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Snow and leverage

Snow and Leverage*

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Abstract

Using a sample of highly (over-)leveraged Austrian ski hotels undergoing debt restructurings, we show that reducing a debt overhang leads to a significant improvement in operating performance (return on assets, net profit margin). In particular, a reduction in leverage leads to a decrease in overhead costs, wages, and input costs, and to an increase in sales. Changes in leverage in the debt restructurings are instrumented with *Unexpected Snow*, which captures the extent to which a ski hotel experienced unusually good or bad snow conditions prior to the debt restructuring. Effectively, *Unexpected Snow* provides lending banks with the counterfactual of what would have been the ski hotel's operating performance in the absence of strategic default, thus allowing to distinguish between ski hotels that are in distress due to negative demand shocks ("liquidity defaulters") and ski hotels that are in distress due to debt overhang ("strategic defaulters").

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1 Introduction

In his seminal article, Myers (1977) shows that owners of debt-ridden firms may forgo profitable investment opportunities and exert too little effort to maintain the firm's value as a going concern, because the returns from such investments would partly accrue to the firm's debtholders.[1] For the same reason, firm owners may strategically pay out cash to themselves (as wages or dividends) or sell vital firm assets on the secondary market and pocket the proceeds.[2] As Myers (1977, p. 162) notes, whether firm owners forgo profitable investments or disinvest is immaterial; the two cases are exactly symmetric. In the extreme case, debt overhang may not only lead to underinvestment, but it may effectively lead to the firm's "strategic default."[3]

In the recent financial crisis, debt overhang plays a key role not only at the level of banks and financial institutions (e.g., Diamond and Rajan, 2010; Veronesi and Zingales, 2010; Philippon and Schnabl, 2011) but also at the individual household level. Many households with negative home equity strategically defaulted on their mortgages even though they could have afforded to make their mortgage payments (Melzer, 2010; Guiso, Sapienza, and Zingales, 2011). In addition, Melzer (2010) finds that households with negative home equity significantly cut back on home improvements and home maintenance spending—investments whose returns would have accrued to the mortgage lender in case of a default. At the same time, they did not reduce spending on automobiles, furniture,

[1] Myers (1977) gives several examples: "The discretionary investment may be maintenance of plant and equipment. It may be advertising or other marketing expenses, or expenditures on raw materials, labor, research and development, etc." (p. 155). Another important discretionary investment is effort: "The value of a going concern can be maintained only by positive action, in a competitive industry the firm should have to work hard to simply keep up. This is not simply a matter of maintaining plant and equipment. There is continual effort devoted to advertising, sales, improving efficiency, incorporating new technology, and recruiting and training employees" (p. 156).

[2] "[S]uppose the firm has plenty of cash on hand. It can either invest the cash or pay it out to the stockholders. In that case the investment is financed not by a stock issue, but by forgoing a dividend" (Myers, 1977, pp. 159-160). Likewise, "[c]onsider a firm which is holding a real asset for which there is a secondary market. [...] The shareholders should attempt to liquidate and run, leaving the creditors holding the empty bag" (p. 162).

[3] In multi-period strategic default models (e.g., Bolton and Scharfstein, 1990), incentive compatibility is achieved by setting the repayment to creditors such that the firm finds it (weakly) optimal to continue rather than to "steal the money and run." Thus, the solution is precisely to make the debt repayment sufficiently low so as to avoid strategic default induced by debt overhang.

and home appliances, suggesting that the problem is indeed one of debt overhang and not simply a liquidity shortage.

Given its importance both for policy and practice, the debt overhang problem has spurred a large empirical literature. An important concern with many studies is that they rely on variation in leverage that is unlikely to be exogenous, making it difficult to establish causality.[4] This paper provides evidence on the debt overhang problem using a sample of highly (over-)leveraged Austrian ski hotels undergoing debt restructurings. Debt restructurings are ideal for the study of debt overhang: by definition, any (ex-post) solution must involve renegotiations with creditors.[5] More importantly, the specific nature of our data allows us to identify plausibly exogenous variation in leverage changes and thus to address whether—for highly (over-)leveraged firms—a reduction in leverage leads to an improvement in operating performance.

In our sample, the average (book) leverage ratio prior to the debt restructuring is 2.40. As a result of the debt restructurings, leverage decreases by 23% on average. This decrease is entirely due to debt reductions (i.e., forgiveness), not due to increases in asset values. In fact, asset values decrease slightly (by 1% on average) due to forced asset sales. However, while there is a significant reduction in leverage on average, there is substantial cross-sectional variation. Indeed, not all ski hotels may be in distress due to debt overhang. Some hotels may be in distress due to negative demand shocks, resulting in weak operating performance and poor liquidity. For such hotels, there is no reason for creditors to forgive debt—it would merely constitute a windfall gain for the hotels. Rather, creditors should extend debt maturity and defer interest payments. By contrast, for hotels that are in distress due to debt overhang, it can be optimal for creditors to forgive debt (see Myers, 1977, p. 158).[6]

[4] We discuss related empirical literature at the end of this section.

[5] See Myers (1977, p. 158) or Tirole (2006, pp. 125-126). Accordingly, what gives the debt overhang problem its bite is the absence of renegotiation, not excessive leverage per se. While renegotiation can solve the debt overhang problem ex post, there are, of course, ex-ante solutions, notably to take on less debt. In fact, this the main point of Myers' article, namely, to argue why the possibility of a (future) debt overhang may prevent firms from taking on too much debt despite the obvious tax advantages.

[6] From the creditors' viewpoint, debt forgiveness is only optimal if it increases the expected debt repayment by the firm (via an improvement in operating performance). In this case, debt forgiveness is

An obvious difficulty for creditors is to distinguish between these two types of distress. As Guiso, Sapienza, and Zingales (2011, p. 2) write: "The main problem in studying strategic defaults is that this is de facto an unobservable event. While we do observe defaults, we cannot observe whether a default is strategic." Looking at operating performance or cash balances might not help: "strategic defaulters" might also exhibit poor operating performance and low cash balances, albeit for different reasons (see footnotes 1 and 2). To identify "strategic defaulters," creditors would effectively need to know the *counterfactual of what would have been the firm's operating performance in the absence of strategic default*.

While this counterfactual is, by definition, unobservable, creditors can—in the specific context studied here—observe a variable that is highly correlated with it: snow. Out-of-sample evidence from over 2,000 Austrian ski hotels that did *not* undergo debt restructurings shows a strong positive relation between snow and operating performance (ROA). This is not surprising. After all, snow affects the demand for ski vacations, which in turn affects the profits of ski hotels. Accordingly, if a ski hotel experienced poor snow conditions prior to the debt restructuring, it is relatively likely that this hotel is a (genuine) "liquidity defaulter." In contrast, if a ski hotel got into distress *despite* having experienced highly favorable snow conditions, it is less likely that this hotel is a "liquidity defaulter" and more likely that it is a "strategic defaulter."

