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ABSTRACT

Snow and Leverage*

This paper examines whether reducing a debt overhang improves borrowers' operating performance using a sample of distressed and highly overleveraged Austrian ski hotels undergoing debt restructurings. The vast majority of the ski hotels experience substantial debt forgiveness, resulting in reductions in leverage of about 23% on average. These reductions in leverage, in turn, bring about statistically and economically significant improvements in operating performance of about 28% on average. Changes in leverage during the debt restructurings are instrumented with the level of snow in the years prior to the debt restructurings. The effect of snow is both statistically and economically significant: a one-standard deviation increase in snow is associated with a reduction in leverage of about 23%.

JEL Classification: G32 and G34
Keywords: debt forgiveness, debt overhang, debt renegotiation and debt restructuring

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1 Introduction

Does too much debt impair incentives? And if borrowers are overindebted, does a reduction in debt improve incentives, and eventually also performance? These questions are at the core of any debate about debt restructurings, be it in the context of sovereign lending or corporate lending. In the sovereign lending literature, Krugman (1988) and Sachs (1989) argue that adverse incentive effects caused by a debt overhang may give rise to a "debt Laffer curve," with the implication that debt forgiveness may constitute a Pareto improvement that benefits both the borrowing country and its lender(s). In the corporate finance literature, Myers (1977) was the first to argue that a debt overhang may distort incentives at the firm level, an argument that has since been revisited in many theory papers (e.g., Hart and Moore, 1995; Holmström and Tirole, 1997; Diamond and He, 2010).

Given its importance both for policy and practice, the debt overhang problem has spurred a large empirical literature, both in development economics and in corporate finance.[1] An important concern with many of these studies is that they rely on variation in leverage that is unlikely to be exogenous, making it difficult to establish causality. The objective of this paper is to provide evidence on the debt overhang problem using plausibly exogenous variation in leverage based on a sample of distressed Austrian ski hotels that undergo debt restructurings. All of the hotels are highly overleveraged—the average (book) leverage ratio prior to the debt restructuring is 2.40. During the debt restructurings, the vast majority of the hotels experience substantial debt forgiveness, resulting in a decrease in leverage of 23% on average.

While there is substantial debt forgiveness in the aggregate, there is considerable cross-sectional variation. Since changes in leverage are endogenous, we need a theory of what determines leverage changes during debt restructurings. In a simple model, Krugman (1988) argues that one important determinant is the extent to which cash flows depend on the borrower's effort. If cash flows are completely exogenous, then it is optimal for lenders not to forgive any debt. In contrast, if cash flows depend (solely) on the borrower's effort, then it may be optimal to forgive debt to improve effort incentives. In the Appendix of this paper, we provide a simple extension of Krugman's model that also includes intermediate cases in which effort matters to varying degrees. The main empirical prediction is that lenders should forgive debt only if the

[1] Empirical studies in the development economics literature include, e.g., Cohen (1993), Deshpande (1997), Arslanalp and Henry (2005), and Cordella, Ricci, and Ruiz-Arranz (2005). Empirical studies in the corporate finance literature are discussed at the end of this section.

borrower's effort is sufficiently important, in which case it is optimal to forgive more debt the more important is effort.

In the real world, it is unlikely that lenders can directly observe how important the borrower's effort is. This is also true in our sample of Austrian ski hotels, where the lending banks must decide whether, and how much, debt they should forgive. However, the banks can apply the following reasoning. If a ski hotel had only little snow in the years prior to the debt restructuring, then it is quite likely that the causes for the hotel's distress are exogenous. In contrast, if a ski hotel got into distress even though it had ample snow in the years prior, then it is less likely that the causes for the hotel's distress are exogenous. By implication, this means it is then relatively more likely that the causes for the hotel's distress may be incentive problems, making it optimal for lenders to forgive debt to improve effort incentives.[2]

Note that "more likely" and "less likely" are not meant in an absolute sense, but in a relative sense, i.e., relative to other ski hotels in distress. After all, the (narrow) objective here is to explain cross-sectional variation in debt restructuring outcomes for a sample of ski hotels that are all in distress. Note also that this reasoning does not address why the hotels got into distress in the first place. It merely argues that, conditional on being in distress, the causes are more likely exogenous if a hotel had only little snow.

There is empirical support for this reasoning. Austrian Census data show a strong positive correlation between snow and bookings made by tourists, suggesting that hotels with more snow should, in principle, also perform better. In our sample of distressed ski hotels, however, the correlation between snow and the return on assets in the year prior to the debt restructuring is virtually zero. Thus, while we would indeed expect hotels with little snow to perform poorly, those with ample snow did not perform any better, despite having ample snow, suggesting that the causes for their distress may be incentive problems.

This reasoning lends itself to a testable hypothesis, which we test in our first-stage regression: ski hotels with relatively little snow in the years prior to the debt restructuring should experience smaller reductions in leverage (i.e., less debt forgiveness) than ski hotels with relatively ample snow. The results of the first-stage regression support this hypothesis. When we regress changes

[2] All hotels in our sample are small family-run ski hotels. Incentive problems in the presence of a debt overhang might be related to the lack of incentives to boost sales through marketing efforts, to keep costs and wages at a low level, to maintain the hotel's interior and exterior, and to provide excellent service. Importantly, as the hotels are non-limited liability firms, incentive problems could also be related to the lack of incentives to contribute personal funds. See Section 3 for an example based on an actual case from our sample.

in leverage on snow in the years prior to the debt restructuring (plus controls), we find that hotels with more snow experience significantly larger reductions in leverage. The effect is also economically significant: a one-standard deviation increase in snow is associated with a reduction in leverage of 23% on average.

The broader objective of our study, which we pursue in our second-stage regression, is to examine whether reducing a debt overhang improves borrowers' operating performance (return on assets, net profit margin). While OLS regressions yield a positive association between changes in leverage and changes in operating performance, it is not difficult to think of a reverse causality explanation. For instance, ski hotels with larger *anticipated* improvements in operating performance might receive less debt forgiveness, resulting in smaller reductions in leverage. However, when we instrument changes in leverage with snow in the years prior to the debt restructuring, we find the opposite result: ski hotels with larger reductions in leverage now experience *greater* improvements in operating performance. The effect is both statistically and economically significant. For instance, when operating performance is measured by the return on assets (ROA), we find that ROA increases by about 28% on average. Thus, consistent with the arguments by Myers (1977), Krugman (1988), Sachs (1989), and others, our results suggest that—at least for highly overleveraged borrowers—a reduction in leverage leads to a significant improvement in operating performance.

In our second-stage regression, we control for any contemporaneous effect of snow on operating performance: when regressing *changes* in operating performance on *changes* in leverage, we always control for *changes* in snow. That said, an important concern is that snow in the years prior to the debt restructuring (our instrument) might have a direct effect on future operating performance. Suppose, for instance, that ski tourists book one year ahead, especially if they had a good skiing vacation with plenty of snow. In that case, past snow might predict future demand and therefore future performance, violating the exclusion restriction. While this is an important concern, we believe it is minimized here, for several reasons.

First, bookings can always be cancelled at short notice, typically at no cost. Thus, if ski tourists who made their booking last year (when there was plenty of snow) realize that this year's snow is poor, they can simply cancel their booking, implying that it is current snow, not past snow, that determines current operating performance. But we already control for any contemporaneous effect of snow on operating performance.

Second, we obtain similar results when using snow *two* years prior to the debt restructuring (i.e., not including snow in the year before) as our instrument. Arguably, only few ski tourists book two years ahead.

Third, there is a strong positive correlation between snow in the years prior to the debt restructuring and deviations of this variable from long-run historical snow levels. Much of this correlation is driven by the left tail of the distribution, i.e., hotels with little snow in the years prior to the debt restructuring also had little snow by their own historical standards. This is not entirely surprising, given that the years prior to the debt restructuring are not just any random time period, but it is precisely the period when the hotels got into distress.

Given this strong correlation, it is not surprising that we obtain similar results when using deviations from long-run historical snow levels as our instrument. In this case, the argument with respect to a possible violation of the exclusion restriction would have to be that ski tourists make their bookings not based on whether snow in their last vacation was plenty, but instead based on the extent to which observed snow levels deviate from long-run historical averages. This is rather unlikely, especially since deviations from long-run average snow levels are uncorrelated over time, i.e., there is no reason to expect that abnormally high snow in one year would predict abnormally high snow in the following year.

Fourth, using a control sample of 2,095 hotels that did not undergo debt restructurings, we construct "locally adjusted" operating performance measures by subtracting the median operating performance of all control hotels in the same year and district. The idea underlying this adjustment is that if past snow had a direct effect on future demand and therefore on future operating performance, then this (direct) effect should also apply to other hotels in the same district, which face similar snow conditions. Using locally adjusted performance measures thus effectively "controls" for any direct effect of past snow on future operating performance. Our results using locally adjusted performance measures are similar to those using non-adjusted performance measures.

Our sample of ski hotels undergoing debt restructurings is a selected sample. In the final part of our analysis, we use Heckman's (1979) correction method to account for possible selection bias. As we will explain below, a necessary condition for a ski hotel to be restructured in our sample is that it must be "structurally important," meaning it must be a large hotel relative to other hotels in the same municipality. Based on this criterion, we construct a new variable, "local capacity share," which we use as an instrument in our selection equation. "Local capacity share" is the number of beds of a hotel in a given year divided by the number of beds of all hotels in the same district and year. Importantly, "local capacity share" is based on the number of *available* beds, not the number of nights stayed. Hence, it does not capture aspects of performance and is therefore likely exogenous in the second-stage regression. Our results remain virtually unchanged, and the Inverse Mills Ratio is not significant, suggesting that they are unlikely to be driven by selection bias.

Debt renegotiations are an ideal environment to study the debt overhang problem.[3] This paper looks at debt renegotiations between Austrian ski hotels and their lending banks. By capturing exogenous variation in leverage changes, it establishes a link between renegotiation outcomes and performance improvements. In a related paper, Andrade and Kaplan (1998) examine 31 highly leveraged transactions (HLTs) that later become financially distressed. The authors show how operating margins improve after the leveraging transaction, decline when the firms become distressed and while they are distressed, and then improve again after the distress is resolved. In the majority of cases (18), the distress is resolved through Chapter 11. In the remaining cases, the distress is resolved through an out-of-court recapitalization (often in combination with either a sale or IPO), outright sale, or liquidation.

Our paper is also related to studies that consider the implications of debt overhang, or leverage in general, for investment, albeit not specifically in the context of debt renegotiations. Lang, Ofek, and Stulz (1996) show that leverage is negatively related to investment, employment growth, and capital expenditure growth. Using a structural approach, Hennessy (2004) derives an empirical proxy for levered equity's marginal Q, generating a direct test for debt overhang. In the empirical test of his model, he finds that debt overhang significantly impairs investment. In related work, Whited (1992) shows that augmenting an investment Euler equation with a credit constraint that includes both leverage and interest coverage ratios greatly improves the Euler equation's fit.

