Snow and Leverage

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Based on a sample of highly leveraged Austrian ski hotels undergoing debt restructurings, we show that reducing a debt overhang leads to a significant improvement in operating performance. 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. *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, allowing them to distinguish between ski hotels that are in distress due to negative demand shocks ("liquidity defaulters") and those that are in distress due to debt overhang ("strategic defaulters"). (*JEL* G32, G34)

In the recent financial crisis, debt overhang played a key role not only at the level of banks and financial institutions (e.g., Veronesi and Zingales 2010; Diamond and Rajan 2011; 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 their mortgage payments (Melzer 2010; Guiso, Sapienza, and Zingales 2011).

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Debt overhang can distort incentives in many ways. In the extreme case, it can lead to strategic default.[1] For instance, owners of debt-ridden firms may intentionally forego crucial investments (e.g., maintenance of plant and equipment), exert too little effort (e.g., effort devoted to marketing, sales, cost-cutting, and improving efficiency), strategically pay out cash to themselves (as wages or dividends), or sell vital firm assets on the secondary market and pocket the proceeds.[2]

Given its importance for both 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. This article sheds light on the debt overhang problem using a sample of highly (over-)leveraged Austrian ski hotels undergoing debt restructurings. The specific nature of our data allows us to identify plausibly exogenous variation in leverage and thus to address whether—for highly leveraged borrowers—reducing a debt overhang leads to a subsequent improvement in operating performance.

In our sample, the average (book) leverage prior to the debt restructuring is 2.40. As a result of the debt restructurings, leverage decreases by 23% on average. This decrease is primarily due to debt forgiveness. 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 may be in distress due to negative demand shocks, resulting in weak operating performance and poor liquidity. For such hotels, there is little reason for creditors to forgive debt—it would merely constitute a windfall gain for the hotels.[3] Rather, creditors should defer interest payments and roll over maturing debt. By contrast, for hotels that are in distress due to debt overhang, it can be optimal for creditors to forgive debt (Myers 1977, p. 158).[4]

1 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.

2 See Myers (1977), especially pp. 155-56, pp. 159-60, and p. 162. In his empirical study of household debt overhang, 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, the households did not reduce spending on automobiles, furniture, and home appliances, suggesting that the problem is indeed debt overhang and not merely a liquidity shortage.

3 Though these hotels may have merely suffered from bad luck (not bad decisions), they may be subject to debt overhang in the future. If this is what creditors expect, they may rationally decide to forgive debt also to these hotels.

4 From the creditors' viewpoint, debt forgiveness is only optimal if it increases the expected repayment by the borrower (via an improvement in operating performance). In this case, debt forgiveness constitutes a Pareto-improvement that benefits both the borrower and its creditor(s). Krugman (1988) 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 can be optimal if there is a temporary (exogenous) liquidity shock. In contrast, forgiving a debt overhang is optimal if the borrower's incentives to make investments and to provide effort are distorted.

A challenge for creditors is to distinguish between borrowers that are in distress due to debt overhang ("strategic defaulters") and those that are in distress due to negative demand shocks ("liquidity defaulters"). As Guiso, Sapienza, and Zingales (2011, p. 2) note: "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 may not help: Strategic defaulters may also exhibit weak operating performance and poor cash balances, albeit for different reasons. To identify strategic defaulters, creditors would effectively need to know the counterfactual of what would have been the borrower'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 correlation 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 plausible that this hotel is a (genuine) liquidity defaulter. In contrast, if a ski hotel got into distress despite having experienced favorable snow conditions, it is less likely that this hotel simply had bad luck. Rather, it is likely that the hotel's owner(s) undermaintained, underinvested, and underprovided effort. In other words, the hotel is a classic strategic defaulter.

