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EVIDENCE FROM HOTELS IN CRISIS

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Real Effects of Rollover Risk: Evidence from Hotels in Crisis
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ABSTRACT

We analyze and find empirical support for a model of strategic renegotiation in which firms scheduled to roll over debt during a crisis reduce operations to discourage lenders from seizing the collateral. Our empirical analysis exploits contractual features of commercial mortgages that generate exogenous variation in whether debt matures during a crisis. A crisis debt maturity causes large relative drops in output, labor, and profits at the collateral property, even holding the borrower fixed. Consistent with the model, these real effects decrease with the lender's operating adjustment costs, reverse after renegotiation, and occur primarily for highly-levered loans without term-extension options.

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When a firm's debt comes due during a crisis, how and why does the firm adjust its real operations in response? Answering these questions is critical for understanding how financial frictions amplify contractions in employment and output during recessions. Some firms with maturing debt temporarily reduce operations to pay off creditors with freed-up cash, a liquidity channel that has been the focus of prior work (e.g., Almeida et al., 2011; Benmelech, Frydman and Papanikolau, 2019; Costello, 2020; Granja and Moreira, 2022). In this paper, we propose an alternative mechanism arising from strategic renegotiation of the debt: borrowers stop making debt payments and cut operations to make it costly for creditors to take over the asset. We formalize this renegotiation channel in a model, and we measure it empirically in a setting where we can isolate the effect.

The empirical setting we study is the hotel sector during the COVID-19 pandemic. Specifically, we study hotels that serve as collateral for commercial mortgages with large balloon payments scheduled to come due just after the pandemic began. We find that this debt rollover event reduces output, labor, and profits at the encumbered hotels, and that creditors overwhelmingly renegotiate the debt rather than foreclose on it. We argue that the combination of high debt burdens, falling profits, and widespread renegotiation make it unlikely that these effects are driven by liquidity constraints and present evidence that the results are, instead, consistent with borrowers who reduce operations as a tactic to strategically renegotiate their debt. In line with this, we also find that the negative effects on output revert after the loan is renegotiated.

To identify the causal effect of the rollover shock, we estimate difference-in-differences regressions that compare outcomes for our "treatment group" hotels— those with loans scheduled to mature just after the pandemic began—to a set of "control group" hotels whose mortgages were scheduled to mature just before. The difference in outcomes between these hotels gives an unbiased estimate of the treatment effect of a crisis debt maturity under the assumption that hotel owners did not choose the month of their loan maturity in anticipation of the COVID crisis. This assumption is plausible given how difficult the crisis was to forecast, along with the fact that the loans we study feature binding prepayment penalties, which limit the scope for bias from endogenous refinancing before maturity (e.g., Mian and Santos, 2018; Xu, 2018).

Implementing this analysis, we find that having debt scheduled to mature in the crisis lowers room revenue and room bookings (i.e., output) by an average of 16% over the first 15 months of the crisis. We also estimate a negative effect on labor and various other forms of operating expenses, including marketing, which suggests that borrowers with crisis debt maturities intentionally scale down operations. Interestingly, the effect on revenue exceeds the effect on expenses, leading treated hotels to experience a relative drop in operating profits. This finding, which we discuss in detail in the context of our model, is exactly the opposite of what would be expected if the motive for scaling back operations was to generate additional short-run liquidity to service debt. Consistent with this, we also find that the main results are robust to the inclusion of borrower-by-month fixed effects, which is difficult to square with borrower-level liquidity constraints as a potential explanation.

As in any difference-in-difference analysis, our key identifying assumption is that outcomes for treated and control hotels would have evolved in parallel throughout the crisis were it not for the fact that treated hotels faced a crisis debt maturity. To support the validity of this assumption, we show that room revenues for both groups of hotels move in lockstep for the three years preceding the pandemic and only diverge afterward. Furthermore, our results are robust to allowing for fully flexible interactions between month fixed effects and an extensive list of hotel characteristics, including hotel chain-by-geographic market (e.g., Hilton DoubleTree in Boston), year of origination, operation type, size, and purpose of stay (e.g., airport versus resort). This analysis helps to address many concerns about potential heterogeneous effects of the pandemic by borrower characteristics that are spuriously correlated with scheduled debt maturities.

Motivated by these findings, we then present a model to clarify how incentives to strategically renegotiate debt can lead firms to cut output when they face debt rollover during a crisis, even in the absence of binding liquidity constraints. As in Hart and Moore (1994), borrowers in our model have negotiating power with their lenders because the firm is worth more with the borrower in place. Unlike Hart and Moore (1994), we endogenize the source of this bargaining power by allowing it to vary with the borrower's operating decisions. Specifically, we assume that increasing the level of operations is cheaper for the borrower than the lender, which implies that the borrower gains a negotiating advantage by cutting current operations. This asymmetry arises, for example, due to the borrower's asset- or personnel-specific expertise.

In this framework, we analyze the debt repayment and operating decisions of a borrower whose debt matures during a crisis, which is modeled as an unexpected drop in the price of the firm's output that may or may not be permanent. At maturity, the borrower can pay the debt or default. In the case of default, the lender can foreclose immediately or extend the maturity to a later time at which the long-run price of output becomes known. Mirroring our empirical analysis, we theoretically characterize the effect of strategic renegotiation by comparing equilibrium outcomes for firms with debt maturing in the crisis ("treated") to outcomes for firms whose debt is scheduled to mature after the long-run price of output becomes known ("control").

The model predicts that both output and profits fall by more at the treated firm than at the control, provided leverage is high but not extreme. In this case, the treated borrower defaults on its debt payment and cuts operations to a level that reduces short-run profits. Doing so staves off foreclosure with positive probability, since the lender may prefer to grant an extension in the hope that the crisis ends rather than foreclose and incur (with certainty) the adjustment cost required to scale operations back to their profit-maximizing level. By contrast, the control borrower makes the scheduled debt payment and maintains operations at a higher level that maximizes short-run profits. Importantly, the range of leverage where such strategic renegotiation occurs is wide, containing levels both above and below the expected present value of the firm's assets. Thus, the model implies that strategic renegotiation arises under empirically relevant parameter values.

After characterizing the strategic renegotiation channel theoretically, we return to the data to provide six additional pieces of evidence in support for this mechanism, beyond our main result that both output and profits fall for treated hotels. First, among borrowers that receive renegotiations, output rebounds exactly in the month when the renegotiation is granted. Second, the decline in operations for crisis-maturity hotels is concentrated among those with higher initial loan-to-value ratios, which is a direct prediction of the model.[1] Third, there are no real effects for treated borrowers who do not need to negotiate an extension because they have an extension option written into their loan contract at origination. Fourth, the effects are stronger if the loan features a lockbox provision, which allows the lender to place operating cash flow in escrow. A lockbox makes strategic renegotiation more attractive because the borrower has less to lose from cutting operations. Fifth, the effects are stronger when the lender can more easily adjust operations at the hotel, based on various proxies for ease-of-adjustment. As we formalize in our model, increasing the ease-of-adjustment lowers the lender's cost of foreclosure, and so the borrower must cut operations by more to prompt such a lender to renegotiate as opposed to foreclosing. Finally, we present a short case study exemplifying how strategic renegotiation may have been used in practice by a particular real estate investment trust (REIT).

Contribution to Related Literature

Our paper contributes to and extends a large literature on strategic renegotiation, which goes back to at least Hart and Moore (1994). This literature often studies how renegotiated payments between borrowers and lenders depend on borrowers' exogenously given cash flows or, as in Benmelech and Bergman (2008), liquidation values. Our conceptual contribution is to emphasize that cash flows are a function of the firm's operating decisions and can thus be altered as a negotiating tactic. Our empirical contribution is to find support for this mechanism in the data.[2] Empirically, we also complement Gilje, Loutskina and Murphy (2020), who show that prescheduled renegotiation events incentivize firms not-in-default to act in a way that inefficiently increases short-run profits. By contrast, we show that endogenous renegotiation incentivizes firms in default to inefficiently decrease short-run profits.[3]

A number of papers have also studied strategic default and renegotiation in the specific context of commercial real estate. As with the broader literature on renegotiation, most papers in this literature

[1]Strictly speaking, the model predicts that the decline is concentrated among hotels with debt that is high but below a relatively extreme threshold at which point foreclosure occurs with certainty. We do not think that this threshold is empirically relevant because foreclosure is rare in the data.

[2]Our model also bears some similarity to Gorton and Kahn (2000), who study how lenders renegotiate debt to avoid subsequent value-destroying actions of the borrower. In our model this ordering is reversed as the borrower takes a value-destroying action to influence the lender. Likewise, Matsa (2010) shows that firms increase debt to renegotiate labor contracts, while we show that firms decrease labor to renegotiate their debt.

[3]Broadly, we also relate to a literature on the prevalence of restrictive covenants in corporate debt, which often leads to technical default and renegotiation before maturity (e.g., Roberts and Sufi, 2009; Denis and Wang, 2014; Roberts, 2015). By contrast, we focus on payment default and renegotiation occurring at maturity.

take the borrower's operating decisions as given and focus on how the likelihood of renegotiation affects default decisions. For example, Brown, Ciochetti and Riddiough (2006) emphasize how asset liquidity affects borrower's default behavior, but do not show that operating choices affect liquidity. Similarly, Flynn, Ghent and Tchistyi (2024) study how borrowers with private information about their asset quality strategically default in an effort to extract favorable loan modifications, but do not endogenize asset quality. Our paper contributes by combining detailed datasets on loan performance and building-level operating outcomes that enable the joint study of operating behavior and renegotiation. Our focus on strategic renegotiation rather than liquidity constraints also aligns with recent evidence indicating the pervasiveness of commercial real estate defaults in which the borrower has sufficient assets to pay off the loan (Dinc and Yönder, 2022). Similarly, our focus on ex-post effects of strategic default complements research on ex-ante contractual features designed to limit it (Glancy, Kurtzman and Loewenstein, 2022; Glancy et al., 2023). More broadly, our paper contributes new evidence to a literature documenting various other ways in which the presence of debt impedes the performance of real estate assets (Sun, Titman and Twite, 2015; Loewenstein, Riddiough and Willen, 2021; Liebersohn, Correa and Sicilian, 2022).

In focusing on hotels, we contribute to a literature making specific use of hotel data to answer broader questions in financial economics. Spaenjers and Steiner (2024) show that private equity firms specializing in hotels operate these assets more efficiently than generalist real estate private equity firms. This finding supports our model assumption that the borrower possesses unique operational advantages specific to the asset. Povel et al. (2016) find that hotels built during booms underperform over subsequent years, while Kosová, Lafontaine and Perrigot (2013), Freedman and Kosová (2014), and Kosová and Sertsios (2018) examine how operating performance and expenses correlate with the hotel's organizational form. Our results hold for a variety of organizational forms, indicating that strategic renegotiation affects outcomes even when the borrower and hotel management are distinct entities. Like us, Steiner and Tchistyi (2022) study hotels during the COVID crisis. They focus on how liquidity from the Paycheck Protection Program (PPP) attenuated the effect of reduced consumer demand on hotel operations, whereas we show how debt rollover reduces operations regardless of the hotel's liquidity constraints.[4]

I Data and Institutional Background

This section describes the data and institutional background for our empirical analysis and highlights several features of the hotel industry during the COVID-19 crisis that make it an instructive context in which to study the real effects of debt rollover. Additional details on the data are provided in Appendix A.

[4] Nguyen et al. (2023) is another study of how debt affects hotel performance during the COVID crisis. 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 crisis.

I.A Data

Hotel operations

We measure hotel operations using data from STR, LLC. STR is a leading data provider in the hotel industry, providing coverage of roughly 60% of all U.S. hotels and 76% of U.S. hotel rooms. STR maintains such large coverage through an incentive scheme where hotels provide data on their operations in exchange for receiving customized benchmarking reports on aggregated groups of competing hotels.

The STR dataset has four components. The first component is a daily hotel-level panel of basic performance metrics from January 2017 through June 2022: room revenues, occupancy rates, and the average daily prices for rooms sold. 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; and total operating expenses by category with a similar degree of detail (e.g., labor expense, spending on sales and marketing). The third component is a monthly panel of hotel profit and loss statements, which is similar to the annual panel but only begins in January 2020. The fourth component is a cross-sectional dataset with time-invariant hotel characteristics, including: geographic market, number of rooms, operating arrangement, purpose of stay (e.g., airport, resort, highway), and anonymized identifiers for hotel brand and for hotel chain within the brand. STR-defined geographic markets generally align with a metropolitan area, per the list of markets in Appendix Table A.I.

Hotel financing

Our primary source of data on mortgages collateralized by hotels comes from Trepp LLC, which is a standard data provider in the literature on commercial mortgage-backed securities (CMBS). We specifically work with Trepp's T-Loan dataset. This dataset covers the near universe of commercial mortgages originated in the U.S. that are placed into CMBS pools. We observe mortgage characteristics at origination, such as maturity date, leverage, the address of the collateral property, and various other contractual features. 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. The RCA data allow us to observe junior, non-securitized liens on the same property, providing us with a more complete measure of the total LTV at origination. RCA also provides the name of the mortgage borrower, which enables us to include borrower fixed effects in our regressions.

Analysis sample

An important hurdle that we overcome in assembling our data is to merge hotel-level data from STR to loan-level data from Trepp, using information on the address of collateral properties.[5] 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 the onset of the COVID-19 crisis (i.e., February 2019 through January 2020) to those with a maturity on or after the crisis' onset (i.e., February 2020 through February 2021). Summary statistics for key variables for these two groups of hotels appear in Table I.

I.B Institutional Background and Motivating Facts

Fact 1. Hotels Finance themselves with Long-Term Debt that is Paid at Maturity

Hotels rely heavily on collateralized debt (i.e., commercial mortgages), and a substantial share of this debt comes in the form of CMBS loans.[6] Most CMBS loans do not fully amortize, implying a balloon payment scheduled at maturity (Glancy et al., 2022). Moreover, the typical CMBS loan comes with conditions that discourage prepayment via contractual lockouts or fees such as yield maintenance and defeasance (An, Deng and Gabriel, 2011). 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 the Trepp dataset to demonstrate this phenomenon during "normal" times (i.e., before the COVID-19 crisis). 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 (January 2019 or earlier). In this sample, all loans have limited ability to prepay up until 8 months before scheduled maturity, as shown in Panel A of Figure I. These limitations dissipate as the loan nears the scheduled maturity date. Coinciding with the timing of prepayment restrictions, about 80% of the original principal balance remains on loans in the sample up to 3 months before maturity, as shown in Panel B of Figure I. Borrowers pay off most of that amount within a narrow time window around their scheduled maturity date. Thus, unanticipated economic shocks that occur just prior to a loan's scheduled maturity date are potentially important events for both the borrower and the lender.

[5] Appendix Section A.D describes the process we use to merge the data and how we preserve the anonymity of individual hotels in doing so.

[6] Hotels rely more extensively on CMBS loans than other commercial property types (Glancy et al., 2022). In the decade before the COVID crisis, CMBS loans accounted for 36% of new hotel loans from medium-to-large banks, life insurers, or asset-backed issuers (Glancy et al., 2022). On a dollar-weighted basis, the volume of hotel loans from CMBS exceeded that from medium-to-large banks (Glancy, Kurtzman and Loewenstein, 2022).

Fact 2. Hotels' Long-Term Debt is Large and Concentrated in a Single Maturity

Hotel debt is large relative to assets and comes due all at the same time. In our data, the average loan-to-value ratio at origination for a mortgage exceeds 70%. This is significantly larger than the share of assets coming due as debt studied in the existing literature on corporate rollover events (Almeida et al., 2011; Benmelech, Frydman and Papanikolau, 2019; Costello, 2020; Granja and Moreira, 2022). Given typical ratios of debt to income, it is infeasible to pay off maturing hotel debt simply by harvesting cash flows from operations.

To substantiate this point, in Figure II we use the STR profit and loss dataset to plot the distribution of 2019 operating profits (EBITDA) relative to scheduled balloon payments for a sample of hotels with loans scheduled to mature in 2020. The figure shows that even an entire year's worth of "normal" operating profits would cover only 24% of the scheduled balloon payment for the median hotel. Even for a hotel at the 95th percentile, a full year of profits would cover only 78% of the scheduled debt payment. Thus, it seems unlikely that hotel owners would find it beneficial to significantly alter operations in an attempt to harvest cash to pay off their maturing debt.

Fact 3. The Crisis Sharply Reduced Hotel Demand

The COVID crisis was a significant negative demand shock for hotels, as people dramatically reduced travel to avoid catching the virus. In Figure III, we quantify this point by plotting the dynamics of room revenue using aggregate data from all hotels in STR's universe. Aggregate monthly revenue for U.S. hotels falls by 80% between February and April of 2020 and does not regain its pre-pandemic level until 2021.

Furthermore, the duration and permanence of this negative shock to hotel demand was highly uncertain as of 2020, depending on factors such as the speed of vaccine development and the long-term effects of work-from-home on business travel (PwC, 2020; Krishnan et al., 2020). The uncertainty around the duration of this shock likely created incentives to renegotiate extensions to these loans.

Fact 4. Debt Maturing During the Crisis was Renegotiated

Most hotel CMBS debt maturing during the crisis did not result in foreclosure; instead, these loans were renegotiated. To demonstrate this fact, we follow a cohort of hotel loans with maturity initially scheduled during the first year of the crisis, tracking their resolution over time in the Trepp dataset. As shown in the yellow region in Figure IV, only 6% of these loans had entered into foreclosure by the end of the pandemic's first year.[7] This frequency contrasts with the widespread renegotiation apparent in the blue regions of the figure, which show that nearly two thirds of loans were renegoti-

[7] The yellow region in the figure may also include dispositions-with-loss that are not foreclosures, such as discounted loan payoffs, which are studied in Flynn, Ghent and Tchistyi (2024).

ated over the same period.[8] Almost all of these renegotiations involve an extension to the maturity date or occur in a loan with an extension option.[9] These loan modifications originated from the private market as opposed to through direct government intervention.[10] Some borrowers paid off their loans over the pandemic's first year, as indicated by the orange region in the figure; this region grows as the crisis subsides over time.

Fact 5. Hotel Owners Can Exert Significant Control Over Operations in a Crisis

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). A given hotel brand may also establish chains (e.g., Aloft by Marriott), which constitute a separate franchise with its own set of standards. Hotel owners rely on one of three primary methods to operate the hotel: operating it themselves, using a brand-provided operating service, or contracting with a third-party operator (Freedman and Kosová, 2014; Kosová and Sertsios, 2018).

Even when the owner delegates management to the brand or a third party, the owner can curtail operations by withholding operating capital, which then discharges the operator from its legal obligation to the property. Management agreements can explicitly include this condition (e.g., Sunstone Hotel Investors, Inc., 2004). Moreover, during financial distress, the owner and operator share similar incentives to avoid foreclosure, as the operator's claims against the owner are often subordinate to the lender's (Butler and Braun, 2008; Marriott International, Inc., 2021). For these reasons, our analysis will not draw strong distinctions between the owner and the operator, except to show that controlling for the operating arrangement does not affect the results.[11]

[8]The ease of modifying private-label, securitized loans has improved since the Great Recession due to a set of subsequent policies intended to avoid widespread foreclosure in future crises. The most relevant policy, IRS Revenue Procedure 2009-45, enabled CMBS special servicers to modify a much broader set of loans without incurring tax burden due to the modification being classified as a new loan. Flynn, Ghent and Tchistyi (2024) study the policy in detail, finding that it encouraged borrowers to strategically request loan modification.

[9]Within the set of formal CREFC modifications, 93% experience an extension of the loan's maturity date, and the remaining 7% have an unknown form of modification. Within the set of loans with an extension not recorded by CREFC, 92% enter the crisis with an extension option that was written into the contract at origination but that had not been executed.

[10]Hotel financing received less government support than other forms of credit during the COVID crisis. Most importantly, CMBS backed by non-multifamily properties are not eligible for purchase by the Government Sponsored Enterprises (GSEs). Consequently, hotel owners with CMBS could not benefit from the federally mandated forbearance that applied to borrowers with multifamily properties (15 U.S.C §9057, 2020). Moreover, while the hotel industry lobbied extensively for the HOPE Act (H.R. 7809), which would effectively provide equity for commercial mortgage borrowers, the bill stalled in Congress and never passed.

[11]This control is important, as the operating arrangement is endogenous and depends on the scope for asymmetric information at the property in question (Freedman and Kosová, 2014). It also depends on the owner's expertise, which applies to the growing share of private equity specialists in the hotel sector (Spaenjers and Steiner, 2024). Kosová, Lafontaine and Perrigot (2013) find that, after controlling for various endogenous forces, there are no meaningful performance differences by operating arrangement. We discuss the implications of operating arrangements for our results in detail in Section III.