Several other studies also consider debt renegotiations, albeit they do not examine implications for operating performance.[4] Gilson, John, and Lang (1990) consider 169 publicly traded

[3]The only way to overcome a debt overhang is through renegotiations with existing debtholders. (This follows directly from the definition of debt overhang, see, e.g., Tirole, 2006, pp. 125-126.) Thus, the inability to renegotiate existing debt claims, not excessive leverage per se, is what gives the debt overhang problem its bite.

[4]Roberts and Sufi (2009b) survey the theoretical and empirical literature on debt contract renegotiation.

U.S. companies that get into financial distress. They examine which of the companies successfully restructure their debt outside of bankruptcy, and which of them end up with a Chapter 11 filing. Similarly, Asquith, Gertner, and Scharfstein (1994) consider 76 companies that issue high-yield "junk" bonds and subsequently get into financial distress. They examine how these firms attempt to resolve their financial distress, and which of them eventually file for Chapter 11.

In recent work, Roberts and Sufi (2009a) consider 1,000 private credit agreements between financial institutions and publicly traded U.S. companies. They show that 90% of the contracts with a maturity in excess of one year are renegotiated prior to maturity. When examining what triggers renegotiation, they find that fluctuations in borrowers' assets, financial leverage, the cost of equity capital, macroeconomic conditions, and the financial health of lenders, play an important role.

Perhaps most closely related to our paper, in terms of both question and empirical design, is an unpublished paper by Kroszner (1999) on the abrogation of "gold clauses" in public and private debt contracts passed by Congress in 1933. Around that time, about $100 billion of outstanding public and private debt contained clauses indexing payments to creditors to the price of gold. In 1935, the Supreme Court upheld the gold clause nullification. Had the gold clauses been enforced, the debt burden of borrowers would have increased by 69%, which means that "the Supreme Court decision is effectively a debt forgiveness equivalent to 69% of the value of a firm's debt" (p. 20). Kroszner shows that both equity prices and corporate bond prices rise upon the announcement of the Supreme Court's decision. As he points out, this result is consistent with the view that debt forgiveness constitutes a Pareto improvement that benefits both equityholders and debtholders.

The rest of this paper is organized as follows. Section 2 discusses institutional details. Section 3 provides an example based on an actual case from our sample. Section 4 discusses sample selection, empirical methodology, and summary statistics. Section 5 contains our main results, including robustness checks. Section 6 discusses the identification strategy. Section 7 addresses sample selection bias. Section 8 concludes. Appendix A explains the timing conventions used in the construction of our variables. Appendix B contains a simple extension of Krugman's (1988) model to motivate our first-stage regression.

2 Institutional Background

As is common in many countries, Austrian firms may attempt to restructure their debt prior to filing for bankruptcy. Typically, debt restructurings are the outcome of direct negotiations between the borrowing firm and its lender(s). In the Austrian tourism industry, however, debt restructurings frequently involve the participation of the Austrian Hotel- and Tourism Bank (AHTB).[5] Founded in 1947, the AHTB is a development bank that administers funds provided by the ERP (European Recovery Program, or "Marshall Plan"). While the AHTB also provides limited financial support, its role in the debt restructurings is primarily that of a mediator, as it does not take on any credit risk.[6] Mediation by the AHTB is desirable as it brings all lending banks together at one table, thus ensuring that the negotiations take place in a coordinated and multilateral fashion. This is especially important in the context of debt renegotiations, where the presence of multiple lending banks can create free-rider problems that may lead to a breakdown of the negotiations (Cline, 1983; Gertner and Scharfstein, 1991). In our sample of 115 debt restructurings, 70 cases involve at least two lending banks, and 33 cases involve at least four lending banks.

As a mediator, the AHTB collects data on the distressed hotels, including P&L and balance sheet data, as well as "soft" information gathered from on-site visits by the AHTB's loan officers. The first main data collection takes place prior to the debt restructuring. These data, which include both "hard" (financial) information and descriptive information, constitute our "before" data. The AHTB also collects post-restructuring data, with varying frequency, to monitor the success of the debt restructuring. These data typically include only "hard" information. In our empirical analysis, they constitute our "after" data.

For the AHTB to be involved in the negotiations, certain eligibility criteria must be met. For instance, the AHTB's mandate is restricted to "structurally important firms" whose operations have positive external effects on the local tourism industry. While this criterion is rather "soft," it is usually satisfied if a hotel is the largest hotel among all hotels in the same municipality and total sales exceed Euro 360,000. In addition, a number of necessary conditions must be met. For instance, the book value of the hotel's debt must be at least 15 times its total sales, the book

[5] The German name is Österreichische Hotel- und Tourismus Bank Ges.m.b.H.

[6] The AHTB provides limited financial support in the form of interest rate subsidies and small loans, though the loans must be fully guaranteed by another lending bank. That the AHTB does not take on any credit risk follows from a requirement by the ERP.

value of equity must be smaller than eight percent of total assets, and the restructuring must not involve investments into the hotel's assets that are not essential for regaining profitability. Among other things, this rules out investments in land, investments to complete projects already under way, and investments in capacity expansion. There are also restrictions imposed by the EU. For instance, the hotel must be a small- or medium-sized enterprise, and it must have been founded more than three years ago.

If the eligibility criteria are met, the mediation starts with an on-site inspection by the AHTB's loan officers. The AHTB then produces a report that is sent to all parties involved, i.e., the hotel's owner(s) and its lending bank(s), along with an invitation to a meeting for the purpose of discussing restructuring options. The report includes, besides "hard" financial information, also other information about the hotel, e.g., the date of the last renovation, number of employees, star category, banking relationships, number of beds, price per night, whether it is a "leading" hotel (Leitbetrieb), and its legal form, as well as information about the hotel's owner(s) and their use of hotel assets, e.g., whether the property is used for private purposes, whether spouses or children work in the hotel, and when the hotel obtained its operating license under the current owner. The report may also include an assessment by the AHTB's loan officers as to the likely causes of the hotel's distress. Unfortunately, the frequency of the information in the reports varies considerably. While financial information is available for most hotels in our sample, other information is sometimes only available for a subset.

The purpose of the restructuring negotiations is to devise a restructuring plan. A restructuring plan must meet several criteria, e.g., it must not encompass new investment that is not absolutely essential, and it must not provide hotels with "excessive" liquidity. The restructuring plan also stipulates that the lending banks contribute financially to the restructuring, e.g., by charging a low interest rate, extending new loans, or writing off debt.

Out of 191 cases known to us in which the AHTB initiated negotiations, there are 145 cases in which the restructuring eventually took place. Typically, the negotiations fail if at least one lending bank is unwilling to agree to the restructuring plan, and this lending bank cannot be removed from the bargaining table, e.g., because no other lender can be found who is willing to buy out the (dissenting) lending bank's claims. In case the negotiations fail, the hotel has essentially three options: it can enter formal bankruptcy, it can remain in distress, or it can negotiate with its lending bank(s) on a bilateral basis. As for the bankruptcy option, the Austrian Insolvency Law specifies two conditions that matter for the status of the hotels in our sample. Accordingly, a firm is insolvent if (i) it is overindebted, and (ii) its future earnings capacity is insufficient to repay its debt. While the first criterion is specified in terms of balance sheet ratios, the second criterion is rather "soft." This second criterion is also the reason why the hotels in our sample are not formally insolvent even though they are heavily overindebted, often having a negative book value of equity.

3 An Example

This example is based on an actual case from our sample. For confidentiality reasons, the example does not contain the names of the hotel and its owner(s), and it also does not contain the name(s) of the hotel's lending bank(s).

There are essentially two types of hotels in our sample: those that got into distress due to exogenous reasons, and those that got into distress due to other reasons, such as incentive problems. The hotel in this example falls into the second category. As described by the AHTB's loan officers, the hotel in question got into distress due to insufficient marketing efforts and poor cost management. Moreover, once the debt overhang was removed, the owner family agreed to contribute funds of their own, while it was unwilling to do so before.

The hotel in question is located in a small village with famous ski areas nearby. Being over 300 years old, it was taken over by the current owner 12 years prior to the debt restructuring. Like virtually all hotels in our sample, the hotel is managed by the owner and his family. The hotel has an average of nine employees (not counting family members), 34 rooms with 71 beds, and a wellness area with sauna and tanning beds, making it a rather typical hotel within our sample. The hotel is structured as a "Gesellschaft nach bürgerlichem Recht," which means each owner is personally liable for all of the hotel's liabilities. This legal form is typical of most hotels in our sample.

As the report by the AHTB's loan officers indicates, the hotel experienced a significant decline in demand in the years prior to the debt restructuring. Compared to four years before the debt restructuring, the number of nights stayed dropped by 31.8%.[7] This decline is unlikely to come from unfavorable snow conditions. In the two years prior to the debt restructuring,

[7] This example is a rare exception in that we have several years of "before" data. In most other cases, we have only one year of "before" data.

"snow" (see Section 4.3 for a definition) was 32.2% above the median in our sample, and it was 18% higher than the average snow experienced by the same hotel in the preceding 15 years. Instead, as the loan officers suggested, the decline is likely due to insufficient marketing efforts. Going forward, the loan officers conjectured that sales could be improved by cooperating with travel agencies. The loan officers also criticized the hotel's poor cost management, especially its failure to sufficiently adjust input costs and wages to the declining demand. As a result, the hotel's net profit margin dropped substantially in the two years prior to the debt restructuring, to 13.2% and 13.9%, respectively, from 28.3% and 20.4% four and three years prior, respectively. The hotel's return on assets in the year prior to the debt restructuring was only 6.3%, placing it below the median hotel within our sample.

During the debt restructuring, the hotel received substantial debt forgiveness. The hotel had only one lending bank (which is rather untypical), which agreed to forgive about ATS 11.5m (approximately Euro 833,333). As a result, the hotel's (book) leverage was reduced from 1.84 to 1.41. This reduction is above the median within our sample—the median (book) leverage in our sample before and after the debt restructuring is 1.77 and 1.56, respectively. After forgiving ATS 11.5m, the original lending bank (a small local bank) dropped out as the hotel's main lender and sold its remaining claims to another lender (a larger regional bank). In response to the debt forgiveness by the hotel's (original) lending bank, the owner family agreed to contribute funds of their own. First, the owner's father contributed ATS 2.3m from his personal wealth. Second, the owner's wife agreed to sell an unrelated private property that was registered under her name, the proceeds of which were expected to be ATS 2m.