We measure "poor" and "favorable" snow conditions prior to the debt restructuring relative to the hotel's own historical snow conditions in the preceding ten years. We call this measure *Unexpected Snow*. Thus, *Unexpected Snow* captures the extent to which a ski hotel experienced *unusually* good or bad snow conditions before the debt restructuring. Indeed, we find that 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, which is consistent with lending banks perceiving these hotels as being in distress due to debt overhang.[5] Similarly, when we regress changes in leverage (after vs. before the debt restructuring) on *Unexpected Snow* before the debt restructuring, 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%.

[5] Nota bene, ski hotels with negative and positive *Unexpected Snow* had both similar (weak) operating performance and cash balances prior to the debt restructuring, suggesting that lending banks cannot easily use this information to identify strategic defaulters.

The main objective of our study is to examine whether—for highly leveraged borrowers—a reduction in leverage leads to a subsequent improvement 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 may receive less debt forgiveness, resulting in smaller reductions in leverage. In stark contrast, if we instrument changes in leverage using *Unexpected Snow* before 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's (1977) argument that debt overhang impairs firm performance, we find that—for highly leveraged borrowers—a reduction in leverage leads to a statistically and economically significant increase in ROA.

To gain a better understanding of why a reduction in leverage leads to an increase in ROA, we examine separately the effects 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 ski hotels in our sample are small, family-owned 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 may also be interpreted as evidence of the owners' willingness to keep cash in the firm rather than to pay it out to themselves.

We also address an alternative story whereby ski hotels that got into distress despite high *Unexpected Snow* are simply incompetent. As we show, restructuring measures aimed at addressing managerial incompetence—such as coaching programs and forced asset sales—are uncorrelated with *Unexpected Snow*, suggesting that our results are not merely picking up the effects of these measures.

To 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. We find that *Unexpected Snow* is uncorrelated with both changes in ROA and future ROA, suggesting that it has no *direct* effect on the dependent variable in our second-stage regression. 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*, by subtracting from ROA the median ROA of all control hotels in the same region and year. Our results remain virtually unchanged, suggesting that 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 in our sample is that it must be "structurally important," meaning that 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. Importantly, *Local Capacity Share* does not capture aspects of the hotel's performance and is therefore likely exogenous in our second-stage regression. Our results remain virtually unchanged, suggesting that they are not driven by selection bias.

The rest of this article is organized as follows. Section 1 discusses institutional details. Section 2 provides an example based on an actual restructuring case from our sample. Section 3 discusses sample selection, empirical methodology, and summary statistics. Section 4 contains our main results. Section 5 examines the strength and validity of our instrument. Section 6 considers an alternative story based on "managerial incompetence." Section 7 accounts for selection bias. Section 8 discusses related literature. Section 9 offers concluding remarks. The Appendix provides a discussion of the timing conventions used in the construction of our variables.

1. Institutional Background

As is common in many countries, Austrian firms may try to restructure their debt prior to filing for formal 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).[6] 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, its role in the debt restructurings is primarily that of a mediator, given that it does not take on any credit risk.[7] 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.

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

[7] The AHTB provides limited financial support in the form of interest rate subsidies and small loans, although 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.

Being a mediator in the debt restructurings, 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 8% of total assets, and the restructuring must not involve investments in the hotel's assets that are not absolutely essential for regaining profitability. Among other things, this precludes investments in land or capacity expansions and investments to complete projects already underway. 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 these 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 to discuss restructuring options. This 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, 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 its 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.

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 (financial and otherwise) of the hotel's lending bank(s). 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 this case, 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.

2. Case Study

This example is based on an actual restructuring case from our sample. For confidentiality reasons, it does not contain the names 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 nine employees (not counting family members), 34 rooms, and 71 beds, making it a rather typical hotel within our sample. The hotel is structured as a “Gesellschaft nach bürgerlichem Recht,” which means all of the owners are individually and personally liable for all of the hotel’s liabilities. This legal form is typical of most hotels in our sample.

