REAL EFFECTS OF ROLLOVER RISK: EVIDENCE FROM HOTELS IN CRISIS*

Anthony A. DeFusco† **Charles G. Nathanson**‡ **Michael Reher**§

Abstract

We show how debt scheduled to mature during an economic crisis leads firms to strategically contract employment and output immediately on crisis impact. Focusing on the hotel industry during the COVID-19 pandemic, we compare hotels with loans scheduled to mature during the pandemic to those with loans scheduled to mature just before. Relative to hotels with pre-pandemic maturities, hotels with pandemic maturities exhibit sharp drops in revenues, occupancy, and labor expenses beginning immediately in March of 2020 and persisting into 2022. Consistent with strategic considerations, this effect is stronger for hotels with higher LTVs. We calibrate a parsimonious model of adaptive firm investment that illustrates how shorter maturity debt induces borrowers to cut operations during a crisis.

*This version: July 19, 2023. We thank seminar and conference participants at the Federal Reserve Bank of Chicago, Duke, the University of Texas, Michigan State, the University of Wisconsin, Northeastern, Emory, the University of Illinois, University of North Carolina, and the City University of New York for helpful comments and Daniel Leshem, Alvin Lumbanraja, Anoushka Nalwa, Matthew Weiss, and Zixin Zhou for research assistance. This paper was made possible by a grant from the Peter G. Peterson Foundation. The statements made and views expressed are solely the responsibility of the authors. The Peterson Foundation did not review this paper.

†Northwestern University (Kellogg) and NBER: anthony.defusco@kellogg.northwestern.edu

‡Northwestern University (Kellogg): nathanson@kellogg.northwestern.edu

§University of California San Diego (Rady): mreher@ucsd.edu

I Introduction

Credit market frictions can amplify the contractionary effects of economic crises (e.g., Bernanke (1983)). This observation has generated policy debates about whether to restrict leverage ex ante with macroprudential regulation, whether to provide relief ex post, and, if so, whether relief should focus on a firm's income statement or its balance sheet.

In this paper, we use loan-level data to document that a debt maturity scheduled during a crisis significantly amplifies the crisis's negative effect on firm outcomes. These results obtain in a unique setting where firms immediately cut inputs, as if to conserve cash for debt payments, yet do so in a manner that *reduces* short-run operating profits, leaving less resources available to service debt. We explain these findings with a model where indebted firms do not adapt their operating practices to a crisis environment because the resulting payoffs might accrue to creditors.

We use the hotel industry during the COVID-19 pandemic as an empirical laboratory. This setting has three useful features. First, hotels experienced a severe downturn during the pandemic, with an 80% decline in industry revenue between February and April 2020. Second, the hotel industry coordinates to maintain detailed, high-frequency performance data that allow us to measure the real effects of different debt maturities at the hotel level, both immediately at crisis onset and throughout the pandemic. Finally, the nature of hotel financing, which involves medium-term balloon loans with large prepayment penalties, affords an ideal strategy for identifying the causal effect of an upcoming debt maturity. In particular, we compare hotels with balloon loans scheduled to mature just before the pandemic's onset to hotels whose balloon loans were scheduled to mature just afterward. The difference 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 month of their loan maturity in anticipation of the COVID shock.

We find that hotels with a crisis maturity ("treatment group") exhibit sharp and sustained drops in operating expenses, output, and profits starting from the onset of the pandemic *relative* to hotels with a pre-pandemic maturity ("control group"). For example, between February and April of 2020, occupancy declines 40 log points more in the treatment group than the control group, and about a third of this gap persists into 2022.

These results are surprising for three reasons. First, operations in treated hotels decline immediately after the COVID shock.[1] In classic models of debt overhang, such as Myers (1977), managers reduce investment but not current operations when facing a large debt maturity. Second, the drop in profits for treated hotels suggests that their owners are not harvesting cash to pay off their debt, which is a channel proposed in recent work in macrofinance (e.g., Benmelech,

[1]We consider February of 2020 to be the beginning of the COVID crisis because that is when the U.S. stock market started dropping in response to the virus (Gormsen and Koijen, 2020).

Frydman and Papanikolau (2019)). Third, we continue to estimate a large drop in operations even when restricting variation to within a given borrower. In particular, the within-borrower treatment effect is largest for hotels with higher loan-to-value (LTV) ratios, suggesting that strategic considerations and not liquidity are driving borrower decisions.

To explain these results, we propose a model in the spirit of Myers (1977) in which a borrower chooses whether to make "adaptive" investments that boost productivity during a crisis, but not once it is over. The length of the crisis is unknown, the borrower has unlimited liquidity, and adaptive investments are non-contractible. The model predicts that when debt maturity is shorter, the borrower spends less on adaptive investments, leading to lower productivity throughout the crisis. This result obtains only when the borrower's debt is sufficiently large to make foreclosure a possibility. As in the data, a hotel with a large upcoming debt maturity therefore experiences immediate drops in employment, profitability, and output when the crisis begins. A simple calibration reproduces the magnitude of our empirical estimates. In summary, debt rollover amplifies the negative real effects of a crisis by weakening the borrower's incentive to operate the firm efficiently during it.

We overcome two methodological hurdles to show this result empirically: data and identification. On the data front, we construct a new data set that merges monthly hotel-level operating data representative of the near universe of U.S. hotels with detailed loan-level origination and performance data for securitized commercial mortgages collateralized by these hotels. Together, these data allow us to trace the causal link from debt maturity through the scaling back of inputs (e.g., labor) to declines in output and profitability. Notably, we track a hotel's real activity after its scheduled debt maturity, which, given our identification strategy, is critical for avoiding sample attrition bias.

We also contribute by proposing a strategy to identify the causal effect of debt maturity on real outcomes during a crisis. Clearly, naive comparisons between firms with and without debt are problematic as the choice to take on debt is likely correlated with many aspects of resiliency during a crisis. In recognition of this issue, the existing literature has focused instead on comparisons between firms with varying amounts of long-term debt coming due during a crisis (Almeida et al., 2011; Benmelech, Frydman and Papanikolau, 2019; Costello, 2020). We build on the insight of this approach by using loan-level data and an intent-to-treat estimator that compares hotels with loans scheduled as-of-origination to mature within a short window after the pandemic's onset to otherwise similar hotels whose loan is scheduled to mature in a symmetric window beforehand. Borrowers in the first group are more likely to face a large debt maturity during the pandemic because hotel mortgages carry steep prepayment penalties and feature balloon payments at maturity. Conversely, borrowers in the second group are more likely to have refinanced just prior to the pandemic and therefore not face a debt rollover during the pandemic.

Given that the typical loan in our sample has a maturity of five years, it seems unlikely that control group borrowers strategically timed their maturity to avoid the pandemic. However, their hotels may have spuriously happened to operate in markets or sectors less exposed to the pandemic. We account for this possibility by including a rich set of interactions between time period and the following hotel characteristics: size, metropolitan area, type (e.g., airport hotel vs. resort), business model (e.g. franchised or third-party operated), and chain. The consistency of our results across these specifications indicates that differential demand shocks are unlikely to be driving our results.

Our paper contributes to both the empirical and theoretical literature on the real effects of debt maturity. Empirically, we build on papers documenting negative real effects of debt maturities during the Great Depression (Benmelech, Frydman and Papanikolau, 2019) and the Global Financial Crisis (Almeida et al., 2011; Costello, 2020; Kalemli-Özcan, Laeven and Moreno, 2018). Relative to these papers, our paper studies maturing debts that are much larger relative to asset values: around 60-90% in our sample versus about 2-5% in Almeida et al. (2011), Benmelech, Frydman and Papanikolau (2019), and Costello (2020). Therefore, our setting affords a better environment for estimating the strategic effects of debt overhang, as opposed to adverse effects of debt maturities on liquidity that is the focus of prior papers.

We contribute to the theory literature investigating whether debt overhang is stronger for short- or long-maturity debt. Early work by Myers (1977) argues informally that debt overhang is stronger for long-maturity debt because firms that borrow short can change their capital structure to be more equity-heavy when investment opportunities arise. Later work by Diamond and He (2014) presents a formal analysis of this problem and shows that the effect of maturity on debt overhang is ambiguous. It depends on factors such as the relative timing of news arrival and information decisions and the extent to which investment increases the volatility of future firm cash flows. Our empirical results provide a setting in which debt overhang is stronger for short-maturity debt, as treated hotels seem likely to have shorter remaining maturities at pandemic onset than control hotels that refinanced just before. We provide a model tailored to this setting that clarifies why debt overhang is stronger for shorter maturities.

Our paper also contributes to a large literature on refinancing frictions and distress in the mortgage market. On the residential side, many papers have shown that frictions inhibiting mortgage refinancing can have substantial effects on households' disposable income and therefore consumption (Agarwal et al., 2017*a*,*b*; Beraja et al., 2019; DeFusco and Mondragon, 2020).[2] Our paper shows that similar frictions can also have effects on firm outcomes. On the commercial side, many papers focus on how the anticipated possibility of renegotiation affects ex-ante

[2] In related work, Melzer (2017) also shows that debt overhang in the residential mortgage market can affect household investment behavior.

loan pricing and borrower incentives (Riddiough and Wyatt, 1994; Harding and Sirmans, 2002; Brown, Ciochetti and Riddiough, 2006; Flynn, Ghent and Tchistyi, 2022). Our focus is on how borrowers behave when renegotiation is anticipated to be unlikely, which survey evidence during the early months of the COVID pandemic indicated was the case. A closely related paper is Liebersohn, Correa and Sicilian (2022), who also show that mortgage debt inhibits adaptation in commercial real estate, although they focus on retail during the rise of e-commerce while we look at hospitality during the COVID crisis.

Finally, we add to the literature on financial frictions during the COVID-19 pandemic. One line of papers focuses on strategic incentives. For example, Brunnermeier and Kirshnamurthy (2020) argue that debt overhang led firms to cut investment during the pandemic, and Crouzet and Tourre (2021) argue that this effect was exacerbated by U.S. government interventions in credit markets. As separate line of papers focuses on cash-flow constraints and, in particular, variation in the ability to roll over short-term credit lines during the pandemic (Greenwald, Krainer and Paul, 2021; Chodorow-Reich et al., 2022). Putting the two lines of research together, we show how the inability to roll over long-term balloon debt led firms (i.e., hotel investors) to strategically scale back their operations. Our model explains this scaling-back as an unwillingness to adapt to the pandemic crisis. This explanation is similar to that of Bloom (2009), in that we both highlight how frictions in adjusting to an economic crisis can amplify the crisis's real effects.[3]

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. Consequently, our setting features important cross-sectional variation in financial constraints faced by

[3] 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.

owners, whereas the major brands plausibly have access to financing from multiple sources. 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 themeselves, 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.[4] 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 this reason, 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.

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. By count, 36% of hotel loans from medium-to-large banks, life insurers, and asset-backed issuers were from CMBS (Glancy et al., 2022); by dollar amount, hotel loans from CMBS exceeded those 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 has several contractual features that, de facto, generate a large required principal payment at the loan's maturity date. Specifically, the middle 50% of hotels have a loan with a loan-to-value ratio at origination of 64-88% and do not fully amortize, implying a balloon payment scheduled at maturity. Moreover, many loans carry covenants that limit prepayment,

[4] Management agreements often explicitly include this condition (e.g., Sunstone Hotel Properties (2004)).

[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)).

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 limit prepayment with either a lockout or fee penalty up until 8 months before scheduled maturity, as shown in Panel A of Figure I. These covenants lift as the loan nears the scheduled maturity date. Corresponding to the timing of these 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 US 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 US 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 changed the type of services that consumers demanded from hotels. For instance, 10-40% of US consumers surveyed in April 2020 reported that 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 closed down (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, 2020*a*).

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 4 years (PwC, 2020*a*,*b*).[6]

These beleifs 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, 2020*b*). Some lenders granted loan modifications, such as forbearance and maturity extensions, that 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, 2020*b*). 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 Smith Travel Research (STR). STR is a leading data provider in the hotel industry and covers over 98% of hotels in the U.S. The STR data is self-reported, meaning that hotel owners send the data to STR.[7] 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, we study all 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.