In the years after the debt restructuring, the hotel's performance improved substantially.[8] The return on assets increased from 6.3% before the debt restructuring to an average of 10.9% in the three years after. This improvement in performance is above the median within our sample. Only 25% of the hotels had a bigger increase in return on assets, and many of those hotels had a negative return on assets to begin with.

[8] There has been no change in ownership or management after the debt restructuring. In fact, only two hotels in our sample experience such changes, and removing them does not affect our results. Hence, it is unlikely that improvements in operating performance after the debt restructurings are due to changes in "ability" (and, by the same token, that poor performance prior to the debt restructuring is due to "low ability"). Rather, both the information in the restructuring reports (which often mention incentive problems, as in this example) and theory (which predicts that incentives should improve once the debt overhang is removed) suggest that a main reason for the performance improvements are better incentives.

4 Data

4.1 Sample Selection

Our primary data source is the Austrian Hotel- and Tourism Bank (AHTB). We have information on 145 hotels that underwent debt restructurings. For 30 hotels, EBITDA is either missing "before" or "after" the debt restructuring, leaving us with a final sample of 115 hotels. (Whenever EBITDA is non-missing, other key financial variables are also non-missing.) In 91 cases, we have data for at least three "after" years. In 24 cases, we have data for only one or two "after" years. To allow consistent comparisons across hotels, we collapse the "after" data into a single observation per hotel by taking the average of the first three "after" years (or whatever is available). Accordingly, our final sample consists of a cross-section of 115 hotels, with one "before" and one "after" observation per hotel. All of the restructurings took place between 1998 and 2005. To account for the different years in which the restructurings took place, we include status-year dummies in all our regressions.

The AHTB also provided us with a "control sample" of 2,095 hotels that did not undergo debt restructurings. All of these hotels applied for and/or received funds under other (non-restructuring) ERP funding programs at some point in time, which is why they are included in the AHTB's database. For most of these hotels, we have several years of consecutive data, though for some, we only have one or two years of data. Also, in some cases, the data are not consecutive. Overall, the control sample consists of 8,931 firm-year observations. We use this control sample on two occasions: (i) to construct "locally adjusted" performance measures, and (ii) to address issues of selection bias.

We have monthly weather data for all Austrian weather stations provided to us by the Austrian Central Institute for Meteorology and Geodynamics.[9] We match each hotel to a nearby weather station by locating the weather station with the minimal Euclidean distance from the co-ordinates of the postal office in the hotel's ZIP code. To ensure that the weather conditions indeed reflect those in the hotel's vicinity, we impose the constraint that the altitudinal distance between the weather station and the hotel must not exceed 500 meters. This constraint only binds in a few cases, and our results are unchanged if the constraint is dropped. Arguably, the weather conditions measured by the closest weather station are a noisy proxy of the weather

[9] The German name is Zentralanstalt für Meteorologie und Geodynamik.

conditions that are truly relevant for the hotel (e.g., snow conditions at a nearby ski slope). While this is unlikely to introduce a systematic bias, it introduces noise into the regression, making it only harder for us to find any significant results.

4.2 Empirical Methodology

To examine whether changes in leverage during the debt restructurings lead to changes in operating performance, we estimate the cross-sectional regression

$$\Delta \text{ operating performance}_i = \alpha + \beta \times \Delta \text{ leverage}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \varepsilon_i, \tag{1}$$

where i indexes hotels, Δ is the difference operator ("after" minus "before" the debt restructuring), and $\mathbf{X}$ is a vector of control variables, which includes size, age, altitude, Δ snow, and status-year dummies. Flow variables, such as EBITDA, are lagged one year behind stock variables, such as leverage, based on the rationale that flow variables are generated by stock variables. Section 4.3 as well as Appendix A discuss what precisely the difference operator Δ measures based on whether a variable is a stock or flow variable.

Including altitude in our regression captures persistent differences across hotels—e.g., it correlates highly with long-run average snow levels—which is useful as our sample is a cross-section and hotel-fixed effects cannot be included. For instance, the correlation between altitude and 10-, 15-, and 20-year average snow levels is between 67.6% and 69.3%.[10] Including Δ snow in our regression controls for any *contemporaneous* effects of snow on operating performance. Hence, if operating performance improves after the debt restructuring, we know it is not because snow conditions have improved. (Section 4.3 describes how "snow" is defined and how it is matched to EBITDA based on the hotels' fiscal year ends.) The status-year dummies capture any effect that is common to all hotels that are restructured in the same year. While our sample period is from 1998 to 2005, the majority of the 115 restructurings took place between 1999 and 2003. There are two events in 1998, 20 events in 1999, 31 events in 2000, 27 events in 2001, 13 events in 2002, 12 events in 2003, four events in 2004, and six events in 2005. In all our regressions, we cluster standard errors at the district level.[11]

[10] All correlations are significant at the 1% level. That the correlations are not (even) higher is likely due to the fact that snow accumulation depends—in addition to altitude—on local factors, such as whether a location has a northern or southern exposure.

[11] Districts ("Bezirk" in German), also referred to as "political districts" by Austria's statistical office, are

Given that Δ leverage is endogenous in equation (1), ordinary least squares (OLS) estimation will produce biased and inconsistent estimates. To address this problem, we use an instrumental variables (IV) approach.

To find a suitable instrument for Δ leverage, we need a theory of what determines changes in leverage during debt restructurings. In a simple model, Krugman (1988) argues that one important determinant is the extent to which cash flows depend on the borrower's effort. If cash flows are completely exogenous, then it is optimal for lenders not to forgive any debt. In contrast, if cash flows depend solely on the borrower's effort, then it may be optimal to forgive debt to improve effort incentives ("debt overhang argument"). In Appendix B, we provide a simple extension of Krugman's model that also includes intermediate cases in which effort matters to varying degrees. The main empirical prediction is that lenders should forgive debt only if the borrower's effort is sufficiently important, in which case it is optimal to forgive more debt the more important is effort.

In the real world, it is unlikely that lenders can directly observe how important the borrower's effort is. This is also true in our sample of Austrian ski hotels, where the lending banks must decide whether, and how much, debt they should forgive. However, the banks can apply the following reasoning. If a ski hotel had only little snow in the years prior to the debt restructuring, then it is quite likely that the causes for the hotel's distress are exogenous. In contrast, if a ski hotel got into distress even though it had ample snow in the years prior, then it is less likely that the causes for the hotel's distress are exogenous. By implication, this means it is then relatively more likely that the causes for the hotel's distress may be incentive problems, making it optimal for lenders to forgive debt to improve effort incentives.

Note that this reasoning does not address why the hotels got into distress in the first place. It merely argues that, conditional on being in distress, the causes are more likely exogenous if a hotel had only little snow. Note also that "more likely" and "less likely" are not meant in an absolute sense, but in a relative sense, i.e., relative to other hotels in distress. After all, the (narrow) objective here is to explain cross-sectional variation in debt restructuring outcomes for a sample of ski hotels that are all in distress.

There is empirical support for this reasoning. Austrian Census data show a strong positive correlation between snow and bookings made by tourists. The data span 37 years from 1971

roughly similar to counties in the US. Excluding Vienna (there are no Viennese hotels in our sample), the average population per political district is 67.5 thousand. The 115 hotels in our sample are located in 42 different districts.

to 2007. For each year, the data show the total number of nights stayed at hotels in each of 611 Austrian "tourism regions." This yields $37 \times 611 = 22,607$ region-year observations, where an observation indicates the total number of nights stayed at hotels per region and year. The correlation between the number of nights stayed at hotels and snow is 19.6% ($p = 0.000$). (As the data include *all* Austrian tourism regions, the correlation is likely higher in regions that are primarily winter tourism regions.) Overall, this suggests that hotels with more snow have more bookings and should thus perform better. In our sample of 115 distressed hotels, however, the correlation between snow and the return on assets in the year before the debt restructuring is 0.7% ($p = 0.942$), meaning it is virtually zero.[12] Thus, while we would indeed expect hotels with little snow to perform poorly, those with ample snow did not perform any better, despite having ample snow, suggesting that the causes for their distress may be incentive problems.

The above reasoning suggests that snow in the years prior to the debt restructuring might be a suitable instrument for Δ leverage. The vast majority of the hotels in our sample experience substantial debt forgiveness, resulting in a decrease in leverage of about 23% on average. However, while there is substantial debt forgiveness in the aggregate, there is considerable cross-sectional variation. The main prediction of our model, which we test in our first-stage regression, is that hotels with relatively little snow in the years prior to the debt restructuring should experience smaller reductions in leverage than hotels with relatively ample snow. That is, we would expect a negative correlation between Δ leverage and snow.

While the results of the first-stage regression support this hypothesis, it is interesting to note that only snow in the two years prior to the debt restructuring is a good predictor of Δ leverage (see Section 6.1). In contrast, snow three and four years prior to the debt restructuring are poor predictors. This is reassuring, as it suggests that lending banks look at the level of snow when the hotels likely got into distress, not at the level of snow many years before. Also noteworthy is that snow in the two years prior to the debt restructuring is highly correlated with deviations of this variable from long-run historical snow levels. Much of this correlation is driven by the left tail of the distribution, i.e., hotels with little snow in the two years prior to the debt restructuring also had little snow by their own historical standards. This is not entirely surprising, given that "two years prior" is not just any random time period, but it is precisely the period when the hotels got into distress. Indeed, instead of using snow in the two years prior

[12] Given that snow and the return on assets in the year prior to the debt restructuring are uncorrelated, we can include the latter as a control variable in our regressions and obtain similar results.

as our instrument, we can use deviations from long-run historical snow levels as our instrument, and the results remain qualitatively similar.

While we control for Δ snow in equation (1) to account for any contemporaneous effect of snow on operating performance, an important concern is that snow in the two years prior to the debt restructuring might have a direct effect on future operating performance (i.e., other than through Δ leverage). Suppose, for instance, that ski tourists book one year ahead, especially if they had a good skiing vacation with plenty of snow. In that case, past snow might predict future demand and therefore future operating performance, violating the exclusion restriction. At the same time, suppose that lending banks make their decision to forgive debt based on their expectations of the hotels' future operating performance. Taken together, past snow would then (directly) predict future operating performance, which in turn would predict changes in leverage during the debt restructurings ("reverse causality").

Alternatively, suppose again that past snow (directly) predicts future demand and therefore future operating performance. At the same time, however, suppose that hotels with ample snow in the years prior to the debt restructuring earn higher profits, which enables them to repay some of their outstanding debt (i.e., suppose there is no debt forgiveness). Overall, past snow would then again (directly) predict future operating performance, but it would simultaneously also predict changes in leverage, implying that any correlation between Δ operating performance and Δ leverage would be spurious.

