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ABSTRACT

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

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Incomplete financial contracts create the possibility of renegotiation when parties encounter unforeseen contingencies (Hart and Moore, 1988; Aghion and Bolton, 1992). Economic crises can expose this contractual incompleteness, triggering renegotiation of the original contract. In this paper, we study how a borrower's desire to renegotiate debt that matures during a crisis affects output, employment, and profits at the underlying firm. Our main contributions are to propose a new theory of how such a borrower strategically reduces the firm's operations as a negotiating tactic, and to present empirical evidence of this behavior.

Our theory rests on two assumptions about the relationship between a borrower and a lender. First, we assume that, after the sudden onset of a crisis, the borrower can adjust the firm's operations faster than the lender can renegotiate the loan. This delay may stem from a variety of factors, such as institutional frictions or asymmetric information, which have been shown to delay bargaining in general settings (Fudenberg and Tirole, 1983; Sobel and Takahashi, 1983; Fudenberg, Levine and Tirole, 1985; Admati and Perry, 1987; Manove and Ma, 1993). Second, we assume that reviving operations is harder for outsiders, such as the lender, than for the borrower, due to their lack of firm-specific expertise—a premise formalized by Shleifer and Vishny (1992) and Hart and Moore (1994), and supported empirically by Kermani and Ma (2023) and references cited therein. As we show, these two assumptions create an incentive for the borrower to swiftly cut operations at the onset of a crisis to improve the borrower's negotiating position with the lender.

We embed these assumptions into a simple model of a borrower with secured debt maturing during a crisis. We model the crisis as an unanticipated drop in demand for the firm's output that is potentially permanent. Because the crisis is unanticipated, the debt contract does not specify whether the maturity extends in a crisis—an example of the contractual incompleteness emphasized by Hart and Moore (1988) and Aghion and Bolton (1992)—so the borrower and lender must negotiate during the crisis itself. In particular, the borrower chooses either to repay the debt or to default and request a term extension until a time when the long-run demand for the firm's output becomes known. Given the borrower's default decision, the lender chooses whether to grant the term extension or foreclose immediately.

Our main theoretical result is that, for a range of debt levels, the borrower defaults and cuts the firm's operations. Doing so both lowers short-run profits and increases the probability that the lender agrees to extend the loan. This range of debt levels is wide, containing levels both above and below the expected present value of the firm's assets, which implies that strategic renegotiation is empirically relevant. A second result is that when the lender can more easily revive the firm's operations, strategic renegotiation becomes less common, but involves sharper cuts to operations when it does occur. This result suggests that a lender's familiarity with the borrower's firm might not ameliorate the costs of strategic renegotiation and, in fact, could even amplify them.

We then present empirical evidence of this phenomenon by studying the hotel sector during the COVID crisis. This setting is ideal for two reasons. First, data are available for the hotel sector allowing us to link granular, high-frequency information on operations (e.g., room bookings, wage bills, profits) to outcomes concerning the renegotiation of the mortgage for which each hotel serves as collateral. Second, the sudden onset of the COVID crisis, coupled with the use of large balloon mortgages in the hotel sector, enables us to credibly measure the effects of maturing debt on real outcomes and link those effects to strategic renegotiation.

In our empirical analysis, we compare hotels collateralizing loans scheduled to mature just after the pandemic begins—"treatment group" hotels—to those collateralizing loans scheduled to mature just before the pandemic begins—"control group" hotels. The difference in outcomes between these two groups gives an unbiased estimate of the treatment effect of a crisis debt maturity under the assumption that hotel owners did not choose the month of their loan maturity in anticipation of the COVID crisis. This assumption is plausible given the unanticipated nature of the crisis. Moreover, the loans that we study feature binding prepayment penalties, which limit the scope for bias from endogenous refinancing before maturity (e.g., Mian and Santos, 2018; Xu, 2018).

In line with our theory, we find that having debt scheduled to mature in the crisis lowers room revenue immediately at crisis onset, with this effect coming entirely through room bookings (i.e., output) and not through differential pricing behavior. Relative to control hotels, treated hotels experience a 40 log point larger drop in revenue during the first two months of the crisis. We also estimate negative effects on labor and various other forms of operating expenses, including marketing, which suggests that borrowers with crisis debt maturities intentionally scale down operations relative to the control group. Interestingly, the effect on revenue exceeds the effect on expenses, leading treated hotels to experience a relative drop in operating profits. This finding suggests that treated hotels intentionally erode some of their immediate profitability as part of the negotiating process, which is the main prediction of our model.

Our key identifying assumption is that outcomes for treated and control hotels would have evolved in parallel throughout the crisis were it not for the fact that treated hotels faced a crisis debt maturity. To support the validity of this assumption, we show that room revenues for both groups of hotels move in lockstep for the three years preceding the pandemic and only diverge afterward. Furthermore, our results are robust to allowing for fully flexible interactions between month fixed effects and an extensive list of hotel characteristics, including hotel chain-by-geographic market (e.g., comparing two Hilton DoubleTrees in Boston), year of origination, operation type, size, and location type (e.g., airport versus resort), and to separately estimating the effect by operating arrangement.[1] This robustness analysis helps to rule out spurious correlation between a hotel's scheduled debt maturity and other characteristics that may affect its behavior during this crisis.

We then present five pieces of evidence that support the role of strategic renegotiation in driving the relative drop in operations at treated hotels. First, among borrowers that receive renegotiations, output rebounds exactly in the month when the renegotiation is granted. We interpret this finding as reflecting how borrowers no longer choose to under-operate their asset once they secure better terms. Second, we estimate heterogenous treatment effects, finding that the decline in operations for crisis-maturity hotels is driven entirely by those with higher initial loan-to-value (LTV) ratios. This discontinuity in the treatment effect with respect to leverage is a direct prediction of the model.[2] Third, there are no real effects for treated borrowers with an extension option written into their loan contract at origination; intuitively, the contractual extension option diminishes the need to engage in strategic renegotiation. Fourth, the effects are stronger if the loan features a lockbox provision, which allows the lender to place operating cash flow in escrow. A lockbox makes strategic renegotiation more attractive because the borrower has less to lose from cutting operations. Fifth, the effects are stronger when the lender (i.e., special servicer) can more easily adjust operations at the hotel, based on various lender- and hotel-level proxies for ease-of adjustment motivated by Benmelech and Bergman (2008). This result is in line with the model's prediction that, conditional on default, strategic renegotiation becomes more severe when lenders can revive the asset more easily. More generally, that lender-level variables predict a borrower's operating decisions is consistent with a role for strategic interaction in explaining

[1] We estimate significant effects on revenue for both owner-operated hotels and for hotels managed by a third party, although the effects are larger for the former. This difference may indicate that management frictions attenuate the negative effects of strategic renegotiation on operations.

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

the effects we find.

Finally, we calibrate the model to match the treatment effect on revenues observed in the data. The required costs for outsiders to revive firm operations align with estimates from the literatures on labor adjustment costs and hotel foreclosure discounts, addressing concerns that the model relies on implausibly high takeover costs to generate real effects. Moreover, consistent with our cross-sectional evidence, the predicted treatment effect actually becomes more negative as these costs decline. This again reinforces that large takeover costs are not needed to fit the data and, in fact, if these takeover costs were larger, then we would have seen smaller real effects. The calibration also addresses the concern that the model depends on counterfactually high foreclosure rates: it matches the low observed frequency of foreclosure among defaulted hotel loans because strategic renegotiation itself endogenously limits foreclosure.

The strategic renegotiation mechanism we propose complements, but differs from, two natural alternative explanations for our results. One is a liquidity-based story: owners of treated hotels may have scaled back operations to raise cash for upcoming debt payments. While liquidity concerns are certainly relevant during crises and may contribute to some of the observed effects, several findings suggest they are unlikely to be the primary driver. First, as our main results show, short-run operating profits at treated hotels actually *fall* relative to control hotels—the opposite of what would be expected if the goal were to generate additional liquidity. Second, the amount of debt coming due typically exceeds the hotel's annual earnings by a wide margin, suggesting that cash harvesting alone would be insufficient to produce enough resources to pay off the loan. Third, our results continue to hold even when including borrower fixed effects, which limits the identifying variation to hotels with different loan maturities that are owned by the same borrower and, thus, subject to the same borrower's ability to inject cash into a hotel's operating account. Finally, very few treated loans are paid off at maturity; most are instead renegotiated and extended. Consistent with this evidence, our model abstracts from liquidity constraints and assumes the borrower can repay the loan if desired, focusing instead on strategic motives for renegotiation.

A second alternative explanation is debt overhang: if owners of treated hotels expect to lose the property in foreclosure, they may prioritize short-run profits over the firm's long-run value and reduce investment accordingly (e.g., Myers, 1977). While this mechanism is theoretically well-founded and contributes in many contexts, two features of our setting suggest it is unlikely to be the main driver here. First, debt overhang typically operates through a high foreclosure rate.

Yet in the episode we study, actual foreclosures are rare, making this channel empirically less salient. Second, even if treated borrowers mistakenly anticipated widespread foreclosure, debt overhang predicts that they would increase short-run profits at the expense of long-term value. Instead, we find that short-run profits fall relative to control hotels. These patterns are more consistent with strategic behavior aimed at influencing lender negotiations than with traditional debt overhang dynamics.

Taken together, our results indicate that contractions in real activity during crises reflect not only exogenous cash flow shocks or reduced incentives to invest, but also endogenous operational decisions intended to win concessions from lenders. In this sense, our findings complement Glode and Opp (2023) and Flynn, Ghent and Tchistyi (2024), who show that information frictions can foster strategic default and inefficient debt resolution, and that well-intentioned policies promoting renegotiation can yield unintended consequences.

Contribution to Related Literature

Our paper makes several contributions to the existing literature. First, we contribute both conceptually and empirically to a large literature on strategic renegotiation of debt contracts, which goes back at least to Hart and Moore (1994, 1998). This literature explains how renegotiated payments between borrowers and lenders depend on borrowers' exogenously given cash flows or, as in Benmelech and Bergman (2008), liquidation values. Our conceptual contribution is to emphasize that cash flows are endogenous to the firm's operating decisions and can thus be altered as a negotiating tactic.[3] This tactic works because the owner has firm-specific operating expertise that allows engaging in a form of managerial entrenchment (Shleifer and Vishny, 1989). Our empirical contribution is to find support for this mechanism in the data. In so doing, we complement empirical work documenting real effects of debt renegotiations that are not endogenous to short-run operating decisions. For example, Gilje, Loutskina and Murphy (2020) show that prescheduled renegotiation incentivizes firms not-in-default to inefficiently increase short-run profits, whereas we show that endogenous renegotiation incentivizes firms in default to inefficiently decrease short-run profits. Giroud et al. (2012) show how debt writedowns for firms that strategically default lead to subsequent improvements in operating performance, while we show

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

that firms stratgically reduce operating performance in order to invite renegotiations that extend their term.[4]

Second, we contribute to the literature on default and renegotiation in mortgage markets. Motivated by the 2008 Global Financial Crisis (GFC), a large branch of this literature has focused on identifying the presence of strategic default, or lack thereof, among residential mortgages and the optimal workout of these loans (Guiso, Sapienza and Zingales, 2013; Agarwal et al., 2017; Piskorski and Seru, 2018; Ganong and Noel, 2020; Agarwal et al., 2023). Our paper focuses, instead, on commercial mortgages, where a parallel literature finds a stronger role for strategic default (e.g., Brown, Ciochetti and Riddiough, 2006; Dinc and Yönder, 2022) and discusses ex-ante contractual features designed to limit it (Glancy, Kurtzman and Loewenstein, 2022; Glancy et al., 2023). In work closely related to ours, Flynn, Ghent and Tchistyi (2024) find that a post-GFC policy intended to facilitate renegotiation of commercial mortgages encouraged strategic default, and Glode and Opp (2023) theoretically analyze the broader impact of such policies along credit chains, finding that they interact with private renegotiation incentives in subtle ways. We contribute to this literature not only by providing further evidence of strategic default among commercial mortgage borrowers, but also by tracing out the real effects of this default down to the operating and employment decisions at the underlying collateral.[5]

Third, we extend the literature on the real effects of crisis debt rollovers by proposing a novel mechanism of how they depress real activity. Prior work on these rollovers finds that firms scale down operations to free up cash, which is then used to pay off maturing debt (Almeida et al., 2011; Benmelech, Frydman and Papanikolau, 2019; Costello, 2020; Granja and Moreira, 2022). In that work, however, the ratio of debt maturing relative to operating income is much smaller than in the rollovers we study, where the median exceeds 400% (as shown below).[6] When rollovers

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

[5]More generally, our paper is also consistent with a variety of other papers showing how the presence of debt impedes the performance of real estate assets (Sun, Titman and Twite, 2015; Loewenstein, Riddiough and Willen, 2021; Liebersohn, Correa and Sicilian, 2022).

[6]In Benmelech, Frydman and Papanikolau (2019), mean profitability in 1928 is 9% of assets, and mean bonds due over 1930–1934 are 7.33% of assets, implying a ratio of maturing debt to income between 16% and 81%, depending on how spaced out the bond maturities are over time. Almeida et al. (2011) and Costello (2020) use data from Compustat, in which the ratio of long-term debt due in one year to EBITDA has a mean of 36% and a median of 7% for firms with positive debt due over 1990–2022. Granja and Moreira (2022) use data from DealScan, to which we do not have access.

become this large, paying off debt from freed up operational cash becomes impractical, while defaulting strategically becomes much more relevant. Hence, our contribution is to study large debt rollovers and to propose a novel mechanism that is relevant in these situations.

Finally, in focusing on hotels, we also contribute to a literature making specific use of hotel data to answer broader questions in financial economics. Spaenjers and Steiner (2024) show that private equity firms specializing in hotels operate these assets more efficiently than generalist real estate private equity firms. This finding supports our model assumption that the borrower possesses unique operational advantages specific to the asset. Povel et al. (2016) find that hotels built during booms underperform over subsequent years, while Kosová, Lafontaine and Perrigot (2013), Freedman and Kosová (2014), and Kosová and Sertsios (2018) examine how operating performance and expenses correlate with a hotel's organizational form. Our results hold for a variety of organizational forms, indicating that strategic renegotiation affects outcomes even when the borrower and hotel management are distinct entities. Like us, Steiner and Tchistyi (2024) study hotels during the COVID crisis. They focus on how the production subsidy embedded in the Paycheck Protection Program (PPP) affected competition through pricing decisions, whereas we show how debt rollover reduces operations via its effects on renegotiation incentives.[7]

I Model

We present a simple model that yields empirical predictions about how a borrower with debt maturing in a crisis may adjust operations to strengthen bargaining, compared to a borrower whose debt matures outside a crisis.

I.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:

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

[7] Nguyen et al. (2023) is another study of how debt affects hotel performance during the COVID crisis. However, their paper looks only at publicly listed firms and does not employ an instrument for the firms' debt position at the beginning of the crisis.

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 is denoted by K_t.

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

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

denote operating profits given labor, L_t, and the output price, p_t. We denote optimized profits by $\pi^*(p_t) = \max_{L_t} \pi(L_t, p_t)$ and the optimal level of labor by $L^*(p_t)$.[8]

Crisis

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

Debt, Renegotiation, and Labor Adjustment Costs

As of time 0, the firm's owner has a debt $\widetilde{D}$ due to a lender for which the firm serves as collateral. A *crisis maturity* borrower has the debt due at time 1, while a *non-crisis maturity* borrower has the debt due at time 2. The debt is non-amortizing and requires coupon payments of $r\widetilde{D}$ each period up to the maturity date, where $r > 0$ is the common discount rate. For notational ease, we denote the total payment due at maturity by $D = (1 + r)\widetilde{D}$. We assume that this total payment due is less than the expected present value of operating profits as of time 0:

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

At maturity, the borrower either pays the required payment to the lender or defaults. If

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

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

We make two key assumptions about the negotiation process. First, if the lender forecloses, then the lender—or any party to whom the lender sells the asset—faces adjustment costs from increasing labor at the firm. The adjustment cost the lender must pay at time $t+1$ equals:

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

where $\gamma > 0$.[9] According to equation (1), the lender's costs of reviving the firm are larger when the level of firm operations is lower. Intuitively, hiring workers—or selling the firm to a third party who must do the same—is more difficult when the base level of operations is lower. Because the borrower possesses familiarity with the firm, the borrower does not face adjustment costs when increasing labor between periods. We assume that the lender knows its own adjustment cost and that the borrower knows the distribution of γ across lenders in the economy but does not know the realization of this parameter for his or her lender.[10] We denote the cumulative distribution function of this distribution $G(\gamma)$, and we assume that the distribution's support is an interval whose greatest lower bound is 0.

Second, we assume an un-modeled friction that delays bargaining beyond the time it takes for the borrower to determine the firm's labor for that period. That is, at time t, the borrower can determine the firm's labor for that period, L_t, before the lender can offer forbearance or execute a foreclosure. The resulting timing within a period is: the borrower can determine labor and

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

[10] Were the borrower to know the value of γ, his or her behavior would become unrealistically precise, as the borrower could cut operations exactly to the point where the lender is indifferent between offering forbearance and foreclosing. Therefore, to smooth out the results, we assume asymmetric information about the value of the lender's adjustment cost parameter.

then either pays or defaults; if default occurs, the lender may either offer forbearance—which the borrower can accept (continuing the loan) or reject (leading to foreclosure)—or foreclose directly; lastly, output accrues to the firm's owner as of the end of the period.[11]

I.B Lender's Problem

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

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

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

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

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

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

The value of forbearance equals the coupon payment at time 1, $rD/(1+r)$, plus a discounted payoff at time 2 that depends on whether the borrower defaults. When the level of debt is low, the borrower always makes the full debt payment to the lender at time 2, leading to a forbearance value of D as shown in the first case in the expression for V^{fb}. In the second case, the level of debt is high enough that the borrower defaults if the price of output does not revert at time 2,

[11] When the borrower is indifferent as to the choice of labor, we assume that the borrower does not commit to labor at the beginning of the period. Therefore, if the borrower anticipates foreclosure with probability 1, the borrower does not commit to labor, and the lender chooses labor for that period upon foreclosing.

which occurs with probability $1-q$ and transfers ownership of the firm to the lender.

The lender forecloses when the value from doing so exceeds the value 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

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

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

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

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

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

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

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

As a result, forbearance becomes more likely as long as the probability of forbearance is not already equal to 1. This probability limits to 1 as labor goes to 0 because foreclosure becomes worthless to the lender for any value of the adjustment cost parameter, γ, while forbearance continues to have value. As long as $D < D^{**}$, a lender with a small enough adjustment cost parameter will always prefer to foreclose than forbear when labor is equal to the static optimum.

Therefore, a borrower with debt below this threshold can strictly increase the probability of forbearance by cutting labor below the static optimum. When $D > D^{**}$, the probability of forbearance equals 1 regardless of the level of labor because the coupon payment that the lender receives at time 1 is so large that it exceeds the expected present value of the borrower's equity.

I.C Borrower's Problem

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

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

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

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

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

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

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

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

- *If $D < D^*$, then both borrowers make the required loan payments and set $L_1 = L^*(p^l)$, the static optimum given the price at time 1.*
- *If $D \in (D^*, D^{**})$, then the crisis maturity borrower defaults, sets $L_1 < L^*(p^l)$, and receives forbearance with positive probability; the non-crisis maturity borrower makes the coupon payment and sets $L_1 = L^*(p^l)$.*
- *If $D > D^{**}$, then both borrowers default, and the lender forecloses and determines L_1.*
- *The default threshold for the crisis maturity borrower lies between the worst-case and expected debt-free values of the firm, while the default threshold for the non-crisis maturity borrower lies above the expected debt-free value of the firm:*

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

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

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

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

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

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

I.D Real Effects of Debt Rollover

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

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

Proposition 3 provides an direct empirical test of strategic renegotiation: real outcomes, including profits, should be lower for crisis maturity than for non-crisis maturity firms during a crisis. The proposition also yields an additional testable implication of this theory: the negative effect of a crisis maturity on real outcomes is stronger for higher levels of debt, $D > D^*$. This prediction holds over the interval $(0, D^{**})$, which we think of as the empirically relevant range. In particular, $D > D^{**}$ represents a debt level so high that borrowers would prefer foreclosure with probability 1 over making just a single coupon payment.