Summary and Implications

In summary, hotels are financed with long-term debt that is due almost entirely in a single large payment at a pre-determined maturity date (Fact 1). This lumpiness in required debt payments generates a rollover shock when the scheduled maturity coincides with an economic crisis (Fact 3). Owners can modify operations to respond to this shock (Fact 5), but it is not obvious why they would do so. Reducing operating expenses is unlikely to generate enough short-term profits to pay off the debt, given the debt's size (Fact 2). Moreover, the widespread renegotiation of maturing debt makes it unlikely that borrowers would reduce operations because they anticipate imminent foreclosure and, thus, lose their incentive to maintain the asset (Fact 4). Yet, empirically, we find that borrowers experiencing a rollover shock actually do reduce their operations, relative to a control group without a rollover shock. The remainder of the paper discusses how we establish this fact and proposes strategic renegotiation as a likely mechanism behind it.

II Research Design

II.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 (i.e., as of origination) scheduled to mature just before versus just after the onset of the 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 had a large amount of debt scheduled to come due during the early months of the pandemic.

Figure V provides direct evidence in support of this assumption. We split hotels into two groups according to whether their loan is initially scheduled to mature sometime during the 12-month period leading up to the pandemic versus the 12-month period immediately after the pandemic began. Then, we plot the dynamics of monthly room revenues separately by group. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. As the figure makes clear, revenues for these two groups of hotels moved in near lockstep during the three years leading up to the pandemic and only began to diverge afterwards. The core idea of our research design is to attribute the relative gap in outcomes that opens up between these two groups of hotels to the fact that one group faced the need to rollover their debt during the crisis while the other group did not.

II.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:

$$y_{imt} = \alpha_i + \delta_{mt} + \psi X'_{it} + \beta \cdot PandemicMaturity_i \times Post_t + \epsilon_{it}, \quad (1)$$

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 $PandemicMaturity_i$ equals one if hotel i has a loan that was initially scheduled to mature in the month when the pandemic began (February 2020) or during the 12-month period following that month, and it equals zero if the hotel had a loan initially scheduled to mature during the 12-month period before the pandemic began.[12] The $Post_t$ indicator is equal to one if month t falls on or after the first month of the pandemic (February 2020).[13] 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 effects related to the loan life cycle: even in normal times, hotels may 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 III.D 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.

The other potential source of bias 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. Moreover, the summary statistics in Table I show that the two cohorts are balanced across observed characteristics like pre-crisis

[12] Using the originally scheduled maturity to assign treatment status means that our research design is effectively an intent-to-treat. In particular, even if the borrower prepays the loan before 2019, we still assign the hotel collateral to one of the two groups according to the loan's original maturity date. Such cases are infrequent, per Figure I.

[13] 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-maturity groups based on the month in which their loan was originally scheduled to mature.

operations. However, the balance is not perfect, and so we include an extensive set of controls and fixed effects to address cases of imbalance. Since location is arguably the most important economic fundamental in real estate, we always include a set of geographic market-by-month fixed effects, δ_{mt}. These fixed effects ensure that our estimates are not being driven by a coincidence where 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 scheduled debt maturity. We conduct robustness to a wide range of different hotel-level controls of this type.

Event Study

We also estimate a more flexible alternative to equation (1) that allows the effects to vary by month. Specifically, we estimate regressions of the following form:

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

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.

III Real Effects of Debt Rollover

III.A Effect on Revenue, Output, and Prices

Table II reports estimates from the pooled difference-in-differences specification in equation (1) using log monthly room revenues as the outcome. In column 1, we report 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 $PandemicMaturity_i \times Post_t$ implies that the decline in room revenues during the pandemic is 17 log points (16%) larger for hotels with loans maturing during the first year of the pandemic than for hotels with loans maturing during the year before.

In Figure VI, we study how the relative decline in revenues for treated hotels varies over time. The figure plots coefficient estimates from a specification of the event study regression in equation (2) analogous to the specification in column 1 of Table II. The figure shows that the relative revenue of treated hotels falls immediately upon the onset of the pandemic. In Figure VII, we show how nearly all of the total relative decline in revenues during the first half of the crisis is driven by a drop in log occupancy rates ("output") rather log average room prices; the two sum to the drop in log room revenue.[14] We stress that the drop in revenue is *relative* to control hotels with a loan that matured before the pandemic. So, the dynamics in Figure VI do not reflect changes in aggregate demand for hotels due, for example, to changes in pandemic-specific policies.

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 II.A, 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. The remaining columns of Table II assess the robustness of our result to this possibility. Additional robustness tests are also reported in Section III.D.

In columns 2–5 of Table II we explore the sensitivity of our baseline estimate to allowing the direct effect of the pandemic to vary non-parametrically across hotel characteristics. Column 2 incorporates size-by-month fixed effects to allow hotels of different sizes to have been differentially affected by the pandemic independently of debt maturity. Column 3 adds a further set of operation type-by-month fixed effects, which allow for independent, franchisee-operated, or brand-operated hotels to have fully flexible and differential trends throughout the sample period. As discussed in Section I, this control is potentially important given that a hotel's operating model is an endogenous choice that may correlate with aspects of the hotel that make it more or less resilient to economic shocks.[15] 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). Column 5 includes origination year-by-month fixed effects that allow for separate dynamics according to the stage of the credit cycle at which the borrower took out the loan. We find economically large and statistically significant point estimates across all specifications.

[14]In Appendix Figure A.II, we show that treated hotels are 1-2 percentage points more likely than control hotels to be closed in a given month during the pandemic's first year. For reference, the average monthly closure rate is 0.5% from February 2020 to April 2022. We impute closure following a procedure described in Appendix A.A.

[15]In Appendix Figure A.III, we also explore the heterogeneity in our revenue and expense results across operating models. We find evidence that owner-operators reduced revenue and expenses more than hotels with brand or third-party management.

Borrower-by-Month Fixed Effects and Liquidity Constraints

Column 6 includes fixed effects for bins defined by the borrower (i.e., hotel owner) and month. This specification limits the identifying variation to hotels with different loan maturities that are owned by the same borrower. Given this restrictiveness, we remove the additional fixed effects introduced in columns 2–5. We estimate a revenue drop of 22 log points in this specification, which remains statistically significant when clustering standard errors by borrower (Appendix Table A.II). This finding strongly suggests that the main results are not due to spurious correlation; the borrower-by-month fixed effects absorb any change in revenue due to correlation between borrower-level characteristics and whether the hotel's loan has a crisis debt maturity.

Moreover, this finding suggests that liquidity constraints do not drive the main results. In particular, the borrower-by-month fixed effects absorb any overall average drop in revenue due to changes in the borrower's access to external capital during the pandemic. The fact that we obtain a slightly larger estimate when including borrower-by-month fixed effects suggests that borrowers reallocate resources away from hotels facing a rollover shock toward other hotels in their portfolio. Importantly, the lender would not be able to seize resources from these other hotels because CMBS debt is almost always non-recourse (Ghent, Torous and Valkanov, 2019).

III.B Effects on Inputs

Next, we provide evidence that the relative decline in output among pandemic-maturity hotels was achieved via a scaling back of inputs into the production process. Our analysis of hotel inputs relies on lower-frequency annual profit and loss statements that are available (in at least one year) for 61% of hotels contained in the monthly data analyzed above. While the monthly data contain information on room revenues only, the annual profit and loss data record revenues from all sources (e.g. food and beverage, golf course, etc.), and we use this more inclusive definition of revenues when working with the annual data. We also extend the sample back to 2017 to allow for a better assessment of low-frequency pre-trends. In Panel A of Figure VIII, we verify that the relative decline in revenues for pandemic-maturity hotels continues to hold at the annual frequency in this smaller sample.

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

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

In Appendix Figure A.IV we also verify that the drop in sales and marketing expense from panel D of Figure VIII occurs quickly, within the first few months of the pandemic. 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 merely responding to a spuriously greater decline in demand than hotels with a pre-pandemic maturity. This result obtains from estimating a variant of the event-study regression equation (2) using the monthly profit and loss dataset described in Section I.A.

III.C Effects on Profit

Comparing Panels A and B of Figure VIII reveals that the relative drop in revenue for hotels with a pandemic maturity exceeds the relative drop in expenses. This observation suggests that having a loan maturing in the pandemic also leads to a relative drop in operating profits. Figure IX verifies this conjecture by reestimating the specification in Figure VIII after replacing the outcome with operating profit. The results reveal that hotels with loans coming due during the early months of the pandemic indeed experienced a relative *decline* in profit compared to hotels with loans due before the pandemic.[16] Thus, the operational changes that hotel owners made in response to their looming balloon payment decreased the cash available to service debt. This effect is exactly the opposite of what occurs when firms scale back operations to generate short-run cash flow to make full or even partial balloon payments.

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

III.D Additional Robustness of Real Effects

We briefly discuss several robustness exercises that support the main empirical results.

Bandwidth Sensitivity and the Loan Life Cycle

Our main specification controls for effects related to the loan life cycle through a post-maturity dummy, which adjusts for any level change in outcomes that would occur at maturity without a rollover shock. Appendix Table A.IV goes further by modifying 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. We also report results that redefine treated and control hotels according to the date at which the loan can be freely prepaid without penalty, rather than the scheduled maturity date. In all cases, we continue to find estimates that are similar to our baseline specification.

Omitted Variables at the Chain Level

Appendix Table A.II provides results based on a version of our main regression that includes a full set of market-by-chain-by-month fixed effects. This restrictive specification identifies the main effect by comparing hotels from the same chain and market (e.g., two Hilton DoubleTrees in Boston) that happen to have loans maturing just before versus just after the pandemic, thereby exploiting less variation than our main regression. We continue to find a significant negative effect of a pandemic maturity, with effect sizes between 8 and 12 log points.

Paycheck Protection Program

In Appendix Figure A.V, we show that treated and control hotels have the same take-up rates of Paycheck Protection Program (PPP) loans over time.[17] This finding addresses the possibility that control borrowers used PPP loans at a higher intensity and therefore retained more of their workers. It also suggests that liquidity constraints did not drive the differential decline in real outcomes at treated hotels, as those hotels would have been more likely to seek PPP credit if they were more constrained and if doing so was costly.

IV Model

In this section, we present a simple model that develops intuition and empirical predictions for how the need to rollover debt during a crisis can affect firm operations. To fully explain the results in the previous sections, a model of debt rollover in a crisis needs to make three predictions: a negative

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

effect on output for any given level of the borrower's liquidity constraints; a negative effect on short-run profits; and the occurrence of renegotiation in equilibrium. We propose a mechanism based on strategic renegotiation: highly-levered borrowers temporarily scale back operations at the collateral to disincentivize creditors from seizing it, which increases renegotiation and prevents creditor takeovers in equilibrium. We formalize this intuition using a tractable model and derive empirical predictions that we subsequently evaluate in Section V.

IV.A Model Setup

Production Environment

Time is discrete and starts at $t = 0$. A firm produces output each period using a Cobb-Douglas production function:

$$F(K_t, L_t) = K_t^{1-\alpha} L_t^{\alpha}.$$

Variable inputs, which we refer to as labor for simplicity, are denoted by L_t and the unit cost of these inputs is w. Physical capital, like building square footage, is denoted by K_t.

We assume that the stock of physical capital remains constant over time ($K_t = K$), and focus instead on the firm's choice of labor inputs. We let

$$\pi(L_t, p_t) = p_t F(K, L_t) - w L_t$$

denote operating profits given labor, L_t, and the output price, p_t. We denote optimized profits by $\pi^*(p_t) = \max_{L_t} \pi(L_t, p_t)$ and the optimal level of labor by $L^*(p_t)$.[18]

Crisis

We model a crisis as a one-time unexpected shock to the firm's output price with unknown persistence. Specifically, we assume that at time 0, the price of the firm's output is $p_0 = p^h$ and is expected to stay at this level forever. At time 1, a crisis occurs in which the price unexpectedly drops to $p_1 = p^l$, where $0 < p^l < p^h$. With probability $q \in (0,1)$, this drop reverts at time 2, so that the price equals p^h from time 2 onward. With probability $1-q$, the price remains at p^l at time 2 and for all future periods. Whether the price reverts or persists at the low level becomes known at the beginning of time 2, before any decisions are made.

Debt, Renegotiation, and Labor Adjustment Costs

As of time 0, the firm's owner has a debt $\widetilde{D}$ due to a lender for which the firm serves as collateral. A *crisis maturity* borrower has the debt due at time 1, while a *non-crisis maturity* borrower has the debt due at time 2. The debt is non-amortizing and requires coupon payments of $r\widetilde{D}$ each period

[18] These values equal $\pi^*(p_t) = (1-\alpha)(\alpha/w)^{\frac{\alpha}{1-\alpha}} p_t^{\frac{1}{1-\alpha}} K$ and $L^*(p_t) = (\alpha p_t/w)^{\frac{1}{1-\alpha}} K$.

up to the maturity date, where $r > 0$ is the common discount rate. For notational ease, we denote the total payment due at maturity by $D = (1+r)\widetilde{D}$. We assume that this total payment due is less than the expected present value of operating profits as of time 0:

$$D < \frac{(1+r)\pi^*(p^h)}{r}.$$

At maturity, the borrower either pays the required payment to the lender or defaults. If the borrower defaults, the lender can foreclose and immediately take possession of the firm. In the event that a crisis maturity borrower defaults at time 1, the lender can alternatively offer to forbear the loan, which requires the coupon payment at time 1 but extends the maturity of the balloon to time 2 (with interest). If the borrower rejects this offer, the lender forecloses. If the borrower accepts this offer, the lender forecloses in the case of default at time 2 on this restructured loan.

If the lender forecloses, it faces adjustment costs from increasing the labor at the firm. Specifically, the adjustment cost the lender must pay at time $t+1$ equals:

$$\phi(L_{t+1}, L_t) = \begin{cases} 0, & L_{t+1} \leq L_t \\ \frac{\gamma}{2}\left(\frac{L_{t+1}}{L_t} - 1\right)^2 L_t, & L_{t+1} > L_t, \end{cases}$$

where $\gamma > 0$.[19] This adjustment cost arises out of the lender's lack of familiarity with the business model of the borrower, so the borrower does not face this adjustment cost.

The lender knows the value of the adjustment cost parameter, γ. In contrast, the borrower knows the distribution of γ across lenders in the economy but does not know the realization of this parameter for his or her lender. We denote the cumulative distribution function of this distribution $G(\gamma)$, and we assume that the distribution's support is an interval whose greatest lower bound is 0. The borrower can commit the firm to a level of labor at time t, before informing the lender about defaulting that period. However, if the borrower anticipates foreclosure with probability 1, then the borrower does not commit to labor, and the lender chooses labor for period t upon foreclosing.

IV.B Lender's Problem

To solve the model, we first characterize the lender's optimal decision of whether to foreclose or forbear given default at time 1. The value to the lender from foreclosing, given a defaulting borrower's

[19]This functional form implies that when the prior level of labor, L_t, equals 0, adjusting labor becomes infinitely costly, leading labor to be fixed at 0 in perpetuity and the firm to be worthless. While this stark feature of the model may not be realistic, it illustrates the mechanism more clearly by simplifying the model, and we do not believe it is necessary for the results to hold.

commitment to labor, L_1, is:

$$V^{fc}(L_1,\gamma)=\pi(L_1,p^l)+\frac{q\mathscr{V}(L_1,p^h,\gamma)+(1-q)\mathscr{V}(L_1,p^l,\gamma)}{1+r},$$

where $\mathscr{V}(L_t,p,\gamma)$ denotes the NPV of operating profits net of adjustment costs from operating the firm perpetually with output price, p, given initial labor, L_t. This function can be written recursively as:

$$\mathscr{V}(L_t,p,\gamma)=\max_{L_{t+1}}\pi(L_{t+1},p)-\phi(L_{t+1},L_t)+\frac{\mathscr{V}(L_{t+1},p,\gamma)}{1+r},$$

when initial labor is positive: $L_t>0$. When initial labor is 0, the NPV of operating profits is 0 because the lender cannot adjust labor: $\mathscr{V}(0,p,\gamma)=0$. The value to the lender from giving forbearance at time 1 is:

$$V^{fb}(L_1,\gamma)=\begin{cases} D & D\le r^{-1}\pi^*(p^l)\\ (1+r)^{-1}\big((r+q)D+(1-q)\mathscr{V}(L_1,p^l,\gamma)\big) & D>r^{-1}\pi^*(p^l).\end{cases}$$

The lender forecloses when the value from doing so exceeds that from offering forbearance, $V^{fc}(L_1,\gamma)>V^{fb}(L_1,\gamma)$, and offers forbearance when this inequality is flipped. The lender's decision depends on its adjustment cost parameter, γ. Given the borrower's prior distribution on this parameter, we let

$$\rho(L_1)=\Pr\big(V^{fb}(L_1,\gamma)>V^{fc}(L_1,\gamma)\big)$$

denote the probability the lender offers forbearance given the borrower's labor commitment, L_1.

In Proposition 1, we show that the borrower can weakly increase this probability by cutting labor at time 1 below the static optimum given the price at that time, $L^*(p^l)$, and can strictly increase the probability when debt lies below a certain threshold (proofs are in Appendix B):

Proposition 1 (Strategic benefit of cutting labor)**.** *The probability of receiving forbearance conditional on defaulting, $\rho(L_1)$, continuously and weakly decreases in the borrower's choice of labor at time 1, L_1, between 0 and the static optimum given the current price, $L^*(p^l)$. The probability limits to 1 as labor approaches 0:* $\lim_{L_1\to 0}\rho(L_1)=1$. *If*

$$D<\frac{1+r}{r}\frac{r\pi^*(p^l)+q\pi^*(p^h)}{r+q}=D^{**},$$

then the probability is less than 1 at the static optimum: $\rho(L^*(p^l))<1$.

The intuition of Proposition 1 is that cutting labor at time 1 lowers the lender's value from foreclosing more than its value from forbearing. Cutting labor can lower the value of the firm in the bad state at time 2, which reduces the value of both foreclosure and forbearance. However, cutting labor additionally reduces the value of foreclosure by lowering both current profits and the value of the firm in the good state at time 2. Therefore, cutting labor makes foreclosure less attractive relative to forbearance.

As a result, forbearance becomes more likely as long as the probability of forbearance is not already equal to 1. This probability limits to 1 as labor goes to 0 because foreclosure becomes worthless to the lender for any value of the adjustment cost parameter, γ, while forbearance continues to have value. As long as $D < D^{**}$, a lender with a small enough adjustment cost parameter will always prefer to foreclose than forbear when labor is equal to the static optimum. Therefore, a borrower with debt below this threshold can strictly increase the probability of forbearance by cutting labor below the static optimum. When $D > D^{**}$, the probability of forbearance equals 1 regardless of the level of labor because the coupon payment that the lender receives at time 1 exceeds the expected present value of the borrower's equity at time 2.

IV.C Borrower's Problem

Our primary interest is the borrower's choice of labor inputs at the onset of the crisis, L_1 as this dictates output, revenue, and profits. For a non-crisis maturity borrower, this choice is simple as the level of labor inputs at time 1 has no effect on the resolution of the loan at time 2. Thus, if the non-crisis maturity borrower chooses to make the coupon payment at time 1, this borrower sets labor equal to the static optimum given the output price at that time: $L_1 = L^*(p^l)$. If the non-crisis maturity borrower defaults on this coupon payment, the lender forecloses and sets labor in time 1.

For a crisis maturity borrower, the problem is more complicated as her choice of labor can influence whether the lender forecloses at time 1. The value to a crisis maturity borrower of paying off the loan is:

$$V^{po} = \pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r} - D.$$

If paying off the loan, the borrower sets labor to the static optimum, $L_1 = L^*(p^l)$, because labor at time 1 does not affect future operating profits. The value from defaulting at time 1 for a crisis maturity borrower is:

$$V^{df} = \sup_{L_1} \rho(L_1)\left(\pi(L_1, p^l) - \frac{rD}{1+r} + q\left(\frac{\pi^*(p^h)}{r} - \frac{D}{1+r}\right) + (1-q)\max\left(\frac{\pi^*(p^l)}{r} - \frac{D}{1+r}, 0\right)\right),$$

where $\rho(L_1)$ is the probability of forbearance as described above. In the event of default, the borrower chooses current labor, L_1, to maximize the expression on the right.