Each of these alternative stories effectively consists of two parts: a reason for why the exclusion restriction might be violated, and a reason for why we might nevertheless observe a correlation between Δ operating performance and Δ leverage in our second-stage regression. In Section 6.2, we argue why a violation of the exclusion restriction—while generally an important concern—might not be a serious concern here. For instance, we show that we obtain similar results when using either snow two years prior to the debt restructuring or deviations of snow from long-run historical averages as our instrument. We also obtain similar results when using "locally adjusted" performance measures, which effectively "control" for any direct effect of past snow on future operating performance. Finally, we argue that alternative stories for why Δ operating performance and Δ leverage might be correlated, based on either reverse causality or a spurious correlation, are difficult to reconcile with the data.

4.3 Definition of Variables and Summary Statistics

We use two measures of operating performance: return on assets (ROA), which is EBITDA divided by the book value of assets, and net profit margin (NPM), which is EBITDA divided by sales. To avoid that outliers drive our results, we winsorize both variables at the 5th and 95th percentiles of their empirical distribution. We obtain similar results if we winsorize at the 1st and 99th percentiles, at the 10th and 90th percentiles, or if we use median regressions instead. (See Table IV for results based on median regressions.)

Given that all hotels in our sample are privately held, market values are not available. Accordingly, "leverage" is the book value of debt divided by the book value of assets. "Size" is the book value of assets (in Euros) in the year prior to the debt restructuring. "Age" is the number of years since the hotel was granted its operating license, measured in the year before the debt restructuring. This information is missing for 28 hotels. For these hotels, we use instead the number of years with available accounting data.[13] In all our regressions, we use the logarithms of size and age. Finally, "altitude" is the surface-weighted average altitude of the area spanned by the hotel's ZIP code (in meters).

"Snow" in any given year is the number of days during the main winter season (December, January, February, and March) with more than 10 centimeters of snow on the ground, as measured by the closest weather station. Winter months are matched to firm-year observations based on the hotels' fiscal year ends. For instance, if the fiscal year ends in December 1999, the relevant winter season includes the months of January 1999, February 1999, March 1999, and December 1999.[14] This matching ensures that—when controlling for any contemporaneous effect of snow on operating performance—we indeed capture the relevant snow in the fiscal year in which EBITDA is recorded.

It should be noted that our results are not sensitive to the choice of snow variable. For instance, we obtain virtually identical results if we use a 5 or 20 centimeter threshold in place of a 10 centimeter threshold. This is not surprising, given that the correlation between our snow variable and snow variables based on either a 5 or 20 centimeter threshold is 98.6% and 95.5%,

[13] The year in which the hotel is granted its operating license is also missing for all hotels in our control sample. For this reason, age is not part of the descriptive statistics in Table I or the selection equation in Table VIII. Instead of omitting age from the selection equation, we could use the number of years with available accounting data as a proxy for age. All our results remain similar when using this alternative proxy.

[14] Most hotels in our sample have their fiscal year end on December 31, though April 30 and November 30 are also common choices.

respectively. Our results are also similar if we use entirely different snow variables, such as the number of days with fresh snowfall, or if we use entirely different weather variables, such as the average temperature during the winter season. In all these cases, the correlation with our snow variable is very high.

Firm-year observations are mapped into either "before" or "after" observations as follows. (Appendix A contains a more comprehensive discussion.) In the case of *stock* variables (e.g., assets, debt), the first "after" observation is measured at the end of the fiscal year in which the restructuring takes place. In the case of *flow* variables (e.g., EBITDA, sales), the first "after" observation is measured one year later, as is common practice, based on the rationale that flow variables are generated by stock variables. The second and third "after" observations, as well as the "before" observation, are defined accordingly. One implication of this timing convention is that ROA in fiscal year t combines accounting data from years t and $t-1$, i.e., $\text{ROA}(t) := \text{EBITDA}(t)/\text{Assets}(t-1)$. (The same is not true for NPM, as EBITDA and sales are both flow variables.)

Table I provides summary statistics. "Restructuring sample" refers to the 115 distressed hotels that underwent debt restructurings. "Control sample" refers to the 2,095 hotels in the control group that did not undergo debt restructurings. In the restructuring sample, "mean" and "median" refer to the year before the debt restructuring. In the control sample, "mean" and "median" refer to averages across all firm-years. As can be seen, restructured hotels are smaller than control hotels (smaller book value of assets, fewer beds, fewer employees), which is consistent with the notion that smaller hotels are more likely to get into distress. Restructured hotels are also located at slightly lower altitudes and have slightly less snow than control hotels do. However, conditional on altitude, snow levels are comparable across restructuring and control hotels.[15] The "quality" of the hotels, as measured by their star rating (five stars being the highest), is the same across restructuring and control hotels.

Importantly, restructured hotels are highly overleveraged. The average leverage ratio in the year before the debt restructuring is 2.40 (median 1.77), which is roughly twice as large as the corresponding number for control hotels (mean 1.26, median 0.99). When comparing these numbers to other samples, (e.g., Compustat firms), it is useful to bear in mind that practically all hotels—including those in the control sample—are small privately held hotels, which tend

[15] That hotels in both samples are located at relatively high altitudes reflects the nature of our data.

to rely heavily on debt financing. Moreover, it is useful to remember that leverage is based on book values, not market values. Finally, restructured hotels are less profitable than control hotels. While the average ROA of control hotels is 13.0% (median 12.0%), the average ROA of restructured hotels in the year before the debt restructuring is only 10.9% (median 9.3%).

Like the hotel in our example in Section 3, the vast majority of the restructured hotels experience substantial debt forgiveness during the debt restructuring. As a result, the average leverage ratio drops to 1.85 (median 1.56) (not reported in Table I), which implies a reduction of about 23%. At the same time, the average ROA increases to 11.9% (median 10.9%). It should be noted that to the extent that it takes several years to improve operating performance, these numbers—which are based on averages in the three years after the debt restructuring—likely understate the true long-run improvements in operating performance.

5 Results

5.1 Return on Assets (ROA)

Table II shows the results when the dependent variable is Δ ROA. In columns [1] and [2], equation (1) is estimated by OLS. In columns [3] and [4], it is estimated by IV, using snow as an instrument for Δ leverage. For both types of regressions, we report the results both with and without control variables. The results of the first-stage regression are discussed separately in Section 6.1.

OLS regressions yield a significant positive association between Δ ROA and Δ leverage, regardless of whether control variables are included. It is not difficult to think of a reverse causality explanation here. For instance, hotels with larger *anticipated* improvements in operating performance might receive less debt forgiveness, resulting in smaller reductions in leverage (i.e., higher Δ leverage). More generally, as Δ leverage is endogenous with respect to Δ ROA, it is not clear how to interpret the OLS results.

When Δ leverage is instrumented with snow, we obtain the opposite result: the coefficient on Δ leverage is now negative and significant. The effect is also economically significant. When control variables are not included, the coefficient on Δ leverage is -0.037 (t = 2.60). When control variables are included, the coefficient is -0.055 (t = 2.49). Given that Δ leverage is -0.55 on average, this corresponds to an average increase in ROA of $-0.055 \times -0.55 =$

0.03, or three percentage points. Given that the average ROA before the debt restructuring is 10.9%, this corresponds to an increase in ROA of about 28%. Thus, consistent with the arguments by Myers (1977), Krugman (1988), Sachs (1989), an others, our IV results suggest that a reduction in leverage leads to statistically and economically significant improvement in operating performance. As for the control variables, size is positively associated with Δ ROA in both the OLS and IV regressions, though it is only significant in the latter. The other control variables are insignificant in both types of regressions.

Following Hausman (1978), we can compare the OLS and IV estimates to test for endogeneity. Regardless of whether control variables are included, we can always reject the null of no endogeneity at high significance levels ($p = 0.009$ without controls, $p = 0.001$ with controls). Thus, provided our instrument is valid, Hausman tests confirm that the OLS estimates are biased, implying that consistent estimation of the effect of Δ leverage on Δ ROA requires an IV estimation.

5.2 Net Profit Margin (NPM)

Table III shows the results when the dependent variable is Δ NPM.[16] In columns [1] and [2], equation (1) is estimated by OLS. In columns [3] and [4], it is estimated by IV, using snow as an instrument for Δ leverage. For both types of regressions, we report the results again with and without control variables. As is shown, the results are similar to our ROA results. OLS regressions yield again a positive relationship between Δ NPM and Δ leverage, albeit this relationship is not significant.

When Δ leverage is instrumented with snow, we obtain again a negative and significant coefficient on Δ leverage. When control variables are not included, the coefficient is -0.036 ($t = 2.18$). When control variables are included, the coefficient is -0.055 ($t = 2.59$). The coefficients are almost identical to those in our ROA regressions, suggesting that the scaling variable (sales versus assets) plays little role. Hausman tests also yield similar results. Regardless of whether control variables are included, we can always reject the null of no endogeneity at high significance levels ($p = 0.033$ without controls, $p = 0.002$ with controls).

[16] The number of observations drops to 114 due to sales being missing for one hotel.

5.3 Median Regressions

To mitigate the effect of outliers, we winsorize both ROA and NPM at the 5th and 95th percentiles of their empirical distribution. As mentioned earlier, we obtain similar results if we winsorize at the 1st and 99th percentiles or at the 10th and 90th percentiles. An alternative way to address this issue is to use median (least absolute deviation) regressions.

A main complication introduced by using median regressions is the computation of the standard errors. In the presence of cross-sectional dependence, the asymptotic covariance matrix of Koenker and Bassett (1978), which assumes independent observations, cannot be used. The standard bootstrap approach cannot be used either, for it only corrects for heteroscedasticity. To circumvent this problem, we use a modified bootstrap approach: block bootstrapping. The difference to standard bootstrapping is that instead of drawing single observations, we draw entire blocks of observations. The underlying idea, which is similar to clustering, is to preserve the existing correlation structure within each block and to use the independence across blocks to consistently estimate the standard errors. In analogy to the clustering method in our main analysis, we construct blocks at the district level, leaving us with 42 blocks. Precisely, we construct 500 bootstrap samples by drawing with replacement 42 districts from our sample. For each bootstrap sample, we estimate our main specification using median regressions and store the coefficients. The standard errors are then calculated based on the empirical distribution of these 500 sets of coefficients.

Table IV shows the results based on median regressions. In columns [1] and [2], the dependent variable is Δ ROA. In columns [3] and [4], the dependent variable is Δ NPM. When Δ leverage is not instrumented (columns [1] and [3]), there is again a positive relationship between either Δ ROA or Δ NPM and Δ leverage. In fact, the coefficient on Δ leverage is now significant in either regression, while it was previously only significant in the ROA regression. When Δ leverage is instrumented with snow (columns [2] and [4]), the results are also similar to our previous results. When Δ ROA is the dependent variable, the coefficient on Δ leverage is -0.044 ($t = 2.10$), while it was previously -0.055 ($t = 2.49$). Likewise, when Δ NPM is the dependent variable, the coefficient on Δ leverage is -0.053 ($t = 2.51$), while it was previously -0.055 ($t = 2.59$). Overall, the evidence based on median regressions suggests that our results are unlikely to be driven by outliers.