We measure "poor" and "favorable" snow conditions prior to the debt restructuring relative to the hotels' own average snow conditions in the previous ten years. We call this measure *Unexpected Snow*. Accordingly, *Unexpected Snow* captures the extent to which a ski hotel experienced *unusually* good or bad snow conditions prior to the debt restructuring. Indeed, and consistent with the above hypothesis, ski hotels with negative *Unexpected Snow* did not receive significant reductions in leverage. In contrast, ski hotels with positive *Unexpected Snow* received substantial reductions in leverage. Moreover, ski

a Pareto-improvement that benefits both the firm and its creditors. Krugman (1989) explicitly models the choice of creditors between "Financing vs. Forgiving a Debt Overhang." In his model, "financing" a debt overhang means to roll over maturing debt, which is optimal if there is a temporary (exogenous) liquidity shock. In contrast, "forgiving" a debt overhang is optimal if the borrower's incentives to invest and to provide effort are distorted. Though Krugman applies these arguments to sovereign lending, they already follow directly from Myers' (1977) seminal analysis.

hotels with negative and positive *Unexpected Snow* had similar (weak) operating performance and cash balances prior to the debt restructuring, suggesting that creditors cannot easily use this information to identify "strategic defaulters."

While comparisons between ski hotels with negative and positive *Unexpected Snow* are insightful, they are based on "raw data." However, we obtain similar results when using a regression framework. When we regress changes in leverage (after versus before the debt restructuring) on *Unexpected Snow* prior to the debt restructuring (our first-stage regression), we find that ski hotels with higher (i.e., more positive) *Unexpected Snow* receive significantly larger reductions in leverage. The effect is also economically significant: a one-standard deviation increase in *Unexpected Snow* is associated with a reduction in leverage of 23% on average.

The main objective of our study is to examine whether—for highly (over-)leveraged firms—reductions in leverage lead to improvements in operating performance. When estimating OLS regressions, we find that smaller reductions in leverage are associated with larger increases in ROA. However, it is not difficult to think of a reverse causality explanation. For instance, ski hotels with larger *anticipated* increases in ROA might receive less debt forgiveness, resulting in smaller reductions in leverage.

In stark contrast, when we regress changes in ROA on changes in leverage using only exogenous variation in leverage—i.e., we instrument changes in leverage using *Unexpected Snow* prior to the debt restructuring—we find the opposite result: ski hotels with larger reductions in leverage now experience significantly larger increases in ROA. The effect is also economically significant: a reduction in leverage of 23%—the average in our sample—is associated with an increase in ROA of 28%. Thus, consistent with Myers' (1977) argument that debt overhang impairs firm performance, we find that—for highly (over-)leveraged firms—a reduction in leverage leads to a statistically and economically significant increase in ROA. We obtain similar results if we measure operating performance using net profit margin (where EBITDA is scaled by sales), and if we estimate median regressions to account for the possibility of outliers.

To gain a better understanding of *why* a reduction in leverage leads to an increase in ROA, we run separate regressions using individual components of ROA as the dependent variable. We find that a reduction in leverage leads to a decrease in overhead costs, wages, and input costs, and to an increase in sales, albeit the input cost result is not statistically significant. The wage result is particularly interesting. As the hotels in our sample are small, family-run hotels, wages are partly transfers to the hotels' owners and their family members. Thus, while a decrease in wages (per employee) may be interpreted as an improvement in operational efficiency, it might also be interpreted—and perhaps especially so—as evidence of the owners' willingness to keep cash in the firm rather than to pay it out strategically to themselves.[7]

When we regress changes in ROA on changes in leverage—instrumented with *Unexpected Snow* prior to the debt restructuring—we always control for changes in snow. Thus, if ROA improves after the debt restructuring, it is not because snow conditions have improved. With respect to the validity of our instrument, this implies any potential direct effect of *Unexpected Snow*—i.e., other than through changes in leverage—due to serial correlation of snow conditions is already accounted for. To further assess the validity of our instrument, we provide out-of-sample evidence from over 2,000 Austrian ski hotels that did *not* undergo debt restructurings. As we show, *Unexpected Snow* is uncorrelated with both changes in ROA and future ROA, suggesting it has no direct effect on the dependent variable in our second-stage regression.[8]

A second test we perform also uses the (control) sample of ski hotels that did not undergo debt restructurings. The idea is straightforward. If the increase in ROA was due to a direct effect of *Unexpected Snow*, then other ski hotels in the same region should also experience an increase in ROA, given that they are exposed to the same snow conditions. Based on this logic, we construct a new performance measure, *Locally Adjusted ROA*,

[7]See footnote 2. From an ex-ante viewpoint, creditors might want to commit to "punish" (e.g., liquidate) "strategic defaulters" knowing that renegotiation is (Pareto-)optimal ex post. Our result that ski hotels with positive *Unexpected Snow* receive significant reductions in leverage is consistent with ex-post optimal behavior on the part of creditors, suggesting it is difficult for creditors to credibly commit not to renegotiate. However, our result is also consistent with creditors pursuing an ex-ante optimal strategy whereby "strategic defaulters" are only liquidated with probability p while with probability $1-p$ the ex-post optimal outcome is implemented. This is possible as we do not observe liquidations. Thus, it might well be that the restructuring cases in our sample are those that are renegotiated with probability $1-p$ under an ex-ante optimal strategy.

[8]Although we always control for changes in snow, it should be noted that *Unexpected Snow* is uncorrelated with future snow, future *Unexpected Snow*, changes in snow, and changes in *Unexpected Snow*.

which is ROA minus the median ROA of all control hotels in the same region and year. Our results remain virtually unchanged, suggesting they are not driven by a direct effect of *Unexpected Snow* on changes in ROA.

In the final part of our analysis, we account for possible selection bias. A necessary condition for a ski hotel to be restructured 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 the selection equation. Importantly, *Local Capacity Share* does not capture aspects of the hotel's 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 they are not driven by selection bias.

As remarked previously, debt renegotiations are ideal for the study of debt overhang. Other studies also examine debt renegotiations, albeit they do not consider subsequent changes in operating performance.[9] Gilson, John, and Lang (1990) consider 169 publicly traded U.S. companies that are in financial distress. The authors examine which of the companies successfully restructure their debt outside of bankruptcy and which of them file for Chapter 11. Similarly, Asquith, Gertner, and Scharfstein (1994) consider 76 companies that issue high-yield "junk" bonds and subsequently become distressed. The authors examine how these firms attempt to resolve their financial distress and which of them eventually file for Chapter 11. Roberts and Sufi (2009a) consider 1,000 private credit agreements between financial institutions and publicly traded U.S. companies. The authors conclude that key triggers of renegotiation are fluctuations in borrowers' assets, financial leverage, the cost of equity capital, macroeconomic conditions, and the financial health of lenders.

