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

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Abstract

We show theoretically how firms scheduled to roll over debt in a crisis reduce operations through a strategic renegotiation channel: borrowers cut operations to discourage lenders from seizing the collateral. Our empirical analysis utilizes contractual features of commercial mortgages generating as-good-as-random variation in whether borrowers must roll over debt during a crisis. Borrowers reduce output, labor, and profit at properties collateralizing loans with debt coming due during the crisis. As in the model, this effect holds with borrower-by-time fixed-effects and is driven by high-leverage loans without term-extension options. Consistent with strategic renegotiation, property-level output falls before modification and then rebounds.

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I Introduction

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

We revisit this question in a novel setting that features a debt rollover shock, high leverage, and widespread renegotiation of debt in default. Our central contributions are to show empirically that debt rollover shocks can still reduce real activity even in a setting such as this, where the debt is renegotiated, and to show theoretically why this can occur. We focus on the commercial real estate sector, which has several features that make it an instructive setting to study the real effects of debt rollover and accounts for 20% of investable U.S. assets. First, commercial mortgages have high leverage ratios of at least two-for-one (Ghent, Torous and Valkanov, 2019; Glancy et al., 2022). They also typically feature large balloon payments at maturity, implying that borrowers with maturing debt must pay off far more debt relative to pledged assets than a standard corporate entity.[1] These balloon payments are rarely prepayable without substantial penalties, which allows us to construct a debt rollover shock that is uncorrelated with endogenous early refinancing (e.g., Mian and Santos, 2018; Xu, 2018). The particular rollover shock is having a commercial mortgage scheduled to mature just after the abrupt onset of the COVID-19 pandemic, which sharply reduced collateral values. Interestingly, most of the debt subject to our shock was renegotiated, in the form of term extensions, and these renegotiations originated from private markets, not government mandate.

A model of debt rollover with endogenous renegotiation and operating adjustment costs can explain why it is strategically optimal for borrowers with debt maturing in a crisis to inefficiently reduce operations. Intuitively, cutting operations at the property serving as collateral

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

would make it costly for lenders to revive operations after seizing it in foreclosure, and so lenders become more willing to renegotiate with the defaulting borrower. In the model, a crisis of unknown duration reduces demand for a firm's output. Firms respond by reducing operations. The resulting drop in collateral values provides an incentive for borrowers with debt maturing in the crisis to default. Defaulting would give lenders the right to seize the collateral, but they may not do so because of two model ingredients. First, lenders incur adjustment costs when modifying operations at a property they have seize. For example, they lack familiarity with the firm's management practices and must search for the appropriate personnel. Second, lenders can choose to renegotiate with defaulting borrowers, which, to match our empirical setting, we model as deciding to extend the loan's term.

Combining these model ingredients leads to the following three theoretical results. First, the borrower can increase the probability that the lender renegotiates the loan's term by reducing operations below the efficient level. We call this channel "strategic renegotiation". Second, borrowers with sufficiently large debt maturing in the crisis default and strategically reduce operations. Importantly, insolvency is not a necessary condition for default. Third, by pursuing strategic renegotiation, borrowers with debt maturing in the crisis experience lower revenue and profits than borrowers whose debt matures far in the future. This last prediction is the focal point of our empirical analysis.

Our empirical evaluation of the model focuses on the hotel sector. Studying hotels lets us exploit detailed, high-frequency microdata on hotel operations, enabling granularity that is typically not possible in other studies of debt rollover. An additional contribution of our paper is to merge this detailed data on hotel operations with equally-detailed data on hotel financing from commercial mortgage-backed securities (CMBS) loan servicing records.

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

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

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

Recalling the widespread renegotiation of commercial mortgages during the COVID crisis, including hotel mortgages, these negative real effects of debt rollover are more consistent with strategic renegotiation than other common theories of corporate debt and investment. A model of debt overhang (Myers, 1977) might predict that borrowers with maturing debt lose the incentive to maintain their hotel, but it would struggle to explain the immediate drop in operations and absence of foreclosure. A model of liquidity constraints would struggle to explain why the results obtain even within a borrower's portfolio (i.e., with borrower-by-month fixed effects).

Turning to evidence that directly supports the strategic renegotiation channel, we examine the dynamics of output for treated hotels around the month in which their loan's term is modified. On average, output sharply declines until the month before modification. Then, once the loan has been modified, output starts to recover. We stress that this V-shaped relation between output and time-to-modification is an equilibrium relation, not a causal one. Indeed, as our model makes clear, renegotiation is endogenous.

Also consistent with strategic renegotiation, the main difference-in-difference effect is almost entirely driven by treated hotels with either high leverage, defined as the top third of loan-to-value (LTV) distribution, or without a term extension option written into the loan's contract at origination. The former result directly supports the model's prediction that strategic renegotiation requires relatively high leverage as a necessary condition. The latter result suggests that term extension options may significantly attenuate the real effects of debt rollover, since they allow borrowers to modify their loan without needing to strategically renegotiate.

From lenders' perspective, the advantage of renegotiating depends on their cost of readjusting operations at the property should they foreclose. We find that the difference-in-difference effect is stronger for treated hotels whose lender plausibly has a lower expected adjustment cost, proxied by the share of other hotels overseen by the same special servicer that are similar to the hotel in question.[2] We interpret this finding as consistent with the core intuition of the model: to impose the same total loss in foreclosure on a lender with low adjustment costs as on a lender with high adjustment costs, the borrower must drive the hotel into a greater state of disrepair.

Related Literature

To the best of our knowledge, our paper is the first to study the causal effect of commercial mortgage rollover on the output, employment, and profits at the properties that serve as collateral. Sun, Titman and Twite (2015) find that REITs with more debt coming due during the Global Financial Crisis suffered worse stock returns, but they do not study real outcomes. Other papers examine the real effects of commercial mortgage debt but do not isolate the effect of rollover. For instance, Loewenstein, Riddiough and Willen (2021) show that mortgaged properties are slower to be redeployed to other sectors; Liebersohn, Correa and Sicilian (2022) estimate that higher leverage leads borrowers in the retail sector to reduce leasing activity, and they argue that the effect works through debt overhang.[3]

Our results point to strategic renegotiation as a novel channel through which rollover risk affects real activity. Since strategic renegotiation is essentially a form of strategic default, we corroborate evidence that strategic default is pervasive in commercial real estate (Dinc and Yönder, 2022; Glancy et al., 2023). More generally, our results speak to a large literature on renegotiation of incomplete contracts (Hart and Moore, 1988, 1994, 1998). In a commercial real estate setting, several papers have applied basic ideas to show how a borrower's propensity to request modification depends on the borrower's operating income (Brown, Ciochetti and Riddiough, 2006; Flynn, Ghent and Tchistyi, 2022; Glancy, Kurtzman and Loewenstein, 2022). Taking this idea one step further, we show that borrowers actually *reduce* their operating income to invite a modification. In a wage bargaining setting, firms use can use the terms of debt as an instrument to bargain with labor (Matsa, 2018), whereas we show how firms use labor as an instrument to bargain with debtors.

We also contribute to the broader corporate finance literature showing that firms scale back employment and investment when their debt comes due during a crisis, like the Great Depression (Benmelech, Frydman and Papanikolau, 2019) or the Global Financial Crisis (Almeida et al., 2011; Costello, 2020). However, our setting differs in three key ways from corporate rollovers

[2] The special servicer is an entity designated at origination to make modification and foreclosure decisions on the part of lenders (i.e., investors in CMBS). A special servicer also oversees foreclosed properties, and so, practically, operating adjustment costs would directly fall on the special servicer. Flynn, Ghent and Tchistyi (2022) provide a detailed discussion of CMBS special servicers.

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

studied in prior work. First, most treated hotels do *not* face an immediate liquidity shock from their maturing debt, as they receive temporary forbearance that pushes their balloon payments to the next year. Second, the large amount of debt scheduled to come due—70% of pre-COVID asset values—makes losing the collateral a possibility. Third, despite the potential for losing the collateral, our setting actually features widespread renegotiation of maturing debt. Therefore, our setting is ideal for measuring the real effects of strategic behavior of distressed borrowers, while most prior work is suited to uncovering the effects of liquidity shocks that result when a much smaller amount of debt must be paid off at a time when new debt is unavailable due to a credit crunch.[4] We make an additional contribution to this literature by examining project-based finance, which enables us to show that borrowers strategically curtail operations specifically at their projects (i.e., hotels) that back debt maturing during a crisis.

Lastly, our specific choice of setting enables us to contribute to the literatures on hotel operations and on corporate finance during the COVID pandemic. A well-developed strand of papers has studied hotel owners' decision to delegate operations to an outside party versus to operate it themselves (Kosová, Lafontaine and Perrigot, 2013; Freedman and Kosová, 2014; Kosová and Sertsios, 2018), and a closely related strand has documented that hotel financial performance depends largely on the expertise of the owner (Povel et al., 2016; Spaenjers and Steiner, 2024). Putting these two strands together, we contribute by showing how the strategic incentives of the hotel's *owner* can significantly affect the management decisions of the hotel's *operator*, regardless of whether the two entities are distinct. Turning to the literature on corporate finance during the pandemic, Brunnermeier and Kirshnamurthy (2020) and Crouzet and Tourre (2021) examine aspects of debt overhang, while Greenwald, Krainer and Paul (2021) and Chodorow-Reich et al. (2022) focus on cash-flow constraints arising from credit lines with banks. In commercial real estate, Steiner and Tchistyi (2022) look at Payment Protection Program (PPP) loans to hotels, while Gupta, Mittal and Nieuwerburgh (2022) investigate the adverse long-run effects of the pandemic on office properties.[5]

II Empirical Setting and Motivation

This section describes the institutional background for our empirical analysis and highlights several features of the hotel industry during the COVID-19 crisis that make it a particularly instructive context in which to study the real effects of debt rollover. We organize our discussion around

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

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

five facts about hotel financing and operations that both motivate our model in Section III and enable our research design in Section IV. In presenting these facts, we rely on datasets to be described in detail in Section IV.

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 typically borrow from three sources: commercial mortgage-backed securities (CMBS) lenders, banks, and life insurance companies. The typical commercial mortgage is structured in a way that, de facto, requires a large principal payment at the loan's maturity date. Specifically, most loans do not fully amortize, implying a balloon payment scheduled at maturity. Moreover, most loans also come with conditions that discourage prepayment, either via lockout restrictions that rule out prepayment entirely or through fees that discourage it. The combination of balloon maturities and prepayment penalties implies that most non-defaulting borrowers pay off the bulk of their mortgage balance in a tight window around the scheduled maturity date.

Figure I uses data from CMBS loan servicing records to demonstrate this phenomenon during "normal" times (i.e., before the COVID-19 crisis).[6] To construct the figure, we restrict attention to loans with a 10-year maturity (the mode) and with a scheduled maturity date at least 12 months before the pandemic (February 2019 or earlier). In this sample, all loans have limited ability to prepay up until 8 months before scheduled maturity, as shown in Panel A of Figure I. These limitations dissipate as the loan nears the scheduled maturity date. Coinciding with the timing of prepayment restrictions, about 80% of the original principal balance remains on loans in the sample up to 3 months before maturity, as shown in Panel B of Figure I. Borrowers pay off most of that amount 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.

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

For firms that receive external financing from multiple sources, economic conditions at the time of a given loan's maturity date may not be all that important. If the loan is sufficiently small, even financially constrained firms with debt coming due may be able to alter their operations to generate enough short-term cash flows to pay off the loan. Indeed, much of the existing literature on

[6] Our analysis restricts to hotels that served as collateral for CMBS loans because their regimented loan servicing protocol produces detailed data on loan contract terms that is not typically available for other types of commercial mortgages. Relative to other commercial property types, hotels rely more extensively on CMBS loans (Glancy et al., 2022). In the decade before the COVID crisis, a substantial share of new hotel mortgages came from CMBS. Among hotel loans from medium-to-large banks, life insurers, and asset-backed issuers (i.e., CMBS), 36% were from CMBS on an equal-weighted basis (Glancy et al., 2022); on a dollar-weighted basis, the volume of hotel loans from CMBS exceeded that from medium-to-large banks (Glancy, Kurtzman and Loewenstein, 2022).

the real effects of debt rollover finds evidence supporting this "cash harvesting" channel. However, hotels differ from the typical corporate entity in the sense that the vast majority of their long-term debt is concentrated in a single loan. The average hotel mortgage has a loan-to-value ratio at origination in excess of 70%. It would be infeasible to pay off so large a debt by harvesting cash flows from operations. Substantiating this point, Figure II uses data from annual hotel profit and loss statements 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 implies that the median hotel with a loan coming due in 2020 would only be able to cover 24% of their scheduled balloon payment even if they were to redirect an entire year's worth of "normal" operating profit toward making debt payments. Even a hotel at the 95th percentile could only cover 78% of their scheduled payment with a full year of profit. Thus, to the extent that hotels alter their operations in anticipation of a scheduled loan maturity it is likely not because they are seeking to harvest cash to pay off their loan.