6 Identification

6.1 First-Stage Regression

In the first-stage regression, we regress Δ leverage on snow plus all control variables from equation (1). We estimate

$$\Delta \text{ leverage}_i = \alpha + \beta \times \text{snow}_i + \boldsymbol{\gamma}'\mathbf{X}_i + \varepsilon_i, \tag{2}$$

where i indexes hotels, Δ is the difference operator ("after" minus "before"), and "snow" is the average snow in the two years prior to the debt restructuring. All other variables are the same as in equation (1). Standard errors are clustered at the district level.

Table V presents the results of the first-stage regression. As is shown, snow is negatively associated with Δ leverage and significant at the 1% level. The effect is also economically significant. The coefficient on snow is -0.014 ($t = 3.15$), which implies that a one-standard deviation (39.32) increase in snow is associated with a reduction in leverage of $-0.014 \times 39.32 = -0.55$. Given that the average leverage ratio before the debt restructuring is 2.40, this corresponds to a reduction in leverage of about 23%. Overall, our results show that hotels with more snow in the years prior to the debt restructuring experience significantly larger reductions in leverage, which is consistent with the hypothesis formulated in Section 4.2. As for the control variables, size is significantly positively associated with Δ leverage, while all other control variables are insignificant.

Instead of using the average snow in the last two years prior to the debt restructuring as our instrument, we can (re-)estimate equation (2) using snow in any particular year (one, two, three, and four years) prior to the debt restructuring as our instrument. The results (not reported) show that the coefficient on snow in the first-stage regression becomes increasingly smaller (and less significant) the further away we move from the year of the debt restructuring. In particular, while the coefficients one and two years prior to the debt restructuring are similar both in terms of magnitude and significance (-0.014 ($t = 3.37$) and -0.011 ($t = 2.98$), respectively), the coefficients three and four years prior are much smaller and insignificant (-0.004 ($t = 1.19$) and -0.003 ($t = 0.93$), respectively). This is reassuring, as it suggests that lending banks look at the level of snow when the hotels likely got into distress, not at the level of snow many years before. Given that the coefficients on snow one and two years prior to the debt restructuring are very similar, both in terms of magnitude and statistical significance, we use the average snow in these two years as our instrument.

Consistency of IV estimation in a finite sample requires that the instrument be sufficiently "strong" (Staiger and Stock, 1997), meaning it must correlate "strongly" with the endogenous variable. In equation (2), the coefficient on snow has a t-statistics of 3.15 ($p = 0.003$), implying that weak identification is unlikely to be a concern. Likewise, the F-statistics for the null that $\beta = 0$ is 9.92, which lies above the 15% critical value in Table 5.2 of Stock and Yogo (2005, p. 101).[17] Again, this suggests that weak identification is unlikely to be a concern.

6.2 Exclusion Restriction

The exclusion restriction is violated if snow in the years prior to the debt restructuring has a direct effect on Δ operating performance (i.e., other than through Δ leverage). Suppose, for instance, that ski tourists book one year ahead, especially if they had a good skiing vacation with plenty of snow. In that case, past snow might predict future demand and therefore future operating performance, violating the exclusion restriction. At the same time, suppose that lending banks make their decision to forgive debt based on their expectations of the hotels' future operating performance. Taken together, past snow would then (directly) predict future operating performance, which in turn would predict changes in leverage during the debt restructurings ("reverse causality").

Alternatively, suppose again that past snow (directly) predicts future demand and therefore future operating performance. At the same time, however, suppose that hotels with ample snow in the years prior to the debt restructuring earn higher profits, which enables them to repay some of their outstanding debt (i.e., suppose there is no debt forgiveness). Overall, past snow would then again (directly) predict future operating performance, but it would also simultaneously predict changes in leverage, implying that any correlation between Δ operating performance and Δ leverage in our second-stage regression would be spurious.

Each of these alternative stories effectively consists of two parts: a reason for why the exclusion restriction might be violated, and a reason for why we might nevertheless observe a correlation between Δ operating performance and Δ leverage in our second-stage regression. In what follows, we first address concerns regarding a possible violation of the exclusion restriction. Subsequently, we argue that alternative stories for why Δ operating performance and Δ leverage

[17] Formally, this means that the maximum size of a 5% level Wald test based on the IV is at most 15%, so that the maximum size distortion is at most 10%.

might be correlated, based on either reverse causality or a spurious correlation, are difficult to reconcile with the data.

While a possible violation of the exclusion restriction is an important concern, we believe this concern is minimized here, for several reasons:

1. Bookings can always be cancelled at short notice, typically at no cost. Thus, if ski tourists who made their booking last year (when there was plenty of snow) realize that this year's snow is poor, they can simply cancel their booking, implying that it is current snow, not past snow, that determines current operating performance. But we already control for any contemporaneous effect of snow on operating performance.

2. We obtain similar results if instead of using the average snow in the last two years prior to the debt restructuring ("snow") as our instrument, we exclusively use snow *two* years prior (i.e., not including snow in the year before) as our instrument. Arguably, only few ski tourists book two years ahead. As column [1] of **Table VI** shows, the coefficient on snow two years prior in the first-stage regression is -0.011 ($t = 2.98$), which is similar both in magnitude and statistical significance to the coefficient on "snow" in Table V. For brevity, we only report the second-stage results when Δ ROA is the dependent variable. The results when Δ NPM is the dependent variable are similar. As column [2] shows, using snow two years prior as our instrument makes the second-stage regression even stronger. The coefficient on Δ leverage is now -0.070 ($t = 2.86$), while it was previously -0.055 ($t = 2.49$).

3. There is a strong positive correlation between "snow" and deviations of this variable from its long-run historical average. Depending on the time horizon (10, 15, or 20 years), the correlation is between 50.7% and 57.6%.[18] Much of this correlation is driven by the left tail of the distribution, i.e., hotels with little snow in the two years prior to the debt restructuring also had little snow by their own historical standards. This is not entirely surprising, given that "two years prior" is not just any random time period, but it is precisely the period when the hotels got into distress.

   Given this strong correlation, it is not surprising that we obtain similar results when

[18] All correlations are significant at the 1% level. Deviations from 10-, 15-, and 20-year historical averages are computed as the difference between the average snow in the last two years prior to the debt restructuring ("snow") and the average snow in the preceding 10, 15, and 20 years, respectively.

using deviations from long-run historical snow levels as our instrument. In that case, the argument with respect to a possible violation of the exclusion restriction would have to be that ski tourists make their bookings not based on whether snow in their last vacation was plenty, but instead based on the extent to which observed snow levels deviate from long-run historical averages. This is rather unlikely, especially since deviations from long-run historical snow levels are uncorrelated over time, i.e., there is no reason to expect that abnormally high snow in one year would predict abnormally high snow in the following year.[19]

In columns [3] and [4], we use the deviation of "snow" from its 15-year historical average as our instrument. Results based on deviations from 10- or 20-year historical averages are similar. We only report the second-stage results when Δ ROA is the dependent variable. The results when Δ NPM is the dependent variable are similar. As is shown, the results are similar to those when "snow" is our instrument. In the first-stage regression, there is a significant negative relationship between Δ leverage and the deviation of "snow" from its 15-year historical average. Likewise, in the second-stage regression, the coefficient on Δ leverage is -0.060 ($t = 2.06$), which is similar in magnitude to the coefficient when Δ leverage is instrumented with "snow."

4. Using our control sample of 2,095 hotels that did not undergo debt restructurings, we can construct "locally adjusted" measures of operating performance. For each of the 115 hotels in our restructuring sample, we subtract from each firm-year observation of ROA (NPM) the median value of ROA (NPM) of all control hotels in the same year and district. (The average number of control hotels per year and district is 10.8.) The idea underlying this adjustment is that if past snow had a direct effect on future demand and therefore on future operating performance, then this (direct) effect should also apply to other hotels in the same district, which face similar snow conditions. Using locally adjusted performance measures thus effectively "controls" for any direct effect of past snow on future operating performance.

   Table VII presents the results based on using locally adjusted performance measures. (Note that the adjustment only affects the second-stage regression.) In columns [1] and [2],

[19] The average autocorrelation of deviations of "snow" from, e.g., its 15-year historical average is 0.6% ($p-$value of 0.89), which means it is virtually zero.

the dependent variable is locally adjusted Δ ROA. In columns [3] and [4], the dependent variable is locally adjusted Δ NPM. Moreover, in columns [2] and [4], we use median regressions, where the standard errors are computed using block boostrapping as described in Section 5.3. Throughout, the results are similar to before. When the dependent variable is locally adjusted Δ ROA, the coefficient on Δ leverage is -0.061 $(t = 2.68)$, while it was previously -0.055 $(t = 2.49)$. Similarly, in the corresponding median regression, the coefficient on Δ leverage is -0.052 $(t = 2.41)$, while it was previously -0.044 $(t = 2.10)$. When the dependent variable is locally adjusted Δ NPM, the coefficient on Δ leverage is -0.058 $(t = 2.35)$, while it was previously -0.055 $(t = 2.59)$. Similarly, in the corresponding median regression, the coefficient on Δ leverage is -0.057 $(t = 2.26)$, while it was previously -0.053 $(t = 2.51)$.

Each alternative story also provides a reason for why we might (nevertheless) observe a correlation between Δ operating performance and Δ leverage in our second-stage regression. In the first story, lending banks make their decision to forgive debt based on their expectations of the hotels' future operating performance. If the latter is exogenously determined (namely, by past snow), this would imply that the correlation between Δ operating performance and Δ leverage is based on reverse causality. However, from a theoretical perspective, it is not clear why the lending banks should forgive any debt at all if the hotels' future operating performance is exogenously determined. (See Krugman's (1998) model in Appendix B, where the only reason to forgive debt is to provide effort incentives. If future cash flows are exogenous, then it is never optimal to forgive any debt.) One possible explanation is that the lending banks view debt forgiveness simply as a write-off, because they do not expect to recoup the full amount of debt anyway. In this case, however, we should see that lending banks forgive more debt to hotels which they expect to perform poorly (and less debt to hotels which they expect to perform well), which is inconsistent with the observed negative correlation between Δ operating performance and Δ leverage.