Andrade and Kaplan (1998) examine 31 highly leveraged transactions that later become financially distressed. In the majority of cases, the distress is resolved through Chapter 11. The authors conclude that the "pure" costs of financial distress are modest at best. Other studies focus on investment. Lang, Ofek, and Stulz (1996) show that

[9] Roberts and Sufi (2009b) survey the theoretical and empirical literature on debt renegotiations.

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.

Perhaps most closely related to our study is an unpublished paper by Kroszner (1999) on the Supreme Court's decision to uphold the abolition of gold indexation clauses in public and private debt contracts passed by Congress in 1933. As Kroszner argues, "the Supreme Court decision is effectively a debt forgiveness equivalent to 69% of the value of a firm's debt" (p. 20). He finds that both equity prices and corporate bond prices rise upon the announcement of the Supreme Court's decision.

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. Section 6 discusses the strength and validity of our instrument. Section 7 addresses selection bias. Section 8 concludes. The Appendix provides a discussion of the timing conventions used in the construction of our variables.

2 Institutional Background

As is common in many countries, Austrian firms may try to restructure their debt prior to filing for bankruptcy. Typically, debt restructurings are the outcome of direct negotiations between the firm and its lender(s). In the Austrian tourism industry, however, debt restructurings often involve the participation of the Austrian Hotel- and Tourism Bank (AHTB).[10] Founded in 1947, the AHTB—which is also our main data provider—is a development bank that administers funds provided by the European Recovery Program (ERP or "Marshall Plan"). While the AHTB also provides limited financial support,

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

its role in the debt restructurings is primarily that of a mediator, given that it does not take on any credit risk.[11] Mediation by the AHTB is desirable as it ensures 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. In our sample of 115 debt restructurings, 70 cases involve at least two lending banks, and 33 cases involve at least four lending banks.

Given its role as a mediator, the AHTB collects data on the distressed hotels, including "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" and "soft" 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, which typically only include "hard" information, 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 hotels." 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 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 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 precludes investments in land or capacity expansions and investments to complete projects already under way. There are also restrictions imposed by the European Union. 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

[11] 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.

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 to discuss 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, banking relationships, number of beds, price per night, whether it is a "leading" hotel (Leitbetrieb), and 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 received 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 level of detail varies considerably across reports. While "hard" financial information is available for most hotels in our sample, other information is sometimes only available for a smaller subset.

The purpose of the negotiations is to devise a restructuring plan, which stipulates—next to the obligations of the hotel's owner(s)—the obligations of the lending bank(s) in the debt restructuring. 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. If 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.

3 Case Study

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

The hotel 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 before 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, and 71 beds, making it a rather typical hotel in our sample. The hotel is structured as a "Gesellschaft nach bürgerlichem Recht," which means each of the owners is individually and 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 suggests, the hotel experienced a sharp 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%.[12] This decline in demand is unlikely to come from unfavorable snow conditions. Indeed, the average snow in the two years before the debt restructuring was 36.1% higher than the average snow experienced by the same hotel in the preceding ten years. Instead, as the loan officers suggested, the decline is due to insufficient effort to boost sales. Going forward, the loan officers conjectured that sales could be improved by cooperating with travel agencies. The loan officers also criticized the hotel's cost management, especially its failure to adjust input costs and wages to the declining demand. As a result, the hotel's net profit margin (EBITDA/sales) dropped sharply 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 ROA in the year prior to the debt restructuring was only 6.3%, which is well below the median in our sample.

In the debt restructuring, the hotel received substantial debt forgiveness. The hotel had only one lending bank, which agreed to forgive about ATS 11.5m (approximately Euro 833,333). As a result, the hotel's (book) leverage ratio was reduced from 1.84 to 1.41. This reduction is above the median in our sample—the median (book) leverage ratio before and after the debt restructuring is 1.77 and 1.56, respectively. In response to the debt forgiveness, 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 substan-

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

tially.[13] ROA increased from 6.3% prior to the debt restructuring to 10.9% in the three years after the debt restructuring. This improvement is above the median in our sample. In fact, only 25% of the hotels had a larger increase in ROA.

4 Data

4.1 Sample Selection

Our primary data source is the Austrian Hotel- and Tourism Bank (AHTB). We have information on 145 ski hotels that underwent debt restructurings. For 30 of these hotels, EBITDA is missing either "before" or "after" the debt restructuring, leaving us with 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 one or two "after" years. To allow a consistent comparison 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 ski hotels with one "before" and one "after" observation per hotel. All of the debt restructurings took place between 1998 and 2005. To account for the different years in which the debt restructurings took place, we include year dummies in all our regressions.

The AHTB also provided us with a "control sample" of 2,095 ski hotels that did not undergo debt restructurings. All of these hotels applied for or received funds under other (non-restructuring) ERP funding programs at some point, which is why they are in the AHTB database. For most of these hotels, we have several years of consecutive data, though for some hotels we only have one or two years worth of data.

We have monthly weather data for all Austrian weather stations provided by the Austrian Central Institute for Meteorology and Geodynamics.[14] We match each hotel to its closest weather station by locating the weather station with the minimal Euclidean

[13] There has been no change in ownership or management after the debt restructuring. In fact, only two hotels in our sample experienced such changes, and removing them does not affect our results.

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

distance from the co-ordinates of the postal office in the hotel's ZIP code. To ensure that the weather conditions reflect those in the hotel's vicinity, we require that the altitudinal distance between the weather station and the hotel must not exceed 500 meters. This constraint is only binding in a few cases, and our results are unchanged if we drop it. Arguably, the weather conditions measured by the closest weather station are a noisy proxy of the weather conditions that are relevant for the hotel (e.g., snow conditions at nearby ski slopes). While it is unlikely that this introduces any bias, it introduces noise into the regressions, making it only harder for us to find any significant results.

4.2 Empirical Methodology

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

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

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 year dummies. In robustness checks, we replace Δ ROA with Δ NPM ("net profit margin"). 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. Appendix A explains in detail what the difference operator Δ measures based on whether a given variable is a stock or flow variable.

Including altitude in our regressions captures certain persistent differences across hotels, 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%. Including Δ snow in our regressions controls for any contemporaneous effect of snow on ROA. Hence, if ROA improves after the debt restructuring, it is not because snow conditions have improved. (Section 4.3 describes how snow is matched to EBITDA based on the hotels' fiscal years.) The year dummies capture any effect that is common to all hotels that are restructured in the same year.