The crisis maturity borrower pays off the loan when $V^{po} > V^{df}$ and $V^{po} > 0$, defaults and accepts the forbearance agreement when $V^{df} > V^{po}$ and $V^{df} > 0$, and defaults and rejects the forbearance agreement when $V^{po} < 0$ and $V^{df} < 0$. In Proposition 2, we characterize the default decision and resulting choice of labor as a function of the level of debt:

Proposition 2 (Strategic default)**.** *There exists a threshold D^* such that the following hold at time 1:*

- *If $D < D^*$, then both borrowers make the required loan payments and set $L_1 = L^*(p^l)$, the static optimum given the price at time 1.*

- *If $D \in (D^*, D^{**})$, then the crisis maturity borrower defaults, sets $L_1 < L^*(p^l)$, and receives forbearance with positive probability; the non-crisis maturity borrower makes the coupon payment and sets $L_1 = L^*(p^l)$.*

- *If $D > D^{**}$, then both borrowers default, and the lender forecloses and determines L_1.*

- *The default threshold for the crisis maturity borrower lies between the worst-case and expected debt-free values of the firm, while the default threshold for the non-crisis maturity borrower lies above the expected debt-free value of the firm:*

$$\frac{(1+r)\pi^*(p^l)}{r} < D^* < \pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r} < D^{**}.$$

We explain the intuition of Proposition 2 by walking through the three debt regions defined in the proposition.

When debt is low, so that $D < D^*$, the crisis maturity borrower always pays off the debt. This is true even when the borrower would otherwise anticipate defaulting at time 2 in the bad state, which happens when the debt level, D, exceeds the worst-case value of the firm. Although there is value in trying to renegotiate the loan at time 1 in order to preserve the default option at time 2, the value at risk from foreclosure at time 1 is large enough to discourage this strategic behavior. As a result, this borrower pays off the loan at time 1 and sets labor to the static optimum. The same logic holds for the non-crisis maturity borrower, who owes only the smaller coupon payment at time 1.

When debt is intermediate, so that $D^* < D < D^{**}$, the crisis maturity borrower always defaults and accepts the forbearance agreement if the lender presents it. Default at time 1 is optimal because the debt level, D, is high enough so that the value of the default option at time 2 exceeds the value at risk from foreclosure at time 1. This is true even when the borrower would have positive equity after paying off the loan at time 1, which holds when the debt level, D, is less than the expected debt-free value of the firm. In contrast, the non-crisis maturity borrower still finds it optimal to make the coupon payment in this region of debt, so the non-crisis maturity borrower does not default.

When the crisis maturity borrower defaults in this debt region, lowering labor trades off increasing the probability of forbearance, $\rho(L_1)$, with decreasing current profits, $\pi(L_1, p^l)$. Some decrease in labor below the static optimum, $L^*(p^l)$, is always optimal for one of two reasons. If the probability of forbearance is 0 at this level of labor, then decreasing labor is optimal because it brings forbearance into play. Alternatively, if the probability of forbearance is positive at the static optimum labor, then a marginal decrease in labor causes a first-order positive gain in the forbearance probability, which is greater than the second-order effect of labor on profits around the static optimum. Therefore, the defaulting crisis maturity borrower optimally cuts labor below the static optimum: $L_1 < L^*(p^l)$. The non-crisis maturity borrower keeps labor at the static optimum because there is no strategic advantage to cutting it below this level.

Finally, when debt is high, so that $D > D^{**}$, both borrowers default. At this high level of debt, the coupon payment at time 1 exceeds the present value of the borrower's equity in the good state at time 2. As a result, the crisis maturity borrower is not willing to accept the forbearance agreement, and the non-crisis maturity borrower is not willing to pay the coupon. The crisis maturity borrower is also unwilling to pay off the debt at time 1 because the debt level, D, exceeds the expected debt-free value of the firm. The outcome for both borrowers is therefore foreclosure. There is no strategic advantage to committing to labor before default, and so the borrowers do not commit to labor, leaving the lender to determine labor at time 1 upon foreclosure.

IV.D Real Effects of Debt Rollover

From Proposition 2, we get an immediate corollary about the effect of debt maturity on the real outcomes of the firm. Labor at time 1, L_1, is either equal at the crisis maturity borrower and non-crisis maturity borrower's firms, or it is below the static optimum at the crisis maturity borrower's firm while equal to the static optimum at the non-crisis maturity borrower's firm. Therefore, real outcomes are either equal or smaller at the crisis maturity borrower's firm:

Proposition 3 (Real effects of debt rollover)**.** *Revenue, output, labor, and profits are weakly lower at time 1 for crisis maturity firms than for non-crisis maturity firms; the relation is strict if* $D \in (D^*, D^{**})$.

Proposition 3 explicitly relates our main empirical findings in Table II to a theory of strategic renegotiation prompted by debt rollover. The proposition also yields an additional testable implication of this theory: the negative effect of a crisis maturity on real outcomes is stronger for higher levels of debt, $D > D^*$. This prediction holds over the interval $(0, D^{**})$, which we think of as the empirically relevant range. In particular, $D > D^{**}$ represents a debt level so high that borrowers would prefer foreclosure with probability 1 over making just a single coupon payment.

IV.E Heterogeneous Real Effects in the Model

Characterizing heterogeneity in the theoretical effects of debt rollover is both interesting and also expands the set of testable implications of the model. Proposition 3 already characterizes heterogeneity along one margin, the borrower's leverage ratio. We now consider heterogeneous effects according to the lender's adjustment cost parameter, γ.

Consider a shift towards 0 in the distribution of γ across lenders in the economy, such that it becomes easier to increase operations at the firm. To generate this shift, we replace the original cumulative distribution function $G(\gamma)$ with an alternative given by $G_a(\gamma) = G(a\gamma)$, where $a > 1$. We denote outcomes under this new distribution by adding a subscript a to outcomes in the baseline model. To compare the chosen level of operations, $L^*_{1,a}$, for different levels of adjustment costs in a well-defined manner, we assume that this optimum is unique for each $a \geq 1$. We report how this shift in the distribution of the adjustment cost affects strategic renegotiation in Proposition 4.

Proposition 4 (Heterogeneity by Ease-of-Adjustment)**.** *If the distribution of γ changes from G to G_a, then:*

- *The range of debt where strategic default occurs weakly shrinks: $D^*_a \geq D^*$ and $D^{**}_a = D^{**}$.*
- *If $\log(1-G)$ is concave, then conditional on strategic default, operations at the firm fall: $L^*_{1,a} \leq L^*_1$ when $D \in (D^*_a, D^{**}_a)$, with strict inequality when $L^*_1 > 0$, which holds for some $D \in (D^*_a, D^{**}_a)$.*

According to the proposition, decreasing lenders' adjustment costs has a subtle effect on the decline in operations caused by strategic renegotiation. On the one hand, the frequency of strategic renegotiation remains constant or falls when ease-of-adjustment rises, as shown by the result that the default threshold, D^*_a, weakly increases. Since the lender's ease-of-adjustment in our model functions very similarly to the asset's redeployability in the model of Benmelech and Bergman (2008), the first part of Proposition 4 echoes their finding that strategic default becomes less common when the lender's cost of taking over the asset falls. In isolation, this effect attenuates the aggregate decline in operations due to strategic renegotiation by making strategic default rarer.

By contrast, the second part of the proposition shows that conditional on strategic default, the borrower cuts operations *more* when ease-of-adjustment is higher, outside of at most a limited range of debt levels where optimal operations equal 0 at baseline. Intuitively, when ease-of-adjustment goes up, greater cuts to operations are necessary to achieve the same increase in the probability of forbearance. This logic holds as long as the regularity condition on G given in the proposition holds. Since Figure IV implies that the majority of treated hotels do not pay off by maturity, it seems plausible that ease-of-adjustment would amplify the negative real effects of debt rollover, not attenuate them.

V Evaluating the Mechanism

This section provides additional empirical support for the strategic renegotiation mechanism. First, we examine how revenue changes around the time of renegotiation. Then, we evaluate several formal and informal predictions of the model by estimating heterogeneous real effects of debt rollover. Lastly, we present a short case study consistent with the strategic renegotiation mechanism.

V.A Dynamics around Loan Modification

In our model, the primary reason a borrower facing a debt rollover during a crisis scales back operations is to incentivize the lender to extend the loan rather than foreclosing. This is costly to the borrower, who loses out on short-run profits from operating the firm at a scale below the static optimum. Given these costs, a borrower who receives a term extension may want to immediately scale up hotel operations after the loan is modified.

Figure X provides descriptive evidence that is consistent with this behavior. In this figure, we restrict attention to the subset of treated hotels whose loan is modified after the crisis begins and plot average monthly room revenue by month relative to the month of modification.[20] We focus on a simple average rather than trying to instrument for loan modification because, as our model makes clear, output and renegotiation are jointly determined in equilibrium. To better align with our model setup, we limit the time period to months after the start of the pandemic and exclude hotels with an extension option written into the initial loan contract, since such hotels can extend their loan term without strategic renegotiation. The results show a roughly 30% decline in revenue during the three months leading up to modification, reaching a nadir in the month just before modification. Revenue then starts to recover in the month of modification and rebounds to nearly the same level after three months.

Plotting a simple average has the advantage of parsimony, but it is possible that the rebound following loan modification is confounded by the market-wide aggregate recovery in hotel demand shown in Figure III. This would be especially concerning if all loan modifications coincided with the low-point in aggregate demand. While 49% of hotels with a modified loan experience modification in 2020 (based on the CREFC indicator described in the note to Figure IV), 24% experience modification in 2022 when aggregate hotel revenues had already returned to pre-crisis levels. Moreover, in Appendix Figure A.VII we show that a similar rebound around the timing of loan modification persists in a regression framework that absorbs aggregate dynamics through our baseline set of fixed effects.

V.B Heterogeneous Effects by Strategic Incentives

Our model also implies that the magnitude of the initial decline in output should be larger for borrowers who have a larger incentive to renegotiate or whose actions would have a larger effects on the lender's incentive to extend the loan. This subsection explores heterogeneity in our main effect across four sets of proxy measures meant to capture these differences in strategic incentives.

To implement this analysis, we interact the treatment variable in equation (1) with a dummy variable denoting the presence of a characteristic, $Characteristic_i$, that should lead to stronger

[20]This analysis conditions on receiving a modification and studies the dynamics of output around that date. In Appendix Figure A.VI, we also reverse the analysis and find that a larger initial drop in revenue makes loan modification more likely in the cross-section of treated hotels.

incentives for strategic renegotiation:

$$\log(Revenue_{imt}) = \alpha_i + \delta_{mt} + \psi_0 X'_{it} + \beta_0 \cdot PandemicMaturity_i \times Post_t + \beta_1 \cdot PandemicMaturity_i \times Post_t \times Characteristic_i + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\lambda_\tau \times Characteristic_i \times \mathbb{1}_{t=\tau} \right] + \epsilon_{it}. \tag{3}$$

Relative to the baseline equation, the specification in (3) allows for an additional treatment effect for hotels with a given characteristic, captured by β_1. Importantly, equation (3) also accounts for the possibility that hotels with that characteristic differ in ways that affect their revenue during the crisis for reasons separate from the need to roll over debt, captured by the coefficients λ_t. As in the rest of our research design, we measure these characteristics as of origination. Econometrically, this approach reduces bias relative to using the contemporaneous value of a characteristic, which endogenously depends on demand for the hotel and the owner's ability to refinance.

High Leverage. The first characteristic we explore is borrower leverage. Our interest in this follows directly from Proposition 3, which predicts that strategic renegotiation arises in cases where the collateral is highly levered. In our setting, these cases correspond to hotels with a high total loan-to-value ratio (LTV), noting that the total LTV ratio includes second-liens and other non-securitized debt on the property as described in Section I.A. 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 estimation sample and corresponding to a ratio of 80%.

Column 1 of Table III shows that the drop in revenue at hotels with an impending balloon payment is almost entirely driven by highly-levered hotels ($HighLTV_i = 1$). While larger effects for higher LTVs is not necessarily a prediction that is unique to our model, this finding nonetheless accords with the model's prediction that borrowers engage in strategic renegotiation when their maturing debt exceeds D^*. Figure XI 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 XI imply that the dynamic effect is again driven by treated hotels in the top one-third of the LTV distribution.

Extension Options. The second dimension of heterogeneity we consider builds on the core idea from our model that borrowers engage in strategic renegotiation to influence their lender to modify the loan's maturity. CMBS loans, however, can often have their initial terms extended in ways that are not reliant on the lender. In particular, many loans come with extension options written into the initial contract, and borrowers with such an option can obtain an extension without needing to incentivize their lender to grant one. Executing this option is not costless (An, Cordell and Smith, 2023). However, when facing a rollover shock of the magnitude that we are studying, borrowers with an extension option would plausibly find it worthwhile to use it. Indeed the execution of extension options accounts for over 90% of the non-CREFC extensions in Figure IV.

Column 2 of Table III finds that the drop in real activity for hotels with debt maturing during the crisis is entirely driven by hotels without an extension option written into their contract at origination ($NoExtensionOption_i = 1$). This finding supports the idea that frictions in renegotiation drive the negative real effects of debt rollover.

Cash Sweeps and Short-term Operating Profits. The third dimension of heterogeneity we consider is the presence of a cash sweep or "lockbox" provision in the loan contract. In our model, borrowers face a tradeoff between short-term operating profits and bargaining power. This tradeoff can lead them to refrain from complete shutdown when the marginal increase in forbearance probability is not worth the marginal loss in profits. In practice, however, a borrower who defaults may have difficulty retaining any profits if their loan contract features a lockbox arrangement. These arrangements are fairly common among CMBS loans and apply to 58% of hotels in our sample. They require that cash flows from the collateral be directly deposited into a separate account from which debt service payments are deducted, after which the borrower can withdraw the remaining cash balance. The precise terms of lockbox arrangements vary across loans, with, for example, some arrangements only introducing a lockbox when certain conditions have been met ("springing lockbox"). Given this heterogeneity, we follow the same practice as with the other loan characteristics in question and simply define an indicator for whether the hotel's loan has a lockbox arrangement of any sort as of origination, $HasCashSweep_i$.

Column 3 of Table III finds a roughly 50% larger drop in revenue for hotels with a lockbox arrangement, consistent with lockboxes limiting the incentive to generate some cash flow from the hotel. From the perspective of our model, lockboxes reduce the sensitivity of a defaulting borrower's payoff, V^{df}, to current profits, $\pi(L_1, p^l)$, thereby reducing the only drawback to cutting labor as a negotiating tactic.

Proxies for Lender Adjustment Costs. The fourth dimension of heterogeneity we explore is variation in lenders' adjustment costs. Borrowers in our model engage in strategic renegotiation because their lender may incur significant costs from rehabilitating a badly-operated hotel, as parameterized by γ. While borrowers do not know their lender's γ with certainty, it seems plausible that its distribution varies across both hotels and lenders, which, in practice, correspond to CMBS special servicers.[21] As Proposition 4 states, borrowers facing lenders with lower expected adjustment costs are less likely to default, but conditional on default they scale back operations more. Thus, the drop in revenues could be larger for borrowers facing lenders with lower expected adjustment costs if the intensive margin of strategic renegotiation dominates the extensive margin of whether to default at all.

We propose three empirical proxies for a shift in the lender's distribution of γ toward zero (i.e., lower adjustment costs). All of these proxies follow from the observation that hotel management practices are often dictated at the chain level, with some chains requiring different standards for the maintenance of furniture, provision of turn-down services, etc. The proxies are: (1) the number of hotels from the same chain as hotel i, $HotelsPerChain_i$; (2) the number of distinct hotel chains assigned to i's special servicer, $ChainsPerServicer_i$; and (3) the share of hotels from the same chain as hotel i among hotels with the same special servicer as i, $ServicerChainShare_i$. The $HotelsPerChain_i$ proxy maps almost exactly to the Benmelech and Bergman (2008) measure of asset redeployability after replacing "airplanes" with "hotels." Hotels with a high value of $HotelsPerChain_i$ are relatively common, and so it seems plausible that they are easier for the average servicer to manage. The other two proxies rely on variation across lenders (i.e., special servicers), not assets. Servicers with a high value of $ChainsPerServicer_i$ plausibly have experience managing various types of hotels, and so they would incur a smaller adjustment cost when taking over any given hotel. Taking this logic one step further, the $ServicerChainShare_i$ proxy captures how much experience a servicer has with hotels similar to the particular hotel i.

Columns 4-6 of Table III test for heterogeneous effects across these three proxies, all of which are normalized to have mean of zero and unit variance. The estimated coefficients imply that the drop in revenue is between 11 and 13 log points larger for hotels with a one standard deviation increase in each proxy variable. Interpreting these variables as proxies for shifting the distribution of γ toward zero, we interpret the estimates as implying that borrowers on average reduce operations more when their servicer can more easily manage the hotel in the event of foreclosure. Hence, the intensive margin seems to dominate the extensive margin of whether to default in our setting, which is consistent with the widespread default behavior during this episode.

Summarizing, Table III implies substantial heterogeneity in the real effects of debt rollover. While some of these margins of heterogeneity do not exactly map to parameters of the model, the broad pattern implied by the estimates supports the basic intuition of the strategic renegotiation mechanism.

[21] As explained in Flynn, Ghent and Tchistyi (2024), the special servicer is an entity designated at the loan's origination to represent creditors in the event of imminent or actual loan default. Consequently, the special servicer assigned to a hotel does not correlate with the hotel's contemporaneous financial condition, although we cannot rule out that it correlates with initial expectations about how the loan would perform should it have debt maturing in a pandemic.

V.C Anecdotal Evidence

As a final piece of evidence, we conclude with a short case study on a particular renegotiation in our data. We focus on the Highland Loan Pool, which was debt that matured in April 2020 borrowed by a REIT named Ashford Hospitality Trust that was split into a senior CMBS mortgage and two mezzanine loans.[22]

When this loan pool matured in April 2020, Ashford did not pay off the loan and did not make its scheduled interest payment. According to Brookfield Property Group, one of the lenders on this loan pool, Ashford pulled $15 million from operating accounts in March, which Brookfield asserted "should be returned to ensure the hotels and their employees have access to essential operating capital." In response to a letter from Brookfield threatening ligation over this distribution, Ashford filed an 8-K defending its decision to default and reduce operations at hotels and complaining that Brookfield has not yet agreed to forbear the loan.

Ashford appeared not to need this $15 million for liquidity. In fact, one of its largest shareholders, Cygnus Capital, wrote in 2020 that it "believes the Company has sufficient cash (approximately $249 million as of Q2 2020) to ride out the impact of COVID-19." Furthermore, Ashford voluntarily returned $59 million in PPP funds it had received due to uncertainty about eligibility, suggesting that liquidity was not a paramount concern.

In July, Ashford entered into an agreement with its lenders to extend the maturity to April 2021, thus avoiding foreclosure during 2020.[23] Interestingly, the drop in operating revenue from 2019 to 2020 for hotels collateralizing the Highland Loan pool was 66% (from the Trepp data), much higher than the 14% drop in revenue over the same time for hotels collateralizing loans from Ashford scheduled to mature in 2025, the latest scheduled maturity date for Ashford in our data. The larger drop for the Highland Loan pool suggests that Ashford intentionally reduced operations specifically at the underlying hotels in a successful attempt to obtain concessions from its lenders, in line with our model.

VI Conclusion

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

[22] This discussion draws on various industry and regulatory sources (Ashford Hospitality Trust, Inc., 2020, 2021; Cygnus Capital, Inc., 2020; Saloway, 2020; Sperance, 2020; Tezuka, 2020). We attempt to validate aspects of this event using information from Trepp but do not identify or attempt to identify the underlying properties in the STR data.

[23] The agreement also allowed Ashford to redirect funds in capital expenditure reserve accounts towards property operations. Given that the loan had an extension option, Ashford's primary goal when strategically defaulting may have been to obtain this concession, which effectively released cash collateralizing the loan back to Ashford.

scheduled to mature just after the pandemic's onset, relative to hotels with mortgages scheduled to mature just before. These findings are consistent with a novel mechanism in which borrowers manipulate operations to strategically renegotiate their debt. We formalize this mechanism in a model and provide empirical support for it.

Our work highlights the potential macroeconomic risks of the way that many owners of commercial real estate finance their investments, via mortgages with large balloon maturities. These balloon maturities make the owners vulnerable to economic problems that occur near the maturity date. To the extent that these problems are correlated across borrowers, the common use of these mortgages can expose the economy to substantial risk given the size and importance of the commercial real estate sector. While it is possible that this mortgage structure is optimal from an ex-ante perspective, our work highlights the potential ex-post costs it can generate. Future research may explore why, from a contract design perspective, commercial mortgages feature such large balloon payments.