In the second story, hotels with ample snow in the years prior to the debt restructuring earn higher profits, which enables them to repay some of their outstanding debt (i.e., there is no debt forgiveness in that story). Accordingly, any correlation between Δ operating performance and Δ leverage in our second-stage regression would be spurious. This story is problematic for two reasons. First, all hotels in our sample are in distress. If a hotel did so well in the years prior to the debt restructuring that it could afford a voluntary debt repayment, then it would likely not be in our sample. (Also, we *know* from the restructuring reports that the hotels receive substantial debt forgiveness; see, e.g., the example in Section 3.) Second, the central assumption underlying this story—namely, that there is a positive relationship between snow in the years prior to the debt restructuring and profits in the same period—is not supported by the data. As mentioned previously, the correlation between "snow" and ROA in the year before the debt restructuring is 0.6% ($p = 0.942$), which means it is virtually zero. Not only is this inconsistent with this particular alternative story, it is inconsistent with any alternative story that presumes a correlation between snow and profitability before the debt restructuring. On the other hand, the absence of such a correlation is consistent with the notion that there are essentially two types of hotels in our sample: those that perform poorly because of bad snow, and those that perform poorly despite having ample snow.

7 Selection Bias

The 115 hotels undergoing debt restructurings are a selected sample. To account for possible selection bias, we use Heckman's (1979) two-step correction method. The first step involves estimation of a selection equation. For this purpose, we extend our sample by including the 2,095 "control hotels" that did not undergo debt restructurings. As mentioned previously, a formal criterion for the Austrian Hotel- and Tourism Bank (AHTB) to be involved in a debt restructuring is that the hotel be "structurally important," meaning it must be a large hotel relative to other hotels in the same municipality. Based on this criterion, we construct a new variable, "local capacity share," which we use as an instrument in our selection equation. "Local capacity share" is the number of beds of a hotel in a given year divided by the number of beds of all hotels in the same district and year. As "structurally important" hotels are more likely to have larger local capacity shares, we would expect to find a positive association between this variable and the likelihood of being selected. Importantly, local capacity share is based on the number of *available* beds, not the number of nights stayed. Hence, it does not capture aspects of performance and is therefore likely exogenous in the second-stage regression.

We estimate the Probit selection equation

$$\text{selection dummy}_{it} = \alpha_t + \beta \times \text{local capacity share}_{it} + \lambda \times \text{snow}_{it} + \boldsymbol{\gamma}'\mathbf{X}_{it} + \varepsilon_{it}, \qquad (3)$$

where i indexes hotels, t indexes years, α_t are year dummies, "selection dummy" is a dummy that equals one if a hotel is restructured in the following year and zero otherwise, "local capacity share" is the number of beds of hotel i in year t divided by the number of beds of all hotels in the same district and year, "snow" is the average snow in the previous two years, and $\mathbf{X}$ is a vector of control variables, which includes size in year $t-1$, altitude, and Δ snow, which is computed as the difference between snow in years t and $t-1$. If a hotel is restructured, its subsequent firm-year observations are dropped from the sample. Age is missing for all control hotels. Accordingly, the selection equation does not include age (see also footnote 13). Also, the number of beds is only available for 74 of the 115 hotels in our restructuring sample and for 1,901 of the 2,095 hotels in the control sample, leaving us with 6,736 firm-year observations. Standard errors are again clustered at the district level.

Panel (A) of **Table VIII** shows the results from estimating equation (3). The coefficient on local capacity share is positive and significant ($t = 2.74$), implying that hotels with larger local capacity shares are more likely to be restructured. (Recall that we control for firm size in all our regressions.) What appears puzzling, however, is that while hotels with larger local capacity shares are more likely to be restructured, the summary statistics in Table I show that restructured hotels are on average smaller than control hotels (smaller book value of assets, fewer beds, fewer employees). There is a simple explanation: debt restructurings are concentrated in districts with smaller hotels. *Within* these districts, restructured hotels are relatively large, which explains the positive coefficient on local capacity share in equation (3). Compared to (control) hotels in non-restructuring districts, however, restructured hotels are relatively small.[20]

Using the estimates from equation (3), we can compute the Inverse Mills Ratio and include it as an explanatory variable in our second-stage regression. Before doing so, however, we wish to verify that the 74 hotels with non-missing bed data are representative of our original sample of 115 hotels. In Panel (B), we therefore re-estimate equation (1) using only the 74 hotels with non-missing bed data. As is shown, regardless of whether we use Δ ROA or Δ NPM as the dependent variable, and regardless of whether we use locally adjusted performance measures or

[20] The average number of beds of all (restructured and control) hotels in districts in which a restructuring occurred, as of the year before the restructuring, is 70.0. In contrast, the average number of beds of only the restructured hotels in the same year is 76.0 (see Table I). Thus, restructured hotels are larger than control hotels in the same district. On the other hand, the average number of beds of (control) hotels in non-restructuring districts is 117.6. Thus, control hotels in non-restructuring districts are *much* larger than restructured hotels, which in turn are larger than control hotels in restructuring districts. As a consequence, the average control hotel (including those in restructuring districts) is larger than the average restructured hotel. Using size or the number of employees instead of the number of beds yields similar results.

non-adjusted performance measures, the results are similar to our previous results.

In Panel (C), we include the Inverse Mills Ratio as an explanatory variable in our second-stage regression. As is shown, the coefficient on Δ leverage is virtually identical to that in Panel (B). Moreover, the Inverse Mills Ratio, while positive, is not significant.[21] Overall, this suggests that our results are unlikely to be driven by selection bias.

8 Conclusion

We provide empirical support for the argument that reducing a debt overhang improves performance. Using a sample of distressed and highly overleveraged Austrian ski hotels undergoing debt restructurings, we find that reductions in leverage bring about statistically and economically significant improvements in operating performance. To identify the effect of leverage changes on changes in operating performance, we instrument leverage changes with the level of snow in the years prior to the debt restructuring. The instrument is motivated by the argument that if a hotel had only little snow in the years prior to the debt restructuring, then it is quite likely that the causes for the hotel's distress are exogenous. In contrast, if a hotel got into distress even though it had ample snow in the years prior, then it is less likely that the causes for the hotel's distress are exogenous. By implication, this means it is then relatively more likely that the causes for the hotel's distress may be incentive problems, making it optimal to forgive debt to improve effort incentives. Our results hold for different measures of operating performance (return on assets, net profit margin) as well as different snow instruments.

Given the importance of the debt overhang problem both for policy and practice, we believe our results are of interest. That said, our results are obtained using a small sample of Austrian ski hotels, implying their external validity remains to be established. In particular, more research is needed to examine whether our results also extend to firms in other industries and countries, bearing in mind the limitations of such exercises imposed by the identification strategy. Along similar lines, as the evidence presented here pertains to firms, not countries, caution must be exercised when trying to extrapolate our results to the context of sovereign lending, where other factors are likely to play an important role.

[21] While including the Inverse Mills Ratio has no impact on the coefficient on Δ leverage, it reduces the magnitude and significance of the coefficient on size. When Δ NPM is the dependent variable, size even becomes insignificant. Hence, at least part of the significant effect of size that we consistently find in our regressions may be due to sample selection.

9 Appendix A: Timing Conventions

In our regressions, the difference operator Δ measures the difference between "after" and "before" the debt restructuring. In the case of *stock* variables (e.g., assets, debt), the first "after" observation is measured at the end of the fiscal year in which the debt restructuring takes place. In the case of *flow* variables (e.g., EBITDA, sales), the first "after" observation is measured one year later, as is common practice, based on the rationale that flow variables are generated by stock variables. The second and third "after" observations, as well as the "before" observation, are defined accordingly.

One implication of this timing convention is that the return on assets (ROA) in fiscal year t combines accounting data from years t and $t-1$. Specifically, denote by T_i the (end of the) fiscal year in which the debt restructuring of hotel i takes place. We then have that:

$$\Delta \text{ ROA}_i := \left(\frac{1}{3} \sum_{t=T_i}^{T_i+2} \frac{\text{EBITDA}_{i,t+1}}{\text{assets}_{i,t}} \right) - \frac{\text{EBITDA}_{i,T_i}}{\text{assets}_{i,T_i-1}}. \tag{4}$$

In contrast, since EBITDA and sales are both flow variables, the net profit margin (NPM) in fiscal year t uses only accounting data from the same year. Hence, we have that:

$$\Delta \text{ NPM}_i := \left(\frac{1}{3} \sum_{t=T_i}^{T_i+2} \frac{\text{EBITDA}_{i,t+1}}{\text{sales}_{i,t+1}} \right) - \frac{\text{EBITDA}_{i,T_i}}{\text{sales}_{i,T_i}}. \tag{5}$$

By the same token, since debt and assets are both stock variables, the leverage ratio in fiscal year t uses only accounting data from the same year. Accordingly, we have that:

$$\Delta \text{ leverage}_i := \left(\frac{1}{3} \sum_{t=T_i}^{T_i+2} \frac{\text{debt}_{i,t}}{\text{assets}_{i,t}} \right) - \frac{\text{debt}_{i,T_i-1}}{\text{assets}_{i,T_i-1}}. \tag{6}$$

Finally, to control for any contemporaneous effect of snow on operating performance, we match snow to EBITDA based on the hotels' fiscal year ends. This implies that:

$$\Delta \text{ snow}_i := \left(\frac{1}{3} \sum_{t=T_i}^{T_i+2} \text{snow}_{i,t+1} \right) - \text{snow}_{i,T_i}, \tag{7}$$

where "$\text{snow}_{i,t}$" is the total number of days during the months of January, February, March, and

December in fiscal year t with more than 10 centimeters of snow on the ground, as measured by the weather station which is closest to hotel i based on the matching procedure outlined in Section 4.1. Thus, snow is treated as a flow variable, like EBITDA, and it is matched exactly to the fiscal years in which EBITDA is generated, implying that "after" and "before" have exactly the same meaning for both variables.

10 Appendix B: Extension of Krugman's (1998) Model

In Krugman's (1998) model, a country is unable to repay its outstanding debt. Krugman considers two polar cases. If the country's (future) cash flows are completely exogenous, then it is optimal for lenders not to forgive any debt. In contrast, if cash flows depend solely on the country's effort, then it may be optimal to forgive debt to improve effort incentives. This Appendix provides a simple extension of Krugman's model. In addition to considering the two polar cases analyzed by Krugman, we consider intermediate cases in which effort is "more or less important."

Krugman's model is arguably better suited for firms than it is for countries, given his (controversial) assumption that lenders can seize a country's assets upon default ("gunboat technology"). In the case of corporate debt, this assumption holds naturally, being an integral part of the law in most countries. Without loss of generality, and given our interest in corporate debt, we thus refer to the borrower as a firm.

There are two periods. In the first period, the firm has outstanding debt D_1 due immediately. For simplicity, we assume that the firm has no cash. In the second period, the firm's cash flow is $x_2 \in \{x_B, x_G\}$, where $p := \Pr(x_2 = x_G)$ is the probability of a high cash flow. The discount rate is zero. We assume that $D_1 > px_G + (1-p)x_B$, implying that the firm cannot raise funds from new investors to repay its outstanding first-period debt. Krugman refers to this situation as *debt overhang*.