I.E *Heterogeneous Real Effects in the Model*

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

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

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

- *The range of debt where strategic default occurs weakly shrinks: $D^*_a \geq D^*$ and $D^{**}_a = D^{**}$.*
- *Suppose $\gamma G'(\gamma)/(1 - G(\gamma))$ increases in γ. Conditional on strategic default, operations at the firm fall: $L^*_{1,a} \leq L^*_1$ when $D \in (D^*_a, D^{**}_a)$, with strict inequality when $L^*_1 > 0$, which holds for some $D \in (D^*_a, D^{**}_a)$.*

According to the proposition, decreasing lenders' adjustment costs has a subtle effect on the decline in operations caused by strategic renegotiation. On the one hand, the frequency of strategic renegotiation remains constant or falls when ease-of-adjustment rises, as shown by the result that the default threshold, D^*_a, weakly increases. Since the lender's ease-of-adjustment in our model functions very similarly to the asset's redeployability in the model of Benmelech and

Bergman (2008), the first part of Proposition 4 echoes their finding that strategic default becomes less common when the lender's cost of taking over the asset falls. In isolation, this effect attenuates the aggregate decline in operations due to strategic renegotiation by making strategic default rarer.

By contrast, the second part of the proposition shows that conditional on strategic default, the borrower cuts operations *more* when ease-of-adjustment is higher, outside of at most a limited range of debt levels where optimal operations equal 0 at baseline. Intuitively, when ease-of-adjustment goes up, greater cuts to operations are necessary to achieve the same increase in the probability of forbearance. This logic holds as long as the regularity condition on G given in the proposition holds. The net effect of these two channels is ambiguous, and therefore, whether ease-of-adjustment amplifies or attenuates the cuts from strategic renegotiation is an empirical question.

II Data and Institutional Background

Our empirical analysis leverages the insights from the model above to provide evidence of how borrowers facing debt that is scheduled to mature during a crisis reduce operations as a negotiating tactic with their lenders. This section describes the data and institutional background for that analysis. We describe several features of this setting that make it particularly well suited for testing our theory. Before doing so, we outline our data sources. Details are in Appendix B.

II.A Data

Hotel Operations

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

The STR dataset has four components. The first is a daily hotel-level panel from January 2017 through June 2022 of the following basic performance metrics: room revenues, occupancy rates, and the average daily prices for rooms sold. The second is a yearly panel from 2017 through 2021 of hotel profit and loss statements, which includes total revenue and operating expenses each broken down into highly detailed categories. Specific expense categories we use include labor, and sales and marketing. The third is a monthly panel of hotel profit and loss statements, which is similar to the annual panel but begins only in January 2020. The final component is a cross-sectional dataset with time-invariant hotel characteristics, such as the number of rooms, location type (e.g., airport, resort, highway), and geographic market, which generally aligns with a metropolitan area as shown in Appendix Table A.I. The characteristics we observe also include anonymized identifiers for hotel brand and chain, as well as the type of operating arrangement. Background on these variables appears in the institutional details below.

Hotel Financing

Our primary source of data on hotel financing comes from Trepp LLC, which is a standard data provider in the literature on commercial mortgage-backed securities (CMBS). We specifically work with Trepp's T-Loan dataset. This dataset covers the near universe of commercial mortgages originated in the U.S. that are placed into CMBS pools. We observe mortgage characteristics at origination, such as maturity date, leverage, the address of the collateral property, and various other contractual features. We further observe monthly performance of the loan. Our data cover all loans that report monthly performance data on or after June 2006.

We supplement the T-Loan dataset with data on loans from Real Capital Analytics (RCA), which tracks sales of and mortgages backed by commercial properties in the U.S. The RCA data allow us to observe junior, non-securitized liens on the same property, providing us with a more complete measure of the total loan-to-value (LTV) ratio at origination. RCA also provides the name of the mortgage borrower, which enables us to include borrower fixed effects in our regressions.

Analysis Sample

An important hurdle that we overcome in assembling our data is to merge hotel-level data from STR to loan-level data from Trepp, using information on the address of collateral properties.[12] While a loan may disappear from the Trepp data when it matures or is paid off, we are able to track property-level outcomes for the hotels securing that loan throughout the entire sample period. In our empirical analysis, we compare hotels that serve as collateral for loans with a maturity before the onset of the COVID-19 crisis (i.e., February 2019 through January 2020) to

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

those with a maturity on or after the crisis' onset (i.e., February 2020 through February 2021). Summary statistics for key variables for these two groups of hotels appear in Table I.

II.B Institutional Background

Hotel Operations and Financing during Normal Times

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), but the brand does not own the physical hotel. A given hotel brand may also establish chains (e.g., Aloft by Marriott), which constitute separate franchises, each with its own set of standards. Brands sometimes manage day-to-day operations at the hotel as well; other times, the owner or a third-party manages the property (Freedman and Kosová, 2014; Kosová and Sertsios, 2018). When a hotel owner delegates management to a brand or third party, a management agreement typically requires the manager to operate the hotel using funds in a working capital account. This arrangement limits the owner's ability to alter operations when the hotel is sufficiently profitable. However, when negative operating profits deplete working capital, the owner can influence operations by withholding funds—a situation that appears to have arisen during the COVID crisis, as we discuss in Section IV.E.

Regardless of the operating arrangement, hotels rely heavily on collateralized debt (i.e., commercial mortgages), and a substantial share of these mortgages are CMBS loans.[13] The typical hotel CMBS loan has contractual features that enable our identification strategy. In particular, most CMBS loans do not fully amortize (Glancy, Kurtzman and Loewenstein, 2022), have terms well in excess of a year, and often contain covenants that prohibit or discourage prepayment, such as defeasance (An, Deng and Gabriel, 2011). As a result, the loan maturity date is when the borrower typically plans to make a large balloon payment to pay off the debt, which implies that we can use the joint timing of the unexpected COVID crisis and the pre-scheduled maturity date a shock to the desire to renegotiate the loan. To substantiate the claim that borrowers typically make balloon payments near the maturity date, we plot the dynamics of loan balances around maturity during non-crisis times in Figure I. In this figure, we consider loans scheduled to mature at least 12 months before the pandemic and with a term of 10 years, which is the mode in the

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

Trepp data. As shown in Panel A, most loans have prepayment restrictions until a few months before maturity, at which point the average principal balance falls precipitously, per Panel B.

The size of the balloon due at maturity is large, typically far in excess of the hotel's annual operating income. This mismatch in magnitudes supports our model set-up, in which the cash to fund debt payoffs is not restricted to the current income from firm operations. To demonstrate this mismatch, we use the STR profit and loss dataset to plot the distribution of EBITDA in 2019, a non-crisis year, relative to scheduled balloon payments for hotels with loans maturing in 2020. As shown in Figure II, the median hotel's balloon payment exceeds operating income in this pre-crisis year by a factor of four. Even hotels in the 95th percentile can cover only 78% of their balloon payment using operating income.

Hotel Operations and Financing During the COVID-19 Crisis

The onset of COVID-19 was a significant negative demand shock for hotels, since the crisis led many people to dramatically reduce their travel. In line with this negative demand shock, aggregate monthly revenue for all U.S. hotels in STR's universe falls 80% between February and April of 2020, as shown in Figure III.

Like the crisis in our model, the duration and permanence of this negative shock was uncertain. Here, the uncertainty stemmed from factors such as the speed of vaccine development and the long-term effects of work-from-home on business travel, which were unknown as of 2020 (PwC, 2020; Krishnan et al., 2020). However, the tendency of uncertainty to rise during economic crises is well-documented and not specific to the COVID-19 shock (Bloom, 2014).

Foreclosure appears to have been a genuine concern for hotel borrowers at the onset of the crisis. According to the American Hotel & Lodging Association, 59% of hotel owners reported being "in danger of losing [their] property to foreclosure" in late 2020 (AHLA, 2020). The perceived risk was likely greater for defaulting CMBS borrowers, given that modifications of CMBS loans were more difficult and far less common than those of bank loans before the crisis (Glancy, Kurtzman and Loewenstein, 2022).[14] To gauge this risk, we construct a placebo sample of loans with scheduled maturities between February 2017 and February 2018 and follow them through

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

June 2019, a 28 month window. Among those with a positive balance after maturity, 35% were ultimately disposed of at a loss. Thus, recent lender behavior in the CMBS market justified borrowers' concern about foreclosure at the onset of the COVID-19 crisis.

Even though many of them defaulted on their loans, most borrowers with loans initially scheduled to mature during the COVID crisis evaded foreclosure by negotiating term extensions. We document this fact in Figure IV, which shows the resolution of loans in both the placebo and treatment samples. Nearly two thirds of loans in Panel B are renegotiated in the first year of the crisis, with almost all of these restructurings involving a maturity extension or occurring in a loan with an extension option.[15] In total, only 11% of loans in Panel B with a positive balance after maturity are disposed of at a loss within 28 months, significantly less than the 35% share for Panel A given above. This decline is consistent with our model of a crisis, which predicts an increase in forbearance resulting from strategic cuts in operations by defaulting borrowers.[16] Our model also predicts borrower payoff and lender takeover as equilibrium outcomes, and smaller shares of loans do resolve in this fashion in the first 12 months of the crisis (25% and 6%, respectively).[17] The prevalence of renegotiation, together with the presence of these other two types of loan resolution, suggests that this crisis presents a good opportunity to test for the strategic renegotiation predicted by our model.

Anecdotal Evidence of Strategic Renegotiation

To illustrate strategic renegotiation in this economic setting, we provide a brief case study of this behavior. We focus on the Highland Loan Pool, which was debt that matured in April 2020 borrowed by a REIT named Ashford Hospitality Trust that was split into a senior CMBS mortgage

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

[16] Guidance from the Internal Revenue Service in April 2020 on the tax treatment of modifications in CMBS also contributed to this increase in forbearance (Glancy, Kurtzman and Loewenstein, 2022). However, these loan modifications ultimately arose from private bargaining between borrowers and lenders, as there was no direct government support of non-multifamily CMBS during the COVID crisis, in contrast to federally mandated forbearance that applied to multifamily properties (15 U.S.C §9057, 2020).

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

and two mezzanine loans.[18]

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

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

In July, Ashford entered into an agreement with its lenders to extend the maturity to April 2021, thus avoiding foreclosure during 2020.[19] Interestingly, the drop in operating revenue from 2019 to 2020 for hotels collateralizing the Highland Loan pool was 66% (from the Trepp data), much higher than the 14% drop in revenue over the same time for hotels collateralizing other loans to Ashford scheduled to mature in 2025, the latest scheduled maturity date for Ashford in our data. The larger drop for the Highland Loan pool suggests that Ashford intentionally reduced operations specifically at the underlying hotels in a successful attempt to obtain concessions from its lenders. Our research design aims to measure this behavior systematically across many hotels.

III Research Design

III.A *Identification Strategy*

We evaluate the model's main prediction by using a difference-in-differences research design to estimate the effect of a crisis debt maturity on real activity. The research design compares outcomes

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

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

for hotels with loans scheduled to mature just before the pandemic (February 2019–January 2020) to outcomes for hotels with loans scheduled to mature just after the pandemic's onset (February 2020–February 2021). We call these hotels the control and treatment groups, respectively. We assign hotels to these groups using the maturity date specified as of origination, making our research design an intent-to-treat. Therefore, the uncommon instances in which borrowers prepay loans early do not alter the assignment of hotels to these two groups.

Our key identification assumption is that outcomes for these two groups would have evolved in parallel were it not for the fact that treatment group hotels had a large amount of debt scheduled to come due during the beginning of the pandemic. In Figure V, we provide direct evidence in support of this assumption by plotting monthly room revenues by group. The dashed vertical line marks February 2020, the month we consider as the pandemic's onset. Revenues for these two groups of hotels move in near lockstep during the three years leading up to the pandemic and begin to diverge only afterwards. In our research design, we attribute this divergence to the crisis debt maturity scheduled for only one of the two groups of hotels.

Further support for our identification assumption comes from the apparently random assignment of hotels to the treatment and control groups. This randomness is visible in Table I, which shows balance between the two groups of hotels in hotel type characteristics and pre-crisis performance outcomes. Additionally, the initially scheduled loan maturities in the two groups are roughly uniformly distributed over time, as shown in Appendix Figure A.I.

III.B Estimation

Difference in Difference

We estimate difference-in-difference regressions of the following form:

$$y_{imt} = \alpha_i + \delta_{mt} + \psi X'_{it} + \beta \cdot PandemicMaturity_i \times Post_t + \epsilon_{it}, \tag{2}$$

where y_{imt} denotes an outcome of interest for hotel i located in market m at time t, α_i is a hotel fixed effect, δ_{mt} is a market-by-time fixed effect, X_{it} is a vector of time-varying hotel-level controls, and ϵ_{it} is an error term. To estimate equation (2), we restrict to hotels that are in either the treatment or the control group. The dummy variable $PandemicMaturity_i$, which equals one if hotel i has a loan initially scheduled to mature on or after February 2020 and zero otherwise, is therefore a dummy for treatment as well. The $Post_t$ indicator captures whether time t occurs after pandemic onset. In regressions with monthly data, it equals one for months on or after February 2020; with annual data, it equals one for years on or after 2020.

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 the loan life cycle: even in normal times, borrowers may modify hotel operations around the time of loan maturity. To address this possibility, we include a post-maturity dummy in the vector of time-varying controls, X_{it}, in all specifications, which prevents any level change in outcomes that occurs at loan maturity from contaminating the estimate of β.

The second potential source of bias is omitted variables: by chance, treated hotels may be more exposed than control hotels to the drop in hotel demand that occurs at pandemic onset. We address this possibility in two ways. First, we include market-by-time fixed effects, δ_{mt}, in all specifications. If treated hotels are more frequently located in markets harder hit by the pandemic than control hotels, then these fixed effects prevent this lack of balance from affecting the estimate of β. Second, we add static hotel characteristic interacted with time fixed effects to X_{it} in progressively more stringent specifications. These fixed effects control directly for lack of balance along characteristics that might be correlated with exposure to the pandemic, such as whether the hotel is close to an airport. We conduct robustness to a wide range of different hotel-level controls of this type.

Event Study

We also estimate an alternative to equation (2) that allows the treatment effects to vary by time:

$$y_{imt} = \alpha_i + \delta_{mt} + \psi X'_{it} + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \Big[\beta_\tau \times PandemicMaturity_i \times \mathbb{1}_{t=\tau} \Big] + \epsilon_{it}, \quad (3)$$

where $\mathbb{1}_{t=\tau}$ is an indicator taking the value one if time t is equal to τ. The sample and other variable definitions are the same as in equation (2). The time varying coefficients β_τ from this regression reveal the dynamics of the treatment effect after pandemic onset and allow us to test for conditional pre-trends prior to that. In monthly specifications, we normalize the coefficient for December 2019 to zero; we normalize the coefficient for 2019 to zero in annual specifications. Therefore, the other coefficient estimates provide the difference between treatment and control hotels in a given month relative to that difference in December 2019, or in a given year relative to that difference in 2019.

IV Real Effects of Crisis Debt Maturity

IV.A Revenues, Output, and Prices

In Figure VI, we report estimates of β_τ, the time-varying coefficients on $PandemicMaturity_i$ from equation (3), using log monthly room revenues as the outcome. Treated hotels experience a large drop in revenues *relative* to control hotels. This drop begins quickly after pandemic onset, appearing in March of 2020 and reaching a low of 45 log points (36%) in April of 2020. The speed of this adjustment is consistent with our key modeling assumption that borrowers can adjust operations faster than lenders can renegotiate loans. Indeed, as shown in Figure IV, lenders renegotiate less than 10% of treated loans active as of pandemic onset by April 2020.

Figure VI reveals two other notable aspects of the timing of the treatment effect. First, there is no significant difference between the two groups of hotels in the two years leading up to the pandemic. This confirms that the lack of pre-trends in the raw comparison in Figure V survives even after conditioning on hotel and market-by-month fixed effects. Second, the initial relative drop in revenue nearly fully reverts by the end of our sample in April 2022. This is consistent with partial reversal of the effect for hotels that successfully renegotiate their loans following the initial shock.[20]

The revenue treatment effect in the beginning of the crisis—including the large drop in April 2020—comes almost entirely from a drop in room bookings, as opposed to prices for rooms booked. To show this, we decompose the revenue effect into occupancy and price effects in Figure VII. This decomposition is consistent with our model, in which treated firms charge the same price as control firms during the crisis but produce less output. Although we restrict to hotels with positive occupancy in Figure VII, we likewise find that treated hotels are 1–2 percentage points more likely than control hotels to be closed in a given month during the pandemic's first year, with these results appearing in Appendix Figure A.II.[21]

[20] Strictly speaking, our model predicts an effect for non-foreclosed properties only up to the date the loan is extended or paid off, which occurs by February 2021 for all treated loans. Some non-modeled potential factors that could explain persistence beyond that date include hysteresis arising from non-zero borrower adjustment costs and continued strategic renegotiation in anticipation of additional desired loan extensions.

[21] For reference, the average monthly closure rate is 0.5% from February 2020 to April 2022. We impute closure following a procedure described in Appendix B.A.

IV.B Robustness of Revenue Effects

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 mentioned in Section III, one threat to this interpretation is that by chance treated hotels may have been more exposed than control hotels to the drop in hotel demand that occurred at the onset of the pandemic. We address that concern by showing that the treatment effect is robust both to the inclusion of an extensive set of control variables and to alternative groupings of treatment and control hotels. In this robustness analysis, we estimate the treatment effect using equation (2), which collapses the dynamic treatment effect in Figure VI to an average effect for months on or after February 2020. As shown in column 1 of Table II, this average effect is −17 log points (−16%) in our baseline specification.

Hotel Characteristic-by-Month Fixed Effects

In columns 2–5 of Table II, we explore the sensitivity of this baseline estimate to allowing the direct effect of the pandemic to vary non-parametrically across hotel characteristics. Column 2 incorporates hotel 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 similar set of fixed effects based on the STR-defined operation type, which allow for branded hotels operated by the brand, branded hotels not operated by the brand, or non-branded hotels to have fully flexible and differential trends throughout the sample period. Column 4 further adds a set of location type-by-month fixed effects, where location type is as defined by STR and reported in Table I (e.g., airport, resort, etc.). Finally, in column 5 we add origination year-by-month fixed effects, which control for separate dynamics across hotels that took out loans at different points in time. The treatment effect remains statistically significant and of roughly the same magnitude across all these specifications. Therefore, even among very similar hotels—those in the same metro, with similar numbers of rooms, of the same operational type, with the same location type, and with loans originated in the same year—we find a negative effect of a pandemic maturity on revenue during the crisis.

Borrower-by-Month Fixed Effects

In column 6 of Table II, we show that our baseline estimate is also robust to the inclusion of fixed effects for borrower (i.e. hotel owner) interacted with month dummies. In this specification, we limit the identifying variation to cases in which the same borrower owns hotels in both the treatment and control groups. In so doing, we address any factor correlated with borrower characteristics that makes treated hotels more exposed to the pandemic-induced drop in hotel demand. We estimate a revenue drop of 22 log points, which is slightly more negative than the estimate in column 1. This estimate remains statistically significant when we cluster standard errors by borrower, as shown in Appendix Table A.II.

