. Rather, strategic considerations such as debt overhang seem to drive the negative effects on real outcomes that we find. Four primary pieces of evidence support this conclusion. First, these negative effects persist even in a specification with borrower fixed effects. This result, which holds borrower-level liquidity constraints constant, implies that hotel owners strategically redirect resources away from properties with loans maturing during the pandemic. Second, hotels in the top third of the loan-to-value (LTV) distribution drive nearly all of the differential drop in real outcomes among treatment group hotels, which is in line with what classic theories of debt overhang would predict (Myers, 1977). Third, short-run operating profits at treatment group hotels actually fall relative to those in the control group, suggesting that treated borrowers are not cutting operations to harvest cash due to external financing constraints. Finally, cash harvesting seems like an unlikely motivation given that the median treatment group hotel faces a balloon payment over four times their annual pre-COVID operating profits.

Taken together, our findings align with the intuition of classic debt overhang: the limited

equity in pandemic-maturity hotels incentivizes borrowers to cut investment, leading to an eventual decline in operations. In our setting, however, it is surprising that operations decline so quickly—within a month of crisis onset—given that real estate investments like capital improvements typically take much longer to affect operating outcomes. To explain this immediacy, we focus on a particular type of investment that became relevant for hotels during the COVID crisis: adaptation. Specifically, we propose a tractable model in which borrowers can choose, on crisis impact, whether to invest time and other resources in "adaptive" inputs (e.g., pandemic workforce management) that boost productivity during the crisis but not once it ends. The model predicts that borrowers facing a debt rollover coinciding with the crisis make smaller adaptive investments than borrowers who rolled over just before the crisis. Consequently, they endogenously reduce operations relative to borrowers with a pre-crisis rollover. As in the data, the gap between these two groups of borrowers exists only among those with high initial leverage ratios. Quantitatively, the model can replicate our empirical results under a calibration of the adaptive investment technology disciplined by the literature on managerial practices (Bloom et al., 2019).

To the best of our knowledge, our paper is the first to study the causal effect of commercial mortgage rollover on the output, employment, and profits at the properties that serve as collateral. Sun, Titman and Twite (2015) find that REITs with more debt coming due during the Global Financial Crisis suffered worse stock returns, but they do not study real outcomes. Other papers examine the real effects of commercial mortgage debt but do not isolate the effect of rollover. For instance, Loewenstein, Riddiough and Willen (2021) show that mortgaged properties are slower to be redeployed to other sectors; Liebersohn, Correa and Sicilian (2022) estimate that higher leverage leads borrowers in the retail sector to reduce leasing activity, and they argue that the effect works through debt overhang.[2] Our results indicate that debt overhang is the channel through which rollover risk affects real activity. Since debt overhang fundamentally reflects strategic considerations, we corroborate evidence that strategic default is pervasive in commercial real estate (Brown, Ciochetti and Riddiough, 2006; Dinc and Yönder, 2022; Flynn, Ghent and Tchistyi, 2022; Glancy, Kurtzman and Loewenstein, 2022; Glancy et al., 2023).

We also contribute to the broader corporate finance literature showing that firms scale back employment and investment when their debt comes due during a crisis, like the Great Depression (Benmelech, Frydman and Papanikolau, 2019) or the Global Financial Crisis (Almeida et al., 2011; Costello, 2020). However, our setting differs in two key ways from corporate rollovers studied in prior work. First, most treated hotels do *not* face an immediate liquidity shock from their maturing debt, as they receive temporary forbearance that pushes their balloon payments to the next year. Second, the large amount of debt scheduled to come due—70% of pre-COVID

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[2]In residential real estate, Melzer (2017) finds evidence of debt overhang, in that homeowners with negative equity spend less on home improvement and maintenance.

asset values—makes losing the collateral a likely possibility. Therefore, our setting is ideal for measuring the real effects of strategic behavior of distressed borrowers, while most prior work is suited to uncovering the effects of liquidity shocks that result when a much smaller amount of debt must be paid off at a time when new debt is unavailable due to a credit crunch.[3] We make an additional contribution to this literature by examining project-based finance, which enables us to show that borrowers strategically curtail operations specifically at their projects (i.e., hotels) that back debt maturing during a crisis.

Our empirical results also speak to the theoretical literature on the relation between time to maturity and debt overhang. Early work by Myers (1977) argues informally that debt overhang should be stronger for long-maturity debt. However, more formal analysis by Diamond and He (2014) shows that the relation between time to maturity and debt overhang is ambiguous, depending on factors such as the timing of news arrival and the effect of investment on cash flow volatility. Because our research design effectively compares borrowers with shorter-vs-longer remaining maturities as of the beginning of the pandemic, our results provide evidence that debt overhang is stronger for shorter maturities. Our model clarifies why debt overhang would be stronger for shorter maturities in our setting.

Lastly, we add to work studying corporate finance and commercial real estate during the COVID pandemic. Brunnermeier and Kirshnamurthy (2020) and Crouzet and Tourre (2021) examine aspects of debt overhang, while Greenwald, Krainer and Paul (2021) and Chodorow-Reich et al. (2022) focus on cash-flow constraints arising from credit lines with banks. In commercial real estate, Steiner and Tchistyi (2022) look at Payment Protection Program (PPP) loans to hotels, while Gupta, Mittal and Nieuwerburgh (2022) investigate the adverse long-run effects of the pandemic on office properties.[4] Our work suggests that balloon maturities on loans backed by distressed real estate can exacerbate debt overhang, leading to adverse effects on the properties' staff and tenants. Going forward, this channel may become increasingly relevant in sectors, such as office, where borrowers are simultaneously facing large upcoming debt maturities and seeking ways to adapt to long-run structural changes like work-from-home (Davis, Ghent and Gregory, 2023; Gupta, Martinez and Van Nieuwerburgh, 2023; Putzier, 2023).

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[3]An exception is Kalemli-Özcan, Laeven and Moreno (2018), who study small businesses in Europe, for whom maturing debts can constitute a large share of assets. They regress investment on ex-ante leverage and firm-level controls and find that high leverage is associated with lower investment after the crisis.

[4]Nguyen et al. (2023) is similar to our paper in that they also examine the effect of debt on hotel performance during COVID. However, their paper looks only at publicly listed firms and does not employ an instrument for the firms' debt position at the beginning of the COVID crisis.

II INSTITUTIONS AND DATA

This section provides background information and describes several features of the hotel industry that make it an attractive setting in which to study our motivating research question. We also describe our main data sources and sample selection criteria. Additional detail regarding the data is contained in Appendix A.

II.A Hotel operations

Most hotels operate under a franchise model, in which the owner of the property buys the right to affiliate with a given brand (e.g., Marriott, Hilton). This model became the industry's standard in the 1990s, when the major brands pivoted toward a strategy of owning very few physical assets. This means that the hotel owners in our analysis range in size from small individual investors to larger property funds or REITs, but they almost never include a major brand itself. A given hotel brand may also establish chains (e.g., Aloft by Marriott), which constitute a separate franchise with its own set of standards. These standards limit the scope for unobserved differences across hotels, which allows for a very tightly identified regression specification as we will describe in Section III.

Hotel owners rely on a variety of operating arrangements to manage their properties on a day-to-day basis. These include operating the hotel themselves, contracting with a third-party operator, or using a brand-provided operating service (Freedman and Kosová, 2014; Kosová and Sertsios, 2018). In the first case, the owner maintains full agency over hotel operations. In the case of delegated operations, the owner can exercise de facto agency by withholding operating capital, which then discharges the operator from its legal obligation to the property. Indeed, management agreements often explicitly include this condition (e.g., Sunstone Hotel Properties (2004)). Moreover, during financial distress, the owner and operator share similar incentives due to the frequent use of subordination clauses, which place both parties in a junior position relative to the lender (Butler, 2008).[5] For these reasons, our analysis will not draw strong distinctions between the owner and the operator, except to show that controlling for the operating arrangement does not affect the results.

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[5]This was a common concern among operating companies during the COVID pandemic. For example Marriott's 2020 annual report highlights that "[m]any of our Operating Agreements are subordinated to mortgages or other liens securing indebtedness of the owners. Many of our Operating Agreements also permit the owners to terminate the agreement if we do not meet certain performance metrics, financial returns fail to meet defined levels for a period of time, and we have not cured those deficiencies" (Marriott (2020)).

II.B Hotel financing

Hotels rely heavily on collateralized debt (i.e., commercial mortgages) and typically borrow from three sources: commercial mortgage-backed securities (CMBS) lenders, banks, and life insurance companies. Relative to other commercial property types, hotels rely more extensively on CMBS loans (Glancy et al., 2022). In the decade before the COVID crisis, a substantial share of new hotel mortgages came from CMBS. Among hotel loans from medium-to-large banks, life insurers, and asset-backed issuers (i.e., CMBS), 36% were from CMBS on an equal-weighted basis (Glancy et al., 2022); on a dollar-weighted basis, the volume of hotel loans from CMBS exceeded that from medium-to-large banks (Glancy, Kurtzman and Loewenstein, 2022). Our analysis restricts to hotels that served as collateral for CMBS loans, partly because their regimented loan servicing protocol produces detailed data and also because CMBS loans have several important contractual features that enable our empirical analysis.

The typical CMBS loan is structured in a way that, de facto, requires a large principal payment at the loan's maturity date. Specifically, the average hotel mortgage has a loan-to-value ratio at origination in excess of 70% and does not fully amortize, implying a balloon payment scheduled at maturity. Moreover, most loans come with conditions that discourage prepayment, either via lockout restrictions that rule out prepayment entirely or through fees that discourage it. The combination of balloon maturities and prepayment penalties implies that most non-defaulting borrowers pay off the bulk of their mortgage balance in a tight window around the scheduled maturity date. Figure I uses our CMBS data to demonstrate this phenomenon during "normal," non-COVID times. To construct the figure, we restrict attention to loans with a 10-year maturity (the mode) and with a scheduled maturity date at least 12 months before the pandemic (February 2019 or earlier). In this sample, all loans have limited ability to prepay up until 8 months before scheduled maturity, as shown in Panel A of Figure I. These limitations dissipate as the loan nears the scheduled maturity date. Coinciding with the timing of prepayment restrictions, about 80% of the original principal balance remains on loans in the sample up to 3 months before maturity, as shown in Panel B of Figure I. Borrowers pay off most of that amount by the maturity date.

II.C Hotels during the COVID-19 pandemic

The COVID crisis had a significant adverse effect on the U.S. hotel industry. To avoid contracting COVID-19, many people curtailed travel plans, and this change in behavior diminished the demand for hotel services. In Figure II, we plot aggregate monthly revenues for U.S. hotels. Between February and April of 2020, revenues drop 80%; they remain depressed for the remainder of 2020 and do not regain their pre-pandemic levels until the summer of 2021.

The pandemic also changed the type of services that consumers demanded from hotels. For

instance, roughly a quarter of U.S. consumers surveyed in April 2020 reported that services like letting rooms sit 72 hours between stays, intense room cleanings, and COVID-19 tests and temperature checks of other guests would make them more likely to stay at a hotel (Krishnan et al., 2020). In response, management practices changed at some hotels. For instance, several global hotel managers introduced thermal scanners at hotel entrances, adopted contact-less check-in protocols, increased the frequency and intensity of cleaning rooms between guest stays, and began enforcing social distancing to various degrees (Kim and Han, 2022). Best practices for labor management may have also changed. Other hotel owners, however, took the opposite approach and drastically scaled back their operations (Rackl, 2020). The aggregate effect of these decisions across hotels was a 50% decline in employment in leisure and hospitality from February to April of 2020, much of which persisted further into the year (AHLA, 2020a). In 2020, most hotel owners expected the adverse effects of the pandemic on consumer demand for hotels to last for several years. According to business executives surveyed by McKinsey, by June the most likely scenario involved a reduction in hotel revenues of 20-50% for at least 3 years (Krishnan et al., 2020). PwC, another consultancy, predicted in May that hotel revenue would remain 25% below pre-crisis levels for almost two years, and further predicted in November that revenues would remain below pre-crisis levels for at least four years (PwC, 2020a,b).

These beliefs about the pandemic's duration imply that hotel owners with mortgages maturing in 2020 or 2021 would have anticipated needing to make balloon payments during the crisis that were large relative to, and possibly exceeded, the value of their hotels in order to satisfy their debt obligations. Consistent with this, a survey of hotel owners by the American Hotel and Lodging Association (AHLA) in November of 2020 found that 59% considered themselves in danger of losing their property in a foreclosure (AHLA, 2020b). Some lenders granted loan modifications, such as forbearance and maturity extensions, which postponed this financial distress (Glancy, Kurtzman and Loewenstein, 2022). However, 82% of surveyed hotel owners reported in November that their lender relief extended only until the end of 2020 (AHLA, 2020b). Relative to portfolio lenders, lenders in securitized mortgage markets are typically less willing to grant modifications (Glancy et al., 2022; Flynn, Ghent and Tchistyi, 2022). Therefore, CMBS borrowers with loan maturities in 2020 and 2021 may have reasonably anticipated losing their hotels in foreclosure should the COVID crisis persist for several years, as was commonly expected in 2020.

II.D Data

Hotel performance data

We measure operational performance at the hotel level using data from STR, LLC. STR is a leading data provider in the hotel industry and covers around 98% of hotels in the U.S. (Povel

et al., 2016). The STR data is self-reported, meaning that hotel owners send the data to STR.[6] In exchange, STR provides submitting hotels with the ability to run benchmarking reports on anonymous groups of competing hotels. Data on individual hotels is available to academics under a confidentiality agreement that requires researchers to work with an anonymized subsample of the STR universe. Accordingly, our sample includes the subset of hotels in our main mortgage dataset, discussed shortly, that: have a loan scheduled to mature between January 2018 and December 2022; and that match to a hotel tracked by STR. For the purposes of identification, we later filter this sample to hotels with a loan scheduled to mature in a tight bandwidth around the pandemic's onset.

The STR dataset has four components. The first component is a daily hotel-level panel of basic performance metrics from January 2017 through June 2022: room revenues, occupancy rates, and the average daily prices for rooms sold. Prior work has used this component (e.g., Povel et al. (2016)). The second component is a yearly panel of hotel profit and loss statements from 2017 through 2021: total revenue broken down by category with a high degree of detail (e.g., revenue from rooms, food and beverage); and total operating expenses by category with a similar degree of detail (e.g., labor expense, spending on sales and marketing). The third component is a monthly panel of hotel profit and loss statements, which is similar to the annual panel but begins in January 2020. The fourth component is a cross-sectional dataset with time-invariant hotel characteristics, including: geographic market, number of rooms, hotel brand (e.g., Marriott), hotel chain within the brand (e.g., Residence Inn by Marriott), operating arrangement, and purpose of stay (e.g., airport, resort, highway). STR defines geographic markets that generally align with a CBSA.[7]

Mortgage data

Our primary source of data on mortgages collateralized by hotels comes from Trepp LLC. We specifically work with Trepp's T-Loan dataset. This dataset covers the majority of commercial mortgages originated in the U.S. that are placed into CMBS pools, including agency and private-label CMBS. We observe mortgage characteristics at origination, such as LTV, maturity date, interest rate, and the address of the collateral property. We further observe monthly performance of the loan. Our data cover all loans that report monthly performance data on or after June, 2006.

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[6]It is possible that owners might submit fraudulent data to STR. However, they have little incentive to do so for a variety of reasons. First, STR strictly preserves the anonymity of hotels. So, a hotel has no incentive to use misreporting as way to deceive competitors. Moreover, many CMBS lenders rely on STR data on hotels that serve as collateral for their loans, submitting fraudulent data to STR could entail loan fraud, which significantly reduces the incentives to misreport. Lastly, much of the data is submitted to STR via automated processes built into hotel property management software.

[7]STR defines a market as "a geographic area typically made up of a Metropolitan Statistical Area (e.g., Atlanta, GA), a group of Metropolitan Statistical Areas (i.e., South Central PA) or a group of postal codes (i.e., Texas North)." A list of markets in our analysis sample appears in Appendix Table A.I.

We supplement the T-Loan dataset with data on loans from Real Capital Analytics (RCA), which tracks sales of and mortgages backed by commercial properties in the U.S. We match the RCA data to Trepp using the property address and the origination month of the loan in Trepp. The RCA data allow us to observe junior, non-securitized liens on the same property, providing us with a more complete measure of the total LTV at origination. In the cases where we observe a junior lien in RCA, we replace the LTV in Trepp with the LTV in RCA.[8] We do not adjust the debt service coverage ratio (DSCR) in Trepp to account for junior liens because RCA does not have sufficient data on required interest payments.

RCA also provides the name of the mortgage borrower. To gauge the borrower's size, we downloaded from RCA the total value of each borrower's real estate assets in the U.S. as of June 2023, as well as the borrower type (e.g., REIT). We match 83% of the loans in the merged STR-Trepp dataset to RCA. We are not able to match 100% because we do not match some loans in Trepp to RCA; in many cases, these loans are originated in the 1990s and do not appear in RCA.

Analysis sample

An important hurdle that we overcome in assembling our data is to merge hotel-level data from STR to loan-level data from Trepp, using information on the address of collateral properties.[9] While a loan may disappear from the Trepp data when it matures or is paid off, we are able to track property-level outcomes for the hotels securing that loan throughout the entire sample period. In our empirical analysis, we compare hotels that serve as collateral for loans with a maturity before COVID (i.e., February 2019 to January 2020) to those with a maturity on or after COVID (i.e., February 2020 to January 2021). Summary statistics for key variables for these two groups of hotels appear in Table I. The assignment of hotels to each group depends on the maturity date at loan origination ("intent to treat"). Therefore, even if the borrower prepays the loan before 2019, we still assign the hotel collateral to one of the two groups according to the loan's original maturity date. As Table I shows, hotels are somewhat but not perfectly balanced across the two groups. Our empirical analysis will address these imbalances in a variety of ways, which we discuss in the next section.

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[8]In cases with multiple liens where we do not observe the property value in RCA, we either use the Trepp LTV or scale up the Trepp LTV by the ratio of total debt to the largest loan in RCA; see further details in Appendix Appendix A.

[9]The merge involves a complicated process that preserves the anonymity of specific hotels. We begin with a directory of hotel addresses from STR's universe. Then, we match these addresses to the addresses of properties that serve as collateral for hotel loans in Trepp. The result is a hotel-level dataset with the STR identifier and various characteristics of the loan for which the hotel serves as collateral. We return this dataset to STR, who then scrambles the original hotel identifier and returns to us an anonymized, hotel-level dataset that includes the static hotel characteristics and various dynamic performance variables. We are contractually prohibited from identifying any of the hotels in STR using these anonymized data.

III EMPIRICAL FRAMEWORK

III.A Identification Strategy

We estimate the effect of debt rollover risk on real activity using a difference-in-differences research design that compares the evolution of outcomes across hotels with loans initially scheduled to mature just before versus just after the onset of the COVID pandemic. The key identification assumption underlying this approach is that outcomes for these two groups of hotels would have evolved in parallel were it not for the fact that hotels in the latter group have a large amount of debt scheduled to come due during the early months of the pandemic.

Figure III provides direct evidence in support of this assumption. In this figure, we split hotels into two groups and plot the dynamics of monthly room revenues separately by group. The dashed blue line plots room revenues for hotels with loans initially scheduled to mature sometime during the 12-month period leading up to the pandemic. The solid orange line plots room revenues for hotels with loans initially scheduled to mature during the 12-month period immediately after the pandemic began. To aid visual comparison of trends, we normalize revenues to one in February 2019 for each group of hotels. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. As the figure makes clear, revenues for these two groups of hotels moved in near lockstep during the three years leading up to the pandemic and only began to diverge afterwards. The core idea of our research design is to attribute the relative gap in outcomes that opens up between these two groups of hotels to the fact that those with post-pandemic maturities were faced with the need to pay off their debt during a time when external financing was difficult to secure.

III.B Estimation

Difference in Difference

Our baseline econometric model is a simple difference-in-differences regression estimated at the individual hotel level. Specifically, we estimate regressions of the following form:

$$y_{imt} = \alpha_i + \delta_{mt} + \gamma X'_{it} + \beta \cdot PandemicMaturity_i \times Post_t + \epsilon_{it}, \tag{1}$$

where y_{imt} denotes an outcome of interest for hotel i, located in market m, at time t. For our main analyses, we restrict the sample to include only hotels with loans initially scheduled to mature within a symmetric 12-month window around the beginning of the pandemic. The dummy variable $PandemicMaturity_i$ is a treatment indicator equal to one if hotel i has a loan that was

initially scheduled to mature during the 12-month period following the beginning of the pandemic and equal to zero if the hotel had a loan maturing during the 12-month period before the pandemic began. The $Post_t$ indicator is equal to one if month t falls on or after the first month of the pandemic (February 2020).[10] The hotel fixed effects α_i control for level differences in mean outcomes across hotels.

The coefficient of interest is β, which measures the differential change in outcomes during the pandemic for hotels with pandemic maturities relative to those with pre-pandemic maturities. This coefficient has a causal interpretation in the absence of two forms of bias. The first concerns omitted variables: hotels with a pandemic maturity may simply be more exposed to the concurrent drop in hotel demand. The most realistic form of omitted variables bias would work through spurious correlation between a loan's maturity month and economic fundamentals. Reassuringly, we show in Appendix Figure A.I that the loan maturities within the two cohorts appear to be distributed uniformly over time. Nonetheless, spurious correlations could still arise in small samples. We address this possibility in our analysis in several ways. Since location is arguably the most important economic fundamental in real estate, we always include a set of geographic market-by-month fixed effects, δ_{mt}. These fixed effects ensure that our estimates are not being driven by a coincidence wherein hotels with pandemic maturities happen to be located in markets where the pandemic had the largest effects on hotel demand. In progressively more-stringent specifications, we also include a vector of time-varying hotel characteristics X_{it} that further account for spurious correlation. As one example, airport hotels may have been differentially exposed to COVID relative to resort hotels even within a given market. Including a set of hotel-type by month fixed effects in X_{it} addresses this concern by allowing outcomes for these two types of hotels to trend differently throughout the pandemic independently of their scheduled debt maturity. Our analysis explores robustness to a wide range of different hotel-level controls of this type.