Going forward, the negative real effects that we document may apply to other distressed commercial property sectors with maturing debt. Practitioners and academics have recently voiced concerns over this possibility, especially in the context of the office and retail sectors, both of which have large amounts of debt maturing over a three-year period and face economic headwinds from trends in remote work and e-commerce (Gupta, Mittal and Nieuwerburgh, 2022; Putzier, 2023).

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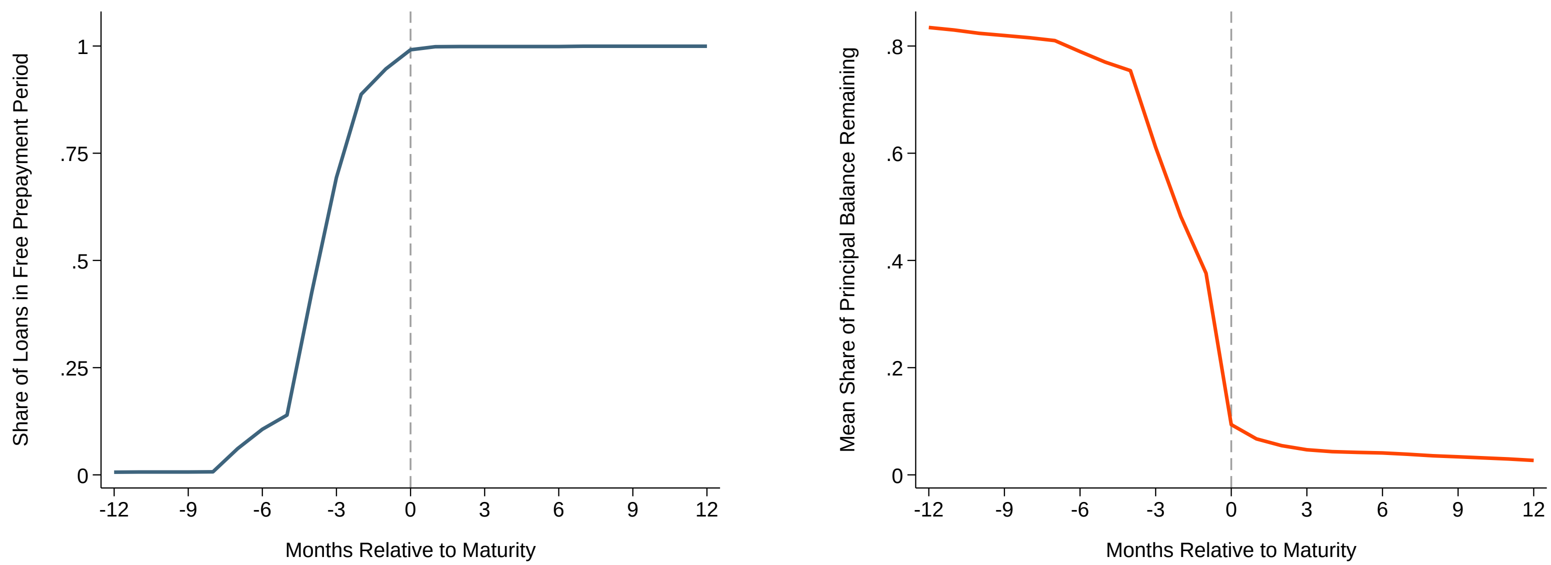


Panel A. Loans in Free Prepayment

Panel B. Principal Balance Remaining

FIGURE I

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)

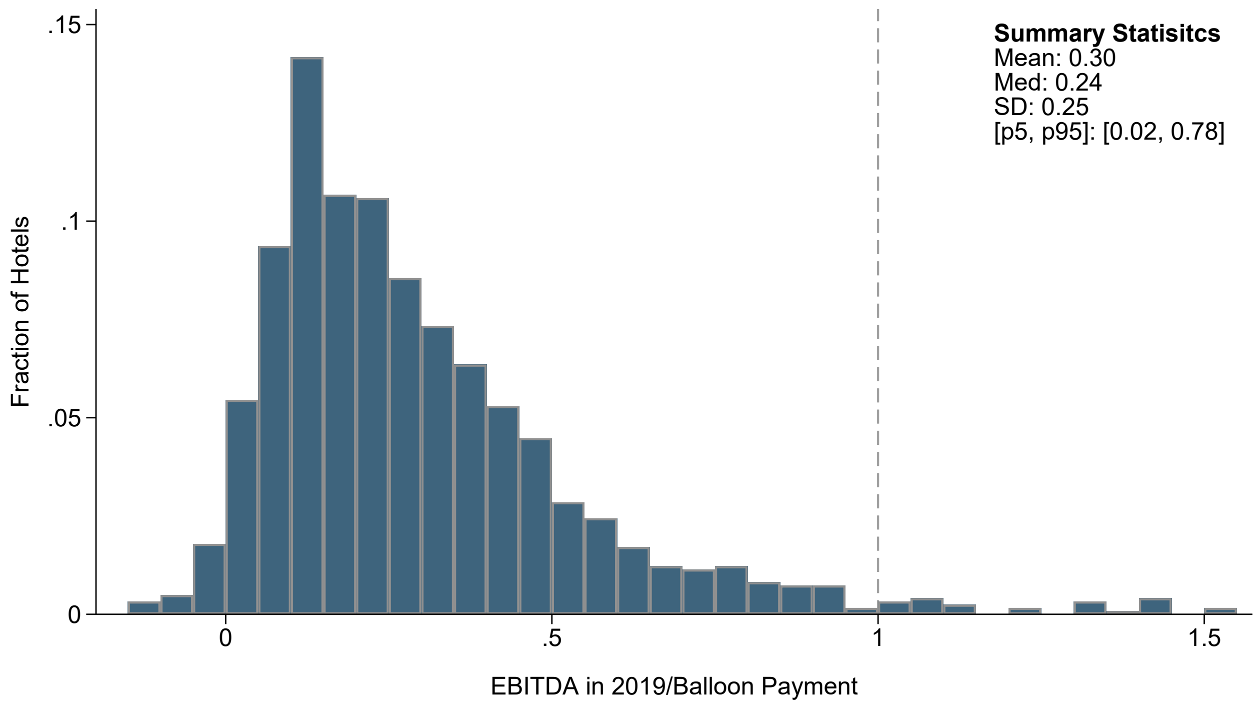


FIGURE II
Operating Profits Relative to Scheduled Balloon Payment.

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. 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)

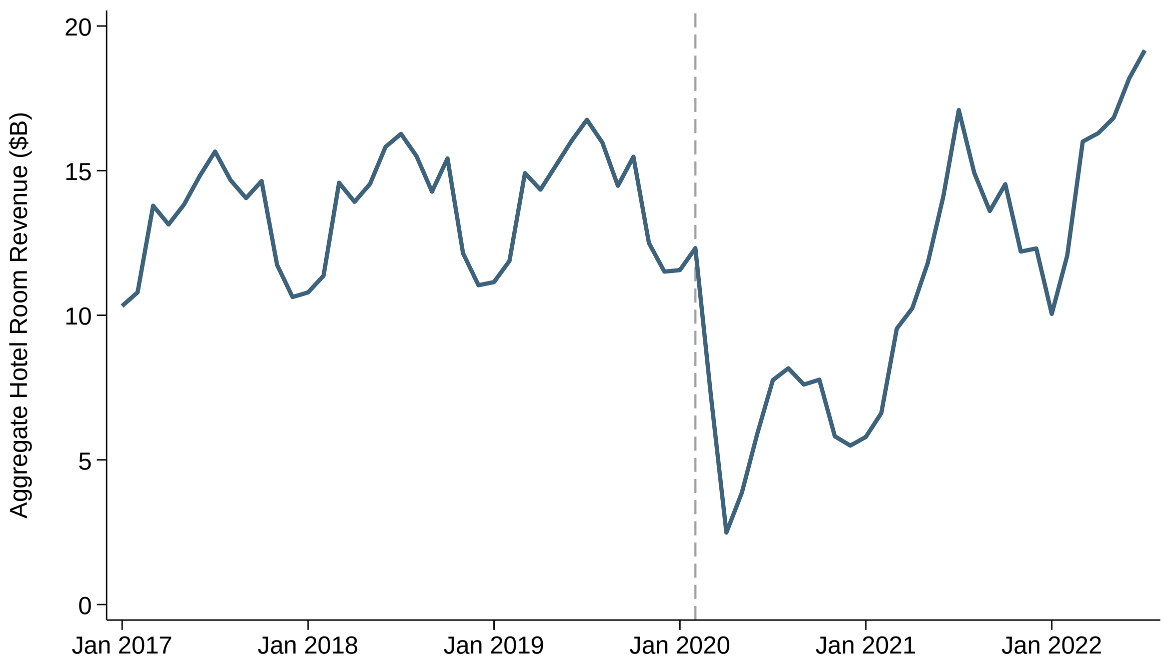


FIGURE III
Aggregate Monthly Revenues for US Hotels.

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 roughly 60% of all U.S. hotels and 76% of U.S. hotel rooms. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. (SOURCE: STR, LLC)

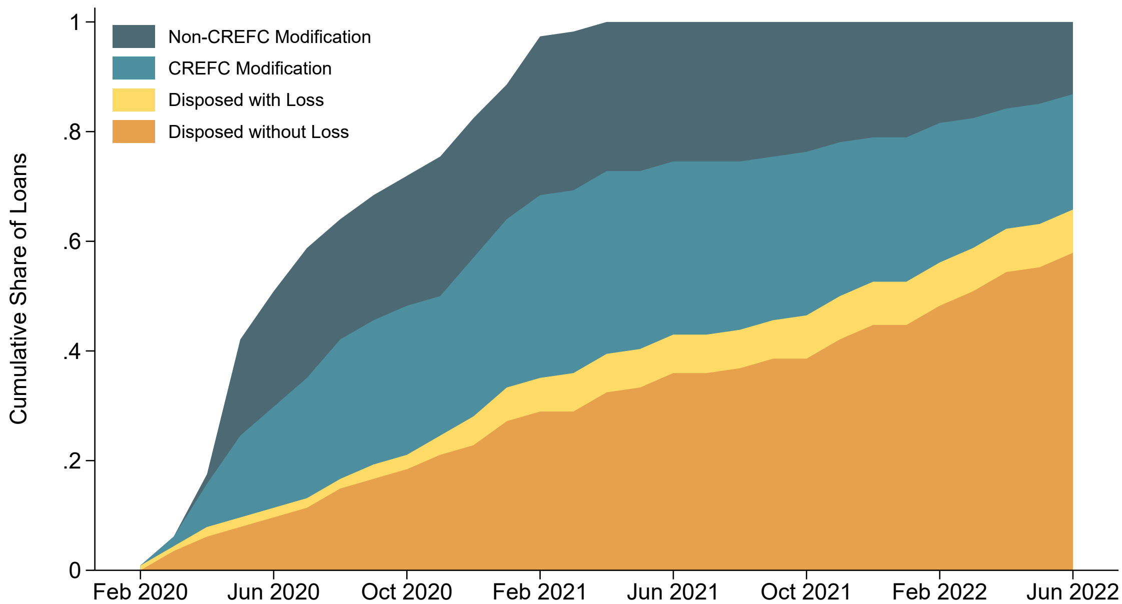


FIGURE IV
Loan Resolution.

NOTE.—This figure plots the share of hotel loans with either an explicit modification or a known disposition (i.e., exit) as of each month from February 2020 through June 2022. 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 a "Non-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 either it makes an unscheduled principal payment that equals or exceeds the loan balance from the previous month, or it was current on its debt service payments in all of the preceding three months. These definitions allow loans to move between categories (e.g., CREFC Modification to Disposed without Loss). The categories are mutually exclusive but do not necessarily sum to one. If a loan does not fit into any of the previous categories in a given month, we assign it to "Non-CREFC Modification" if Trepp's internal modification description is non-empty. If the loan is still uncategorized, then we assign it to "Disposed with Loss" if Trepp's internal delinquency description indicates that a foreclosure is in process, even if the loan is not yet disposed. (SOURCE: Trepp)

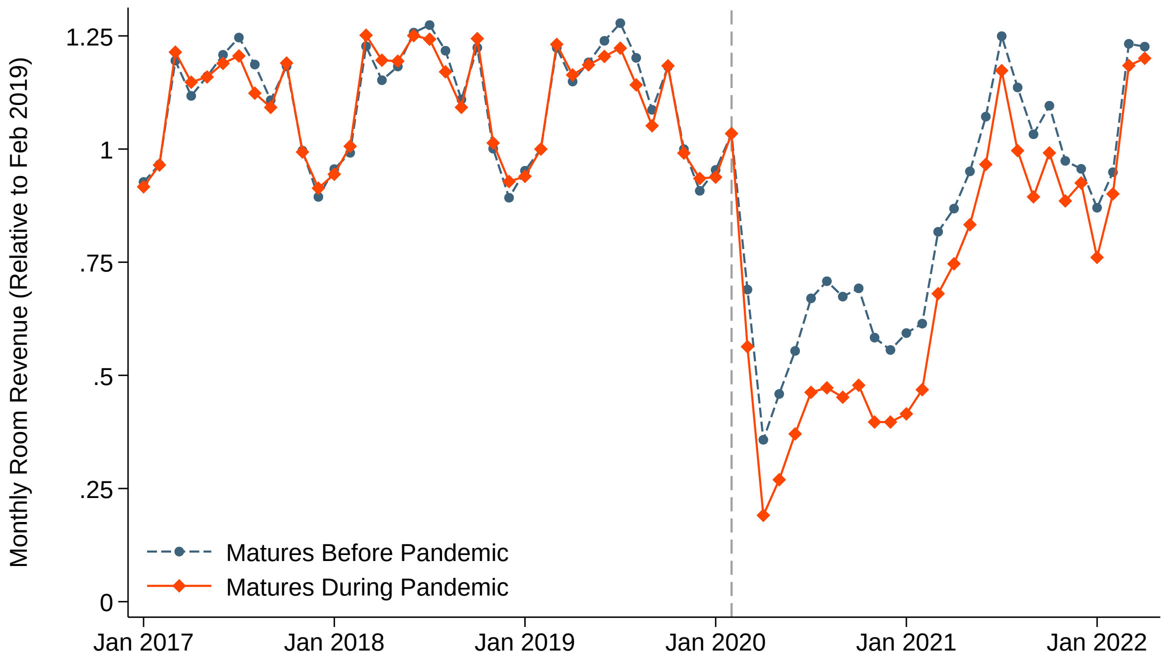


FIGURE V

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 from February 2019 through January 2020 (Before Pandemic) and those with loans maturing from February 2020 through February 2021 (During Pandemic). Loan maturities are measured as of origination. The average is normalized by the February 2019 value for each maturity cohort. Data on loan maturities are from the Trepp dataset. Data on hotel revenue are from the STR performance dataset. (SOURCE: STR, LLC and Trepp)

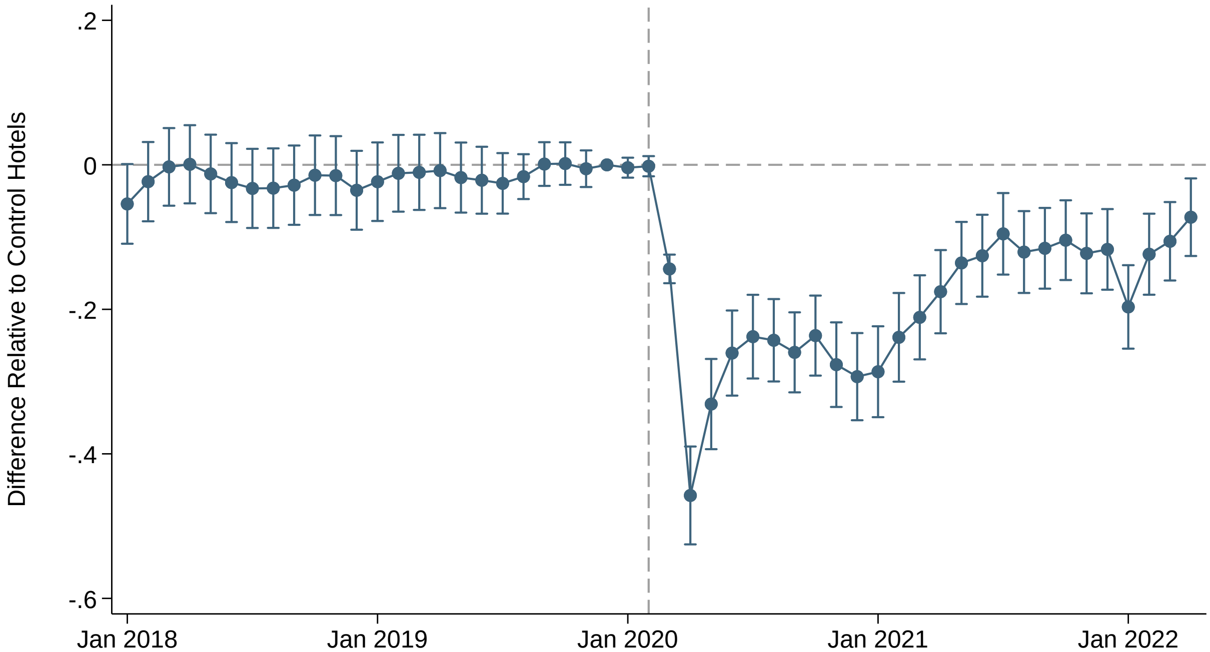


FIGURE VI
Effect of Pandemic Maturity on Hotel Room Revenues.

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

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

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

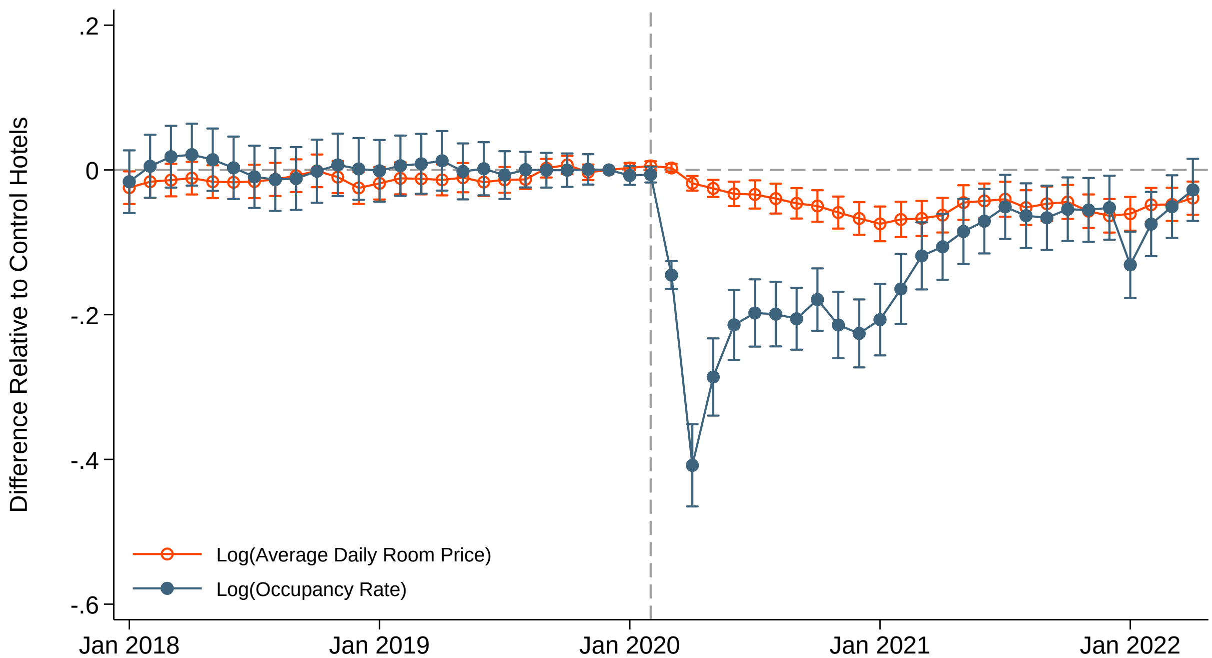
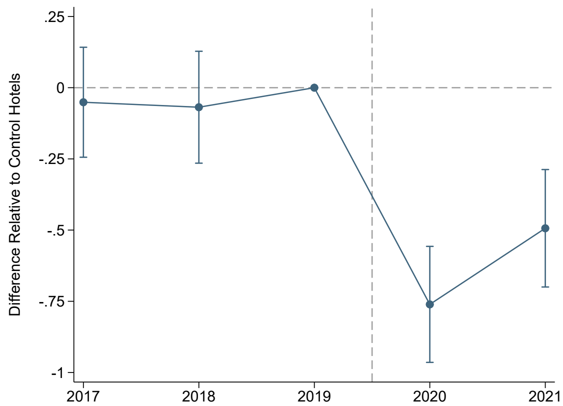


FIGURE VII
Effect of Pandemic Maturity on Hotel Occupancy and Prices.