Fact 3. The Crisis was Expected to Reduce Hotel Demand for an Extended Period

The COVID crisis was a significant and unexpected negative demand shock for hotels. Figure III clearly makes this point, as it shows how aggregate monthly revenue for U.S. hotels falls by 80% between February and April of 2020. Aggregate revenue remains depressed for the remainder of 2020 and does not regain its pre-pandemic level until the end of 2021. Hotel owners and other market participants expressed a belief early in the crisis that revenues could potentially remain depressed for much longer. PwC, a consultancy, predicted in May 2020 that hotel revenue would take as long to recover as it did in the Great Recession (PwC, 2020). McKinsey, another consultancy, found that around 30% of surveyed business executives expected the pandemic to have a permanent effect (Krishnan et al., 2020). These beliefs about the pandemic's duration imply that hotel owners with mortgages maturing in 2020 would have anticipated needing to make balloon payments during the crisis that were large relative to, and possibly exceeded, the value of their hotels in order to satisfy their debt obligations. Our paper studies the implications of this fact for hotel operating outcomes during the crisis.

Fact 4. Hotel Owners are Franchisees

We clarify that most hotels operate under a franchise model, in which the owner of the property buys the right to affiliate with a given brand (e.g., Marriott, Hilton). This model became the industry's standard in the 1990s, when the major brands pivoted toward a strategy of owning very few physical assets. This means that the hotel owners in our analysis range in size from small individual investors to larger property funds or REITs, but they almost never include a major brand itself. A given hotel brand may also establish chains (e.g., Aloft by Marriott), which constitute a separate franchise with its own set of standards.

As an implication of the franchise model, hotel owners rely on a variety of operating arrangements to manage their properties on a day-to-day basis. These include operating the hotel themselves, contracting with a third-party operator, or using a brand-provided operating service (Freedman and Kosová, 2014; Kosová and Sertsios, 2018). In the first case, the owner maintains full agency over hotel operations. In the case of delegated operations, the owner can exercise de facto agency by withholding operating capital, which then discharges the operator from its legal obligation to the property. Indeed, management agreements often explicitly include this condition (e.g., Sunstone Hotel Properties (2004)). Moreover, during financial distress, the owner and operator share similar incentives due to the frequent use of subordination clauses, which place both parties in a junior position relative to the lender (Butler, 2008).[7] 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.[8] In particular, we shall simply use "owner" to describe the agent that makes operating decisions.

Fact 5. Debt Maturing During the Crisis was Renegotiated

Even though the COVID crisis severely impaired the hotel industry, most hotel debt maturing during the crisis did not result in foreclosure. Instead, these loans were renegotiated. Figure IV uses CMBS servicing data to demonstrate this fact. The figure follows a cohort of hotel loans with initially scheduled maturity dates during the first year of the crisis and tracks their eventual resolution. The yellow region in the figure shows the share of loans that, as of a given month, had entered foreclosure. By the end of 2020, less than 5% of loans maturing during that year had been foreclosed upon.[9] This is in stark contrast to what is indicated by the blue regions

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

[8] 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 will discuss the implications of operating arrangements for our results in detail in Section V.

[9] Foreclosure rates in the Great Recession were higher, with, for example, a cumulative foreclosure rate of 22% for hotel CMBS loans scheduled to mature in the 12 months beginning September 2009. 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 (2022) study the policy in detail, finding that it encouraged borrowers to strategically request loan modification.

of the figure, which show the share of loans that had been renegotiated.[10] By the end of 2020, nearly 50% of all loans scheduled to mature that year had already been renegotiated. Almost all of these renegotiations involved an extension of the loan's maturity date.[11] Some of these renegotiated loans subsequently paid off as the crisis subsided, which is indicated by the growing orange region plotting the share of loans "disposed without loss."

Summary and Implications

Putting things together, hotels finance themselves 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 can generate a rollover shock if the scheduled maturity coincides with an economic crisis (Fact 3). Owners can modify operations to respond to this shock (Fact 4), 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 reduce operations because they truly anticipate foreclosure and, thus, lose their incentive to maintain the asset (Fact 5). 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 next section proposes a model to understand why it is strategically optimal for them to do so.

III 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. Motivated by the facts in the previous section, our model focuses specifically on the role that a borrower's operating decisions play in altering her bargaining position with her lender rather than cash flow or liquidity constraints.

[10] Hotel financing received less government support than other forms of credit during the COVID crisis, so the modifications shown in Figure IV do not reflect direct intervention by, say, the FHFA. 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. Code §9057, 2020). Moreover, while the hotel industry lobbied extensively for the HOPE ACT, which would effectively provide equity for commercial mortgage borrowers, the bill stalled in Congress and never passed (H.R.7809, 2020). So, Figure IV documents widespread loan modification originating from the private market.

[11] We consider two definitions of loan renegotiation: a modification recorded by the Commercial Real Estate Finance Council (CREFC), a trade organization that provides standardized procedures for CMBS loan servicing; and a case in which the loan's maturity date is extended without a formal note by CREFC. Within the set of formal CREFC renegotiations, 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.

III.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 $L_t^*(p_t)$.[12]

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 $p_1 = p^l < p^h$. 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

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

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

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 an early 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 equals:

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

where $\gamma > 0$.[13] 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, but the borrower does not. The borrower has a prior that $\gamma \in (0, \overline{\gamma}]$ where $\overline{\gamma} > 0$, with a probability density function with support on this entire interval. 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.

III.B Lender's Problem

To solve the model, we first characterize the lender's optimal decision of whether to foreclose or forbear given an early maturity borrower default at time 1. The value to the lender from foreclosing, given a defaulting borrower's commitment to labor, L_1, is:

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

[13] This functional form implies that when the prior level of labor, L_{t-1}, 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.

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

$$\mathcal{V}(L,p,\gamma)=\max_{L'}\pi(L',p)-\phi(L',L)+\frac{\mathcal{V}(L',p,\gamma)}{1+r},$$

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

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

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

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

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 below the static optimum, $L_1^*(p^l)$, and can strictly decrease the probability when debt lies below a certain threshold:

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, $L_1^*(p^l)$. 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: $\rho(L_1^*(p^l))<1$.

The intuition of Proposition 1 is that cutting labor at time 1 lowers the value of foreclosure more than the value of forbearance. Indeed, cutting labor lowers current profits as well as the value of the firm in the good state at time 2, both of which affect the value of foreclosure. It also can lower the value of the firm in the bad state at time 2, but that channel applies to forbearance as well. 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. If $D > D^{**}$, then forbearance is more valuable than foreclosure to the lender even for higher values of labor, as the coupon the lender receives at time 1 exceeds the present value of the borrower's equity at time 2. However, when $D < D^{**}$, 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.

III.C Borrower's Problem

Our primary interest is in the borrower's choice of labor inputs at the onset of the crisis, L_1. For a late 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 late maturity borrower chooses to make the coupon payment at time 1, this borrower sets labor equal to the static optimum given the output price: $L_1 = L_1^*(p^l)$. If late maturity borrower defaults on this coupon payment, the lender forecloses and sets labor in time 1.

For an early maturity borrower, the problem is slightly more complicated as her choice of labor can influence whether the lender forecloses at time 1. The value to an early 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, $L_1 = L_1^*(p^l)$, because labor at time 1 does not affect future operating profits. The value from defaulting at time 1 for an early 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 early 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 forebearance 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)**.** *If r is sufficiently small and $\overline{\gamma}$ is sufficiently large, then there exists* *a threshold D^* such that the following hold at time 1:*

- *If $D < D^*$, then both the early and late maturity borrowers make the required loan payments and set $L_1 = L_1^*(p^l)$.*

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

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

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

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

The necessary upper bound on the discount rate, r, appears in the proof of Proposition 2. This bound ensures that a single period of operating profits in the low state is not enough to sway the lender's decision of whether to foreclose or forbear. 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 early maturity borrower always pays off the debt. This is true even when this borrower anticipates defaulting at time 2 in the bad state, which holds 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 late maturity borrower, who owes only the smaller coupon payment at time 1.

When debt is intermediate, so that $D^* < D < D^{**}$, the early 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 late maturity borrower still finds it optimal to make the coupon payment in this region of debt, so the late maturity borrower does not default.

When the early 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, $L_1^*(p^l)$, 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 early maturity borrower optimally cuts labor below the static optimum: $L_1 < L_1^*(p^l)$. The late 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 the early and late maturity 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 early maturity borrower is not willing to accept the forbearance agreement, and the late maturity borrower is not willing to pay the coupon. The early 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, so the borrowers do not commit to labor, leaving the lender to determine labor at time 1 upon foreclosure.

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 early maturity borrower and late maturity borrower's firms, or it is below the static optimum at the early maturity borrower's firm while equal to the static optimum at the late maturity borrower's firm. Therefore, real outcomes are either equal or smaller at the early maturity borrower's firm:

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

Proposition 3 implies that the negative effect of an early maturity on real outcomes is stronger for higher levels of debt over the range $(0, D^{**})$. We think of this range as the empirically plausible one, as $D > D^{**}$ represents a debt level so high that a single coupon payment is enough to lead the borrower to hand the firm back to the lender. Below this threshold, Proposition 3 suggests that the real effects of an early maturity hold only for high levels of debt, that is, $D > D^*$.

IV Data and Research Design

We empirically evaluate the model using a research design that estimates the effects of debt rollover risk on real activity. This requires us to assemble a novel dataset that we describe in Section IV.A. We describe the research design in Section IV.C. Additional detail on the data is in Appendix A.

IV.A Data

Hotel performance data

We measure operational performance at the hotel level using data from STR, LLC. STR is a leading data provider in the hotel industry and covers around 98% of hotels in the U.S. (Povel et al., 2016). The STR data is self-reported, meaning that hotel owners send the data to STR.[14] In exchange, STR provides submitting hotels with the ability to run benchmarking reports on anonymous groups of competing hotels. Data on individual hotels is available to academics under a confidentiality agreement that requires researchers to work with an anonymized subsample of the STR universe. Accordingly, our sample includes the subset of hotels in our main mortgage dataset, discussed shortly, that: have a loan scheduled to mature between January 2018 and December 2022; and that match to a hotel tracked by STR. For the purposes of identification, we later filter this sample to hotels with a loan scheduled to mature in a tight bandwidth around the pandemic's onset.

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

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

airport, resort, highway). STR defines geographic markets that generally align with a CBSA.[15]

Mortgage data

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

We supplement the T-Loan dataset with data on loans from Real Capital Analytics (RCA), which tracks sales of and mortgages backed by commercial properties in the U.S. We match the RCA data to Trepp using the property address and the origination month of the loan in Trepp. The RCA data allow us to observe junior, non-securitized liens on the same property, providing us with a more complete measure of the total LTV at origination. In the cases where we observe a junior lien in RCA, we replace the LTV in Trepp with the LTV in RCA.[16] We do not adjust the debt service coverage ratio (DSCR) in Trepp to account for junior liens because RCA does not have sufficient data on required interest payments.

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

Analysis sample

An important hurdle that we overcome in assembling our data is to merge hotel-level data from STR to loan-level data from Trepp, using information on the address of collateral properties.[17] While a loan may disappear from the Trepp data when it matures or is paid off, we are able

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

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

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

to track property-level outcomes for the hotels securing that loan throughout the entire sample period. In our empirical analysis, we compare hotels that serve as collateral for loans with a maturity before COVID (i.e., February 2019 to January 2020) to those with a maturity on or after COVID (i.e., February 2020 to January 2021). Summary statistics for key variables for these two groups of hotels appear in Table I. The assignment of hotels to each group depends on the maturity date at loan origination ("intent to treat"). Therefore, even if the borrower prepays the loan before 2019, we still assign the hotel collateral to one of the two groups according to the loan's original maturity date. As Table I shows, hotels are somewhat but not perfectly balanced across the two groups. Our empirical analysis will address these imbalances in a variety of ways, which we discuss in the next section.

IV.B Identification Strategy

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

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

IV.C 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:

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

where y_{imt} denotes an outcome of interest for hotel i, located in market m, at time t. For our main analyses, we restrict the sample to include only hotels with loans initially scheduled to mature within a symmetric 12-month window around the beginning of the pandemic. The dummy variable $PandemicMaturity_i$ is a treatment indicator equal to one if hotel i has a loan that was initially scheduled to mature during the 12-month period following the beginning of the pandemic and equal to zero if the hotel had a loan maturing during the 12-month period before the pandemic began. The $Post_t$ indicator is equal to one if month t falls on or after the first month of the pandemic (February 2020).[18] The hotel fixed effects α_i control for level differences in mean outcomes across hotels.