The report by the AHTB’s loan officers shows that 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%.[8] This decline in demand is unlikely to come from poor 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. Rather, as the loan officers suggested, the decline is likely 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 before the debt restructuring was 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 was reduced from 1.84 to 1.41. This reduction is above the median in our sample—the median (book) leverage before and after the debt restructuring is 1.77 and 1.56, respectively. In response to the debt forgiveness, the owner family also 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 operating performance improved sharply. ROA increased from 6.3% prior to the debt restructuring to

[8] 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.

10.9% in the three years after the debt restructuring.[9] This improvement is well above the median in our sample. In fact, only 25% of the hotels in our sample had a larger increase in ROA.

3. Data

3.1 Sample selection

Our primary data source is the Austrian Hotel and Tourism Bank (AHTB). We have information about 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 available, other key financial variables are also available.) 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 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). Hence, 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.

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, although for some hotels we only have one or two years of data.

We have monthly weather data for all Austrian weather stations provided by the Austrian Central Institute for Meteorology and Geodynamics. We match each hotel to its closest weather station by locating the weather station with the minimal Euclidean distance from the coordinates of the postal office associated with the hotel's ZIP code. To ensure that the weather conditions indeed reflect those in the hotel's vicinity, we additionally 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 nearest weather station are a noisy proxy of the weather conditions that are truly relevant for the hotel (e.g., the snow conditions at the nearest ski slope). While this is unlikely to introduce any bias, it introduces noise into the regression, making it only harder for us to find significant results.

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[9] 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.

3.2 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:

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

where i indexes hotels, Δ is the difference operator ("after" minus "before" the debt restructuring), and **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. The Appendix describes in detail what the difference operator Δ measures based on whether a given variable is a stock or flow variable.

Including altitude in our regression 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 regression 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 3.3 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 restructuring 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. We cluster standard errors at the district level in all our regressions.[10]

Our identification strategy has been already laid out in the Introduction. For this reason, we shall be brief here. 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 future snow and

[10] Districts ("Bezirke" in German), also referred to as "political districts" by Austria's statistical office, are roughly similar to counties in the United States 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.

future changes in snow, although it should be noted that we already control for Δ snow in all our regressions.

Unexpected Snow effectively provides lending banks with the counterfactual of what would have been the ski hotel's operating performance in the absence of strategic default, allowing them to distinguish between ski hotels that are in distress due to negative demand shocks ("liquidity defaulters") and those that are in distress due to debt overhang ("strategic defaulters").[11] Accordingly, if a ski hotel experienced unusually bad snow conditions prior to the debt restructuring, it is plausible 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 simply had bad luck. Rather, it is likely that the hotel's owner(s) undermaintained, underinvested, and underprovided effort. In other words, the hotel is a classic strategic defaulter. In this case, it can be optimal for the hotel's lending bank(s) to forgive debt to restore incentives (Myers 1977, p. 158).[12]

Note that the lending banks cannot easily use other information, such as operating performance and cash balances, to identify strategic defaulters. Arguably, strategic defaulters may also exhibit weak operating performance and poor 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%. Likewise, ski hotels with negative *Unexpected Snow* had a median cash-to-asset ratio of 1.3%, while ski hotels with positive *Unexpected Snow* had a median cash-to-asset ratio of 1.0%. Ski hotels with negative and positive *Unexpected Snow* also had virtually identical median (book) leverage ratios: 1.76 and 1.77, respectively. None of these differences is statistically significant.[13]

In stark contrast, 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. Given

[11] To validate this conjecture, we have regressed ROA on (contemporaneous) *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%.

[12] From an ex-ante viewpoint, lending banks might want to commit to liquidate strategic defaulters, knowing that renegotiation will be (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 lending banks, suggesting that it is difficult for them to credibly commit not to renegotiate. However, our result is also consistent with lending banks 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.