There are two restructurings 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.[15]

Our identification strategy has already been laid out in the Introduction. For this reason, we shall be brief. To obtain consistent and unbiased estimates, we instrument Δ leverage in equation (1) with *Unexpected Snow. Unexpected Snow* is the average snow experienced by a given hotel in the two years prior to the debt restructuring minus the average snow experienced by the *same* hotel in the preceding ten years. Accordingly, *Unexpected Snow* captures the extent to which a ski hotel experienced *unusually* good or bad snow conditions in the two years before the debt restructuring, which is the period when it likely got into distress. Note that *Unexpected Snow* is serially uncorrelated (0.005, $p = 0.916$), which also makes it uncorrelated with any (persistent) unobserved hotel characteristic that might explain cross-sectional variation in Δ ROA. In addition, *Unexpected Snow* is uncorrelated with snow in future years, though it should be noted that we already control for Δ snow in all our regressions.

As explained in the Introduction, *Unexpected Snow* provides lending banks with the counterfactual of what would have been the hotel's operating performance in the absence of strategic default, thus allowing to distinguish between ski hotels that are in distress due to adverse demand shocks ("liquidity defaulters") and ski hotels that are in distress due to debt overhang ("strategic defaulters").[16] Accordingly, if a ski hotel experienced unusually bad snow conditions prior to the debt restructuring, it is relatively likely that this hotel is a (genuine) "liquidity defaulter." In contrast, if a ski hotel got into distress *despite* having experienced unusually favorable snow conditions, it is less likely that this

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

[16] To validate this conjecture, we regress ROA on (contemporanous) *Unexpected Snow* in the *same* (fiscal) year—controlling for size, altitude, and year dummies—using our "control sample" of 2,095 ski hotels that did not undergo debt restructurings (5,910 firm-year observations). As conjectured, the coefficient on *Unexpected Snow* is positive and highly significant ($t = 3.25$). The effect is also economically significant: a one-standard deviation increase in *Unexpected Snow* leads to an increase in (contemporaneous) ROA of 0.8 percentage points, or about 6.2%.

hotel is a "liquidity defaulter" and more likely that it is a "strategic defaulter."[17] Note also that lending banks cannot easily use other information—such as operating performance and cash balances—to identify "strategic defaulters." As we argued in the Introduction, "strategic defaulters" might also exhibit poor operating performance and low cash balances, albeit for different reasons. Indeed, ski hotels with negative *Unexpected Snow* (64 of the 115 hotels) had a median ROA of 9.4% before the debt restructuring, while ski hotels with positive *Unexpected Snow* (51 of the 115 hotels) had a median ROA of 9.0%. The difference is not statistically significant.[18] Likewise, ski hotels with negative *Unexpected Snow* had a median cash-to-asset ratio of 1.3% before the debt restructuring, while ski hotels with positive *Unexpected Snow* had a median cash-to-asset ratio of 1.0%. The difference is again not significant.

While the median Δ leverage for ski hotels with negative *Unexpected Snow* is only -0.07, the median Δ leverage for ski hotels with positive *Unexpected Snow* is -0.33, which is almost five times larger.[19] Thus, ski hotels with positive *Unexpected Snow*—but not those with negative *Unexpected Snow*—received substantial reductions in leverage, which is consistent with lending banks perceiving these hotels as being in distress due to debt overhang.[20] While comparisons between ski hotels with negative and positive *Unexpected Snow* are insightful, they are based on "raw data." In Section 6, we formally explore the relationship between Δ leverage and *Unexpected Snow* in a regression framework. In that section, we also provide tests to examine both the strength and validity of our instrument.

[17] Debt overhang can lead to strategic default through various channels (see footnotes 1 and 2). For example, hotel owners may intentionally cut down on crucial investments such as maintenance, advertising, and marketing expenditures. Likewise, they may provide too little effort to boost sales, keep wages and input cost low, and improve operational efficiency. Finally, they may pay out cash to themselves (as wages or dividends) or sell vital firm assets and pocket the proceeds.

[18] As there is no correlation between *Unexpected Snow* and ROA before the debt restructuring (0.001, $p = 0.994$), we can include the latter in our regressions and obtain virtually identical results.

[19] Ski hotels with negative and positive *Unexpected Snow* have virtually identical median leverage ratios before the debt restructuring: 1.76 and 1.77, respectively. Hence, the *percentage* reduction in leverage is also (almost) five times larger for ski hotels with positive *Unexpected Snow*.

[20] An alternative hypothesis is that ski hotels that got into distress despite positive *Unexpected Snow* are simply "bad types." In other words, the problem might be incompetent management and not debt overhang. However, only two (out of 115) hotels in our sample experienced a change in ownership or management after the debt restructuring. (And one of the two hotels had negative *Unexpected Snow*.) Also, if the problem was incompetent management, it is not clear why the lending banks would try to solve the problem by forgiving large amounts of debt.

4.3 Definition of Variables and Summary Statistics

Our main measure of operating performance is the return on assets (ROA), which is EBITDA divided by the book value of assets. In robustness checks, we also use 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 or at the 10th and 90th percentiles, or if we use median regressions instead. (See Tables II, III, and VII for results based on median regressions.)

Given that all hotels in our sample are privately held, market values are not available.[21] Accordingly, "leverage" is the book value of debt divided by the book value of assets. "Size" is the book value of assets in the year prior to the debt restructuring. "Age" is the number of years since the hotel was granted its operating license as of 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.[22] In all our regressions, we use the logarithms of size and age. "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 15 cm 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 years. For example, if the fiscal year ends on December 31, "snow in 1999" is the number of days with more than 15 cm of snow on the ground in the months of January 1999, February 1999, March 1999, and December 1999. This matching ensures that—when controlling for Δ snow in our regressions—we indeed capture accurately any contemporaneous effect of snow on EBITDA. As already mentioned above, *Unexpected Snow* is the average snow experienced by a given hotel in

[21] See Myers (1977, pp. 149-150), however, who argues that leverage ratios based on book values may be more informative, because they refer to assets already in place.

[22] The year in which the hotel was granted its operating license is also missing for all control hotels. For this reason, age is not part of the descriptive statistics in Table I, the out-of-sample regressions in Table VI, and the selection equation in Table VIII. Rather than omitting age altogether, we could use the number of years with available accounting data as a proxy for age. All our results would remain similar.

the two years prior to the debt restructuring minus the average snow experienced by the *same* hotel in the preceding ten years.

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 10 or 20 cm threshold in place of a 15 cm threshold. This is not surprising, given that the correlation with our snow variable is 92.8% and 97.9%, respectively. Our results are also similar if we use entirely different snow variables, such as the number of days with fresh snowfall.

Firm-year observations are mapped into either "before" or "after" observations as follows (see Appendix A for further details). 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 took 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., $\text{ROA}(t) := \text{EBITDA}(t)/\text{Assets}(t-1)$.

Table I provides summary statistics. "Restructuring sample" refers to the 115 ski hotels that underwent debt restructurings. "Control sample" refers to the 2,095 ski 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" are averages across all firm-years.

As is shown, restructured hotels are smaller than control hotels (smaller book value of assets, fewer beds, fewer employees), consistent with the notion that smaller hotels are more likely to get into distress. Importantly, restructured hotels are highly leveraged. 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), it is useful to bear in mind that practically all hotels (including control hotels) are small privately held hotels, which tend to rely heavily on debt financing. Moreover, it is useful to remember that leverage is based on book values, not market values.