The second potential source of bias concerns effects related to the loan life cycle. It may be that, even in normal times, hotels modify their operating behavior around the time of loan maturity. We address this concern in two ways. First, in every specification we include a post-maturity dummy in the set of time-varying controls X_{it}. Doing so removes any level change in outcomes that occurs naturally at loan maturity. Second, in Section IV.C we show that our results are robust to the size of the bandwidth we use to define pre- versus post-pandemic maturities. This robustness is reassuring as using a narrower bandwidth limits the time frame over which differences between pre- versus post-maturity hotels may arise.

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[10]For outcomes that we can only observe annually, we date the beginning of the pandemic to January 2020 and consider all years from 2020 onward as being post-pandemic. However, we continue to classify hotels into pre- versus post-pandemic maturity groups based on the month in which their loan was originally scheduled to mature.

Event Study

As a more flexible alternative to equation (1), we also present estimates from a version of the specification that allows the effects to vary by month. Specifically, we estimate regressions of the following form:

$$y_{imt} = \alpha_i + \delta_{mt} + \gamma X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\beta_\tau \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \right] + \epsilon_{it}, \qquad (2)$$

where $\mathbb{1}_{t=\tau}$ is an indicator variable taking the value one if month t is equal to τ (e.g. February 2020) and all other variables are as previously defined. The time varying coefficients β_τ from this regression provide a non-parametric measure of the differential trend in outcomes for hotels with loans scheduled to mature just before versus just after the onset of the pandemic. We normalize the coefficient for December 2019 to zero so that all estimates can be interpreted as the difference in outcomes between hotels with pre- versus post-pandemic maturities in a given month relative to that same difference as of the last month of 2019. Plotting the time-path of these coefficients allows us to both trace out the dynamics of the effect throughout the post-pandemic period and test for conditional pre-trends prior to that period.

IV RESULTS

This section presents our core empirical results. Following the evidence from Figure III, we begin by exploring the differential effect of the pandemic on revenues and output (i.e., occupancy) for hotels with loans maturing during the pandemic. We then turn to analyzing the effects on hotel inputs. Finally, we conclude by providing evidence that the effects we find are likely to be driven by strategic considerations such as debt overhang rather than cash flow constraints.

IV.A Effects on Hotel Revenues and Output

Baseline Result

Table II presents estimates from the pooled difference-in-differences specification given by equation (1) using log monthly room revenues as the outcome. Column 1 reports estimates from a baseline specification that includes only hotel fixed effects, market-by-month fixed effects, and a post-maturity dummy as controls. The coefficient on the $PandemicMaturity_i \times Post_t$ interaction term indicates that the decline in room revenues during the pandemic is 17 log points (16%) larger for hotels with loans maturing during the first year of the pandemic relative to those with loans maturing during the year before. Interestingly, the results in Table III show that this

relative decline in revenues for treated hotels during the pandemic is twice as strong if the loan is scheduled to mature in the first six months of the pandemic, as opposed to the next six months. This suggests that borrowers fearing foreclosures sooner may have cut their revenues more aggresively at the beginning of the pandemic, a result to which we will return when discussing the model in Section V.

Figure IV further shows that the larger relative decline in revenues for hotels with pandemic loan maturities is not constant throughout the pandemic. This figure plots coefficient estimates from a version of the event study regression in equation (2) that directly parallels the specification from column 1 of Table II. These estimates reveal that the relative drop in revenues materialized immediately upon the onset of the pandemic and was largest during its earliest months. By April 2020, hotels with loans maturing during the first year of the pandemic had revenue declines that were roughly 45 log points (36%) larger than the revenue declines experienced by hotels with loans that matured just before the pandemic began. This is consistent with the raw averages from Figure III, which show revenues declining by about 60% for hotels with pre-pandemic maturities and 80% for hotels with loans maturing during the pandemic. This gap remains positive throughout the pandemic but closes to roughly 10% by the time our sample ends in April 2022.

We interpret the relative decline in revenues at hotels with loans maturing during the pandemic as evidence that the owners and managers of these hotels chose not to maintain operations at the same level as they would have had they not been facing a looming balloon payment. As described in Section III.B, an alternative interpretation is that this group of hotels faced a larger COVID-induced demand shock. Econometrically, this would induce bias through spurious correlation between the treatment variable and omitted variables related to economic fundamentals. Section IV.C pursues an exhaustive assessment of this possibility.[11]

As a first pass, columns 2–5 of Table II explore the sensitivity of our baseline estimate to allowing the direct effect of the pandemic to vary non-parametrically across hotel characteristics. Column 2 incorporates size-by-month fixed effects to allow hotels of different sizes to have been differentially affected by the pandemic independently of debt maturity. Column 3 adds a further set of operation type-by-month fixed effects, which allow for independent, franchisee-operated, or brand-operated hotels to have fully flexible and differential trends throughout the sample period. Column 4 adds a similar set of fixed effects based on the hotel's location type, which generally may be interpreted as "purpose of stay" (e.g., airport hotel, resort). Lastly, the

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[11]An alternative possibility is that hotel owners with a pandemic maturity may have worked out their loan and used the workout period to renovate the property. To asses this possibility, we measure property renovations as in Reher (2021) using the associated flag in the Trepp dataset and find that there are only 6 hotels with a pandemic maturity that experienced a renovation in 2020 or later, before their loan matured and exited Trepp. Dropping these hotels from the sample results in almost the same estimate of -0.17 shown in column 1 of Table II. So, the drop in revenue at hotels with a pandemic maturity does not reflect a cessation of normal operations to conduct a renovation.

origination year-by-month fixed effects in column 5 allow for separate dynamics according to the stage of the credit cycle at which the borrower took out the loan. We find economically large and statistically significant point estimates across all specifications.[12]

Decomposition into Quantities and Prices

Revenues can decline as a result of either falling real output or falling prices. To decompose the overall relative decline in revenues for hotels with pandemic maturities into these two components, we re-run the baseline dynamic difference-in-differences regression using log occupancy rates and log average daily room prices as the outcome. Changes in these two variables sum to equal the change in log total room revenues. Figure V displays the results from this exercise. The series in solid blue circles reports coefficients from the regression using the log occupancy rate as the outcome while the series in hollow orange circles reports analogous results for log daily room prices.

In the early half of the sample, nearly all of the total relative decline in revenues is driven by falling output rather than falling prices. For example, In April 2020 hotels with loans maturing during the pandemic had reduced their occupancy rates by roughly 45 log points (36%) more than hotels with loans maturing earlier while exhibiting essentially no differential change in prices. Over time, however, the gap in output narrows and a modest gap in prices materializes. By the end of the sample, roughly half of the remaining 10% gap in revenues is driven by lower occupancy while the remaining half is due to lower prices.[13]

IV.B Effects on Hotel Inputs

The results presented in the previous section indicate that hotels with loans maturing during the pandemic experienced reductions in real output that were significantly larger than those experienced by otherwise similar hotels with loans maturing just before the pandemic began. In this section, we provide evidence that the relative decline in output among pandemic-maturity hotels was achieved via a concomitant scaling back of inputs into the production process.

Our analysis of hotel inputs relies on lower-frequency annual profit and loss statements that are only available for about 45% of hotels contained in the monthly data analyzed above. Nonetheless, in Panel A of Figure VI we verify that the relative decline in revenues for pandemic-maturity

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[12]We measure size using the total number of rooms and group hotels into 5 categories following STR reporting practices (less than 75, 75–149, 150–299, 300–500, more than 500). The possible location types are urban, suburban, airport, highway, resort, or rural.

[13]On the extensive margin, Appendix Figure A.VI provides evidence that hotels with a pandemic maturity are also significantly more likely to be closed in the first year of the pandemic. It is difficult to interpret the magnitude of the effect because we do not observe closure directly and must impute it, as Appendix A.A describes. The estimates imply that treated hotels are 1-2 pps more likely to be closed in the pandemic's first year, relative to an average monthly closure rate of 0.5% over the post-pandemic period.

hotels continues to hold at the annual frequency in this smaller sample. This figure reports regression coefficients from an annual version of equation (2) containing the same controls used in Figure IV.[14] While the monthly data only contain information on room revenues, the annual profit and loss data record revenues from all sources (e.g. food and beverage, golf course, etc.). We use this more inclusive definition of revenues here. We also extend the sample back to 2017 to allow for a better assessment of low-frequency pre-trends. The results continue to indicate large relative declines in revenues for hotels with loans maturing during the pandemic.

In the remaining three panels of the figure, we show that these revenue declines were accompanied by similarly large declines in hotel inputs. In Panel B, we run the same regression using total hotel operating expenses as the outcome. The estimates from this regression indicate that hotels with loans maturing during the first year of the pandemic scaled back operating expenses in that year by roughly 50 log points (40%) more than hotels with loans maturing just before the pandemic began. As with the results for revenue, this relative decline in inputs reverts slightly but remains large and persists through the end of 2021.

Panels C and D of the figure report analogous results for two specific operating expenses of interest: labor, and sales and marketing. In both cases we document similarly large relative declines for pandemic-maturity hotels that begin immediately upon pandemic onset and persist through the end of the sample. The results for labor expense are of interest because they indicate that the effects of debt rollover risk on real activity include cutting employment and therefore extend to the employees of the hotel. The effects on sales and marketing expense are also of interest because they are linked to an aspect of hotel operations that is directly related to the attempt to fill room vacancies. For example, advertising available rooms on third-party services such as TripAdvisor would show up in this line item. The relative decline in expenditures on both of these inputs is consistent with the idea that hotels with pandemic-maturity loans chose to retain fewer workers through the pandemic and work less aggressively to fill their rooms, leading to larger declines in real output and revenues. Appendix Table A.V reports a negative effect on a variety of other expense categories including: room, administrative, food and beverage service, property maintenance, reserve for capital replacement, and payments to the hotel's operator.[15]

In Appendix Figure A.V we also verify that the drop in sales and marketing expense from panel D of Figure VI occurs immediately. This timing supports our interpretation that hotels

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[14]By necessity, in this specification the market-by-month fixed effects are replaced with market-by-year fixed effects, and the dummy for whether the hotel's loan has already matured is coded as one if the scheduled maturity month falls in or before the year of observation.

[15]The rightmost columns of the table normalize expenses by revenue. Consistent with our finding that operating profit falls by more for treated hotels, we find that the expense-to-revenue ratio for these hotels rises by more. Interestingly, there is an insignificant effect on the ratio of payments to the operator relative to revenue. Insofar as these payments are the sum of a base fee plus a share of revenue, the non-negative effect actually suggests that treated hotel owners may also default on paying their operator.

with a pandemic maturity actively seek to reduce bookings (e.g., by not advertising on TripAdvisor), rather than merely responding to a spuriously greater decline in demand than hotels with a pre-pandemic maturity. This result obtains from estimating a variant of the event-study regression equation (2) using the monthly profit and loss dataset. As described in Section II, the monthly profit and loss data cover a subset of hotels in the larger, yearly dataset and begin in January 2020.

IV.C Robustness of Main Effect

Bandwidth Sensitivity and the Loan Life Cycle

In the results so far, we control for effects related to the loan life cycle through a post-maturity dummy, which adjusts for any level change in outcomes at maturity. To further alleviate this concern, Table IV assesses the robustness of our estimates to changes in the size of the bandwidth used to define pre- versus post-pandemic maturities. A more narrow bandwidth implies that the treatment and control groups are at a similar stage in the loan life cycle once the pandemic arrives. Consequently, life cycle considerations should have minimal impact on our estimates.

For reference, column 1 of Table IV repeats our baseline specification that relies on a 12-month bandwidth on either side of the pandemic. In columns 2 and 3 we report estimates based on 18- and 6-month bandwidths, respectively. Results from this analysis yield estimates that are, if anything, larger than those from the baseline analysis. For example, the results in column 3 indicate that hotels with loans maturing during the first 6 months of the pandemic experienced revenue declines that were 27 log points (24%) larger than those experienced by hotels with loans maturing during the 6-month period preceding the pandemic. In column 4, we return to the 12-month bandwidth but use the date at which the loan can be freely prepaid without penalty rather than the scheduled maturity date to group hotels. This date typically precedes the scheduled maturity date by several months and may be a better indicator of when hotel owners might naturally seek to begin arranging rollover financing. Results from this specification indicate that revenues fell by 11 log points (10%) more among hotels entering their free prepayment period within the first 12 months of the pandemic relative to those that became able to freely prepay during the preceding 12 months.

Omitted Variables at the Chain Level

In Appendix Table A.II we explore the robustness of our results to specifications that include a full set of market-by-chain-by-month fixed effects.[16] This restrictive specification identifies the main

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[16]Unbranded hotels are grouped into a single category in this specification. We obtain the same results without such hotels because there are few unbranded hotels in the estimation sample.

effect using only variation across hotels within a given chain and market (e.g. Hilton DoubleTree in Boston) that happen to have loans maturing just before versus just after the pandemic. While this stringency reduces external validity through the associated drop in effective sample size, it improves internal validity by shutting down bias from unique cases wherein certain chains tend to: have loan maturities on a particular side of the pandemic; locate in geographic markets with differential hotel demand during the pandemic; and, within those markets, cater to guests with differential demand.

The estimate from column 1 of the table indicates that hotels with a pandemic maturity experienced a drop in revenues at the onset of the pandemic that was 12 log points larger than that experienced by other hotels in the same chain and market with loans maturing prior to the pandemic. As in Table II, we incrementally add in fixed effects related to hotel size, purpose of stay, and operating arrangement. The results in columns 2–4 lie between 8 and 12 log points. We take the midpoint, around 10 log points, as a credible lower bound on the effect of interest. It seems unlikely that spurious correlation within a given chain and geographic market could be so strong as to generate a 10% difference in revenue by loan maturity, after already residualizing against nonlinear trends by purpose of stay and the other controls included in the table.

Omitted Variables at the Borrower Level

In the spirit of the previous exercise, we also estimate our baseline specification with fixed effects for bins defined by the borrower (i.e., hotel owner) and month. Effectively, this specification compares revenue of hotels with different loan maturities that are owned by the same borrower. The sample size falls by 16% relative to Table II because information on the borrower comes from RCA and is not available for all hotels. We estimate a revenue drop of 22 log points in this specification, shown in column 5 of Appendix Table A.II. The statistical significance of the estimate does not change when we cluster standard errors by borrower and month (column 6). These results further support the consensus across our analysis that having a loan maturity during the pandemic causally leads to lower revenue.

IV.D Borrower Incentives as a Mechanism

Why did hotels with loans coming due during the early months of the pandemic scale back operations more than otherwise similar hotels with loans due just before the pandemic began? We consider two sets of explanations.

The first set of explanations concern the hotel owner's ability to repay the loan through available cash ("cash channel"). Within this set, we can further consider explanations related to cash generated from operations versus cash generated through financing. In terms of operations, the

inability to secure external financing during the pandemic may have led hotels with impending debt maturities to reduce operating costs to harvest enough short-term cash to meet their scheduled balloon payments. In terms of financing, it is possible that hotels with a pre-pandemic maturity may have more liquidity because they extracted cash when they refinanced. These hotels would have the resources necessary to ensure that the property remains guest-friendly during a public health crisis.

The second set of explanations concern the owner's incentive to repay the loan and are more strategic in nature ("strategic channel"). We specifically focus on strategic explanations related to debt overhang: the borrower's reduced incentive to maintain the property because the lender may seize it in foreclosure.[17] We present evidence suggesting that our findings are more consistent with the strategic channel than the cash channel.

Cash Channel

Suppose that a hotel owner can generate cash flow from operations to pay off their loan. For example, if demand responds sluggishly to changes in quality-adjusted hotel rates, then reducing expense on property maintenance or housekeeping would raise short-term profit.[18] While hotels with a pandemic maturity indeed reduce their labor and overall expense (Figure VI), three pieces of evidence suggest that this finding does not derive from a cash-harvesting motive.

First, most hotels have a balloon payment so large relative to earnings that cash-harvesting could not plausibly cover the entire payment. This is especially so given the fact that most principal remains outstanding by maturity (Figure I). Substantiating this point, Figure VII uses our annual profit and loss data to plot the distribution of 2019 operating profit (EBITDA) relative to scheduled balloon payments for the set of hotels with loans due during the first 12 months of the pandemic. The median hotel in our sample would only be able to cover 24% of their scheduled balloon payment even if they were to redirect an entire year's worth of pre-COVID operating profit toward making debt payments. Even a hotel at the 95th percentile could only cover 78% of their scheduled payment with a full year of profit. Summarizing, short-term cash flow harvesting is unlikely to generate the funds required to pay off the loan.

Second, hotels with a pandemic maturity actually experience a drop in operating profit. This finding makes it unlikely that the drop in expenses documented in Figure VI reflects an attempt to make *partial* balloon payments. Making partial payments could be optimal if doing so increases

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[17]A separate set of explanations relate to the borrower's strategic motive to incentivize the lender to favorably renegotiate the loan (Riddiough and Wyatt, 1994; Brown, Ciochetti and Riddiough, 2006). For example, depreciating the property would discourage the lender from foreclosing. As we cannot separate this strategic renegotiation channel from debt overhang in the data, we do not rule it out.

[18]There are several other theories under which cost-cutting could raise short-term profit. For example, Benmelech, Frydman and Papanikolau (2019) propose a setting where firms pay labor in advance, such that choosing not to renew labor contracts leads to a jump in current profit at the expense of lower profit in the future.

the likelihood that the CMBS special servicer would enter into a renegotiation or forbearance agreement with the borrower. However, this approach requires an increase in short-run profit. In Figure VIII, we show that the exact opposite occurs. This figure plots coefficient estimates from an annual version of equation (2) using operating profit as the outcome. The results reveal that hotels with loans coming due during the early months of the pandemic experienced a relative *decline* in profit compared to hotels with loans due before the pandemic.[19] This fact, combined with the sheer scale of the anticipated balloon payments, makes it unlikely that the drop in output we document is driven by an attempt to redirect cash flows toward meeting debt obligations. Consistent with this, Appendix Figure A.III also shows that borrowers with a pandemic maturity actually reduce the payments they make to their lenders during the first year of COVID more than other borrowers.

Third, Appendix Figure A.II shows that hotels with loans scheduled to mature before and during the pandemic have the same take-up rate of Paycheck Protection Program (PPP) loans over time.[20] This finding suggests that liquidity constraints did not drive the differential decline in real outcomes at treated hotels, as those hotels would have been more likely to seek PPP credit if they were more constrained.[21]

Putting the previous evidence together, it seems unlikely that our main results reflect an attempt to generate cash flow from *operations*. However, hotels with a pandemic maturity may also have had limited ability to generate cash flow from *financing* during the crisis, via either internal or external capital markets. As described earlier, hotels with a pre-pandemic maturity may have access to a larger internal capital market (i.e., more liquid assets) through any equity extracted when they refinanced. They may also have easier access to external capital markets in the form of non-secured working capital, which would be junior to a CMBS loan and, thus, difficult for borrowers with maturing CMBS debt to access (Chodorow-Reich et al., 2022; Brown, Gustafson and Ivanov, 2021; Greenwald, Krainer and Paul, 2021). Either way, the cash-from-financing channel would predict an insignificant effect when estimating equation (1) with borrower-by-month fixed effects. This specification identifies β using loans made to the same borrower but scheduled to mature on different sides of the pandemic's onset. So, the cash-from-financing channel would

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[19]Columns 3-4 of Appendix Table A.VI tabulate the results of the analogous difference-in-difference equation and show that they are robust to heterogeneous trends by operating profit in 2017. This last result confirms that the absence of parallel trends in 2017 in Figure VIII does not drive the results. In Appendix Figure A.V, we show that profits are lower for the treatment group throughout the initial months of the pandemic.

[20]We define a hotel as having a PPP loan if it matches to an approved PPP loan in the Small Business Administration's (SBA) directory, as described in Section A.D. So, we cannot distinguish between cases in which a hotel actually does not have an approved PPP loan versus cases in which the matching procedure fails to correctly identify the hotel in the SBA's directory. Steiner and Tchistyi (2022) perform a similar match for airport hotels and find that 16% received PPP credit in 2020, which lies close to the share shown in Appendix Figure A.V.

[21]This finding also rules out the concern that our main results merely reflect an inability of treated borrowers to access PPP credit because their CMBS loan terms prohibited new lines of credit around the maturity date.

predict that such borrowers reallocate funds from the hotel with the pre-pandemic maturity to maintain the hotel with a pandemic maturity. However, Section IV.C already discussed how the main effect remains quite large when including borrower-by-month fixed effects, in the context of Appendix Table A.II.

Collectively, we consider various forms of cash constraints as explanations for our main results, but we find little evidence in favor of them. So, we turn our attention from explanations rooted in constraints to explanations rooted in incentives.

Strategic Channel

The strategic channel predicts a larger drop in revenue for treated hotels with less incentive to maintain the property or adapt it for pandemic conditions. We primarily measure the strength of this incentive using hotel's total leverage ratio (i.e., LTV), which, in most models of debt overhang, parameterizes the marginal effect of investment on the value of debt. In keeping with the rest of our research design, we measure the LTV ratio as of origination. Econometrically, this approach reduces bias relative to using a measure of the current LTV ratio, which endogenously depends on demand for the hotel and the owner's ability to refinance. However, using the initial LTV ratio also increases measurement error that reduces the efficiency of the estimates. We address this measurement error by relying on the *total* LTV ratio obtained from the merger of the Trepp and RCA datasets, described in Section II. This measure of the LTV ratio includes second-liens and other non-securitized debt on the property. For ease of interpretation, we transform the LTV ratio into an indicator for whether the LTV ratio is "high" ($HighLTV_i$), defined as the top one-third of the sample and corresponding to a ratio of 80%.