In addition to demonstrating robustness, this exercise sheds additional light on the mechanism generating the main result in column 1. In particular, the exercise suggests that treated borrowers do not cut operations at the affected properties in an attempt to raise cash to pay off their maturing debt. Were this the case, treated borrowers would presumably cut operations at all of their hotels a comparable amount in order to raise cash efficiently by equalizing the marginal value of cash across properties. That would lead the estimate in column 6 to be close to zero, as we include borrower-by-month fixed effects in that column's specification. Because the estimate is in fact significantly negative, this channel does not seem to drive the main result in column 1.

Market-by-Chain-by-Month Fixed Effects

In Appendix Table A.II, we show that the baseline treatment effect is also robust to including market-by-chain-by-month fixed effects in addition to the fixed effects in columns 1–5 of Table II. These restrictive specifications identify the treatment effect by comparing treatment and control hotels in the same chain and market (e.g., two Hilton DoubleTrees in Boston), thereby exploiting less variation than the specifications in Table II. Because hotels in the same chain have similar quality standards and clientele, controlling for chain addresses many differences between treatment and control hotels that might increase the exposure of treatment hotels to the pandemic-induced drop in hotel demand. As shown in Appendix Table A.II, the estimates in columns 1–5 of Table II remain negative and significant, ranging from -0.08 to -0.12.

Alternative Treatment and Control Groups

The baseline treatment effect is also robust to alternative divisions of hotels into treatment and control groups. Appendix Table A.III reports results from our main regression under three alternative classifications. In the first two, we assign treatment status using 6- and 18-month bandwidths around February 2020 of the initially scheduled maturity date, in contrast to the 12-month bandwidth used in the baseline treatment definition. In the third, we assign treatment status using the initially scheduled month in which the loan becomes freely prepayable instead of the month in which the loan matures. In all three approaches, the estimated treatment effect remains similar to the baseline, which addresses the possibility that the baseline treatment definition yields a significant negative effect by chance.

Paycheck Protection Program

As a final robustness exercise, we show in Appendix Figure A.III that take-up rates of PPP loans are virtually identical at treated and control hotels.[22] Through PPP loans, the U.S. government provided cash incentives to business owners to continue employing their workers during the COVID crisis (Granja et al., 2022). Owners of less profitable hotels more exposed to the crisis demand shock were more likely to take up these loans, while others refrained from participating due to program costs such as reputational risks (Steiner and Tchistyi, 2024). Hence, the similar take-up rates of treated and control hotels provide further evidence that these two groups are similarly exposed to the pandemic-induced drop in hotel demand.

The similar take-up rates also speak to two alternative stories for the baseline treatment effect. One possibility is that PPP itself drives this effect because treatment borrowers have less access to the program, perhaps due to covenants in their still-to-mature debt ruling out secondary financing. If so, we would expect higher PPP take-up from control hotels, which we do not find. A second possibility is that treated borrowers have greater liquidity needs and therefore scale back hotel operations to raise cash. While this channel is plausible in principle, it would imply higher PPP take-up among treated hotels, which again we do not find.

IV.C Inputs

A key prediction of the model is that owners of treated hotels decrease output by scaling down variable inputs. We test this prediction by looking at the effect of treatment status on total ex-

[22] 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 B.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 (2024) perform a similar match for airport hotels and find that 16% received PPP credit in 2020, which lies close to the share shown in Appendix Figure A.III.

penses, labor expenses, and sales and marketing expenses during the pandemic. To measure these inputs, we rely on the yearly panel of profit and loss statements, which is available for roughly 60% of the hotels in our main sample. Given the lower-frequency nature of the annual data, we extend the sample back to 2017 to examine pre-trends.

Before analyzing expenses, we first verify that the main result shown in Figure VI—that revenues fall more for treated than control hotels at pandemic onset—continues to hold in the yearly profit and loss data. We estimate treatment effects using an annual version of equation (3), with market-by-time fixed effects and post-maturity dummies as in the specification underlying Figure VI. As shown in Panel A of Figure VIII, revenues fall more for treated than control hotels starting in 2020 in the yearly data.

In Panels B–D of Figure VIII, we show analogous estimates of treatment effects on the three expense categories. Consistent with the model, total expenses, labor expenses, and sales and marketing expenses all fall more for treated than control hotels in 2020, with a treatment magnitude of about 50 log points (40%).[23] We find no pre-trend for total expenses and labor expenses and only a small pre-trend for sales and marketing expenses, which supports the causal interpretation that a pandemic loan maturity led to a contraction in hotel expenses.

The drop in labor—a key variable input for hotels that is subject to adjustment costs—is consistent with the model's prediction that borrowers cut variable inputs specifically because of the costs of increasing them. The decline in sales and marketing expenses suggests that the owners of treated hotels intentionally reduced operations by cutting back on advertising their rooms on third-party services such as TripAdvisor, which also accords with the model.

Due to the annual frequency of the data, these results cannot show that treated borrowers reduced operations before loan renegotiations, many of which occurred in 2020. To address this limitation, we conduct a similar analysis using the monthly panel of profit and loss statements, which is available starting only in January 2020 and for a smaller set of hotels. As shown in Appendix Figure A.IV, the three expense categories decline differentially for the treated hotels in the first few months of the pandemic, which is consistent with strategic renegotiation.

[23] In Appendix Table A.IV, we report negative effects on a variety of other expense categories including room, administrative, food and beverage service, property maintenance, and reserve for capital replacement.

IV.D Profits

The model also predicts that owners of treated hotels cut operations in a way that decreases operating profits during the pandemic. To test this prediction, we re-estimate the same annual version of equation (3) using hotel profits as the outcome. We scale profits by dividing EBITDA in a given year by total baseline revenue for the hotel in 2019. As shown in Figure IX, profits decline more for treated than control hotels in 2020, as predicted by the model. The size of lost earnings is 13% of 2019 revenue for the same hotel.[24] In Appendix Figure A.IV, we show that the relative decline in profits for treated hotels happens within the first few months of the pandemic among hotels that we observe in the monthly profit and loss data.[25] Thus, the operational changes that hotel owners made in response to their looming balloon payment decreased the cash available to service debt. This pattern aligns with our model and is less consistent with explanations based on cash harvesting driven by liquidity constraints.

IV.E Role of Operating Arrangement

Given that 93% of hotels in our data are operated by brands or third-party management, one concern with our results is that borrowers—that is, hotel owners—may not be able to set the level of operations at the collateral properties. If they indeed lack this ability, our results may be spurious or driven by some alternative mechanism that does not involve a strategic choice about operational cash flows at the treated hotels.

During COVID, hotel owners likely were able to exert much greater authority over the level of operations than during normal times because of negative operating profits. As shown in Appendix Figure A.V, the average profit margin (EBITDA divided by contemporaneous revenue) was negative in the initial months of the COVID crisis among hotels in our monthly profit and loss data. Negative operating profits deplete the operator's working capital, necessitating replenishment from the owner to allow the operator to continue operating the hotel. By choosing how much to replenish this capital, the owner can effectively set the level of operations at the hotel.

[24] This estimated decline in 2020 becomes 14 p.p. in normalized profits (std. err: 2.5 p.p.) when we control for 2017 profits interacted with year fixed effects, indicating that the slight pre-trend in Figure IX does not drive the baseline estimated decline of 13 p.p. As context, our normalized profits measure has a mean of 0.34 in 2019 and 0.21 in 2020.

[25] As shown in both Figure IX and Appendix Figure A.IV, profits remain depressed for treated hotels in 2021, which may reflect the same factors outside our model noted in footnote 20 that generate the persistent drop in room revenues for treated hotels in Figure VI.

An example of this dynamic appears in a lawsuit between the owner and operator of the Marriott Wardman Park Hotel in Washington, D.C. In late 2020, the operator, Marriott Hotel Services, Inc., sued the owner, Wardman Hotel Owner, L.L.C., for failing to meet an obligation in their management agreement to inject $10 million of working capital needed to fulfill shortfalls in operational cash flow. As explained in the case documents, Wardman denied Marriott's repeated requests for additional working capital throughout early 2020, leading Marriott to temporarily close the hotel.[26] Hence, Wardman was able to set the level of operations at the hotel despite not operating the property itself.

To substantiate our assertion that owners could set the level of operations during COVID, we show that negative treatment effects on revenues and expenses continue to hold among the subset of hotels that delegate their operations. We consider that a hotel has delegated operations either if the hotel is brand-managed, or if the hotel pays a management fee in the annual profit and loss data and the management company identifier is non-empty. As shown in Appendix Figure A.VI, the treatment effects for these hotels on revenues and expenses in 2020 and 2021 remain negative and of a similar magnitude to the effects in Panels A and B of Figure VIII. In Appendix Figure A.VI, we further show that the treatment effects are even more negative for the minority of hotels that do not delegate their operations. Intuitively, owner-operators can alter operations more easily than owners who delegate—even during the COVID crisis—which may explain why the treatment effects are more negative in the absence of delegation.

V Evaluating the Mechanism

In this section, we provide evidence that strategic renegotiation drives the decline in real activity for treated hotels. First, we examine how hotel revenue evolves in the months just before and after the time of renegotiation. Second, we evaluate predictions from our model of strategic renegotiation by estimating heterogeneity in the treatment effect on revenues. Lastly, we calibrate the model to assess whether a plausible degree of lender adjustment costs can fit the data.

V.A Dynamics around Loan Modification

In our model, the crisis maturity borrower sacrifices profits during the crisis to increase the likelihood of receiving a term extension from the lender. If the extension is granted, there is no

[26] We accessed the case documents here: https://www.mdcourts.gov/sites/default/files/import/businesstech/opinions/2020/mdbt7-20.pdf.

longer any reason to depress output below the profit-maximizing level, leading the borrower to increase output at the first opportunity. In our model, this opportunity comes at $t = 2$, when uncertainty is resolved. In practice, the borrower's first opportunity to increase output may come immediately after the renegotiation is granted. Therefore, we evaluate the strategic renegotiation mechanism by examining whether hotel revenues rebound immediately after renegotiation.

To test for this rebound effect, we focus on a subset of treated hotels whose loan is modified on or after May 2020. We choose this month so that we can look at revenues three months before the renegotiation month and have those revenues be earned during the crisis, which begins in February 2020. We also drop treated hotels with an extension option included in the loan at origination because the corresponding borrowers can extend their loan term without strategic renegotiation, as discussed below. In the remaining sample, we plot average monthly room revenue by month relative to the renegotiation month, from three months before to three months after.

As shown in Figure X, average revenues rebound exactly in the month when the loan is modified. In particular, average revenues decline 30% over the three months just before modification, reaching a nadir in the month prior to modification. They then begin a steady ascent in the month of the modification that culminates in a near-full recovery by three months post-modification.[27] One confounder of this pattern is aggregate hotel demand: modifications may be more likely to occur during one of the low-points of aggregate hotel revenues shown in Figure III, which could render the results in Figure X spurious. To address this concern, we show in Appendix Figure A.IX that the pattern in Figure X remains robust in a regression framework that absorbs aggregate dynamics through our baseline set of fixed effects.

V.B Heterogeneous Effects by Strategic Incentives

According to our model, the decline in output at crisis onset should be larger when the incentive for strategic renegotiation is greater. Guided by the model, we identify four loan and property characteristics that are associated with a greater incentive for strategic renegotiation. We then test whether the decline in revenue at crisis onset is larger for hotels with these characteristics.

[27] By contrast, average revenues do not rise after foreclosures, despite falling significantly in the months leading up to lender takeover (Appendix Figure A.VII). The lack of a rebound in revenues post-foreclosure is consistent with the model assumption that lenders face adjustment costs when reviving operations at a distressed hotel. Another result consistent with this assumption is that a larger initial drop in revenue predicts an increased likelihood of a loan modification, which we show in Appendix Figure A.VIII.

To conduct this test for each characteristic, we enrich the regression specification in equation (2) with time-varying controls for the characteristic as well as with a interaction term between the characteristic and the treatment effect:

$$\begin{aligned}\log(Revenue_{imt}) = \alpha_i + \delta_{mt} + \psi_0 X'_{it} \\ + \beta_0 \cdot PandemicMaturity_i \times Post_t \\ + \beta_1 \cdot PandemicMaturity_i \times Post_t \times Characteristic_i \\ + \sum_{\tau=\underline{t}}^{\tau=\overline{t}} \left[\lambda_\tau \times Characteristic_i \times \mathbb{1}_{t=\tau} \right] + \epsilon_{it}.\end{aligned} \tag{4}$$

We test the model by examining whether the coefficient on the triple interaction term, β_1, is negative. Importantly, by including time-varying controls for the characteristic, we address the possibility that hotels with that characteristic differ in a way that affects their revenue during the crisis for reasons unrelated to scheduled debt maturity. As with treatment status, we measure loan characteristics as of origination to avoid bias that could arise from modifications to loan characteristics over time. The results from this analysis appear in Table III.

High Leverage. The first characteristic we consider is borrower leverage. Proposition 3 predicts that strategic renegotiation occurs only if the debt for which the firm serves as collateral is sufficiently large. In our setting, we measure the size of the debt using the hotel's LTV ratio. As explained in Section II.A, we calculate LTV using both the securitized loan appearing in Trepp as well as non-securitized, junior liens appearing in RCA. To capture whether the LTV ratio is large, we create a dummy variable, $HighLTV_i$, indicating whether the ratio lies in the top third of the distribution across hotels in the estimation sample summarized in Table I, which corresponds to a threshold of 80%.

As shown in Column 1 of Table III, the coefficient on the triple interaction term with the $HighLTV_i$ indicator is negative and significant, as predicted by our model. Furthermore, highly-levered hotels account for essentially all of the baseline treatment effect, which is apparent from the fact that the coefficient on $PandemicMaturity_i \times Post_t$ becomes close to zero in this specification.[28] The key role that highly-levered hotels have in accounting for the main effect accords

[28] Appendix Figure A.X performs a similar exercise using our event study research design. Specifically, we re-estimate a variant of equation (3) that, like equation (4), 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

with Proposition 3, which predicts no strategic renegotiation at firms with low levels of debt.

Extension Options. The second characteristic we analyze is whether the loan lacks an extension option, which we denote $NoExtensionOption_i$. Many CMBS loans come with such options written into the initial contract, which allow borrowers to extend the term of the loan without a formal modification. While executing such an option is not costless (An, Cordell and Smith, 2023), it facilitates extending the term of the loan by removing the need to renegotiate the initial terms of the loan with the lender. Many treatment borrowers did execute such options during the COVID crisis, with such cases accounting for over 90% of the non-CREFC modifications in Figure IV. Given the ability to extend the loan without a full-blown modification, we consider treated borrowers with extension options to be closer to the model's non-crisis maturity borrower than to the crisis maturity borrower. Hence, we predict a stronger treatment effect when this option is absent and an effect close to 0 when it is present.

As shown in Column 2 of Table III, this prediction bears out in the data. While the coefficient on the triple interaction with $NoExtensionOption_i$ is negative and significant, the coefficient on $PandemicMaturity_i \times Post_t$ is close to 0, implying no treatment effect on average among hotels with an extension option included at origination.

Cash Sweeps and Short-term Operating Profits. The third characteristic we consider is the presence of a cash sweep provision in the loan contract, also known as a lockbox. These provisions, which apply to 58% of the hotels in our sample, require cash flows from the collateral property to be deposited directly into an account controlled by the lender when certain conditions are met. The precise terms of cash sweep provisions vary across loans, so we simply define an indicator for whether any lockbox arrangement exists in the loan, which we call $HasCashSweep_i$, and use that as our characteristic.

While we do not explicitly analyze lockbox arrangements in our model, we view them as being likely to increase the incentive to cut operations strategically because they limit the borrower's access to cash flows during the crisis. In particular, a lockbox would reduce the sensitivity of a defaulting borrower's value function, V^{df}, to profits at $t = 1$, $\pi(L_1, p^l)$, making it optimal to cut labor, L_1, even further conditional on default. Hence, we predict a more negative treatment

top one-third of the LTV distribution. The results shown in Appendix Figure A.X imply that the dynamic effect is again driven by treated hotels in the top one-third of the LTV distribution.

effect among hotels with cash sweep provisions in their loans at origination.

As shown in Column 3 of Table III, the coefficient on the triple interaction with the indicator $HasCashSweep_i$ is negative and significant, in line with this prediction. Interestingly, a negative treatment effect persists among hotels that lack a lockbox provision, as shown by the coefficient on $PandemicMaturity_i \times Post_t$. This result is in line with the model, in which even crisis maturity borrowers with full access to profits at $t = 1$ choose to cut operations strategically.

Proxies for Lender Adjustment Costs. The fourth characteristic we analyze is the expected ease with which the lender can adjust operations at the hotel in the event of a foreclosure. As predicted by Proposition 4, strategic cuts to operations become more severe when borrowers are facing lenders with lower expected adjustment costs. Strategic default also becomes (weakly) less common, implying that the combined effect is ambiguous. Rather than try to isolate each channel, we measure the combined effect in the data by including three proxies for ease-of-adjustment as characteristics in equation (4).

The three proxies we consider are: (1) the number of hotels in our data from the same chain as hotel i, $HotelsPerChain_i$; (2) the number of distinct hotel chains assigned to hotel i's special servicer, $ChainsPerServicer_i$; and (3) the share of hotels from the same chain as hotel i among hotels with the same special servicer as hotel i, $ServicerChainShare_i$. $HotelsPerChain_i$ maps almost exactly to the measure of asset redeployability used by Benmelech and Bergman (2008) in the context of airlines. Hotels with a high value of $HotelsPerChain_i$ are relatively common, and so it seems plausible that they are easier for the average lender to manage. The other two proxies rely on variation across special servicers, which are the empirical counterpart to lenders in the model.[29] Servicers with a high value of $ChainsPerServicer_i$ have experience managing various types of hotels, and so they would incur a smaller adjustment cost when taking over any given hotel. Conversely, the $ServicerChainShare_i$ proxy captures how much experience a servicer has with hotels similar to the particular hotel i.

As shown in Columns 4–6 of Table III, the coefficients on the triple interactions with each proxy are negative and significant. For ease of interpretation, we normalize each proxy measure

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

to have a mean of zero and standard deviation of one. Quantitatively, the results show that a one standard deviation increase in each proxy for ease of adjustment amplifies the negative treatment effect on revenues between 11 and 14 log points. Hence, the combined effect of the lender's ease of adjustment on revenues is negative: while increasing the ease of adjustment encourages some borrowers to pay off their loan and to not cut operations, it leads to an even deeper cut in operations among borrowers that, instead, choose to strategically default. The widespread default among treated borrowers is consistent with the relatively small role played by the former channel during this episode.

Summarizing, Table III implies substantial heterogeneity in the real effects of debt rollover. The broad pattern implied by the estimates supports the basic intuition of the strategic renegotiation mechanism.

V.C Model Calibration

Our empirical results indicate that owners of hotels collateralizing debt that was scheduled to mature at the beginning of the pandemic scaled back operations in a manner that is qualitatively consistent with the predictions of the model of strategic renegotiation presented in Section I. In this section, we calibrate that model to assess whether the strategic renegotiation mechanism is a quantitatively plausible explanation for our empirical results. While our model is not designed for precise quantitative statements, this exercise can still inform whether a plausible degree of adjustment costs can explain the results we find empirically.

Parameter values. As we show in Appendix C, calculating the outcomes of interest in our model necessitates calibrating only the following combinations of parameters: α, r, q, p^l/p^h, and the cumulative distribution function of γ/w. That is, the overall level of output prices does not affect our results; only the drop in prices during the pandemic matters. Similarly, the results do not depend on the overall level of labor costs; only the ratio of potential adjustment costs to wages matters. We directly calibrate α, r, q, and p^l/p^h as described briefly below. We then select the CDF of γ/w so that our model matches the data.