5 Results

5.1 Return on Assets

Table II shows our main results. The dependent variable is the change in ROA "after" versus "before" the debt restructuring (Δ ROA). The main independent variable of interest is the change in leverage in the debt restructuring (Δ leverage). The control variables are size, age, altitude, and Δ snow, where snow is matched to EBITDA to account for any contemporaneous effect of snow on ROA (see Section 4.3 for details). The results of the first-stage regression are discussed separately in Section 6.1.

In columns [1] and [2] of **Panel (A)**, equation (1) is estimated by OLS. Regardless of whether control variables are included, the coefficient on Δ leverage is positive and significant. Thus, OLS regressions suggest that ski hotels with smaller reductions in leverage experience larger increases in ROA.[23] However, it is not difficult to think of a reverse causality explanation. For instance, ski hotels with larger *anticipated* increases in ROA might receive less debt forgiveness, resulting in smaller reductions in leverage. More generally, as Δ leverage is potentially endogenous in equation (1), it is not clear how to interpret the OLS results.

In columns [1] and [2] of **Panel (B)**, equation (1) is estimated by IV using *Unexpected Snow* before the debt restructuring as an instrument for Δ leverage. Regardless of whether control variables are included, the coefficient on Δ leverage is now negative and significant. Thus, ski hotels with larger reductions in leverage experience larger increases in ROA. The effect is also economically significant. When control variables are included, the coefficient on Δ leverage is -0.052 ($t = 2.48$). Given that Δ leverage is -0.55 on average, this corresponds to an average increase in ROA of $-0.052 \times -0.55 = 0.03$, 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 Myers' (1977) argument that debt overhang impairs firm performance, our results show that—for highly (over-)leveraged firms—a reduction in leverage leads to a statistically

[23] Both the average and median Δ leverage in our sample are negative. Accordingly, we refer to larger (smaller) values of Δ leverage as "smaller (larger) reductions in leverage."

and economically significant increase in ROA. As for the control variables, the coefficients on size and Δ snow are both positive and significant, while those on age and altitude are both insignificant.

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 ($p = 0.015$ without control variables; $p = 0.001$ with control variables). Thus, provided our instrument is valid, Hausman tests confirm that the OLS estimates are biased.

To mitigate the effect of outliers, we winsorize ROA at the 5th and 95th percentiles of its empirical distribution. An alternative approach 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 as 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 used in our main analysis, we construct blocks at the district level, leaving us with 42 blocks. Specifically, 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.

Column [3] of Panels (A) and (B) reports the results. As is shown, they are very similar to our previous results. In the IV regression (Panel (B)), the coefficient on Δ leverage has become slightly smaller, but it remains statistically significant (-0.037; $t = 2.18$). Importantly, the results based on median regressions suggest that our previous results are not driven by outliers.

5.2 Net Profit Margin

In **Table III**, the dependent variable is the change in net profit margin (Δ NPM). Otherwise, the regression specification is identical to that in Table II.[24]

Similar to our previous ROA results, OLS regressions yield again a positive coefficient on Δ leverage, though it is only significant in the median regression. When Δ leverage is instrumented with *Unexpected Snow* prior to the debt restructuring, we again find that the coefficient on Δ leverage is negative and significant (-0.042; $t = 2.25$), suggesting that ski hotels with larger reductions in leverage experience larger increases in net profit margin. Interestingly, the coefficient on Δ leverage is now slightly larger in the median regression (-0.050; $t = 2.51$). As for the control variables, the coefficients on size and Δ snow are again both positive, though the coefficient on Δ snow is only significant in the median regression. The coefficients on age and altitude are again both insignificant. Importantly, that the results are similar to our previous ROA results suggests that the choice of scaling variable (assets versus sales) plays little role.

Hausman (1978) 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 control variables; $p = 0.002$ with control variables).

5.3 Costs and Revenues

To gain a better understanding of *why* a reduction in leverage leads to an increase in ROA, we consider separately the effect on individual components of ROA. Unfortunately, we have data on individual components of ROA only for a subset of our sample. Thus, to the extent that our results are based on a small sample, they should be taken with caution. For brevity, we only report the results of the IV regressions.

The results are shown in **Table IV**. In columns [1] to [3], the dependent variable is the change in overhead costs (SG&A), the change in wages, and the change in input costs, respectively. Since all these variables are cost components, all coefficients should have the opposite sign as those in our previous ROA regressions. In column [4], the dependent

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

variable is the change in sales. Here, we would expect all coefficients to have the same sign as those in our previous ROA regressions.

In columns [1] to [3], the coefficient on Δ leverage is positive and—except for the input cost regression in column [3]—significant. In column [4], the coefficient on Δ leverage is negative and significant. Hence, a reduction in leverage leads to a significant decrease in overhead costs and wages and to a significant increase in sales. It also leads to a decrease in input costs, though the effect is not significant ($t = 1.53$). That the effect is not a pure "sales effect" is not entirely surprising: we already know from Table III that a reduction in leverage leads to a significant increase in net profit margin, which is EBITDA *divided* by sales. The wage result is particularly interesting. As the ski hotels in our sample are small, family-run hotels, wages are partly transfers to the hotels' owners and their family members. Thus, while a decrease in wages may be interpreted as an improvement in operational efficiency, it might also be interpreted—and perhaps especially so—as evidence of the owners' willingness to keep cash in the firm rather than to pay it out to themselves (see footnote 2).

All control variables have the expected signs. As in our previous ROA regressions, the coefficient on size is always significant, while the coefficients on age and altitude are insignificant. Interestingly, the coefficient on Δ snow is only significant in column [4]. Accordingly, the significant coefficient on Δ snow in our previous ROA regressions is likely to come from a positive effect of snow on (contemporaneous) sales.

6 Identification

6.1 First-Stage Regression

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

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

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

Table V presents the results. As is shown, the coefficient on *Unexpected Snow* is negative and significant at the 1% level (-0.014; $t = 3.21$). The effect is also economically significant. A one-standard deviation (39.20) increase in *Unexpected Snow* is associated with a reduction in leverage of $-0.014 \times 39.20 = -0.55$. Given that the average leverage ratio before the debt restructuring is 2.40, this corresponds to a decrease in leverage of about 23%. Accordingly, our results show that ski hotels with unusually good snow conditions before the debt restructuring receive significantly larger reductions in leverage, which is consistent with lending banks perceiving these hotels as being in distress due to debt overhang (see Section 4.2).[25]

Consistency of IV estimation in a finite sample requires that the instrument must be sufficiently "strong," meaning it must correlate strongly with the troublesome endogenous variable. In equation (2), the F-statistics for the null that $\beta = 0$ is 10.30, which exceeds the "rule of thumb" for strong instruments ($F \geq 10$) proposed by Staiger and Stock (1997) as well as 15% critical threshold value in Table 5.2 of Stock and Yogo (2005, p. 101). Hence, weak identification is unlikely to be a concern.