We test for the strategic channel by re-estimating our difference-in-difference equation (1) after interacting the treatment effect with $HighLTV_i$. Having a high LTV ratio alters the incentive of hotel owners with a pandemic maturity, but, since the LTV was a choice variable at the time of origination, it may also correlate with pandemic operations through margins distinct from the strategic channel. Accordingly, we interact $HighLTV_i$ with a vector of time fixed effects as an additional control. Explicitly, we estimate

$$\log(Revenue_{imt}) = \beta_0 \cdot PandemicMaturity_i \times Post_t + \ldots \quad (3)$$
$$\ldots \beta_1 \cdot PandemicMaturity_i \times Post_t \times HighLTV_i + \ldots$$
$$\ldots \gamma_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\lambda_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

where, again, $HighLTV_i$ indicates if the total LTV ratio lies in the top one-third of the estimation sample, and $Revenue_{imt}$ is the room revenue for hotel i in market m and month t.

Table V reports the results. The estimate in column 1 implies that the drop in revenue at hotels with an impending balloon payment is almost entirely driven by highly-levered hotels. Column 2 includes a borrower-by-month fixed effect, and the result further supports this interpretation. The latter finding provides especially strong support for the strategic channel because it relies only on variation within a given borrower. Namely, it implies that borrowers do not reallocate cash to smooth performance across hotels but, rather, significantly reduce operations at hotels with maturing debt in which they have a weaker equity stake.[22]

Figure IX performs a similar exercise using our event study research design. Specifically, we re-estimate a variant of equation (2) that, like equation (3), interacts the treatment effect with $HighLTV_i$. Then, we plot the estimated effect of having a pandemic maturity separately for hotels in the bottom two-thirds versus the top one-third of the LTV distribution. The results shown in Figure IX imply that the dynamic effect is again driven by treated hotels in the top one-third of the LTV distribution.

While a hotel's initial maturity month is plausibly as-good-as-random relative to the timing of the pandemic, the initial LTV may not be. It is possible that the heterogeneous treatment effect by LTV ratio shown in columns 1–2 of Table V actually reflects heterogeneity by another, omitted variable that correlates with the LTV ratio. The best we can do to address this possibility is to examine how hotels with a high LTV ratio differ from the rest of the sample, and then to modify our regression accordingly. We produce a balance table akin to Table I in terms of the variable $HighLTV_i$ and summarize the results in Appendix Table A.III.

Relative to hotels in the bottom two-thirds of the LTV distribution, those with a top-tercile LTV ratio: are made to larger borrowers; have longer terms; are more likely to be operated by the brand, as opposed to the franchisee or a third party; had lower revenue in 2019; and are assigned more-stringent special servicers, based on the servicer's historical propensity to foreclose on delinquent borrowers. We evaluate whether these correlations drive the results in columns 1–2 of Table V by interacting the correlate in question with our treatment variable and with a vector of month fixed effects. The differential treatment effects for hotels with a high LTV range from 34 to 44 log points, which lie close to the uncontrolled specification in column 2 (42 log points) and so support its validity.

Columns 3 and 5 of Table V merit additional discussion. Column 3 finds that the treatment effect does not vary by the borrower's size, measured by log real estate assets owned in June 2023. We interpret this variable as a proxy for the borrower's total liquid assets. Under that interpretation, the estimated lack of heterogeneity goes against the cash channel, which would

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[22]Appendix Table A.IV verifies that these findings are not driven by the precise specification of the $HighLTV_i$ variable: columns 1–2 trace out the treatment effect tercile-by-tercile, finding that it is monotonically increasing; and column 3 estimates a linear-quadratic specification in the LTV ratio, finding that the treatment effect has a convex relationship with the LTV ratio.

predict that larger borrowers have a smaller drop in output.

Next, column 5 shows how the estimated treatment effect is 11 log points larger for hotels with a special servicer whose historical propensity to foreclose is one standard deviation larger. This result is broadly consistent with the strategic channel: a borrower with a historically-stringent special servicer may expect to lose the hotel in foreclosure and, so, has less incentive to maintain it.

Together, these findings support the basic intuition of debt overhang: hotels with a pandemic maturity reduce operations because their limited equity stake in the property disincentivizes them from maintaining it. That said, the original Myers (1977) notion of debt overhang was conceived in a simpler setting than our empirical environment. So, it would be premature to conclude that our results work through debt overhang without thinking through important theoretical subtleties related to the nature of investment, the timing of the effect, and expectations of financial distress in our setting relative to the settings of canonical models. Accordingly, the next section investigates whether our empirical results logically fit together in a model that preserves the same Myers (1977) intuition.

V MODEL

The goal of our model is to explain how an upcoming debt maturity can lead to an immediate decline in output, expenses, and profits at the onset of a crisis. Motivated by our empirical findings, we present a model in which classic debt overhang, not cash flow constraints, drives the results. We calibrate our model to show that it can quantitatively match the effects we find in the data under realistic parameter values.

V.A Model Setup

Production Environment

Time, denoted by t, is continuous. There are two possible states of the economy, indexed by j: normal times ($j = 0$) and a pandemic ($j = 1$). We assume that the economy begins in normal times at $t = 0$ and that a pandemic *unexpectedly* arrives at a time that we denote by $t_p > 0$. Once the pandemic arrives, the economy transitions back to normal times with constant Poisson hazard q, known to all agents.

The firm produces output that it sells in competitive markets at a state-dependent price $p(j) > 0$. To reflect the fact that demand for the firm's output is lower during the pandemic than normal

times, we assume that $p(1) < p(0)$. The production function is Cobb-Douglas:

$$F(L_t, K_t, M_t) = L_t^\alpha K_t^{1-\alpha-\beta} M_t^\beta, \tag{4}$$

where $0 < \alpha, \beta$ and $\alpha + \beta < 1$. Variable inputs, such as labor and electricity, are denoted by L_t, and the price of these inputs is w. Physical capital, like building square footage, is denoted by K_t.

We assume that the stock of physical capital remains constant over time ($K_t = K$), and focus instead on the incentive to invest in management practices, M_t. Bloom and Reenen (2007) and Bloom et al. (2019) provide empirical evidence that better management practices increase output, and Bloom, Sadun and Reenen (2017) propose equation (4) as a firm production function. In our setting, management practices combine process innovations that are suited to normal times, $M_{0,t}$, with those suited to a pandemic, $M_{1,t}$, as follows:

$$M_t = M_{0,t}^{1-\zeta(j)} M_{1,t}^{\zeta(j)}, \tag{5}$$

where $0 \leq \zeta(j) \leq 1$. As a simplification, we assume that $\zeta(0) = 0$, which implies that pandemic-specific management practices are useless during normal times. However, these pandemic-specific management practices do become useful during the pandemic, which means that $\zeta(1) > 0$.

Managerial Investments

At any time, the owner of the firm can choose to make an *adaptive investment* that increases the firm's pandemic-specific management practices at a unit cost of c. Management practices do not depreciate, so an adaptive investment of I_t permanently raises the stock of pandemic-specific management practices by I_t. For simplicity, we assume that the initial stock of pandemic-specific management practices, $M_{1,0}$, is equal to 0. Because we focus primarily on adaptive investments, we abstract from investments in normal-time management practices by assuming that their level remains fixed over time ($M_{0,t} = M_0$).

Debt

At time 0, the firm is born encumbered by debt that comes due at fixed intervals of time. As in other models of debt rollover, the face value of debt and the frequency at which it comes due are specified outside the model and are taken as given by the owner of the firm (Leland and Toft, 1996; Leland, 1998; He and Xiong, 2012; Diamond and He, 2014). In our setting, the debt has a maturity of T units of time at origination. It mandates a payment of D at maturity and zero coupons before that.

At maturity, the owner of the firm either defaults or rolls over the debt. In the case of a

rollover at time t, the firm owner pays D to the lender and then receives $\widetilde{D}_t$ in exchange for the new obligation to pay the face value of debt, D, at time $t + T$. In the case of default, the lender takes possession of the firm which consists of the physical capital stock, K, as well as the managerial capital stocks, M_0 and $M_{1,t}$. Importantly, management practices attach to the firm, so the borrower cannot institute these management practices at another firm without paying additional costs. The lender is risk neutral and discounts future cash flows at rate r. The amount the lender disburses at rollover, $\widetilde{D}_t$, equals the discounted expected value of the lender's new debt claim at time t.

An important object for studying the effects of rollover risk during the pandemic is the amount of time remaining until the next scheduled rollover when the pandemic begins. We denote this amount of time by $\tau = \lceil t_p / T \rceil \times T - t_p$, where $\lceil \cdot \rceil$ is the ceiling function.

V.B Borrower Optimization

The borrower maximizes the net present value of cash flow to equity by choosing the variable input, L_t, the adaptive investment, I_t, and whether to default or roll over the debt at maturity. Like the lender, the borrower discounts cash flows at rate r. In this subsection, we characterize the borrower's decisions about adaptive investments and debt rollover both in normal times and in the pandemic.

Optimization During Normal Times

In normal times, the borrower's decisions are relatively simple, and we describe them in Proposition 1 (proofs of Propositions appear in Appendix B).

Proposition 1. *In normal times, the borrower's chosen level of adaptive investments, I_t^*, equals 0. The borrower rolls over the debt at each maturity if $D < V^*$ and defaults at maturity if $D > V^*$, where $V^* = r^{-1}(1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}} p(0)^{\frac{1}{1-\alpha}} w^{-\frac{\alpha}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M_0^{\frac{\beta}{1-\alpha}}$ is the net present value of the maximized cash flows from operating the firm.*

Because pandemic-specific management practices are not useful during normal times, the borrower chooses not to pay the cost needed to make adaptive investments. Therefore, $I_t^* = 0$ in normal times. The borrower defaults when the face value of the debt, D, exceeds the net present value of the maximized cash flows from operating the firm, V^*. When the face value of the debt is smaller than this threshold, the borrower always chooses to rollover during normal times. For the rest of the analysis, we restrict attention to this case of $D < V^*$.

Optimization During the Pandemic

When the pandemic begins, the price of the firm's output falls, and pandemic-specific management practices become relevant. In Proposition 2, we describe how adaptive investments and default behavior change in response to this unexpected shock to parameter values.

Proposition 2. *When the pandemic begins at time t_p, the borrower makes the following lump-sum adaptive investment:*

$$
I^*_{t_p} = \begin{cases} \widetilde{I}, & D < D^*(\tau) \\ \widetilde{I} \times \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}, & D > D^*(\tau), \end{cases} \tag{6}
$$

where $\widetilde{I} > 0$ is a constant and $D^*(\tau)$ is an increasing function of τ. The borrower makes no further adaptive investments during the pandemic: $I^*_t = 0$ for $t > t_p$. The borrower rolls over the debt at each pandemic maturity when $D < D^*(\tau)$ and defaults at pandemic maturity if $D > D^*(\tau)$. If the unit cost of adaptive investments, c, is sufficiently large, then $D^*(\tau) < V^*$ for all τ.

When pandemic-specific management practices become relevant at time t_p, the borrower responds by making an adaptive investment. Because the probability that the pandemic ends remains constant throughout the pandemic, it is optimal for the borrower to make the entire adaptive investment up front. Therefore, there are no further adaptive investments once the pandemic begins: $I^*_t = 0$ for $t > t_p$.

Importantly, the size of the investment the borrower makes at pandemic onset depends on both the level of the firm's debt going into the pandemic, D, as well as the remaining time until that debt matures, τ. The reason for this is the anticipation of default if the pandemic lasts until the maturity date. When the face value of debt is sufficiently low, the borrower anticipates rolling over the debt at maturity even if the pandemic is still ongoing. In this case, the borrower makes an adaptive investment, $\widetilde{I}$, that reflects the fact that she expects to reap its benefits for the entire duration of the pandemic. In contrast, when the debt value is high, the borrower expects to default at maturity if the pandemic is still ongoing at that time.[23] Consequently, the borrower makes a lower adaptive investment, as she expects to reap its benefits for at most τ units of time. This adaptive investment depends positively on τ because the investment is larger if the borrower expects to benefit from it for longer.

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[23] As stated in Proposition 2, this default region is guaranteed to appear only if the investment cost, c, is sufficiently large. If c is small, then the pandemic can actually raise the value of the firm by leading to a productivity boost coming from management practices that exceed M_0, the level during normal times. In this case, the borrower always rolls over the debt.

Real Effects of Debt Rollover During the Pandemic

The adaptive investment made at pandemic onset, $I^*_{t_p}$, determines real outcomes during the pandemic. A larger adaptive investment boosts management practices during the pandemic, leading to higher levels of chosen inputs, outputs, and operational profit. Therefore, differences in adaptive investments directly translate into differences in real outcomes during the pandemic. Proposition 3 characterizes how these differences depend on the time until the next scheduled rollover at pandemic onset, τ.

Proposition 3. *Let $Y^*(\tau)$ denote the borrower's chosen level of the variable input during the pandemic, or the associated levels of output or operational profits. If $\tau_1 < \tau_2$, then*

$$Y^*(\tau_2) - Y^*(\tau_1) \geq 0,$$

with equality if $D < D^*(\tau_1)$ and strict inequality if $D > D^*(\tau_1)$.

Proposition 3 explains our empirical results in the context of our model. By definition, hotels in the treatment group have low values of τ, as their debt is scheduled to mature within a year of pandemic onset. In contrast, hotels in the control group, who faced a debt rollover event in the year before the pandemic, likely refinanced and therefore have high values of τ. Therefore, holding everything else constant, Proposition 3 predicts that real outcomes for treated hotels should be weakly less than real outcomes for control hotels during the pandemic. Moreover, any differences in real outcomes between the two groups should be driven by hotels with high levels of debt going into the pandemic. These differences should arise immediately upon pandemic onset, as they are driven entirely by differences in lump sum adaptive investments occurring at that time. Proposition 3 also predicts that drops in revenue within the treatment group should be larger for hotels that are closer to maturity at pandemic onset, which is consistent with Table III.

V.C Calibration

Parameter Values

We calibrate the model to see whether a reasonable parametrization can produce the magnitude of our empirical results. Calibrating the model requires taking a stand on M_0, the level of normal-time management practices before the pandemic. We set M_0 equal to the value that maximizes the net present value of the firm in normal times, net of the cost of investing in these management practices. We assume that the unit cost of such investments is c, the same as the unit cost for

adaptive investments.[24] In Appendix C, we report the implied value of M_0.

We focus on the ratio of revenues, output, profits, and inputs during the pandemic to their level before the pandemic. As we show in Appendix C, these ratios depend only on the following parameters: D/V^*, τ, q, r, α, β, $\zeta(1)$, and $p(1)/p(0)$. To calibrate α, we use the average ratio of variable expenses to revenue in our data before the pandemic, which is 0.7; we show in Appendix C that this ratio equals α. To calibrate β, we use an estimate from Bloom, Sadun and Reenen (2017), who calculate that the management share of the production function is 0.1. We use a discount rate of $r = 0.1$, in line with discount rates used to value unlevered hotel investments in 2019 (hotelAVE, 2019). We set $p(1)/p(0) = 0.8$, which matches the approximate drop in room rates observed in our data during the pandemic relative to before. We set $q = 1/4$, representing an expected pandemic length of 4 years, corresponding to the forecasts discussed in Section II. Calibrating q to ex-ante forecasts is important. Indeed, Appendix Figure A.IV documents a low cumulative foreclosure rate of 5.3% among loans in our treatment group through June 2022, and using that realized rate to calibrate q would generate predictions that are inconsistent with what we find empirically.

The remaining parameters are D/V^*, τ, and $\zeta(1)$. Rather than choose a single value for τ, we form two groups of firms corresponding to the treated and control firms in our data. In the control group, the remaining time to maturity when the pandemic begins, τ, is uniformly distributed between $T-1$ and T. In the treated group, τ is uniformly distributed between 0 and 1. The uniform distribution is consistent with Appendix Figure A.I. We choose T, the maturity at origination, to be 5 years, corresponding to the average maturity at origination in Table I. We show results for the full range of initial LTV (D/V^*) between 0 and 100%. Finally, we choose $\zeta(1)$ to match the treatment effect in column 1 of Table V of -0.275 on log revenues for highly levered firms.

Results

We plot the results in Figure X, showing revenues in Panel A and other outcomes in Panel B. For low values of LTV below 74%, the treated and control groups experience the same outcomes during the pandemic. In particular, revenues fall to about half of their pre-pandemic levels, which is reassuringly close to the data in Figure III. For such firms, there is no debt overhang, as borrowers make the adaptive investment $\widetilde{I}$, which is the optimum with no default. Outcomes fall because of the real effects of the pandemic itself.

For larger debt levels, outcomes during the pandemic become lower for both control and treated groups, reflecting the debt overhang coming from the possibility of defaulting if the pan-

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[24]This assumption implies that the ratio of real outcomes during the pandemic to before the pandemic does not depend on c, so that we do not need to take a stand on the value of c.

demic continues until maturity. This overhang is much larger for firms in the treated group, as there is less time until maturity, leading to a lower adaptive investment, as shown in Proposition 2. The log of the ratio of the treated and control outcomes for highly levered firms is −0.275, which matches the effect in Table V. We choose $\zeta(1) = 0.379$ to match this effect, implying that about one third of the managerial practices required to run a hotel during the COVID crisis were specific to the pandemic and not in place before that. To match the highest treatment effect of −0.442 in Table V, we require a value for $\zeta(1)$ of 0.566, implying a specificity of management practices during the pandemic of almost two thirds. The magnitudes of these estimates for $\zeta(1)$ strike us as plausible, given the degree of upheaval and amount of adaptation required to operate hotels during the early part of the pandemic.

Our calibration is also consistent with the results in Table III showing a larger treatment effect for hotels with loans scheduled to mature in the first six months of the COVID pandemic. To show this consistency, we calculate the average drop in revenue when τ, the time until maturity at pandemic onset, is uniformly distributed between 0 and 0.5 years, and we likewise calculate this average when τ is between 0.5 and 1 year. We subtract from these the average revenue drop for control hotels. In our baseline calibration that matches a treatment effect for highly levered firms of −0.275, this exercise implies a treatment effect for hotels with an early pandemic maturity of −0.369 and those with a late pandemic maturity of −0.181. The treatment effect for the first group is double that of the second, which matches the result in Table III.

In summary, this calibration reproduces the large, negative effect of pandemic debt maturities on operational outcome during the pandemic for highly levered firms. The effect comes solely through debt overhang arising from adaptive investments that firms make to boost productivity during the crisis and not from any cash flow constraints.

VI Conclusion

This paper documents that the need to roll over mortgages in a crisis leads commercial real estate investors to strategically reduce operations at the encumbered property, leading to significant drops in output and labor spending. Our evidence comes from the hotel sector during the COVID-19 pandemic. We specifically document substantial declines in real activity at hotels with mortgages scheduled to mature just after the pandemic's onset, relative to hotels with mortgages scheduled to mature just before.

Our work highlights the potential macroeconomic risks of the way that many owners of commercial real estate finance their investments, via mortgages with large balloon maturities. These balloon maturities make the owners vulnerable to economic problems that occur near the maturity date. To the extent that these problems are correlated across borrowers, the common use of

these mortgages can expose the economy to substantial risk given the size and importance of the commercial real estate sector. While it is possible that this mortgage structure is optimal from an ex-ante perspective, our work highlights the potential ex-post costs it can generate. We hope that future research will explore why, from a contract design perspective, commercial mortgages feature such large balloon payments.

Going forward, the negative real effects that we document may also apply to other commercial property sectors with maturing debt that cannot be rolled over. Practitioners have recently voiced concerns over this possibility, especially in the context of the office and retail sectors, both of which have large amounts of debt maturing over the next three years and face economic headwinds from trends in remote work and e-commerce (Putzier, 2023).

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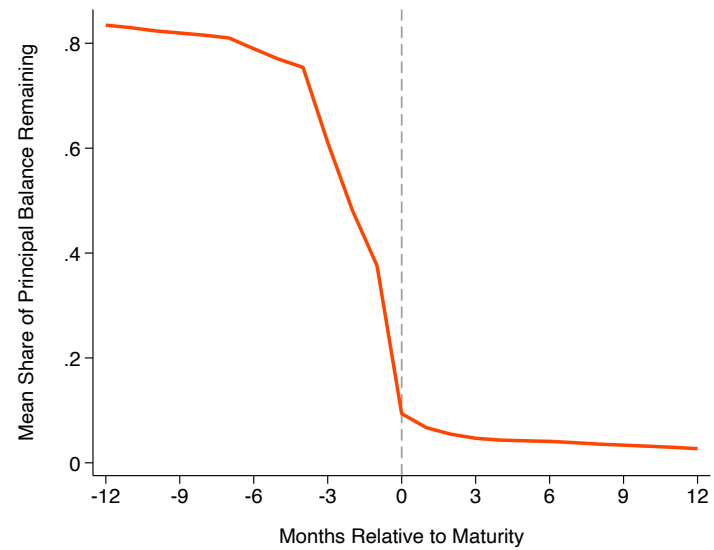
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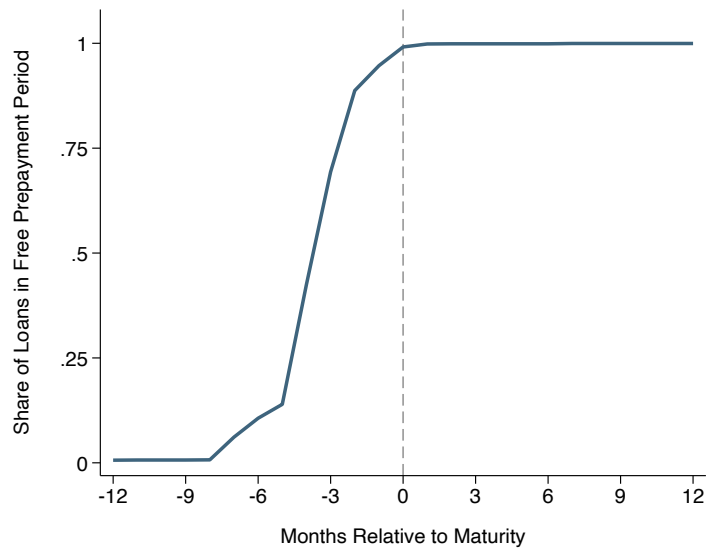
Panel A. Loans in Free Prepayment   *Panel B. Principal Balance Remaining*

FIGURE I

Key Features of Hotel Loans. Prepayment Penalties and Principal Balance Remaining at Maturity.