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

[6]Given that hotel revenues regained pre-crisis levels in the summer of 2021, the industry recovered much more quickly than people expected in 2020.

[7]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. Therefore, we treat the STR data as truthful in our analysis.

rates, number of rooms available, 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 operating income, 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, hotel chain within the brand, operating arrangement, and purpose of stay (e.g., airport, resort, highway). STR defines geographic markets that generally align with a CBSA.[8]

Mortgage data

Our primary source of data on mortgages collateralized by hotels comes from Trepp LLC. We specficially work with Trepp's T-Loan dataset. This dataset covers the majority of commercial mortgages originated in the US 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 or addresses 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.

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 picture of the total LTV at origination. In the cases where we observe a junior lien in RCA, we replace the LTV from Trepp with the LTV in RCA.[9] 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 some loans in Trepp are originated in the 1990s and do not appear in RCA.

[8]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.

[9]In a small number of cases, we cannot observe the property value in RCA, so we scale up the LTV in Trepp by the ratio of total to securitized debt in RCA.

Analysis sample

To form our primary analysis sample, address data for the collateral properties in Trepp are used to perform a match to the STR data.[10] 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. Therefore, even if the borrower prepays the loan before 2019, we still assign the hotel collateral to one of the two groups. As Table I shows, hotels are somewhat but not perfectly balanced across the two groups. Hotels serving as collateral for post-pandemic maturity loans are slightly larger, more likely to be in urban locations, and have lower LTVs and slightly shorter maturities. Our empirical analysis will address these imbalances in several ways, which we discuss in the next section.

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 faced a need to payoff their debt 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

[10] Because STR data are anonymized, we do not observe address information in STR. An employee at STR used the address list from Trepp to match the data. We are contractually prohibited from identifying any of the hotels in STR using these matched data.

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 payoff 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).[11] 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

[11] 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.

of geographic market-by-month fixed effects, δ_{mt}. These fixed effects ensure that our estimates are not begin 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.

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:

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

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 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 percent) 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 in 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 dynamic difference-in-differences 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 percent) 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 percent for hotels with pre-pandemic maturities and 80 percent for hotels with loans maturing during the pandemic. This gap remains positive throughout the pandemic but closes to roughly 10 percent 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. As a first pass, columns 2–4 of Table II explore the sensitivity of our baseline estimate to alternative specifications that allow the direct effect of the pandemic to vary non-parametrically across a range of different hotel characteristics. Column 2, for example, 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). Across all of these specifications, we continue to find point estimates that are both economically large and statistically significant.[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 percent) 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 percent gap in revenues is driven by lower occupancy while the remaining half is due to lower prices.

[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.

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 percent 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 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.[13] 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 percent) 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 extend to the employees of the hotel and potentially have implications for job separations. 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

[13] 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.

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.[14]

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 percent) 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 percent) 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.

[14] 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.

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-hotel chain-by-month fixed effects.[15] This restrictive specification identifies the main effect using only variation across hotels within a given chain and market (e.g. Marriott Residence Inn hotels 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 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 maurities that are owned by the same borrower. The sample size falls by 16% relative to Table II because information on the borrower comes from the RCA dataset. Nevertheless, the stringency of this exercise makes it highly unlikely that spurious correlation would drive the results. We estimate a revenue drop of 22 log points, shown in column 5 of Appendix Table A.II. This result further supports the consensus across our analysis that having a loan maturity during the pandemic causally leads to lower revenue.

Role of Access to External Financing

A key step in the logic of our research design is that hotels that needed to refinance to pay off maturing debt during the pandemic could not easily do so. Otherwise, there would be no economic

[15] 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.

reason for a difference in outcomes between the treatment and control groups. Consistent with the importance of external financing, Appendix Figure A.V verifies that our results are driven by hotels with a pandemic maturity that, indeed, did not pay off their loan. Precisely, we plot the estimates from a variant of equation (2) that separates the results in Figure IV according to whether the loan paid off during the pandemic. Loosely, one can think of hotels with a pandemic maturity that actually did pay off during the pandemic as "non-compliers." Figure A.V shows how revenue at these hotels remains quite similar, both economically and statistically, to that of hotels with a pre-pandemic maturity. Of course, loan payoff is endogenous, and so we do not interpret these results as the causal effect of the ability to refinance. Rather, we view the fact that our results are driven by hotels that did not pay off their loan as supporting the basic premise of our research design.

Renovations by Hotels with a Pandemic Maturity

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, which derives directly from standardized (i.e., CREFC) loan servicing records and is well-populated. Using this definition, we 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.

Immediate Drop in Marketing Expense

Appendix Figure A.VI verifies that the drop in sales and marketing expense from panel D of Figure VI occurs immediately and slightly leads the drop in operating profit that we document in the next section. This timing supports our interpretation that hotels with a pandemic maturity actively seek to reduce bookings (e.g., by not advertising on TripAdvisor), rather than spuriously responding to a 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.

Differences in Paycheck Protection Program Take-up

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. So, it is unlikely that the drop in revenue at treated hotels reflects an inability to secure PPP financing.

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 explanations related to debt overhang: the borrower's reduced incentive to maintain the property because the lender may seize it in foreclosure.[16] 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.[17] 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

[16] 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.

[17] 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. More generally, most models with labor adjustment costs predict that firms can shift profit forward in time by reducing current net hiring.

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 percent 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 percent 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 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. 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.

Third, hotels with a pandemic maturity reduce their routine debt servicing payments by around half, as documented in Appendix Figure A.III. We produce the figure using the Trepp dataset and the subset of hotels that have not yet paid off their loan. Following the logic of the previous paragraph, staying current on debt servicing may encourage the special servicer to extend more generous terms of renegotiation. Empirically, though, this does not occur.

Putting the previous three pieces of 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 (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 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

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

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 (β) 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 in which they have a weaker equity stake.[18]

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.[19]

While a hotel's initial maturity month appears randomly assigned, it seems less likely that the initial LTV ratio varies with the same degree of randomness. 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 35 and 48 log points, which lie close to the uncontrolled specification in column 2 (45 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

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

[19]A careful visual inspection reveals a slightly negative pre-trend in the average treatment effect beginning in December 2019, which was not apparent in the baseline event study Figure IV. Since the estimation sample is almost the same, this difference reflects the inclusion of fixed effects defined by $HighLTV_i$ and month.

predict that larger borrowers have a smaller drop in output. Next, column 5 shows how the estimated treatment effect is 10 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 reduces their incentive to maintain it. The original Myers (1977) notion of debt overhang was conceived in a simpler setting than our empirical environment. 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, drive the results. We calibrate our model to show that it can quantitatively match the effects we find in the data.

V.A *Firm during normal times*

We begin by modeling a firm during normal times, when there is not a pandemic. Below in Section V.B, we discuss what occurs when a pandemic unexpectedly occurs.

Production

The firm produces output that it sells in competitive markets at a price p. The instantaneous 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 $\alpha + \beta < 1$. L_t denotes variable inputs, such as labor and electricity, and the price of these inputs is w. K_t is the stock of physical capital, like building square footage, and this stock remains constant over time, allowing us to drop the time subscript.

M_t gives the stock of management practices, such as use of computer systems. 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:

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

where $0 \leq \zeta \leq 1$. We simplify the model by assuming that pandemic management practices are not useful in normal times, so that $\zeta = 0$. As an additional simplification, we assume that normal management practices remain fixed over time and denote this constant value M_0.

Debt

As in other models of debt rollover (Leland and Toft, 1996; Leland, 1998; He and Xiong, 2012; Diamond and He, 2014), 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. 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 a maturity date t, the owner of the firm either defaults or rolls over the debt. In the case of a rollover, 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, T units of time later.

The firm, which serves as collateral for the loan, consists of the physical capital stock, K_t, as well as the managerial capital stocks, $M_{0,t}$ and $M_{1,t}$. Management practices attach to the firm: in the case of default, the lender acquires the firm's management practices, and the borrower cannot institute these management practices at another firm without paying additional costs. We abstract from foreclosure costs by allowing the lender to fully seize all capital in case of default. 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.

Borrower optimization

The borrower maximizes the net present value of cash flows by choosing the variable input, L_t, and whether to default or roll over the debt at maturity. Proposition 1 characterizes firm outcomes when the borrower optimizes (proofs of Propositions appear in Appendix B).

Proposition 1 (Normal times)**.** *In normal times, the levels of variable inputs, operational profits,* *and output are $L^*(M_0, p)$, $\pi^*(M_0, p)$, and $F^*(M_0, p)$, where*

$$
\begin{aligned}
L^*(M,p) &= \alpha^{\frac{1}{1-\alpha}} p^{\frac{1}{1-\alpha}} w^{-\frac{1}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}} \\
\pi^*(M,p) &= (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}} p^{\frac{1}{1-\alpha}} w^{-\frac{\alpha}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}} \\
F^*(M,p) &= \alpha^{\frac{\alpha}{1-\alpha}} p^{\frac{\alpha}{1-\alpha}} w^{-\frac{\alpha}{1-\alpha}} K^{\frac{1-\alpha-\beta}{1-\alpha}} M^{\frac{\beta}{1-\alpha}}.
\end{aligned}
\tag{6}
$$

The value of the firm (debt plus equity) is $V^* = r^{-1}\pi^*(M_0, p)$. The borrower rolls over the debt at each maturity if $D < V^*$, and defaults at maturity if $D > V^*$.

For the rest of the analysis, we restrict attention to the case in which $D < V^*$, meaning that the borrower always rolls over the debt in normal times.

V.B Firm during a pandemic

At a time that we normalize to $t = 0$, a pandemic unexpectedly begins. The pandemic entails a temporary change to the price of the firm's good, p, as well as the relative importance of the pandemic management practice, ζ. To keep track of these different parameter values, we introduce a new variable, $j \in \{0, 1\}$, which equals 1 during the pandemic and 0 in normal times, letting us denote these variables by p_j and ζ_j. The price of the firm's output is lower during the pandemic, so that $p_1 < p_0$, representing a decline in demand for the firm's output. The pandemic also increases the relative importance of pandemic management practices, so that $\zeta_1 > \zeta_0 = 0$. The pandemic ends with a constant Poisson hazard $q > 0$, after which these parameters revert to their values in normal times.[20]

At the beginning of the pandemic, the borrower chooses to make a one-time, adaptive investment $I > 0$ in pandemic management practices, raising $M_{1,t}$ from its initial value of $M_{1,0}$ to $M_{1,0} + I$ for $t > 0$. The cost of this investment is cI. The borrower has sole discretion in making this adaptive investment, and cannot contract with the lender over it. We simplify the analysis by assuming that the initial value of pandemic management practices, $M_{1,0}$, equals 0, so that the level of these practices during the pandemic coincides with the adaptive investment, I.

Proposition 2 characterizes the adaptive investment as a function of the face value and remaining maturity of the debt at the time the pandemic begins.

Proposition 2 (Adaptive investments)**.** *Let τ denote the remaining time until debt maturity when*

[20] Crouzet and Tourre (2021) similarly model the COVID pandemic as a temporary shock to parameter values.

the pandemic begins. There exists $D^*(\tau) > 0$ such that

$$I^* = \begin{cases} \widetilde{I}, & D < D^*(\tau) \\ \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \widetilde{I} & D > D^*(\tau), \end{cases} \tag{7}$$

where

$$\widetilde{I} = \beta^{\frac{1-\alpha}{1-\alpha-\beta\zeta_1}} \zeta_1^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} c^{-\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} (r+q)^{-\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \alpha^{\frac{\alpha}{1-\alpha-\zeta_1\beta}} p_1^{\frac{1}{1-\alpha-\zeta_1\beta}} w^{-\frac{\alpha}{1-\alpha-\zeta_1\beta}} K^{\frac{1-\alpha-\beta}{1-\alpha-\zeta_1\beta}} M_0^{\frac{(1-\zeta_1)\beta}{1-\alpha-\zeta_1\beta}}. \tag{8}$$

The borrower rolls over the debt at each pandemic maturity when $D < D^*(\tau)$, and defaults at pandemic maturity if $D > D^*(\tau)$. The default threshold $D^*(\tau)$ strictly increases in τ. If the unit cost of adaptive investments, c, is sufficiently large, then $D^*(\tau) < V^*$ for all τ.