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

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

set of hotel-type by month fixed effects in X_{it} addresses this concern by allowing outcomes for these two types of hotels to trend differently throughout the pandemic independently of their scheduled debt maturity. Our analysis explores robustness to a wide range of different hotel-level controls of this type.

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

Event Study

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

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

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.

V Empirical Results

This section presents our main empirical results. Section V.A builds on the evidence from Figure V and estimates how needing to rollover debt during the crisis affects hotel revenue, output (i.e. occupancy), and inputs. This exercise provides a direct test of Proposition 3 of our model, which predicts that all of these outcomes should fall by more for hotels with loans maturing during the COVID crisis. Section V.B further assesses the model's predictions through a series of additional tests designed to differentiate between mechanisms that are based on strategic incentives, such as renegotiation, as opposed to cash flow constraints. Section V.C conducts robustness tests.

V.A Real Effects of Debt Rollover

Effect on Revenue

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

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

We interpret the relative decline in revenues at hotels with loans maturing during the pandemic as evidence that the owners and managers of these hotels chose not to maintain operations at the same level as they would have had they not been facing a looming balloon payment. As described in Section IV.C, 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 V.C.

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 II, 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.[19] 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.[20]

Lastly, 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, and so we remove the additional fixed effects introduced in columns 2–5. The sample size also falls by 16% because information on the borrower comes from RCA and is not available for all hotels. Despite the loss of power, we estimate a revenue drop of 22 log points in this specification. This finding not only confirms the robustness of the main result but also helps to rule out cash flow constraints as a plausible mechanism, as we shall discuss in Section V.B

Decomposition into Quantities and Prices

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

In the early half of the sample, nearly all of the total relative decline in revenues is driven by

[19] In Appendix Figure XVII, we also explore the heterogeneity in our results across operating models. Consistent with the idea that hotel owners are able to exert control over operations during a crisis, we find very little evidence of significant heterogeneity along this dimension.

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

falling output rather than falling prices. For example, In April 2020 hotels with loans maturing during the pandemic had reduced their occupancy rates by roughly 45 log points (36%) more than hotels with loans maturing earlier while exhibiting essentially no differential change in prices. Over time, however, the gap in output narrows and a modest gap in prices materializes. By the end of the sample, roughly half of the remaining 10% gap in revenues is driven by lower occupancy while the remaining half is due to lower prices.[21]

Effects on Inputs

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

Our analysis of hotel inputs relies on lower-frequency annual profit and loss statements that are only available for about 45% of hotels contained in the monthly data analyzed above. Nonetheless, in Panel A of Figure VIII we verify that the relative decline in revenues for pandemic-maturity hotels continues to hold at the annual frequency in this smaller sample. This figure reports regression coefficients from an annual version of equation (2) containing the same controls used in Figure VI.[22] While the monthly data only contain information on room revenues, the annual profit and loss data record revenues from all sources (e.g. food and beverage, golf course, etc.). We use this more inclusive definition of revenues here. We also extend the sample back to 2017 to allow for a better assessment of low-frequency pre-trends. The results continue to indicate large relative declines in revenues for hotels with loans maturing during the pandemic.

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

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

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

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 IX 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 XV we also verify that the drop in sales and marketing expense from panel D of Figure VIII occurs immediately. 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. As described in Section IV.A, the monthly profit and loss data cover a subset of hotels in the larger, yearly dataset and begin in January 2020.

V.B Evaluating the Mechanism

Why did hotels with loans coming due during the early months of the pandemic scale back operations more than otherwise similar hotels with loans due just before the pandemic began? As discussed in Section II, the nature of hotel financing arrangements makes it highly unlikely that cash flow considerations are the primary culprit. There is no plausible change to hotel operations that could generate enough short-term cash flow to satisfy a looming balloon payment. Similarly, given that hardly any loans were actually foreclosed upon, standard theories of debt overhang and disinvestment driven by fears of foreclosure seem unlikely to apply. Instead, the model we present in Section III proposes an alternative mechanism based on strategic renegotiation: highly-levered borrowers temporarily scale back operations at the collateral to to disincentivize creditors from seizing it. This section evaluates and finds support for the empirical relevance of this mechanism.

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. Thus, after actually receiving a modification, our theory would predict that hotels should immediately scale up their operations.

Figure X presents evidence consistent with this prediction.[23] In this figure, we restrict attention to the subset of treated hotels whose loan is modified during the crisis and plot average monthly room revenue by month relative to the month of modification. 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 result in Figure X shows 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.

Figure X plots simple averages and includes no control variables. Thus, 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 modifications did occur in 2020, before the market had recovered, a full 25% occur in 2022, when the market had already returned to its pre-crisis levels. Moreover, in Appendix Figure XIV 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.

Heterogeneous Effects by Strategic Incentives

In addition to predicting that output should rebound after loan modification, 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 five 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 higher

[23] Importantly, this prediction describes an equilibrium outcome, not the causal effect of a modification, so we do not attempt to instrument for modifications in this analysis.

strategic incentives:

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

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. In keeping with 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.

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).[24] 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 ($HighLTV_i = 1$).[25] 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.

[24] We take great care to measure the *total* LTV ratio, which is obtained from the merger of the Trepp and RCA datasets from Section IV.A. This measure of the LTV ratio includes second-liens and other non-securitized debt on the property.

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

The second dimension of heterogeneity we consider builds on the core idea from our model that borrowers engage in strategic renegotiation because they rely on their lender (i.e., special servicer) 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 modifications 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 ($NoExtOption_i = 1$), accounting for 37% of hotels in the estimation sample. This finding supports the idea that frictions in renegotiation drive the negative real effects of debt rollover.

Third, borrowers in the model face a tradeoff between short-term operating profits and bargaining power. This leads them to refrain from complete shutdown in the crisis because they wish to collect any profits earned below the level that is required to trigger a modification. In practice, however, a borrower who defaults may have difficulty retaining any profits if their loan contract features a cash sweep, or "lockbox" arrangement. These arrangements are fairly common among CMBS loans and, for example, 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, $InititalLockbox_i$.

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 $\pi(L_1, p^l)$ to inputs, L_1, thereby reducing the main drawback to engaging in strategic renegotiation.

Fourth, and related to the previous prediction, borrowers with debt maturing later in the pandemic period have a higher probability that the market will have recovered by the time they need to pay off their loan (i.e., higher q). Consequently, they have an incentive to postpone strategic renegotiation until learning more about the expected duration of the crisis. Consistent with this view, column 4 of Table III finds a smaller drop in revenue of 9.8 log points for hotels with a maturity in the latter six months of the pandemic, whereas the drop is 18.8 log points for hotels with a loan maturing in the first six months ($EarlyCrisisMaturity_i = 1$).[26]

Fifth, 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 the expected value of γ varies across lenders, which, in practice, correspond to CMBS special servicers. We proxy for the inverse of this expected value using the share of hotels in the same chain as hotel i among all other hotels in the sample with the same special servicer as i, denoted $ServicerChainShare_i$. We motivate this proxy with the observation that hotel management practices are often dictated at the chain level, with some chains, for example, requiring different standards for the maintenance of furniture, provision of turn-down services, etc. If a special servicer concentrates most of its loans among hotels of a given chain, then it seems plausible that the servicer has acquired some knowledge about the operations of that chain. Consequently, it could bring operating expertise from the other hotels it oversees, or the operators that manage them, to the hotel in question. By this logic, a higher $ServicerChainShare_i$ corresponds to a lower expected value of γ from the borrower's perspective. When the expected value of γ is lower, the borrower needs to reduce operations by a larger amount to disincentivize the servicer from seizing the collateral.

Column 5 of Table III tests this hypothesis. We normalize $ServicerChainShare_i$ to have mean of zero and unit variance for ease of interpretation. The resulting coefficient implies that the drop in real activity is 13 log points (67%) larger when hotel i has a special servicer that lies one standard deviation above the mean in terms of the share of its hotels in the same chain as i. Interpreting $ServicerChainShare_i$ as a proxy for the inverse of γ, this finding suggests that borrowers reduce operations more when their servicer can more easily operate the hotel in the event of foreclosure, which is consistent with the model.

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 channel.

Additional Results Ruling Out Cash Flow Constraints

A common explanation for why debt rollover events can lead to a deterioration in real outcomes is cash flow constraints. That is, firms faced with external financing frictions scale back current operations to harvest short run cash flows to service their debts. As discussed in Section II, we

[26] Unlike the other characteristics, we cannot interact $EarlyCrisisMaturity_i$ with month fixed effects because there is no variation in $PandemicMaturitiy_i$ among hotels with the same value of $EarlyCrisisMaturity_i$.

do not think this explanation is likely to hold in our setting, as the amount of debt coming due for the typical hotel is so large that no change to operations could plausibly generate enough cash to cover the balloon payment. This subsection provides two empirical tests that help to further rule out this possibility.

First, in Figure IX we plot coefficient estimates from an annual version of equation (2) using operating profit as the outcome. The results reveal that hotels with loans coming due during the early months of the pandemic experienced a relative *decline* in profit compared to hotels with loans due before the pandemic.[27] This is exactly the opposite of what would be expected if the motive for scaling back operations was to generate additional short-run cash flow to make full or even partial balloon payments.

Second, as discussed in Section V.A, column 6 of Table II shows that our main results on output hold even in a specification that conditions on borrower-by-month fixed effects. This specification holds cash flow constraints constant and identifies β using loans made to the same borrower but scheduled to mature on different sides of the pandemic's onset. This means that the effects we find in this specification are a result of the borrower explicitly reallocating resources away from the hotel facing a rollover shock toward other hotels in its portfolio.

This result also helps to rule out more subtle explanations based on cash flow considerations. In particular, one concern might be that hotels with a pandemic maturity may have a particularly limited ability to generate cash flow from financing during the crisis, relative to control hotels with a pre-crisis debt maturity. For example, hotels with a pre-pandemic maturity may have access to a larger internal capital market (i.e., more liquid assets) through any equity extracted when they refinanced. They may also have easier access to external capital markets in the form of non-secured working capital, which would be junior to a CMBS loan and, thus, difficult for borrowers with maturing CMBS debt to access (Chodorow-Reich et al., 2022; Brown, Gustafson and Ivanov, 2021; Greenwald, Krainer and Paul, 2021). In either case, these explanations would predict an insignificant effect when estimating equation (1) with borrower-by-month fixed effects.

V.C Additional Robustness of Real Effects

Bandwidth Sensitivity and the Loan Life Cycle

In the results so far, we control for effects related to the loan life cycle through a post-maturity dummy, which adjusts for any level change in outcomes that would occur at maturity even the absence of a rollover shock. To further alleviate this concern, Table IV assesses the robustness of

[27] Columns 3-4 of Appendix Table X 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 XV, we show that profits are lower for the treatment group throughout the initial months of the pandemic.

our estimates to changes in the size of the bandwidth used to define pre- versus post-pandemic maturities. A more narrow bandwidth implies that the treatment and control groups are at a similar stage in the loan life cycle once the pandemic arrives.

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

Omitted Variables at the Chain Level

In Appendix Table VI we explore the robustness of our results to specifications that include a full set of market-by-chain-by-month fixed effects.[28] This restrictive specification identifies the main effect using only variation across hotels within a given chain and market (e.g. Hilton DoubleTree in Boston) that happen to have loans maturing just before versus just after the pandemic. While this stringency reduces external validity through the associated drop in effective sample size, it improves internal validity by shutting down bias from unique cases wherein certain chains tend to: have loan maturities on a particular side of the pandemic; locate in geographic markets with differential hotel demand during the pandemic; and, within those markets, cater to guests with differential demand.

The estimate from column 1 of the table indicates that hotels with a pandemic maturity experienced a drop in revenues at the onset of the pandemic that was 12 log points larger than that experienced by other hotels in the same chain and market with loans maturing prior to the pandemic. As in Table II, we incrementally add in fixed effects related to hotel size, purpose of stay, and operating arrangement. The results in columns 2–4 lie between 8 and 12 log points. We take the midpoint, around 10 log points, as a credible lower bound on the effect of interest. It seems

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

unlikely that spurious correlation within a given chain and geographic market could be so strong as to generate a 10% difference in revenue by loan maturity, after already residualizing against nonlinear trends by purpose of stay and the other controls included in the table.

Differences in Paycheck Protection Program Take-up

Appendix Figure XIII shows that hotels with loans scheduled to mature before and during the pandemic have the same take-up rate of Paycheck Protection Program (PPP) loans over time.[29] This finding suggests that liquidity constraints did not drive the differential decline in real outcomes at treated hotels, as those hotels would have been more likely to seek PPP credit if they were more constrained.[30]

VI Conclusion

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

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

Going forward, the negative real effects that we document may also apply to other commercial property sectors with maturing debt that cannot be rolled over. Practitioners have recently voiced concerns over this possibility, especially in the context of the office and retail sectors,

[29] 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 XV.