6.2 Validity of the Instrument

In the specific context of our study, the exclusion restriction requires that *Unexpected Snow* prior to the debt restructuring has no direct effect on changes in ROA—i.e., other than through its effect on changes in leverage. While the exclusion restriction cannot be tested directly (within sample), its validity can be supported using out-of-sample evidence. Using

[25] When we estimate equation (2) using Δ assets as the dependent variable, we find that the coefficient on *Unexpected Snow* is literally zero (0.000) and highly insignificant ($t = 0.23$). Thus *Unexpected Snow* has no effect on changes in assets, implying that the variation in leverage in our IV regressions is due to variation in debt reductions.

our control sample of 2,095 ski hotels that did not undergo debt restructurings, we examine whether *Unexpected Snow* has a direct effect on changes in ROA by regressing Δ ROA on *Unexpected Snow* while controlling for size, altitude, Δ snow, and year dummies.[26] Age is not included as a control variable because it is missing for all control hotels.[27] **Panel (A)** of **Table VI** shows the results.[28] Regardless of whether control variables are included, the coefficient on *Unexpected Snow* is never significant ($t = 0.09$ without control variables; $t = 0.04$ with control variables). Thus, out-of-sample evidence suggests that *Unexpected Snow* has no direct effect on changes in ROA.

Instead of estimating the effect of *Unexpected Snow* on *changes* in ROA, we can (somewhat similarly) estimate its effect on *future* ROA. In **Panel (B)**, we regress ROA on *Unexpected Snow* lagged by one year while controlling for (lagged) size, altitude, (contemporaneous) snow, and year dummies. In columns [3] and [4], we additionally include hotel-fixed effects. Regardless of whether control variables or hotel-fixed effects are included, the coefficient on *Unexpected Snow* is never significant (t-statistic between 0.15 and 0.68). Accordingly, out-of-sample evidence suggests that *Unexpected Snow* has no direct effect on future ROA.

A second test we perform to assess the validity of our instrument also makes use of our control sample of 2,095 ski hotels that did not undergo debt restructurings. The idea is straightforward. If the increase in ROA documented in Panel (B) of Table II was due to a direct effect of *Unexpected Snow*, then other ski hotels in the same region should also experience an increase in ROA, given that they are exposed to the same snow conditions. Based on this logic, we construct a new performance measure, *Locally Adjusted ROA*, which is defined as ROA minus the median ROA of all control hotels in the same district

[26]In the spirit of equation (1), Δ ROA in year t is the difference between ROA in year t and $t+1$, *Unexpected Snow* and size are both measured in year t, and Δ snow in year t is the difference between snow in year t and $t+1$ to account for any contemporaneous effect of snow on EBITDA. Moreover, *Unexpected Snow* in year t is the difference between snow in year t and the average snow experienced by the same hotel in the preceding ten years (i.e., years $t-1$ to $t-10$).

[27]See Section 4.3. Note that age was never significant in any of our previous regressions.

[28]The number of observations in Panel (A) is less than in Panel (B), because we always lose the "last" observation of a given hotel when computing Δ ROA. For instance, suppose a hotel is in our sample in 1999, 2000, and 2001. In Panel (B), this implies we have three firm-year observations. In Panel (A), however, we only have two firm-year observations as Δ ROA in 2001 cannot be computed.

and year.[29] Using *Locally Adjusted ROA* thus effectively "controls" for any direct effect of *Unexpected Snow* on changes in ROA—at least to the extent that the effect is common to all ski hotels in the same district.

Table VII shows the results. Except for the fact that ROA is locally adjusted, the regression specification is identical to that in Table II. For brevity, we only report the results of the IV regressions. Regardless of whether control variables are included, the coefficients on Δ leverage are remarkably similar to the corresponding coefficients in Panel (B) of Table II.[30] Hence, once again, the evidence suggests that our previous results are not driven by a direct effect of *Unexpected Snow*. Also reassuring is that the coefficient on Δ snow is insignificant, while it was previously always significant. If ski hotels located in the same district are indeed exposed to the same snow conditions, then this is precisely what one would expect.

7 Selection Bias

Ski 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 estimating a selection equation. For this purpose, we augment our sample by including the 2,095 control hotels that did not undergo debt restructurings. As mentioned in Section 2, a formal criterion for the Austrian Hotel- and Tourism Bank (AHTB) to be involved in the debt restructuring is that the hotel 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 serves 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

[29]For each firm-year observation in our sample, there are on average 10.8 firm-year observations in the control sample in the same district and year (see also footnote 15).

[30]Likewise, OLS results—which we do not report here for brevity—are very similar to those in Panel (A) of Table II. Hausman (1978) tests confirm that the OLS estimates are biased ($p = 0.018$ without control variables; $p = 0.001$ with control variables).

number of nights stayed. Hence, it does not capture aspects of the hotel's performance and is therefore likely exogenous in the second-stage regression.

We estimate the following Probit selection equation:

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

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, *Unexpected Snow* is the average snow in years t and $t-1$ minus the average snow in the preceding ten years ($t-2$ to $t-11$), and $\mathbf{X}$ is a vector of control variables, which includes size in year $t-1$, altitude, and Δ snow, where the latter is computed as the difference between snow in years t and $t-1$. If a given hotel is restructured, its subsequent firm-year observations are dropped. Since age is missing for all control hotels, the selection equation does not include age (see Section 4.3). Unfortunately, the number of beds is only available for 74 of the 115 hotels in our restructuring sample. Standard errors are clustered at the district level.

Panel (A) of **Table VIII** reports the results. The coefficient on *Local Capacity Share* is positive and significant ($t = 2.72$), implying that ski hotels with larger local capacity shares are more likely to be restructured. (Recall that we always control for size in our regressions.) What seems puzzling, however, is that while hotels with larger local capacity shares are more likely to be restructured, Table I shows that restructured hotels are on average smaller than control hotels. There is a simple explanation: debt restructurings are concentrated in districts with smaller hotels. *Within* these districts, restructured hotels are relatively larger, which explains the positive coefficient on *Local Capacity Share* in equation (3). Relative to (control) hotels in non-restructuring districts, however, restructured hotels are relatively smaller.[31]

[31] The average number of beds of all (restructured and control) hotels in districts in which a restructuring took place—measured in the year before the restructuring—is 70. In contrast, the average number of beds of only the restructured hotels in the same year is 76 (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

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. For this purpose, we have re-estimated equation (1) using only the 74 hotels with non-missing bed data. The results (not reported) are very similar to those in Table II (column [2] of Panel (B)). Importantly, the coefficient on Δ leverage is -0.055 ($t = 2.39$), while the corresponding coefficient in Table II is -0.052 ($t = 2.48$).