[13] Ski hotels with negative and positive *Unexpected Snow* are also similar in other dimensions (except for Δ leverage): The median size is 985,952 euro versus 1,023,016 euro, the median number of beds is 65 versus 67, and the median number of employees is 13.5 versus 12.5. None of these differences is statistically significant.

that ski hotels with negative and positive *Unexpected Snow* had virtually identical leverage ratios before the debt restructuring, this implies that the *percentage* reduction in leverage is also five times larger. 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.[14]

Though our main variable of interest is leverage, it should be noted that most of the reduction in leverage comes from debt forgiveness (i.e., write-offs). In our sample, debt forgiveness constitutes on average 23.2% of the book value of assets before the debt restructuring. In contrast, new lending constitutes only 7.1% of the book value of assets, while new equity injections constitute only 7.8%. At the same time, the book value of assets itself remains virtually unchanged: It decreases only slightly (by 1% on average) due to some forced asset sales.[15] With new lending being roughly equal to new equity injections, their net effect on leverage is roughly zero. Given that the book value of assets is also unchanged, this implies that the average reduction in leverage in our sample (22.9%) is of the same order of magnitude as the average debt forgiveness (23.2%).

3.3 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 the net profit margin (NPM), which is EBITDA divided by sales. We winsorize both variables at the 5th and 95th percentiles of their empirical distribution to avoid that outliers drive our results. 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.

Since 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 the year before the debt restructuring. Age is the number of years since the hotel was granted its operating license as measured in the year before the debt restructuring. This information is missing for 28 hotels. For these hotels, we use the number of years with available accounting data.[16] In all our regressions, we use the

14 An alternative hypothesis is that ski hotels that got into distress despite positive *Unexpected Snow* are simply "bad types." In other words, the problem may be managerial incompetence, not debt overhang. However, only two (out of 115) hotels in our sample experienced a change in ownership or management after the debt restructuring. We address this issue in more detail in Section 6.

15 That the book value of assets does not increase is consistent with the requirement imposed by the AHTB that the debt restructuring must not involve substantial investments into the hotel's assets (see Section 1).

16 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 1, the out-of-sample regressions in Table 6, and the selection equation in Table 9. Rather than omitting age altogether, we can use the number of years with available accounting data as a proxy for age. All our results remain similar.

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 any contemporaneous effect of snow on EBITDA. Finally, *Unexpected Snow* is the average snow experienced by a hotel in 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 for 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 1 provides summary statistics. "Restructuring sample" refers to the 115 ski hotels that underwent debt restructurings. "Control sample" refers to the 2,095 ski hotels that did not undergo debt restructurings. 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. 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 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.

Table 1
Summary statistics

	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

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.

4. Results

4.1 Return on assets

Table 2 presents our main results. The dependent variable is the change in ROA "after" versus "before" the debt restructuring (Δ ROA). The main explanatory 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 3.3). The results of the underlying first-stage regression are discussed separately in Section 5.1.

In columns 1 and 2 of Panel A in Table 2, 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.[17] However, it is not difficult to think of a reverse causality explanation. For instance, ski hotels with larger *anticipated* increases in ROA may 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 in Table 2, 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 now 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

[17] 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."

Table 2
Return on assets: OLS and IV regressions

Panel A: OLS regressions

Dependent Variable:	Δ ROA [1]	Δ ROA [2]	Δ ROA [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 [1]	Δ ROA [2]	Δ ROA [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

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 1. 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

restructuring is 10.9%, this corresponds to an increase in ROA of about 28%. Thus, consistent with Myers's (1977) argument that debt overhang impairs firm performance, our results show that—for highly leveraged borrowers—a reduction in leverage leads to a statistically and economically significant increase in ROA.[18] 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 controls; $p = 0.001$ with controls). Thus, provided our instrument is valid, Hausman tests confirm that the OLS estimates are biased.

We winsorize ROA at the 5th and 95th percentiles of its empirical distribution to mitigate the effect of outliers. An alternative approach is to use median (least absolute deviation) regressions. A main issue associated with 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 idea, which is similar to clustering, is to preserve the existing correlation structure within each block while using the independence across blocks to consistently estimate the standard errors. In analogy to our clustering approach, 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 in Table 2 shows the results. As can be seen, they are similar to our previous results. In the IV regression in Panel B, the coefficient on Δ leverage has become slightly smaller, but it remains statistically significant (-0.037; $t = 2.18$). Importantly, this evidence suggests that our results are not driven by outliers.