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

both of which have large amounts of debt maturing over the next three years and face economic headwinds from trends in remote work and e-commerce (Putzier, 2023).

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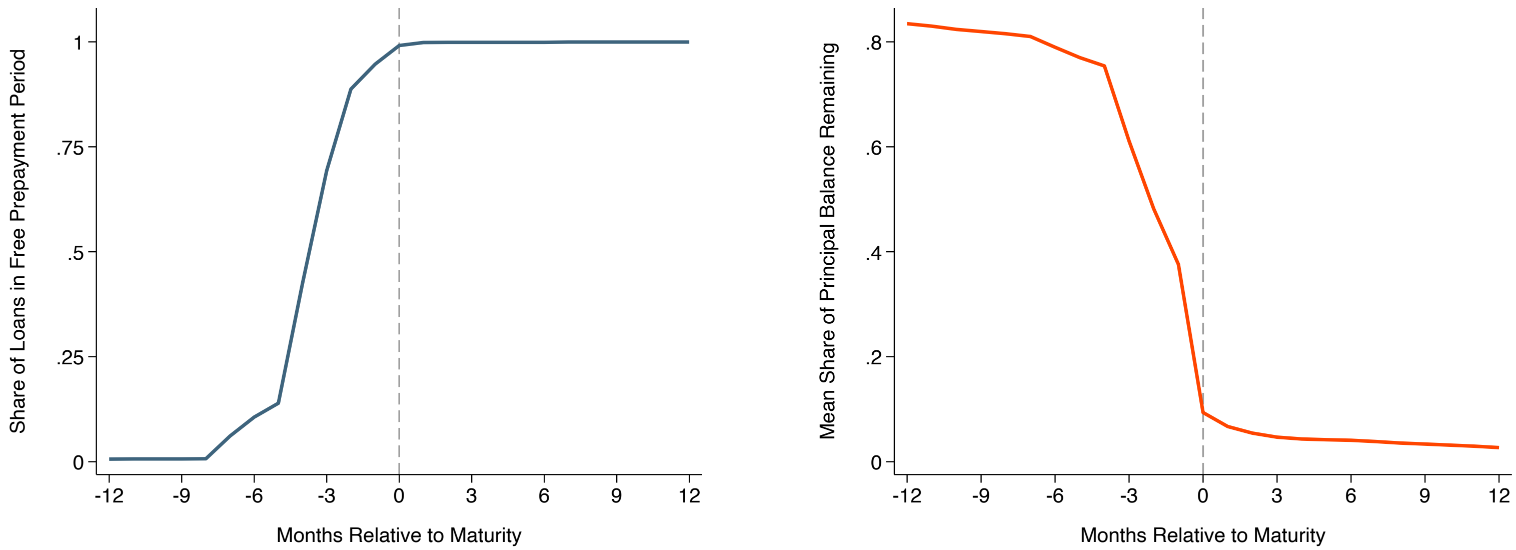


Panel A. Loans in Free Prepayment

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)

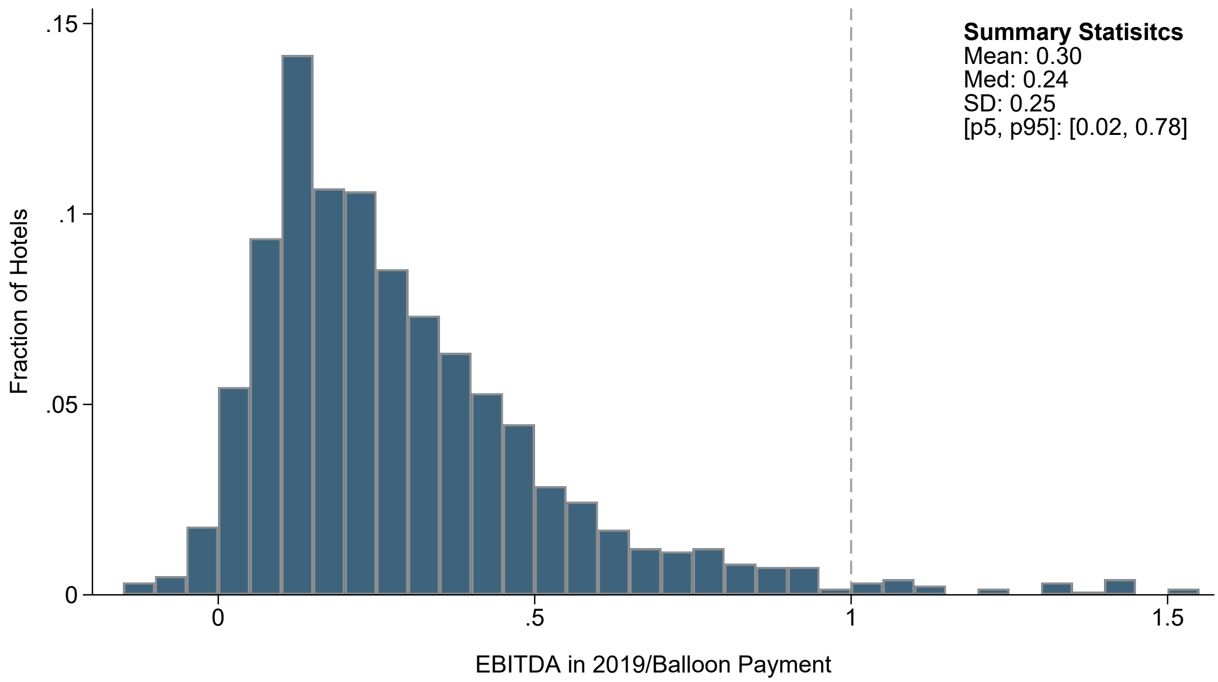


FIGURE II

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

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

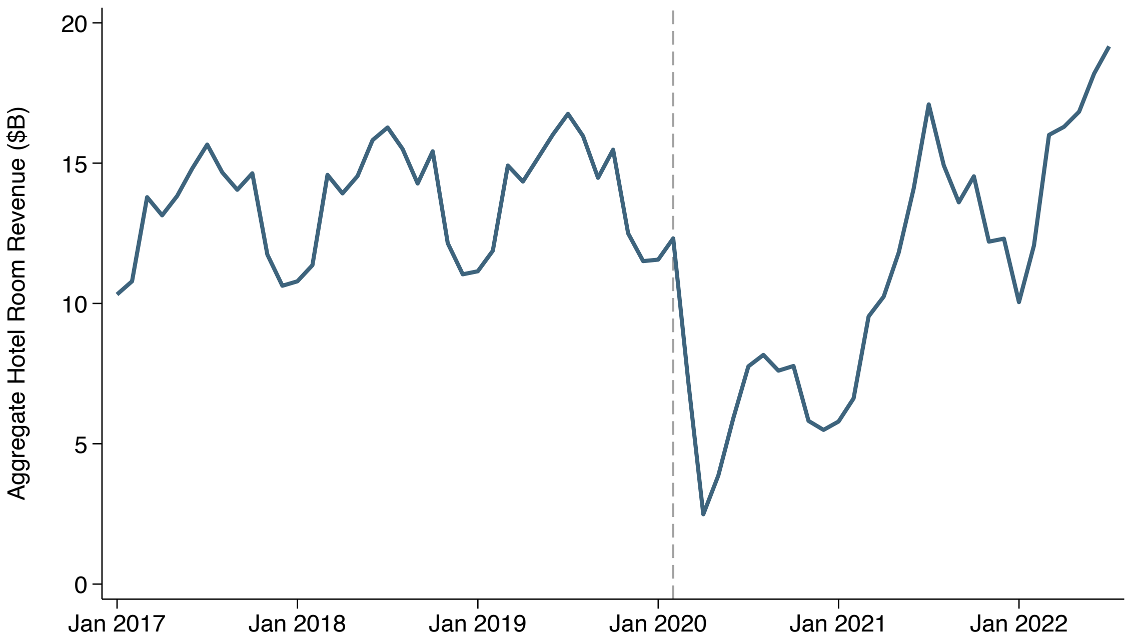


FIGURE III
Aggregate Monthly Revenues for US Hotels.

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 98% of U.S. hotels. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. (SOURCE: STR, LLC)

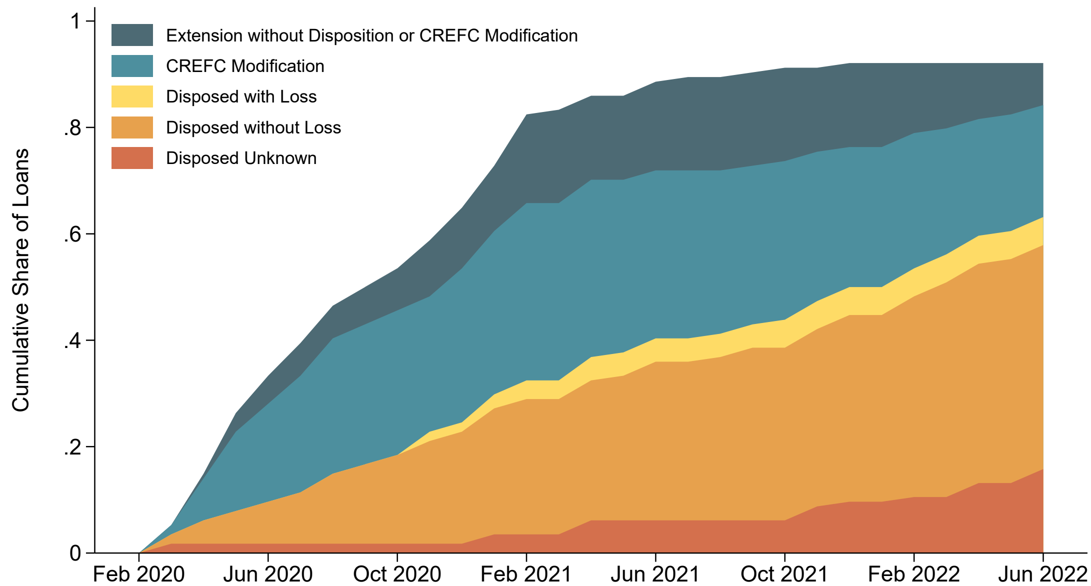


FIGURE IV
Loan Resolution.

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 an "Extension without Disposition or CREFC Modification" in a given month if, in that month, the maturity date switches to a later date. A loan has a "CREFC Modification" in a given month if, in that month, the CREFC modification field becomes non-empty. A loan becomes "Disposed with Loss" in a given month if it has zero loan balance, a non-empty loan disposition field, and the disposition field takes on the values "Loss", "Impaired", or close variants of these terms. A loan becomes "Disposed without Loss" in a given month if it has zero loan balance, a non-empty loan disposition field, and the disposition field takes on the values "Paid", "Prepaid", or close variants of these terms. We infer that a loan has paid off if its balance goes to zero and it makes an unscheduled principal payment that exceeds the loan balance from the previous month. A loan becomes "Disposed Unknown" in a given month if it has zero loan balance, it does not have an inferred payoff, and the loan disposition field is either empty or explicitly says "Unknown". These definitions allow loans to move between categories (e.g., CREFC Modification to Disposed without Loss). The categories are mutually exclusive. A loan can move from "Extension without Disposition or CREFC Modification" to one of the other categories in the legend. In addition, a loan can move from "CREFC Modification" to one of the disposition categories. Data are from the Trepp dataset. (SOURCE: Trepp)