We set $\alpha = 0.7$ based on the average ratio of variable expenses to revenue in our profit and loss data from 2017 to 2019, which is 0.73; this ratio equals α given the Cobb-Douglas production function. We use a discount rate of $r = 0.1$, in line with discount rates used to value unlevered hotel investments in 2019 (hotelAVE, 2019). We set $p^l/p^h = 0.8$, which is based approximately on a 23% drop in room rates observed in STR's national hotel data from 2019 to 2020. Finally, we set $q = 0.84$, implying an 84% chance that prices fully rebound in period 2. We calibrate q to match a 12.5% drop in unlevered hotel values at the onset of the pandemic, as estimated by the real estate research firm Green Street Advisors in April of 2020 (Hartwich, Lumb and Hemnani, 2020).[30]

Fitting the data. To match the data, we target the average drop in log revenues at pandemic onset for crisis-maturity borrowers relative to non-crisis-maturity borrowers, conditional on staying open ($L_1 > 0$). This comparison corresponds to the main treatment effect on log revenues estimated in Section IV. We target the average treatment effect in April and May of 2020 shown in Figure VI, which is approximately −0.4.

To average across borrowers in the model, we must specify a distribution of debt levels, D. We make a simple assumption that D is uniformly distributed between the worst-case value of the firm, $(1+r)\pi^*(p^l)/r$, and the debt threshold at which foreclosure occurs with probability 1, D^{**}. Given the parameters used, this assumption corresponds to a minimum pre-crisis LTV of 0.48 and a maximum of 0.94. Although we use this uniform distribution for simplicity and not to match the data, it seems broadly reasonable given the summary statistics on LTV shown in Table I.

We select the CDF of γ/w in order to match the targeted treatment effect. To do so, we make a functional form assumption that $G(\cdot)$, the CDF of γ, is an exponential distribution. The CDF of γ/w is hence determined by its median, which we select so that the model's predicted treatment effect equals −0.4. Computational details of how this is done appear in Appendix C.

Results. The median value we calculate for γ/w is 5.0, which is close to the positive estimates of labor adjustment costs between 1 and 5 in the literature as calculated by Bloom (2009). To give a sense of the magnitude of this median, we calculate how much value is lost due to these adjustment costs for a foreclosing lender who revives the firm starting in period 2 with the realization of the good state ($p = p^h$). If the borrower had cut labor 50 log points below the static optimum at time 1—corresponding to the treatment effect on labor in Figure VIII—the lender loses 9% of the pre-crisis value of the firm due to adjustment costs; 4% arises because the static optimum at

[30] Green Street Advisors estimated declines of 10% and 15% at different points in April, so we use the average. In the model, this decline is $1-((r+1-q)\pi^*(p^l)+q\pi^*(p^h))/((1+r)\pi^*(p^h))$; setting this to 12.5% pins down q.

time 1 is less than the static optimum at time 2, and 5% arises because the borrower cut labor an additional 50 log points at time 1. These discounts are well within the 40–45% foreclosure discount that Singh (2020, 2021) estimates for hotels. Hence, the distribution of adjustment costs used to fit our empirical results on strategic renegotiation seems broadly consistent with prior work on labor adjustment costs and hotel foreclosure costs.

In Figure XI, we plot revenues for crisis-maturity borrowers at time 1 relative to those for non-crisis-maturity borrowers, across different levels of debt. We normalize debt by the pre-crisis value of the firm to express debt in terms of pre-crisis LTV. Below D^*—corresponding here to an LTV of 0.77—the revenue for these two groups of borrowers is the same, with a negative treatment effect appearing above that. This pattern exactly matches the estimated non-effect for hotels with low leverage in Table III, which, incidentally, are defined by a similar LTV cutoff of 0.8. Interestingly, the treatment effect is also non-monotnic: within borrowers who default, those with higher LTVs shade labor less. We also illustrate Proposition 4 by plotting results for an exponential distribution of γ/w whose median is double that of the baseline.[31] As predicted by Proposition 4, default becomes more common as adjustment costs increase because D^* decreases. However, the strategic drop in revenues becomes less severe for each debt level where default occurs in the baseline.

Table IV shows that the baseline calibration aligns with other model outcomes as well. Among firms that remain open, the treatment effect on log labor is −0.57, close to the −0.47 estimate for 2020 in Figure VIII. Normalized profits also decline, though less so than in the data (−0.02 versus −0.13).[32] The model produces a 10% foreclosure rate conditional on default, consistent with the rarity shown in Panel B of Figure IV. Hence, large strategic cuts to labor arise in our model despite infrequent foreclosure, and, in fact, prevent it: without strategic labor cuts, the foreclosure rate rises to 50% in our model. Overall, the model offers a strong quantitative fit to the data, which is remarkable given its parsimony.

To explore sensitivity to the distribution of adjustment costs, we also show outcomes in the alternative calibrations with a higher and lower median values of γ/w. The overall treatment effect on revenues is similar across these calibrations, indicating that the quantitative plausibil-

[31] Proposition 4 holds in the calibration because an exponential distribution satisfies the condition on G in that proposition.

[32] The smaller effect in the model may reflect that normalized profits in 2020 were higher in the data than in the model's period 1: the empirical mean is 0.24, compared to 0.14 at the model's static optimum. This difference may arise from factors not captured in the model, such as wage declines.

ity of our model does not hinge on the exact distribution of adjustment costs we choose. This treatment effect becomes larger as the distribution of adjustment costs shifts towards 0, consistent with what we find in Table III. This result reinforces that the model does not require large adjustment costs to fit the data.

Lastly, we consider a counterfactual without strategic renegotiation, in which $\rho(\cdot)$ is constant instead of a function of labor in period 1, so that the probability of foreclosure is exogenous and fixed. We set this exogenous probability equal to the endogenous probability in the baseline, 0.1. In this counterfactual, the strategic effects on operations go away, as there is no reason to reduce labor below the static optimum. We also find that the threshold for default rises from 0.77 to 0.87, meaning that default becomes less common. Hence, strategic renegotiation leads to more default than would occur given the same observed probability of foreclosure conditional on default.

VI Conclusion

This paper analyzes a novel mechanism in which borrowers manipulate operations to strategically renegotiate debt that matures in an economic crisis. We formalize this mechanism in a model. Then, we provide empirical evidence from the hotel sector during the COVID-19 economic crisis. 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. Consistent with the model, these effects are larger when the hotel is highly-levered and when the lender can more easily take over the asset.

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

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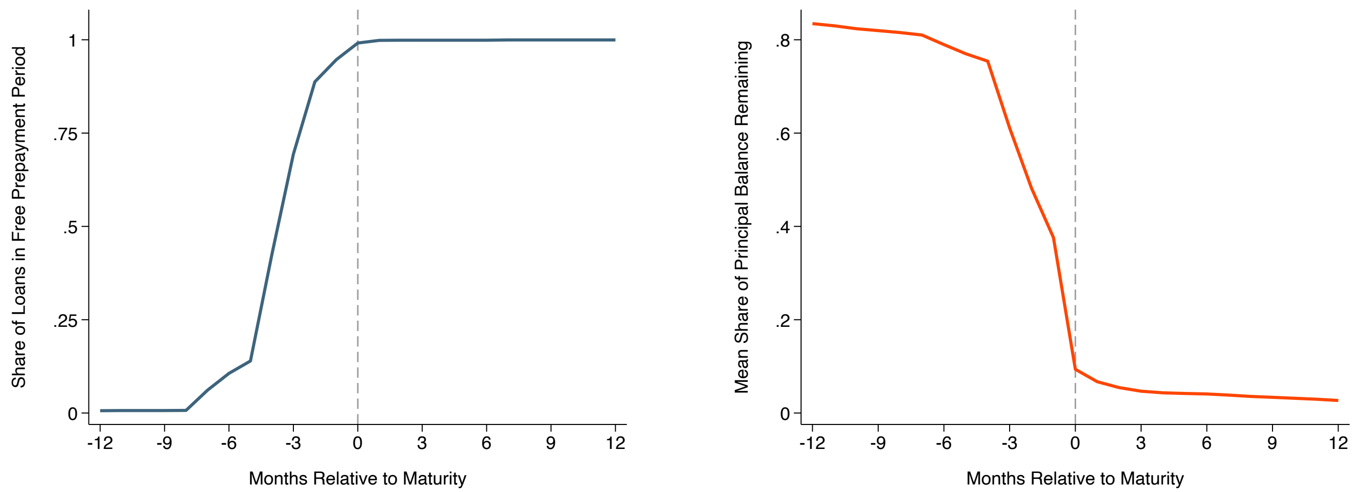


Panel A. Loans in Free Prepayment

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 2019. The sample consists of all hotel loans in the Trepp dataset with the modal loan term (10 years) to ensure that the horizontal axis consistently measures a loan's age. (SOURCE: Trepp)

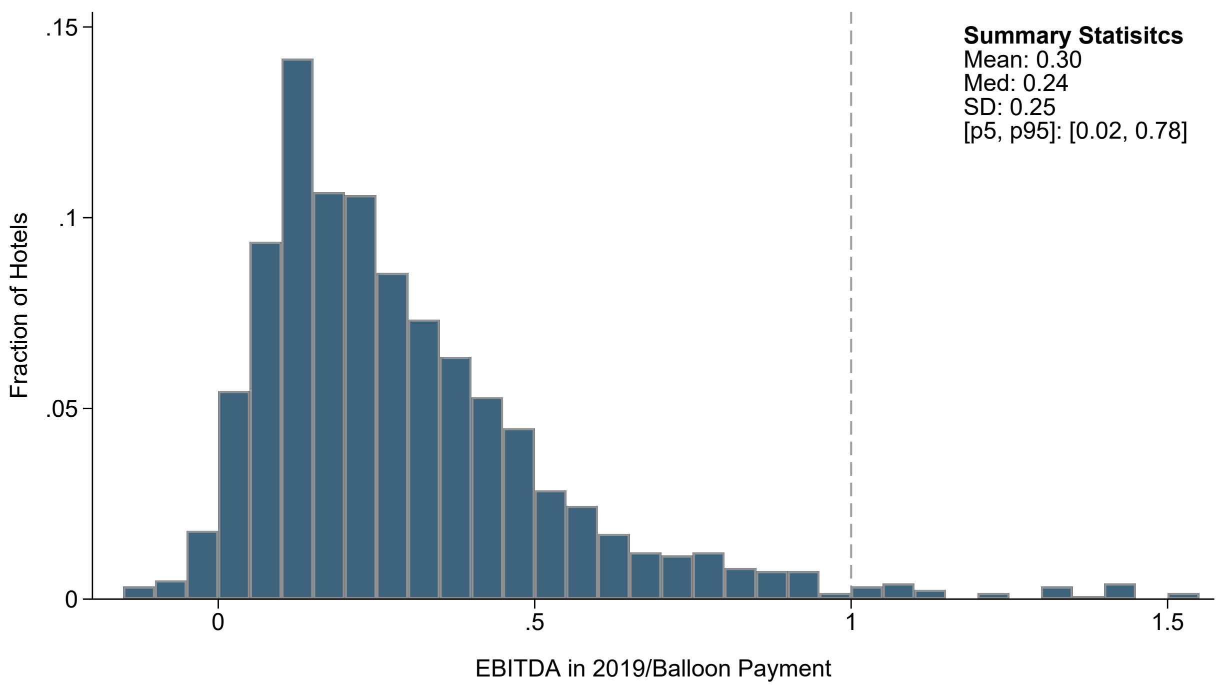


FIGURE II
Operating Profits Relative to Scheduled Balloon Payment.

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

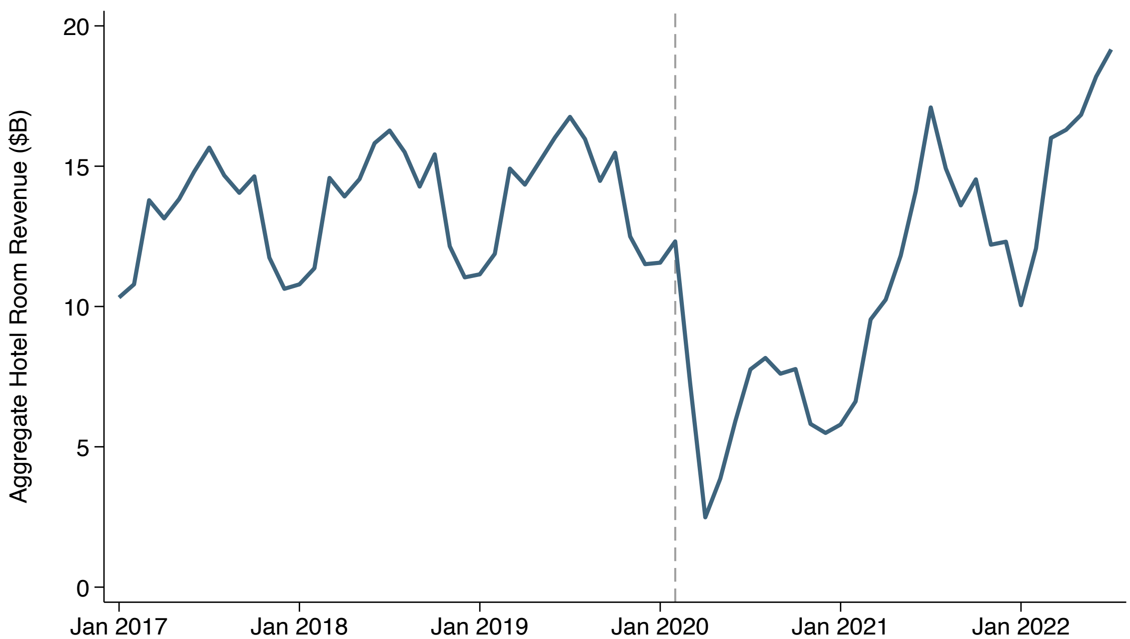
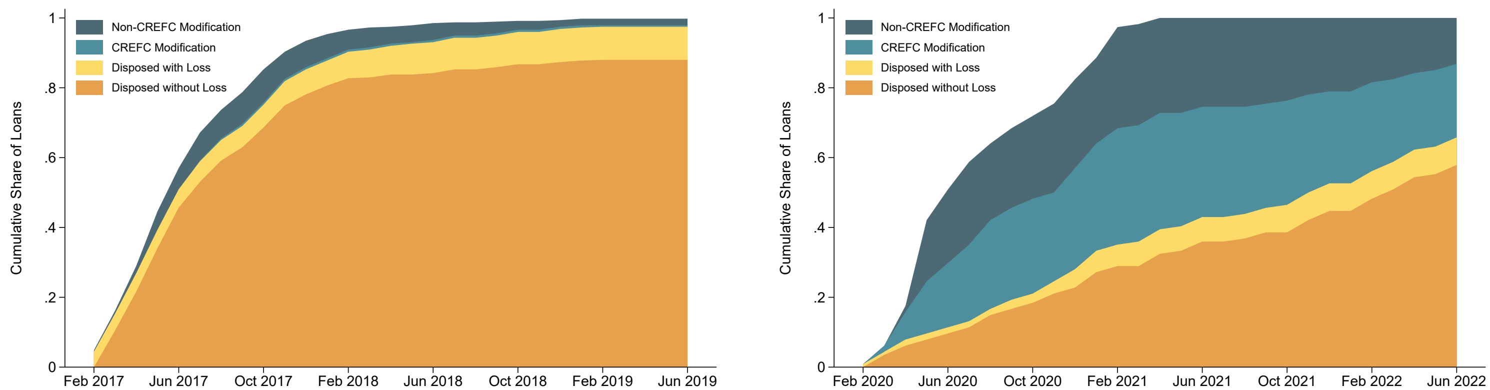


FIGURE III
Aggregate Monthly Revenues for U.S. Hotels.

NOTE.—This figure plots aggregate monthly room revenue for all hotels in STR's universe, of which our analysis sample is a subset. The STR universe comprises roughly 60% of all U.S. hotels and 76% of U.S. hotel rooms. The vertically dashed grey line marks the beginning of the pandemic, which we date to February 2020. (SOURCE: STR, LLC)



Panel A. Placebo Period *Panel B. Treatment Period*

FIGURE IV
Loan Resolution.

NOTE.— This figure plots the share of hotel loans with either a modification or a known disposition each month. The sample begins with all loans with an initially scheduled maturity from February 2017 to February 2018 in Panel A and from February 2020 to February 2021 in Panel B. In both panels, we then restrict the sample to loans with a positive balance and no prior modification as of the first month in the panel. Modifications are identified using indicators from the Commercial Real Estate Finance Council (CREFC), which standardizes CMBS servicing. A loan is labeled as having a "Non-CREFC Modification" if its maturity date is extended in a given month. A "CREFC Modification" occurs when the CREFC modification field becomes non-empty. A loan is categorized as "Disposed with Loss" if it has a zero balance, a non-empty disposition field, and the disposition is labeled as "Loss," "Impaired," or a similar variant. A loan is "Disposed without Loss" if it has a zero balance, a non-empty disposition field, and the disposition is labeled as "Paid," "Prepaid," or a similar term. We also infer that a loan has paid off if its balance reaches zero and it either makes an unscheduled principal payment that equals or exceeds the prior month's balance, or it was current on debt service for the previous three months. Loans may move between categories over time. The categories are mutually exclusive but do not necessarily sum to one. If a loan remains uncategorized, we assign it to "Non-CREFC Modification" if Trepp's internal modification description is non-empty, and then to "Disposed with Loss" if Trepp's delinquency notes indicate foreclosure in process, even without formal disposition. (SOURCE: Trepp)

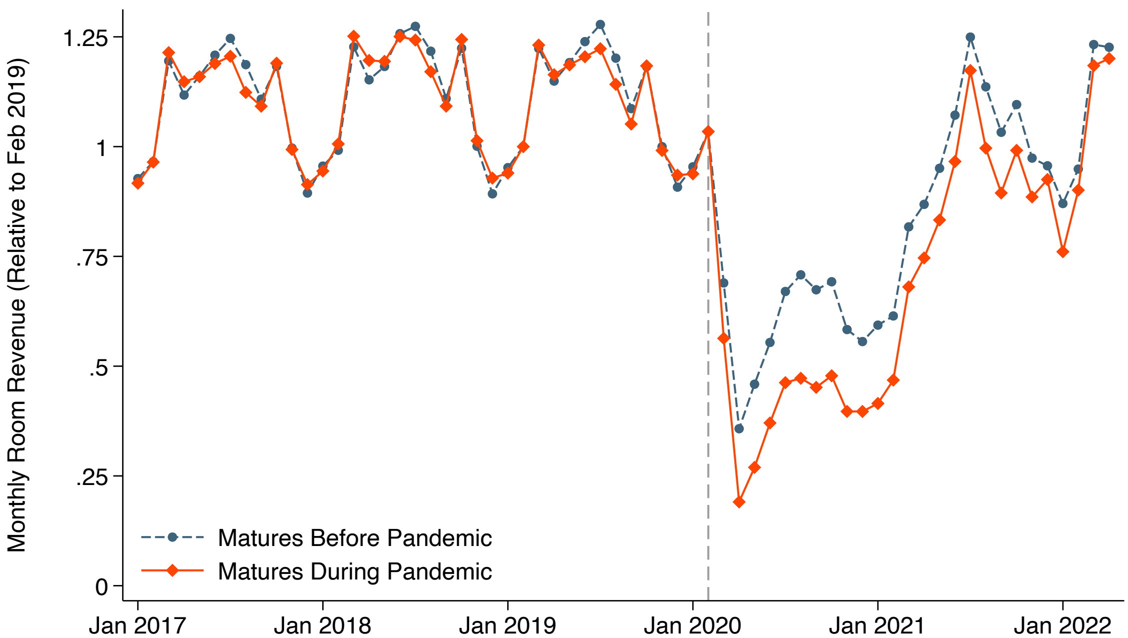


FIGURE V
Monthly Hotel Room Revenues by Scheduled Loan Maturity at Origination.