One feasible strategy for the existing lender is to let the firm default in the first period, in which case the lender receives nothing. The question examined by Krugman is under what conditions is this strategy dominated by another strategy under which the firm lives (at least) another period. Krugman considers two polar cases. In the first case, the firm's second-period cash flow is exogenous. In the second case, the second-period cash flow depends solely on the firm's effort.

10.1 Exogenous Cash Flows

If the second-period cash flow is exogenous, the lender's optimal strategy is to roll over the outstanding first-period debt at an interest rate i such that she receives *all* of the firm's second-period cash flow. Thus, the optimal second-period debt is $D_2^* = (1+i^*)D_1 = x_G$. This solution is formally equivalent to one in which the firm is granted a new one-period loan D_1 at interest rate i^* with the requirement that it must use the loan to repay its outstanding first-period debt. (In other words, the lender gives the firm D_1, the firm immediately pays back D_1, and it owes the lender $D_2^* = (1+i^*)D_1$ in the second period.) The lender's expected payoff under the optimal strategy is $\Pi^* = px_G + (1-p)x_B$, which is clearly better than letting the firm default in the first period. As Krugman (p. 258) writes, "lending that would be unprofitable viewed in isolation is worth doing as a way of defending the value of existing debt."

Under the optimal solution, the lender receives all of the firm's second-period cash flow. While the lender may still have to write off some debt (if $D_1 > D_2^* = x_G$), there is no voluntary *debt forgiveness*, i.e., there is no reduction in the firm's debt below the maximum which the lender could potentially obtain. Given this outcome, Krugman asks whether there is "any circumstance under which new lending (or rescheduling of existing debt) will take place at *concessional* rates? To develop any motivation for debt forgiveness, we need to have an example in which the creditors have to be concerned about the incentives they give to the debtor" (p. 259, italics added).

10.2 Cash Flows Depending Solely on Effort

In the other polar case, the probability of a high cash flow is solely a function of the firm's effort, i.e., $p := \Pr(x_2 = x_G) = e$.[22] For simplicity, suppose that effort costs are quadratic, i.e., $c(e) = \frac{1}{2}e^2$. To ensure an interior first-best solution $e_{FB} < 1$, we also need to assume that $x_G - x_B < 1$. As the second-best effort is always less than e_{FB}, this also ensures that the second-best solution is feasible, i.e., that $e^* \leq 1$. Given this assumption, it is straightforward to show that there is a unique interior first-best effort $e_{FB} = x_G - x_B$. As will become clear shortly, the condition for a debt overhang—i.e., the condition that the firm cannot raise funds from new investors to repay its outstanding first-period debt—is $(\frac{x_G - x_B}{2})^2 + x_B < D_1$.

[22] Krugman does not explicitly solve the model with effort. However, he notes that the optimal solution if the firm's cash flow is exogenous would result in no effort and therefore cannot be optimal.

The question of interest is, again, what is the lender's optimal strategy? Without loss of generality, we can solve directly for the optimal second-period debt D_2^*, noting that $i^* = \frac{D_2^*}{D_1} - 1$. We can safely ignore any candidate solution where the interest rate is so high that $D_2 > x_G$. As the maximum which the lender could obtain in the good state is x_G, any such solution would yield the same expected payoff to the lender—and would result in the same effort by the firm (namely, $e^* = 0$)—as a solution in which $D_2 = x_G$. Likewise, we can ignore any candidate solution where the interest rate is so low that $D_2 < x_B$. As the lender would then obtain D_2 for sure (i.e., in both states), he would always want to raise the interest rate a little further, implying there exists no solution in which $D_2 < x_B$ ("open set problem").

Given that $x_G > D_2 \geq x_B$, the firm's problem is

$$\max_e U = e(x_G - D_2) - \frac{1}{2}e^2,$$

which has a unique solution $e^* = x_G - D_2$. Note that if the lender were to extract all of the firm's cash flows—as was the optimal solution in the case with exogenous cash flows—the firm's optimal response would be to exert no effort.

The lender's problem is

$$\max_i \Pi \ = eD_2 + (1-e)x_B$$

subject to

$$e^* = x_G - D_2,$$

which has a unique solution

$$D_2^* = \frac{x_B + x_G}{2} < x_G.$$

Under this solution, the firm's optimal effort is $e^* = \frac{x_G - x_B}{2}$, which is strictly less than the first-best effort $e_{FB} = x_G - x_B$. Moreover, the lender's expected payoff under the optimal solution is $\Pi^* = (\frac{x_G - x_B}{2})^2 + x_B$, which explains the condition for the debt overhang stated above.

10.3 Intermediate Cases

We now extend Krugman's framework to allow for intermediate cases in which effort matters to varying degrees. In general, we could write $p := \Pr(x_2 = x_G) = p(e, \varphi)$, where φ is a parameter indicating how important the firm's effort is. Given that we want a closed-form solution, however, we shall refrain from using such a general specification and instead assume a particular functional form of $p(e, \varphi)$. In the two polar cases above, the optimal solution was $D_2^* = x_G$ if cash flows are exogenous and $D_2^* = \frac{x_B + x_G}{2} < x_G$ if cash flows depend solely on the firm's effort. In intermediate cases, we would thus expect that D_2^* lies somewhere in between $\frac{x_B + x_G}{2}$ and x_G, and we would furthermore expect that D_2^* should be larger the less important is the firm's effort. Interestingly, this intuitive outcome does not obtain for all "natural" specifications of $p(e, \varphi)$. For example, if $p(e, \varphi) = e\varphi$, the optimal second-period debt is *independent* of how important the firm's effort is.[23]

An additive specification of the form $p(e, \varphi) = e + \varphi$, where $\varphi < 1$, delivers the intuitive outcome. Under this specification, the marginal productivity of effort is $x_G - x_B$ for all $e < 1 - \varphi$ and zero otherwise.[24] Accordingly, while the marginal productivity of effort does not vary continuously with φ, it determines the range of effort levels over which effort is productive. For example, if $\varphi = 0.1$, effort can raise the success probability by up to 90 percent. In contrast, if $\varphi = 0.9$, effort can only raise the success probability by at most 10 percent. It is in this sense that the parameter φ measures the importance of effort, where higher values of φ imply that effort is less important.

To ensure an interior first-best solution $e_{FB} + \varphi < 1$, we assume that $x_G - x_B + \varphi < 1$. As previously, this assumption also ensures that the second-best solution is feasible, i.e., that $e^* + \varphi \leq 1$. Given this assumption, it is straightforward to show that there is a unique interior first-best effort $e_{FB} = x_G - x_B$. Finally, as will become clear shortly, the condition for a debt overhang is $(\frac{x_G - x_B + \varphi}{2})^2 + x_B < D_1$ if $\varphi < x_G - x_B$ and $\varphi x_G + (1 - \varphi) x_B < D_1$ if $\varphi \geq x_G - x_B$.

We can again safely ignore any candidate solution where either $D_2 > x_G$ or $D_2 < x_B$. Given that $x_G > D_2 \geq x_B$, the firm's problem is

$$\max_e U = (e + \varphi)(x_G - D_2) - \frac{1}{2} e^2,$$

which has a unique solution $e^* = x_G - D_2$.

[23] Given the isomorphism between a multiplicative parameter in the production function versus a multiplicative parameter in the cost function, this is also true if $p = e$ but $c(e, \varphi) = \frac{1}{2\varphi} e^2$.

[24] That is, $p(e, \varphi)$ is increasing in e for all $e < 1 - \varphi$ and equal to one for all $e \geq 1 - \varphi$.

The lender's problem is

$$\max_i \Pi = (e+\varphi)D_2 + (1-e-\varphi)x_B$$

subject to

$$e^* = x_G - D_2,$$

which has a unique solution

$$D_2^* = \min\{\frac{x_B + x_G + \varphi}{2}, x_G\},$$

implying that the optimal second-period debt is $D_2^* = \frac{x_B+x_G+\varphi}{2} < x_G$ if $\varphi < x_G - x_B$ and $D_2^* = x_G$ if $\varphi \geq x_G - x_B$. Thus, the optimal second-period debt is weakly increasing in φ, and it is strictly increasing in φ for all $\varphi < x_G - x_B$.

Under the optimal solution, the firm's optimal effort is $e^* = \frac{x_G - x_B - \varphi}{2}$ if $\varphi < x_G - x_B$ and $e^* = 0$ if $\varphi \geq x_G - x_B$, which is strictly less than the first-best effort e_{FB}. Moreover, the lender's expected payoff under the optimal solution is $\Pi^* = (\frac{x_G - x_B + \varphi}{2})^2 + x_B < D_1$ if $\varphi < x_G - x_B$ and $\Pi^* = \varphi x_G + (1-\varphi)x_B < D_1$ if $\varphi \geq x_G - x_B$, which explains the condition for the debt overhang given above.

In sum, if effort is sufficiently important (i.e., φ is sufficiently small), the lender charges an interest rate that makes the firm the residual claimant in the good state, motivating it to exert effort. Krugman refers to this as *debt forgiveness*, as the lender voluntarily reduces the firm's debt below the maximum which he could potentially obtain in the good state. On the other hand, if effort is not very important (i.e., φ is sufficiently large), the lender charges the maximum possible interest rate—i.e., there is no debt forgiveness—and the firm provides no effort.

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Table I
Summary Statistics

"Restructuring Sample" refers to the 115 distressed hotels that underwent debt restructurings. "Control Sample" refers to the 2,095 hotels in the control group that did not undergo debt restructurings. In the restructuring sample, "Mean" and "Median" refer to the value in the year before the debt restructuring. In the control sample, "Mean" and "Median" refer to firm averages across all firm-years. Size is the book value of assets (in Euros). Beds and employees are the number of beds and employees, respectively. Star rating is the star classification (from 1 to 5). Altitude is the surface-weighted average altitude of the area associated with the hotel's ZIP code (in meters). Snow is the number of days during the main Winter season (December, January, February, March) with more than 10 centimeters of snow on the ground, as measured by the closest weather station. Leverage is the book value of debt divided by the book value of assets. Return on assets (ROA) is EBITDA divided by the book value of assets. ROA is winsorized at the 5th and 95th percentiles of its empirical distribution.