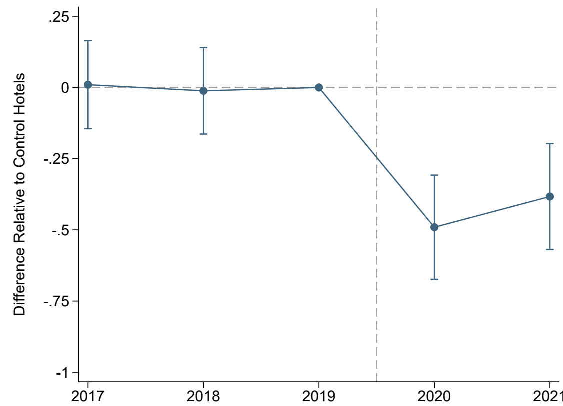
NOTE.—This figure decomposes the effect on revenue from Figure VI into the part that reflects reduced quantity (i.e., occupancy rate) and the part that reflects a lower room price. Explicitly, the figure summarizes the estimates from the same regression equation as in Figure VI after replacing the outcome 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,

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

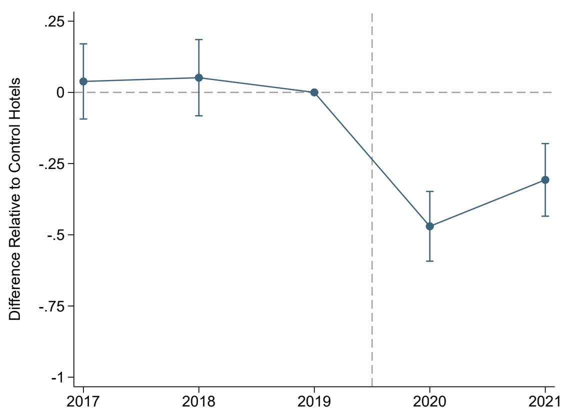
so the sum of the estimated coefficients each month in this figure approximately equals the estimated coefficient for the same month in Figure VI. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)



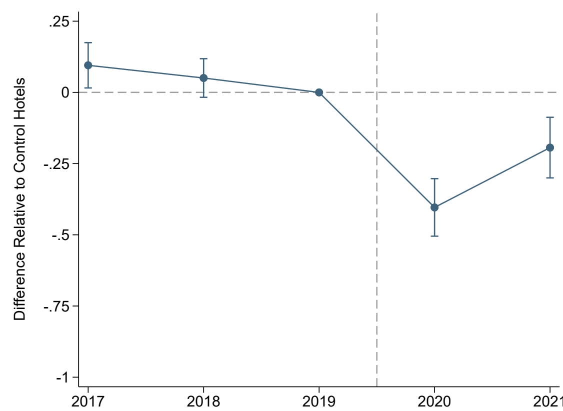
Panel A. Total Revenues



Panel B. Total Expenses



Panel C. Labor Expenses



Panel D. Sales and Marketing Expenses

FIGURE VIII

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 VI reflects a cutting back of inputs by treated hotels. The regression equation is of the same form as that in Figure VI, except that the frequency is annual because the data on hotel expenses come from STR's annual profit and loss dataset. The treatment variable, $PandemicMaturity_i$, is still defined as it is in Figure VI. The definitions of all other variables are the same as in Figure VI 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 VI. (SOURCE: STR, LLC and Trepp)

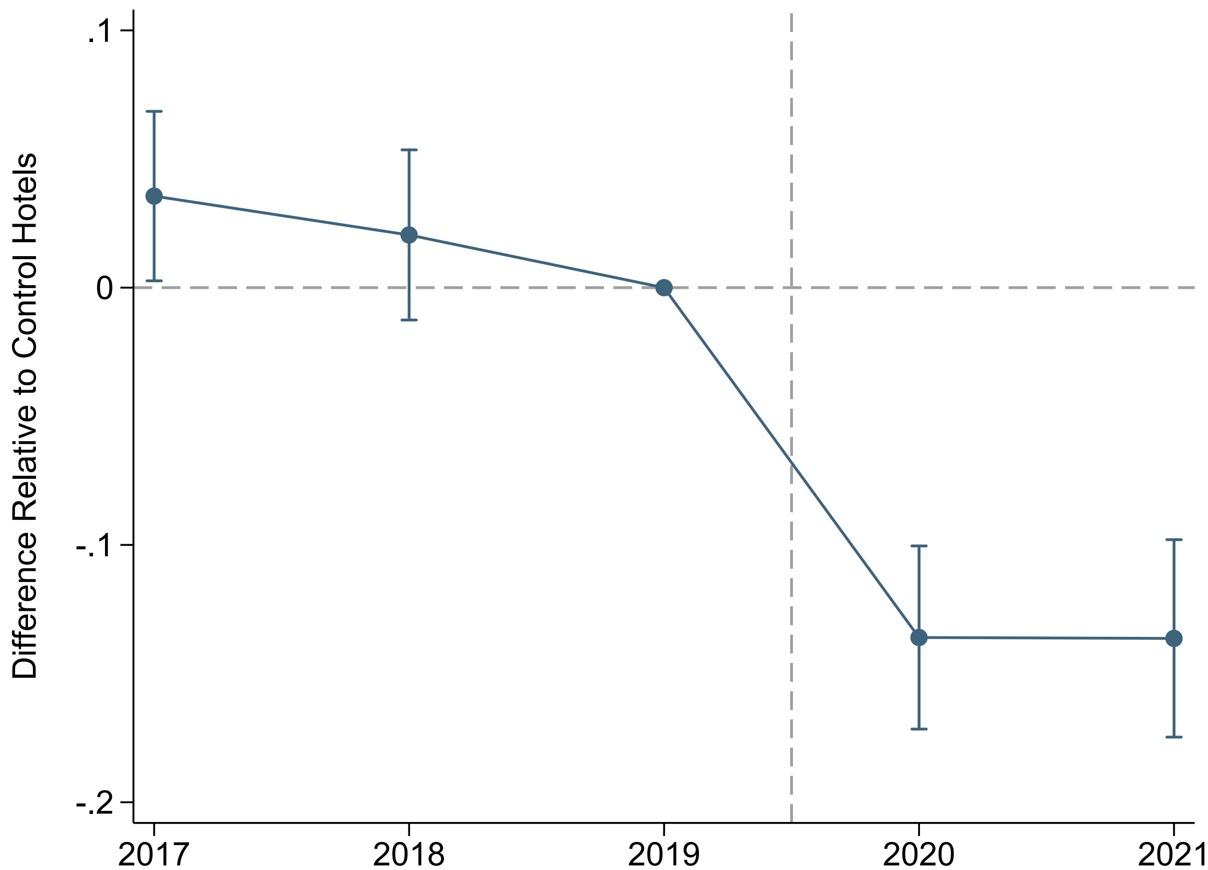


FIGURE IX
Effect of Pandemic Maturity on Hotel Operating Profits.

NOTE.—This figure estimates a variant of (2) that assesses the effect of a pandemic maturity on operating profits. The regression equation is the same as in Figure VIII 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 VIII. (SOURCE: STR, LLC and Trepp)

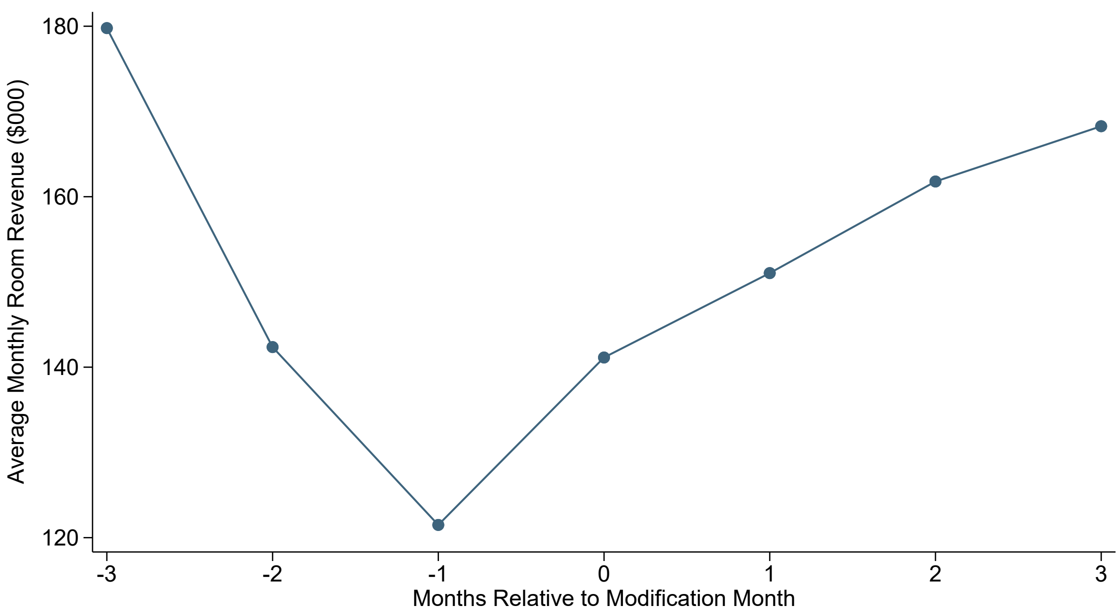


FIGURE X
Revenue around Loan Modification.

NOTE.—This figure plots average monthly room revenue around the month of modification for hotels with loans with a scheduled maturity from February 2020 through February 2021 that are first modified in the pandemic. Modification is measued using the indicator from the Commercial Real Estate Finance Council (CREFC), as described in Figure IV. The figure excludes loans with an extension option as of origination. To ensure that the figure captures dynamics within the pandemic, the figure is restricted to months in February 2020 or later. Data on loan maturities are from the Trepp dataset. Data on hotel revenue are from the STR performance dataset. (SOURCE: STR, LLC and Trepp).

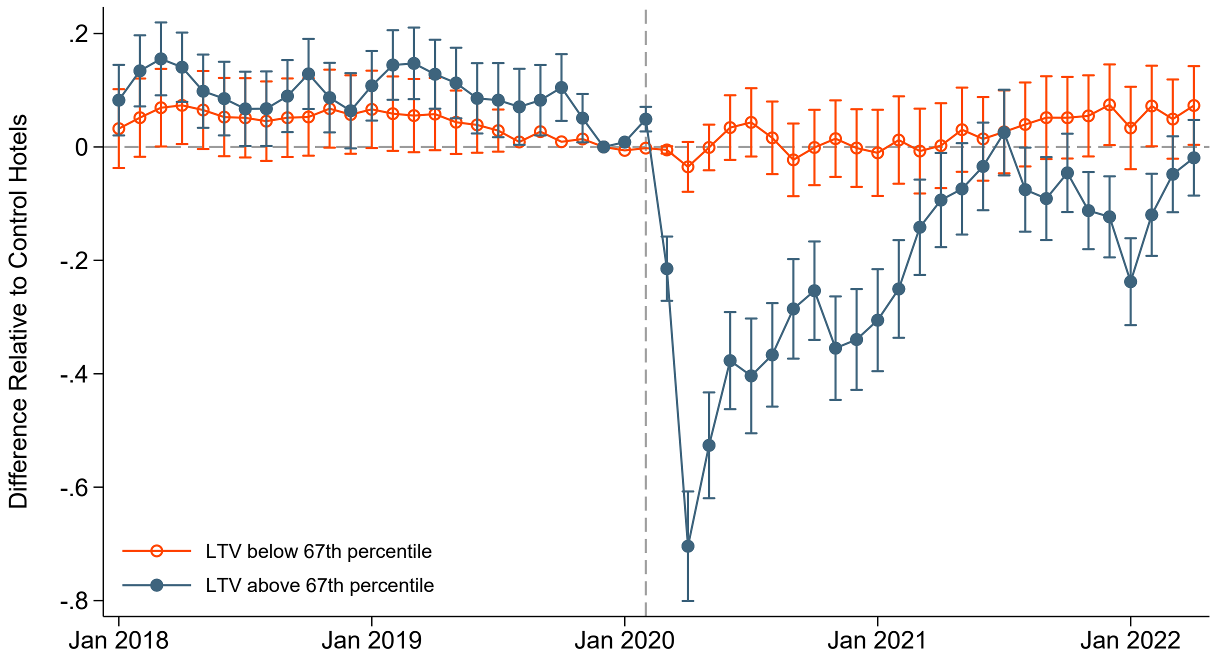


FIGURE XI
Effect of Pandemic Maturity on Hotel Revenues by Initial LTV.

NOTE.—This figure estimates a variant of equation (2) that separates the results in Figure VI 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 III,

$$y_{imt} = \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\beta_{0,\tau} \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \right] + \ldots$$

$$\sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\beta_{1,\tau} \times PandemicMaturity_i \times HighLTV_i \mathbb{1}_{t=\tau} \right] + \ldots$$

$$\psi_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\psi_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

where the notation is the same as in Table III. 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, $\beta_{0,t}$, which measure the effect for hotels in the bottom two terciles of the LTV distribution, and the sum of the coefficients, $\beta_{0,t} + \beta_{1,t}$, which measure the effect for hotels in the top tercile. Brackets are 95% confidence intervals. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC, Trepp, and RCA)

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 from February 2020 through February 2021 (Pandemic Maturity). The unit of observation in all panels is the hotel. The Hotel Performance panel summarizes hotel performance observed in May 2019. The Hotel Location panel summarizes indicator variables for whether the hotel categorizes its location as close to an airport, a resort, urban, suburban, or close to the highway. The Loan Characteristics 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. Balloon means that the loan has a balloon amortization. Data in the Loan Characteristics panel are from the Trepp dataset. The LTV ratios from Trepp are modified to account for second-liens observed in the RCA dataset. Data in the Performance and Location panels are from the STR performance and cross-sectional datasets, respectively. Additional details are in Section I.A and Appendix A. (SOURCE: STR, LLC, Trepp, and RCA).

TABLE II

EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES

	(1)	(2)	(3)	(4)	(5)	(6)
PandemicMaturity × Post	−0.171***	−0.126***	−0.180***	−0.182***	−0.192***	−0.217***
	(0.024)	(0.020)	(0.025)	(0.025)	(0.037)	(0.028)
Hotel FEs	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X
Market × Month FEs	X	X	X	X	X	X
Size × Month FEs		X	X	X	X	
Operation Type × Month FEs			X	X	X	
Location Type × Month FEs				X	X	
Origination Year × Month FEs					X	
Borrower × Month FEs						X
Number of Observations	133,095	133,095	133,095	133,095	133,095	111,452

NOTE.—This table shows estimates of 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

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

where $Revenue_{imt}$ is room revenue for hotel i, located in market m, in month t; $PandemicMaturity_i$ is a treatment indicator that equals one if hotel i has a loan that was initially scheduled to mature in the month when the pandemic began (February 2020) or during the 12-month period following that month, and it equals 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 of controls. All columns control for the effect of the loan life cycle with an indicator for whether t equals or exceeds the month of the maturity date of the loan on hotel i (Post Maturity FE). The other controls are fixed effects for bins defined by month and: hotel size, in number of rooms (Size × Month FEs); whether the hotel is brand-managed, branded but not managed by the brand, or unbranded (Operation Type × Month FEs); location type, which can take the values shown in Table I (Location Type × Month FEs); and year of origination (Origination Year × Month FEs). The rightmost column includes fixed effects for bins defined by borrower and month. The sample size also falls by 16% because information on the borrower comes from RCA and is not available for all hotels. There are 46 borrowers used in estimation, of which 30% have hotels in both the treatment and control groups. Details are in Section II. 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

EVALUATING THE MODEL. HETEROGENEITY IN THE EFFECT ON HOTEL REVENUES.

	(1)	(2)	(3)	(4)	(5)	(6)
PandemicMaturity × Post	−0.023	−0.008	−0.133***	−0.105***	−0.188***	−0.197***
	(0.019)	(0.020)	(0.026)	(0.021)	(0.027)	(0.027)
PandemicMaturity × Post × HighLTV	−0.275***					
	(0.050)					
PandemicMaturity × Post × NoExtensionOption		−0.379***				
		(0.064)				
PandemicMaturity × Post × HasCashSweep			−0.072**			
			(0.034)			
PandemicMaturity × Post × HotelsPerChain				−0.126***		
				(0.031)		
PandemicMaturity × Post × ChainsPerServicer					−0.110***	
					(0.022)	
PandemicMaturity × Post × ServicerChainShare						−0.135***
						(0.019)
Hotel FEs	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X
MSA × Month FEs	X	X	X	X	X	X
Characteristic × Month FEs	X	X	X	X	X	X
Number of Observations	133,043	133,095	131,286	133,095	125,202	125,202

NOTE.—This table shows estimates of a variant of equation (1) that assesses variation in the real effects of debt rollover as predicted by the model. The regression equation is of the same form as equation (1) after interacting the treatment variable with characteristics of the loan, in columns (1)-(3), of the hotel, in column (4), and of the loan's special servicer, in columns (5)-(6). Explicitly, the regression equation is

$$y_{imt} = \beta_0 \cdot PandemicMaturity_i \times Post_t + \beta_1 \cdot PandemicMaturity_i \times Post_t \times Characteristic_i \ldots$$

$$\psi_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \left[\lambda_\tau \times Characteristic_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

where the characteristics are: (1) an indicator for whether the initial LTV ratio is in the top one-third across hotels in the estimation sample, corresponding to an LTV ratio of 80% ($HighLTV_i$); (2) an indicator for whether the loan has no option to extend its maturity as of origination ($NoExtensionOption$); (3) an indicator for whether the loan has a lockbox (i.e., cash sweep) contingency in place as of origination ($HasCashSweep$); (4) the number of hotels from the same chain as hotel i ($HotelsPerChain$); (5) the number of distinct hotel chains assigned to i's special servicer, omitting non-branded hotels ($ChainsPerServicer$); and (6) the share of hotels from the same chain as hotel i among all hotels in the sample with the same special servicer as i ($ServicerChainShare$). The characteristics in columns (4)-(6) are normalized to have mean of zero and unit variance because they are continuous. Data on LTV ratios are from Trepp and are modified to account for second-liens observed in RCA. The number of observations fluctuates because some of the variables used to construct the interaction terms are not observed for all loans in Trepp. The remaining notes are the same as in Table II. (SOURCE: STR, LLC, Trepp, and RCA)

For Online Publication: Internet Appendix

A Data Appendix

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

A.A STR Datasets

As described in the text, we use data from STR, LLC to study hotel output, labor, and profitability. STR covers the majority of U.S. hotels, and it maintains this large coverage through an incentive scheme were partner hotels provide data on their operations in exchange for receiving customized benchmarking reports on their competitors.[1] Data on individual hotels is available to academics under a confidentiality agreement that requires researchers to work with an anonymized subsample of the STR universe. Accordingly, our full STR dataset includes the subset of hotels in our Trepp dataset that have a loan scheduled to mature between January 2018 and December 2022 (which is a broad window around the onset of the pandemic) and that match to a hotel tracked by STR.

A.A.1 Anonymization Procedure

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

We do so through the following protocol. First, we construct a list of all zip codes in the Trepp dataset that have a loan maturing between January 2018 and December 2022. Second, we obtain from STR a directory of all hotels with an address in one of these zip codes. This directory includes the address of the hotel, its universal STR identifier, and its name, which will subsequently be masked. Third, we match each hotel in the Trepp dataset to a hotel in the STR universe, achieving a 90% match rate. Section A.D elaborates on this procedure. Fourth, we return this crosswalk file from Trepp to STR, including the unique Trepp loan identifier and the other relevant loan-level variables described in Section A.B below. Lastly, STR scrambles the original hotel identifier, and it 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. 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 the average room price across occupied rooms (average daily rate, or ADR). We often use the terms "price" and "ADR" synonymously in the text.

[1] 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, because 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 may be submitted to STR via automated processes built into hotel property management software.

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.[2]

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 that in (Steiner and Tchistyi, 2022), who also use STR's data. For months in which the hotel is closed, we code room revenue, room demand, and rooms available as zero, which leads to the dropping of these observations when we 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 subsample of the hotels in the basic performance dataset. Over 2017 through 2021, 61% of hotels in the basic performance dataset appear in the yearly profit and loss dataset at some point. The variables in the profit and loss 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, which we define as the sum of wages and additional payroll expenses.