When debt is low, the impaired value of the firm is still greater than the face value of debt. As a result, the borrower intends to roll over the debt during the pandemic, and makes the adaptive investment that is optimal given the potentially unlimited future duration of the pandemic, $\widetilde{I}$. In contrast, when the debt value is high, the borrower now defaults at maturity if the pandemic persists until then. Consequently, the borrower makes a lower adaptive investment that reflects the reduced amount of time that the borrower will benefit from it. In this default region, the adaptive investment depends positively on the amount of time until maturity, τ, because the investment is larger if the borrower benefits from it for longer.[21]

The default region is guaranteed to appear for some values of $D < V^*$ 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. The case where c is large creates the realistic possibility that some firms with high levels of debt will default if the pandemic persists until their maturity date.

The chosen adaptive investment, I^*, determines real outcomes during the pandemic. A larger adaptive investment boosts management practices during the pandemic, leading to high 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 derives these differences in real outcomes using the results of Proposition 2.

Proposition 3 (Real effects of pandemic)**.** *Let τ denote the remaining time until debt maturity when the pandemic begins. Let $Y^*(\tau)$ denote operational profits, output, or the chosen level of the*

[21]This result is related to Example 2 in Diamond and He (2014). As in their example, the borrower faces a one-time investment decision, and debt overhang is stronger for short-term debt. Furthermore, in both their example and our setting, volatility is lower in future good states of the world (here, the end of the pandemic).

variable input during the pandemic before maturity. 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 findings using our model. Control hotels, whose borrowers refinanced in the year before the pandemic began, have high values of τ, specifically between $T-1$ and T, where T is the maturity at the time of refinance. In contrast, treated hotels have much lower values of τ between 0 and 1, as their debt is scheduled to mature within a year. According to Proposition 3, real outcomes for treated hotels are no greater than the outcomes for control hotels, and the outcomes are smaller when the level of debt is sufficiently high. In this case of high debt, either more treated than control borrowers plan to default, or both groups plan to default but treated borrowers have shorter investment horizons due to their sooner maturities. In either case, the treated borrowers make smaller adaptive investments at the onset of the pandemic, leading to lower real outcomes immediately. Proposition 3 is also consistent with Table III: within the treatment group, the revenue decline is larger for hotels closer to maturity at pandemic onset.

V.C Calibration

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 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. 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, ζ_1, and p_1/p_0. To parametrize α, we use the average ratio of variable expenses to revenue in our data before the pandemic, which is 0.7. As is clear from the formulas in Proposition 1, 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 $r = 0.1$, which is the discount rate used to value unlevered hotel investments in 2019 according to a PwC investor survey. 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 ζ_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. 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 ζ_1 to match the treatment effect in column 1 of Table V of -0.285 on log revenues for highly levered firms.

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 pandemic 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 -0.285, which matches the effect in Table V. We choose $\zeta_1 = 0.391$ to match this effect, implying that about one third of useful management practices were specific to the pandemic during the COVID crisis. To match the highest treatment effect of -0.48 in Table Table V, we require a value for ζ_1 of 0.604, implying a specificity of management practices during the pandemic of almost two thirds. Both numbers strike us as plausible, although we cannot be sure without estimating the hotel production function during COVID in more detail.

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 -0.285, this exercise implies a treatment effect for hotels with an early pandemic maturity of -0.363 and those with a late pandemic maturity of -0.188. 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

In this paper, we document large, negative effects on real outcomes of debt that is scheduled to mature during a crisis. We argue that the effect is more likely to be due to debt overhang rather than liquidity constraints. Consistent with our argument, the effect is driven by hotels with high LTV, even within the same borrower.

One novel aspect of our findings is that a purely strategic effect could lead to an immediate decline in labor expense and output. Prior work has resorted to cash flow constraints to connect high levels of debt during a crisis to immediate cuts in output and employment (e.g., Benmelech, Frydman and Papanikolau (2019) and Brunnermeier and Kirshnamurthy (2020)). We explain this result using a model of adaptive investments that boost a firm's productivity exclusively during a crisis. Such investments—e.g., disinfecting protocols, temperature checks of guests, managing labor worried about contracting the virus—were a salient aspect of hotels' response to the COVID crisis, and a calibrated model of this phenomenon can match the large size of our empirical results. Therefore, our work highlights how large debt maturities can depress economic activity during a crisis even when liquidity is plentiful.

Our work also highlights the 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 economic to rollover risk from commercial real estate. At the time of writing, a large amount of commercial real estate debt is scheduled to mature in the next three years, stoking concerns about widespread financial distress in this market due to rising interest rates (Putzier, 2023). The design of these mortgages may impede efficient adaptation to the structural issues facing commercial real estate, such as work-from-home.

References

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, and Amit Seru. 2017*a*. "Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program." *Journal of Political Economy*, 125(3): 654–712.

Agarwal, Sumit, Gene Amromin, Souphala Chomsisengphet, Tim Landvoigt, Tomasz Piskorski, Amit Seru, and Vincent Yao. 2017*b*. "Mortgage Refinancing, Consumer Spending, and Competition: Evidence from the Home Affordable Refinancing Program." NBER Working Paper No. 21512.

AHLA. 2020*a*. "State of the Hotel Industry Analysis: COVID-19 Six Months Later." American Hotel & Lodging Association.

AHLA. 2020*b*. "Survey of Hotels on Financial Crisis." American Hotel & Lodging Association.

Almeida, Heitor, Murillo Campello, Bruni Laranjeira, and Scott Weisbenner. 2011. "Corporate Debt Maturity and the Real Effects of the 2007 Debt Crisis." *Critical Finance Review*, 1: 3–58.

Benmelech, Efraim, Carola Frydman, and Dimitris Papanikolau. 2019. "Financial frictions and employment during the Great Depression." *Journal of Financial Economics*, 133: 541–563.

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra. 2019. "Regional Heterogeneity and the Refinancing Channel of Monetary Policy." *Quarterly Journal of Economics*, 134(1): 109–183.

Bernanke, Ben S. 1983. "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression." *American Economic Review*, 73(3): 257–276.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 77(3): 623–685.

Bloom, Nicholas, and John Van Reenen. 2007. "Measuring and Explaining Management Practices across Firms and Countries." *Quarterly Journal of Economics*, 122(4): 1351–1408.

Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen. 2019. "What Drives Differences in Management Practices?" *American Economic Review*, 109(5): 1648–1683.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen. 2017. "Management as a Technology?" National Bureau of Economic Research Working Paper 22327.

Brown, David T., Brian A. Ciochetti, and Timothy J. Riddiough. 2006. "Theory and Evidence on the Resolution of Financial Distress." *Review of Financial Studies*, 19(4): 1357–1397.

Brown, James R., Matthew T. Gustafson, and Ivan T. Ivanov. 2021. "Weathering Cash Flow Shocks." *Journal of Finance*, 76(4): 1731–1772.

Brunnermeier, Markus, and Arvind Kirshnamurthy. 2020. "Corporate Debt Overhang and Credit Policy." *Brookings Papers on Economic Activity*, 2020(2): 447–502.

Butler, Jim. 2008. "Hospitality Lawyer: Hotel Management Agreements: SNDAs or Subordination Agreements." Global Hospitality Group.

Chodorow-Reich, Gabriel, Olivier Darmouni, Stephan Luck, and Matthew Plosser. 2022. "Bank Liquidity Provision across the Firm Size Distribution." *Journal of Financial Economics*, 144: 908–932.

Costello, Anna M. 2020. "Credit Market Disruptions and Liquidity Spillover Effects in the Supply Chain." *Journal of Political Economy*, 128(9): 3434–3468.

Crouzet, Nicolas, and Fabrice Tourre. 2021. "Can the cure kill the patient? Corporate credit interventions and debt overhang." Northwestern University.

DeFusco, Anthony A., and John Mondragon. 2020. "No Job, No Money, No Refi: Frictions to Refinancing in a Recession." *Journal of Finance*, 75(5): 2327–2376.

Diamond, Douglas W., and Zhiguo He. 2014. "A Theory of Debt Maturity: The Long and Short of Debt Overhang." *Journal of Finance*, 69(2): 719–762.

Flynn, Sean, Andra Ghent, and Alexei Tchistyi. 2022. "The Imitation Game: How Encouraging Renegotiation Makes Good Borrowers Bad." Working Paper.

Freedman, Matthew, and Renáta Kosová. 2014. "Agency and Compensation: Evidence from the Hotel Industry." *Journal of Law, Economics, and Organization*, 30(1): 72–103.

Glancy, David, John R. Krainer, Robert J. Kurtzman, and Joseph B. Nichols. 2022. "Intermediary Segmentation in the Commercial Real Estate Market." *Journal of Money, Credit and Banking*, 54(7): 2029–2080.

Glancy, David, Robert J. Kurtzman, and Lara Loewenstein. 2022. "Loan Modifications and the Commercial Real Estate Market." Board of Governors of the Federal Reserve System. Finance and Economics Discussion Series 2022-050.

Gormsen, Niels Joachim, and Ralph S.J. Koijen. 2020. "Coronavirus: Impact on Stock Prices and Growth Expectations." *Review of Asset Pricing Studies*, 10(4): 574–597.

Greenwald, Daniel L., John Krainer, and Pascal Paul. 2021. "The Credit Line Channel." *Federal Reserve Bank of San Francisco Working Paper*.

Harding, John P., and C.F. Sirmans. 2002. "Renegotiation of Troubled Debt: The Choice between Discounted Payoff and Maturity Extension." *Real Estate Economics*, 30(3): 475–503.

He, Zhiguo, and Wei Xiong. 2012. "Rollover Risk and Credit Risk." *Journal of Finance*, 67(2): 391–429.

Kalemli-Özcan, Şebnem, Luc Laeven, and David Moreno. 2018. "Debt Overhang, Rollover Risk, and Corporate Investment: Evidence from the European Crisis." Center for Economic Policy Research Discussion Paper 12881.

Kim, Jinkyung Jenny, and Heesup Han. 2022. "Saving the hotel industry: Strategic response to the COVID-19 pandemic, hotel selection analysis, and customer retention." *International Journal of Hospitality Management*, 102.

Kosová, Renáta, and Giorgo Sertsios. 2018. "An Empirical Analysis of Self-Enforcement Mechanisms: Evidence from Hotel Franchising." *Management Science*, 64(1): 43–63.

Krishnan, Vik, Ryan Mann, Nathan Seitzman, and Nina Wittkamp. 2020. "Hospitality and COVID-19: How long until 'no vacancy' for US hotels?" McKinsey & Company.

Leland, Hayne E. 1998. "Agency Costs, Risk Management, and Capital Structure." *Journal of Finance*, 53(4): 1213–1243.

Leland, Hayne E., and Klaus Bjerre Toft. 1996. "Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads." *Journal of Finance*, 51(3): 987–1019.

Liebersohn, Jack, Ricardo Correa, and Martin Sicilian. 2022. "Debt Overhang and the Retail Apocalypse." University of California, Irvine.

Marriott. 2020. "Annual Report."
`http://media.corporate-ir.net/media_files/IROL/10/108017/marriott20AR/10k-item1-p1.html`.

Melzer, Brian T. 2017. "Mortgage Debt Overhang: Reduced Investment by Homeowners at Risk of Default." *Journal of Finance*, 72(2): 575–612.

Myers, Stewart C. 1977. "Determinants of Corporate Borrowing." *Journal of Financial Economics*, 5(2): 147–175.

Nguyen, Lan Thi Mai, Dung Le, Kieu Trang Vu, and Trang Khanh Tran. 2023. "The role of capital structure management in maintaining the financial stability of hotel firms during the pandemic—A global investigation." *International Journal of Hospitality Management*, 109.