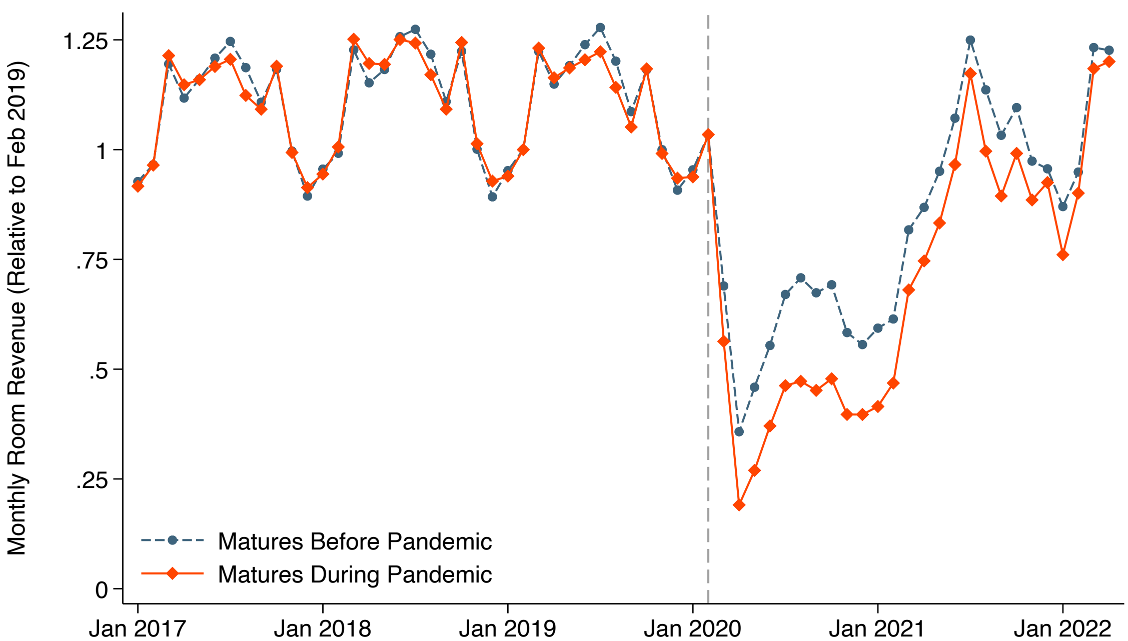


FIGURE V

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

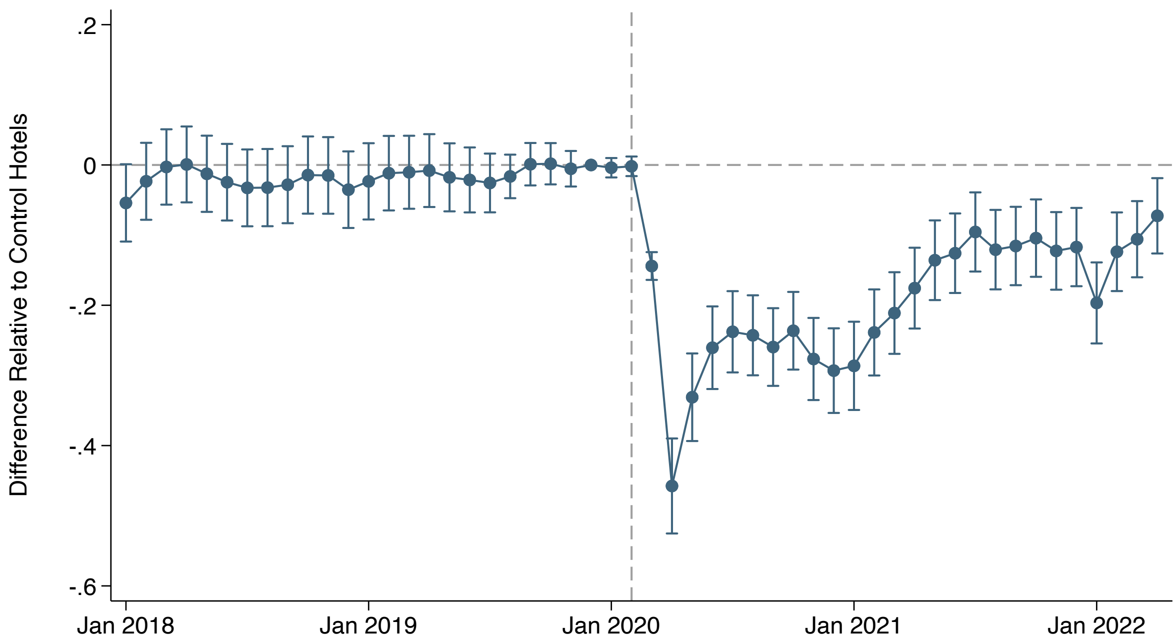


FIGURE VI
Effect of Pandemic Maturity on Hotel Room Revenues.

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

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

where i and t index hotel and month; the outcome y_{imt} is 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)

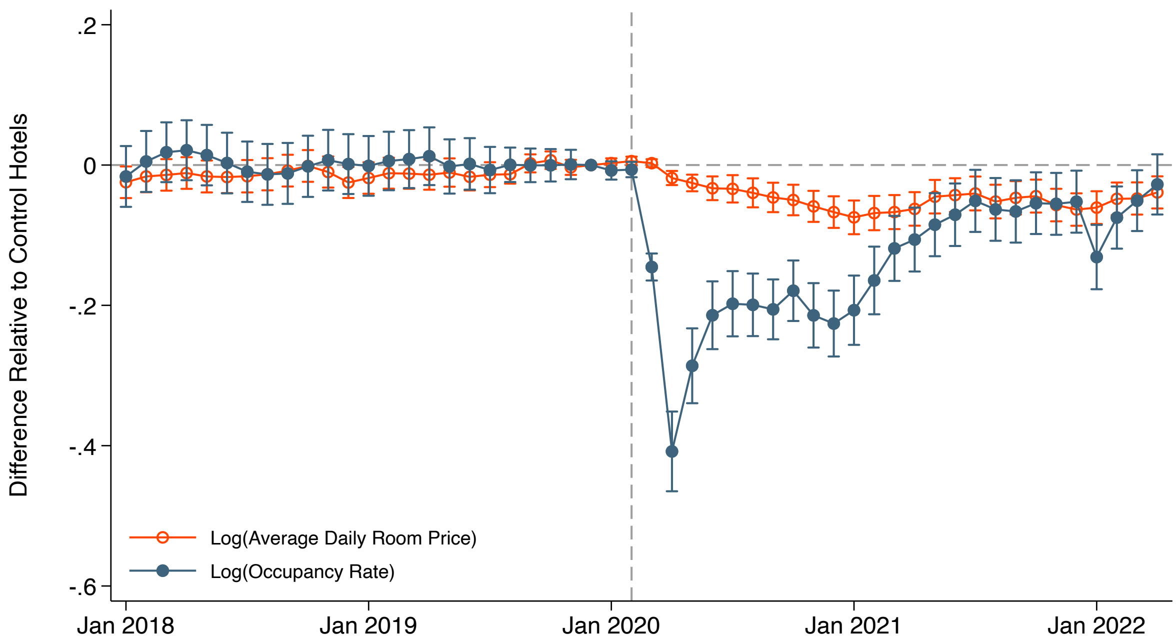
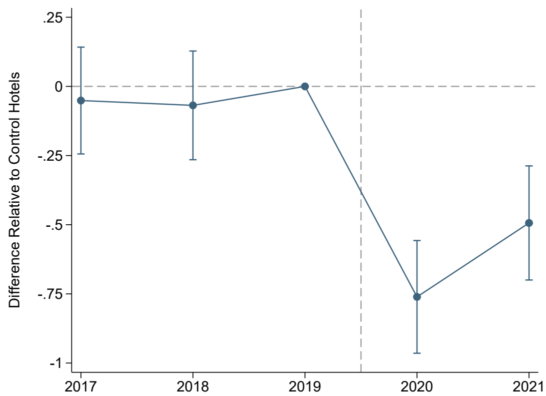


FIGURE VII
Effect of Pandemic Maturity on Hotel Occupancy and Prices. Decomposing the Revenue Effect.

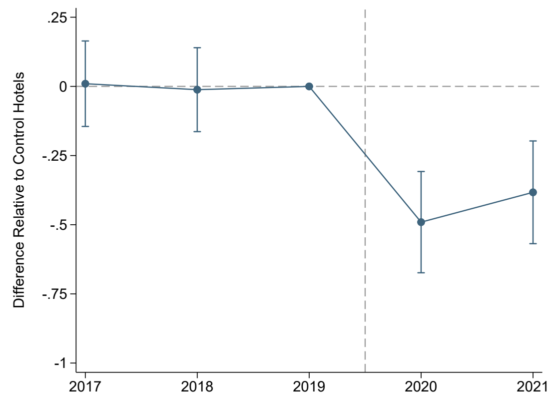
NOTE.—This figure decomposes the effect on revenue from Figure VI into the part that reflects reduced quantity (i.e., occupancy rate) and the part that reflects a lower room price. Explicitly, the figure summarizes the estimates from the same regression equation as in Figure VI after replacing the outcome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

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

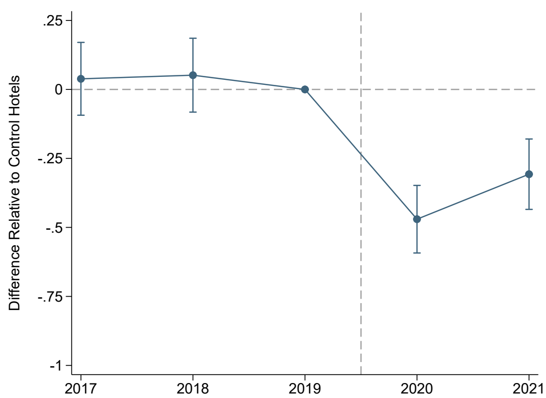
so the sum of the estimated coefficients each month in this figure approximately equals the estimated coefficient for the same month in Figure VI. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)



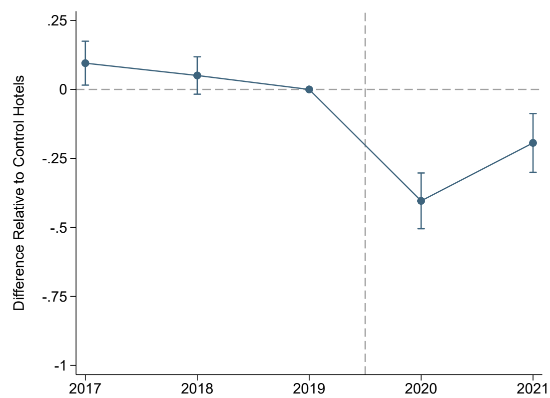
Panel A. Total Revenues



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)

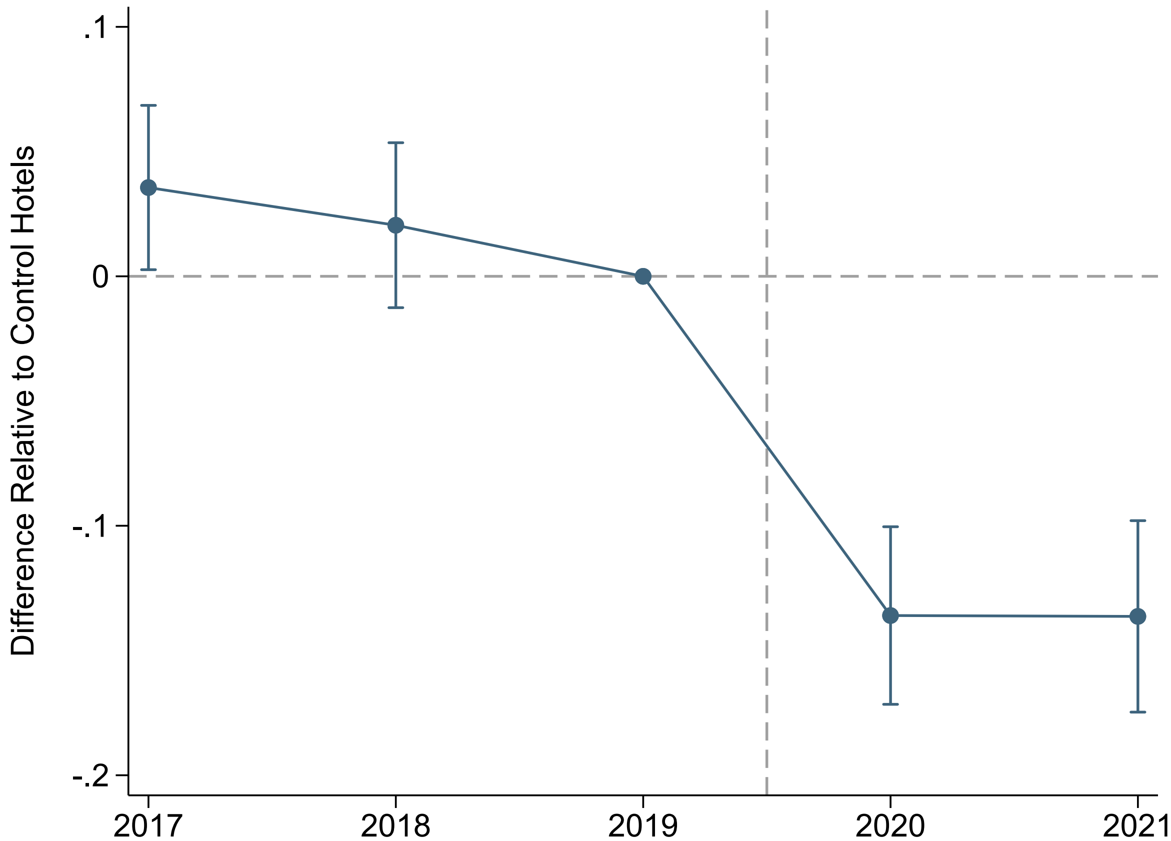


FIGURE IX
Effect of Pandemic Maturity on Hotel Operating Profits.