[18] It is not obvious that reducing a debt overhang should always lead to an *instant* increase in accounting profitability. For instance, increasing maintenance expenditures lowers current profits while (hopefully) raising profits in the future. In contrast, reducing excessive payments to family members instantly raises profits. As explained in Section 3.1, Δ ROA captures any effect on EBITDA that arises in the three years after the debt restructuring. Hence, to the extent that some of the increase in profitability shows up after three years, our results would understate the positive effects of reducing a debt overhang.

4.2 Net profit margin

In Table 3, the dependent variable is the change in net profit margin (Δ NPM). Other than that, the regression specification is identical to that in Table 2.[19]

Similar to our previous results, OLS regressions yield again a positive coefficient on Δ leverage, although it is only significant in the median regression. When Δ leverage is instrumented with *Unexpected Snow* prior to the debt restructuring, we find again that the coefficient 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 is slightly larger in the median regression (-0.050; $t = 2.51$). As for the control variables, the coefficients on size and Δ snow are both positive, although the coefficient on Δ snow is only significant in the median regression. The coefficients on age and altitude are both insignificant. Importantly, that the results are similar to our previous 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 controls; $p = 0.002$ with controls).

4.3 Costs and revenues

To gain a better understanding of why a reduction in leverage leads to an increase in ROA, we examine separately the effects 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 4. 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.[20] 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 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 of Table 4, the coefficient on Δ leverage is positive and, except for 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

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

[20] We have run similar regressions with changes in capital expenditures (Capex) as the dependent variable. As the debt restructurings must not involve substantial investments into the hotels' assets (see Sections 1 and 3.2), we would not expect to find much of an effect here. Indeed, while the coefficient on Δ leverage has the right sign (-0.075 and -0.108 depending on whether Capex is normalized by PPE or assets), it is statistically insignificant.

Table 3
Net profit margin: OLS and IV regressions

Panel A: OLS regressions

Dependent Variable:	Δ NPM [1]	Δ NPM [2]	Δ NPM [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 [1]	Δ NPM [2]	Δ NPM [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

Net profit margin (NPM) is EBITDA divided by sales. Δ NPM is defined analogously to Δ ROA in Table 2. All other variables are defined in Table 2. In Panel B, Δ leverage is instrumented with *Unexpected Snow* as defined in Table 2. 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Costs and revenues: IV regressions

Dependent Variable:	Δ Overhead [1]	Δ Wages [2]	Δ Input Costs [3]	Δ Sales [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

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 2. 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

also leads to a decrease in input costs, albeit the effect is not significant ($t = 1.53$). That the effect is not a pure "sales effect" is not surprising: We already know from Table 3 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-owned 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 may also be interpreted as evidence of the owners' willingness to keep cash in the firm rather than to pay it out to themselves.

All control variables have the expected signs in Table 4. As in our previous ROA regressions, the coefficient on size is (almost) 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 positive and significant coefficient on Δ snow in our previous regressions is likely to come from a positive effect of snow on (contemporaneous) sales, which makes sense intuitively.

5. Identification

5.1 First-stage regression

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

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

Table 5
First-stage regression

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

All variables are defined in Table 2. 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 hotel in the two years before 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 5 presents the results. As is shown, the coefficient on *Unexpected Snow* is negative and highly significant (-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 reduction in leverage of about 23%.[21] Accordingly, ski hotels with favorable snow conditions prior to the debt restructuring receive significantly larger reductions in leverage.

Consistency of IV estimation in a finite sample requires that the instrument be sufficiently "strong," meaning that it must correlate strongly with the troublesome endogenous variable. In Equation (2), the F-statistic 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). Thus, weak identification is unlikely to be a major concern.