Povel, Paul, Giorgo Sertsios, Renáta Kosová, and Praveen Kumar. 2016. "Boom and Gloom." *Journal of Finance*, 71(5): 2287–2332.

Putzier, Konrad. 2023. "Commercial Property Faces Loan Crunch — A $1.5 trillion bill for mortgages is coming due for landlords over the next three years." *Wall Street Journal*.

PwC. 2020*a*. "Hospitality Directions US, May 2020." PwC.

PwC. 2020*b*. "Hospitality Directions US, November 2020." PwC.

Rackl, Lori. 2020. "'We haven't seen anything like this': Outbreak makes empty rooms, staff cuts, closures the new reality for Chicago's hotels." *Chicago Tribune*.

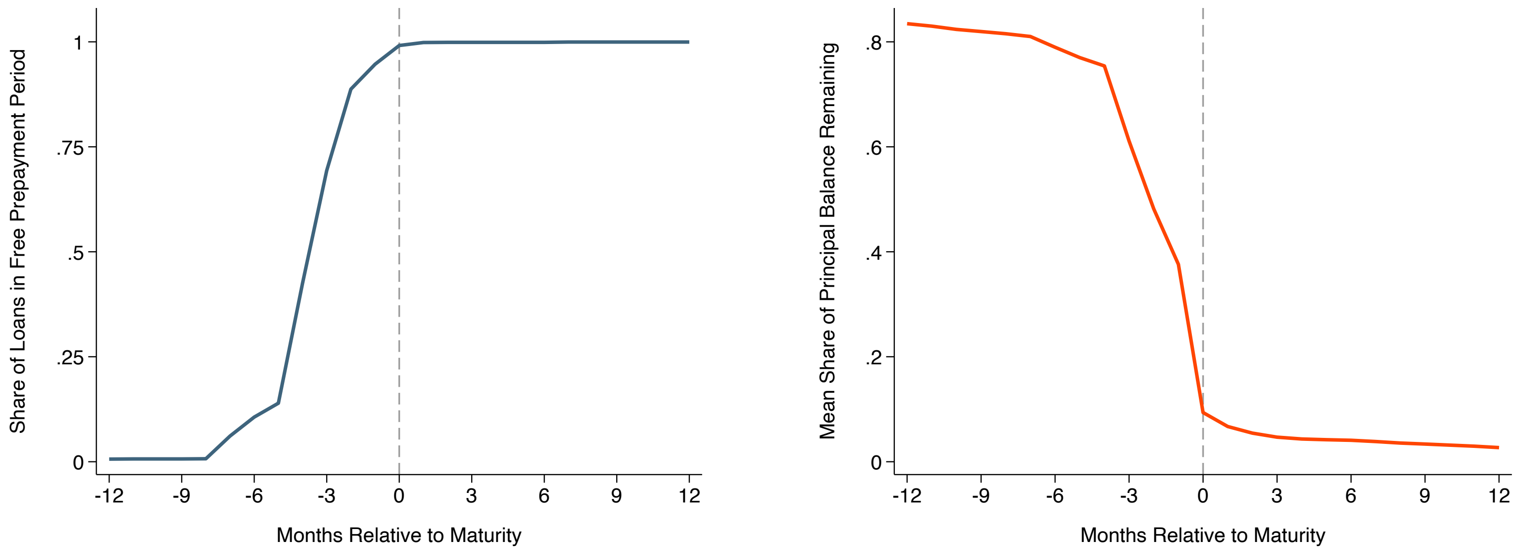
Reher, Michael. 2021. "Finance and the supply of housing quality." *Journal of Financial Economics*, 142(1): 357–376.

Riddiough, Timothy J., and Steve B. Wyatt. 1994. "Strategic Default, Workout, and Commercial Mortgage Valuation." *Journal of Real Estate Finance and Economics*, 9: 5–22.

Steiner, Eva, and Alexei Tchistyi. 2022. "Did PPP Loans Distort Business Competition? Evidence from the Hotel Industry." Working Paper.

STR. 2019. "Data Reporting Guidelines." Smith Travel Research.

Sunstone Hotel Properties. 2004. "Hotel Management Agreement with Sunstone Hotel Trs Lessee."
https://www.sec.gov/Archives/edgar/data/1295810/000119312504143744/dex103.htm.



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)

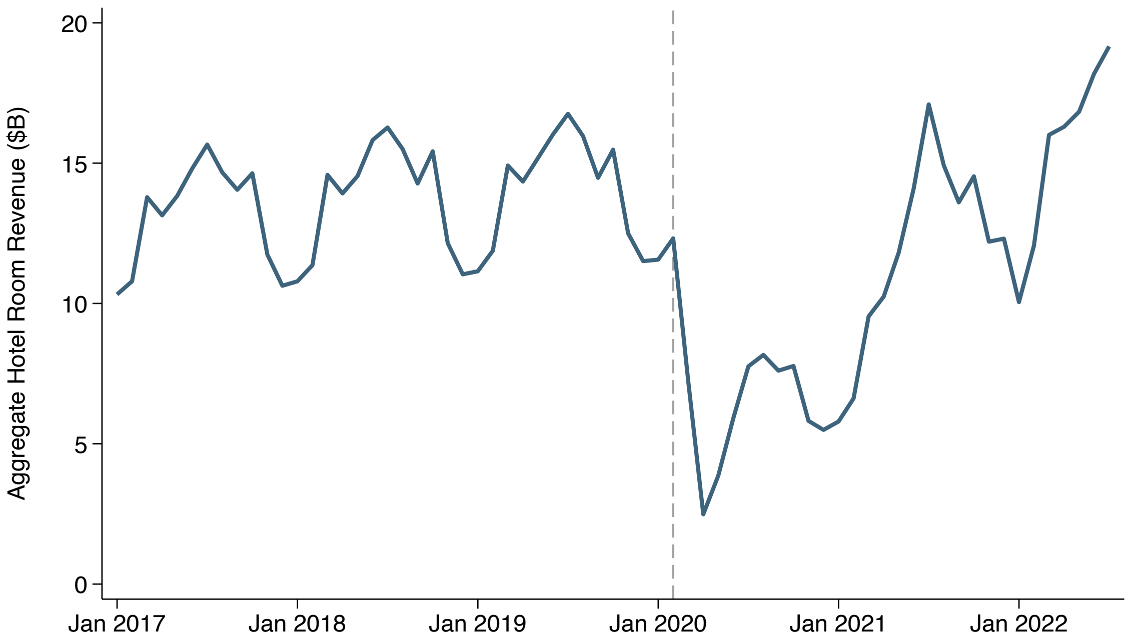


FIGURE II
Aggregate Monthly Revenues for US Hotels.

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)

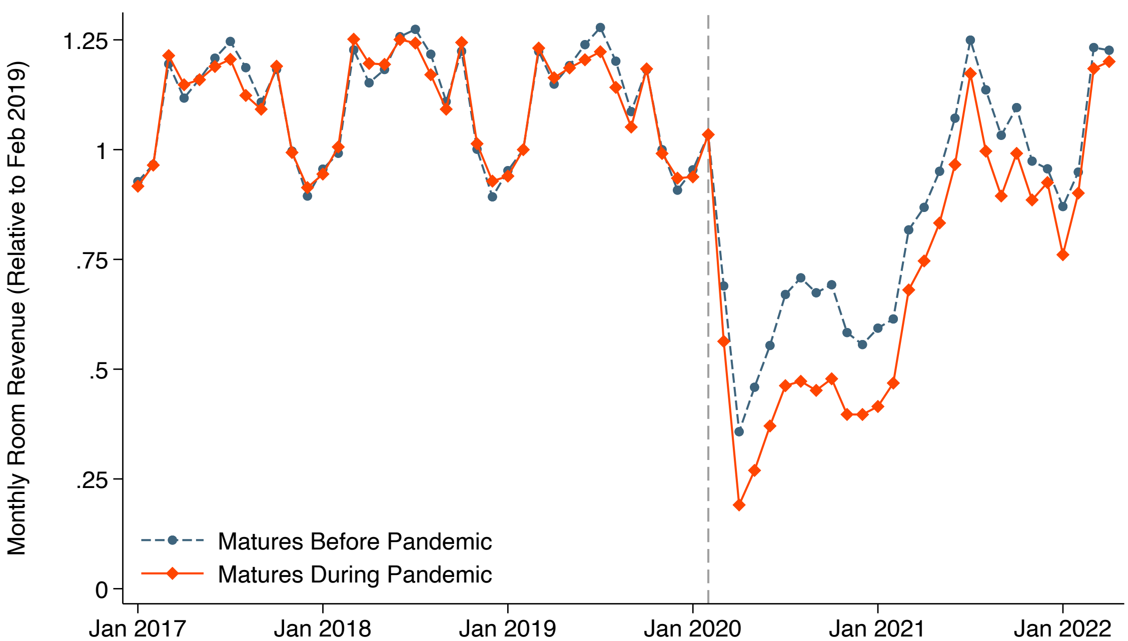


FIGURE III

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 Feburuary 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)

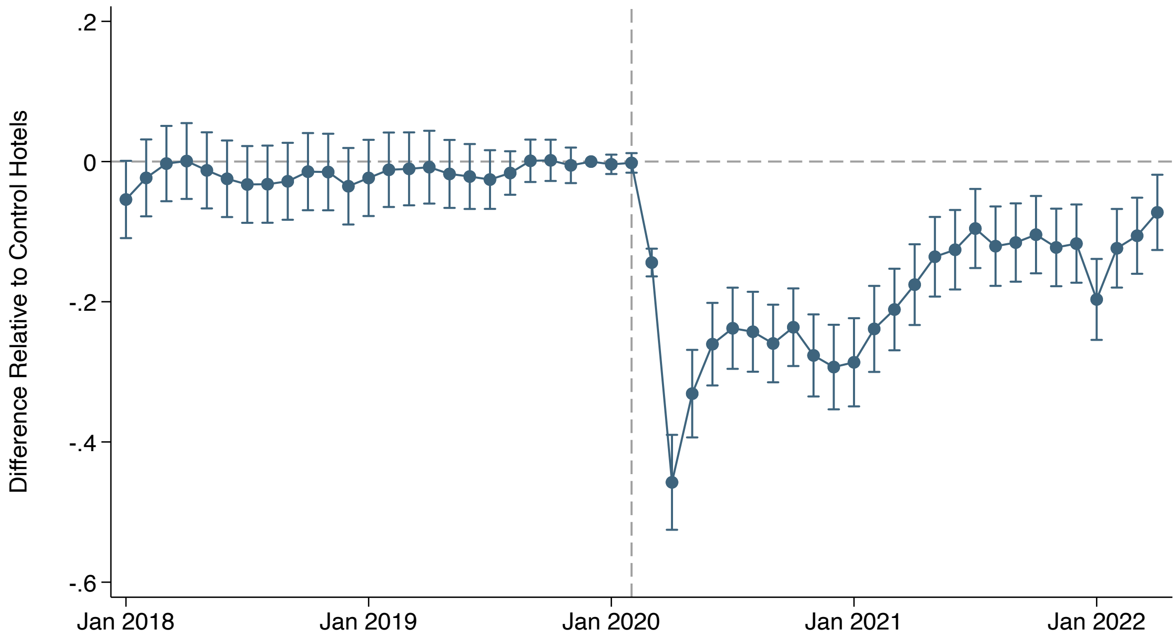


FIGURE IV
Effect of Pandemic Maturity on Hotel Room Revenues.