NOTE.—This figure plots the typical dynamics of prepayment penalties and principal payoff around a loan's original maturity date. The horizontal axis shows the number of months relative to the loan's maturity date as of origination. The vertical axis in Panel A. shows the share of loans that have passed their prepayment lockout period and that can prepay without penalty or yield maintenance. Panel B. plots the average share of principal outstanding. The sample period covers all loans with initially scheduled maturities between January 2006 through January 2020. The sample consists of all hotel loans in the Trepp dataset with the modal loan term (10 years) to ensure that the horizontal axis consistently measures a loan's age. (SOURCE: Trepp)
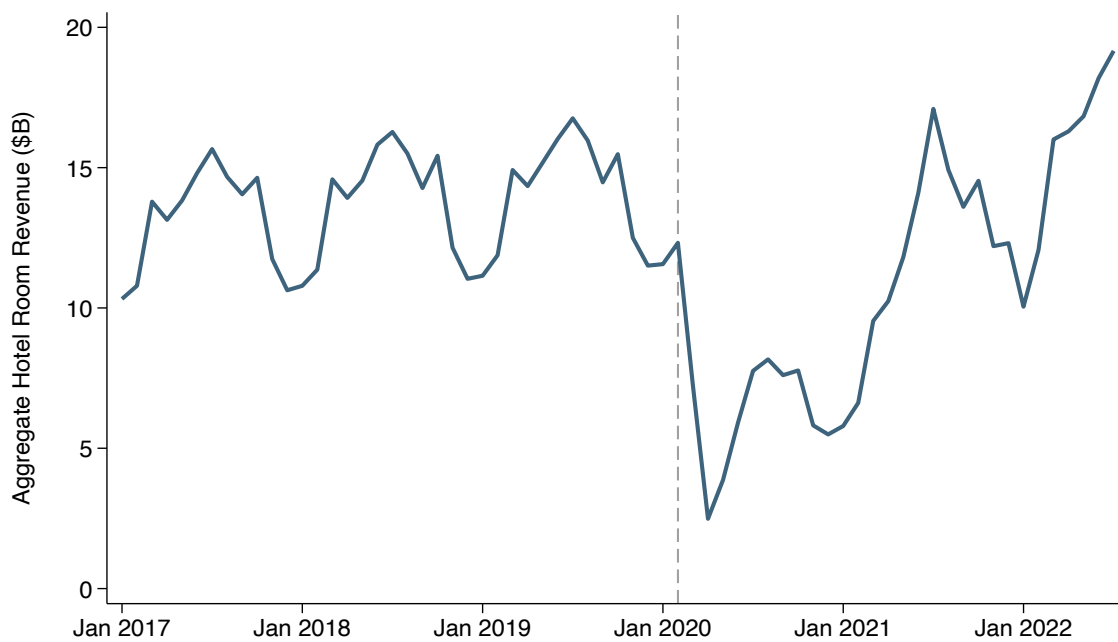
FIGURE II

Aggregate Monthly Revenues for US Hotels.

NOTE.—This figure plots aggregate monthly room revenue for all hotels in STR's universe, of which our analysis sample is a subset. The STR universe comprises 98% of U.S. hotels. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. (SOURCE: STR, LLC)
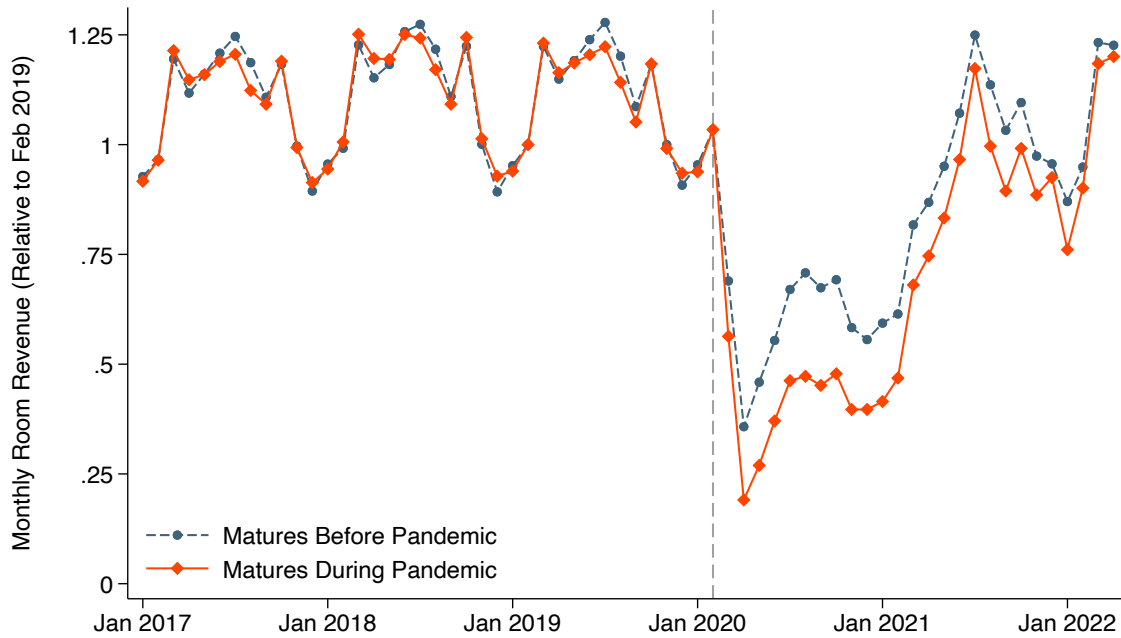
FIGURE III

Monthly Hotel Room Revenues by Scheduled Loan Maturity at Origination.

NOTE.—This figure plots the time series of total monthly room revenue, averaged separately across hotels with loans maturing between January 2019 to January 2020 (Before Pandemic) and those with loans maturing between February 2020 to February 2021 (During Pandemic). Loan maturities are measured as of origination. The average is normalized by the February 2019 value for each maturity cohort. Data on loan maturities are from the Trepp dataset. Data on hotel revenue are from the STR performance dataset (SOURCE: STR, LLC and Trepp)
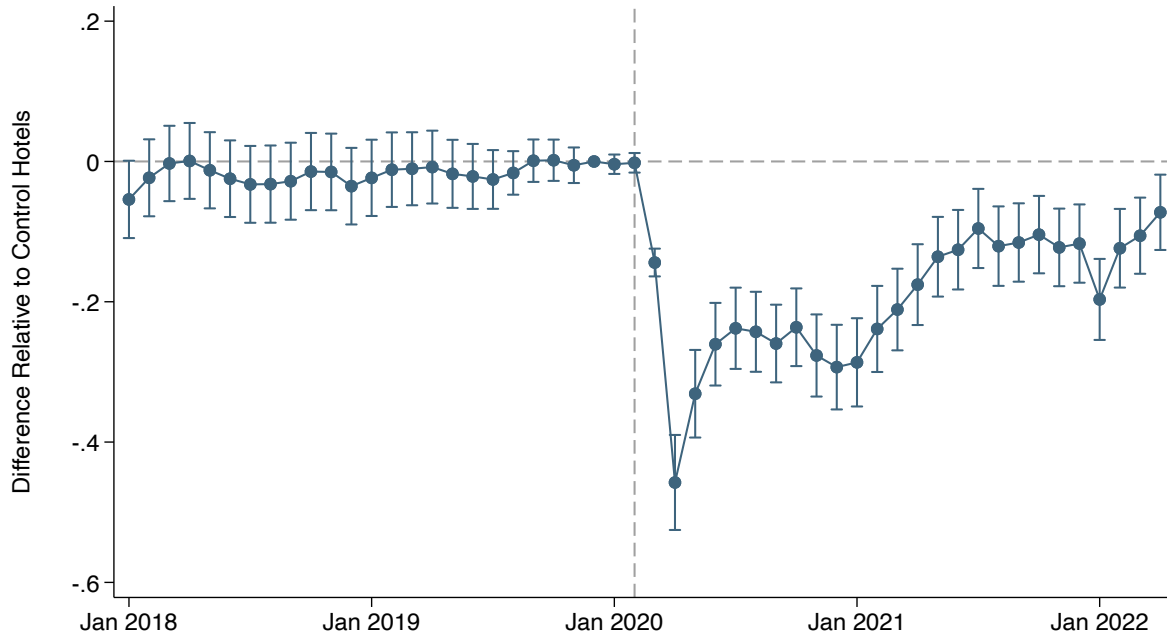
FIGURE IV

Effect of Pandemic Maturity on Hotel Room Revenues.

NOTE.—This figure estimates equation (2), which is an event study that accompanies the main difference-in-difference equation Table II. Explicitly, the figure plots the estimated coefficients $\{\beta_\tau\}$ from the equation

$$y_{imt} = \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\beta_\tau \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \Big] + \alpha_i + \delta_{mt} + \gamma X'_{it} + \epsilon_{it},$$

where i and t index hotel and month; the outcome y_{imt} is room revenue for hotel i, located in market m, in month t; and the remaining notation is the same as in Table II. The specification of X'_{it} corresponds to column 1 of Table II. Brackets are 95% confidence intervals for $\{\beta_t\}$. The remaining notes are the same as in Table II. (SOURCE: STR, LLC and Trepp)
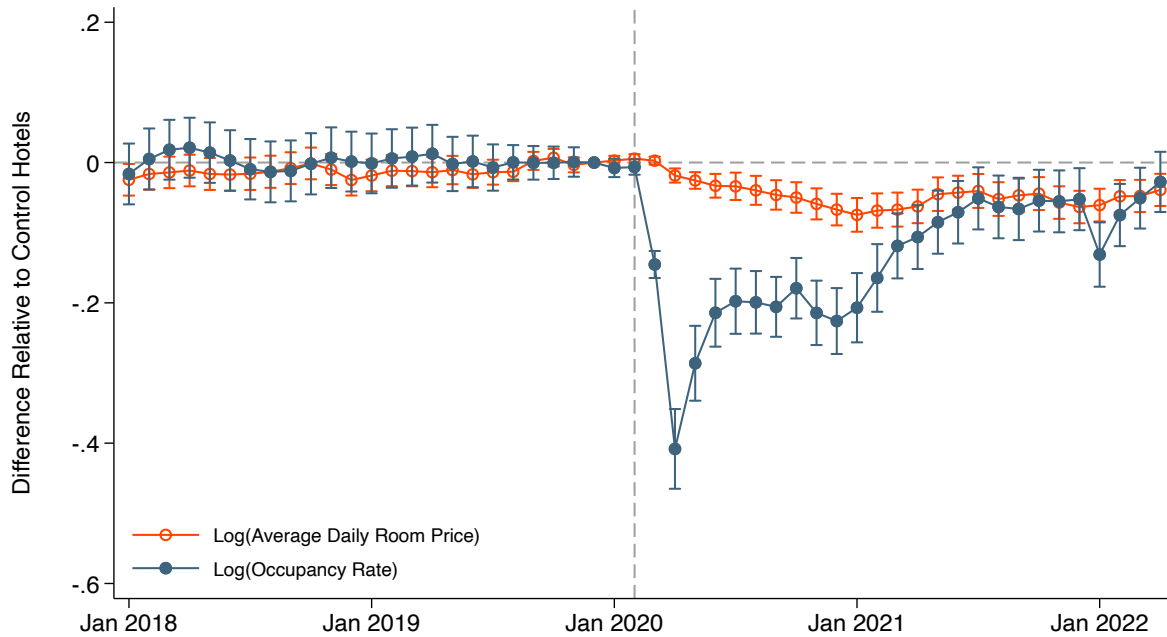
FIGURE V

Effect of Pandemic Maturity on Hotel Occupancy and Prices. Decomposing the Revenue Effect.

NOTE.—This figure decomposes the effect on revenue from Figure IV into the part that reflects reduced quantity (i.e., occupancy rate) and the part that reflects a lower room price. Explicitly, the figure summarizes the estimates from the same regression equation as in Figure IV after replacing the outcome variable with the log of the average daily room price and the log of the occupancy rate. These variables are related to total room revenue as follows,

$$RoomRevenue_{i,t} = RoomPrice_{i,t} \times OccupancyRate_{i,t} \times RoomStock_{i},$$

so the sum of the estimated coefficients each month in this figure approximately equals the estimated coefficient for the same month in Figure IV. The remaining notes are the same as in Figure IV. (SOURCE: STR, LLC and Trepp)
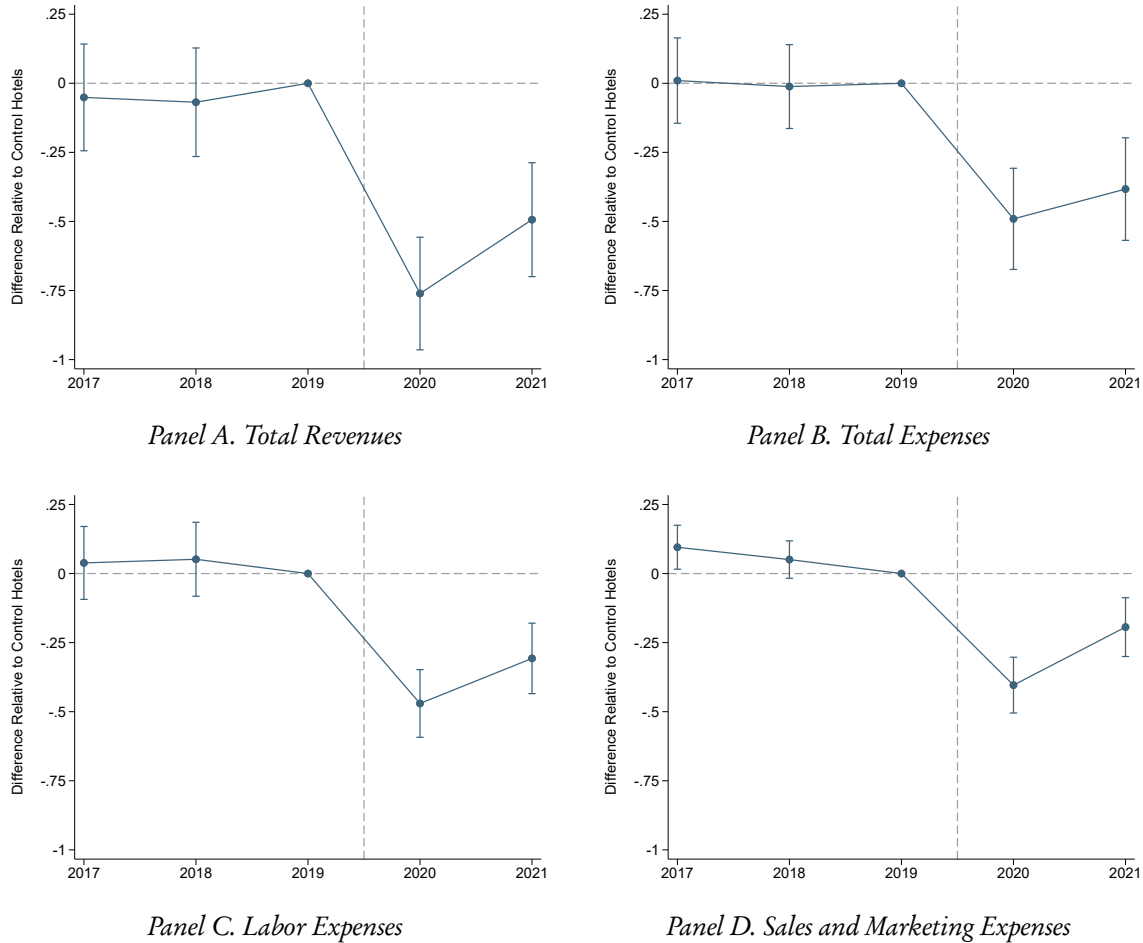
FIGURE VI
Effect of Pandemic Maturity on Hotel Revenues and Expenses.

NOTE.—This figure estimates a variant of equation (2) that assesses whether the effect on revenue from Figure IV reflects a cutting back of inputs by treated hotels. The regression equation is of the same form as that in Figure IV, except that the frequency is annual because the data on hotel expenses come from STR's annual profit and loss dataset. The treatment variable, $PandemicMaturity_i$, is still defined as it is in Figure IV. The definitions of all other variables are the same as in Figure IV after replacing "month" with "year". The outcomes in panels A-D are, respectively: log of total annual revenue, which includes room revenue and revenue from other hotel departments (e.g., food and beverage); log of total annual expense; log of total annual labor expense, which includes wages, salaries, and all other payroll expenses; and the log of annual expense on sales and marketing. The remaining notes are the same as in Figure IV. (SOURCE: STR, LLC and Trepp)
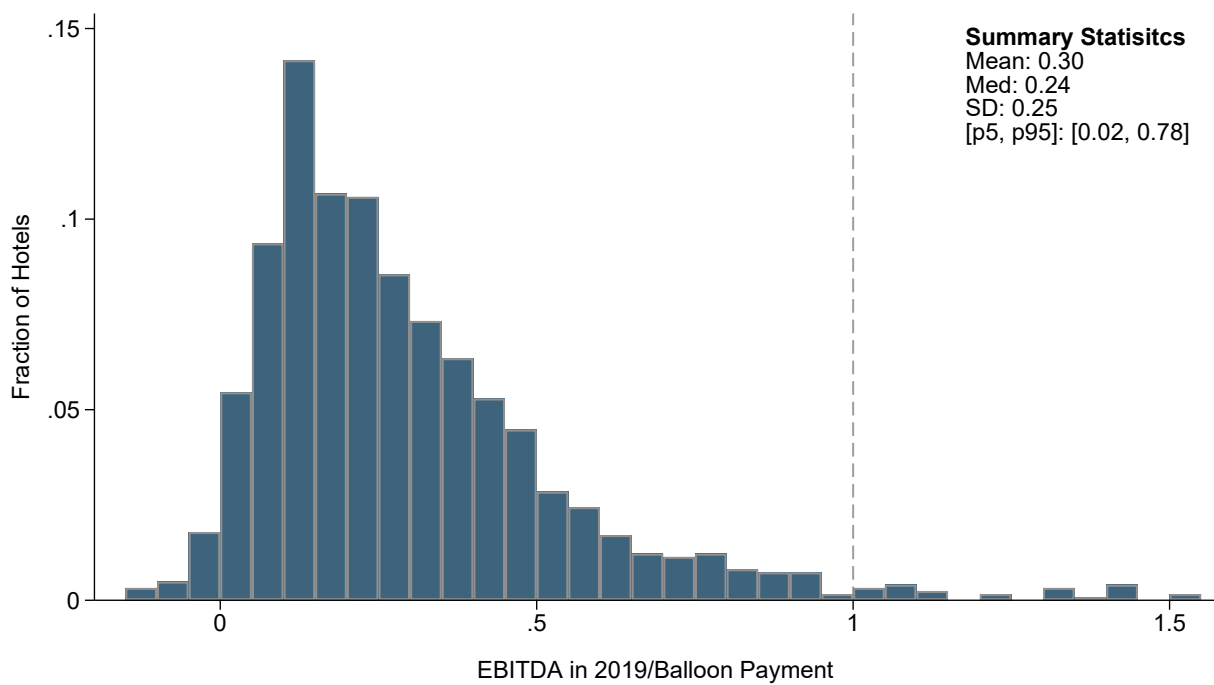
FIGURE VII

Assessing the Cash Flow Channel. Operating Profits Relative to Scheduled Balloon Payment.