	Restructuring Sample			Control Sample		
Variable	# Hotels	Mean	Median	# Hotels	Mean	Median
Size (Euro)	115	1,603,494	997,071	2,095	4,532,693	1,570,291
Beds	74	76.0	65	1,901	96.4	75
Employees	74	16.9	13	1,893	26.4	16
Star Rating (1 - 5)	73	3.5	4	1,924	3.4	4
Altitude (meters)	115	1,180	1,152	2,095	1,275	1,368
Snow (days)	115	56.9	53	2,095	62.3	61
Leverage	115	2.40	1.77	2,095	1.26	0.99
ROA (%)	115	10.9	9.3	1,958	13.0	12.0

Table II
Return on Assets (ROA)

ROA, leverage, altitude, and snow are defined in Table I. Δ ROA is ROA after the debt restructuring (average ROA in the three years after the debt restructuring) minus ROA in the year before the debt restructuring. Δ Leverage and Δ Snow are defined accordingly. Size is the logarithm of the book value of assets (in Euros) in the year before the debt restructuring. Age is the logarithm of one plus the number of years since the hotel was granted its license, measured in the year before the debt restructuring. If this information is missing, we use instead the number of years with available accounting data. In rows [3] and [4], Δ Leverage is instrumented with the average snow in the two years prior to the debt restructuring. Standard errors are clustered at the district level. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses; *p*-values are in brackets. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ ROA	Δ ROA	Δ ROA	Δ ROA
	[1]	[2]	[3]	[4]
Δ Leverage	0.005**	0.005*	-0.037**	-0.055**
	(0.002)	(0.002)	(0.014)	(0.022)
Size		0.001		0.071**
		(0.008)		(0.028)
Age		0.002		-0.011
		(0.006)		(0.009)
Altitude		0.002		-0.013
		(0.009)		(0.010)
Δ Snow		-0.149		-0.080
		(0.334)		(0.297)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	OLS	OLS	IV	IV
Observations	115	115	115	115
R-squared	0.10	0.10	0.12	0.16
Hausman Test			7.023***	12.110***
			[0.009]	[0.001]

Table III
Net Profit Margin (NPM)

NPM is EBITDA divided by sales. Δ NPM is NPM after the debt restructuring (average NPM in the three years after the debt restructuring) minus NPM in the year before the debt restructuring. All other variables are defined in Table II. Standard errors are clustered at the district level. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses; *p*-values are in brackets. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ NPM	Δ NPM	Δ NPM	Δ NPM
	[1]	[2]	[3]	[4]
Δ Leverage	0.003	0.005	-0.036**	-0.055**
	(0.003)	(0.004)	(0.016)	(0.021)
Size		-0.011		0.061**
		(0.009)		(0.028)
Age		0.009		-0.004
		(0.010)		(0.011)
Altitude		0.004		-0.012
		(0.013)		(0.013)
Δ Snow		0.228		0.304
		(0.445)		(0.411)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	OLS	OLS	IV	IV
Observations	114	114	114	114
R-squared	0.05	0.07	0.08	0.12
Hausman Test			4.709**	9.672***
			[0.033]	[0.002]

Table IV
Median Regressions

This table presents variants of the regressions in columns [2] and [4] of Table II and columns [2] and [4] of Table III, respectively, in which median regressions are used instead of OLS. The standard errors are computed using block bootstrapping with 500 bootstraps and 42 blocks based on the 42 districts in which the restructured hotels are located. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ ROA	Δ ROA	Δ NPM	Δ NPM
	[1]	[2]	[3]	[4]
Δ Leverage	0.004**	-0.044**	0.008*	-0.053**
	(0.002)	(0.021)	(0.005)	(0.021)
Size	-0.003	0.055**	-0.012	0.058**
	(0.007)	(0.027)	(0.012)	(0.029)
Age	0.001	-0.008	0.004	-0.007
	(0.001)	(0.013)	(0.012)	(0.010)
Altitude	-0.001	-0.019	0.007	-0.010
	(0.007)	(0.020)	(0.087)	(0.014)
Δ Snow	0.019	0.409	0.038	0.036
	(0.541)	(1.683)	(0.244)	(0.238)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	Median	Median/IV	Median	Median/IV
Observations	115	115	114	114
R-squared	0.08	0.09	0.07	0.10

Table V
First-Stage Regression

Snow is the average snow in the two years prior to the debt restructuring. All other variables are defined in Table II. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ Leverage
Snow	-0.014***
	(0.004)
Size	1.142**
	(0.526)
Age	-0.258
	(0.168)
Altitude	0.368
	(0.295)
Δ Snow	-3.987
	(7.337)
Status-Year Dummies	Yes
Observations	115
R-squared	0.34

Table VI
Alternative Instruments

In column [1], "Snow Two Years Prior" is the snow two years prior to the debt restructuring (i.e., not including snow in the year before). In column [2], "Deviation from 15-year Average Snow" is the difference between the average snow in the two years prior to the debt restructuring and the average snow in the *preceding* 15 years (i.e., years -3 to -17). In columns [2] and [4], Δ Leverage is instrumented with "Snow Two Years Prior" and "Deviation from 15-year Average Snow", respectively. All other variables are defined in Table II. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses; *p*-values are in brackets. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ Leverage	Δ ROA	Δ Leverage	Δ ROA
	[1]	[2]	[3]	[4]
Snow Two Years Prior	-0.011***			
	(0.004)			
Deviation from 15-year Average Snow			-0.016**	
			(0.008)	
Δ Leverage		-0.070***		-0.060**
		(0.024)		(0.029)
Size	1.147**	0.088***	1.178**	0.077**
	(0.533)	(0.031)	(0.550)	(0.037)
Age	-0.280	-0.014	-0.206	-0.012
	(0.172)	(0.009)	(0.184)	(0.010)
Altitude	0.246	-0.017	-0.155	-0.015
	(0.263)	(0.010)	(0.203)	(0.011)
Δ Snow	-4.272	-0.063	-3.256	-0.074
	(7.002)	(0.303)	(7.265)	(0.307)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	First-stage Regression	IV	First-stage Regression	IV
Observations	115	115	115	115
R-squared	0.33	0.18	0.32	0.12
Hausman Test		9.502***		5.476**
		[0.004]		[0.024]

Table VII
Locally Adjusted Performance Measures

This table presents variants of the regressions in column [4] of Table II, column [4] of Table III, and columns [2] and [4] of Table IV, respectively, in which locally adjusted ROA and NPM are used instead of ROA and NPM. Locally adjusted ROA (NPM) is computed by subtracting from each firm-year observation of ROA (NPM) the median value of ROA (NPM) of all control hotels in the same district and year. In columns [1] and [3], standard errors are clustered at the district level. In columns [2] and [4], standard errors are computed using block bootstrapping with 500 bootstraps and 42 blocks based on the 42 districts in which the restructured hotels are located. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses; *p*-values are in brackets. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ ROA (adjusted)	Δ ROA (adjusted)	Δ NPM (adjusted)	Δ NPM (adjusted)
	[1]	[2]	[3]	[4]
Δ Leverage	-0.061***	-0.052**	-0.058**	-0.057**
	(0.023)	(0.022)	(0.024)	(0.025)
Size	0.069**	0.049**	0.065**	0.065**
	(0.027)	(0.025)	(0.029)	(0.032)
Age	-0.009	-0.012	-0.009	-0.019
	(0.010)	(0.016)	(0.011)	(0.015)
Altitude	-0.018	-0.005	-0.010	-0.029
	(0.014)	(0.019)	(0.016)	(0.045)
Δ Snow	0.025	0.252	0.041	-0.243
	(0.325)	(0.854)	(0.485)	(0.597)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	IV	Median/IV	IV	Median/IV
Observations	115	115	114	114
R-squared	0.20	0.11	0.09	0.07
Hausman Test	12.674***		9.120***	
	[0.001]		[0.003]	

Table VIII
Sample Selection

Panel (A) presents the results from a Probit regression in which the dependent variable ("Selection Dummy") is a dummy that equals one if the hotel is restructured in the following year and zero otherwise. The sample includes all restructured (74) and control (1,901) hotels with non-missing bed data, amounting to 6,736 firm-year observations. If a hotel is restructured, its subsequent firm-year observations are dropped from the sample. "Local Capacity Share" is the number of beds of a hotel in a given year divided by the total number of beds of all hotels in the same district and year. All other variables are defined in Table II. Panel (B) estimates the same regressions as in column [4] of Table II, column [4] of Table III, and columns [1] and [3] of Table VII, respectively, for the subsample of 74 hotels with non-missing bed data. Panel (C) estimates the same regressions as in Panel (B), except that the Inverse Mills Ratio from the selection equation in Panel (A) is included as an additional explanatory variable. Standard errors are clustered at the district level. The coefficients (and standard errors) on Altitude and Δ Snow are multiplied by 1,000. The debt restructurings took place between 1998 and 2005. Standard errors are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Selection Equation

Dependent Variable:	Selection Dummy
Local Capacity Share	0.384***
	(0.140)
Snow	0.000
	(0.002)
Size	-0.172***
	(0.040)
Altitude	-0.068
	(0.110)
Δ Snow	-2.850
	(3.744)
Year Dummies	Yes
Observations	6,736
R-squared	0.12

Panel (B): Regressions without Heckman Correction

Dependent Variable:	Δ ROA	Δ ROA (adjusted)	Δ NPM	Δ NPM (adjusted)
	[1]	[2]	[3]	[4]
Δ Leverage	-0.052**	-0.064**	-0.063***	-0.064**
	(0.024)	(0.025)	(0.023)	(0.029)
Size	0.069**	0.078***	0.061**	0.066**
	(0.031)	(0.030)	(0.028)	(0.032)
Age	0.003	0.001	-0.001	-0.001
	(0.010)	(0.013)	(0.012)	(0.015)
Altitude	-0.016	-0.013	-0.012	-0.021
	(0.014)	(0.017)	(0.014)	(0.020)
Δ Snow	-0.063	-0.097	-0.212	-0.078
	(0.337)	(0.402)	(0.345)	(0.531)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	IV	IV	IV	IV
Observations	74	74	73	73
R-squared	0.25	0.23	0.21	0.22

Panel (C): Regressions with Heckman Correction

Dependent Variable:	Δ ROA	Δ ROA (adjusted)	Δ NPM	Δ NPM (adjusted)
	[1]	[2]	[3]	[4]
Δ Leverage	-0.051**	-0.062***	-0.061***	-0.062**
	(0.023)	(0.024)	(0.020)	(0.027)
Size	0.064**	0.063**	0.041	0.043
	(0.027)	(0.029)	(0.027)	(0.037)
Age	0.003	0.001	0.001	0.000
	(0.010)	(0.012)	(0.012)	(0.015)
Altitude	-0.019	-0.022	-0.026	-0.038
	(0.017)	(0.019)	(0.018)	(0.023)
Δ Snow	-0.132	-0.298	-0.478	-0.385
	(0.399)	(0.490)	(0.428)	(0.666)
Inverse Mills Ratio	0.026	0.076	0.107	0.124
	(0.063)	(0.075)	(0.077)	(0.111)
Status-Year Dummies	Yes	Yes	Yes	Yes
Regression Type	IV	IV	IV	IV
Observations	74	74	73	73
R-squared	0.25	0.24	0.23	0.24