NOTE.—This figure estimates a variant of Figure VIII that assesses whether treated hotels experience an increase in operating profits, which would be consistent with the cash flow mechanism. The regression equation is the same as in Figure 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)

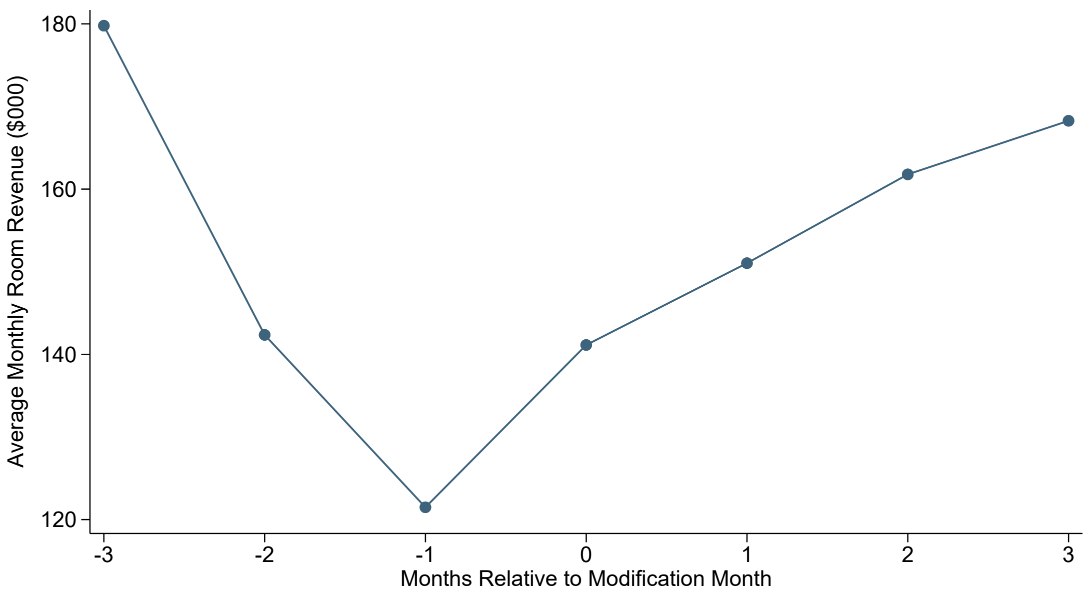


FIGURE X
Revenue around Loan Modification.

NOTE.—This figure plots average monthly room revenue around the month of modification for hotels with loans with a scheduled maturity between February 2020 to 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).

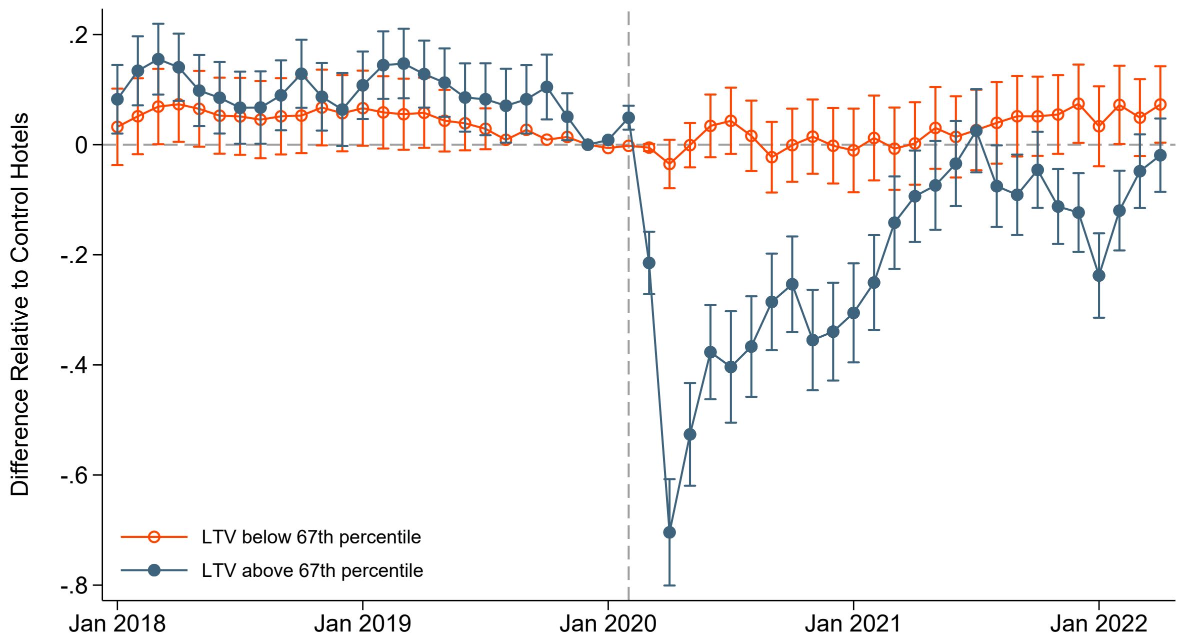


FIGURE XI

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,

$$
\begin{aligned}
y_{imt} = & \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\beta_{0,\tau} \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \right] + \ldots \\
& \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\beta_{1,\tau} \times PandemicMaturity_i \times HighLTV_i \mathbb{1}_{t=\tau} \right] + \ldots \\
& \psi_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\psi_\tau \times HighLTV_i \times \mathbb{1}_{t=\tau} \right] + \alpha_i + \delta_{mt} + \epsilon_{it},
\end{aligned}
$$

where the notation is the same as in Table 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, $\beta_{0,\tau}$, which measure the effect for hotels in the bottom two terciles of the LTV distribution, and the sum of the coefficients, $\beta_{0,\tau} + \beta_{1,\tau}$, which measure the effect for hotels in the top tercile. Brackets are 95% confidence intervals. The remaining notes are the same as in Figure 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	—
Owner and Operations				
Log(Borrower Real Estate Assets)	24.31	(2.33)	23.97	(2.12)
Operated by Brand	0.42	—	0.64	—
REIT	0.23	—	0.08	—
Loan Characteristics at Origination				
Servicer Stringency	−0.33	(0.81)	0.61	(1.03)
Log(Loan Amount)	20.58	(1.36)	19.36	(1.39)
Loan-to-Value Ratio (LTV)	0.78	(0.09)	0.59	(0.20)
Debt-Service Coverage Ratio (DSCR)	3.78	(0.89)	3.49	(1.33)
Loan Term (Months)	68.02	(27.59)	56.20	(25.37)
Balloon Flag	1.00	—	0.99	—
Number of Hotels	1,655		955	

NOTE.—This table summarizes hotels based on whether the hotel has a loan with original maturity date from February 2019 through January 2020 (Pre-Pandemic Maturity) or February 2020 through February 2021 (Pandemic Maturity). The Hotel Performance panel summarizes hotel performance observed in May 2019. The Hotel Location panel summarizes indicator variables for whether the hotel categorizes its location as: close to an airport; a resort; urban; suburban; or close to the highway. The Owner and Operation panel summarizes characteristics of the hotel's owner and the hotel's operating arrangement. Borrower real estate assets are the borrower's total dollar real estate holdings in the U.S. as of June 2023. The alternative arrangements to "operated by brand" are either cases where the franchisee operates the hotel or partners with a third party (95% of cases) or cases where the hotel is unbranded (5% of cases). The Loan Characteristics panel summarizes characteristics of the hotel's loan, all measured as of origination. The variable Servicer Stringency is the share of delinquent loans on which the loan's special servicer foreclosed over 2005-2019, normalized to have unit variance. The debt service coverage ratio is the ratio of debt service to operating income. The balloon flag indicates whether the hotel has a balloon amortization. Data on loan maturities and the variables in the Loan Characteristics panel are from the Trepp dataset. The LTV ratios from Trepp are modified to account for second-liens observed in the RCA dataset. Data in the Performance and Location panels are from the STR performance and cross-sectional datasets, respectively. Data on borrower-level variables in the Owner and Operation panel are from RCA. Additional details are in Section IV.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 estimates equation (1), which tests for a difference between treated hotels with a loan maturity during the pandemic and control hotels with a loan maturity beforehand. The regression equation is

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

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

	(1)	(2)	(3)	(4)	(5)
PandemicMaturity × Post	−0.023	−0.008	−0.133***	−0.098***	−0.198***
	(0.019)	(0.020)	(0.026)	(0.035)	(0.027)
PandemicMaturity × Post × HighLTV	−0.275***				
	(0.050)				
PandemicMaturity × Post × NoExtOption		−0.379***			
		(0.064)			
PandemicMaturity × Post × InitialLockbox			−0.072**		
			(0.034)		
PandemicMaturity × Post × EarlyCrisisMaturity				−0.090**	
				(0.038)	
PandemicMaturity × Post × ServicerChainShare					−0.132***
					(0.019)
Hotel FEs	X	X	X	X	X
Post Maturity FE	X	X	X	X	X
MSA × Month FEs	X	X	X	X	X
Characteristic × Month FEs	X	X	X		X
Number of Observations	133,043	133,095	131,286	133,095	125,489

NOTE.—This table estimates 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)-(4), and characteristics of the loan's special servicer, in column (5). Explicitly, the regression equation is

$$y_{imt} = \beta_0 \cdot PandemicMaturity_i \times Post_t + \beta_1 \cdot PandemicMaturity_i \times Post_t \times Characteristic_i \ldots$$
$$\psi_0 X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\bar{t}} \Big[\lambda_\tau \times Characteristic_i \times \mathbb{1}_{t=\tau} \Big] + \alpha_i + \delta_{mt} + \epsilon_{it},$$

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 ($NoExtOption$); (3) an indicator for whether the loan has a lockbox (i.e., cash sweep) contingency in places as of origination ($InitialLockbox$); (4) an indicator for whether the loan has a scheduled maturity within the first six months of the pandemic ($EarlyCrisisMaturity$); and (5) the share of hotels in the same chain as hotel i among all hotels in the sample with the same special servicer as i, which we normalize to have mean of zero and unit variance ($ServicerChainShare$). We cannot include characteristic-by-month fixed effects in column (4) because there is no variation in $PandemicMaturity$ among hotels with the same value of $EarlyCrisisMaturity$. Data on LTV ratios are from Trepp and are modified to account for second-liens observed in RCA. The remaining notes are the same as in Table II. (SOURCE: STR, LLC, Trepp, and RCA)

TABLE IV

EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES: ALTERNATIVE BANDWIDTHS

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

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

VII Additional Figures and Tables

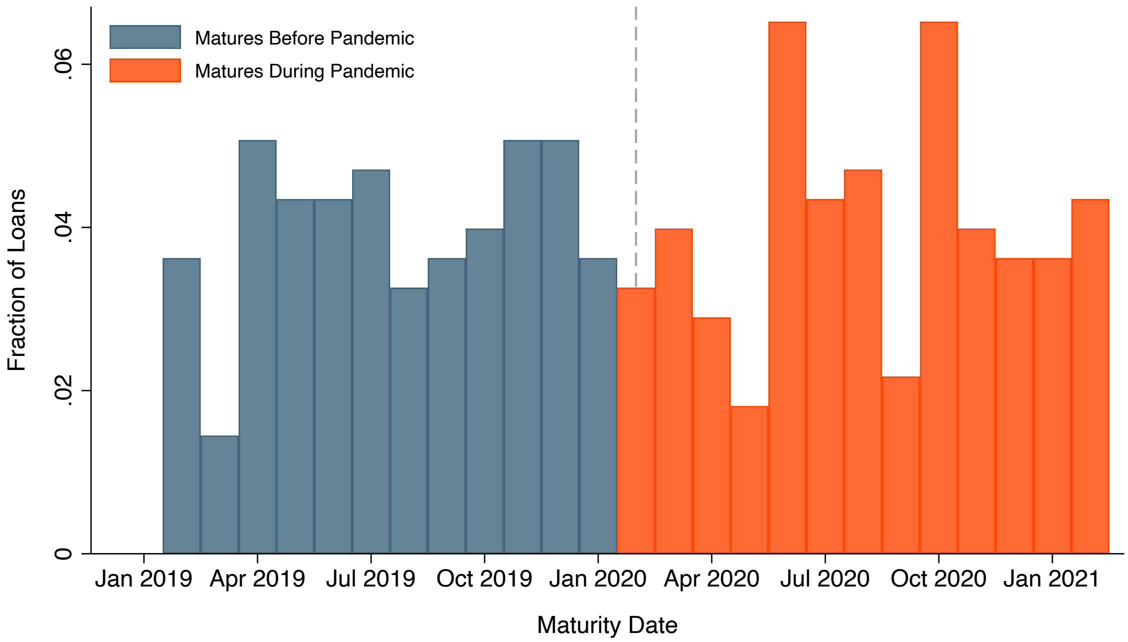


FIGURE XII
Distribution of Scheduled Loan Maturity at Origination.