NOTE.—This figure plots a histogram of the ratio of a hotel's EBITDA in 2019 to the required balloon payment at maturity on the hotel's loan, which assesses the plausibility of generating cash flow to pay off the loan. Data on EBITDA are from the STR profit and loss dataset. Data on scheduled balloon payments are from the Trepp dataset. (SOURCE: STR, LLC and Trepp)
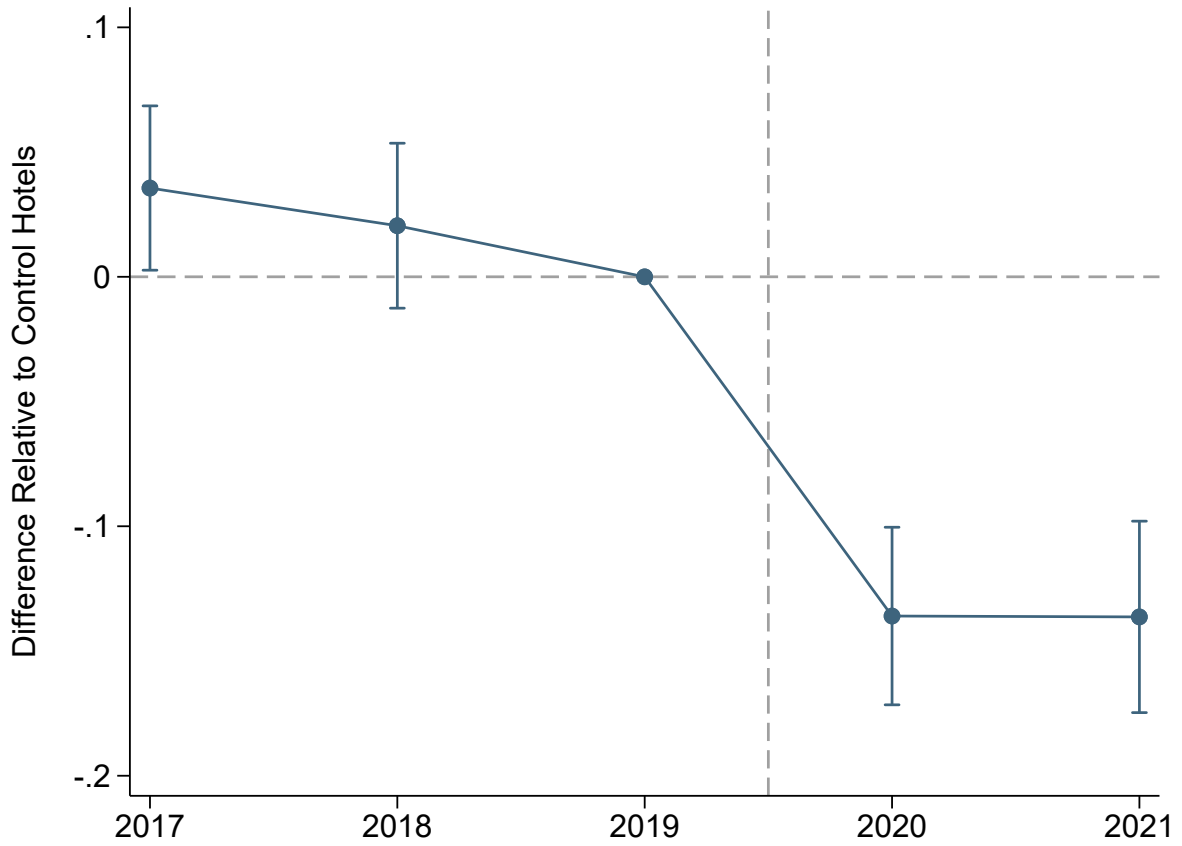
FIGURE VIII

Effect of Pandemic Maturity on Hotel Operating Profits.

NOTE.—This figure estimates a variant of Figure VI that assesses whether treated hotels experience an increase in operating profits, which would be consistent with the cash flow mechanism. The regression equation is the same as in Figure VI except that the outcome variable equals the hotel's annual operating profit, measured as the ratio of EBITDA in a given year to total revenue in a base year (2019). The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)

FIGURE IX

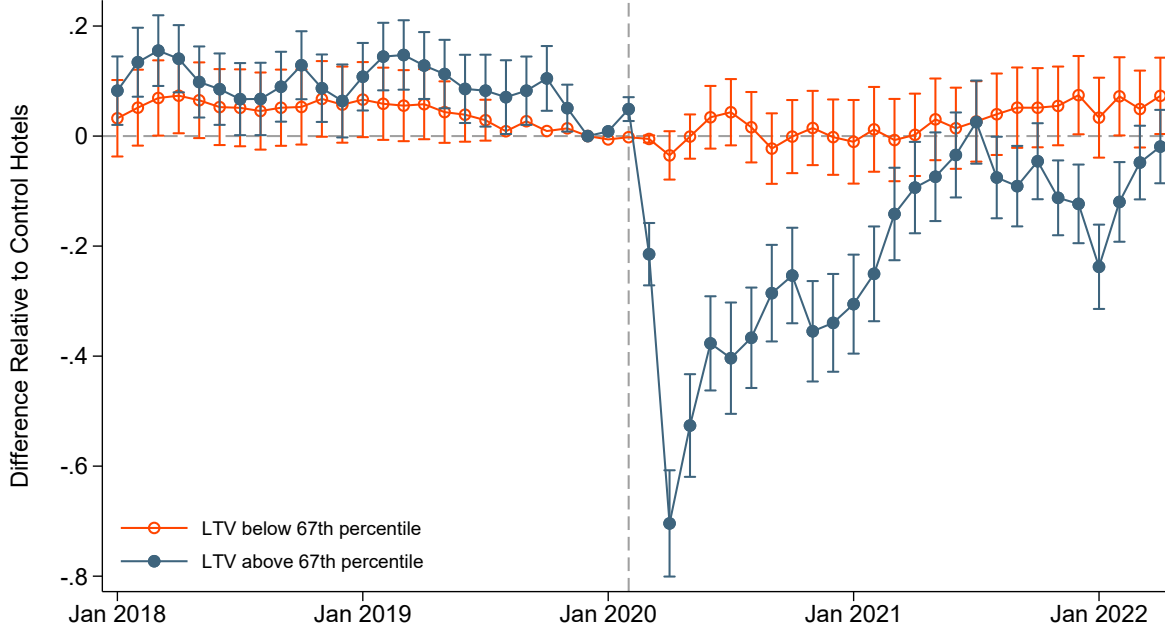Assessing Strategic Channels. Effect of Pandemic Maturity on Hotel Revenues by Initial LTV.

NOTE.—This figure estimates a variant of equation (2) that separates the results in Figure IV according to the strength of strategic motivations, as proxied by initial loan-to-value ratio. The regression equation is an event study analogue of the difference-in-difference equation in Table V,

$$
y_{imt} = \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\beta_{0,\tau} \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \Big] + \dots
$$

$$
\sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\beta_{1,\tau} \times PandemicMaturity_i \times HighLTV_i \mathbb{1}_{t=\tau} \Big] + \dots
$$

$$
\gamma_0 X_{it}' + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\gamma_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \Big] + \alpha_i + \delta_{mt} + \epsilon_{it},
$$

where the notation is the same as in Table V. In particular, $HighLTV_i$ indicates if the initial LTV ratio is in the top one-third across hotels in the estimation sample (i.e., above the 67th percentile), corresponding to an LTV ratio of 80%. The figure plots the estimated coefficients, $\beta_{0,\tau}$, which measure the effect for hotels in the bottom two terciles of the LTV distribution, and the sum of the coefficients, $\beta_{0,\tau} + \beta_{1,\tau}$, which measure the effect for hotels in the top tercile. Brackets are 95% confidence intervals. The remaining notes are the same as in Figure IV. (SOURCE: STR, LLC, Trepp, and RCA)
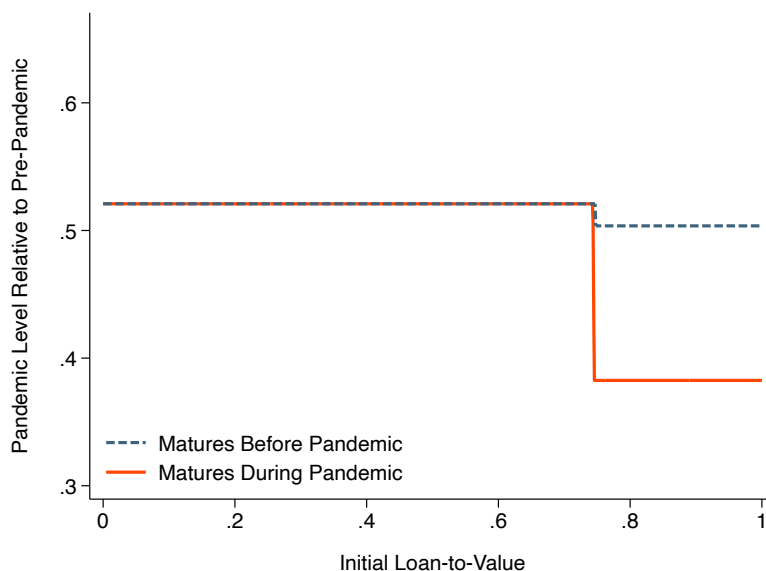
Panel A. Revenues
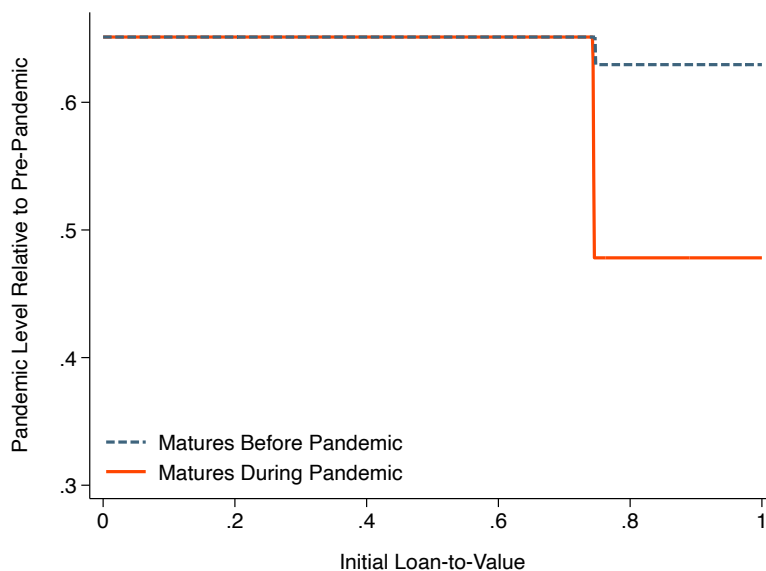
Panel B. Output, Profits, and Labor Inputs

FIGURE X

Model-Implied Drop in Outcomes at Pandemic Onset.

NOTE.—This figure explains the estimated drop in hotel revenue and other outcomes from Figure IX using the model from Section V. Panel A plots the ratio of revenue after the pandemic to revenue before the pandemic for hotels with a loan that matures before versus after the pandemic. The ratio is shown as a function of the hotel's loan-to-value ratio (LTV) before the pandemic. The log difference in revenue for hotels with a pandemic during the pandemic versus before equals −0.275, which matches the effect in column 1 of Table V. Panel B contains a similar plot in terms of output, profits, and inputs. According to Proposition 1, the ratio of pandemic to pre-pandemic values for output, profits, and inputs all have the same expression, which is why the model-implied drop for all three variables is the same. Additional details on the model and calibration are in Section V.

TABLE I
DESCRIPTIVE STATISTICS

	Pre-Pandemic Maturity		Post-Pandemic Maturity	
	Mean	Std. Dev.	Mean	Std. Dev.
Hotel Performance (May 2019)				
Log(Room Revenue)	12.27	(0.71)	12.48	(0.86)
Log(Rooms Occupied)	7.87	(0.44)	8.04	(0.48)
Log(Average Daily Room Price)	4.41	(0.44)	4.44	(0.54)
Occupancy Rate	0.75	(0.13)	0.73	(0.13)
Hotel Location				
Urban	0.08	—	0.10	—
Suburban	0.66	—	0.61	—
Small Town	0.07	—	0.06	—
Airport	0.10	—	0.12	—
Resort	0.04	—	0.05	—
Highway	0.05	—	0.07	—
Owner and Operations				
Log(Borrower Real Estate Assets)	24.31	(2.33)	23.97	(2.12)
Operated by Brand	0.42	—	0.64	—
REIT	0.23	—	0.08	—
Loan Characteristics at Origination				
Servicer Stringency	−0.33	(0.81)	0.61	(1.03)
Log(Loan Amount)	20.58	(1.36)	19.36	(1.39)
Loan-to-Value Ratio (LTV)	0.78	(0.09)	0.59	(0.20)
Debt-Service Coverage Ratio (DSCR)	3.78	(0.89)	3.49	(1.33)
Loan Term (Months)	68.02	(27.59)	56.20	(25.37)
Balloon Flag	1.00	—	0.99	—
Number of Hotels	1,655		955	

NOTE.—This table summarizes hotels based on whether the hotel has a loan with original maturity date from February 2019 through January 2020 (Pre-Pandemic Maturity) or February 2020 through February 2021 (Pandemic Maturity). The Hotel Performance panel summarizes hotel performance observed in May 2019. The Hotel Location panel summarizes indicator variables for whether the hotel categorizes its location as: close to an airport; a resort; urban; suburban; or close to the highway. The Owner and Operation panel summarizes characteristics of the hotel's owner and the hotel's operating arrangement. Borrower real estate assets are the borrower's total dollar real estate holdings in the U.S. as of June 2023. The alternative arrangements to "operated by brand" are either cases where the franchisee operates the hotel or partners with a third party (95% of cases) or cases where the hotel is unbranded (5% of cases). The Loan Characteristics panel summarizes characteristics of the hotel's loan, all measured as of origination. The variable Servicer Stringency is the share of delinquent loans on which the loan's special servicer foreclosed over 2005-2019, normalized to have unit variance. The debt service coverage ratio is the ratio of debt service to operating income. The balloon flag indicates whether the hotel has a balloon amortization. Data on loan maturities and the variables in the Loan Characteristics panel are from the Trepp dataset. The LTV ratios from Trepp are modified to account for second-liens observed in the RCA dataset. Data in the Performance and Location panels are from the STR performance and cross-sectional datasets, respectively. Data on borrower-level variables in the Owner and Operation panel are from RCA. Additional details are in Section II and Appendix A. (SOURCE: STR, LLC, Trepp, and RCA)

TABLE II
EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES

	(1)	(2)	(3)	(4)	(5)
PandemicMaturity × Post	−0.171***	−0.126***	−0.180***	−0.182***	−0.192***
	(0.024)	(0.020)	(0.025)	(0.025)	(0.037)
Hotel FEs	X	X	X	X	X
Post Maturity FE	X	X	X	X	X
Market × Month FEs	X	X	X	X	X
Size × Month FEs		X	X	X	X
Operation Type × Month FEs			X	X	X
Location Type × Month FEs				X	X
Origination Year × Month FEs					X
Number of Observations	133,095	133,095	133,095	133,095	133,095

NOTE.—This table estimates equation (1), which tests for a difference between treated hotels with a loan maturity during the pandemic and control hotels with a loan maturity beforehand. The regression equation is

$$\log(Revenue_{imt}) = \beta \cdot PandemicMaturity_i \times Post_t + \alpha_i + \delta_{mt} + \gamma X'_{it} + \epsilon_{it},$$

where $Revenue_{imt}$ is room revenue for hotel i, located in market m, in month t; $PandemicMaturity_i$ is a treatment indicator equal to one if hotel i has a loan that was initially scheduled to mature during the 12-month period following the beginning of the pandemic in February 2020 and equal to zero if the hotel had a loan maturing during the 12-month period before the pandemic began; $Post_t$ is an indicator equal to one if month t falls on or after February 2020; α_i and δ_{mt} are hotel and market-by-month fixed effects, respectively; and X'_{it} contains various combinations controls. All columns control for the effect of the loan life cycle with an indicator for whether t equals or exceeds the month of the maturity date of the loan on hotel i (Post Maturity FE). The other controls are fixed effects for bins defined by month and: hotel size, in number of rooms (Size × Month FEs); whether the hotel is brand-managed, branded but not managed by the brand, or unbranded (Operation Type × Month FEs); location type, which can take the values shown in Table I (Location Type × Month FEs); and year of origination (Origination Year × Month FEs). Details are in Section III. The sample includes all hotels in the merged STR and Trepp datasets with a loan initially scheduled to mature within a 12-month bandwidth of February 2020. Standard errors twoway clustered by hotel and month are shown in parentheses. (SOURCE: STR, LLC and Trepp)

TABLE III

HETEROGENEITY IN EFFECT ON HOTEL REVENUES BY TIME TO MATURITY

	(1)
EarlyPandemicMaturity × Post	−0.188***
	(0.026)
LaterPandemicMaturity × Post	−0.098***
	(0.035)
Hotel FEs	X
Post Maturity FE	X
Market × Month FEs	X
Share of Treated Hotels with Later Maturity	0.196
Number of Observations	133,095

NOTE.—This table estimates a variant of equation (1) that replaces $PandemicMaturity_i$ with two separate variables that indicate whether the loan has an initial maturity: within the first six months that define a pandemic maturity (February 2020 through August 2020); or within the latter six months (September 2020 through February 2021). These two variables are denoted EarlyPandemicMaturity and LaterPandemicMaturity in the table, respectively. The remaining notes are the same as in Table II. (SOURCE: STR, LLC and Trepp)

TABLE IV

EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES: ALTERNATIVE BANDWIDTHS

	Scheduled Maturity			Free Prepayment
	(1)	(2)	(3)	(4)
PandemicMaturity × Post	−0.171***	−0.186***	−0.272***	−0.110***
	(0.024)	(0.025)	(0.034)	(0.033)
Hotel FEs	X	X	X	X
Post Maturity FE	X	X	X	X
Market × Month FEs	X	X	X	X
Bandwidth (Months)	12	18	6	12
Number of Observations	133,095	148,975	104,957	62,624

NOTE.—This table assesses robustness of the main results in Table II to the definition of treatment and control groups. For reference, column (1) reproduces our main result from column (1) of Table II, in which treatment status is defined according to whether the loan on a hotel has an initial maturity within the 12 month window beginning in February 2020 (treated) or within the 12 month window ending in January 2020 (control). Columns (2)-(3) instead use bandwidths of 18 months and 6 months. Column (4) defines treatment status according to the first date on which the loan can prepay without penalty or yield maintenance, as opposed to the maturity date. The remaining notes are the same as in Table II. (SOURCE: STR, LLC and Trepp)

TABLE V
EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES BY LTV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PandemicMaturity × Post × HighLTV	−0.275***	−0.416***	−0.419***	−0.419***	−0.335***	−0.366***	−0.313***	−0.442***
	(0.050)	(0.100)	(0.100)	(0.098)	(0.110)	(0.102)	(0.077)	(0.104)
PandemicMaturity × Post	−0.023	0.064**	0.067***	0.090***	0.001	0.084**	−0.004	−0.163
	(0.019)	(0.025)	(0.024)	(0.029)	(0.032)	(0.032)	(0.030)	(0.119)
PandemicMaturity × Post × Log(BorrowerAssets)			0.004					
			(0.011)					
PandemicMaturity × Post × REIT				−0.147***				
				(0.053)				
PandemicMaturity × Post × ServicerStringency					−0.114***			
					(0.033)			
PandemicMaturity × Post × BrandOperated						−0.082*		
						(0.045)		
PandemicMaturity × Post × Log(Revenue19)							−0.015	
							(0.034)	
PandemicMaturity × Post × LoanTerm								0.004*
								(0.002)
Hotel FEs	X	X	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X	X	X
Market × Month FEs	X	X	X	X	X	X	X	X
HighLTV × Month FEs	X	X	X	X	X	X	X	X
Borrower × Month FEs		X	X	X	X	X	X	X
Interaction × Month FEs			X	X	X	X	X	X
Number of Observations	133,043	111,400	108,632	111,400	105,907	111,400	111,082	111,400

NOTE.—This table estimates a variant of equation (1) that assesses the role of strategic motivations in driving the main results in Table II. The regression equation is of the same form as equation (1) after interacting the treatment variable with an indicator for whether the hotel has a high initial loan-to-value ratio, a proxy for the strength of the strategic channel. Explicitly, the regression equation is

$$y_{imt} = \beta_0 \cdot PandemicMaturity_i \times Post_t + \beta_1 \cdot PandemicMaturity_i \times Post_t \times HighLTV_i + \psi_0 \cdot PandemicMaturity_i \times Post_t \times Interaction_i + \ldots$$

$$\gamma_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\lambda_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\psi_\tau \times Interaction_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

where $HighLTV_i$ indicates if the initial LTV ratio is in the top one-third across hotels in the estimation sample, corresponding to an LTV ratio of 80%; $Interaction_i$ is one of the other variables shown in the table that is also interacted with $PandemicMaturity_i \times Post_t$; and the remaining notation is the same as in Table II. Columns (2)-(8) include a vector of fixed effects for bins defined by borrower and month. The interaction variables are: the log of the borrower's total dollar real estate holdings as of June 2023 (Log(BorrowerAssets)); an indicator for whether the borrower is a REIT; the share of delinquent loans on which the loan's special servicer foreclosed over 2005-2019, normalized to have unit variance (ServicerStringency); an indicator for whether the hotel is operated by the brand; the log of the hotel's room revenue in May 2019 (Log(Revenue19)); and the loan's term, in months. Borrower and loan-level information are as of the date of origination. Data on LTV ratios are from Trepp and are modified to account for second-liens observed in RCA. The remaining notes are the same as in Table II. (SOURCE: STR, LLC, Trepp, and RCA)

For Online Publication: Internet Appendix

A DATA APPENDIX

This appendix provides full details on the paper's datasets.

A.A STR Datasets

As described in the text, we use data from Smith Travel Research (STR) to study hotel output, labor, and profitability. Briefly repeating the main details from the text in Section II: STR covers 98% of hotels and collects its data from partner hotels in exchange for providing research and benchmarking reports.

A.A.1 Anonymization Procedure

STR sustains its method of data collection through its reputation for preserving the anonymity of its clients. For researchers, this preservation of anonymity necessitates restricting the sample to a subset of hotels that satisfy certain criteria, such as a particular operating arrangement or geographic location. Given that our research design restricts to hotels with a loan maturing around the onset of the COVID-19 pandemic, we restrict our analysis to hotels with a maturity between January 2018 and December 2022.