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

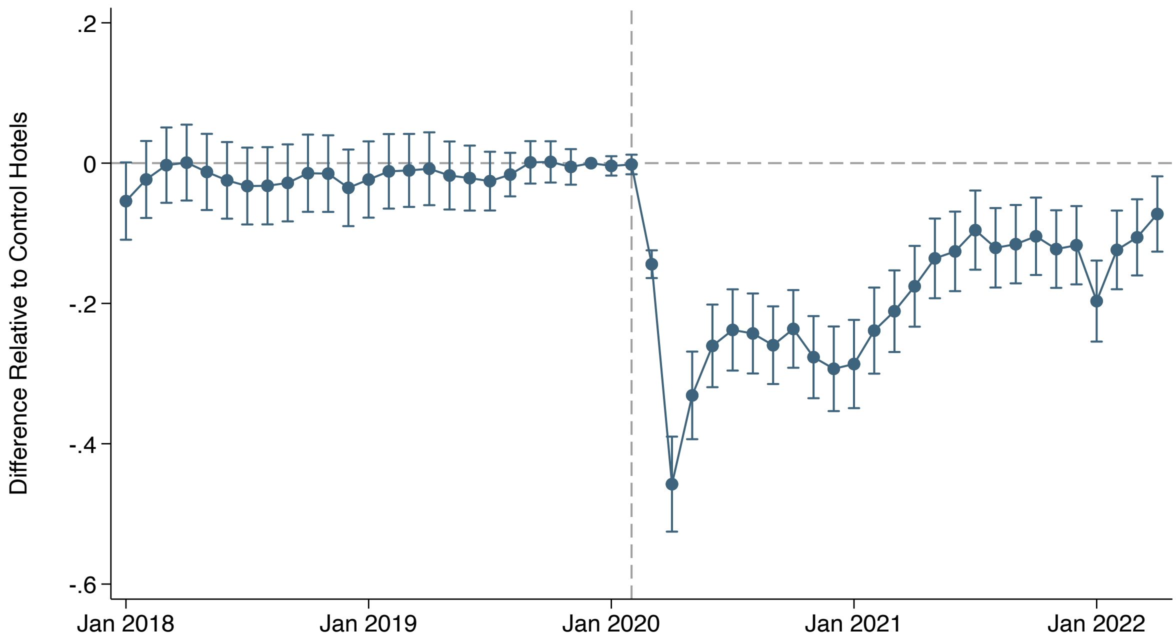


FIGURE VI
Effect of Pandemic Maturity on Hotel Room Revenues.

NOTE.—This figure displays estimates of the time-varying coefficients β_τ from the event study in equation (3), where X_{it}' consists of a post-maturity fixed effect and market-by-month fixed effects. Brackets are 95% confidence intervals. (SOURCE: STR, LLC and Trepp)

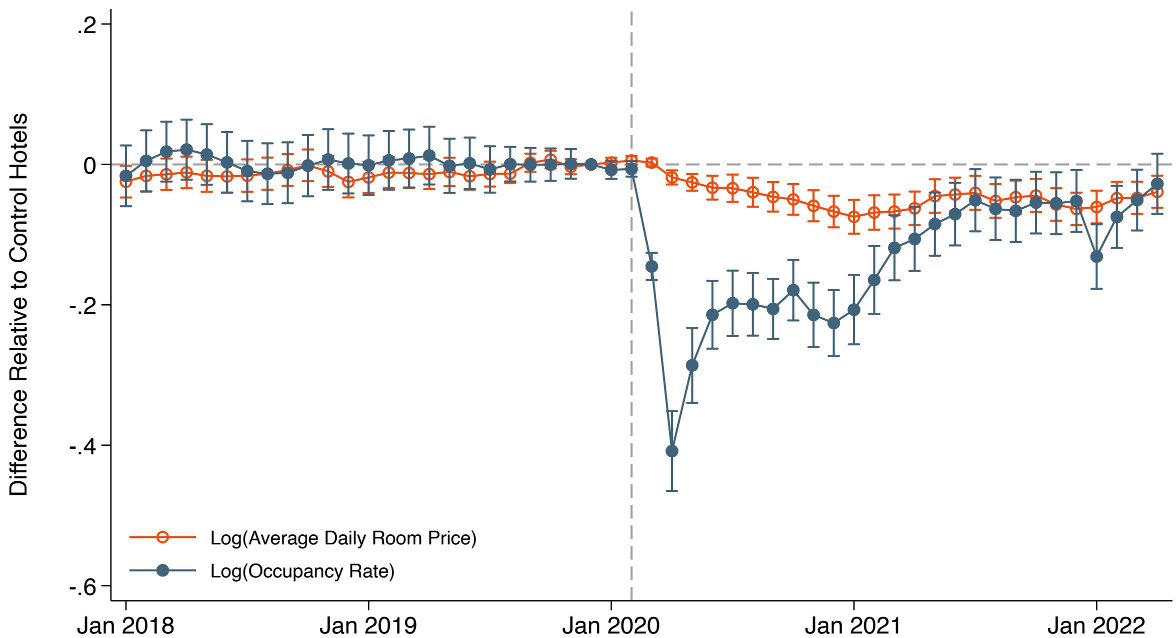
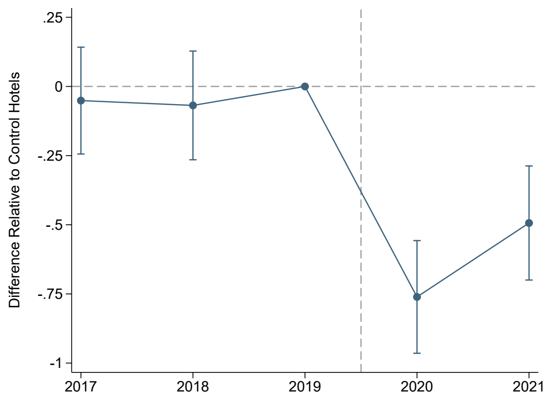


FIGURE VII
Effect of Pandemic Maturity on Hotel Occupancy and Prices.

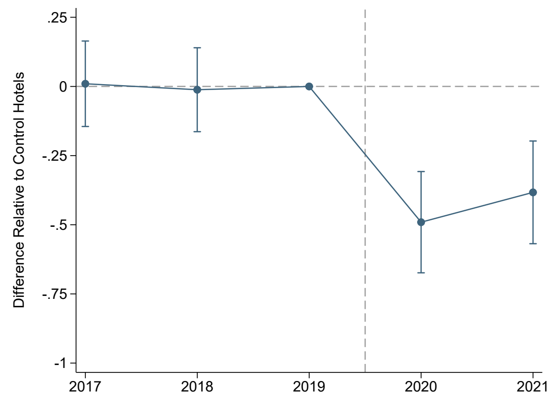
NOTE.—This figure decomposes the effect on revenue from Figure VI into the part that reflects reduced quantity (i.e., occupancy rate) and the part that reflects a lower room price. Explicitly, the figure summarizes the estimates from the same regression equation as in Figure VI after replacing the outcome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

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

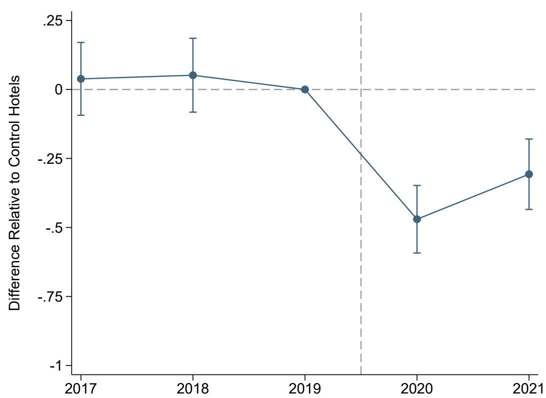
so the sum of the estimated coefficients each month in this figure approximately equals the estimated coefficient for the same month in Figure VI. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)



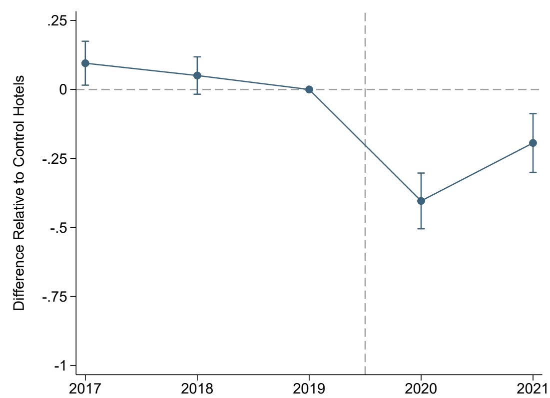
Panel A. Total Revenues



Panel B. Total Expenses



Panel C. Labor Expenses



Panel D. Sales and Marketing Expenses

FIGURE VIII

Effect of Pandemic Maturity on Hotel Revenues and Expenses.

NOTE.—This figure estimates a variant of equation (3) 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)

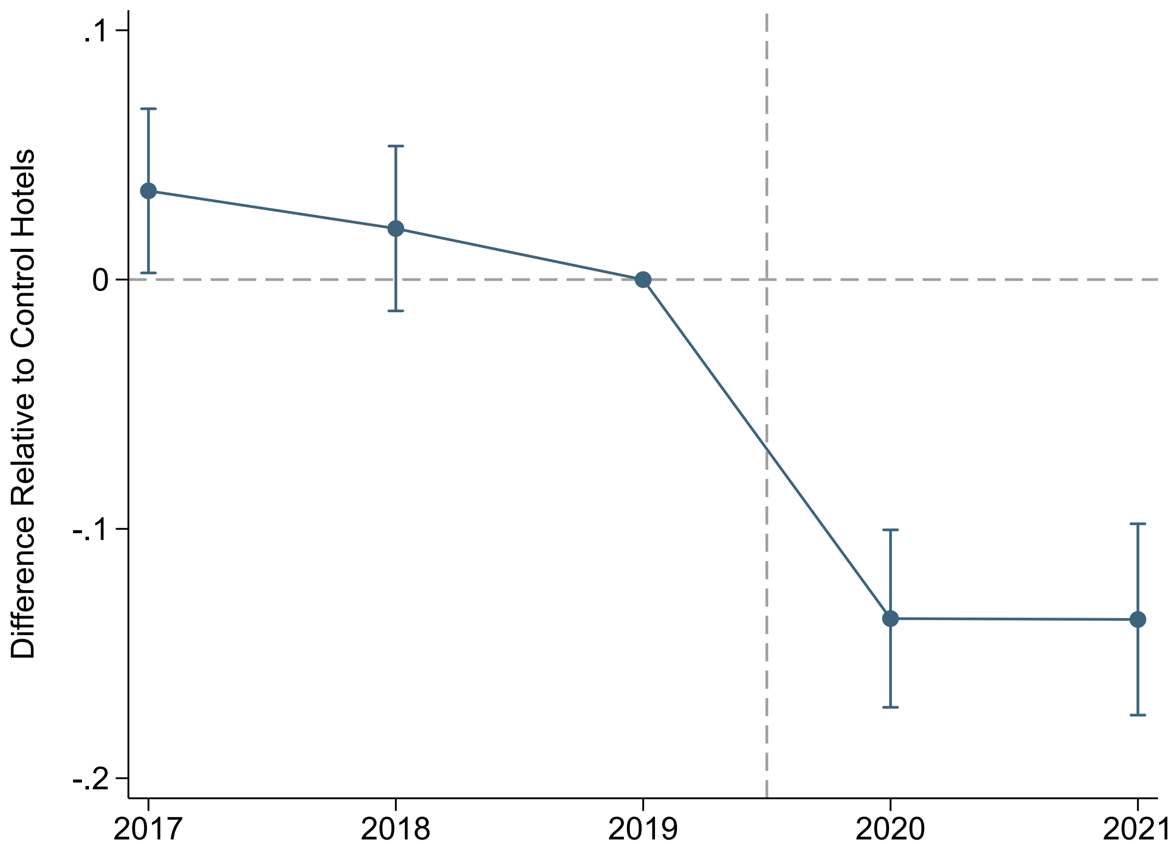


FIGURE IX
Effect of Pandemic Maturity on Hotel Operating Profits.

NOTE.—This figure estimates a variant of equation (3) that assesses the effect of a pandemic maturity on operating profits. The regression equation is the same as in Figure VIII except that the outcome variable equals the hotel's annual operating profit, measured as the ratio of EBITDA in a given year to total revenue in a base year (2019). The remaining notes are the same as in Figure VIII. (SOURCE: STR, LLC and Trepp)

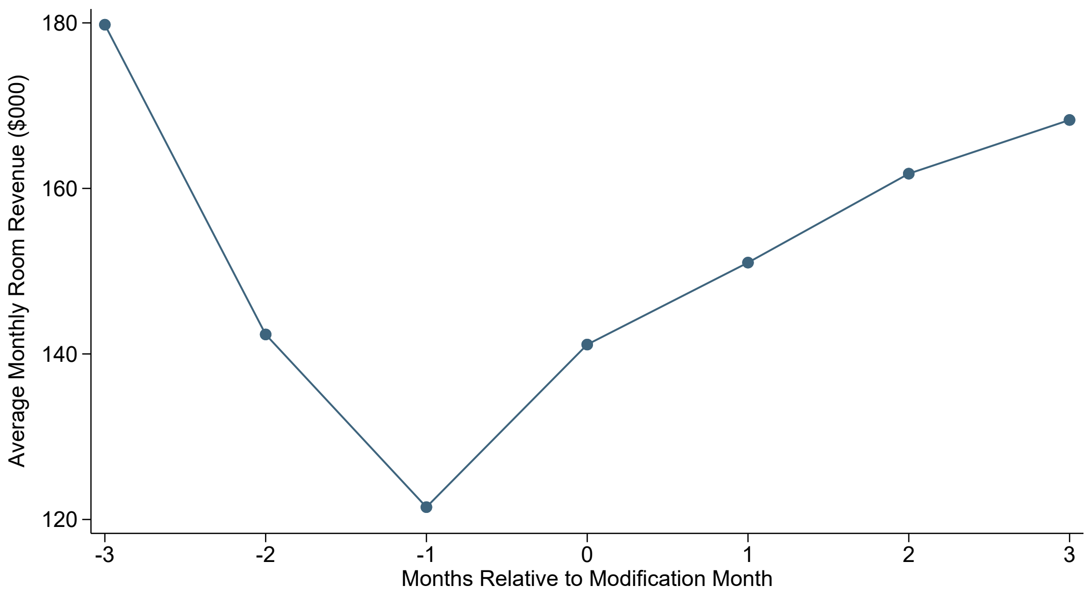


FIGURE X
Revenue around Loan Modification.

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

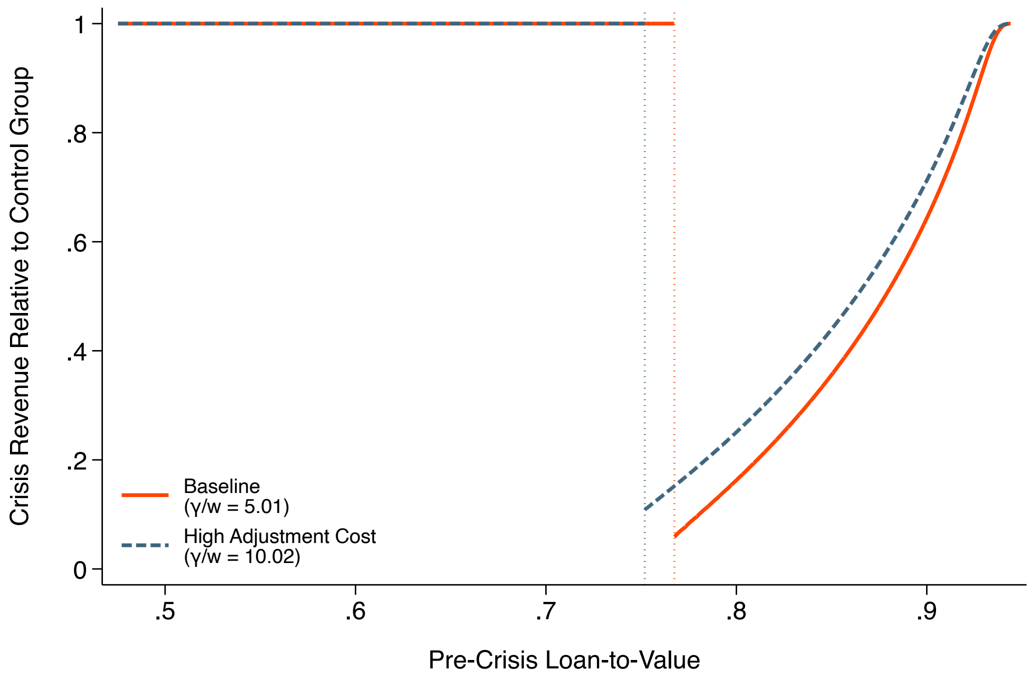


FIGURE XI

Model-Implied Revenue in the Crisis as a Function of LTV.

NOTE.—This figure plots the model-implied relation between revenue at treated borrowers relative to control borrowers during the crisis, shown on the vertical axis, and the borrower's pre-crisis loan-to-value ratio, shown on the horizontal axis. Relative revenue is calculated based on the calibration of the model described in Section V.C and two different distributions of the ratio of adjustment costs to wages, γ/w. Both distributions are exponential, but they differ in their value of the scale parameter. In the Baseline distribution, the median value of γ/w is 5.01. In the High Adjustment Cost distribution, the median value of γ/w is 10.02. (SOURCE: Author calculations).

TABLE I
DESCRIPTIVE STATISTICS

	Pre-Pandemic Maturity		Pandemic Maturity	
	Mean	Std. Dev.	Mean	Std. Dev.
Panel A. 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)
Panel B. 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	—
Panel C. Loan Characteristics at Origination				
Log(Loan Amount)	20.58	(1.36)	19.36	(1.39)
Loan-to-Value Ratio (LTV)	0.78	(0.09)	0.59	(0.20)
Debt-Service Coverage Ratio (DSCR)	3.78	(0.89)	3.49	(1.33)
Loan Term (Months)	68.02	(27.59)	56.20	(25.37)
Balloon Flag	1.00	—	0.99	—
Number of Hotels	1,655		955	

NOTE.—This table summarizes hotels based on whether the hotel has a loan with original maturity date from February 2019 through January 2020 (Pre-Pandemic Maturity) or from February 2020 through February 2021 (Pandemic Maturity). The unit of observation in all panels is the hotel. In Panel A, we summarize hotel performance observed in May 2019. In Panel B, we summarize indicator variables for whether the hotel's location is close to an airport, a resort, urban, suburban, or close to the highway. In Panel C, we summarize characteristics of the hotel's loan, all measured as of origination. The debt service coverage ratio is the ratio of debt service to operating income. Balloon means that the loan has a balloon amortization. Data in Panel C are from the Trepp dataset, with the LTV ratios modified to account for second-liens observed in the RCA dataset. Data in Panels A and B are from the STR performance and cross-sectional datasets, respectively. Additional details are in Section II.A and Appendix B. (SOURCE: STR, LLC, Trepp, and RCA).