[21] When estimating Equation (2) with 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 identifying variation in our second-stage regression is primarily due to variation in debt (not assets) caused by variation in *Unexpected Snow*.

5.2 Validity of the instrument

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 changes in leverage). While the exclusion restriction cannot be tested directly, its validity can be supported using out-of-sample evidence. Using 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.[22] Age is not included as it is missing for all control hotels.[23] Panel A of Table 6 presents the results.[24] Regardless of whether control variables are included, the coefficient on *Unexpected Snow* is never significant ($t = 0.09$ without controls; $t = 0.04$ with controls). Hence, out-of-sample evidence suggests that *Unexpected Snow* has no direct effect on changes in ROA.

Rather than estimating the effect of *Unexpected Snow* on *changes* in ROA, we can (somewhat similarly) estimate its effect on *future* ROA. In Panel B of Table 6, 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 of Panel B in Table 6, 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). Hence, 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 2 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*, by subtracting from ROA the median ROA of all control hotels in the same district and year. 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. Effectively, *Locally Adjusted ROA* thus "controls" for any direct effect

[22] In the spirit of Equation (1), Δ ROA in year t is the difference between ROA in years 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 years t and $t+1$ to control for any contemporaneous effect of snow on EBITDA. Finally, *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 $t-10$).

[23] See Section 3.3. Note that age was never significant in any of our previous regressions.

[24] The number of observations in Panel A is less than in Panel B, because we 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 means we have three firm-year observations. In Panel A, however, we have only two firm-year observations, as Δ ROA in 2001 cannot be computed.

Table 6
Out-of-sample evidence

Panel A: ROA (first differences)

Dependent Variable:	Δ ROA [1]	Δ ROA [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 [1]	ROA [2]	ROA [3]	ROA [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

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 2. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. The sample is based on the 2,095 control hotels that did not undergo debt restructurings. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Locally adjusted ROA: IV regressions

Dependent Variable:	Δ ROA (Loc. Adj.) [1]	Δ ROA (Loc. Adj.) [2]	Δ ROA (Loc. Adj.) [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

This table presents variants of the regressions in Panel B of Table 2 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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

of *Unexpected Snow* on changes in ROA, at least to the extent that the effect is common to all ski hotels located in the same district.

Table 7 shows the results. Except for the fact that ROA is locally adjusted, the regression specification is identical to that in Table 2. For brevity, we only report the results of the IV regressions.[25] Regardless of whether control variables are included, the coefficients on Δ leverage are remarkably similar to those in Panel B of Table 2. Hence, evidence from using *Locally Adjusted ROA* suggests that our previous results are not driven by a direct effect of *Unexpected Snow*. Also reassuring is the fact that the coefficient on Δ snow is now 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.

6. Coaching and Forced Asset Sales

The results of our first-stage regression are consistent with lending banks perceiving ski hotels with high (i.e., positive) *Unexpected Snow* as strategic defaulters. If a ski hotel experienced unusually bad snow conditions prior to the debt restructuring, it is plausible that this hotel got into distress due to bad luck.

25 The OLS results mirror those in Panel A of Table 2. Hausman (1978) tests confirm that the OLS estimates are biased.

However, if a ski hotel got into distress despite experiencing favorable snow conditions, it is less likely that this hotel simply had bad luck. Rather, it is likely that the hotel's owner(s) undermaintained, underinvested, and underprovided effort. In other words, the hotel is a classic strategic defaulter. In this case, it can be optimal for the hotel's lending banks to forgive debt to restore incentives.

An alternative hypothesis is that ski hotels that got into distress despite high *Unexpected Snow* are simply incompetent. Thus, the reason for their distress may not be distorted incentives but simply ineptitude. Though only two of the 115 hotels in our sample experienced a change in ownership or management, some of the debt restructurings are accompanied by measures that could plausibly be interpreted as being put in place because the lending banks felt that management is incompetent.[26] In ten cases, the lending banks arranged (and paid) for the hotel's management to receive professional coaching. In 30 cases, the lending banks intervened directly in the hotel's operations by forcing it to sell assets. While such asset sales may reflect a need for liquidity, they could also reflect differences in opinion as to what is the right scope of the hotel's operations. Either way, that the asset sale is *forced* suggests that the lending banks did not fully trust management to make the right decisions.