In **Panel (B)**, we include the *Inverse Mills Ratio* as an explanatory variable in our second-stage regression. Column [1] shows the results with Δ ROA as the dependent variable, and column [2] shows the results with locally adjusted Δ ROA as the dependent variable. In both cases, the coefficient on Δ leverage is remarkably close to the corresponding coefficients in Table II (column [2] of Panel (B)) and Table VII (column [2]), respectively. Moreover, the *Inverse Mills Ratio*, though positive, is never significant. Overall, this evidence suggests that our previous results are unlikely to be driven by selection bias.

8 Conclusion

Using a sample of highly (over-)leveraged Austrian ski hotels undergoing debt restructurings, this paper provides evidence in support of Myers' (1977) argument that debt overhang impairs firm performance. The main contribution is to identify plausibly exogenous variation in leverage and thus to address whether observed changes in firm performance are indeed caused by changes in leverage. Our instrument, *Unexpected Snow*, captures the extent to which a ski hotel experienced *unusually* good or bad snow conditions prior to the debt restructuring. Effectively, *Unexpected Snow* provides lending banks with the counterfactual of what would have been the ski hotel's operating performance in the absence

(control) hotels in non-restructuring districts is 118. 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 result, the average control hotel (including those in restructuring districts) is larger than the average restructured hotel. Using size or the number of employees yields similar results.

of strategic default, allowing to distinguish between ski hotels that are in distress due to adverse demand shocks ("liquidity defaulters") and ski hotels that are in distress due to debt overhang ("strategic defaulters"). Indeed, we find that ski hotels with unusually good snow conditions before the debt restructuring receive significantly larger reductions in leverage, which is consistent with lending banks perceiving these hotels as being in distress due to debt overhang (e.g., Myers, 1977, p. 158). When instrumenting changes in leverage with *Unexpected Snow* prior to the debt restructuring, we find that a reduction in leverage leads to a significant increase in ROA, which is the opposite of what we find in OLS regressions.

To understand better *why* a reduction in leverage leads to an increase in ROA, we examine separately the effect on individual components of ROA. We find that a reduction in leverage leads to a decrease in overhead costs, wages, and input costs, and to an increase in sales, albeit the input cost result is not significant. The wage result is particularly interesting. As the hotels in our sample are small, family-run hotels, wages are partly transfers to the hotels' owners and their family members. Thus, while a decrease in wages may be interpreted as an improvement in operational efficiency, it might also be interpreted as evidence of the owners' willingness to keep cash in the firm rather than to pay it out to themselves.

9 Appendix: 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 took place. In the case of *flow* variables (e.g., EBITDA, sales), the first "after" observation is measured one year later 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 $t-1$. 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, 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 years. 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 15 cm of snow on the ground as measured by the weather station that 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 year in which EBITDA is generated, implying that "after" and "before" have exactly the same meaning for snow and EBITDA.

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Table I
Summary Statistics

"Restructuring sample" refers to the 115 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). Altitude is the surface-weighted average altitude of the area spanned by the hotel's ZIP code (in meters). Leverage is the book value of debt divided by the book value of assets.

	Restructuring Sample			Control Sample		
Variable	# Hotels	Mean	Median	# Hotels	Mean	Median
Size	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
Altitude (meters)	115	1,180	1,152	2,095	1,275	1,368
Leverage	115	2.40	1.77	2,095	1.26	0.99

Table II
Return on Assets: OLS and IV Regressions

Return on assets (ROA) is EBITDA divided by the book value of assets. Δ ROA is the average ROA in the three years after the debt restructuring minus the ROA in the year before the debt restructuring. Δ Leverage and Δ snow are defined accordingly. Leverage is defined in Table I. Snow is the number of days during the months of January, February, March, and December in a given fiscal year with more than 15 cm of snow on the ground as measured by the closest weather station. 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 operating license as of the year before the debt restructuring. In Panel (B), Δ leverage is instrumented with *Unexpected Snow*, which is the average snow in the two years prior to the debt restructuring minus the average snow in the preceding ten years. In columns [1] and [2] of both panels, standard errors are clustered at the district level. In column [3] of both panels, median regressions are used, where the standard errors are computed using block bootstrapping with 500 bootstraps and 42 blocks based on the 42 districts in which the hotels are located. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): OLS Regressions

Dependent Variable:	Δ ROA	Δ ROA	Δ ROA
	[1]	[2]	[3]
Δ Leverage	0.005**	0.005*	0.004**
	(2.16)	(1.98)	(2.10)
Size		-0.000	-0.001
		(0.04)	(0.37)
Age		0.006	0.007
		(1.09)	(1.12)
Altitude		0.002	-0.003
		(0.17)	(0.35)
Δ Snow		0.373	0.520**
		(1.41)	(2.04)
Year Dummies	Yes	Yes	Yes
Regression Type	OLS	OLS	Median
Observations	115	115	115
R-squared	0.10	0.11	0.10

Panel (B): IV Regressions

Dependent Variable:	Δ ROA	Δ ROA	Δ ROA
	[1]	[2]	[3]
Δ Leverage	-0.034**	-0.052**	-0.037**
	(2.45)	(2.48)	(2.18)
Size		0.066**	0.046*
		(2.41)	(1.79)
Age		-0.006	-0.003
		(0.86)	(0.38)
Altitude		-0.013	-0.020
		(1.28)	(1.40)
Δ Snow		0.538*	0.535**
		(1.98)	(2.14)
Year Dummies	Yes	Yes	Yes
Regression Type	IV	IV	Median/IV
Observations	115	115	115
R-squared	0.11	0.17	0.11

Table III
Net Profit Margin: OLS and IV Regressions

Net profit margin (NPM) is EBITDA divided by sales. Δ NPM is defined analogously to Δ ROA in Table II. All other variables are defined in Table II. In Panel (B), Δ leverage is instrumented with *Unexpected Snow* as defined in Table II. In columns [1] and [2] of both panels, standard errors are clustered at the district level. In column [3] of both panels, median regressions are used, where the standard errors are computed using block bootstrapping with 500 bootstraps and 42 blocks based on the 42 districts in which the hotels are located. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): OLS Regressions

Dependent Variable:	Δ NPM	Δ NPM	Δ NPM
	[1]	[2]	[3]
Δ Leverage	0.003	0.005	0.008**
	(0.89)	(1.27)	(2.35)
Size		-0.011	-0.011
		(1.16)	(1.13)
Age		0.011	0.004
		(1.22)	(0.43)
Altitude		0.003	0.007
		(0.26)	(0.39)
Δ Snow		0.375	0.612*
		(0.90)	(1.67)
Year Dummies	Yes	Yes	Yes
Regression Type	OLS	OLS	Median
Observations	114	114	114
R-squared	0.05	0.08	0.07