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

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.

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 metropolitan area. 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).
- **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." The variable $HotelsPerChain_i$ used in Section V.B equals the number of hotels from the same chain as hotel i. For unbranded hotels, this variable equals one. We calculate this variable using our merged STR-Trepp dataset. Since we only observe an anonymized code for the hotel's brand, we interpret this variable as an approximation for the actual number of hotels from a given chain.
- **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), and 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 Dataset

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*), the servicer's identifier for the debt claim (*masterloanidtrepp*), and, for debt claims with a multiple note capital structure, the order of the note (*notenum*). In the property-level panel, a property is identified using the unique combination of: the pool in which the debt claim on the property has been issued (*dosname*); and the servicer's identifier for the property (*masterpropidtrepp*). The majority of the variables used in our analysis come from the loan-level panel. The property-panel contains information about the property's type and address, which enables the merge with the STR dataset as described in Appendix A.D below. In addition, the property-level panel contains the aforementioned identifiers for the associated loan. So, we first merge the Trepp loan-level panel with the Trepp property-level panel, which we then merge to the STR datasets.

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

- **Critical Dates:** We observe the loan's origination date, maturity date at origination, and maturity date as of month t. For loans that have reached a disposition as of June 2022, we observe the loan's disposition date. We also observe the date on which the loan makes any unscheduled principal payments, which would include the date on which the loan prepays, 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 (DSCR) is the ratio of net operating income to debt service as of the most recent fiscal year.

- **Special Servicer:** We observe the name of the loan's special servicer, which is assigned at origination. We use a standard string grouping algorithm to assign different spellings of the same name to the same special servicer identifier.

  We calculate the variables $ChainsPerServicer_i$ and $ServicerChainShare_i$ using both the derived special servicer identifier and information on the chain of hotels that serve as collateral, which comes from the STR cross-sectional dataset described above. The variable $ChainsPerServicer_i$ equals the number of distinct hotel chains assigned to the loan's special servicer in our merged STR-Trepp dataset, omitting non-branded hotels. The variable $ServicerChainShare_i$ equals the share of hotels from the same chain as hotel i among all hotels with the same special servicer as i, again omitting non-branded hotels and based on the hotels in our merged STR-Trepp dataset.

- **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.

- **Cash Sweeps and Extension Options:** We define a loan as having an extension option as of origination if, in the earliest month for which the loan is observed in the data, the loan has a non-empty value of the remaining-terms-to-extend. We define a loan as having a cash sweep (i.e., lockbox) as of origination if, in the earliest month for which the loan is observed in the data, the current-lockbox-status variable takes on a value other than "N". In this case, the variable $HasCashSweep_i$ equals 1. If the current-lockbox-status variable takes on the value "N" in the earliest month for which the loan is observed in the data, then the variable $HasCashSweep_i$ equals 0. If the current-lockbox-status variable is always empty, then $HasCashSweep_i$ is undefined. Both the remaining-terms-to-extend and the current-lockbox-status variables come from the CREFC servicing file.

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

A.C Other Datasets

A.C.1 RCA

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

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

Second, we provide this list to two research assistants (RAs). They manually find the hotels in RCA using the hotel names and addresses. For each hotel, they make an attempt to identify the corresponding loan in Trepp. RCA records all loans originated at the same time in a graphical user interface. The RAs record the number of distinct loans as well as the amount of each loan. RCA repeats the same loan when there are multiple lenders for a given loan, so we instructed the RAs not to double-record loan amounts that are identical. The RAs also record RCA's reported value of the property. Finally, the RAs record the name of the borrower reported in RCA for the matched loan.

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

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

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

RCA. Our final LTV variable is non-missing for all cases where the original LTV variable in Trepp is populated. We do not adjust the DSCR in Trepp to account for junior liens because RCA does not have sufficient data on required interest payments.

To collect data on borrower identity, we query the RCA investor database using the names of all borrowers in the raw data from the RAs. In the case of borrowers with human names, there are sometimes multiple investors in RCA under the same name. In those cases, we select the name where the city in the investor database matches the location of a property owned by that borrower in the Trepp data. There are also instances of companies with multiple trade names, and RCA reveals these by autocorrecting in their search box. We hand collect these autocorrects to replace the borrower names in the raw RA data with the primary trade name that RCA uses in its investor database. This procedure provides data in all instances where we can find a loan event in RCA corresponding to the one in Trepp.

A.C.2 PPP Dataset

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

A.D Merging Procedures

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

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

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

- **RCA-to-Trepp Crosswalk:** We match the RCA data to Trepp using the property address and the origination month of the loan in Trepp. We match 83% of the loans in the merged STR-Trepp dataset to RCA. We are not able to match 100% because we do not match some loans in Trepp to RCA; in many cases, these loans are originated in the 1990s and do not appear in RCA.

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

B Proofs

B.A Proposition 1

We first prove a technical lemma about the function giving the NPV of operating profits net of adjustment costs, $\mathcal{V}(L_t, p, \gamma)$.

Lemma 1. *The function $\mathcal{V}(L_t, p, \gamma)$ is continuous in L_t and γ. It strictly increases in L_t over $[0, L^*(p)]$ and is constant for $L_t \geq L^*(p)$. It strictly decreases in γ and has the pointwise limit $\lim_{\gamma\to 0} \mathcal{V}(L_t, p, \gamma) = r^{-1}(1+r)\pi^*(p)$ if $L_t > 0$.*

Proof. We can write the function $\mathcal{V}$ as:

$$\mathcal{V}(X_0, p, \gamma) = \max_{X_1, X_2, \dots} \sum_{j=1}^{\infty} (1+r)^{1-j} \left(\pi(X_j, p) - \phi(X_j, X_{j-1}) \right).$$

It can never be optimal to set $X_j > L^*(p)$. One could always do better by setting $X_{j'} = L^*(p)$ for all $j' \geq j$, which would increase operating profits (by achieving the static maximum each period) and weakly decrease adjustment costs. Therefore, at the optimum, we must have $X_j \leq L^*(p)$ for all j.

If $X_0 \geq L^*(p)$, it is clearly optimal to set $X_j = L^*(p)$ for all $j \geq 1$, as that maximizes operating profits and leads to an adjustment cost of 0. That proves that

$$\mathcal{V}(X_0, p, \gamma) = \frac{(1+r)\pi^*(p)}{r}$$

for $X_0 \geq L^*(p)$.

Now consider the case where $0 < X_0 < L^*(p)$. We show that a unique, strictly increasing sequence $X_0 < X_1 < X_2 < \dots$ is optimal. For a contradiction, suppose that the optimal sequence is not strictly increasing. Let j be the first instance such that $X_{j-1} \geq X_j$. There are two possibilities. First, it could be that $X_{j-1} = L^*(p)$, in which case it must be that $j \geq 2$ and $X_{j-2} < X_{j-1}$. However, the first-order condition with respect to X_{j-1} is then

$$0 = \pi_1(X_{j-1}, p) - \phi_1(X_{j-1}, X_{j-2}) - (1+r)^{-1}\phi_2(X_j, X_{j-1}),$$

which is a contradiction because the first and last terms equal 0 while the intermediate term has a positive derivative (because $X_{j-1} > X_{j-2}$). The second possibility is that $X_{j-1} < L^*(p)$. In this case, the first-order condition with respect to X_j is

$$0 = \pi_1(X_j, p) - \phi_1(X_j, X_{j-1}) - (1+r)^{-1}\phi_2(X_{j+1}, X_j),$$

which is also a contradiction because the first term is positive (because $X_j \leq X_{j-1} < L^*(p)$), the second term equals 0, and the third term is non-negative. Therefore, the optimal sequence of X_j must strictly increase in j. Uniqueness follows because the function

$$f(X_j) = \pi(X_j, p) - \phi(X_j, X_{j-1}) - (1+r)^{-1}\phi(X_{j+1}, X_j)$$

is concave for $X_j \in [X_{j-1}, L^*(p)]$, as the profit function is concave while the adjustment cost function is convex in both arguments.

We can now prove that $\mathcal{V}(X_0, p, \gamma)$ continuously increases in $X_0 > 0$ and decreases in γ using the envelope theorem. If we let X_j denote the unique optimum, then the envelope theorem implies that

$$\mathcal{V}_1(X_0, p, \gamma) = -\phi_2(X_1, X_0) = -\frac{\gamma}{2}\left(1 - \left(\frac{X_1}{X_0}\right)^2\right) > 0$$

and

$$\mathcal{V}_3(X_0, p, \gamma) = -\frac{1}{2}\sum_{j=1}^{\infty}(1+r)^{1-j}\left(\frac{X_j}{X_{j-1}} - 1\right)^2 < 0,$$

which demonstrates the required monotonicity and continuity (in fact differentiability).

The next task is to show that $\mathcal{V}(X_0, p, \gamma)$ is a continuous function of X_0 at $X_0 = 0$ and $X_0 = L^*(p)$. The latter is obvious, because each X_j limits to $L^*(p)$. Showing continuity at $X_0 = 0$ is less straightfoward. The value of the function is 0 at that point, so we must show that the limit is 0 as well. For any $\epsilon > 0$, we show that there exists $\delta > 0$ such that $\mathcal{V}(X_0, p, \gamma) < \epsilon$ if $X_0 < \delta$. We exploit the following upper bound:

$$\mathcal{V}(X_0, p, \gamma) \leq \sum_{j=1}^{\infty}(1+r)^{1-j}\pi(X_j, p),$$

which states that the value of the firm, net of adjustment costs, is bounded above by the NPV of operating profits. We pick a positive integer J such that

$$\frac{\epsilon}{2} > \sum_{j=J}^{\infty}(1+r)^{1-j}\pi^*(p) = \frac{\pi^*(p)}{(1+r)^{J-2}r},$$

which is clearly possible to do by selecting a J that is sufficiently large. This selection gives us a bound on part of the sum in the upper bound of $\mathcal{V}$:

$$\sum_{j=J}^{\infty}(1+r)^{1-j}\pi(X_j, p) < \frac{\epsilon}{2}$$

because $\pi(X_j, p) \leq \pi^*(p)$. To bound the other part of the sum in the upper bound of $\mathcal{V}$, we use a bound on how much X_j can possibly increase for $j < J$. Specifically, it is never optimal to adjust X_{j-1} to X_j so much so that the adjustment cost exceeds the maximal possible NPV of operating profits from that point onward:

$$\phi(X_j, X_{j-1}) \leq \frac{(1+r)\pi^*(p)}{r}$$

If such a large adjustment happened, then the value of the firm would be negative, which is not optimal because keeping the inputs at a constant positive level yields a positive value. Simplifying this bound yields:

$$X_j \le X_{j-1} + \sqrt{\frac{2(1+r)\pi^*(p)X_{j-1}}{\gamma r}}.$$

Applying this bound iteratively back to X_0 yields:

$$X_j = O\left(X_0^{2^{-j}}\right), \quad X_0 \to 0,$$

meaning that $X_j / X_0^{1/2^j}$ is bounded as X_0 limits to 0. It follows that

$$\pi(X_j, p) = O\left(X_0^{\alpha 2^{-j}}\right), \quad X_0 \to 0.$$

Because $\lim_{X_0 \to 0} X_0^{\alpha/2^j} = 0$, it follows that there exists $\delta > 0$ such that for $X_0 < \delta$,

$$\sum_{j=1}^{J-1} (1+r)^{1-j} \pi(X_j, p) < \frac{\epsilon}{2}.$$

Therefore, for such X_0, $\mathcal{V}(X_0, p, \gamma) < \epsilon$, as claimed.

Finally, we solve for the limit as γ goes to 0. The value of $\mathcal{V}$ is bounded below by the value from setting $X_j = L^*(p)$ for all j, and is bounded above from the NPV of operating profits in this case:

$$\frac{(1+r)\pi^*(p)}{r} - \phi(L^*(p), X_0) \le \mathcal{V}(X_0, p, \gamma) \le \frac{(1+r)\pi^*(p)}{r}.$$

If $X_0 > 0$, then $\lim_{\gamma \to 0} \phi(L^*(p), X_0) = 0$. The limit in the lemma follows immediately. □

We now prove Proposition 1. The function $\rho(L_1)$ is clearly continuous because $\mathcal{V}(L_1, p, \gamma)$ is continuous in L_1 and the distribution of γ is atomless and has full support over an interval.

To show that $\rho(L_1)$ weakly decreases over $[0, L^*(p^l)]$, we examine the difference between the values of foreclosure and forbearance for the lender:

$$V^{fc}(L_1, \gamma) - V^{fb}(L_1, \gamma) = \begin{cases} \pi(L_1, p^l) + \frac{q\mathcal{V}(L_1, p^h, \gamma) + (1-q)\mathcal{V}(L_1, p^l, \gamma)}{1+r} - D, & D \le \frac{(1+r)\pi^*(p^l)}{r} \\ \pi(L_1, p^l) + \frac{q\mathcal{V}(L_1, p^h, \gamma) - (r+q)D}{1+r}, & D > \frac{(1+r)\pi^*(p^l)}{r}. \end{cases}$$

By Lemma 1, $\mathcal{V}(L_1, p, \gamma)$ increases in L_1 over $[0, L^*(p^l)]$ for $p \in \{p^l, p^h\}$. Therefore, the difference between the values of foreclosure and forbearance increases over this interval, implying that $\rho(L_1)$ weakly decreases over this interval.

If $L_1 = 0$, then the value of foreclosing is 0: $V^{fc}(0, \gamma) = 0$. However, the value of forbearance is positive because $D > 0$. Therefore, forbearance yields a higher value than foreclosure regardless of the value of γ, implying that $\rho(0) = 1$.

If $L_1 > 0$, then Lemma 1 implies that the value of foreclosure has the following limit:

$$\lim_{\gamma \to 0} V^{fc}\left(L^*(p^l), \gamma\right) = \pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r},$$

while the value of forbearance has the following limit:

$$\lim_{\gamma\to 0} V^{fb}\left(L^*(p^l),\gamma\right)=\frac{r+q}{1+r}D+(1-q)\min\left(\frac{D}{1+r},\frac{\pi^*(p^l)}{r}\right).$$

The value of forbearance increases in D. Therefore, when $D<D^{**}$, this value is less than the value when $D=D^{**}$:

$$\lim_{\gamma\to 0} V^{fb}\left(L^*(p^l),\gamma\right)<\pi^*(p^l)+\frac{q\pi^*(p^h)+(1-q)\pi^*(p^l)}{r}.$$

Therefore, when $D<D^{**}$ and $L_1=L^*(p^l)$, foreclosure is more valuable than forbearance for sufficiently small values of γ. For these values of D and this value of L_1, there is a positive probability of foreclosure because there is a positive probability of γ arbitrarily close to 0, as the lower bound of the support of γ is 0 by assumption.

B.B Proposition 2

We first show that when $D>D^{**}$, both types of borrowers default and reject the forbearance offer, leading to foreclosure with probability 1. We denote the function that the crisis maturity borrower maximizes when defaulting by:

$$f(L_1)=\rho(L_1)h(L_1),$$

where

$$h(L_1)=\pi(L_1,p^l)-\frac{rD}{1+r}+q\left(\frac{\pi^*(p^h)}{r}-\frac{D}{1+r}\right)+(1-q)\max\left(\frac{\pi^*(p^l)}{r}-\frac{D}{1+r},0\right)$$

gives the value of an accepted forbearance agreement. When $D>D^{**}$, the max operator in this function equals 0 because $D>D^{**}>r^{-1}(1+r)\pi^*(p^l)$. Because $\rho(L_1)\leq 1$ and $\pi(L_1,p^l)\leq\pi^*(p^l)$, the borrower always rejects the forbearance offer when

$$\pi^*(p^l)-\frac{rD}{1+r}+q\left(\frac{\pi^*(p^h)}{r}-\frac{D}{1+r}\right)<0,$$

which reduces to $D>D^{**}$ and thus holds for debt in this region. The condition governing whether the non-crisis maturity borrower defaults at time 1 is identical, which shows that the non-crisis maturity borrower defaults in this region as well. Thus, for both borrowers, there is default and sure foreclosure at time 1, as claimed.

Having dealt with the case when $D>D^{**}$, we assume that $D<D^{**}$ for the remainder of the proof. We first show that, conditional on defaulting, the borrower chooses a value of labor less than the static optimum by setting $L_1<L^*(p^l)$.

We proceed in several steps. First, we show that there exists a level of labor less than the static optimum, $L_1\in[0,L^*(p^l))$, such that the value of defaulting is positive: $f(L_1)>0$. If $h(0)>0$, then because $\rho(0)=1$ by Proposition 1, the value of defaulting is positive at 0: $f(0)=\rho(0)h(0)>0$. Now suppose that $h(0)\leq 0$. We claim that the value of forbearance at the static optimum is positive:

$h(L^*(p^l)) > 0$. To show that this claim is true, we write:

$$h(L^*(p^l)) = \begin{cases} \pi^*(p^l) + \frac{q\pi^*(p^h)+(1-q)\pi^*(p^l)}{r} - D, & D \leq \frac{(1+r)\pi^*(p^l)}{r} \\ \pi^*(p^l) + \frac{q\pi^*(p^h)}{r} - \frac{(r+q)D}{1+r}, & D > \frac{(1+r)\pi^*(p^l)}{r}. \end{cases}$$

The value in the top condition is positive because $p^h > p^l$, and the value in the bottom condition is positive because $D < D^{**}$. Because $h(0) \leq 0$ and $h(L^*(p^l)) > 0$, it follows from the intermediate value theorem that there exists a unique $L_1 \in [0, L^*(p^l))$ such that $h(L_1) = 0$, and that $h(\cdot)$ is positive above this threshold. By Lemma 1 and the expression for difference between the foreclosure and forbearance values from the proof of Proposition 1, we have:

$$V^{fc}(L_1,\gamma) - V^{fb}(L_1,\gamma) < \begin{cases} \pi(L_1, p^l) + \frac{q\pi^*(p^h)+(1-q)\pi^*(p^l)}{r} - D, & D \leq \frac{(1+r)\pi^*(p^l)}{r} \\ \pi(L_1, p^l) + \frac{q\pi^*(p^h)}{r} - \frac{(r+q)D}{1+r}, & D > \frac{(1+r)\pi^*(p^l)}{r}. \end{cases}$$

This upper bound coincides with $h(L_1)$, which equals 0. Therefore, $V^{fc}(L_1,\gamma) - V^{fb}(L_1,\gamma) < 0$ for all $\gamma > 0$, which implies that $\rho(L_1) = 1$. By continuity (which holds for $\rho(\cdot)$ as stated in Proposition 1), there exists $\epsilon > 0$ such that $L_1 + \epsilon < L^*(p^l)$, $h(L_1+\epsilon) > 0$, and $\rho(L_1+\epsilon) > 0$. It follows that $f(L_1+\epsilon) > 0$, which proves the desired claim.

Second, we note that it can never be optimal to set L_1 at at value where $\rho(L_1) = 0$, that is, foreclosure happens with certainty. At such a level, the borrower's value is 0: $f(L_1) = 0$. That is never optimal because there exists $L_1 \geq 0$ such that $f(L_1) > 0$, as just shown. Therefore, at an optimum, we must have $\rho(L_1) > 0$.

Third, we show that it is never optimal to set labor greater than the static optimum: $L_1 > L^*(p^l)$. For a contradiction, suppose such an optimum exists. If profits are negative at this level, so that $\pi(L_1, p^l) < 0$, then we have a contradiction because $\pi(0, p^l) = 0 > \pi(L_1, p^l)$ and $\rho(0) = 1 \geq \rho(L_1)$, implying that $f(0) > f(L_1)$. Therefore, profits must be non-negative at this optimum: $\pi(L_1, p^l) \geq 0$. In this case, by the intermediate value theorem, we can find labor below the static optimum, $L_1' \in [0, L^*(p^l))$, with the same level of operating profits: $\pi(L_1', p^l) = \pi(L_1, p^l)$. The value of the firm net of adjustment costs is then lower at L_1' than at L_1; that is, by Lemma 1, $\mathscr{V}(L_1', p, \gamma) < \mathscr{V}(L_1, p, \gamma)$ for $p \in \{p^l, p^h\}$ and all $\gamma > 0$. Therefore, the difference between the value of foreclosure and forbearance (see proof of Proposition 1 for a closed form) is smaller at L_1' than at L_1:

$$V^{fc}(L_1',\gamma) - V^{fb}(L_1',\gamma) < V^{fc}(L_1,\gamma) - V^{fb}(L_1,\gamma)$$

for all $\gamma > 0$. If $\rho(L_1) = 1$—that is, the lender always gives forbearance—then the same is true at L_1', but the same is then true at $L_1' + \epsilon$ for ϵ sufficiently small. Then $\rho(L_1) = \rho(L_1' + \epsilon)$ but $\pi(L_1, p^l) < \pi(L_1' + \epsilon, p^l)$, contradicting the optimality of L_1. If $\rho(L_1) < 0$, then $0 < \rho(L_1) < 1$, which implies the existence of a marginal value of γ interior to the support of the borrower's prior, which we denote γ_1, such that $V^{fc}(L_1,\gamma_1) = V^{fb}(L_1,\gamma_1)$. It follows that $V^{fc}(L_1',\gamma_1) < V^{fb}(L_1',\gamma_1)$, meaning that at this marginal value of γ, the lender strictly prefers forbearance over foreclosure at the level of labor given by L_1'. Because this marginal value, γ_1, is interior to the support of γ, it follows that $\rho(L_1') > \rho(L_1)$, so that forbearance is more likely at L_1' than at L_1. As discussed above, this result implies that it is impossible that L_1 is an optimum.