We do so through the following protocol. First, we construct a list of all zip codes in the Trepp dataset that have a loan maturing between January 2018 and December 2022. Second, we obtain from STR a directory of all hotels with an address in one of these zip codes. This directory includes the address of the hotel, its universal STR identifier, and its name, which will subsequently be masked. Third, we match each hotel in the Trepp dataset to a hotel in the STR universe, achieving a 90% match rate. Section A.D elaborates on this procedure. Fourth, we return this crosswalk file from Trepp to STR, including the unique Trepp loan identifier and the other relevant loan-level variables described in Section A.B below. Lastly, STR returns to us four datasets with: an anonymized hotel identifier, called the SHARE identifier, which is unique across datasets; and the loan identifier and loan-level variables that we initially provided to STR. No variable in any of the four datasets provides enough information to uncover the identity of the hotel. We now describe these datasets and how we prepare them for our analysis.

A.A.2 Monthly Panel of Basic Performance

The first dataset is a daily hotel-level panel of basic performance metrics from January 2017 through June 2022. The metrics are: room revenue; occupancy rate; number of available rooms; number of occupied rooms; and average daily rate (ADR), defined as the average room price across occupied rooms. We often use the terms "price" and "ADR" synonymously in the text.

We aggregate the daily panel to a monthly panel by taking the sum of: room revenue; number of available rooms; and number of occupied rooms. We then redefine ADR at the monthly frequency by taking the ratio of room revenue to number of occupied rooms. Similarly, we redefine the occupancy rate as the ratio of occupied rooms to available rooms. There is very little empirical within-hotel variation in the reported number of available rooms, since STR defines

this variable essentially as a stock, not as a flow.[1]

STR does not have a closure field. We define a hotel as closed as follows. First, we flag whether the hotel does not report to STR within a given month. Then, for each spell of non-reporting, we calculate a hotel's occupancy in the month before it entered that spell. If the occupancy rate is less than 25%, then we define the hotel as closed during the ensuing non-reporting month. Otherwise, we define the hotel as open during the ensuing non-reporting month. Imposing a maximum occupancy threshold is important because, in the pre-pandemic period, there are several cases in which a hotel enters a non-reporting period for a short number of months with almost-full occupancy just before and just after the non-reporting spell. While, contractually, we cannot recover the identity of these hotels, we believe it is highly unlikely that such hotels actually were closed during that period. More likely, their non-reporting reflects administrative error. We choose a 25% threshold because it implies a hotel closure rate during the pandemic that matches the rate found among various industry reports. Our classification strategy has the same form as other academic papers studying STR's data (Steiner and Tchistyi, 2022). For months in which the hotel is closed, we code room revenue, room demand, and rooms available as zero, although this has no bearing on our results because we always take the log transform of these variables. We do not re-code the occupancy rate or ADR for closed hotels because they are undefined.

A.A.3 Yearly Panel of Operating Statements

The second dataset is a yearly panel of hotel profit and loss statements from 2017 through 2021. The hotels in the operating statement data comprise a 43% subsample of the hotels in the basic performance dataset. Broadly, the variables in each dataset can be grouped into the following categories:

- **Revenue by Hotel Department:** We observe total hotel revenue, revenue from rook bookings, revenue from food and beverage services, and revenue from various other hotel amenities (e.g., spa, golf).

- **Total Expense by Hotel Department:** We observe total hotel operating expense, room operating expense, and operating expense from the following departments: food and beverage; administrative and general; telecom; sales and marketing; and property operations and management. We also observe expense on utilities, insurance, taxes, and fees to the hotel management company, including base fee and incentive compensation.

- **Labor Expense by Hotel Department:** For each line item in the previous point, we observe the expense allocated to labor. We define labor expense as the sum of wages and additional payroll expenses.

A.A.4 Monthly Panel of Operating Statements

The third dataset is a monthly panel of hotel profit and loss statements, which contains the same variables as in our annual dataset at a monthly frequency. The data begin in January 2020,

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[1]This is because STR explicitly advises its partner hotels to report a room as unavailable only if it is "closed for an extended period of time (typically over six months) due to natural or man-made disaster" or "all operations of a hotel are closed for a minimum of 30 consecutive days due to seasonal demand patterns" (STR (2019)). In particular, "There should be NO adjustment in room availability reported to STR if rooms temporarily are out of service for renovation."

which is when STR began collecting monthly operating statements.

A.A.5 Cross-Sectional Dataset

The fourth dataset is a cross-section of hotels. We observe the following characteristics as of January 2022, when we obtained the data:

- **Size and Market:** We observe the hotel's total stock of rooms as well as its "market". STR's notion of a "market" approximately corresponds to a CBSA. Certain resorts that do not lie in an CBSA would have a market of, for example, "[State Name], other".

- **Hotel Brand and Chain:** We observe anonymized codes for the hotel's brand and chain within the brand, if applicable. Branded hotels account for 90% of the sample, and the remaining 10% are classified as "independent".

- **Hotel Management and Owner Company:** Similarly, we observe anonymized codes for the company that manages the hotel and the company that owns it, if applicable. Among branded hotels, 26% are managed by the hotel brand, and the remainder are managed either by owner directly or through a third-party management company. We classify a hotel as managed by such a third-party if it has a non-missing Management Company and pays management fees, according to the operating statement dataset. This condition applies to 91% of branded hotels that are not managed by their brand and to 90% of non-branded hotels. Otherwise, we assume it is managed by the owner directly. Individual owners are coded with an empty Owner Company. This condition applies to 50% of hotels in the sample.

- **Purpose of Stay:** We observe a code that describes the general purpose of guests at a hotel, which STR calls the hotel's "Location Type". The possible values are: urban ("A densely populated area in a large metropolitan area"); suburban ("Suburbs of metropolitan markets. Distance from center city varies based on population and market orientation."); airport ("Hotels in close proximity of an airport that primarily serve demand from airport traffic"); interstate ("Hotels in close proximity of major highways, motorways or other major roads whose primary source of business is through passerby travel. Hotels located in suburban areas have the suburban classification."); resort ("Any hotel located in a resort area or market where a significant source of business is derived from leisure/destination travel.); small metro ("Areas with either smaller population or limited services, in remote locations. Size can vary dependent on market orientation. Suburban locations do not exist in proximity to these areas. In North America, metropolitan small town areas are populated with less than 150,000 people.")

A.B Trepp Datasets

A.B.1 Securitized Loans

Information about securitized hotel loans come from Trepp's T-Loan dataset. This dataset covers loans collateralized by commercial properties that have been securitized as commercial mortgage backed securities (CMBS). The raw data derive from CMBS servicing files collected by the Commercial Real Estate Finance Council (CREFC), the public CMBS prospectus along with its Annex A, and various other third party resources consulted by Trepp.

The T-Loan dataset consists of a loan-level panel and a property-level panel. In both panels, the time-series unit of observation is the month. In the loan-level panel, a loan is identified using the unique combination of: the pool in which the debt claim has been issued (*dosname*); servicer's identifier for the debt claim (*masterloanidtrepp*); and, for debt claims with a multiple note capital structure, the order of the note (*notenum*). In the property-level panel, a property is identified using the unique combination of: the pool in which the debt claim on the property has been issued (*dosname*); and the servicer's identifier for the property (*masterpropidtrepp*). The majority of the variables used in our analysis come from the loan-level panel. The property-panel contains information about the property's type and address, which enables the merge with the STR dataset as described in Appendix A.D below. In addition, the property-level panel contains the aforementioned identifiers for the associated loan. So, we first merge the Trepp loan-level panel with the Trepp property-level panel, which we then merge to the STR datasets.

We use the following sets of variables from the T-Loan dataset:

- **Critical Dates:** We observe the loan's origination date, maturity date at origination, and maturity date as of month t. For loans that have not reached a disposition as of June 2022, we observe the loan's disposition date. If relevant, we also observe the date on which: the loan prepays, either in full or in part; the date on which the loan enters into special servicing; the date on which the special servicer modifies the loan's terms; and the date on which foreclosure proceedings begin.

- **Underwriting Information:** We observe the following underwriting variables as of origination: loan size, loan-to-value ratio, and debt service coverage ratio. The debt service coverage ratio is the ratio of monthly net operating income to monthly debt service.

- **Prepayment Penalties:** We define a loan as in prepayment lockout in month t if that month lies within the required number of lockout months from origination reported in Annex A, which Trepp supplements using third party sources. We use analogous criteria to define loans in the period during which they can prepay either with yield maintenance or a specified penalty.

- **Additional Loan Terms:** We observe the following terms of the loan as of origination: term, in months; and an indicator for whether the loan has a balloon amortization.

A.C Other Datasets

A.C.1 RCA

We obtain information on total property debt, borrower assets, and borrower type from Real Capital Analytics (RCA). Our data gathering works as follows.

First, we create a list of loans in our Trepp data sample. For each loan, we take the identifying information from Trepp's name for the securitization (dosname), as well as the origination month, maturity month, and original balance. We also randomly select one hotel for each loan and record the name and address of that hotel in Trepp.

Second, we provide this list to two research assistants (RAs). They manually find the hotels in RCA using the hotel names and addresses. For each hotel, they make an attempt to identify the corresponding loan in Trepp. RCA records all loans originated at the same time in a graphic user interface. The RAs record the number of distinct loans as well as the amount of each loan.

RCA repeats the same loan when there are multiple lenders for a given loan, so we instructed the RAs not to double-record loan amounts that are identical. The RAs also record RCA's reported value of the property. Finally, the RAs record the name of the borrower reported in RCA for the matched loan.

In cases where multiple hotels collateralize a single loan, RCA allocates the loan amounts and estimates of property value across the different hotels. They use the same allocation factors for the loan amounts and the valuations, meaning that we can infer RCA's estimate of LTV just from data on a single hotel. Therefore, to conserve on RA time, we asked the RAs to collect information only on a single hotel for each loan.

Third, we spot check the hand-recorded data from the RAs, which includes examining all instances where they provide different data than each other. We make corrections to their files based on our own reading of the RCA data. This step leaves us with the raw data that we use in our analysis for LTV.

To form the LTV variable, we use the LTV in Trepp for all loans where RCA does not record more than one mortgage on the matching property. In these instances, we do not suspect a second lien, so we see no reason to change the data in Trepp. When there is a second mortgage in RCA, we use the LTV implied by RCA. This method works except in a few instances in which RCA provides loan information but not data on property valuation. In these instances, we proceed as follows. If a single hotel collateralizes the loan, and the total loan amount in RCA is within 1% of the loan amount in Trepp, then we use the LTV in Trepp. In these cases, we suspect that the single loan in Trepp was broken into multiple pieces in RCA, and we have no reason to correct the LTV in Trepp. When this condition does not hold, we calculate the ratio of the total debt in RCA to the size of the largest mortgage in RCA, for each observation. We then multiply this ratio by the LTV in Trepp. This procedure scales up the Trepp LTV to reflect the possibility of additional liens in RCA. Our final LTV variable is non-missing for all cases where the original LTV variable in Trepp is populated.

To collect data on borrower assets and type, we query the RCA investor database using the names of all borrowers in the raw data from the RAs. In the case of borrowers with human names, there are sometimes multiple investors in RCA under the same name. In those cases, we select the name where the city in the investor database matches the location of a property owned by that borrower in the Trepp data. There are also instances of companies with multiple trade names, and RCA reveals these by autocorrecting in their search box. We hand collect these autocorrects to replace the borrower names in the raw RA data with the primary trade name that RCA uses in its investor database. We collect data on the total dollar holdings of US real estate of each investor as of June 27, 2023, as well as the borrower's type as of this date. We record a borrower as a REIT if the borrower type is "Private REIT" or "Public REIT." This procedure provides data in all instances where we can find a loan event in RCA corresponding to the one in Trepp.

A.C.2 PPP Dataset

We use data from the Small Business Administration's (SBA) Paycheck Protection Program (PPP) dataset to assess whether treated hotels disproportionately seek liquidity through the PPP. The PPP dataset contains information on the NAICS code, approval date, address, business name, and zip code of approved PPP loans.

A.D Merging Procedures

We perform a number of fuzzy merging procedures when building our data. Most of these procedures involve building crosswalks between hotels in different datasets according to the hotel's location.

- **Trepp-to-STR Crosswalk:** The most important merge builds a crosswalk from the Trepp dataset to STR. This merge occurs early in our data build, referenced in Section A.A.1. We apply a standard string matching algorithm by hotel zip code, street address, and name, respectively, to map each unique zip code-address-name triplet in the Trepp dataset into the STR universe. We first filter the Trepp dataset to the subset of loans secured by hotels with an initial maturity between January 2018 and December 2022. We match 90% of hotels in the filtered Trepp dataset to a unique hotel in the STR dataset.

  Since the Trepp dataset is at the loan-month level whereas most of our regressions are specified at the hotel-month level, we must choose which loan to match to a given hotel. We simply use the earliest initial maturity date over the 2018-2022. For example, if a hotel has a loan with initial maturity of February 2018 and a separate loan with initial maturity of December 2021, then we would code such a hotel as a "control hotel", that is, with a "pre-pandemic maturity". Thus, our research design has the interpretation of an "intent-to-treat".

- **STR-to-PPP Crosswalk:** We use a standard string matching algorithm by NAICS code, zip code, street address, name, respectively, to match each hotel in our STR dataset to firm in the PPP dataset.

B PROOFS

B.A Proposition 1

Given the current price of output, p, and level of managerial practices, M, the borrower chooses L to maximize current cash flows:

$$L^* = \arg\max_L pF(L, K, M_t) - wL.$$

Given the production function in equation (4), the optimized variable input, profit, and production are the results of a standard optimization problem and are:

$$
\begin{aligned}
L^*(M, p) &= \alpha^{\frac{1}{1-\alpha}} p^{\frac{1}{1-\alpha}} w^{-\frac{1}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}} \\
\pi^*(M, p) &= (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}} p^{\frac{1}{1-\alpha}} w^{-\frac{\alpha}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}} \\
F^*(M, p) &= \alpha^{\frac{\alpha}{1-\alpha}} p^{\frac{\alpha}{1-\alpha}} w^{-\frac{\alpha}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}}.
\end{aligned}
\tag{IA1}
$$

In normal times, the level of management practices coincides with M_0, the constant level of practices suited to normal times. As a result, the net present value of maximized cash flows from operating the firm is $V^* = r^{-1}\pi(M_0, p(0))$, which coincides with the formula in the text. Furthermore, pandemic-specific management practices, $M_{1,t}$, do not enter the production function

in normal times and do not appear in the formula for optimized profits, $\pi(M_0, p(0))$. In normal times, the borrower expects to remain in normal times forever, either because the pandemic in unanticipated (pre-pandemic normal times) or because the pandemic is a one-time event (post-pandemic normal times). Therefore, the borrower never makes adaptive investment in normal times, as doing so entails a unit cost of c. This argument shows that $I_t^* = 0$ in normal times.

To solve for the optimal rollover decision of the borrower, we let $V_{0,0}^e$ denote the equity value at maturity. This value can be written recursively as

$$V_{0,0}^e = \max\left(0, r^{-1}(1 - e^{-rT})\pi^*(M_0, p(0)) + e^{-rT}V_{0,0}^e - D + \widetilde{D}\right). \tag{IA2}$$

The value from defaulting is 0, and the value of paying off the debt is the expression on the right. If paying off the debt is optimal, then the present value of the new debt claim is $\widetilde{D} = e^{-rT}D$, and we can equate $V_{0,0}^e$ to the expression on the right of the max to obtain

$$V_{0,0}^e = V^* - D. \tag{IA3}$$

Give that paying off the debt is optimal, this expression must be at least 0, so that $D \leq V^*$. Conversely, if default is optimal, then the present value of the new debt claim is $\widetilde{D} = e^{-rT}V^*$. The right side of the max in equation (IA2) can be no more than 0, and given that $V_{0,0}^e = 0$, this inequality reduces to $D \geq V^*$. In summary, when $D < V^*$, the only optimum is perpetual rollover, and when $D > V^*$, the only optimum is default, as claimed.

B.B *Proposition 2*

We prove the proposition by solving for the equity value at different times before maturity, both in normal times and during the pandemic. Let $V_{j,x}^e$ denote the value of equity x units of time before maturity in state j (0 if normal, 1 if pandemic). This value function depends on the level of pandemic-specific management practices, M_1, during the pandemic but not during normal times. For convenience, we let $\pi_0^*(M_0) = \pi^*(M_0, p(0))$ and $\pi_1^*(M_1) = \pi^*(M_0^{1-\zeta(1)}M_1^{\zeta(1)}, p(1))$ denote optimized operational profits in each state.

The value in normal times satisfies the relation:

$$r V_{0,x}^e = \pi_0^*(M_0) - \frac{\partial V_{0,x}^e}{\partial x}.$$

The solution is $V_{0,x}^e = r^{-1}\pi_0^*(M_0) + A_0 e^{-rx}$, where A_0 is a constant. Given equation (IA3), $A_0 = -D$, so

$$V_{0,x}^e = r^{-1}\pi_0^*(M_0) - e^{-rx}D. \tag{IA4}$$

We now describe the value during the pandemic, $V_{1,x}^e(M_1)$. To solve for this value function, we make three assumptions about optimal borrower behavior, all of which we then verify in the solution:

1. The value function $V_{1,x}^e(\cdot)$, is right differentiable.

2. The borrower makes a lumpy investment only at pandemic onset, time t_p.

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3. The borrower either defaults at first pandemic maturity or perpetually rolls over the debt.

It is natural to work with the right derivative of $V_{1,x}^e(\cdot)$ because its argument, M_1, cannot decrease over time. For simplicity, we will use the notation $(V_{1,x}^e)'(\cdot)$ to denote this right derivative for the remainder of the proof.

We can describe the value function with two equations. The first is:

$$V_{1,x}^e(M_1) = \sup_I V_{1,x}^e(M_1 + I) - cI,$$

which states that the borrower chooses the optimal lumpy investment, which we denote $I_{l,x}^*(M_1)$. When this optimal lumpy investment is 0, it must be the case that $(V_{1,x}^e)'(M_1) \leq c$. In this case, a second equation holds:

$$r V_{1,x}^e(M_1) = \sup_I \pi_1^*(M_1) - cI + q(V_{0,x}^e - V_{1,x}^e(M_1)) - \frac{\partial V_{1,x}^e(M_1)}{\partial x} + (V_{1,x}^e)'(M_1)I.$$

This equation describes the optimal marginal investment. If the gain to investment is less than c, so that $(V_{1,x}^e)'(M_1) < c$, then the optimal investment is $I_x^*(M_1) = 0$. If the gain to investment is exactly c, so that $(V_{1,x}^e)'(M_1) = c$, then any investment is optimal: $I_x^*(M_1) \in [0, \infty)$. In either case, the terms involving I drop out, leaving us with:

$$r V_{1,x}^e(M_1) = \pi_1^*(M_1) + q(V_{0,x}^e - V_{1,x}^e(M_1)) - \frac{\partial V_{1,x}^e(M_1)}{\partial x}.$$

Substituting in equation (IA4) and solving yields :

$$V_{1,x}^e = \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} - e^{-rx}D + A_1(M_1)e^{-(r+q)x}, \qquad \text{(IA5)}$$

where $A_1(\cdot)$ does not depend on x.

To solve for this function $A_1(\cdot)$, we impose the boundary condition that the borrower chooses default or rollover optimally at maturity:

$$V_{1,0}^e(M_1) = \max\left(0, V_{1,T}^e(M_1) - D + \tilde{D}\right). \qquad \text{(IA6)}$$

If paying off the debt is optimal, then the present value of the new debt claim is $\tilde{D} = e^{-rT}D$, and the term on the right of the max is at least 0. In this case, substituting equation (IA5) into equation (IA6) yields $A_1 = 0$, so that

$$V_{1,x}^e = \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} - e^{-rx}D.$$

This solution is valid only if the right side of the max is at least 0, which is equivalent to:

$$\frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} \geq D.$$

Conversely, if default is optimal, then $V_{1,0}^e = 0$. We can then solve for A_1 in equation (IA5) to obtain:

$$V_{1,x}^e = \left(1 - e^{-(r+q)x}\right) \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} - \left(e^{-rx} - e^{-(r+q)x}\right) D.$$

This solution is valid only if the right side of the max in equation (IA6) is at most 0. To calculate the right side of the max, we solve for the present value of the new debt claim:

$$\tilde{D} = e^{-rT} \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)},$$

the discounted present value of the firm, which can be found by solving for the equity value when the level of debt, D, equals 0. Substituting equations (??) and (??) into (IA6) yields the default condition:

$$\frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} \leq D.$$

In summary, the value of the equity during the pandemic after pandemic onset is:

$$V_{1,x}^e(M_1) = \begin{cases} \left(1 - e^{-(r+q)x}\right) \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} - \left(e^{-rx} - e^{-(r+q)x}\right) D, & \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} \leq D \\ \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} - e^{-rx} D, & \frac{r \pi_1^*(M_1) + q \pi_0^*(M_0)}{r(r+q)} > D. \end{cases} \quad \text{(IA7)}$$

We next show that, given this value function solution, having 0 marginal investment is optimal. At pandemic onset, the borrower makes a lumpy investment equal to $I_{l,\tau}^*(0)$, as the initial level of pandemic-specific management practices, M_{1,t_p}, equals 0 (see Proposition 1). As argued above, it must be the case that $(V_{1,\tau}^e)'(I_{l,\tau}^*(0)) \leq c$. From equation (IA7), it is clear that $(V_{1,x}^e)'(M_1) \leq (V_{1,\tau}^e)'(M_1)$ for $x < \tau$. Therefore, $(V_{1,x}^e)'(I_{l,\tau}^*(0)) \leq c$ for all $x \in (0, \tau)$, which implies that an optimal solution for investment after pandemic onset is 0: $I_x^*(I_{l,\tau}^*(0)) = 0$.

We can now verify the three conditions assumed above. First, the value function is clearly right differentiable, as it is fully differentiable everywhere except possibly at a single point.