Panel (B): IV Regressions

Dependent Variable:	Δ NPM	Δ NPM	Δ NPM
	[1]	[2]	[3]
Δ Leverage	-0.029*	-0.042**	-0.050**
	(1.94)	(2.25)	(2.51)
Size		0.044*	0.053*
		(1.74)	(1.86)
Age		0.001	-0.005
		(0.15)	(0.54)
Altitude		-0.009	-0.011
		(0.68)	(0.90)
Δ Snow		0.510	0.733*
		(1.26)	(1.98)
Year Dummies	Yes	Yes	Yes
Regression Type	IV	IV	Median/IV
Observations	114	114	114
R-squared	0.07	0.10	0.09

Table IV
Costs and Revenues: IV Regressions

Δ Overhead is the average overhead cost in the three years after the debt restructuring minus the overhead cost in the year before the debt restructuring. Δ Wages, Δ input costs, and Δ sales are defined accordingly. All variables are scaled by sales, except for wages, which is scaled by the number of employees. 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. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ Overhead	Δ Wages	Δ Input Costs	Δ Sales
	[1]	[2]	[3]	[4]
Δ Leverage	0.042**	0.427**	0.032	-0.039*
	(2.10)	(2.07)	(1.53)	(1.85)
Size	-0.011*	-0.431*	-0.046*	0.092
	(1.77)	(1.69)	(1.72)	(1.41)
Age	0.006	0.092	0.006	-0.034
	(1.06)	(0.57)	(0.82)	(0.89)
Altitude	0.006	0.180	0.001	-0.016
	(1.02)	(1.02)	(0.08)	(0.40)
Δ Snow	-0.094	-0.273	-0.182	0.563**
	(0.47)	(0.48)	(0.52)	(2.04)
Year Dummies	Yes	Yes	Yes	Yes
Regression Type	IV	IV	IV	IV
Observations	35	74	35	114
R-squared	0.42	0.22	0.43	0.16

Table V
First-Stage Regression

All 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. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ Leverage
Unexpected Snow	-0.014***
	(3.21)
Size	1.130**
	(2.20)
Age	-0.205
	(1.18)
Altitude	0.354
	(1.23)
Δ Snow	2.694
	(0.57)
Year Dummies	Yes
Observations	115
R-squared	0.34

Table VI
Out-of-Sample Evidence

In Panel (A), Δ ROA (Δ snow) is the difference between ROA (snow) in year *t* and ROA (snow) in year *t* + 1, while *Unexpected Snow* and size are both measured in year *t*. In Panel (B), ROA and snow are both measured in year *t*, while *Unexpected Snow* and size are both measured in year *t* - 1, where *Unexpected Snow* in year *t* - 1 is the difference between snow in year *t* - 1 and snow in the preceding ten years (i.e., *t* - 2 to *t* - 11). ROA, size, altitude, and snow are defined in Table II. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): ROA (First Differences)

Dependent Variable:	Δ ROA	Δ ROA
	[1]	[2]
Unexpected Snow	-0.003	-0.002
	(0.09)	(0.04)
Δ Snow		0.165***
		(3.38)
Size		0.004***
		(4.95)
Altitude		-0.001
		(0.95)
Year Fixed Effects	Yes	Yes
Observations	4,253	4,253
R-squared	0.01	0.01

Panel (B): ROA (Levels)

Dependent Variable:	ROA	ROA	ROA	ROA
	[1]	[2]	[3]	[4]
Unexpected Snow (*t* - 1)	0.045	0.033	-0.010	0.021
	(0.68)	(0.40)	(0.15)	(0.28)
Snow		0.159***		0.166**
		(3.19)		(2.28)
Size (*t* - 1)		-0.022***		-0.052***
		(12.19)		(10.12)
Altitude		0.002		
		(0.53)		
Year Fixed Effects	Yes	Yes	Yes	Yes
Hotel Fixed Effects	No	No	Yes	Yes
Observations	5,910	5,910	5,910	5,910
R-squared	0.13	0.13	0.72	0.72

Table VII
Locally Adjusted ROA: IV Regressions

This table presents variants of the regressions in Panel (B) of Table II in which *Locally Adjusted ROA* is used instead of ROA. *Locally Adjusted ROA* is computed by subtracting from each firm-year observation of ROA the median value of ROA of all control hotels in the same district and year. In columns [1] and [2], standard errors are clustered at the district level. In column [3], a median regression is used, where 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. All debt restructurings took place between 1998 and 2005. *t*-statistics are in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable:	Δ ROA (Loc. Adj.)	Δ ROA (Loc. Adj.)	Δ ROA (Loc. Adj.)
	[1]	[2]	[3]
Δ Leverage	-0.038**	-0.058**	-0.038**
	(2.12)	(2.60)	(2.10)
Size		0.064**	0.032*
		(2.44)	(1.68)
Age		-0.007	-0.004
		(0.80)	(0.60)
Altitude		-0.016	0.001
		(1.23)	(0.11)
Δ Snow		0.183	0.012
		(0.47)	(0.14)
Year Dummies	Yes	Yes	Yes
Regression Type	IV	IV	Median/IV
Observations	115	115	115
R-squared	0.16	0.19	0.10

Table VIII
Heckman (1979) Correction

Panel (A) presents the results from a Probit regression in which the dependent variable is a dummy that equals one if a hotel is restructured in the following year and zero otherwise (*Selection Dummy*). The sample includes all restructured and control hotels with non-missing bed data. If a hotel is restructured, its subsequent firm-year observations are dropped. *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. In Panel (B), the regression specification is the same as in Table II (column [2] of Panel (B)) and Table VII (column [2]), respectively, except that the *Inverse Mills Ratio* computed from the selection equation in Panel (A) is included as an explanatory variable. The sample in Panel (B) is restricted to the 74 restructured hotels with non-missing bed data. Standard errors are clustered at the district level. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. All debt restructurings took place between 1998 and 2005. *t*-statistics 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	0.376***
	(2.72)
Unexpected Snow	-0.000
	(0.14)
Size	-0.172***
	(4.31)
Altitude	-0.043
	(0.40)
Δ Snow	-2.680
	(0.74)
Year Dummies	Yes
Observations	6,736
R-squared	0.12

Panel (B): IV Regressions with Heckman Correction

Dependent Variable:	Δ ROA	Δ ROA (adjusted)
	[1]	[2]
Δ Leverage	-0.054**	-0.059**
	(2.45)	(2.62)
Size	0.069**	0.060**
	(2.53)	(2.02)
Age	0.009	0.003
	(1.00)	(0.22)
Altitude	-0.022	-0.019
	(1.32)	(1.02)
Δ Snow	0.706**	0.079
	(2.42)	(0.15)
Inverse Mills Ratio	0.021	0.069
	(0.34)	(0.86)
Year Dummies	Yes	Yes
Regression Type	IV	IV
Observations	74	74
R-squared	0.28	0.24