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

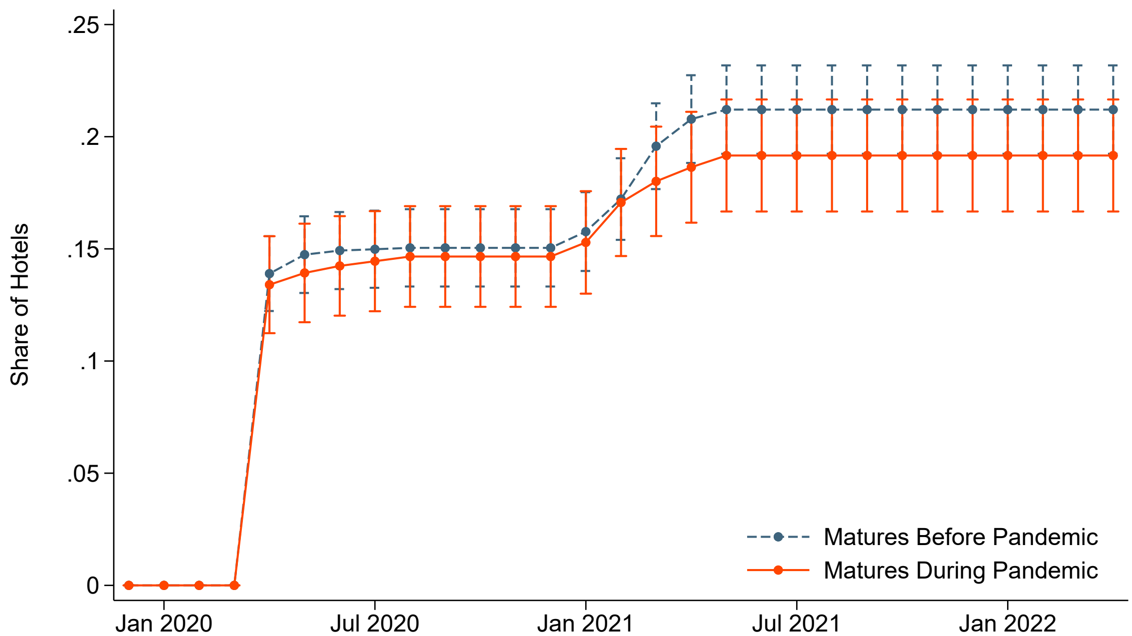


FIGURE XIII
Paycheck Protection Program Takeup Rate by Maturity Cohort.

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)

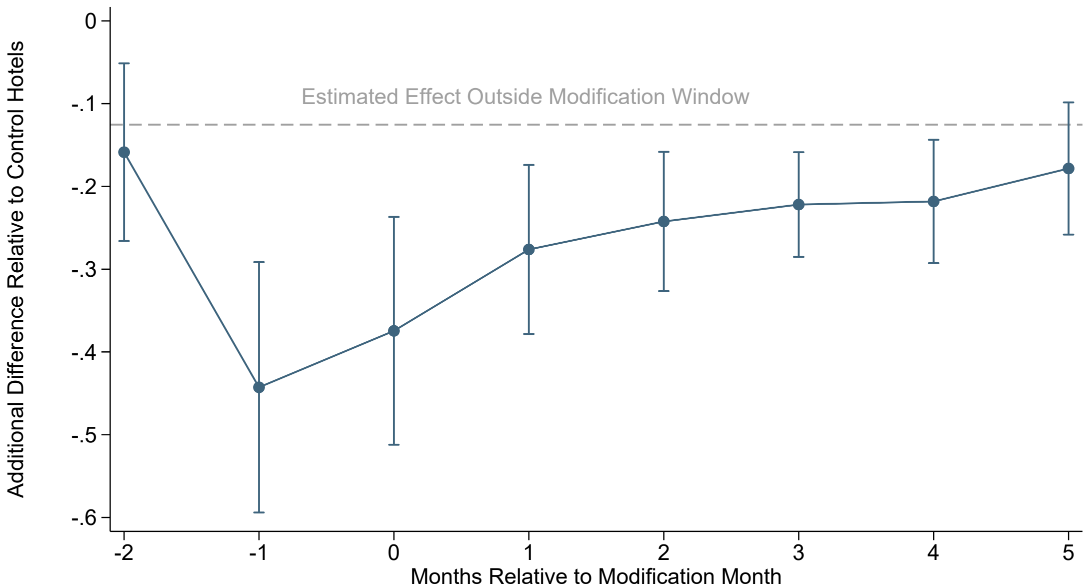
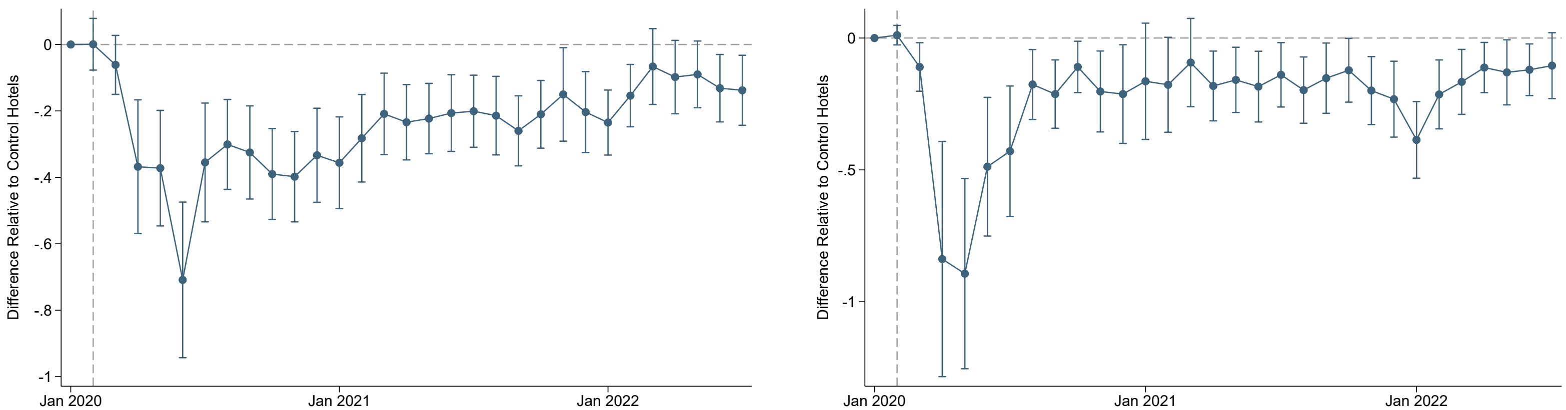


FIGURE XIV
Revenue around Loan Modification.

NOTE.—This figure estimates 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,

$$\begin{aligned}\log(Revenue_{imt}) = &\sum_{m=\underline{m}}^{m=\overline{m}}\left[\tilde{\beta}_m \times PandemicMaturity_i \times Post_t \times NoExtOption_i \times \mathbb{1}_{t-t_m=m}\right] + \ldots\\ &\beta_0 \cdot PandemicMat_i \times Post_t + \beta_1 \cdot PandemicMat_i \times Post_t \times NoExtOption_i + \ldots\\ &\psi_0 X_{it}' + \sum_{\tau=\underline{t}}^{\tau=\overline{t}}\left[\lambda_\tau \times NoExtOption_i \times \mathbb{1}_{t=\tau}\right] + \alpha_i + \delta_{mt} + \epsilon_{it},\end{aligned}$$

where m indexes months relative to the month of modification, t_m; $NoExtOption_i$ 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, including via extension option. 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, m, for each m in the modification window on the horizontal axis: $\beta_0 + \beta_1 + \tilde{\beta}_m$. 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 ($\tilde{\beta}_m = 0$). Standard errors are clustered by hotel. The remaining notes are the same as in Table III. (SOURCE: STR, LLC and Trepp).



Panel A. Marketing Expense *Panel B. Profit*

FIGURE XV

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)

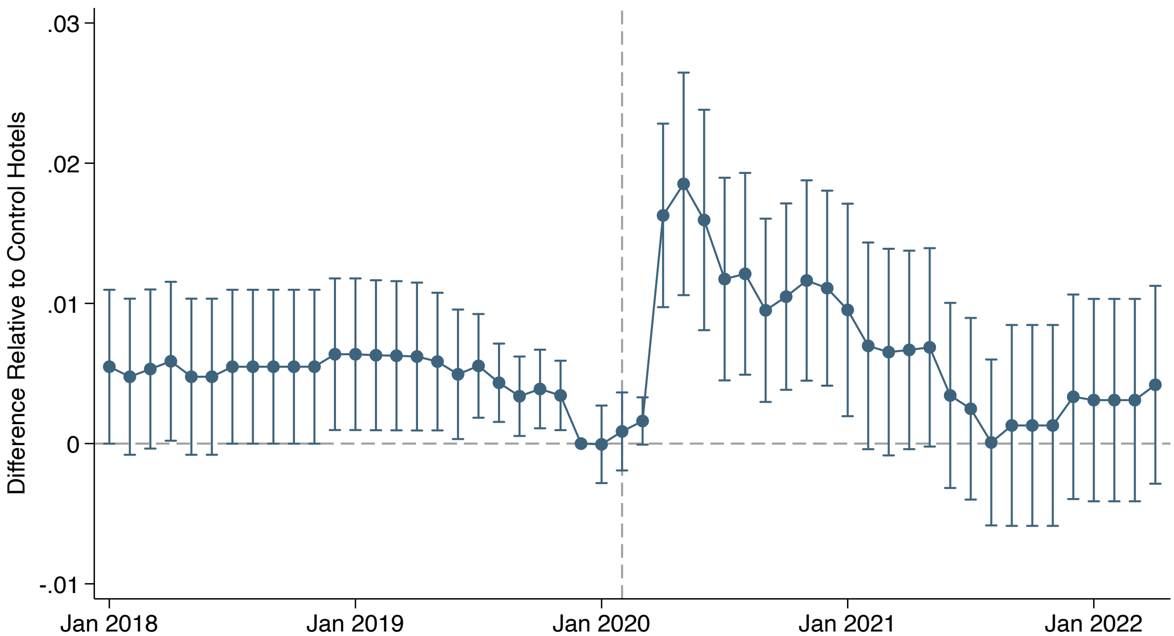
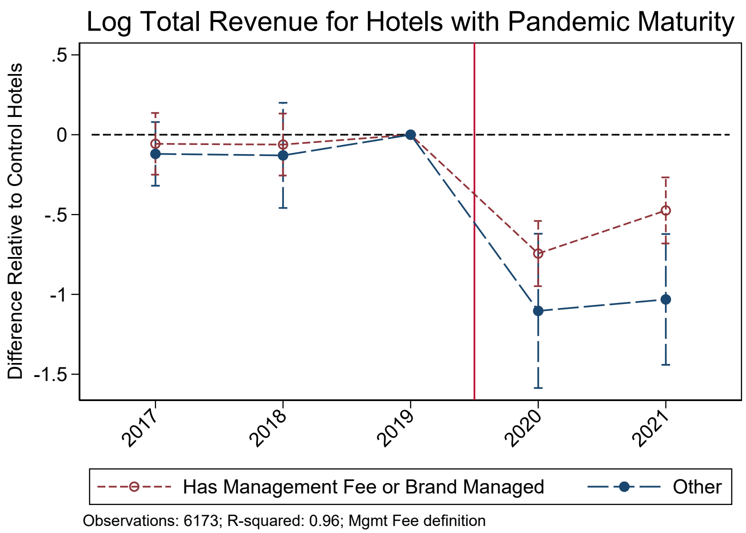
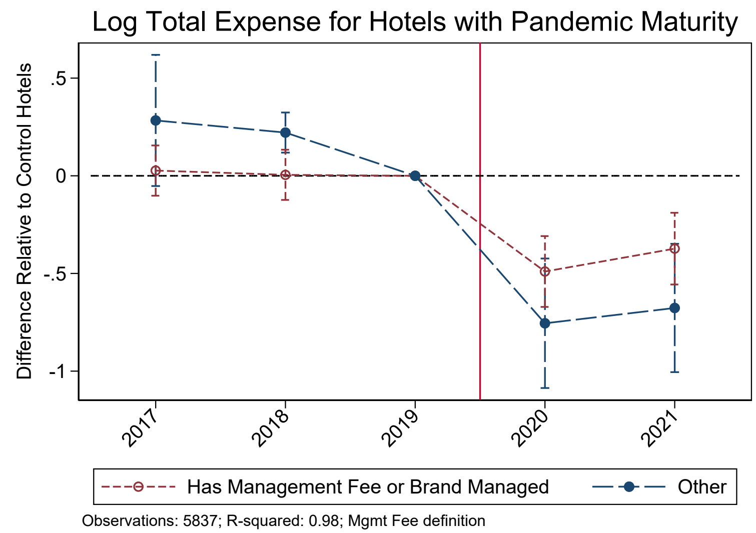


FIGURE XVI
Effect of Pandemic Maturity on Hotel Closure.