TABLE II

EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES

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

NOTE.—This table shows estimates of equation (2), 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

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

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

TABLE III
Evaluating the Model: Heterogeneity in the Effect on Hotel Revenues

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

Note.—This table shows estimates of a variant of equation (2) 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 (2) after interacting the treatment variable with characteristics of the loan, in columns (1)–(3), of the hotel, in column (4), and of the loan's special servicer, in columns (5)–(6). Explicitly, the regression equation is

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

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

TABLE IV
MODEL CALIBRATION

	Data	Model			
		Low γ/w	Baseline γ/w	High γ/w	Exogenous Foreclosure Rate
Panel A. Means across firms					
$\Delta \log \text{revenue}$	−0.40	−0.41	−0.40	−0.37	0.00
$\Delta \log \text{labor}$	−0.47	−0.59	−0.57	−0.53	0.00
$\Delta \text{profits}/\text{revenue}_0$	−0.13	−0.03	−0.02	−0.02	0.00
Pr(foreclosure | default)	0.11	0.10	0.10	0.08	0.10
Panel B. Constants across firms					
Median γ/w	–	1.00	5.01	10.02	–
Min. default LTV	–	0.81	0.77	0.75	0.87

NOTE.—This table summarizes the calibration from Section V.C. The leftmost column summarizes statistics from the data: $\Delta \log \text{revenue} = -0.40$ comes from the estimated treatment effect for April and May 2020 in Figure VI; $\Delta \log \text{labor} = -0.47$ and $\Delta \text{profits}/\text{revenue}_0 = -0.13$ come from the estimated treatment effects for 2020 in Figure VIII and Figure IX, respectively; and Pr(foreclosure | default) = 0.11 comes from the share of loans with an initially scheduled maturity from February 2020 through February 2021 that were disposed with loss as of June 2022, based on the same definition as in Figure IV, conditional on still having a positive balance after the loan's initially scheduled maturity date. In Panel A, the changes in revenue, labor, and profits are calculated across crisis maturity borrowers relative to the equivalent change for non-crisis maturity borrowers. The middle three columns summarize model-implied statistics for different distributions of the ratio of adjustment costs to wages, γ/w. All of the distributions are exponential, but they differ in the scale parameter. The median value of γ/w in each distribution is summarized in Panel B. Also summarized in Panel B is the minimum LTV thresholds at which the firm defaults, D^*. The rightmost column summarizes model-implied statistics under a fixed conditional foreclosure rate of 10%, so that $\rho(\cdot)$ is a constant (SOURCE: Author calculations, STR, LLC, and Trepp).

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A Proofs

A.A Proposition 1

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

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

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

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

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:

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

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

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

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

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

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

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

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

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

Applying this bound iteratively back to X_0 yields:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

while the value of forbearance has the following limit:

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

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

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

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

A.B Proposition 2

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

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

where

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

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

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

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

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

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

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

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

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

This upper bound coincides with $h(L_1)$, which equals 0. Therefore, $V^{fc}(L_1, \gamma) - V^{fb}(L_1, \gamma) < 0$ for all $\gamma > 0$, which implies that $\rho(L_1) = 1$. By continuity (which holds for $\rho(\cdot)$ as stated in

Proposition 1), there exists $\epsilon > 0$ such that $L_1 + \epsilon < L^*(p^l)$, $h(L_1 + \epsilon) > 0$, and $\rho(L_1 + \epsilon) > 0$. It follows that $f(L_1 + \epsilon) > 0$, which proves the desired claim.

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

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

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

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

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

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

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

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

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

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

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

It follows that

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

It follows that:

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

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

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

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

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

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

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

A.C Proposition 4

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

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

The first inequality follows because the baseline distribution of γ, G, first-order stochastic dominates the new distribution, G_a. The second inequality follows from the optimality of L^*_1. This sequence of inequalities implies that $V^{df}_a(D^*) - V^{po}_a(D^*) \leq 0$, which implies that $D^*_a \geq D^*$ given that $V^{df}_a(D) - V^{po}(D)$ strictly increases, as shown in the proof of Proposition 2.

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

We now prove the next claim, that $L^*_{1,a} < L^*_1$ in the strategic default region as long as $L^*_1 > 0$. We first prove a lemma that builds on results from the proof of Proposition 2.

Lemma 2. *If $D \in (D^*, D^{**})$, then at any positive optimum level of operations, $L^*_1 > 0$, $\rho(L^*_1) \in (0, 1)$.*

Proof. In the proof of Proposition 2, we showed that when $D \in (D^*, D^{**})$, the value of defaulting is always positive at an optimum level of operations: $f(L^*_1) = \rho(L^*_1)h(L^*_1) > 0$. Therefore, $\rho(L^*_1) > 0$. Here, we show by means of a contradiction that $\rho(L^*_1) < 1$ as well. Suppose $\rho(L^*_1) = 1$. Because $L^*_1 > 0$, this equality implies that $V^{fc}(L^*_1, 0) \leq V^{fb}(L^*_1, 0)$. If $V^{fc}(L^*_1, 0) < V^{fb}(L^*_1, 0)$, then by continuity there exists $\epsilon > 0$ such that $L^*_1 + \epsilon \leq L^*_1(p^l)$ and $V^{fc}(L^*_1 + \epsilon, 0) \leq V^{fb}(L^*_1 + \epsilon, 0)$, implying $\rho(L^*_1 + \epsilon) = 1$ and $h(L^*_1 + \epsilon) > h(L^*_1)$, which contradicts the optimality of L^*_1. Therefore, $V^{fc}(L^*_1, 0) = V^{fb}(L^*_1, 0)$. However, we showed in the proof of Proposition 2 that $V^{fc}(L_1, 0) - V^{fb}(L_1, 0) = h(L_1)$. Therefore, $h(L^*_1) = 0$, which also contradicts the optimality of L^*_1. □

To continue the proof, we transform the objective function that determines L^*_1. Before transforming the objective function, we first define a new function. Let L^{min}_1 be the smallest value at least 0 such that for all $L_1 \in [0, L_1^{min}]$, $\rho_a(L_1) = 1$. Note that $L_1^{min} < L^*(p^l)$ by Proposition 1. This threshold does not depend on a because the lower bound of the support of γ is always 0 regardless of a. We similarly define $L_{1,a}^{max}$ to be the largest value no more than $L^*(p^l)$ such that for all $L_1 \in (L_{1,a}^{max}, L^*(p^l)]$, $\rho_a(L_1) = 0$. Note that $L_{1,a}^{max} > 0$ because by Proposition 1, $\rho_a(0) = 1$. If $\rho_a(L^*(p^l)) > 0$, then $L_{1,a}^{max} = L^*(p^l)$ by the way it is defined. Hence, we have $0 \leq L_1^{min} < L_{1,a}^{max} \leq L^*(p^l)$ such that $\rho_a(L_1) \in (0,1)$ for $L_1 \in (L_1^{min}, L_{1,a}^{max})$ and such that $\rho_a(L_1)$ strictly decreases over this range, starting from a value of 1. It follows that there exists a unique increasing function $\gamma^*(L_1)$ defined on $[L_1^{min}, L_{1,a}^{max})$ giving the value of γ at which the lender is indifferent between foreclosure and forbearance; this is the solution to:

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

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

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

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

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

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

Because γ_a is a local maximum, $\tilde{f}_{11}(\gamma_a, a) < 0$. It follows that:

$$\operatorname{sgn}\left(\frac{\partial \gamma_a}{\partial a}\right) = \operatorname{sgn}(\tilde{f}_{12}(\gamma_a, a)).$$

To solve for this sign of this cross derivative, we note that:

$$\tilde{f}_2(\gamma_a, a) = -\frac{\gamma_a G'(a\gamma_a)}{1 - G(a\gamma_a)}.$$

Because $a > 0$, the condition on $G(\cdot)$ in the proposition implies that $\tilde{f}_{12}(\gamma_a, a) < 0$. Therefore:

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

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

Finally, we show that $L^*_1 > 0$ for at least some $D \in (D^*_a, D^{**}_a)$. If $L^*_1 = 0$, then the expected payoff from defaulting and setting $L_1 = 0$ must be positive, as we showed in the proof of Proposition 2 that the expected payoff from defaulting is always positive:

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

As a result,

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

Therefore, we must always have $L^*_1 > 0$ for

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

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

B Data Appendix

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

B.A STR Datasets

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

B.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 B.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 B.B below. Lastly, STR scrambles the original hotel identifier, and it returns to us four datasets with an anonymized hotel identifier (called the SHARE identifier, which is unique across datasets) and the loan identifier and loan-level variables that we initially provided to STR. We now describe these datasets and how we prepare them for our analysis.

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

B.A.2 Monthly Panel of Basic Performance

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

We aggregate the daily panel to a monthly panel by taking the sum of room revenue, number of available rooms, and number of occupied rooms. We then redefine ADR at the monthly frequency by taking the ratio of room revenue to number of occupied rooms. Similarly, we redefine the occupancy rate as the ratio of occupied rooms to available rooms. There is very little empirical within-hotel variation in the reported number of available rooms, since STR defines this variable essentially as a stock, not as a flow.[2]

STR does not have a closure field. We define a hotel as closed as follows. First, we flag whether the hotel does not report to STR within a given month. Then, for each spell of non-reporting, we calculate a hotel's occupancy in the month before it entered that spell. If the occupancy rate is less than 25%, then we define the hotel as closed during the ensuing non-reporting month. Otherwise, we define the hotel as open during the ensuing non-reporting month. Imposing a maximum occupancy threshold is important because, in the pre-pandemic period, there are several cases in which a hotel enters a non-reporting period for a short number of months with almost-full occupancy just before and just after the non-reporting spell. While, contractually, we cannot recover the identity of these hotels, we believe it is highly unlikely that such hotels actually were closed during that period. More likely, their non-reporting reflects administrative error. We choose a 25% threshold because it implies a hotel closure rate during the pandemic that matches the rate found among various industry reports. For months in which the hotel is closed, we code room revenue, room demand, and rooms available as zero, which leads to the dropping of these observations when we take the log transform of these variables. We do not re-code the occupancy rate or ADR for closed hotels because they are undefined.

B.A.3 Yearly Panel of Operating Statements

The second dataset is a yearly panel of hotel profit and loss statements from 2017 through 2021. The hotels in the operating statement data comprise a subsample of the hotels in the basic performance dataset. Over 2017 through 2021, 61% of hotels in the basic performance dataset appear in the yearly profit and loss dataset at some point. The variables in the profit and loss dataset can be grouped into the following categories:

- **Revenue by Hotel Department:** We observe total hotel revenue, revenue from rook book-

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

ings, revenue from food and beverage services, and revenue from various other hotel amenities (e.g., spa, golf).

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

B.A.4 Monthly Panel of Operating Statements

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

B.A.5 Cross-Sectional Dataset

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

- **Size and Market:** We observe the hotel's total stock of rooms as well as its "market." STR's notion of a "market" approximately corresponds to a metropolitan area. We measure size using the total number of rooms and group hotels into 5 categories following STR reporting practices (less than 75, 75–149, 150–299, 300–500, more than 500).
- **Hotel Brand and Chain:** We observe anonymized codes for the hotel's brand and chain within the brand, if applicable. Branded hotels account for 90% of the sample, and the remaining 10% are classified as "independent." The variable $HotelsPerChain_i$ used in Section V.B equals the number of hotels from the same chain as hotel i. For unbranded hotels, this variable equals one. We calculate this variable using our merged STR-Trepp dataset. Since we only observe an anonymized code for the hotel's brand, we interpret this variable as an approximation for the actual number of hotels from a given chain.
- **Hotel Management and Owner Company:** Similarly, we observe anonymized codes for the company that manages the hotel and the company that owns it, if applicable. Among branded hotels, 26% are managed by the hotel brand, and the remainder are managed either by owner directly or through a third-party management company. We classify a hotel as managed by such a third-party if it has a non-missing Management Company and pays management fees, according to the operating statement dataset. This condition applies to 91% of branded hotels that are not managed by their brand and to 90% of non-branded hotels. Otherwise, we assume it is managed by the owner directly. Individual owners are coded with an empty Owner Company. This condition applies to 50% of hotels in the sample.

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

B.B Trepp Dataset

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

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

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

- **Critical Dates:** We observe the loan's origination date, maturity date at origination, and maturity date as of month t. For loans that have reached a disposition as of June 2022, we observe the loan's disposition date. We also observe the date on which the loan makes any unscheduled principal payments, which would include the date on which the loan prepays, the date on which the loan enters into special servicing, the date on which the special servicer modifies the loan's terms, and the date on which foreclosure proceedings begin.

- **Underwriting Information:** We observe the following underwriting variables as of origination: loan size, loan-to-value ratio, and debt service coverage ratio. The debt service coverage ratio (DSCR) is the ratio of net operating income to debt service as of the most recent fiscal year.
- **Special Servicer:** We observe the name of the loan's special servicer, which is assigned at origination. We use a standard string grouping algorithm to assign different spellings of the same name to the same special servicer identifier.

  We calculate the variables $ChainsPerServicer_i$ and $ServicerChainShare_i$ using both the derived special servicer identifier and information on the chain of hotels that serve as collateral, which comes from the STR cross-sectional dataset described above. The variable $ChainsPerServicer_i$ equals the number of distinct hotel chains assigned to the loan's special servicer in our merged STR-Trepp dataset, omitting non-branded hotels. The variable $ServicerChainShare_i$ equals the share of hotels from the same chain as hotel i among all hotels with the same special servicer as i, again omitting non-branded hotels and based on the hotels in our merged STR-Trepp dataset.
- **Prepayment Penalties:** We define a loan as in prepayment lockout in month t if that month lies within the required number of lockout months from origination reported in Annex A, which Trepp supplements using third party sources. We use analogous criteria to define loans in the period during which they can prepay either with yield maintenance or a specified penalty.
- **Cash Sweeps and Extension Options:** We define a loan as having an extension option as of origination if, in the earliest month for which the loan is observed in the data, the loan has a non-empty value of the remaining-terms-to-extend. We define a loan as having a cash sweep (i.e., lockbox) as of origination if, in the earliest month for which the loan is observed in the data, the current-lockbox-status variable takes on a value other than "N". In this case, the variable $HasCashSweep_i$ equals 1. If the current-lockbox-status variable takes on the value "N" in the earliest month for which the loan is observed in the data, then the variable $HasCashSweep_i$ equals 0. If the current-lockbox-status variable is always empty, then $HasCashSweep_i$ is undefined. Both the remaining-terms-to-extend and the current-lockbox-status variables come from the CREFC servicing file.
- **Additional Loan Terms:** We observe the following terms of the loan as of origination: term, in months; and an indicator for whether the loan has a balloon amortization.

B.C Other Datasets

B.C.1 RCA

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

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

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

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

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

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

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

B.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.

B.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 B.A.1. We apply a standard string matching algorithm by hotel zip code, street address, and name, respectively, to map each unique zip code-address-name triplet in the Trepp dataset into the STR universe. We first filter the Trepp dataset to the subset of loans secured by hotels with an initial maturity between January 2018 and December 2022. We match 90% of hotels in the filtered Trepp dataset to a unique hotel in the STR dataset.

  Since the Trepp dataset is at the loan-month level whereas most of our regressions are specified at the hotel-month level, we must choose which loan to match to a given hotel. We simply use the earliest initial maturity date over the 2018-2022. For example, if a hotel has a loan with initial maturity of February 2018 and a separate loan with initial maturity of December 2021, then we would code such a hotel as a "control hotel", that is, with a "pre-pandemic maturity." Thus, our research design has the interpretation of an "intent-to-treat."
- **RCA-to-Trepp Crosswalk:** We match the RCA data to Trepp using the property address and the origination month of the loan in Trepp. We match 83% of the loans in the merged STR-Trepp dataset to RCA. We are not able to match 100% because we do not match some loans in Trepp to RCA; in many cases, these loans are originated in the 1990s and do not appear in RCA.
- **STR-to-PPP Crosswalk:** We use a standard string matching algorithm by NAICS code, zip code, street address, name, respectively, to match each hotel in our STR dataset to firm in the PPP dataset.

C Calibration Details

C.A Necessary parameters

We show that the outcomes presented in Section V.C depend only on α, r, q, p^l/p^h, and the cumulative distribution function of γ/w. To do so, we let d denote the pre-crisis LTV of the firm:

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

We also let l denote the level of labor relative to the pre-crisis optimum: $l = L/L^*(p^h)$. We rewrite the lender and borrower problems in terms of d and l, showing that the only parameters that matter are those listed above. Then, we show that the outcomes in Section V.C can be written as functions of d, l, and these parameters.

To recast the lender problem in terms of d and l, we define a new profit function:

$$\tilde{\pi}\left(l, \frac{p}{p^h}\right) = \frac{p}{p^h}\frac{l^\alpha}{\alpha} - l.$$

We define a new adjustment cost function:

$$\tilde{\phi}(l_{t+1}, l_t) = \begin{cases} 0, & l_{t+1} \leq l_t \\ \frac{1}{2}\frac{\gamma}{w}\left(\frac{l_{t+1}}{l_t} - 1\right)^2 l_t, & l_{t+1} > l_t. \end{cases}$$

We define a new value function:

$$v\left(l_t, \frac{p}{p^h}, \frac{\gamma}{w}\right) = \max_{l_{t+1}} \tilde{\pi}\left(l_{t+1}, \frac{p}{p^h}\right) - \tilde{\phi}(l_{t+1}, l_t) + (1+r)^{-1} v\left(l_{t+1}, \frac{p}{p^h}, \frac{\gamma}{w}\right).$$

Note that:

$$\pi(L, p) = wL^*(p^h)\tilde{\pi}\left(l, \frac{p}{p^h}\right),$$

which is clear because the first-order condition for optimal labor in the high state is equivalent to $\alpha p^h K^{1-\alpha} L^*(p^h)^\alpha = wL^*(p^h)$. We also have:

$$\phi(L_{t+1}, L_t) = wL^*(p^h)\tilde{\phi}(l_{t+1}, l_t).$$

It follows that:

$$\mathcal{V}(L_t, p, \gamma) = wL^*(p^h) v\left(l_t, \frac{p}{p^h}, \frac{\gamma}{w}\right).$$

As a result, the value of foreclosure can be written as:

$$V^{fc}(L_1,\gamma) = wL^*(p^h)\left(\tilde{\pi}\left(l_1,\frac{p^l}{p^h}\right)+(1+r)^{-1}\left(qv\left(l_1,1,\frac{\gamma}{w}\right)+(1-q)v\left(l_1,\frac{p^l}{p^h},\frac{\gamma}{w}\right)\right)\right).$$

We now similarly rewrite the value of forbearance. Given the formula for $\pi(L,p)$ just derived, we have:

$$\pi^*(p^h) = \pi(L^*(p^h),p^h) = wL^*(p^h)\tilde{\pi}(1,1) = wL^*(p^h)(1-\alpha)\alpha^{-1}.$$

It follows that:

$$D = wL^*(p^h)(1+r)r^{-1}(1-\alpha)\alpha^{-1}d.$$

Given the equation for $\pi^*(p)$ in footnote 8, we have:

$$\frac{\pi^*(p^l)}{\pi^*(p^h)} = \left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}}.$$

Therefore, the value of forbearance can be written as:

$$V^{fb}(L_1,\gamma) = \begin{cases} wL^*(p^h)\frac{(1+r)(1-\alpha)}{\alpha r}d & d \leq (1+r)^{-1}\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}} \\ wL^*(p^h)\left(\frac{(r+q)(1-\alpha)}{\alpha r}d+\frac{1-q}{1+r}v\left(l_1,\frac{p^l}{p^h},\frac{\gamma}{w}\right)\right) & d > (1+r)^{-1}\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}} \end{cases}.$$

Given that $wL^*(p^h)$ factors out of both V^{fc} and V^{fb}, it follows that the lender's decision to foreclose or forbear depends only on α, r, q, p^l/p^h, and γ/w once d and l_1 are specified, as desired. We let $\tilde{\rho}(l_1)$ denote the probability that the lender chooses forbearance, given α, r, q, p^l/p^h, d, and the CDF of γ/w.