Fourth, we show that an optimal value of L_1 must exist. The function $f(L_1)$ is continuous on $[0, L^*(p^l)]$ because $\rho(L_1)$ and $\pi(L_1, p^l)$ are continuous, the continuity of the former being demonstrated in Proposition 1. We just showed that any optimum for $f(L_1)$ must be in the interval $[0, L^*(p^l)]$. Therefore, by the Weierstrass theorem, $f(L_1)$ attains its maximum on this interval.

Finally, we show that $L_1 = L^*(p^l)$ cannot maximize $f(L_1)$. For a contradiction, suppose that this level does maximize $f(L_1)$. As argued above, $\rho(L^*(p^l)) > 0$, as there is always some chance of forbearance at the optimum. By Proposition 1, $\rho(L^*(p^l)) < 1$, as there is always some chance of foreclosure at the static optimum when $D < D^{**}$, which is the case being considered. Therefore, $\gamma^*(L^*(p^l))$ is interior to the support of the borrower's prior on γ, where $\gamma^*(L_1)$ solves:

$$V^{fc}(L_1, \gamma^*(L_1)) = V^{fb}(L_1, \gamma^*(L_1)).$$

This value for gamma is the cutoff above which a lender gives forbearance and below which a lender forecloses. Differentiating this equation with respect to L_1 and solving yields:

$$(\gamma^*)'(L_1) = -\frac{(1+r)\pi_1(L_1, p^l) + q\mathcal{V}_1(L_1, p^h, \gamma^*(L_1)) + (1-q)\mathcal{V}_1(L_1, p^l, \gamma^*(L_1))}{q\mathcal{V}_3(L_1, p^h, \gamma^*(L_1)) + (1-q)\mathcal{V}_3(L_1, p^l, \gamma^*(L_1))}.$$

Given Lemma 1, the following hold when labor equals the static optimum, $L_1 = L^*(p^l)$:

$$\begin{aligned}
\mathcal{V}_1(L_1, p^h, \gamma^*(L_1)) &> 0,\\
\mathcal{V}_3(L_1, p^h, \gamma^*(L_1)) &< 0,\\
\mathcal{V}_1(L_1, p^l, \gamma^*(L_1)) &\geq 0,\\
\mathcal{V}_3(L_1, p^h, \gamma^*(L_1)) &= 0.
\end{aligned}$$

It follows that

$$(\gamma^*)'(L^*(p^l)) > 0.$$

Therefore, the probability of forbearance decreases in L_1 at this point, given that $\gamma^*(L^*(p^l))$ is interior to the support of the borrower's prior on γ:

$$\rho'(L^*(p^l)) < 0.$$

As a result, $f(L_1)$ cannot be maximized at $L_1 = L^*(p^l)$, as:

$$f'(L^*(p^l)) = \rho(L^*(p^l))g'(L^*(p^l)) + \rho'(L^*(p^l))h(L^*(p^l)) = \rho'(L^*(p^l))h(L^*(p^l)) < 0,$$

where we used the results that g is positive at the static optimum (shown above) and that its derivative is 0 there (g depends on L_1 only through static profits). This result concludes the proof that when the borrower defaults, the borrower chooses a value of L_1 that is less than $L^*(p^l)$.

We now turn to the remainder of the proposition, in which we claim the existence of a debt threshold, D^*, such that the borrower pays off when $D < D^*$ and defaults when $D > D^*$.

We start with the case when the level of debt is no greater than the smallest possible value of the firm: $D \leq r^{-1}(1+r)\pi^*(p_l)$. In this case, the valuing of defaulting can be written as:

$$V^{df} = \max_{L_1} \rho(L_1)\big(\pi(L_1, p^l) - \pi^*(p^l) + V^{po}\big),$$

which is less than V^{po} because $\rho(L_1) \leq 1$ and $\pi(L_1, p^l) < \pi^*(p^l)$, which holds because $L_1 < L^*(p^l)$ at a maximum as shown above. Therefore, for a borrower with such a low level of debt, default is never optimal.

We now consider the case when debt is higher, so that $r^{-1}(1+r)\pi^*(p^l) < D < D^{**}$. We show that the difference between the values of defaulting and paying off, $V^{df} - V^{po}$, increases in D over this entire range from a negative number at one extreme to a positive number at the other extreme. The cutoff, D^*, is then the greatest lower bound of the debt levels where this difference is positive, and it follows immediately that the difference is positive above this threshold and negative below.

To show that this difference strictly increases, we consider two debt levels in the interval under consideration, D' and D'', such that $D' < D''$. We let $V^{df}(D)$ and $V^{po}(D)$ denote the values of defaulting and paying off, respectively, given the debt level D. We let L_1' be a value of labor that maximizes the default value when the level of debt equals D', and we similarly define L_1''. These levels of labor exist as shown above. The difference in the value of paying off between the two debt levels is

$$V^{po}(D'') - V^{po}(D') = -(D'' - D').$$

We show that the value of defaulting increases by less than this amount between the two debt levels. To do so, we let $\rho(L_1, D)$ denote the forbearance probability given L_1 and D. Because the foreclosure value, $V^{fc}(L_1, \gamma)$, does not depend on D, but the forbearance value, $V^{fb}(L_1, \gamma)$, strictly increases in D (over the range of debt we are considering), the forbearance probability $\rho(L_1, D)$ weakly increases in D for any L_1. We therefore have:

$$\begin{aligned} V^{df}(D') &= \rho(L_1', D')\left(\pi(L_1', p^l) - \frac{rD''}{1+r} + q\left(\frac{\pi^*(p^h)}{r} - \frac{D''}{1+r}\right)\right) + \frac{\rho(L_1'')(q+r)(D''-D')}{1+r} \\ &\leq \rho(L_1', D'')\left(\pi(L_1', p^l) - \frac{rD''}{1+r} + q\left(\frac{\pi^*(p^h)}{r} - \frac{D''}{1+r}\right)\right) + \frac{\rho(L_1'')(q+r)(D''-D')}{1+r} \\ &\leq V^{df}(D'') + \frac{\rho(L_1'')(q+r)(D''-D')}{1+r}. \end{aligned}$$

It follows that:

$$(V^{df}(D'') - V^{po}(D'')) - (V^{df}(D') - V^{po}(D')) \geq \left(1 - \frac{\rho(L_1'')(q+r)}{1+r}\right)(D'' - D') > 0,$$

which shows that the difference in the values of defaulting and paying off strictly increases in the debt level, D.

We now demonstrate that default is optimal when the level of debt, D, is near the upper bound, D^{**}. The value from default is positive as argued above. The value from payoff is negative because

$$D^{**} - \left(\pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r}\right) = \frac{q}{r}\frac{1-q}{r+q}\left(\pi^*(p^h) - \pi^*(p^l)\right) > 0,$$

which also proves the lower bound on D^{**} in the proposition. Therefore, for debt levels near D^{**}, default is optimal. When debt is at $r^{-1}(1+r)\pi^*(p^l)$, we can write:

$$f(L_1) = \rho(L_1)(\pi(L_1, p^l) - \pi^*(p^l) + V^{po}),$$

which is strictly less than V^{po}: either $L_1 < L^*(p^l)$ (in which case the profit difference is negative) or $L_1 = L^*(p_l)$ (in which case $\rho(L^*(p_l)) < 1$ by Proposition 1). Therefore, payoff is optimal for this debt level. When $D = \pi^*(p_l) + r^{-1}(q\pi^*(p^h) + (1-q)\pi^*(p^l)$, the value of paying off the debt is 0 while the value of default is positive, so D^* is less than this threshold, as claimed.

B.C *Proposition 4*

We first prove the first claim in Proposition 4, that $D_a^* > D^*$. Recall that D^* is the unique debt level at which the borrower is indifferent between defaulting and paying off the loan: $V^{df}(D) = V^{po}(D)$. The value of paying off does not depend on the distribution of γ, so $V_a^{po}(D^*) = V^{po}(D^*)$. In contrast, we have:

$$V_a^{df}(D^*) = \rho_a(L_{1,a}^*)h(L_{1,a}^*) \leq \rho(L_{1,a}^*)h(L_{1,a}^*) \leq V^{df}(D^*).$$

The first inequality follows because the baseline distribution of γ, G, first-order stochastic dominates the new distribution, G_a. The second inequality follows from the optimality of L_1^*. This sequence of inequalities implies that $V_a^{df}(D^*) - V_a^{po}(D^*) \leq 0$, which implies that $D_a^* \geq D^*$ given that $V_a^{df}(D) - V^{po}(D)$ strictly increases, as shown in the proof of Proposition 2.

The second claim in Proposition 4, that $D_a^{**} = D^{**}$, is clear from the definition of D^{**} in Proposition 1, which shows that D^{**} does not depend on the distribution of γ.

We now prove the next claim, that $L_{1,a}^* < L_1^*$ in the strategic default region as long as $L_1^* > 0$. We first prove a lemma that builds on results from the proof of Proposition 2.

Lemma 2. *If $D \in (D^*, D^{**})$, then at any positive optimum level of operations, $L_1^* > 0$, $\rho(L_1^*) \in (0,1)$.*

Proof. In the proof of Proposition 2, we showed that when $D \in (D^*, D^{**})$, the value of defaulting is always positive at an optimum level of operations: $f(L_1^*) = \rho(L_1^*)h(L_1^*) > 0$. Therefore, $\rho(L_1^*) > 0$. Here, we show by means of a contradiction that $\rho(L_1^*) < 1$ as well. Suppose $\rho(L_1^*) = 1$. Because $L_1^* > 0$, this equality implies that $V^{fc}(L_1^*, 0) \leq V^{fb}(L_1^*, 0)$. If $V^{fc}(L_1^*, 0) < V^{fb}(L_1^*, 0)$, then by continuity there exists $\epsilon > 0$ such that $L_1^* + \epsilon \leq L_1^*(p^l)$ and $V^{fc}(L_1^* + \epsilon, 0) \leq V^{fb}(L_1^* + \epsilon, 0)$, implying $\rho(L_1^* + \epsilon) = 1$ and $h(L_1^* + \epsilon) > h(L_1^*)$, which contradicts the optimality of L_1^*. Therefore, $V^{fc}(L_1^*, 0) = V^{fb}(L_1^*, 0)$. However, we showed in the proof of Proposition 2 that $V^{fc}(L_1, 0) - V^{fb}(L_1, 0) = h(L_1)$. Therefore, $h(L_1^*) = 0$, which also contradicts the optimality of L_1^*. □

To continue the proof, we transform the objective function that determines L_1^*. Before transforming the objective function, we first define a new function. Let L_1^{min} be the smallest value at least 0 such that for all $L_1 \in [0, L_1^{min}]$, $\rho_a(L_1) = 1$. Note that $L_1^{min} < L^*(p^l)$ by Proposition 1. This threshold does not depend on a because the lower bound of the support of γ is always 0 regardless of a. We similarly define $L_{1,a}^{max}$ to be the largest value no more than $L^*(p^l)$ such that for all $L_1 \in (L_{1,a}^{max}, L^*(p^l)]$, $\rho_a(L_1) = 0$. Note that $L_{1,a}^{max} > 0$ because by Proposition 1, $\rho_a(0) = 1$. If $\rho_a(L^*(p^l)) > 0$, then $L_{1,a}^{max} = L^*(p^l)$ by the way it is defined. Hence, we have $0 \leq L_1^{min} < L_{1,a}^{max} \leq L^*(p^l)$ such that $\rho_a(L_1) \in (0,1)$ for $L_1 \in (L_1^{min}, L_{1,a}^{max})$ and such that $\rho_a(L_1)$ strictly decreases over this range, starting from a value of 1. It follows that there exists a unique increasing function $\gamma^*(L_1)$ defined on $[L_1^{min}, L_{1,a}^{max})$ giving the value of γ at which the lender is indifferent between foreclosure and forbearance; this is the solution to:

$$0 = \pi(L_1, p^l) + \frac{q\mathscr{V}(L_1, p^h, \gamma) - (r+q)D}{1+r}.$$

Let $\Gamma_a = \gamma^*\left([L_1^{min}, L_{1,a}^{max})\right)$ denote the range of this function. We define $L_1(\gamma)$ to be the inverse of the function $\gamma^*(L_1)$, which is defined over Γ_a. The function $L_1(\gamma)$ strictly increases because $\gamma^*(L_1)$ does.

We can now transform the objective function. Note that $f_a(L_1) = \rho_a(L_1)h(L_1)$ is positive for $L_1^{min} < L_1 < L_{1,a}^{max}$, as $\rho_a \in (0,1)$ on this range, and we showed above in the proof of Proposition 2 that $h(L_1) > 0$ if $\rho(L_1) < 1$ because the difference in values between foreclosure and forbearance when $\gamma = 0$ coincides with g. Therefore, the borrower equivalently maximizes $\log f_a$, which can be written as follows:

$$\tilde{f}(\gamma, a) = \log(1 - G(a\gamma)) + \log h(L_1(\gamma));$$

the maximization is over $\gamma \in \Gamma_a$. The optimum must lie in the interior of Γ_a because the function f cannot be maximized at L_1^{min} or L_1^{max} (the former because $\rho_a = 1$ there which contradicts Lemma 2; the latter because either $\rho_a = 0$ which contradicts Lemma 2 or because $L_{1,a}^{max} = L^*(p^l)$ which contradicts Proposition 2). Therefore, if we let γ_a be the optimal value, then $\tilde{f}_1(\gamma_a, a) = 0$. It follows that:

$$\frac{\partial \gamma_a}{\partial a} = -\frac{\tilde{f}_{12}(\gamma_a, a)}{\tilde{f}_{11}(\gamma_a, a)}.$$

Because γ_a is a local maximum, $\tilde{f}_1 1(\gamma_a, a) < 0$. It follows that:

$$\text{sgn}\left(\frac{\partial \gamma_a}{\partial a}\right) = \text{sgn}(\tilde{f}_{12}(\gamma_a, a)) = -\text{sgn}\left((1 - G(a\gamma_a))G''(a\gamma_a) + G'(a\gamma_a)^2\right).$$

By assumption, the second derivative of $\log(1 - G(\gamma))$ is negative, which implies that:

$$(1 - G(\gamma))G''(\gamma) + G'(\gamma)^2 > 0.$$

Therefore,

$$\frac{\partial \gamma_a}{\partial a} < 0,$$

which implies that $L_{1,a}^* = L_1(\gamma_a)$ strictly decreases in a, as desired.

Finally, we show that $L_1^* > 0$ for at least some $D \in (D_a^*, D_a^{**})$. If $L_1^* = 0$, then the expected payoff from defaulting and setting $L_1 = 0$ must be positive, as we showed in the proof of Proposition 2 that the expected payoff from defaulting is always positive:

$$\frac{q\pi^*(p^h)}{r} - \frac{(r+q)D}{1+r} > 0.$$

As a result,

$$D < \frac{1+r}{r}\frac{q\pi^*(p^h)}{r+q}.$$

Therefore, we must always have $L_1^* > 0$ for

$$D \in \left(\frac{1+r}{r}\frac{q\pi^*(p^h)}{r+q}, D^{**}\right),$$

which is non-empty because $p^l > 0$.

C Additional Figures and Tables

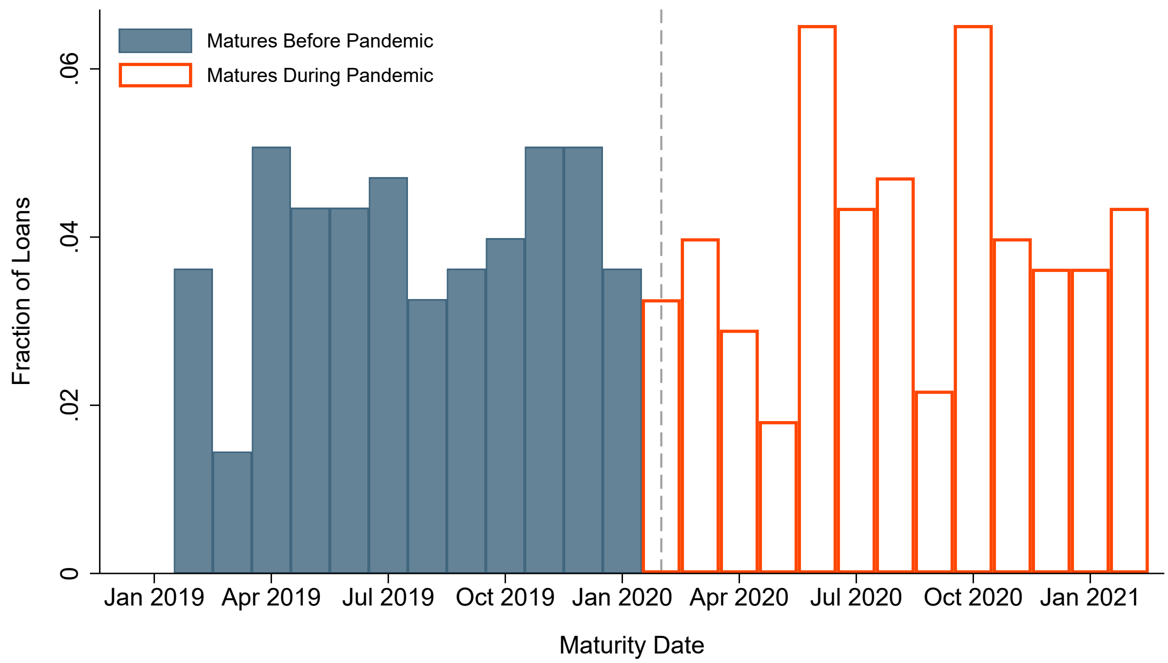


FIGURE A.I
Distribution of Scheduled Loan Maturity at Origination.