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



Panel A. Revenue



Panel B. Expense

FIGURE XVII
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) 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)

TABLE V
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 VI

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

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

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

TABLE VII

DESCRIPTIVE STATISTICS BY INITIAL LTV

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

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

TABLE VIII

SENSITIVITY OF EFFECT ON REVENUES BY INITIAL LTV

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

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

TABLE IX

EFFECT ON HOTEL EXPENSE BY CATEGORY

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

NOTE.—This table estimates a variant of equation (1) that assesses the drop in expenses documented in Figure 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). The outcome variables in columns (8)-(9) are the ratios of: room expense divided by total hotel revenue, in the same year; and total fees paid to the company operating the hotel divided by total hotel revenue, again in the same year. Standard errors twoway clustered by hotel and year are shown in parentheses. The remaining notes are the same as in Figure VIII and Table II. (SOURCE: STR, LLC and Trepp)

TABLE X

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 log of: total expense; and total expense divided by total room nights sold. The outcome in columns 3-4 is the hotel's operating profit, defined as the ratio of EBITDA to total revenue in a base year (2019). Column 4 controls for the interaction between the hotel's operating profit in 2017 and a vector of year fixed effects, which assesses robustness to the absence of parallel trends in operating profit in 2017 shown in Figure IX. The remaining notes are the same as in Figure VIII and Figure IX. (SOURCE: STR, LLC and Trepp)

For Online Publication: Internet Appendix

A Data Appendix

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

A.A STR Datasets

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

A.A.1 Anonymization Procedure

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

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

A.A.2 Monthly Panel of Basic Performance

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

We aggregate the daily panel to a monthly panel by taking the sum of: room revenue; number of available rooms; and number of occupied rooms. We then redefine ADR at the monthly frequency by taking the ratio of room revenue to number of occupied rooms. Similarly, we redefine the occupancy rate as the ratio of occupied rooms to available rooms. There is very little empirical within-hotel variation in the reported number of available rooms, since STR defines this variable essentially as a stock, not as a flow.[1]

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

A.A.3 Yearly Panel of Operating Statements

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

- **Revenue by Hotel Department:** We observe total hotel revenue, revenue from rook bookings, revenue from food and beverage services, and revenue from various other hotel amenities (e.g., spa, golf).
- **Total Expense by Hotel Department:** We observe total hotel operating expense, room operating expense, and operating expense from the following departments: food and beverage; administrative and general; telecom; sales and marketing; and property operations and management. We also observe expense on utilities, insurance, taxes, and fees to the hotel management company, including base fee and incentive compensation.
- **Labor Expense by Hotel Department:** For each line item in the previous point, we observe the expense allocated to labor. We define labor expense as the sum of wages and additional payroll expenses.

A.A.4 Monthly Panel of Operating Statements

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

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

which is when STR began collecting monthly operating statements.

A.A.5 Cross-Sectional Dataset

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

- **Size and Market:** We observe the hotel's total stock of rooms as well as its "market". STR's notion of a "market" approximately corresponds to a CBSA. Certain resorts that do not lie in an CBSA would have a market of, for example, "[State Name], other".
- **Hotel Brand and Chain:** We observe anonymized codes for the hotel's brand and chain within the brand, if applicable. Branded hotels account for 90% of the sample, and the remaining 10% are classified as "independent".
- **Hotel Management and Owner Company:** Similarly, we observe anonymized codes for the company that manages the hotel and the company that owns it, if applicable. Among branded hotels, 26% are managed by the hotel brand, and the remainder are managed either by owner directly or through a third-party management company. We classify a hotel as managed by such a third-party if it has a non-missing Management Company and pays management fees, according to the operating statement dataset. This condition applies to 91% of branded hotels that are not managed by their brand and to 90% of non-branded hotels. Otherwise, we assume it is managed by the owner directly. Individual owners are coded with an empty Owner Company. This condition applies to 50% of hotels in the sample.
- **Purpose of Stay:** We observe a code that describes the general purpose of guests at a hotel, which STR calls the hotel's "Location Type". The possible values are: urban ("A densely populated area in a large metropolitan area"); suburban ("Suburbs of metropolitan markets. Distance from center city varies based on population and market orientation."); airport ("Hotels in close proximity of an airport that primarily serve demand from airport traffic"); interstate ("Hotels in close proximity of major highways, motorways or other major roads whose primary source of business is through passerby travel. Hotels located in suburban areas have the suburban classification."); resort ("Any hotel located in a resort area or market where a significant source of business is derived from leisure/destination travel.); small metro ("Areas with either smaller population or limited services, in remote locations. Size can vary dependent on market orientation. Suburban locations do not exist in proximity to these areas. In North America, metropolitan small town areas are populated with less than 150,000 people.")

A.B Trepp Datasets

A.B.1 Securitized Loans

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

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

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

- **Critical Dates:** We observe the loan's origination date, maturity date at origination, and maturity date as of month t. For loans that have not reached a disposition as of June 2022, we observe the loan's disposition date. If relevant, we also observe the date on which: the loan prepays, either in full or in part; the date on which the loan enters into special servicing; the date on which the special servicer modifies the loan's terms; and the date on which foreclosure proceedings begin.
- **Underwriting Information:** We observe the following underwriting variables as of origination: loan size, loan-to-value ratio, and debt service coverage ratio. The debt service coverage ratio is the ratio of monthly net operating income to monthly debt service.
- **Prepayment Penalties:** We define a loan as in prepayment lockout in month t if that month lies within the required number of lockout months from origination reported in Annex A, which Trepp supplements using third party sources. We use analogous criteria to define loans in the period during which they can prepay either with yield maintenance or a specified penalty.
- **Additional Loan Terms:** We observe the following terms of the loan as of origination: term, in months; and an indicator for whether the loan has a balloon amortization.

A.C Other Datasets

A.C.1 RCA

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

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

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

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

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

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

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

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

A.C.2 PPP Dataset

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

A.D Merging Procedures

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

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

  Since the Trepp dataset is at the loan-month level whereas most of our regressions are specified at the hotel-month level, we must choose which loan to match to a given hotel. We simply use the earliest initial maturity date over the 2018-2022. For example, if a hotel has a loan with initial maturity of February 2018 and a separate loan with initial maturity of December 2021, then we would code such a hotel as a "control hotel", that is, with a "pre-pandemic maturity". Thus, our research design has the interpretation of an "intent-to-treat".
- **STR-to-PPP Crosswalk:** We use a standard string matching algorithm by NAICS code, zip code, street address, name, respectively, to match each hotel in our STR dataset to firm in the PPP dataset.

B Proofs

B.A Proposition 1

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

Lemma 1. *The function $\mathcal{V}(L,p,\gamma)$ is continuous in L and γ. It strictly increases in L over $[0,L^*(p)]$ and is constant for $L \geq L^*(p)$. It strictly decreases in γ and has the pointwise limit $\lim_{\gamma\to 0}\mathcal{V}(L_1,p,\gamma) = r^{-1}(1+r)\pi^*(p)$ if $L_1 > 0$.*

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 $X_0 < X_1 < X_2 < \ldots$ 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:

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

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 $\pi(X_j, p) \le \pi^*(p)$. 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:

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

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 interatively 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, $\mathscr{V}(X_0, p, \gamma) < \epsilon$, as claimed.

Finally, we solve for the limit as γ goes to 0. The value of $\mathscr{V}$ 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:

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

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

We now prove Proposition 1. The function $\rho(L_1)$ is clearly continuous because $\mathscr{V}(L_1, p, \gamma)$ 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 $[0, L_1^*(p^l)]$, we examine the difference between the values of foreclosure and forbearance for the lender:

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

By Lemma 1, $\mathscr{V}(L_1, p, \gamma)$ increases in L_1 over $[0, L_1^*(p^l)]$ 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:

$$\lim_{\gamma \to 0} V^{fc}\left(L_1^*(p^l), \gamma\right) = \pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r},$$

while the value of forbearance has the following limit:

$$\lim_{\gamma \to 0} V^{fb}\left(L_1^*(p^l), \gamma\right) = \frac{r+q}{1+r}D + (1-q)\min\left(\frac{D}{1+r}, \frac{\pi^*(p^l)}{r}\right).$$

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

$$\lim_{\gamma \to 0} V^{fb}\left(L_1^*(p^l), \gamma\right) < \pi^*(p^l) + \frac{q\pi^*(p^h) + (1-q)\pi^*(p^l)}{r}.$$

Therefore, when $D < D^{**}$ and $L_1 = L_1^*(p^l)$, 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 early maturity borrower maximizes when defaulting by:

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

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 $\rho(L_1, p^l) \leq \pi^*(p^l)$, 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 late maturity borrower defaults at time 1 is identical, which shows that the late 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 $L_1 < L_1^*(p^l)$.

We proceed in several steps. First, we show that if the discount rate r is sufficiently small, and if the maximum possible adjustment cost $\overline{\gamma}$ is sufficiently large, then either $f(0) > 0$ or $f(L_1^*(p^l)) > 0$: the borrower receives positive value from forbearance when setting labor equal to 0 or equal to the static optimum. The precise condition we require on r is the following:

$$r < \frac{q((\pi^*(p^h) - \pi(L_1^*(p^l), p^h))}{\pi^*(p^l)} = \overline{r}.$$

If $D \leq r^{-1}(1+r)\pi^*(p^l)$, then

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

which is positive when $r < \overline{r}$ because $\rho(0) = 1$ by Proposition 1 and because $\pi^*(p^l) < \pi(L_1^*(p^l), p^h)$. If $D > r^{-1}(1+r)\pi^*(p^l)$, then

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

which is positive if

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

If D is at least this amount, then:

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

which is positive if and only if $\rho(L_1^*(p^l)) > 0$. This probability is positive if $V^{fc}(L_1^*(p^l),\overline{\gamma}) - V^{fb}(L_1^*(p^l),\overline{\gamma}) < 0$, which reduces to:

$$\pi^*(p^l) + \frac{q\mathscr{V}(L_1^*(p^l), p^h, \overline{\gamma})}{1+r} < \frac{(r+q)D}{1+r}.$$

Given that $D \geq (q/(r+q))(1+r)\pi^*(p^h)/r$, this inequality holds for all D under consideration if:

$$\pi^*(p^l) + \frac{q\mathscr{V}(L_1^*(p^l), p^h, \overline{\gamma})}{1+r} < \frac{q\pi^*(p^h)}{r}.$$

When the adjustment cost γ gets arbitrarily large, the value of the firm limits to the present value of keeping labor at the initial level for the rest of time. Therefore, there exists $\overline{\gamma}$ such that this inequality holds if:

$$\pi^*(p_l) + \frac{q\pi(L_1^*(p^l), p^h)}{r} \leq \frac{q\pi^*(p^h)}{r},$$

which simplifies to $r \leq \overline{r}$, which holds by assumption.

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 either $f(0) > 0$ or $f(L_1^*(p^l)) > 0$, as shown above. 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: $L_1 > L_1^*(p^l)$. 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, $L_1' \in [0, L_1^*(p^l))$, 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, which we denote $\gamma_1 \in (0, \overline{\gamma})$, 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 $[0, L_1^*(p^l)]$. 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 for any positive labor choice. Therefore, $\gamma^*(L^*(p^l)) \in (0, \overline{\gamma})$, 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, $L_1 = L_1^*(p^l)$:

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

It follows that

$$(\gamma^*)'(L_1^*(p^l)) > 0.$$

Therefore, the probability of forbearance decreases in L_1 at this point, given that $\gamma^*(L_1^*(p^l))$ is interior to $(0, \overline{\gamma})$:

$$\rho'(L_1^*(p^l)) < 0.$$

As a result, $f(L_1)$ cannot be maximized at $L_1 = L_1^*(p^l)$, as $f'(L_1^*(p^l)) < 0$. This result concludes the proof that when the borrower defaults, the borrower chooses a value of L_1 that is less than $L_1^*(p^l)$.

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 $L_1 < L_1^*(p^l)$ 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 $L_1 < L_1^*(p^l)$ (in which case the profit difference is negative) or $L_1 = L_1^*(p_l)$ (in which case $\rho(L_1^*(p_l)) < 1$ 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.