If ski hotels with higher *Unexpected Snow* also had more coaching and more forced asset sales, our results might be plausibly picking up the effects of these operating interventions.[27] To examine this hypothesis, we construct four measures of lending banks' operating interventions. *Coaching* is a dummy variable that equals one if the hotel receives professional coaching (ten cases), *Forced Asset Sales* is a dummy variable that equals one if the hotel is forced to sell assets (30 cases), *CA Index I* is a dummy variable that equals one if either one or both of the two previous dummies equals one (39 cases), and *CA Index II* is a count variable taking the value zero if neither of the two dummies equals one (76 cases), one if exactly one of the two dummies equals one (38 cases), and two if both dummies equal one (one case).

Panel A of Table 8 shows the raw correlations between *Unexpected Snow* and any of the four measures. All correlations are extremely small (between 0.3% and 3.9%) and highly insignificant (p-value between 0.680 and 0.972). Panel B of Table 8 shows the results from estimating Equation (2) with the dependent variable being one of the four measures (in place of Δ leverage). Consequently, the coefficient on *Unexpected Snow* is an indicator of the *conditional* correlation between *Unexpected Snow* and any of the four measures—conditional on size, age, altitude, and Δ snow. In all four cases, the coefficient on *Unexpected Snow* is virtually zero (between -0.001 and 0.000)

[26] A possible reason why changes in management are so rare is that the hotels are family owned and operated. Thus, it is difficult to change the hotel's management without also changing its ownership.

[27] Our results are identified off of variation in Δ leverage caused by variation in *Unexpected Snow*. Thus, if *Unexpected Snow* was correlated with either coaching or forced asset sales, the increase in ROA documented in Panel B of Table 2 might be plausibly due to lending banks' operating interventions (to address managerial incompetence) and not due to reductions in debt overhang.

Table 8
Coaching and forced asset sales

Panel A: Raw correlations

	Unexpected Snow	Coaching	Forced Asset Sales	CA Index I	CA Index II
Unexpected Snow	1.000				
Coaching	0.003	1.000			
	(0.972)				
Forced Asset Sales	−0.034	−0.113	1.000		
	(0.715)	(0.229)			
CA Index I	−0.039	0.431***	0.829***	1.000	
	(0.680)	(0.000)	(0.000)		
CA Index II	−0.029	0.470***	0.824***	0.983***	1.000
	(0.761)	(0.000)	(0.000)	(0.000)	

Panel B: "Conditional correlations"

Dependent Variable:	Coaching	Forced Asset Sales	CA Index I	CA Index II
	[1]	[2]	[3]	[4]
Unexpected Snow	0.000	−0.001	−0.001	−0.000
	(0.01)	(0.23)	(0.30)	(0.09)
Size	−0.227	−0.002	−0.067	−0.097
	(1.16)	(0.02)	(0.62)	(0.78)
Age	0.397	−0.196	−0.042	−0.035
	(1.61)	(1.01)	(0.23)	(0.19)
Altitude	−0.247	−0.019	−0.052	−0.110
	(0.62)	(0.07)	(0.18)	(0.33)
Δ Snow	0.706	4.012	1.462	3.893
	(0.16)	(0.84)	(0.32)	(0.73)
Year Dummies	Yes	Yes	Yes	Yes
Observations	115	115	115	115
R-squared	0.08	0.04	0.02	0.02