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

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

where i and t index hotel and month; 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)

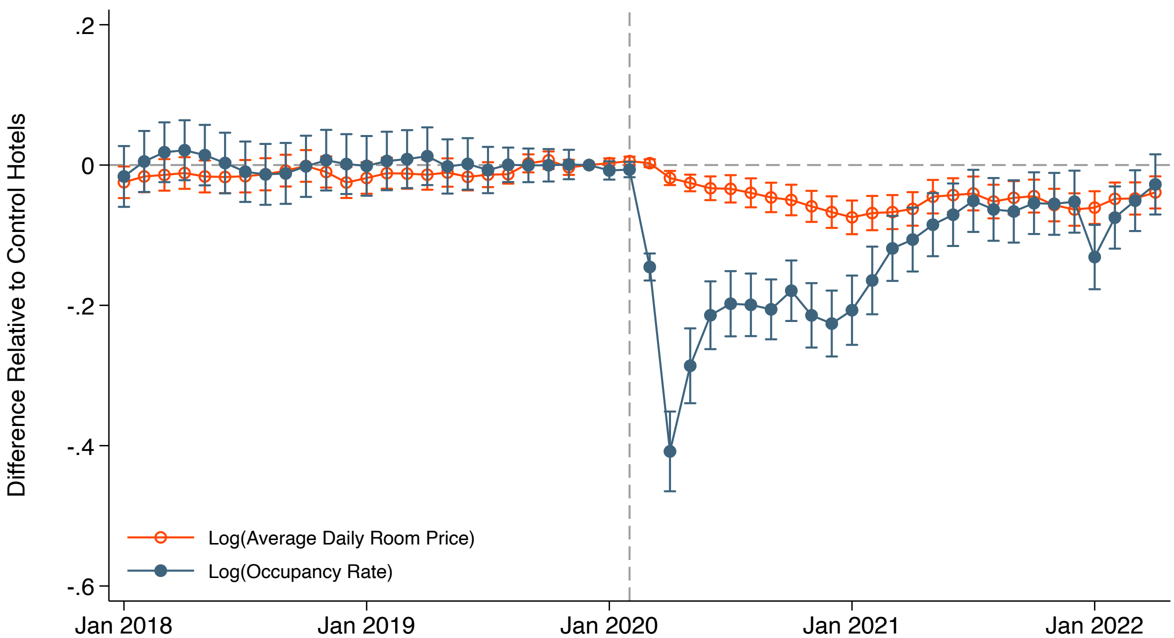


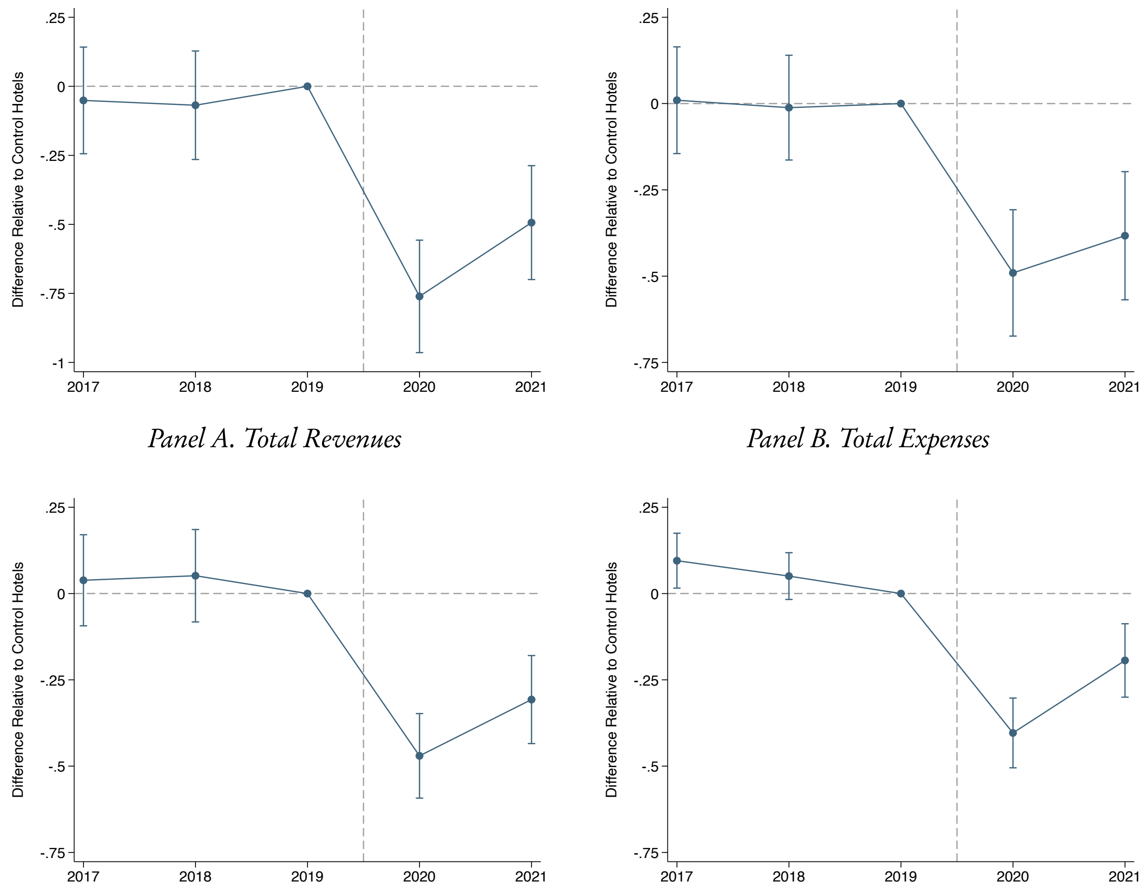
FIGURE V

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)



Panel A. Total Revenues

Panel B. Total Expenses

Panel C. Labor Expenses

Panel D. Sales and Marketing Expenses

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. In particular, the treatment variable $PandemicMaturity_i$ now indicates whether the maturity date for the loan on hotel i is in 2020 or later. 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)

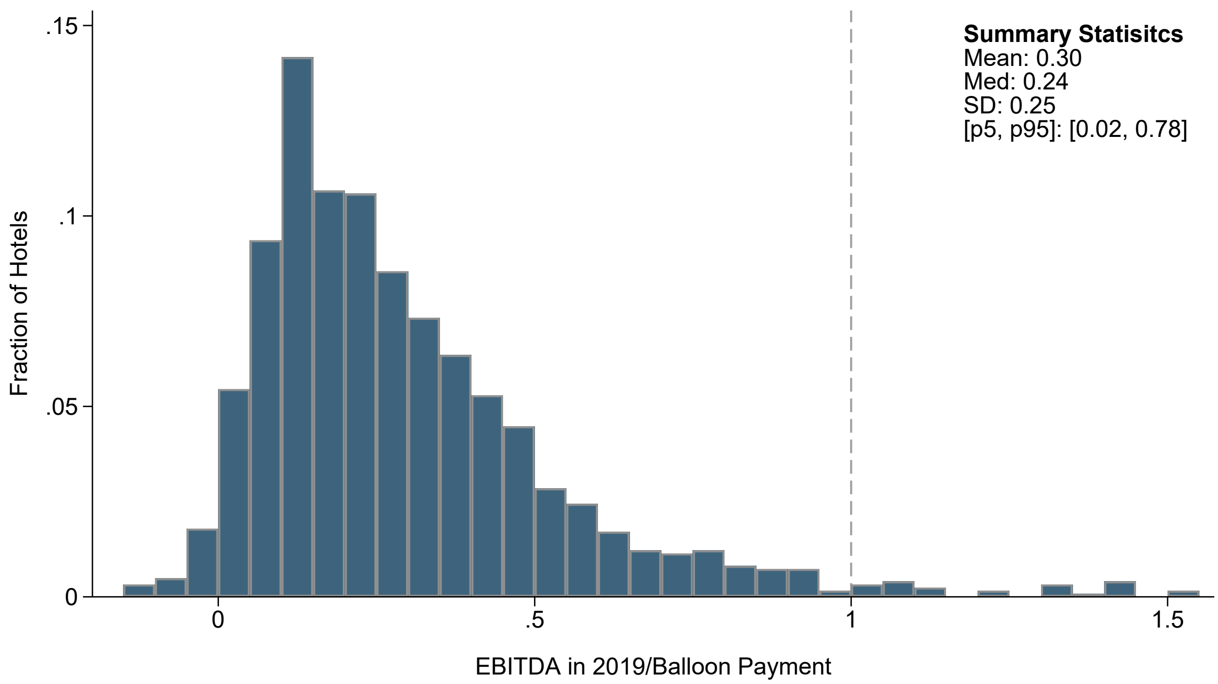


FIGURE VII
Assessing the Cash Flow Channel. Operating Profits Relative to Scheduled Balloon Payment.

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)

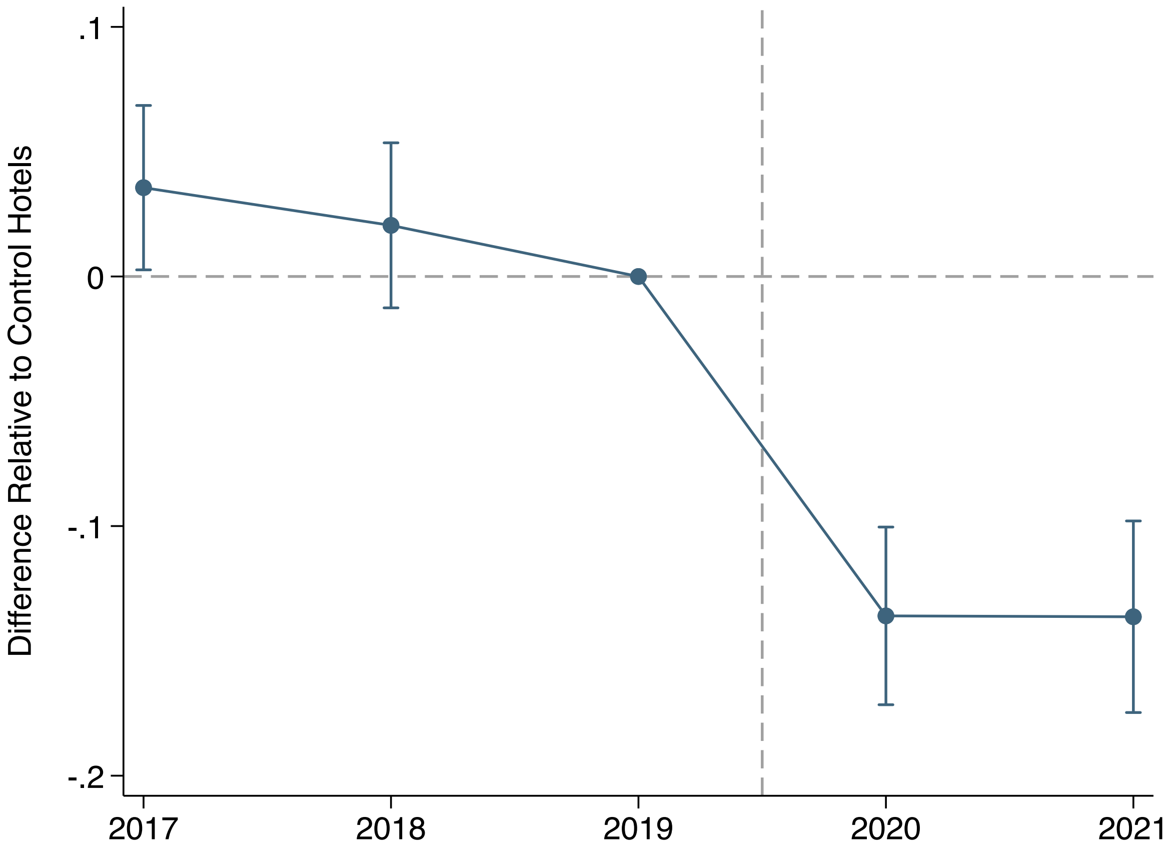


FIGURE VIII
Effect of Pandemic Maturity on Hotel Operating Profits.