To prove the second condition, we note that the gains to any further lumpy investment decreases over time, which rules out further lumpy investment. To show this claim formally, we consider $V_{1,x}^e(I_{l,\tau}^*(0) + I) - V_{1,x}^e(I_{l,\tau}^*(0))$, which has one of three forms. If $M_1 = I_{l,\tau}^*(0) + I$ is in the default region, then the difference equals

$$\left(1 - e^{-(r+q)x}\right) \frac{\pi_1^*(I_{l,\tau}^*(0) + I) - \pi_1^*(I)}{r+q},$$

which weakly increases in x. If $M_1 = I_{l,\tau}^*(0)$ is in the payoff region, then the difference equals

$$\frac{\pi_1^*(I_{l,\tau}^*(0) + I) - \pi_1^*(I)}{r+q},$$

which does not depend on x. Finally, if $M_1 = I_{l,\tau}^*(0)$ is in the default region but $M_1 = I_{l,\tau}^*(0) + I$

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is in the payoff region, then the difference equals

$$\frac{\pi_1^*(I_{l,\tau}^*(0)+I)-\pi_1^*(I_{l,\tau}^*(0))}{r+q}-e^{-(r+q)x}\left(D-\frac{r\,\pi_1^*(I_{l,\tau}^*(0))+q\,\pi_0^*(M_0)}{r(r+q)}\right),$$

which weakly increases in x because the parenthetical term involving D is positive. The optimal jump investment after pandemic onset maximizes $V_{1,x}^e(\pi_1^*(I_{l,\tau}^*(0))+I)-V_{1,x}^e(\pi_1^*(I_{l,\tau}^*(0)))-cI-cI_{l,\tau}^*(0)$. If this optimal investment I is positive, then the maximizer of $V_{1,\tau}^e(\pi_1^*(I_{l,\tau}^*(0))+I)-V_{1,\tau}^e(\pi_1^*(I_{l,\tau}^*(0)))-cI-cI_{l,\tau}^*(0)$ is also positive based on the fact that $\tau>x$. This conclusion contradicts the fact that $I_{l,\tau}^*(0)$ is the optimal jump investment at pandemic onset. Therefore, $I=0$, and the optimal jump investment after pandemic onset must always be 0.

Finally, the third condition is clear from the fact that the default condition depends only on M_1, which we just showed does not change after pandemic onset: $M_{1,t}=I_{l,\tau}^*(0)$ throughout the pandemic for $t>t_p$.

For the remainder of the proof, we solve for the optimal jump investment at pandemic onset, $I_{l,\tau}^*(0)$. To conserve on notation, we denote it by I^*. It maximizes $V_{1,\tau}^e(I)-cI$. By equation (IA7), there are two possible local maxima for I: one that holds in the default region (top condition in equation (IA7)), which we denote I^d, and one that holds in the payoff region (bottom condition in equation (IA7)), which we denote I^f. We solve for these local maxima by substituting equation (IA1) into equation (IA7) and setting the derivative equal to c to obtain:

$$I^f=\widetilde{I}$$
$$I^d=\left(1-e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}\widetilde{I},$$

where

$$\widetilde{I}=\beta^{\frac{1-\alpha}{1-\alpha-\beta\zeta(1)}}\zeta(1)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}c^{-\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}(r+q)^{-\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}\alpha^{\frac{\alpha}{1-\alpha-\zeta(1)\beta}}p(1)^{\frac{1}{1-\alpha-\zeta(1)\beta}}w^{-\frac{\alpha}{1-\alpha-\zeta(1)\beta}}K^{\frac{1-\alpha-\beta}{1-\alpha-\zeta(1)\beta}}M_0^{\frac{(1-\zeta(1))\beta}{1-\alpha-\zeta(1)\beta}}.$$
(IA8)

Given the conditions in equation (IA7), I^d is a possible global maximum only if

$$D\geq\frac{r\,\pi_1^*(I^d)+q\,\pi_0^*(M_0)}{r(r+q)}\equiv D^d,$$

and I^f is a possible global maximum only if

$$D\leq\frac{r\,\pi_1^*(I^f)+q\,\pi_0^*(M_0)}{r(r+q)}\equiv D^f.$$

Therefore, if $D<D^d$, then $I^*=I^f$, and if $D>D^f$, then $I^*=I^d$. If $D\in[D^d,D^f]$, then both maxima are possible, and the borrower selects the one that maximizes $V_{1,\tau}^e(I)-cI$. By comparing

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the expressions in equation (IA7), we find that the maximizing investment is I^f when

$$D < \frac{q\pi_0^*(M_0)}{r(r+q)} + e^{(r+q)\tau}\left(\frac{\pi_1^*(I^f) - \left(1 - e^{-(r+q)\tau}\right)\pi_1^*(I^d)}{r+q} - c(I^f - I^d)\right) \equiv D^*(\tau)$$

and that the maximizing investment is I^d when $D > D^*(\tau)$. Substituting the expressions for I^f and I^d and using equation (IA1) yield:

$$D^*(\tau) = \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1 - \alpha - \zeta(1)\beta}{\zeta(1)\beta} e^{(r+q)\tau}\left(1 - \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}\right)c\widetilde{I}. \tag{IA9}$$

Similar substitutions yield the expressions:

$$D^d = \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1-\alpha}{\zeta(1)\beta}\left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}c\widetilde{I}$$

$$D^f = \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1-\alpha}{\zeta(1)\beta}c\widetilde{I}. \tag{IA10}$$

We would like to show that $D^*(\tau) \in [D^d, D^f]$. Doing so would prove that equation (6) gives the optimal adaptive investment. To proceed, we make use of the following lemma:

Lemma 1. *Suppose $z \in (0,1]$ and $a > 0$. Then:*

$$(1-z)^a < (1+az)^{-1}. \tag{IA11}$$

If $a \geq 1$, then

$$1 - az \leq (1-z)^a. \tag{IA12}$$

Proof. The two expressions in inequality (IA11) coincide when $x = 0$. The derivative of the logs of the left and right sides are $-a/(1-z)$ and $-a/(1+az)$, respectively, and the first one is more negative because $a > 0$. Therefore, inequality (IA11) holds.

The two expressions in inequality (IA12) coincide when $z = 0$. The derivative with respect to z of the first is $-a$, and of the second is $-a(1-z)^{a-1}$, which is at least $-a$ because $a \geq 1$ and $z \in (0,1]$. Therefore, the inequality (IA12) holds. $\square$

The inequality $D^*(\tau) \geq D^d$ reduces to

$$1 \geq \left(1 + \frac{1-\alpha}{1-\alpha-\zeta(1)\beta}e^{-(r+q)\tau}\right)\left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}},$$

which holds due to inequality (IA11), with $a = (1-\alpha)/(1-\alpha-\zeta(1)\beta)$ and $z = e^{-(r+q)\tau}$. The inequality $D^*(\tau) \leq D^f$ reduces to

$$1 - \frac{1-\alpha}{1-\alpha-\zeta(1)\beta}e^{-(r+q)\tau} \leq \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}},$$

which holds due to inequality (IA12), with the same substitutions for a and z. Therefore, equation (6) delivers the optimal adaptive investment, as claimed.

Next, we show that $D^*(\tau)$ strictly increases in τ. The derivative of the log of $D^*(\tau) - q\pi_0^*(M_0)/(r(r+q))$ is greater than 0 if and only if:

$$0 < (r+q) - \frac{1-\alpha}{1-\alpha-\zeta(1)\beta} \frac{(r+q)e^{-(r+q)\tau}\left(1-e^{-(r+q)\tau}\right)^{\frac{\zeta(1)\beta}{1-\alpha-\zeta(1)\beta}}}{1-(1-e^{-(r+q)\tau})^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}}.$$

This inequality simplifies to:

$$1 + \frac{\zeta(1)\beta}{1-\alpha-\zeta(1)\beta} e^{-(r+q)\tau} < \left(1-e^{-(r+q)\tau}\right)^{-\frac{\zeta(1)\beta}{1-\alpha-\zeta(1)\beta}},$$

which holds due to inequality (IA11), with $a = \zeta(1)\beta/(1-\alpha-\zeta(1)\beta)$ and $z = e^{-(r+q)\tau}$.

Finally, we show that $D^*(\tau) < V^*$ for all τ if c is sufficiently large. Because $D^*(\tau) \leq D^f$, it suffices to show that $D^f < V^*$ for large values of c. From equations (6) and (IA10), we see that D^f is an affine function of $c^{-\zeta(1)\beta/(1-\alpha-\zeta(1)\beta)}$, which implies that D^f strictly decreases in c. It limits to $qV^*/(r+q)$ as $c \to \infty$, which proves that $D^*(\tau) < V^*$ for all τ if c is sufficiently large.

B.C *Proposition 3*

The levels of inputs, profits, and output equal $L^*(M_0^{1-\zeta(1)}(I^*)^{\zeta(1)}, p_1)$, $\pi^*(M_0^{1-\zeta(1)}(I^*)^{\zeta(1)}, p_1)$, and $F^*(M_0^{1-\zeta(1)}(I^*)^{\zeta(1)}, p_1)$, where these functions are as they appear in the proof of Proposition 1 and I^* is shorthand for $I_{t_p}^*$, the optimal lumpy investment from Proposition 2. All three outcomes strictly increase in I^*. Therefore, it suffices to prove that $I^*(\tau_2) - I^*(\tau_1) \geq 0$, with equality if $D < D^*(\tau_1)$ and strict inequality if $D > D^*(\tau_1)$. If $D < D^*(\tau_1)$, then by Proposition 2, $D < D^*(\tau_2)$ as well, implying that $I^*(\tau_2) = I^*(\tau_1) = \tilde{I}$. If $D > D^*(\tau_1)$, then $I^*(\tau_1) < I^*(\tau_2)$ because

$$\left(1-e^{-(r+q)\tau_1}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \tilde{I} < \left(1-e^{-(r+q)\tau_2}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \tilde{I} < \tilde{I},$$

meaning that the adaptive investment is smaller under τ_1 than τ_2 regardless of whether D is greater or smaller than $D^*(\tau_2)$.

C CALIBRATION DETAILS

As discussed in the text, we set M_0 equal to the value that maximizes the net present value of the firm net of the cost of investing in management practices. We assume that the unit cost of investing in management practices suited to normal times equals c, the same as the unit cost for adaptive investments. Therefore, $M_0 = \arg\max_M r^{-1}\pi^*(M, p(0)) - cM$. The solution is:

$$M_0 = \beta^{\frac{1-\alpha}{1-\alpha-\beta}} c^{-\frac{1-\alpha}{1-\alpha-\beta}} (r+q)^{-\frac{1-\alpha}{1-\alpha-\beta}} \alpha^{\frac{\alpha}{1-\alpha-\beta}} p(0)^{\frac{1}{1-\alpha-\beta}} w^{-\frac{\alpha}{1-\alpha-\beta}} K. \qquad \text{(IA13)}$$

Substituting equation (IA13) into equation (IA8) yields:

$$\widetilde{I} = \zeta(1)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \left(\frac{r}{r+q}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \left(\frac{p(1)}{p(1)}\right)^{\frac{1}{1-\alpha-\zeta(1)\beta}} M_0. \tag{IA14}$$

This equation demonstrates three reasons that adaptive investment is less than management practices suited to normal times, $\widetilde{I} < M_0$. First, pandemic management practices are no more useful during a pandemic than normal practices during normal times, and may be less useful ($\zeta(1) \le 1$). Second, the pandemic is expected to last a limited amount of time ($q > 0$). Finally, the market price for the firm's output is lower during the pandemic ($p(1) < p(0)$).

It is straightforward to show that:

$$V^* = r^{-1}\pi_0^*(M_0) = \beta^{-1}(1-\alpha)cM_0.$$

Therefore, by using equation (IA14), we can simplify equation (IA9) to:

$$\frac{D^*(\tau)}{V^*} = \frac{q}{r+q} + \frac{1-\alpha-\zeta(1)\beta}{1-\alpha} \times$$
$$\zeta(1)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \left(\frac{r}{r+q}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}} \left(\frac{p(1)}{p(0)}\right)^{\frac{1}{1-\alpha-\zeta(1)\beta}} e^{(r+q)\tau} \left(1 - \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta(1)\beta}}\right).$$

Therefore, the default cutoff relative to the initial value of the firm (the default LTV) only depends on q, r, α, β, $\zeta(1)$, and $p(1)/p(0)$, as claimed in the text. The ratio between adaptive investments for different values of τ depends on only these variables as well, as is clear from equation (IA8). The ratio between real outcomes during the pandemic for different τ depends on the ratio of adaptive investments raised to the power $\zeta(1)\beta/(1-\alpha)$, so the same list of parameters is sufficient for calculating those ratios. Finally, the ratio between real outcomes during the pandemic and before the pandemic depends on the ratio of management practices between these times, which equals $(I_{t_p}^*/M_0)^{\zeta(1)}$. By equation (IA14), this ratio depends only on the same list of parameters.

In the text, we assert that the ratio of variable expenses to revenue for the firm equals α. Using the notation from the proof of Proposition 1, we can write this ratio as $wL^*(M, p)/(pF^*(M, p))$, which simplifies to α, as claimed.

D Additional Figures and Tables
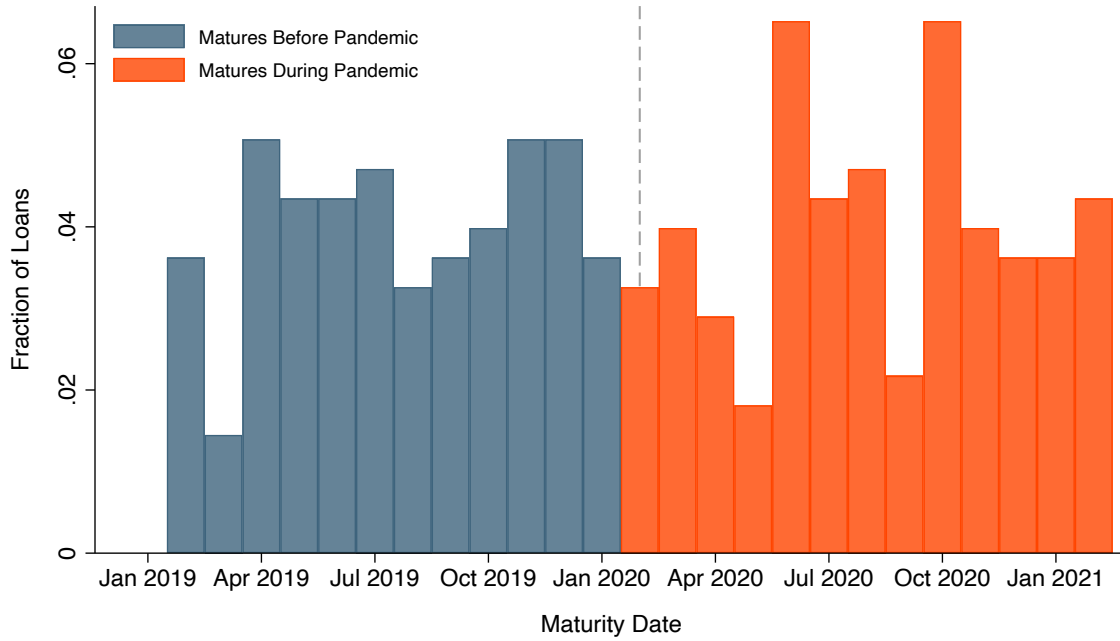

FIGURE A.I
Distribution of Scheduled Loan Maturity at Origination.

NOTE.—This figure assesses the distribution of the treatment exposure variable, PandemicMaturity, by plotting the distribution of initial loan maturity across months for hotels in our main estimation sample. The vertical axis shows the share of loans with an initial maturity in the indicated month. (SOURCE: Trepp)
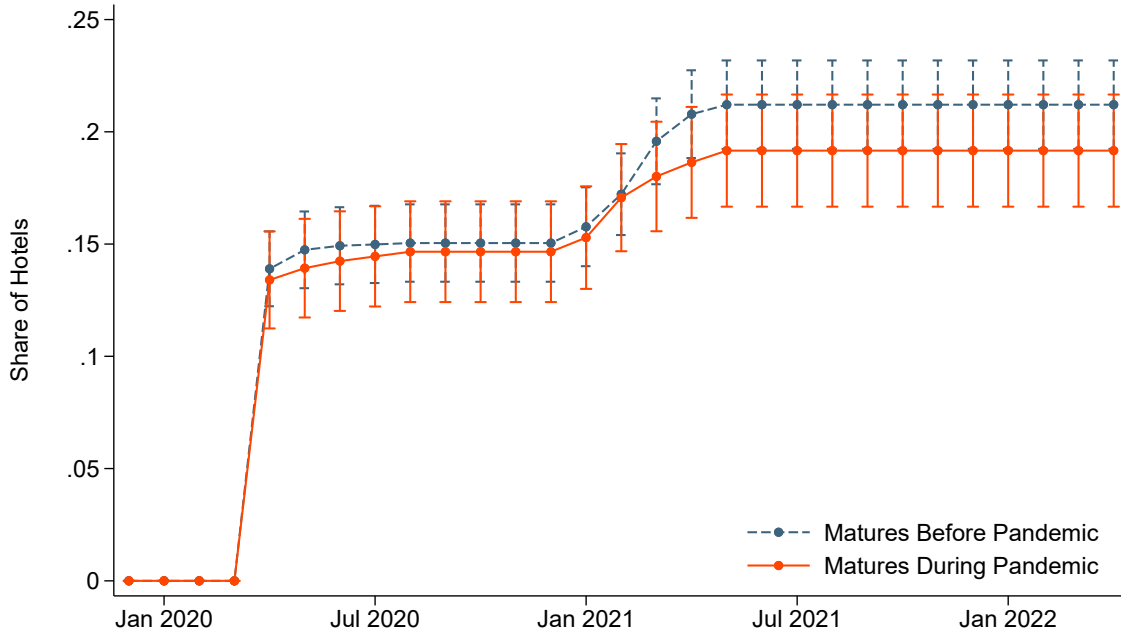
FIGURE A.II

Paycheck Protection Program Takeup Rate by Maturity Cohort.

NOTE.—This figure plots the time series of the share of hotels in our sample that have received a Paycheck Protection Program (PPP) loan origination. Explicitly, the figure shows the mean of an indicator variable for whether the hotel has received a PPP loan as of the given month, and the bars are standard errors for this mean. These statistics are calculated separately for hotels with a scheduled loan maturity before versus during the pandemic, using the same 12 month bandwidth as in Figure III. A hotel is defined as receiving a PPP loan in a given month if it: (a) has a match in the PPP dataset; and (b) has a PPP loan approved in that month. Details on the PPP dataset are in Appendix A. (SOURCE: Trepp and SBA)
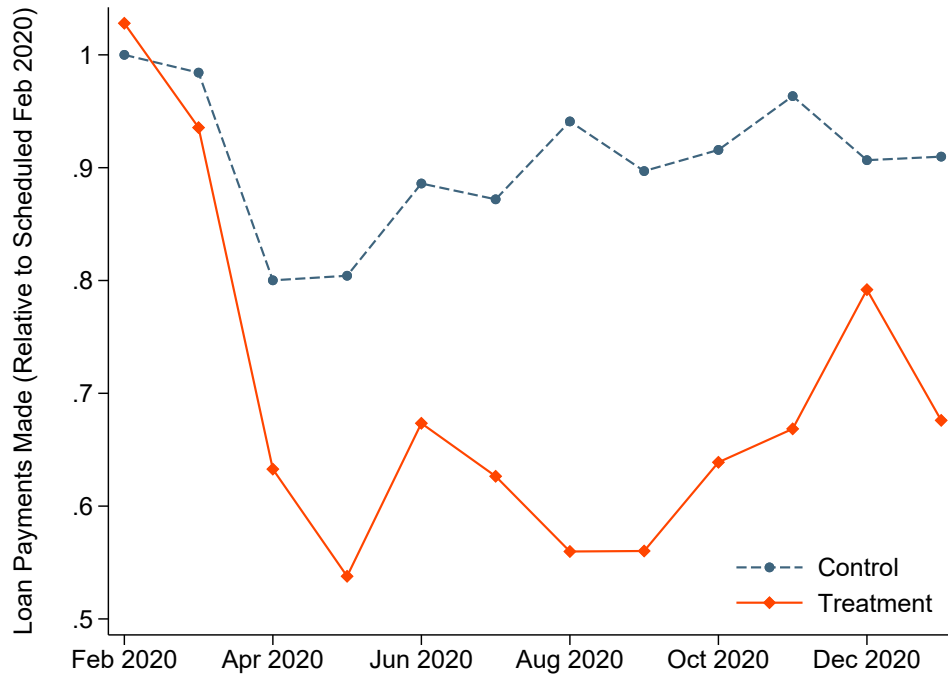
FIGURE A.III
Debt Payments by Maturity Cohort.