We now recast the borrower's problem in terms of d and l. We rewrite the value of payoff by factoring out $\pi^*(p^h)$ and applying the formula for this object derived above:

$$V^{po} = wL^*(p^h)\frac{1-\alpha}{\alpha}\left(\left(1+\frac{1-q}{r}\right)\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}}+\frac{q}{r}-\frac{1+r}{r}d\right). \quad \text{(IA1)}$$

We rewrite the value of defaulting as:

$$V^{df} = wL^*(p^h) \times \sup_{l_1} \tilde{\rho}(l_1)\left(\tilde{\pi}\left(l_1, \frac{p^l}{p^h}\right) + \frac{1-\alpha}{\alpha r}\left(q-(r+q)d+(1-q)\max\left(\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}} - d, 0\right)\right)\right). \tag{IA2}$$

Conditional on defaulting, an optimal choice for l_1 maximizes this expression. Clearly, such an optimum depends only on α, r, q, p^l/p^h, d, and the CDF of γ/w. Furthermore, the borrower's choice of paying off or defaulting depends on comparing V^{po} to v^{df}, and given that $wL^*(p^h)$ cancels out in this comparison, only the same set of parameters are relevant for that choice as well. Finally, optimal labor conditional on paying off can be written as:

$$\frac{L^*(p^l)}{L^*(p^h)} = \left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},$$

where I have used the formula for $L^*(p_t)$ in footnote 8. As desired, we have shown that the borrower's choice of l_1 and defaulting depends only on d and the stated list of parameters.

We now show that the outcomes in Section V.C depend only on l_1^*, d, α, r, q, p^l/p^h, and the CDF of γ/w. In Figure XI, the x-axis is d, and the y-axis is:

$$\frac{p^l K^{1-\alpha}(L_1^*)^\alpha}{p^l K^{1-\alpha} L^*(p^l)^\alpha} = (l_1^*)^\alpha \left(\frac{p^h}{p^l}\right)^{\frac{\alpha}{1-\alpha}}.$$

In Table IV, the averages in Panel A involve integrating over levels of D, which is distributed uniformly from $(1+r)\pi^*(p^l)/r$ to D^{**}, which is equivalent to a uniform distribution in d from a minimum of

$$\frac{\pi^*(p^l)}{\pi^*(p^h)} = \left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}}$$

to a maximum of

$$\frac{r\pi^*(p^l) + q\pi^*(p^h)}{(r+q)\pi^*(p^h)} = \frac{r\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}} + q}{r+q}.$$

Some averages are taken conditional on $L_1^* > 0$, which is the same as $l_1^* > 0$. For each value of d

for which $l_1^* > 0$, the log change in revenue relative to a non-crisis maturity firm is:

$$\frac{\alpha}{1-\alpha}\log\left(\frac{p^h}{p^l}\right)+\alpha\log l_1^*.$$

The log change in labor relative to a non-crisis maturity firm is:

$$\log\left(\frac{L_1^*}{L^*(p^l)}\right)=\frac{1}{1-\alpha}\log\left(\frac{p^h}{p^l}\right)+\log l_1^*.$$

The change in profits relative to a non-crisis maturity firm (normalized by pre-crisis revenue) is:

$$\frac{(\pi(L_1^*,p^l)-\pi^*(p^h))-(\pi^*(p^l)-\pi^*(p^h))}{p^h K^{1-\alpha}L^*(p^h)^\alpha}=\alpha\tilde{\pi}\left(l_1^*,\frac{p^l}{p^h}\right)-(1-\alpha)\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},$$

where we have employed formulas for terms on the left that have been derived above. The probability of foreclosure conditional on default is $1-\tilde{\rho}(l_1^*)$. The outcomes in Panel B clearly depend only on the stated parameters. In the text, we provide the share of the pre-crisis value of the firm that is lost by a foreclosing lender due to adjustment costs, given a 50 log-point decline in labor below the static optimum in the crisis. This quantity is given by:

$$\frac{r^{-1}(1+r)\pi^*(p^h)-\mathcal{V}(L^*(p^l),p^h,\gamma)}{r^{-1}(1+r)\pi^*(p^h)}+\frac{\mathcal{V}(L^*(p^l),p^h,\gamma)-\mathcal{V}(e^{-0.5}L^*(p^l),p^h,\gamma)}{r^{-1}(1+r)\pi^*(p^h)},$$

where the first term gives the loss due to the fact that the static optimum during the crisis is lower than in normal times, and the second term gives the loss specifically due to the shading of labor below the static optimum. Above, we showed that $\pi^*(p^h)=wL^*(p^h)(1-\alpha)\alpha^{-1}$. Therefore, this loss reduces to:

$$\frac{\frac{(1+r)(1-\alpha)}{r\alpha}-v\left(\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},1,\frac{\gamma}{w}\right)}{\frac{(1+r)(1-\alpha)}{r\alpha}}+\frac{v\left(\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},1,\frac{\gamma}{w}\right)-v\left(e^{-0.5}\left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},1,\frac{\gamma}{w}\right)}{\frac{(1+r)(1-\alpha)}{r\alpha}},$$

where we used the formula above for $L^*(p^l)/L^*(p^h)$. Each component of this expression depends only on the stated parameters, as desired. In Table IV, we report the default threshold when $\rho(\cdot)$ is fixed, at a value that here we denote $\overline{\rho}>0$. In this scenario, the value of defaulting becomes:

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

which is positive because $D < D^{**}$ in the calibration. Therefore, the default threshold is the value of D at which $V^{po} = V^{df}$, which can be simplified to:

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

The corresponding pre-crisis LTV is:

$$d^* = \frac{1+r}{r} \frac{((1-\overline{\rho})r + 1 - q)\frac{\pi^*(p^l)}{\pi^*(p^h)} + (1-\overline{\rho})q}{1+r-\overline{\rho}(r+q)}.$$

Given that we showed above that $\pi^*(p^l)/\pi^*(p^h)$ depends on only the desired parameters, d^* does as well. Finally, we report the probability of foreclosure conditional on default when the borrower cannot cut labor: $L_1^* = L^*(p^l)$. In this case, the value of default is that given in equation (IA2) with

$$l_1^* = \frac{L^*(p^l)}{L^*(p^h)} = \left(\frac{p^l}{p^h}\right)^{\frac{1}{1-\alpha}},$$

as show above, and the value of payoff is given by equation (IA1). The cutoff d^* at which these are equal clearly depends only on the desired parameters. For $d > d^*$, the conditional default probability is $\tilde{\rho}(l_1^*)$, which depends on d and the other desired parameters.

C.B Computational details

To solve the model, we normalize $w = 1$ and $p^h = 1$, which is without loss of generality given the previous subsection of this appendix. We then specify a mesh for L_1 that includes both $L^*(p^l)$ and $L^*(p^h)$ and values below $L^*(p^l)$ and between that level and $L^*(p^h)$. We then specify a mesh of values for γ. For each value of γ, we solve for the function $L_1 \mapsto \mathscr{V}(L_1, p^h, \gamma)$ by iteratively optimizing at each value in the L mesh using the equation defining $\mathscr{V}$ in Section I; we interpolate this function between the mesh points using a shape-preserving cubic spline.

For each value of L in this mesh at or below $L^*(p^l)$ as well as the first point above $L^*(p^l)$, we then approximate the function $\gamma \mapsto \mathscr{V}(L, p^h, \gamma)$ using a shape-preserving cubic spline, given the estimates of this function value at each point in the γ mesh. The mesh for L_1 used in this step is smaller than the initial mesh, and we call this the small L_1 mesh.

Then, we form a mesh of potential mean values of γ, which we denote x. For each triplet of mesh values (D, L_1, x) (for L_1 in the small L_1 mesh), we calculate $\rho(L_1)$, the probability of forbearance conditional on default, as follows. The lender is indifferent between forbearance and foreclosure when:

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

preferring forbearance when the left side is larger and foreclosure when the right side is larger. If

$$\frac{(r+q)D}{1+r} \geq \pi(L_1, p^l) + \lim_{\gamma \to 0} \frac{q\mathcal{V}(L_1, p^h, \gamma)}{1+r} = \pi(L_1, p^l) + \frac{q\pi^*(p^h)}{r},$$

then $\rho(L_1) = 1$ because the lender prefers forbearance for all $\gamma > 0$. Conversely, if

$$\frac{(r+q)D}{1+r} \leq \pi(L_1, p^l) + \lim_{\gamma \to \infty} \frac{q\mathcal{V}(L_1, p^h, \gamma)}{1+r} = \pi(L_1, p^l) + \frac{q\pi(L_1, p^h)}{r},$$

then $\rho(L_1) = 0$ because the lender prefers foreclosure for all $\gamma > 0$. If neither inequality holds, then we use the function $\gamma \mapsto \mathcal{V}(L_1, p^h, \gamma)$ calculated above to solve for the γ at which the lender is indifferent and calculate $\rho(L_1)$ as 1 minus the CDF of the exponential distribution with mean x at this value of γ.

Now that we have $\rho(L_1)$, then for each D and x, we can calculate the value of L_1 that maximizes the borrower's objective function conditional on defaulting, V^{df}. We calculate this objective function for each L_1 value in the small L_1 mesh and also for $L_1 = 0$. If the function is maximized at $L_1 = 0$, then we set $L_1^* = 0$. Otherwise, we focus on the focus on the maximum among the points in the small L_1 mesh, which we denote L_1^d. If somehow there are multiple maxima, we use the first one. We calculate L_1^* by refining this maximum to adjust for discretization error, as follows. We calculated the value of defaulting at L_1^d and at the points in the small L_1 mesh just below and just above it. If L_1^d is the first point in the mesh, then we use 0 as the point just below it. L_1^d is never the last point in the small L_1 mesh because this mesh includes a point above $L^*(p^l)$, and L_1^d cannot be above that. We then form a quadratic that runs through these three values of L_1 and the corresponding values of the objective function, and select the maximum of this quadratic as L_1^*.

Given the value of L_1^* just calculated, it is straightforward to calculate other model outcomes given D and x. We integrate over D using numerical integration built in to MATLAB. We select x so that the treatment effect on revenues equals -0.4. This mean value implies a median of $\log(2)x$ given that we are using an exponential distribution.

D Additional Figures and Tables

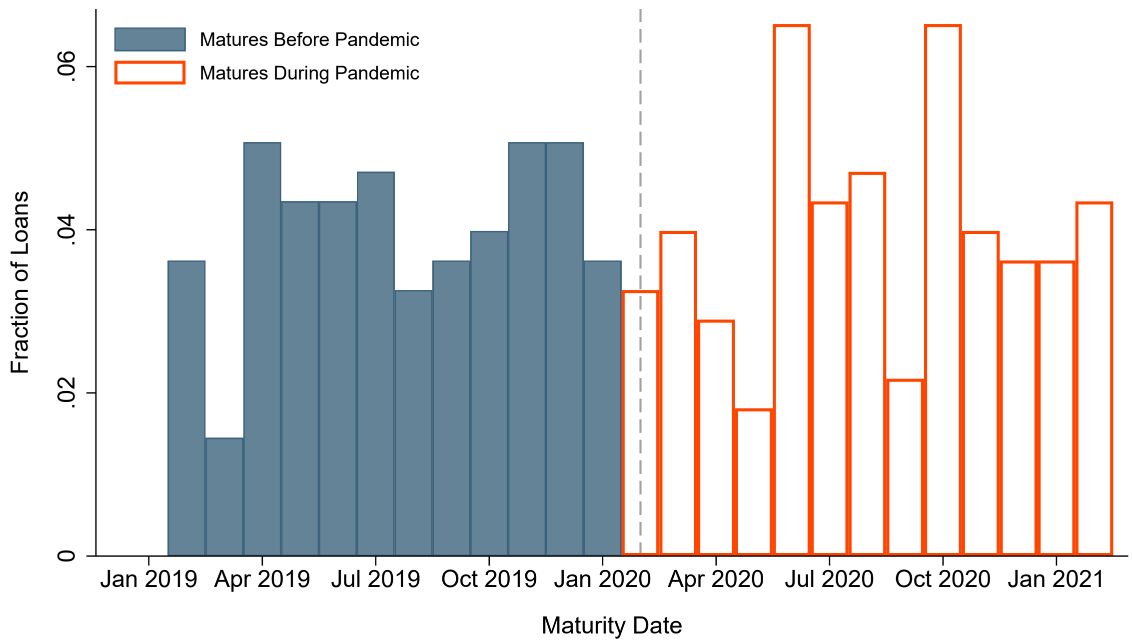


FIGURE A.I
Distribution of Scheduled Loan Maturity at Origination.

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

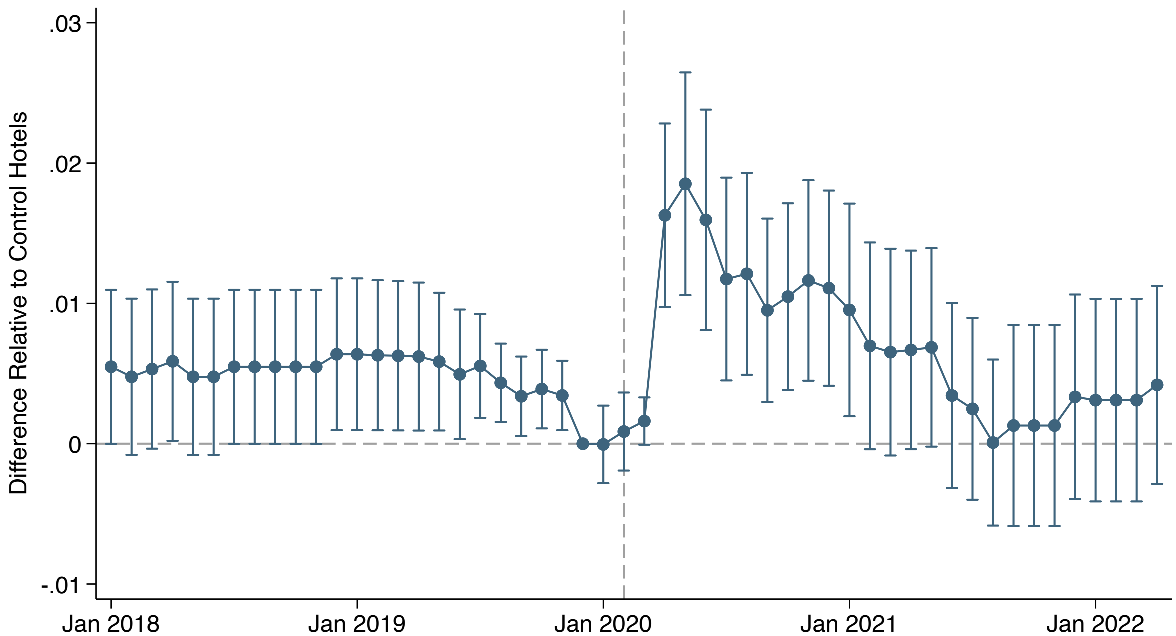


FIGURE A.II
Effect of Pandemic Maturity on Hotel Closure.

NOTE.—This figure estimates a specification of equation (3) 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 B.A. For reference, the average share of hotels closed before February 2020, on and after February 2020, and from March 2020 to May 2020 are: 0.04%, 0.52%, and 1.07%. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)

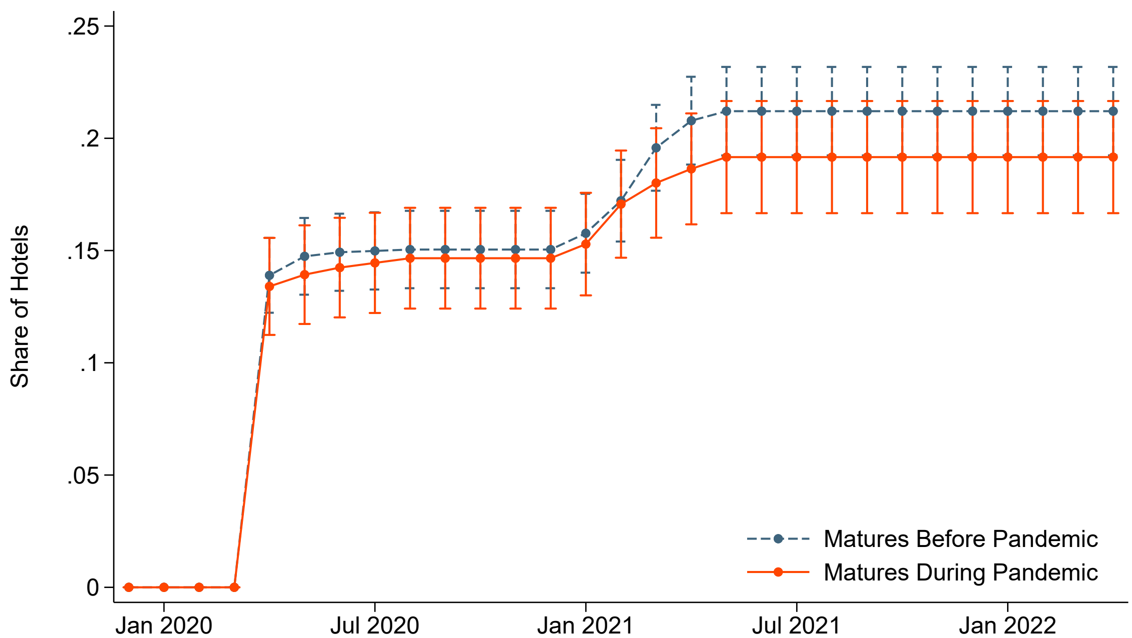
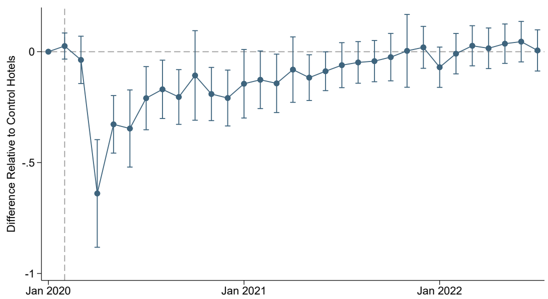
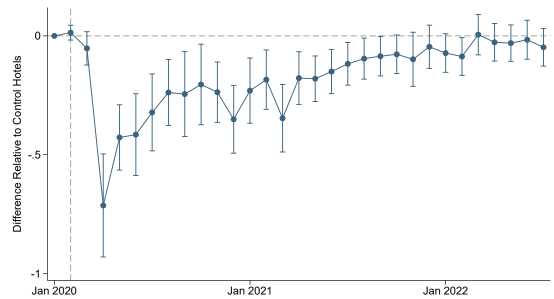


FIGURE A.III
Paycheck Protection Program Takeup Rate by Maturity Cohort.

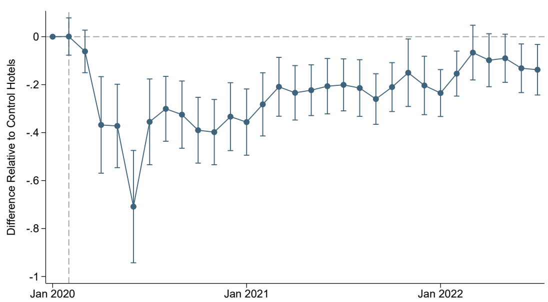
NOTE.—This figure plots the time series of the share of hotels in our sample that have received a Paycheck Protection Program (PPP) loan origination. Explicitly, the figure shows the mean of an indicator variable for whether the hotel has received a PPP loan as of the given month, and the bars are standard 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 B. (SOURCE: Trepp and SBA)



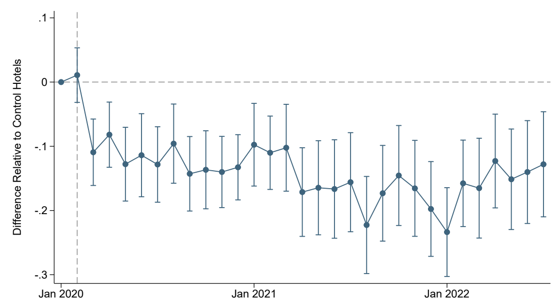
Panel A. Total Expense



Panel B. Labor Expense



Panel C. Marketing Expense



Panel D. Profit

FIGURE A.IV
Effect of Pandemic Maturity on Monthly Expenses and Profit.