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)

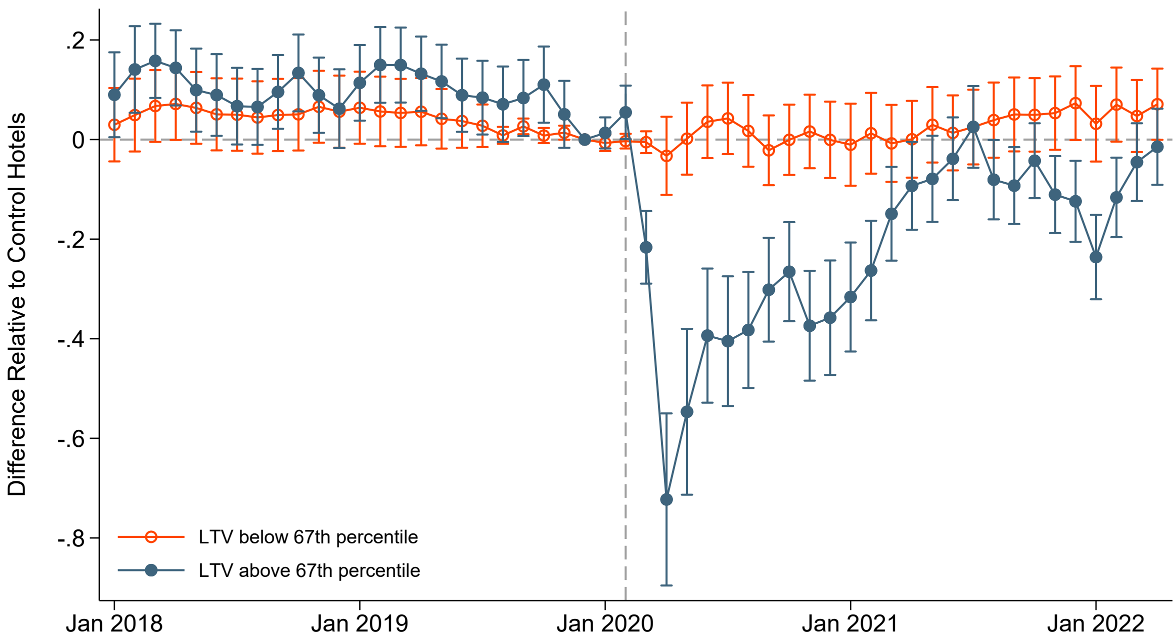


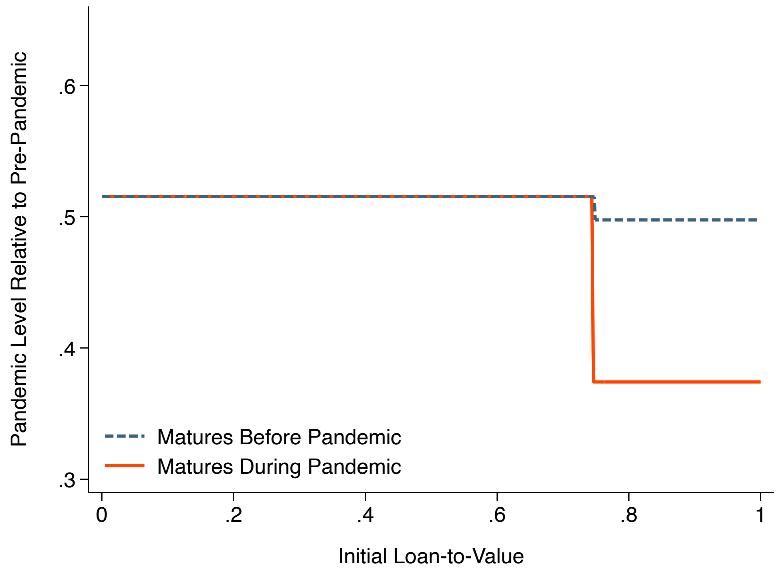
FIGURE IX

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

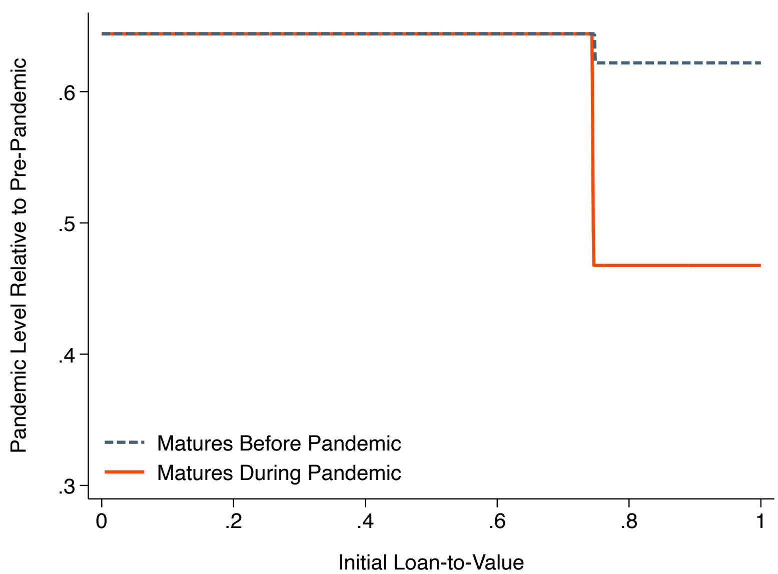
NOTE.—This figure estimates a variant of equation (2) that separates the results in Figure IV according to the strength of strategic motivations, as proxied by initial loan-to-value ratio. The regression equation is an event study analogue of the difference-in-difference equation in Table V,

$$
\begin{aligned}
y_{imt} = & \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\beta_{0,\tau} \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \right] + \ldots \\
& \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\beta_{1,\tau} \times PandemicMaturity_i \times HighLTV_i \mathbb{1}_{t=\tau} \right] + \ldots \\
& \gamma_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\gamma_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},
\end{aligned}
$$

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 −0.285, which matches the effect in column 1 of Table V. Panel B contains a similar plot in terms of output, profits, and inputs. 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	—
Loan Characteristics at Origination				
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 first panel summarizes hotel performance observed in May 2019. The second 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 third panel summarizes characteristics of the hotel's loan, all measured as of origination. 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 third 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 first and second panels are from the STR performance and cross-sectional datasets, respectively. 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)
PandemicMaturity × Post	−0.171***	−0.126***	−0.180***	−0.182***
	(0.024)	(0.020)	(0.025)	(0.025)
Hotel FEs	X	X	X	X
Post Maturity FE	X	X	X	X
Market × Month FEs	X	X	X	X
Size × Month FEs		X	X	X
Operation Type × Month FEs			X	X
Location Type × Month FEs				X
Number of Observations	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); and location type, which can take the values shown in Table I (Location Type × Month FEs). Details are in Section 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 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 replacing $PandemicMaturity_i$ 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	−0.285***	−0.452***	−0.456***	−0.456***	−0.381***	−0.403***	−0.346***	−0.480***
	(0.051)	(0.102)	(0.102)	(0.101)	(0.111)	(0.102)	(0.081)	(0.107)
PandemicMaturity × Post	−0.022	0.065**	0.068***	0.091***	0.010	0.084**	−0.004	−0.162
	(0.019)	(0.025)	(0.024)	(0.030)	(0.031)	(0.032)	(0.030)	(0.119)
PandemicMaturity × Post × Log(BorrowerAssets)			0.003					
			(0.011)					
PandemicMaturity × Post × REIT				−0.146***				
				(0.053)				
PandemicMaturity × Post × ServicerStringency					−0.103***			
					(0.029)			
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

$$y_{imt} = \beta_0 \cdot PandemicMaturity_i \times Post_t + \beta_1 \cdot PandemicMaturity_i \times Post_t \times HighLTV_i + \psi_0 \cdot PandemicMaturity_i \times Post_t \times Interaction_i + \ldots$$
$$\gamma_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\lambda_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\psi_\tau \times Interaction_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

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 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)

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 an 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]

[1]This is because STR explicitly advises its partner hotels to report a room as unavailable only if it is "closed for

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, which is when STR began collecting monthly operating statements.

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."

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 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 2021, 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 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, 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. We match 42% of hotels in the merged Trepp-STR dataset. Most likely, this statistic constitutes a lower bound on the true PPP takeup rate.

B Proofs

B.A Proposition 1

Given K_t and M_t, the borrower chooses L_t to maximize current cash flows:

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

Given the production function in equation (4), the optimized variable input, profit, and production are the results of a standard optimization problem and are as they appear in Proposition 1. The net present value of the firm's perpetual cash flows equals $V^* = r^{-1}\pi^*(M_0, p)$.

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

$$V_{0,0}^e = \max\Big(0, r^{-1}(1 - e^{-rT})\pi^*(M_0, p) + e^{-rT} V_{0,0}^e - D + \widetilde{D}\Big). \tag{B1}$$

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

$$V_{0,0}^e = V^* - D. \tag{B2}$$

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 (B1) 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 $V^e_{j,\tau}$ denote the value of equity τ units of time before maturity in state j (0 if normal, 1 if pandemic). For convenience, we let $\pi^*_j(M) = \pi^*(M, p_j)$ denote the optimized operational profits in state j.

The value in normal times satisfies the relation:

$$rV^e_{0,\tau} = \pi^*_0(M_0) - \frac{\partial V^e_{0,\tau}}{\partial \tau}.$$

The solution is $V^e_{0,\tau} = r^{-1}\pi^*_0(M_0) + A_0 e^{-r\tau}$, where A_0 is a constant. Given equation (B2), $A_0 = -D$, so

$$V^e_{0,\tau} = r^{-1}\pi^*_0(M_0) - e^{-r\tau}D. \tag{B3}$$

The value during the pandemic satisfies:

$$rV^e_{1,\tau} = \pi^*_1(M(I)) + q(V^e_{0,\tau} - V^e_{1,\tau}) - \frac{\partial V^e_{1,\tau}}{\partial \tau}, \tag{B4}$$

where

$$M(I) = M_0^{1-\zeta_1} I^{\zeta_1}. \tag{B5}$$

Substituting equation (B3) into equation (B4) and solving yields

$$V^e_{1,\tau} = \frac{r\pi^*_1(M(I)) + q\pi^*_0(M_0)}{r(r+q)} - e^{-r\tau}D + A_1 e^{-(r+q)\tau}, \tag{B6}$$

where A_1 is a constant. To solve for A_1, we impose the boundary condition that the borrower chooses default or rollover optimally at maturity:

$$V^e_{1,0} = \max\left(0, V^e_{1,T} - D + \widetilde{D}\right). \tag{B7}$$

If paying off the debt is optimal, then the present value of the new debt claim is $\widetilde{D} = e^{-rT}D$, and the term on the right of the max is at least 0. In this case, substituting equation (B6) into equation (B7) yields $A_1 = 0$, so that

$$V^e_{1,\tau} = \frac{r\pi^*_1(M(I)) + q\pi^*_0(M_0)}{r(r+q)} - e^{-r\tau}D.$$

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

$$\frac{r\pi^*_1(M(I)) + q\pi^*_0(M_0)}{r(r+q)} \geq D.$$

Conversely, if default is optimal, then $V^e_{1,0} = 0$. We can then solve for A_1 in equation (B6) to obtain:

$$V_{1,\tau}^{e} = \left(1 - e^{-(r+q)\tau}\right) \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)} - \left(e^{-r\tau} - e^{-(r+q)\tau}\right) D. \tag{B8}$$

This solution is valid only if the right side of the max in equation (B7) is at most 0. To calculate the right side of the max, we solve for the present value of the new debt claim:

$$\widetilde{D} = e^{-rT} \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)}, \tag{B9}$$

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 Eqs. (B8) and (B9) into (B7) yields the default condition:

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

In summary, given the adaptive investment I, the value of the equity during the pandemic is:

$$V_{1,\tau}^{e} = \begin{cases} \left(1 - e^{-(r+q)\tau}\right) \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)} - \left(e^{-r\tau} - e^{-(r+q)\tau}\right) D, & \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)} \leq D \\ \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)} - e^{-r\tau} D, & \frac{r\pi_1^*(M(I)) + q\pi_0^*(M_0)}{r(r+q)} > D. \end{cases} \tag{B10}$$