NOTE.—This figure plots actual debt service payments made for two groups of loans, which assesses whether the main results reflect increased debt service payments by borrowers facing a maturity during the pandemic. To form the sample, we start with loans maturing during the pandemic from the treatment group in our main analysis. We then define any Lodging loans in Trepp originated between February 2019 and January 2020 that are scheduled to mature after January 2021 as the control group. This group of loans serves as a proxy for the loans that the borrowers with pre-pandemic maturities in the control group for our main analysis likely refinanced into. We further restrict both groups to loans that are active for each month between February 2020 and January 2021, which excludes any treatment loans that pay off before this later date. We then drop loans in special servicing or with a zero balance in February 2020. Of these remaining loans, we finally drop 6% that have missing values for the scheduled monthly payment in Trepp. We impute payments made using the difference between this scheduled monthly payment and the amount of principal and interest advanced by the servicer to CMBS investors. We normalize by the scheduled payment for each loan for February 2020, and we report the average normalized value for each group and month. The initial average may not equal 1 because the realized payment might not equal the scheduled payment in February 2020. (SOURCE: Trepp).
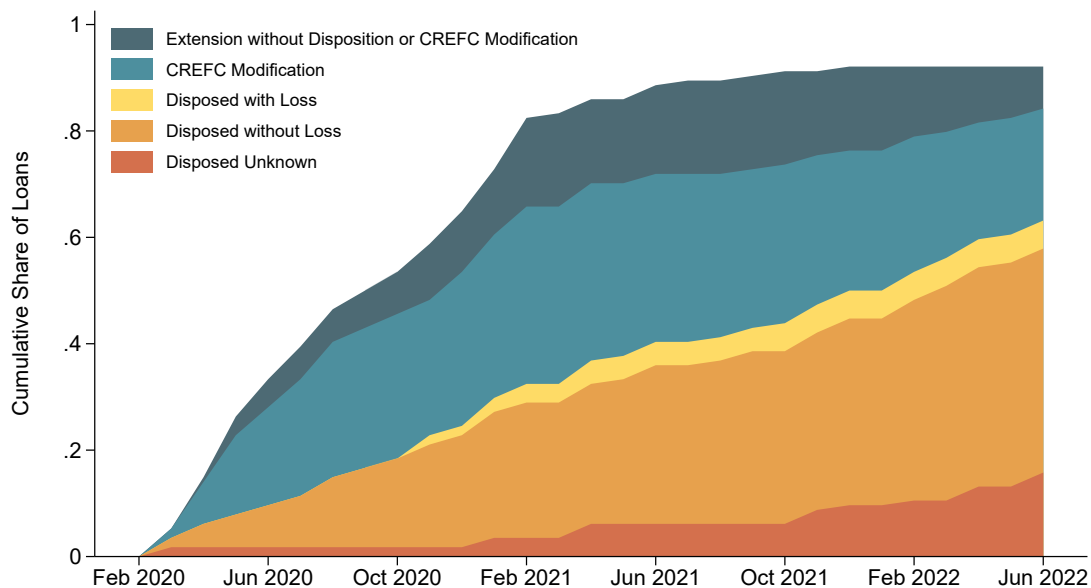
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FIGURE A.IV
Loan Resolution.

NOTE.—This figure plots the share of hotel loans with either an explicit modification or a known disposition (i.e., exit) by the year of maturity. The sample restricts to loans with a positive balance that have not been modified as of February 2020. We measure loan modifications using indicators for such events from the Commercial Real Estate Finance Council (CREFC), a trade organization that provides standardized procedures for CMBS loan servicing. The terms in the figure's legend are as follows. A loan receives an "Extension without Disposition or CREFC Modification" in a given month if, in that month, the maturity date switches to a later date. A loan has a "CREFC Modification" in a given month if, in that month, the CREFC modification field becomes non-empty. A loan becomes "Disposed with Loss" in a given month if it has zero loan balance, a non-empty loan disposition field, and the disposition field takes on the values "Loss", "Impaired", or close variants of these terms. A loan becomes "Disposed without Loss" in a given month if it has zero loan balance, a non-empty loan disposition field, and the disposition field takes on the values "Paid", "Prepaid", or close variants of these terms. We infer that a loan has paid off if its balance goes to zero and it makes an unscheduled principal payment that exceeds the loan balance from the previous month. A loan becomes "Disposed Unknown" in a given month if it has zero loan balance, it does not have an inferred payoff, and the loan disposition field is either empty or explicitly says "Unknown". These definitions allow loans to move between categories (e.g., CREFC Modification to Disposed without Loss). The categories are mutually exclusive. A loan can move from "Extension without Disposition or CREFC Modification" to one of the other categories in the legend. In addition, a loan can move from "CREFC Modification" to one of the disposition categories. Data are from the Trepp dataset. (SOURCE: Trepp)
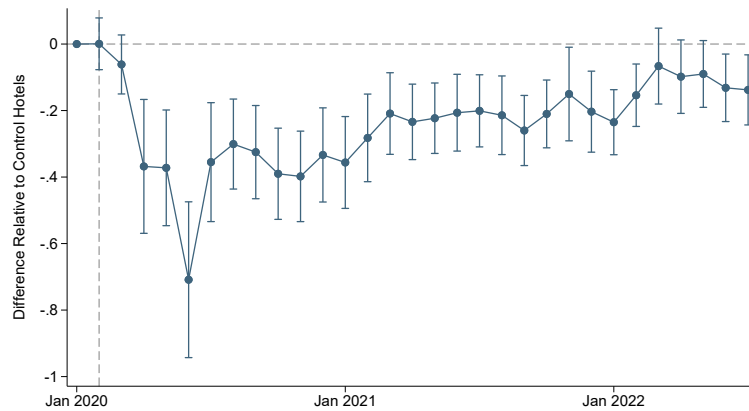
Panel A. Marketing Expense
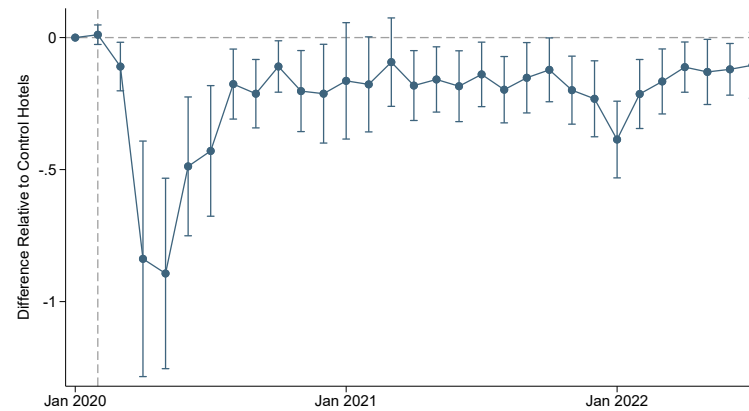
Panel B. Profit

FIGURE A.V
Effect of Pandemic Maturity on Monthly Marketing Expense and Profit.

NOTE.—This figure estimates a variant of equation (2) that assesses whether reductions in marketing expense and profit occur on impact. Data are from the STR monthly profit and loss dataset, which begin in January 2020. The regression equation is similar to that in Figure IV, except that the Post Maturity fixed effect is omitted because there is no variation among control hotels that can be used to identify it. The outcome in panel A is the log of sales and marketing expense. The outcome in panel B is the ratio of EBITDA to total revenue. EBITDA is winsorized at the 2.5% level. Standard errors are clustered by hotel. The remaining notes are the same as in Figure IV. (SOURCE: STR, LLC and Trepp)
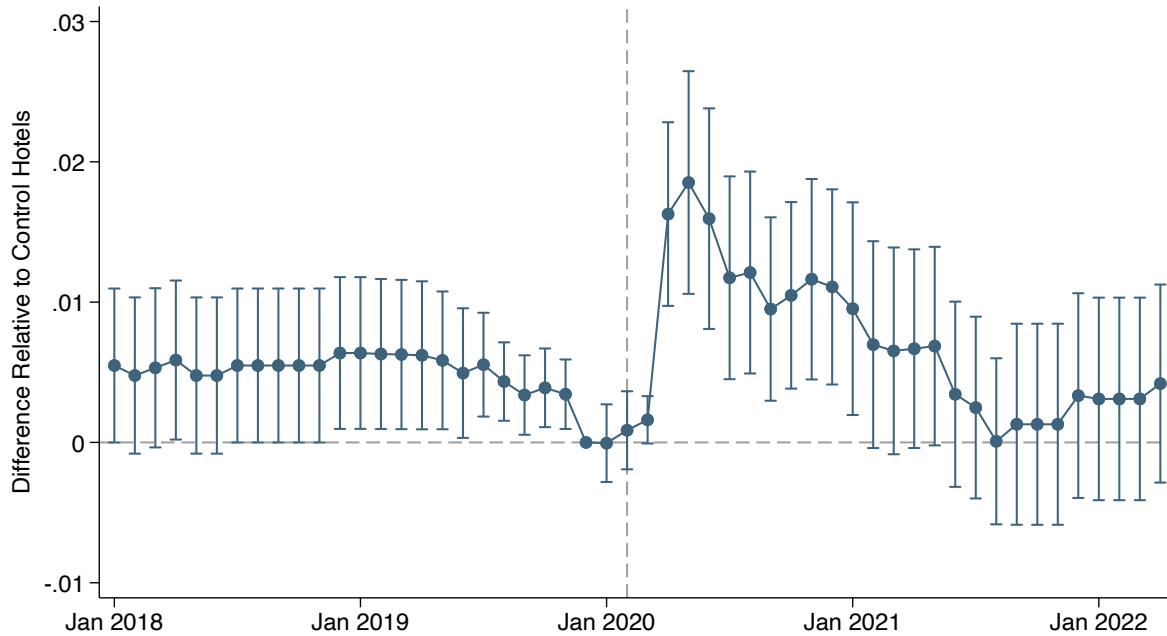
FIGURE A.VI
Effect of Pandemic Maturity on Hotel Closure.

NOTE.—This figure estimates a specification of equation (2) in which the outcome variable is an indicator for whether the hotel is likely closed in a given month. We do not directly observe whether a hotel is closed. We impute closure status according to whether the hotel reports data to STR and has declining occupancy leading up to the first month of non-reporting. Details on this procedure are in Appendix A.A. For reference, the average share of hotels closed in the pre-pandemic period, the post-pandemic period, and in March 2020 through May 2020 are: 0.04%, 0.52%, and 1.07%. The remaining notes are the same as in Figure IV. (SOURCE: STR, LLC and Trepp)

TABLE A.I
STR GEOGRAPHIC MARKETS IN ESTIMATION SAMPLE

Alabama North	Dayton/Springfield, OH	Kentucky Area	Nebraska	Rhode Island
Alabama South	Daytona Beach, FL	Knoxville, TN	Nevada Area	Richmond/Petersburg, VA
Alaska	Delaware	Las Vegas, NV	New Hampshire	Rochester, NY
Albany, NY	Denver, CO	Lexington, KY	New Jersey Shore	Sacramento, CA
Albuquerque, NM	Des Moines, IA	Little Rock, AR	New Mexico North	Saint Louis, MO
Allentown and Reading, PA	Detroit, MI	Long Island	New Mexico South	Salt Lake City/Ogden, UT
Arizona Area	Florida Central	Los Angeles, CA	New Orleans, LA	San Antonio, TX
Arkansas Area	Florida Keys	Louisiana North	New York State	San Diego, CA
Atlanta, GA	Florida Panhandle	Louisiana South	New York, NY	San Francisco/San Mateo, CA
Augusta, GA	Fort Lauderdale, FL	Louisville, KY	Newark, NJ	San Jose/Santa Cruz, CA
Austin, TX	Fort Myers, FL	Lower Hudson Valley, NY	Norfolk/Virginia Beach, VA	Sarasota, FL
Baltimore, MD	Fort Worth/Arlington, TX	Macon/Warner Robins, GA	North Carolina East	Savannah, GA
Bergen/Passaic, NJ	Georgia North	Madison, WI	North Carolina West	Seattle, WA
Birmingham, AL	Georgia South	Maine Area	North Dakota	South Carolina Area
Boston, MA	Grand Rapids and Michigan West	Maryland Area	Oahu Island, HI	South Dakota
Buffalo, NY	Greensboro/Winston Salem, NC	Massachusetts Area	Oakland, CA	Syracuse, NY
California Central Coast	Greenville/Spartanburg, SC	Maui Island, HI	Ohio Area	Tampa, FL
California North	Harrisburg, PA	McAllen/Brownsville, TX	Oklahoma Area	Tennessee Area
California North Central	Hartford, CT	Melbourne, FL	Oklahoma City, OK	Texas East
California South/Central	Hawaii/Kauai Islands	Memphis, TN	Omaha, NE	Texas North
Central New Jersey	Houston, TX	Miami, FL	Orange County, CA	Texas South
Charleston, SC	Idaho	Michigan North	Oregon Area	Texas West
Charlotte, NC	Illinois North	Michigan South	Orlando, FL	Tucson, AZ
Chattanooga, TN	Illinois South	Milwaukee, WI	Palm Beach , FL	Tulsa, OK
Chicago, IL	Indiana North	Minneapolis, MN	Pennsylvania Area	Utah Area
Cincinnati, OH	Indiana South	Minnesota	Pennsylvania Northeast	Vermont
Cleveland, OH	Indianapolis, IN	Mississippi	Pennsylvania South Central	Virginia Area
Colorado Area	Inland Empire, CA	Missouri North	Philadelphia, PA	Washington State
Colorado Springs, CO	Iowa Area	Missouri South	Phoenix, AZ	Washington, DC
Columbia, SC	Jackson, MS	Mobile, AL	Pittsburgh, PA	West Virginia
Columbus, OH	Jacksonville, FL	Montana	Portland, ME	Wisconsin North
Connecticut Area	Kansas	Myrtle Beach, SC	Portland, OR	Wisconsin South
Dallas, TX	Kansas City, MO	Nashville, TN	Raleigh/Durham/Chapel Hill, NC	Wyoming

Note.–This table shows the name of the STR-defined geographic markets for the hotels in the baseline estimation sample from Table II. (SOURCE: STR, LLC)

ROBUSTNESS OF EFFECT ON REVENUES. CHAIN-BY-MARKET-BY-MONTH OR
BORROWER-BY-MONTH FIXED EFFECTS

	(1)	(2)	(3)	(4)	(5)	(6)
PandemicMaturity × Post	−0.120***	−0.115***	−0.115***	−0.080**	−0.217***	−0.217***
	(0.032)	(0.032)	(0.031)	(0.030)	(0.028)	(0.041)
Hotel FEs	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X
Market × Chain × Month FEs	X	X	X	X		
Size × Month FEs		X	X	X		
Location × Month FEs			X	X		
Operation × Month FEs				X		
Borrower × Month FEs					X	X
Market × Month FEs					X	X
Borrower Clustered SEs						X
Number of Observations	133,095	133,095	133,095	133,095	111,452	111,452

NOTE.—This table assesses the robustness of the main results in Table II to including very stringent sets of fixed effects. Columns (1)-(4) include fixed effects for bins defined by month, hotel chain, and geographic market. There are 466 chain-by-market pairs used in estimation, of which 18% have hotels in both the treatment and control groups. Column (5) includes fixed effects for bins defined by borrower and month. There are 46 borrowers used in estimation, of which 30% have hotels in both the treatment and control groups. Column (6) twoway clusters standard errors by borrower and month, whereas the other columns twoway cluster standard errors by hotel and month as in Table II. The remaining notes are the same as in Table II. (SOURCE: STR, LLC and Trepp)

TABLE A.III
DESCRIPTIVE STATISTICS BY INITIAL LTV

	Low LTV		High LTV	
	Mean	Std. Dev.	Mean	Std. Dev.
Hotel Performance (May 2019)				
Log(Room Revenue)	12.47	(0.85)	12.10	(0.52)
Log(Rooms Occupied)	7.97	(0.49)	7.84	(0.38)
Log(Average Daily Room Price)	4.50	(0.52)	4.25	(0.35)
Occupancy Rate	0.73	(0.13)	0.77	(0.12)
Hotel Location				
Urban	0.10	—	0.06	—
Suburban	0.60	—	0.74	—
Small Town	0.08	—	0.03	—
Airport	0.10	—	0.11	—
Resort	0.05	—	0.02	—
Highway	0.07	—	0.04	—
Owner and Operations				
Log(Borrower Real Estate Assets)	23.64	(2.41)	24.97	(1.66)
Operated by Brand	0.37	—	0.77	—
REIT	0.19	—	0.13	—
Loan Characteristics at Origination				
Servicer Stringency	−0.10	(1.15)	0.19	(0.58)
Log(Loan Amount)	19.76	(1.63)	20.87	(0.72)
Loan-to-Value Ratio (LTV)	0.63	(0.15)	0.87	(0.05)
Debt-Service Coverage Ratio (DSCR)	3.53	(1.15)	3.96	(0.85)
Loan Term (Months)	56.13	(29.52)	78.93	(12.57)
Balloon Flag	0.99	—	1.00	—
Number of Hotels	1,741		868	

NOTE.—This table summarizes hotels according to whether the initial LTV ratio is in the top one-third across hotels in the estimation sample, corresponding to an LTV ratio of 80%. The variables are as in Table II. The remaining notes are the same as in Table I. (SOURCE: STR, LLC, Trepp, and RCA)

TABLE A.IV
SENSITIVITY OF EFFECT ON REVENUES BY INITIAL LTV

	(1)	(2)	(3)
PandemicMaturity × Post	0.133***	0.073**	0.090
	(0.035)	(0.034)	(0.154)
PandemicMaturity × Post × Tercile(LTV, 2)	−0.312***	−0.535***	
	(0.063)	(0.094)	
PandemicMaturity × Post × Tercile(LTV, 3)	−0.435***	−0.859***	
	(0.070)	(0.126)	
PandemicMaturity × Post × LTV			1.153***
			(0.303)
PandemicMaturity × Post × LTV^2			−1.490***
			(0.238)
Hotel FEs	X	X	X
Post Maturity FE	X	X	X
Market × Month FEs	X	X	X
Tercile(LTV) × Month FEs	X	X	
HasJuniorDebt × Month FEs		X	
HasJuniorDebt × PandemicMaturity × Month FEs		X	
LTV × Month FEs			X
LTV^2 × Month FEs			X
Number of Observations	133,043	133,043	133,043

NOTE.—This table assesses sensitivity to the heterogeneous effects by LTV ratio documented in Table V. The specifications are analogous to column (1) of Table V, after replacing HighLTV with: indicators for whether the initial LTV ratio lies in the second or third tercile across hotels in the estimation sample; and the level of the initial LTV ratio and its square. The reference group in column (1) is the first tercile of the LTV distribution. The second and third terciles are defined by LTV ratios of 70.5% and 80.0%, respectively. Column (2) includes combinations of interactions between month fixed effects, the indicator for whether the hotel has a pandemic maturity, and an indicator for whether the hotel has junior debt, measured as having a total LTV ratio greater than the LTV ratio on the most-senior, CMBS loan. Note that the treatment effect implied by column (3) depends on the initial LTV according to the sum of: the coefficient on PandemicMaturity × Post × LTV; plus two times the coefficient on PandemicMaturity × Post × LTV^2. The remaining notes are the same as in Table V. (SOURCE: STR, LLC and Trepp)

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TABLE A.V

EFFECT ON HOTEL EXPENSE BY CATEGORY

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	Levels (000,000)							Ratio to Revenue	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PandemicMaturity × Post	−7.977**	−4.054***	−2.397**	−1.259*	−9.051**	−1.209**	−1.218**	0.030**	0.010
	(1.795)	(0.805)	(0.766)	(0.485)	(2.099)	(0.308)	(0.331)	(0.010)	(0.010)
Category Name	Room	Marketing	Admin	Operator	Food	Property	Reserve	Room	Operator
Category Mean in 2019	10.742	5.345	5.074	2.093	6.069	2.722	0.780		
Hotel FEs	X	X	X	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X	X	X	X
Market × Year FEs	X	X	X	X	X	X	X	X	X
Number of Observations	6,525	6,525	6,525	6,525	6,525	6,525	6,525	6,525	6,525

NOTE.—This table estimates a variant of equation (1) that assesses the drop in expenses documented in Figure VI across expense categories. The regression equation is similar to that in Table II, except that the frequency is annual because the data on hotel expenses come from STR's annual profit and loss dataset. The treatment variable, $PandemicMaturity_i$, is still defined as it is in Table II. The remaining notes are the same as in Table II after replacing "month" with "year". The outcome variables in columns (1)-(7) are the hotel's annual expense within a given category, in hundreds of thousands of U.S. dollars ($000,000). The outcome is specified in levels, as opposed to logs, to allow for cases where a hotel has expense of zero within a given category. For reference, the sample mean of each category in 2019 is reported in the table. The categories are: room; sales and marketing (Marketing); administrative and general (Admin); total fees paid to the company operating the hotel (Operator); food and beverage services (Food); property operations and maintenance (Property); and reserve for capital replacement (Reserve). The outcome variables in columns (8)-(9) are the ratios of: room expense divided by total hotel revenue, in the same year; and total fees paid to the company operating the hotel divided by total hotel revenue, again in the same year. Standard errors twoway clustered by hotel and year are shown in parentheses. The remaining notes are the same as in Figure VI and Table II. (SOURCE: STR, LLC and Trepp)

TABLE A.VI

ADDITIONAL ANALYSIS OF THE EFFECT ON EXPENSE AND PROFIT

	Log(Expense)	log(ExpensePerNight)	Operating Profit	
	(1)	(2)	(3)	(4)
PandemicMaturity × Post	−0.439***	0.010	−0.166***	−0.212***
	(0.056)	(0.108)	(0.017)	(0.034)
Hotel FEs	X	X	X	X
Post Maturity FE	X	X	X	X
Market × Year FEs	X	X	X	X
Profit2017 × Year FEs				X
Number of Observations	6,519	6,519	5,812	5,812

NOTE.—This table estimates a difference-in-difference equation analogous to the event studies in Figure VI and Figure VIII. The frequency is annual because the data come from STR's annual profit and loss dataset. The outcomes in columns 1-2 are the log of: total expense; and total expense divided by total room nights sold. The outcome in columns 3-4 is the hotel's operating profit, defined as the ratio of EBITDA to total revenue in a base year (2019). Column 4 controls for the interaction between the hotel's operating profit in 2017 and a vector of year fixed effects, which assesses robustness to the absence of parallel trends in operating profit in 2017 shown in Figure VIII. The remaining notes are the same as in Figure VI and Figure VIII. (SOURCE: STR, LLC and Trepp)