NOTE.—This figure plots the distribution of initial loan maturity across months for loans in our main estimation sample. The vertical axis shows the share of loans with an initial maturity in the indicated month. (SOURCE: Trepp)

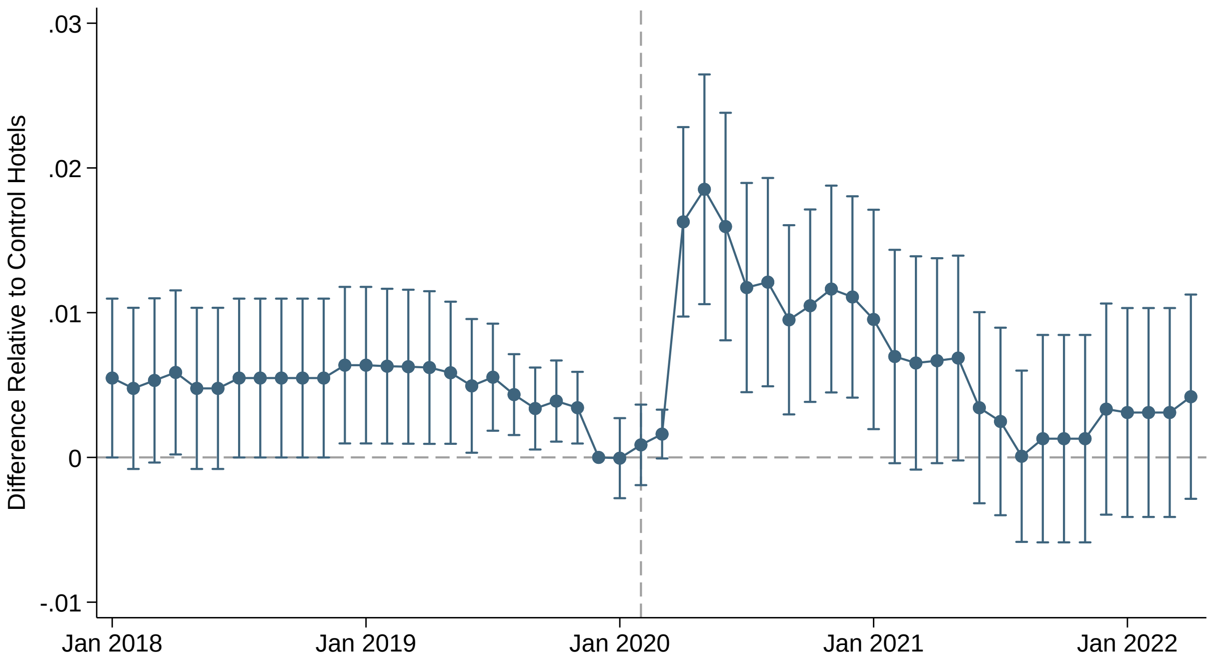
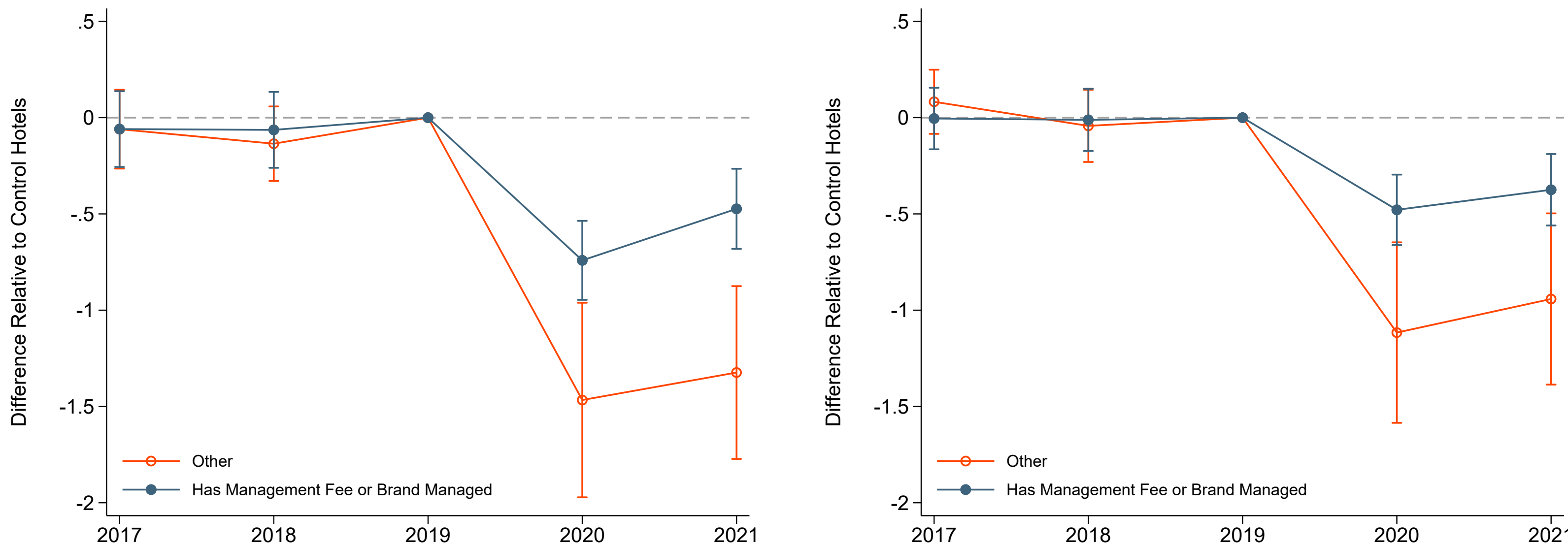


FIGURE A.II
Effect of Pandemic Maturity on Hotel Closure.

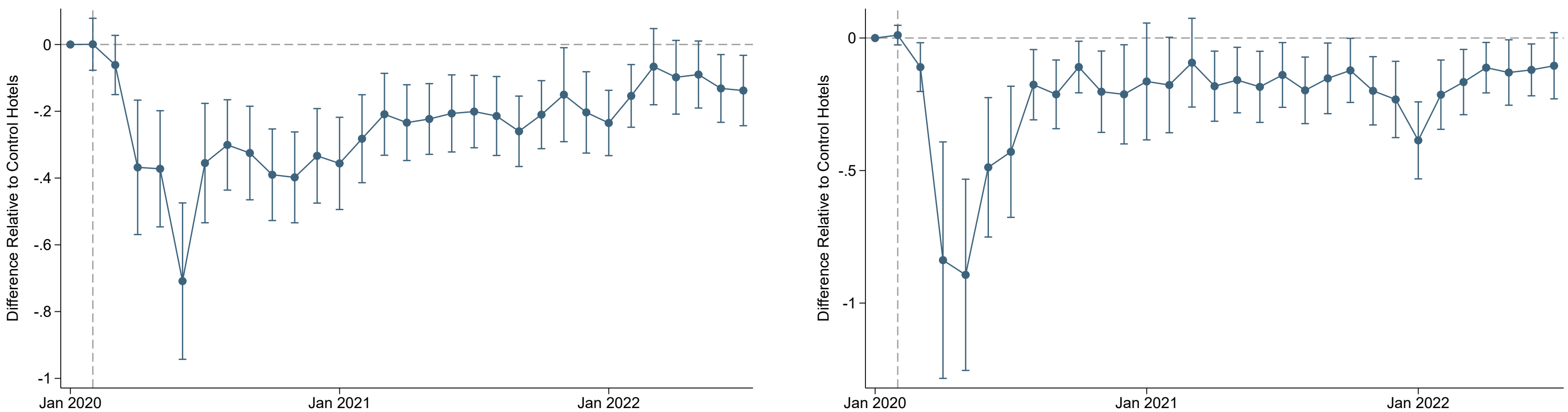
NOTE.—This figure estimates a specification of equation (2) in which the outcome variable is an indicator for whether the hotel is likely closed in a given month. We do not directly observe whether a hotel is closed. We impute closure status according to whether the hotel reports data to STR and has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



Panel A. Revenue *Panel B. Expense*

FIGURE A.III
Heterogeneity by Delegtation of Operations.

NOTE.—This figure is analogous to Figure VIII, but it separately includes an interaction between the treatment variable and an indicator for whether a hotel has delegated its operations (Has Management Fee or Brand Managed) or not (Other). We measure delegation of operations according to whether a hotel: (a) is operated by the brand, based on the STR operating arrangement field equalling "Management Agreement"; or (b) has a non-empty management company identifier and paid a management fee the first year it appears in the P&L data, which will ensure that our measure includes third-party operators that are different from the brand. In particular, condition (b) is important because condition (a) does not distinguish between cases where the franchisee manages the hotel itself versus when it pays a third-party to do so. Condition (b) applies to 88% of hotels not operated by their brand in the P&L regression sample. The outcomes come from the STR P&L dataset, since our measure of delegated operations requires us to use data from the P&L dataset. (SOURCE: STR, LLC and Trepp)



Panel A. Marketing Expense

Panel B. Profit

FIGURE A.IV

Effect of Pandemic Maturity on Monthly Marketing Expense and Profit.

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

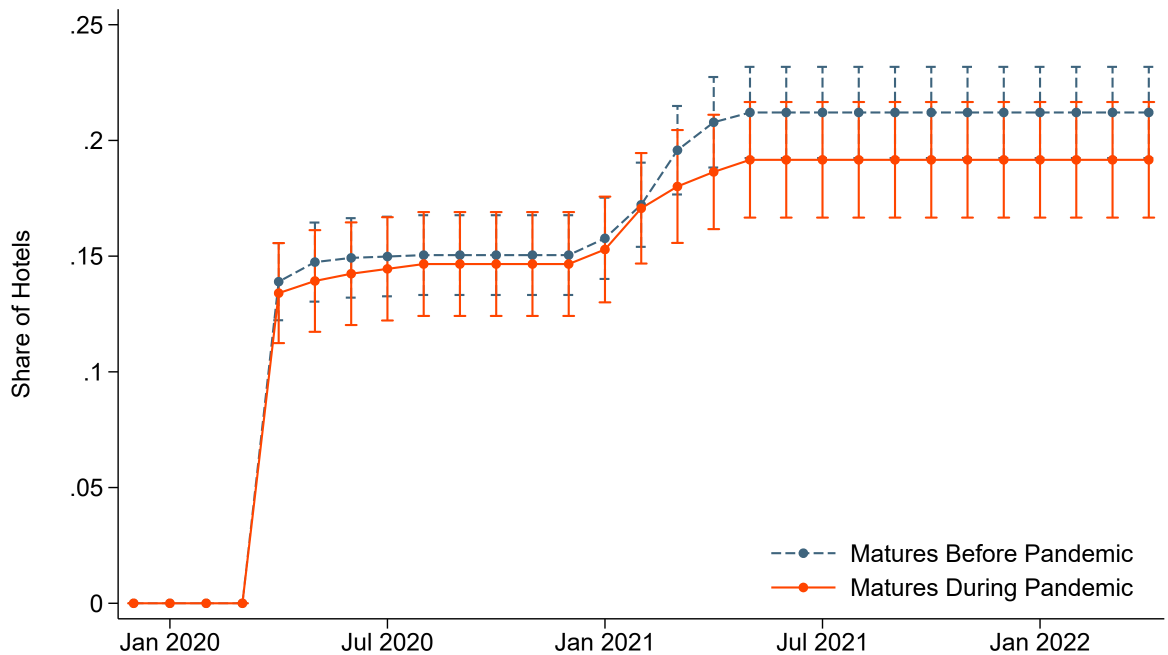


FIGURE A.V
Paycheck Protection Program Takeup Rate by Maturity Cohort.

NOTE.—This figure plots the time series of the share of hotels in our sample that have received a Paycheck Protection Program (PPP) loan origination. Explicitly, the figure shows the mean of an indicator variable for whether the hotel has received a PPP loan as of the given month, and the bars are standard errors for this mean. These statistics are calculated separately for hotels with a scheduled loan maturity before versus during the pandemic, using the same 12 month bandwidth as in Figure V. 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)

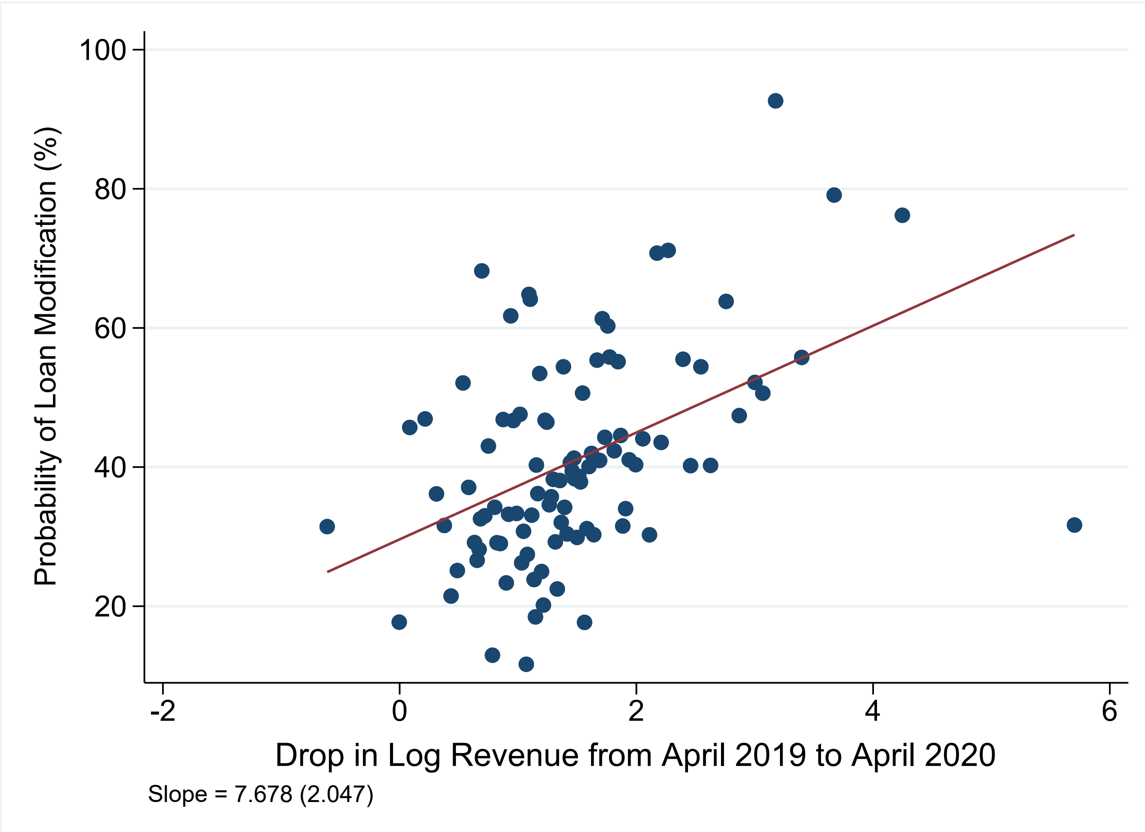


FIGURE A.VI
Revenue around Loan Modification.

NOTE.—This figure is a binned scatterplot of the relation between the probability of receiving a loan modification and the decline in log room revenue from April 2019 to April 2020. Measuring the year-on-year drop in log revenue limits variation due to differences in seasonal hotel demand. Modification is measued using the indicator from the Commercial Real Estate Finance Council (CREFC), as described in Figure IV. The sample consists of hotels with a scheduled maturity from February 2020 through February 2021 that enter February 2020 having not paid off their loan, having not been foreclosed on, and having not been modified. The plot is binned so that each point represents the average of around eight hotels. The average is residualized against market fixed effects, which function similarly to δ_{mt} in the main difference-in-difference specification in equation Table II, and against fixed effects for initial maturity month, which function similarly to the Post Maturity fixed effects in the main specification. Data on loan maturities are from the Trepp dataset. Data on hotel revenue are from the STR performance dataset. (SOURCE: STR, LLC and Trepp)

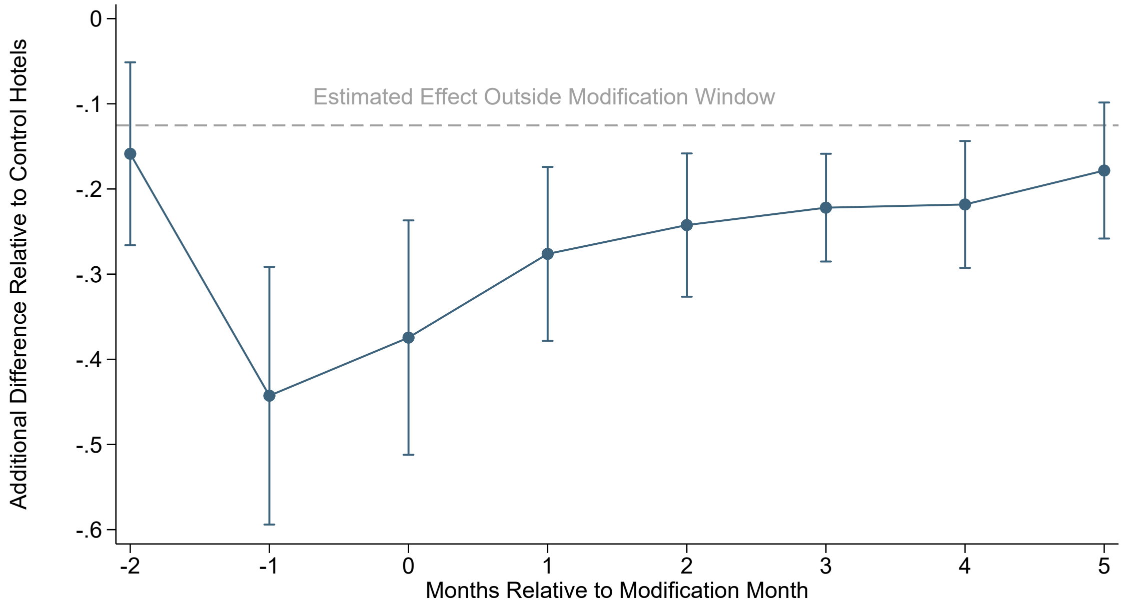


FIGURE A.VII
Revenue around Loan Modification.

NOTE.—This figure displays estimates of a variant of equation (3) that separately estimates the effect of debt rollover as a function of months relative to the month of modification for loans without an extension option,

$$\begin{aligned}\log(Revenue_{i\mu t}) = &\sum_{\tilde{\mu}=\underline{\mu}}^{\tilde{\mu}=\overline{\mu}} \Big[\tilde{\beta}_{\tilde{\mu}} \times PandemicMaturity_i \times Post_t \times NoExtOption_i \times \mathbb{1}_{t-t_{\mu}=\tilde{\mu}}\Big] + \ldots \\ &\beta_0 \cdot PandemicMaturity_i \times Post_t + \ldots \\ &\beta_1 \cdot PandemicMaturity_i \times Post_t \times NoExtOption_i + \ldots \\ &\psi_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\lambda_\tau \times NoExtOption_i \times \mathbb{1}_{t=\tau}\Big] + \alpha_i + \delta_{mt} + \epsilon_{it},\end{aligned}$$

where μ indexes months relative to the month of modification, t_μ; $NoExtOption_i$ indicates if i does not have an extension option as of origination, as in column (2) of Table III; and the treatment group is restricted to the subset of hotels with a pandemic maturity that are first modified in the pandemic, based on the indicator from the Commercial Real Estate Finance Council (CREFC) described in Figure IV. The figure plots the estimated treatment effect for hotels with a pandemic maturity and no extension option as a function of months relative to modification month, μ, for each μ in the modification window on the horizontal axis: $\beta_0+\beta_1+\tilde{\beta}_\mu$. The gray dashed line shows the estimated treatment effect for these hotels in months outside the modification window: $\beta_0+\beta_1$. Brackets are 95% confidence intervals for the null hypothesis that the estimated treatment effect in month m relative to modification equals the treatment effect outside the modification window ($\tilde{\beta}_\mu = 0$). Standard errors are clustered by hotel. The remaining notes are the same as in Table III. (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)	(6)
PandemicMaturity × Post	−0.120***	−0.115***	−0.115***	−0.080**	−0.217***	−0.217***
	(0.032)	(0.032)	(0.031)	(0.030)	(0.028)	(0.041)
Hotel FEs	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X
Market × Chain × Month FEs	X	X	X	X		
Size × Month FEs		X	X	X		
Location × Month FEs			X	X		
Operation × Month FEs				X		
Borrower × Month FEs					X	X
Market × Month FEs					X	X
Borrower Clustered SEs						X
Number of Observations	133,095	133,095	133,095	133,095	111,452	111,452

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

TABLE A.III

EFFECT ON HOTEL EXPENSE BY CATEGORY

	Levels ($000,000)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PandemicMaturity × Post	−7.977**	−4.054***	−2.397**	−1.259*	−9.051**	−1.209**	−1.218**
	(1.795)	(0.805)	(0.766)	(0.485)	(2.098)	(0.308)	(0.331)
Category Name	Room	Marketing	Admin	Operator	Food	Property	Reserve
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
Post Maturity FE	X	X	X	X	X	X	X
Market × Year FEs	X	X	X	X	X	X	X
Number of Observations	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 VIII across expense categories. The regression equation is similar to that in Table II, except that the frequency is annual because the data on hotel expenses come from STR's annual profit and loss dataset. The treatment variable, $PandemicMaturity_i$, is still defined as it is in Table II. The remaining notes are the same as in Table II after replacing "month" with "year." The outcome variables in columns (1)-(7) are the hotel's annual expense within a given category, in hundreds of thousands of U.S. dollars ($000,000). The outcome is specified in levels, as opposed to logs, to allow for cases where a hotel has expense of zero within a given category. For reference, the sample mean of each category in 2019 is reported in the table. The categories are room, sales and marketing (Marketing), administrative and general (Admin), total fees paid to the company operating the hotel (Operator), food and beverage services (Food), property operations and maintenance (Property), and reserve for capital replacement (Reserve). Standard errors twoway clustered by hotel and year are shown in parentheses. The remaining notes are the same as in Figure VIII and Table II. (SOURCE: STR, LLC and Trepp)

TABLE A.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 in February 2020 or within the 12 month window following that month (treated) versus 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 A.V
ADDITIONAL ANALYSIS OF THE EFFECT ON EXPENSE AND PROFIT

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

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