When the pandemic begins, the borrower chooses I to maximize this equity value, $V_{1,\tau}^{e}$, net of investment costs, cI: $I^* = \arg\max_I V_{1,\tau}^{e} - cI$. The are two possible local maxima for I: one that holds in the default region (top condition in equation (B10)), which we denote I_d, and one that holds in the payoff region (bottom condition in equation (B10)), which we denote I_p. We solve for these local maxima by substituting equations (6) and (B5) into equation (B10) and setting the derivative equal to c to obtain:

$$I_p = \widetilde{I}$$
$$I_d = \left(1 - e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \widetilde{I},$$

where $\widetilde{I}$ equals the expression in equation (8). Given the conditions in equation (B10), I_d is a possible global maximum only if

$$D \geq \frac{r\pi_1^*(M(I_d)) + q\pi_0^*(M_0)}{r(r+q)} \equiv D_d,$$

and I_p is a possible global maximum only if

$$D \leq \frac{r\pi_1^*(M(I_p)) + q\pi_0^*(M_0)}{r(r+q)} \equiv D_p.$$

Therefore, if $D < D_d$, then $I^* = I_p$, and if $D > D_p$, then $I^* = I_d$. If $D \in [D_d, D_p]$, then both maxima are possible, and the borrower selects the one that maximizes $V_{1,\tau}^{e} - cI$. By comparing the expressions in equation (B10), we find that the maximizing investment is I_p when

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

and that the maximizing investment is I_d when $D > D^*(\tau)$. Substituting the expressions for I_p and I_d and using equations (6) and (B5) yield:

$$D^*(\tau) = \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1-\alpha-\zeta_1\beta}{\zeta_1\beta}e^{(r+q)\tau}\left(1-\left(1-e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}}\right)c\tilde{I}. \tag{B11}$$

Similar substitutions yield the expressions:

$$\begin{aligned} D_d &= \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1-\alpha}{\zeta_1\beta}\left(1-e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}}c\tilde{I} \\ D_p &= \frac{q\pi_0^*(M_0)}{r(r+q)} + \frac{1-\alpha}{\zeta_1\beta}c\tilde{I}. \end{aligned} \tag{B12}$$

We would like to show that $D^*(\tau) \in [D_d, D_p]$. Doing so would prove that equation (7) gives the optimal adaptive investment. To proceed, we make use of the following lemma:

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

$$(1-x)^a < (1+ax)^{-1}. \tag{B13}$$

If $a \geq 1$, then

$$1 - ax \leq (1-x)^a. \tag{B14}$$

Proof. The two expressions in inequality (B13) coincide when $x = 0$. The derivative of the logs of the left and right sides are $-a/(1-x)$ and $-a/(1+ax)$, respectively, and the first one is more negative because $a > 0$. Therefore, inequality (B13) holds.

The two expressions in inequality (B14) coincide when $x = 0$. The derivative with respect to x of the first is $-a$, and of the second is $-a(1-x)^{a-1}$, which is at least $-a$ because $a \geq 1$ and $x \in (0,1]$. Therefore, the inequality (B14) holds. □

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 (B13), with $a = (1-\alpha)/(1-\alpha-\zeta_1\beta)$ and $x = e^{-(r+q)\tau}$. The inequality $D^*(\tau) \leq D_p$ 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 (B14), with the same substitutions for a and x. Therefore, equation (7) 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 (B13), with $a = \zeta_1\beta/(1-\alpha-\zeta_1\beta)$ and $x = e^{-(r+q)\tau}$.

Finally, we show that $D^*(\tau) < V^*$ for all τ if c is sufficiently large. Because $D^*(\tau) \leq D_p$, it suffices to show that $D_p < V^*$ for large values of c. From Eqs. (7) and (B12), we see that D_p is an affine function of $c^{-\zeta_1\beta/(1-\alpha-\zeta_1\beta)}$, which implies that D_p 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 $L^*(M(I^*), p_1)$, $\pi^*(M(I^*), p_1)$, and $F^*(M(I^*), p_1)$, where these functions are as they appear in Proposition 1. 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 $I^*(\tau_2) = I^*(\tau_1) = \widetilde{I}$. If $D > D^*(\tau_1)$, then $I^*(\tau_1) < I^*(\tau_2)$ because

$$\left(1-e^{-(r+q)\tau_1}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}}\widetilde{I} < \left(1-e^{-(r+q)\tau_2}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}}\widetilde{I} < \widetilde{I},$$

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:

$$M_0 = \beta^{\frac{1-\alpha}{1-\alpha-\beta}} c^{-\frac{1-\alpha}{1-\alpha-\beta}} (r+q)^{-\frac{1-\alpha}{1-\alpha-\beta}} \alpha^{\frac{\alpha}{1-\alpha-\beta}} p_0^{\frac{1}{1-\alpha-\beta}} w^{-\frac{\alpha}{1-\alpha-\beta}} K. \tag{C15}$$

Substituting equation (C15) into equation (8) yields:

$$\widetilde{I} = \zeta_1^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \left(\frac{r}{r+q}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \left(\frac{p_1}{p_0}\right)^{\frac{1}{1-\alpha-\zeta_1\beta}} M_0. \tag{C16}$$

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 ($\zeta_1 \leq 1$). Second, the pandemic is expected to last a limited amount of time ($q > 0$). Finally, the market price for the firm's input 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 (C16), we can simplify equation (B11) to:

$$\begin{aligned} \frac{D^*(\tau)}{V^*} =& \frac{q}{r+q} \\ &+ \frac{1-\alpha-\zeta_1\beta}{1-\alpha}\zeta_1^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \left(\frac{r}{r+q}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}} \left(\frac{p_1}{p_0}\right)^{\frac{1}{1-\alpha-\zeta_1\beta}} e^{(r+q)\tau}\left(1-\left(1-e^{-(r+q)\tau}\right)^{\frac{1-\alpha}{1-\alpha-\zeta_1\beta}}\right). \end{aligned}$$

Therefore, the default cutoff relative to the initial value of the firm (the default LTV) only depends on q, r, α, β, ζ_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 (8). 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 $(I^*/M_0)^{\zeta_1}$. By equation (C16), this ratio depends only on the same list of parameters.

D Additional Figures and Tables

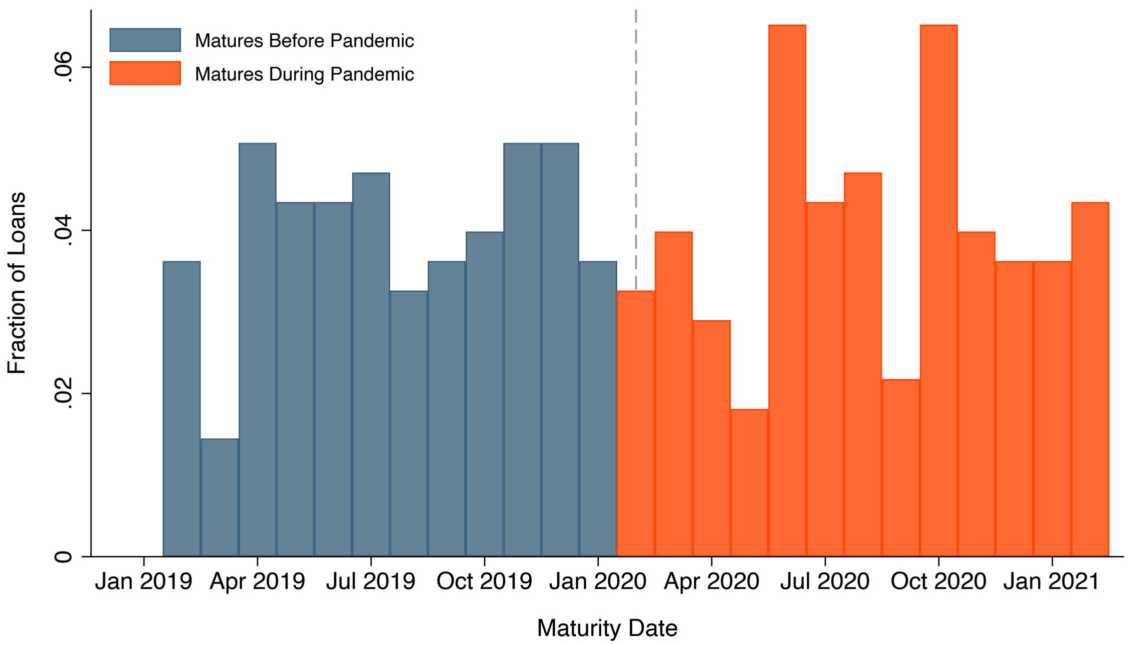


FIGURE A.I
Distribution of Scheduled Loan Maturity at Origination.

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)

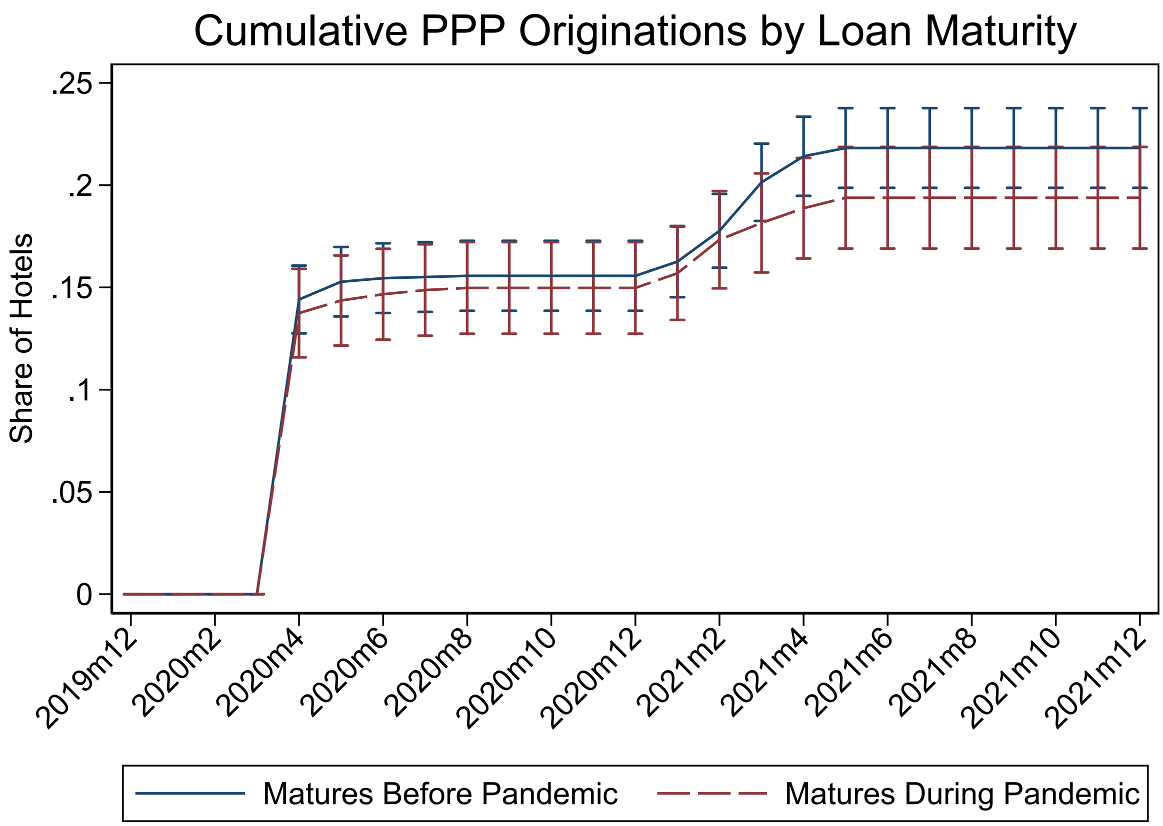


FIGURE A.II
Paycheck Protection Program Takeup by Maturity Cohort.