NOTE.—This figure estimates a variant of equation (3) that assesses whether reductions in operating expenses 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 outcomes in Panels A, B, and C are the log of total expense, labor expense, and sales and marketing expense, respectively. The outcome in Panel D is the ratio of EBITDA to total revenue in January 2020. This ratio is winsorized at the 2.5% level. Standard errors are clustered by hotel. The remaining notes are the same as in Figure VI. (SOURCE: STR, LLC and Trepp)

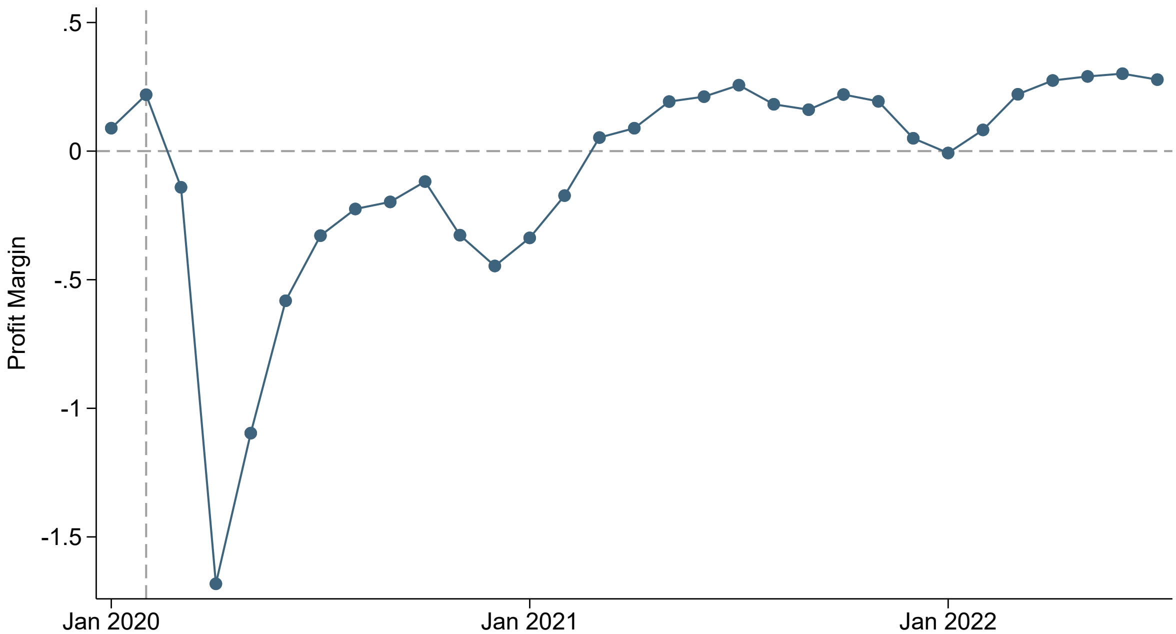
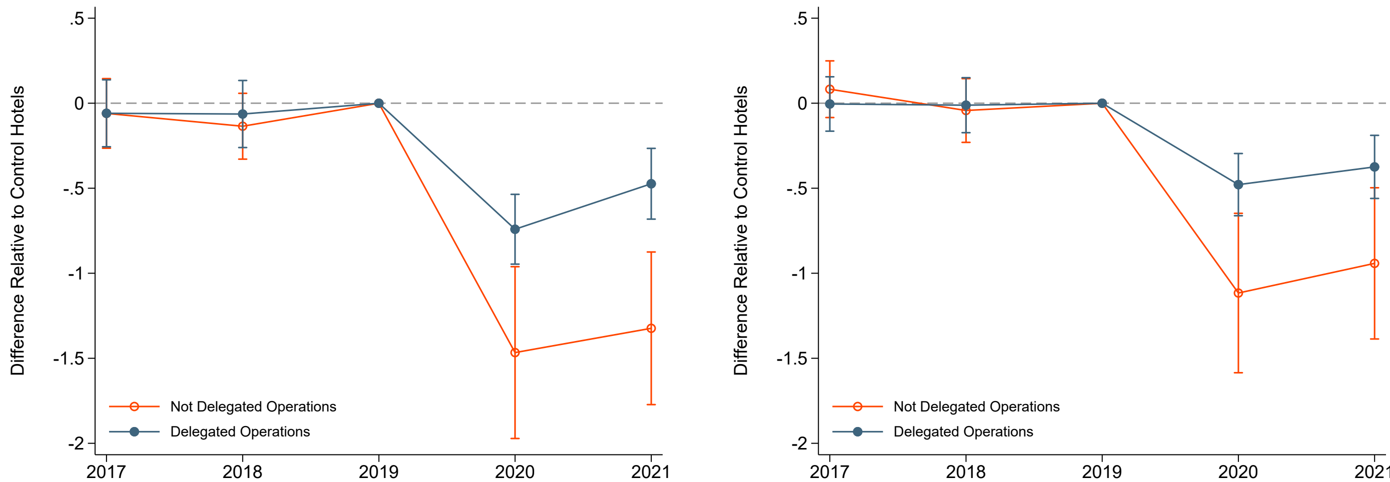


FIGURE A.V
Average Profit Margin.

NOTE.—This figure plots the average profit margin for hotels in the STR monthly profit and loss dataset, which begins in January 2020. Profit margin is the ratio of EBITDA to total revenue in the same month. This ratio is winsorized at the 2.5% level. (SOURCE: STR, LLC)



Panel A. Revenue *Panel B. Expense*

FIGURE A.VI
Heterogeneity by Delegation 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 (Delegated Operations) or not (Not Delegated Operations). Delegation of operations applies to 93% of hotels in the regression sample. The regression includes interactions between whether the hotel has delegated operations and year fixed effects to absorb the time-varying direct effect of delegation. We measure delegation of operations according to whether a hotel: (a) is operated by the brand, based on the STR operating arrangement field equalling "Management Agreement"; or (b) has a non-empty management company identifier and paid a management fee the first year it appears in the P&L data, which will ensure that our measure includes third-party operators that are different from the brand. 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)

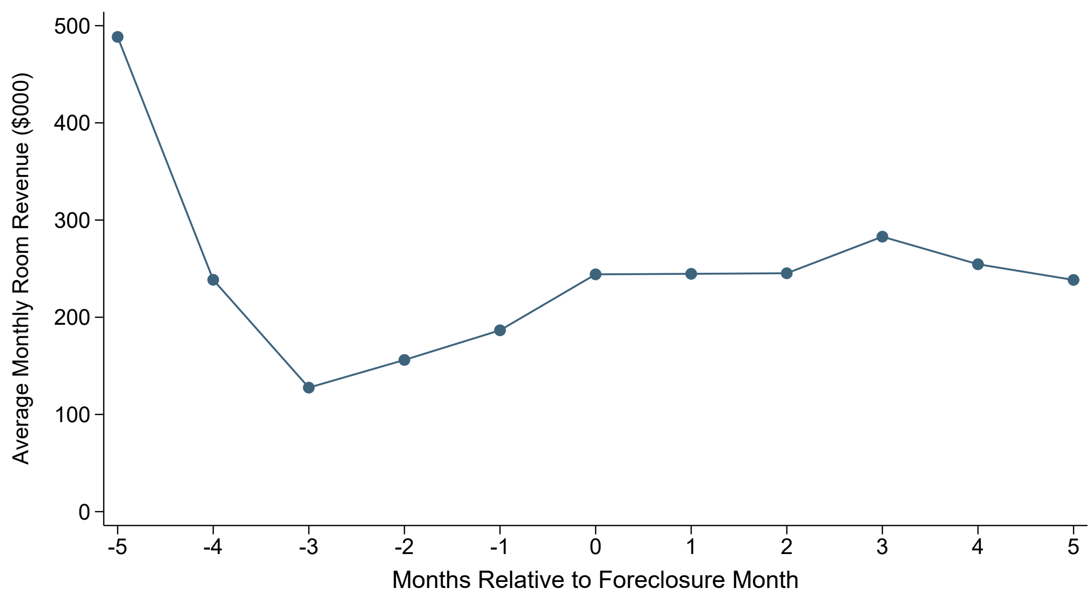


FIGURE A.VII
Revenue around Foreclosure.

NOTE.—This figure plots average monthly room revenue around the month of foreclosure for hotels with loans with a scheduled maturity from February 2020 through February 2021 that enter foreclosure in the post-pandemic period. As in Figure X, the figure is restricted to months in February 2020 or later. The remaining notes are the same as in Figure X. (SOURCE: STR, LLC and Trepp)

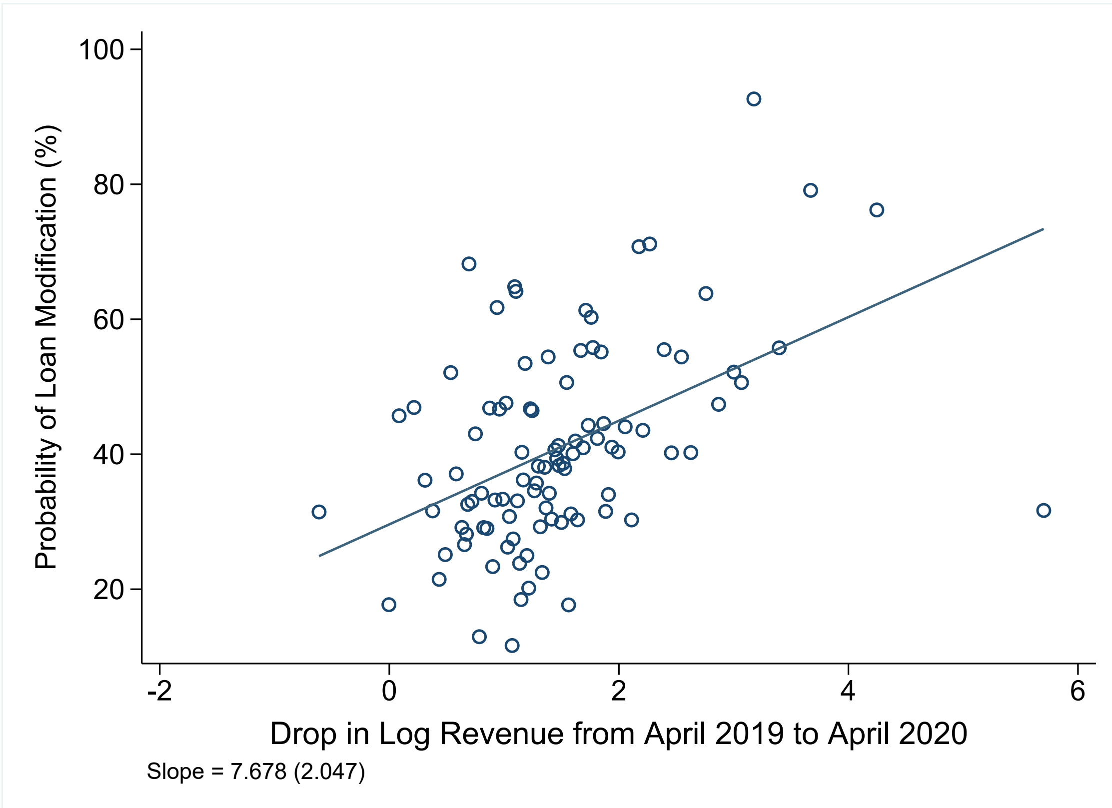


FIGURE A.VIII
Probability of Loan Modification based on Initial Drop in Revenue.

NOTE.—This figure is a binned scatterplot of the relation between the probability of receiving a loan modification and the decline in log room revenue from April 2019 to April 2020. Measuring the year-on-year drop in log revenue limits variation due to differences in seasonal hotel demand. Modification is measued using the indicator from the Commercial Real Estate Finance Council (CREFC), as described in Figure IV. The sample consists of hotels with a scheduled maturity from February 2020 through February 2021 that enter February 2020 having not paid off their loan, having not been foreclosed on, and having not been modified. The plot is binned so that each point represents the average of around eight hotels. The average is residualized against market fixed effects, which function similarly to δ_{mt} in the main difference-in-difference specification in equation (2), and against fixed effects for initial maturity month, which function similarly to the Post Maturity fixed effects in the main specification. Data on loan maturities are from the Trepp dataset. Data on hotel revenue are from the STR performance dataset. (SOURCE: STR, LLC and Trepp)

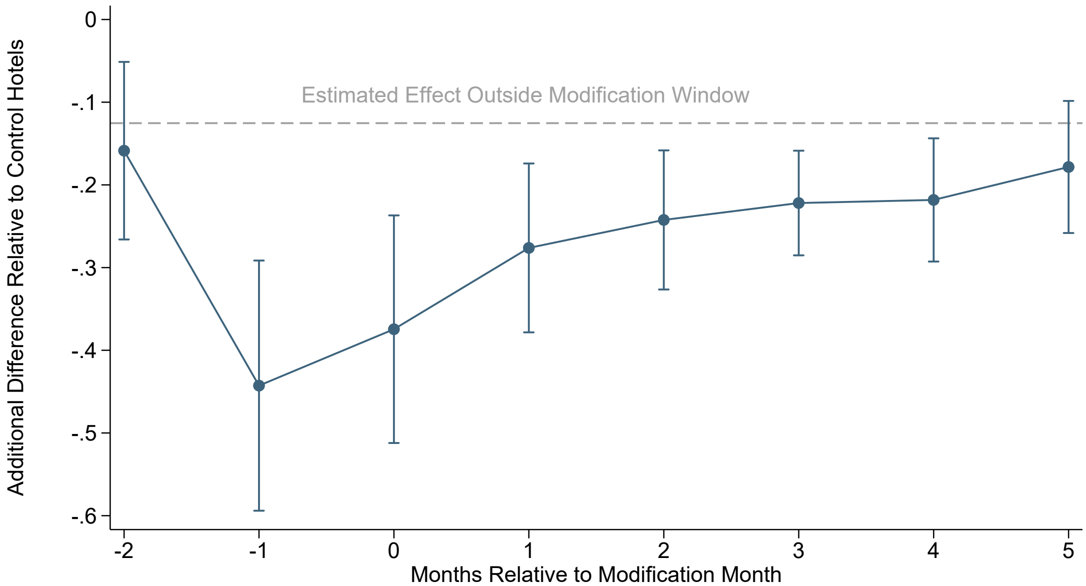


FIGURE A.IX
Revenue around Loan Modification.

NOTE.—This figure displays estimates of a variant of equation (4) that separately estimates the effect of debt rollover as a function of months relative to the month of modification for loans without an extension option:

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

where μ indexes months relative to the month of modification, t_μ; $NoExtOption_i$ indicates if i does not have an extension option as of origination, as in column (2) of Table III; and the treatment group is restricted to the subset of hotels with a pandemic maturity that are first modified in the pandemic, based on the indicator from the Commercial Real Estate Finance Council (CREFC) described in Figure IV. The figure plots the estimated treatment effect for hotels with a pandemic maturity and no extension option as a function of months relative to modification month, μ, for each μ in the modification window on the horizontal axis: $\beta_0 + \beta_1 + \tilde{\beta}_\mu$. The gray dashed line shows the estimated treatment effect for these hotels in months outside the modification window: $\beta_0 + \beta_1$. Brackets are 95% confidence intervals for the null hypothesis that the estimated treatment effect in month m relative to modification equals the treatment effect outside the modification window ($\tilde{\beta}_\mu = 0$). Standard errors are clustered by hotel. The remaining notes are the same as in Table III. (SOURCE: STR, LLC and Trepp)

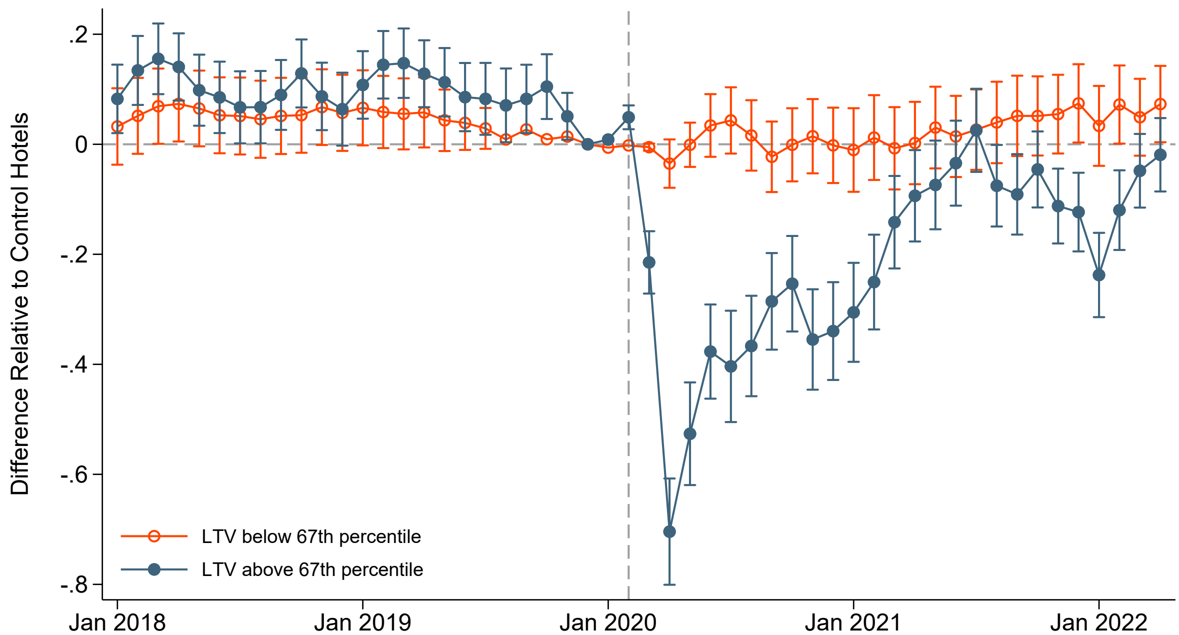


FIGURE A.X
Effect of Pandemic Maturity on Hotel Revenues by Initial LTV.

NOTE.—This figure estimates a variant of equation (3) 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:

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

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

TABLE A.I
STR GEOGRAPHIC MARKETS IN ESTIMATION SAMPLE

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

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

TABLE A.II

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

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

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

TABLE A.III

EFFECT OF PANDEMIC MATURITY ON HOTEL REVENUES: ALTERNATIVE BANDWIDTHS

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

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

TABLE A.IV
EFFECT ON HOTEL EXPENSE BY CATEGORY

	Levels ($000,000)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PandemicMaturity × Post	−7.977**	−4.054***	−2.397**	−1.259*	−9.051**	−1.209**	−1.218**
	(1.795)	(0.805)	(0.766)	(0.485)	(2.098)	(0.308)	(0.331)
Category Name	Room	Marketing	Admin	Operator	Food	Property	Reserve
Category Mean in 2019	10.742	5.345	5.074	2.093	6.069	2.722	0.780
Hotel FEs	X	X	X	X	X	X	X
Post Maturity FE	X	X	X	X	X	X	X
Market × Year FEs	X	X	X	X	X	X	X
Number of Observations	6,525	6,525	6,525	6,525	6,525	6,525	6,525

NOTE.—This table estimates a variant of equation (2) that assesses the drop in expenses documented in Figure VIII across expense categories. The regression equation is similar to that in Table II, except that the frequency is annual because the data on hotel expenses come from STR's annual profit and loss dataset. The treatment variable, $PandemicMaturity_i$, is still defined as it is in Table II. The remaining notes are the same as in Table II after replacing "month" with "year." The outcome variables in columns (1)–(7) are the hotel's annual expense within a given category, in hundreds of thousands of U.S. dollars ($000,000). The outcome is specified in levels, as opposed to logs, to allow for cases where a hotel has expense of zero within a given category. For reference, the sample mean of each category in 2019 is reported in the table. The categories are room, sales and marketing (Marketing), administrative and general (Admin), total fees paid to the company operating the hotel (Operator), food and beverage services (Food), property operations and maintenance (Property), and reserve for capital replacement (Reserve). Standard errors twoway clustered by hotel and year are shown in parentheses. The remaining notes are the same as in Figure VIII and Table II. (SOURCE: STR, LLC and Trepp)