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. The time series is plotted separately for hotels with a CMBS loan with initial maturity date 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)

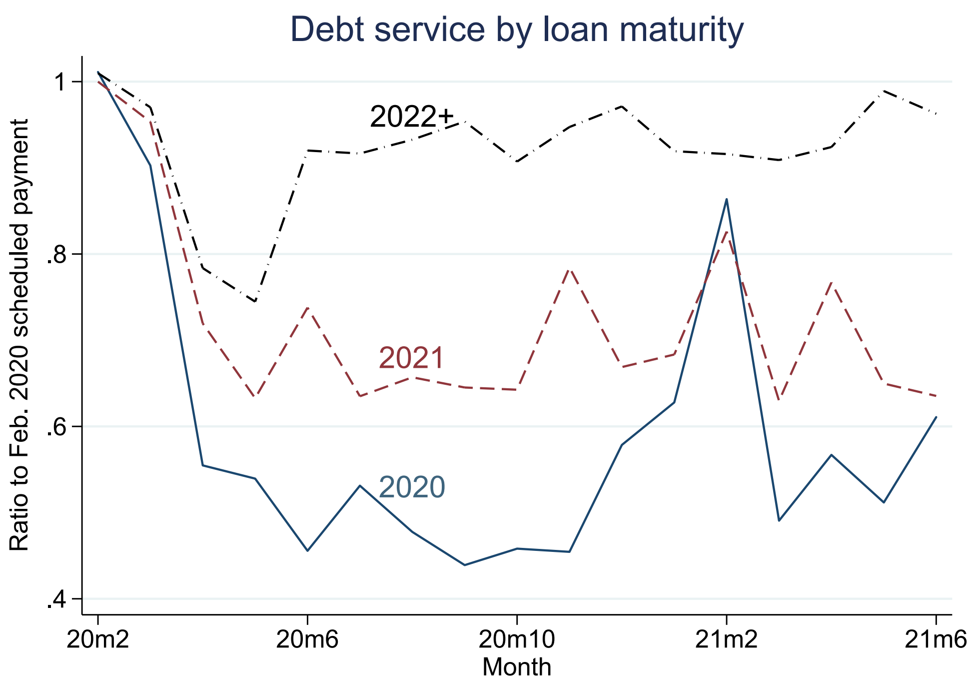


FIGURE A.III
Debt Payments by Maturity Cohort.

NOTE.—This figure plots debt service by the year of a hotel loan's maturity, which assesses whether the main results reflect increased debt service by loans with a maturity during the pandemic. The sample restricts to loans with a positive balance and not in special servicing as of February 2020. Loans must maintain a positive balance to remain in the data. We further restrict loans maturing on or after 2022 to those originated in 2018 or 2019. Debt service gives the average payments made by borrowers, normalized by the scheduled debt service in February 2020. We impute debt service using the difference between scheduled payments and advances made by the servicer to CMBS investors on behalf of the borrower. For loans marked non-coverable (in which case the servicer stops forwarding payments), we set debt service to 0. Data are from the Trepp dataset. (SOURCE: Trepp)

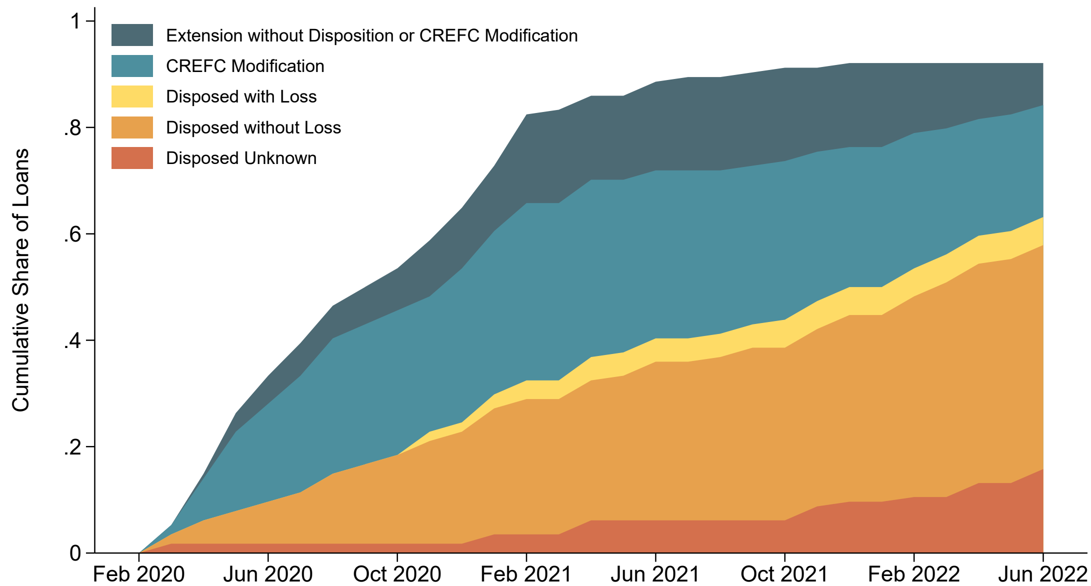


FIGURE A.IV
Loan Resolution.

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 Disposied 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)

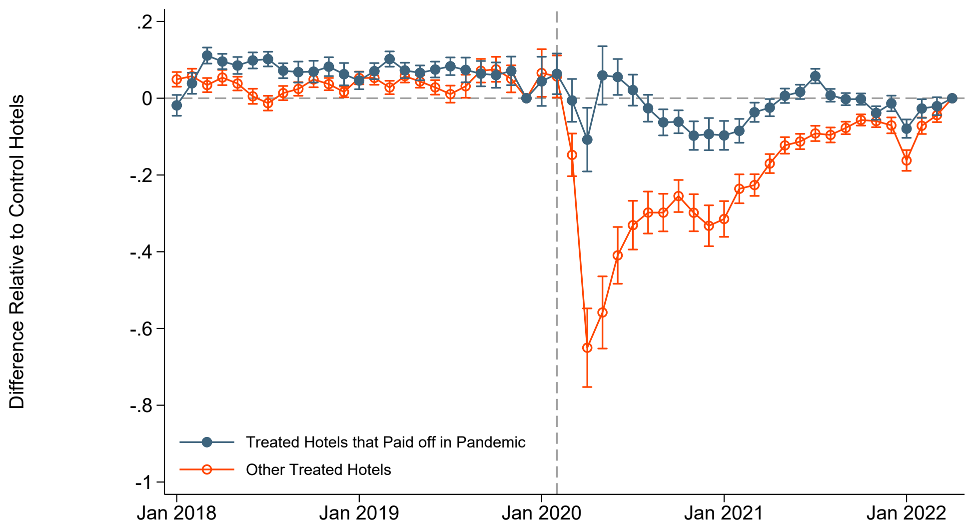
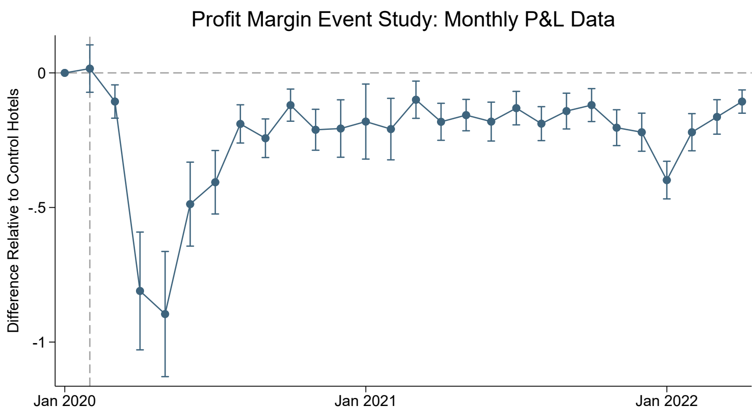
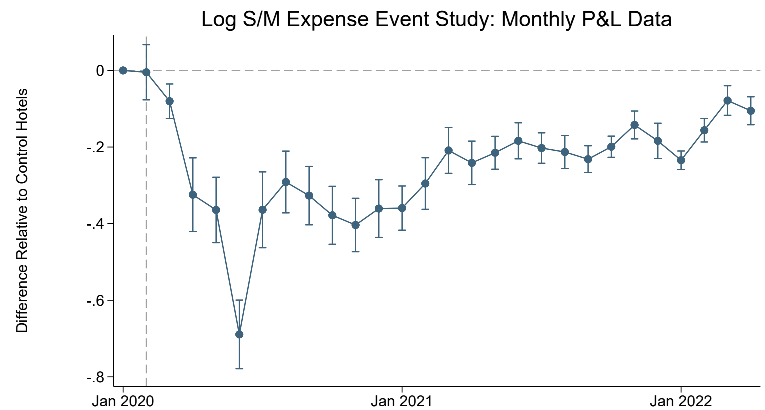


FIGURE A.V
Effect of Pandemic Maturity on Hotel Revenues by Endogenous Loan Payoff.

NOTE.—This figure estimates a variant of equation (2) that separates the results in Figure IV according to whether the loan paid off during the pandemic, an endogenous variable. The regression equation is similar to that Figure IX, after replacing $HighLTV_i$ with an indicator for whether the hotel has a loan that both: was initially scheduled to mature within the pandemic period; and paid off during the pandemic period. Note that this indicator equals zero for all hotels in the control group, and so we cannot include its interaction with a vector of month fixed effects. Additional details on the definition of loan payoff are in the note to Figure A.IV. The remaining notes are the same as in Figure IX. (SOURCE: STR, LLC and Trepp)



Panel A. Profit



Panel B. Marketing Expense

FIGURE A.VI

Monthly Profit and Marketing Expense. Assessing the Timing of When Hotels Cut Back.

NOTE.—This figure estimates a variant of equation (2) that assesses whether the timing of hotels cutting back aligns with the drop in profit. 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 a hotel's operating profit, measured as the ratio of EBITDA to total revenue in January 2020. The outcome in panel B is log of sales and marketing expense. EBITDA is winsorized at the 2.5% level. 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)

TABLE A.II

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

	(1)	(2)	(3)	(4)	(5)
PandemicMaturity × Post	−0.120***	−0.115***	−0.115***	−0.080**	−0.217***
	(0.032)	(0.032)	(0.031)	(0.030)	(0.028)
Hotel FEs	X	X	X	X	X
Post Maturity FE	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
Market × Month FEs					X
Number of Observations	133,095	133,095	133,095	133,095	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. 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)	7.85	(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 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	(1.16)	0.19	(0.58)
Log(Loan Amount)	19.76	(1.63)	20.87	(0.73)
Loan-to-Value Ratio (LTV)	0.63	(0.15)	0.87	(0.05)
Debt-Service Coverage Ratio (DSCR)	3.53	(1.15)	3.96	(0.86)
Loan Term (Months)	56.12	(29.53)	78.91	(12.58)
Balloon Flag	0.99	—	1.00	—
Number of Hotels	1,740		869	

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 in the panels Hotel Performance and Hotel Location are as in Table II. The variables in the panel Owner and Operation are: the log of the borrower's total dollar real estate holdings as of June 2023; an indicator for whether the borrower is a REIT; and an indicator for whether the hotel is operated by the brand. 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. Data on LTV ratios are from Trepp and are modified to account for second-liens observed in RCA. Data on borrower-level variables are from RCA. 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)
PandemicMaturity × Post	0.160***	0.074
	(0.034)	(0.154)
PandemicMaturity × Post × Tercile(LTV, 2)	−0.376***	
	(0.067)	
PandemicMaturity × Post × Tercile(LTV, 3)	−0.475***	
	(0.072)	
PandemicMaturity × Post × LTV		1.209***
		(0.310)
PandemicMaturity × Post × LTV^2		−1.525***
		(0.244)
Hotel FEs	X	X
Post Maturity FE	X	X
Market × Month FEs	X	X
Tercile(LTV) × Month FEs	X	
LTV × Month FEs		X
LTV^2 × Month FEs		X
Number of Observations	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. Note that the treatment effect implied by column (2) 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)

TABLE A.V

EFFECT ON HOTEL EXPENSE BY CATEGORY

	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. In particular, the treatment variable $PandemicMaturity_i$ now indicates whether the maturity date for the loan on hotel i is in 2020 or later. 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)