Panel C: First-stage regression

Excluded Cases:	Coaching	Forced Asset Sales	Coaching or Forced Asset Sales
Dependent Variable:	Δ Leverage	Δ Leverage	Δ Leverage
	[1]	[2]	[3]
Unexpected Snow	−0.014***	−0.014***	−0.012**
	(2.88)	(2.69)	(2.11)
Size	1.216**	1.446**	1.585**
	(2.23)	(2.09)	(2.15)
Age	−0.314*	−0.173	−0.341*
	(1.93)	(0.98)	(1.70)
Altitude	0.356	0.454	0.375
	(1.11)	(1.23)	(0.90)
Δ Snow	1.851	−3.371	−4.624
	(0.32)	(0.54)	(0.59)
Year Dummies	Yes	Yes	Yes
Observations	105	85	76
R-squared	0.36	0.43	0.47

(*continued*)

Table 8
Continued

Panel D: Second-stage regression

Excluded Cases:	Coaching	Forced Asset Sales	Coaching or Forced Asset Sales
Dependent Variable:	Δ ROA [1]	Δ ROA [2]	Δ ROA [3]
Δ Leverage	−0.057**	−0.036*	−0.051*
	(2.44)	(1.97)	(1.94)
Size	0.076**	0.058*	0.087*
	(2.41)	(1.98)	(1.98)
Age	−0.015	−0.007	−0.021
	(1.56)	(0.87)	(1.57)
Altitude	−0.017	−0.001	−0.004
	(1.49)	(0.10)	(0.34)
Δ Snow	0.534*	0.425	0.342
	(1.81)	(1.59)	(1.02)
Year Dummies	Yes	Yes	Yes
Observations	105	85	76
R-squared	0.17	0.25	0.24

Coaching is a dummy variable that equals one if the hotel is to receive professional coaching, *Forced Asset Sales* is a dummy variable that equals one if the hotel is forced to sell assets, *CA Index I* is a dummy variable that equals one if either one or both of the two previous dummies equals one, and *CA Index II* is a count variable taking the value zero if neither of the two dummies equals one, one if exactly one of the two dummies equals one, and two if both dummies equal one. All other variables are defined in Table 2. In Panel B, columns 1, 2, and 3 are based on probit regressions, while column 4 is based on a Poisson regression. Panels C and D contain variants of the regressions in Tables 5 and 2 (column 2 of Panel B), respectively, as specified in Section 6 of the main text. The coefficients and standard errors on altitude and Δ snow are multiplied by 1,000. All debt restructurings took place between 1998 and 2005. p-values (in Panel A) and t-statistics (in Panels B, C, and D) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

and highly insignificant (t-statistic between 0.01 and 0.30). Thus, regardless of whether we consider raw or conditional correlations, there is no significant relationship between *Unexpected Snow* and either coaching or forced asset sales.

In Panels C and D of Table 8, we verify that our results are similar if we exclude cases with either coaching or forced asset sales. Panel C shows the results from re-estimating our first-stage regression, while Panel D shows the results from re-estimating our second-stage regression. In both panels, column 1 includes cases in which the Coaching dummy is zero (105 cases), column 2 includes cases in which the Forced Asset Sales dummy is zero (85 cases), and column 3 includes cases in which both dummies are zero (76 cases). As shown, all results are similar to our previous results. In Panel C, the coefficient on *Unexpected Snow* varies between −0.012 and −0.014 (t-statistic between 2.11 and 2.88), which is similar to the coefficient in Table 5 (−0.014; $t = 3.21$). Likewise, in Panel D, the coefficient on Δ leverage varies between −0.036 and −0.057 (t-statistic between 1.94 and 2.44), which is similar to the coefficients in Panel B of Table 2 (between −0.034 and −0.052; t-statistic between 2.18 and 2.48).

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 explained in Section 1, a formal criterion for the AHTB to be involved in the debt restructurings is that the hotel must be "structurally important," meaning that 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 the hotel's performance and is therefore likely exogenous in our second-stage regression.

We estimate the following probit selection equation:

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

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 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. Also, 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 9 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 all our regressions.) What seems puzzling, however, is that while hotels with larger local capacity shares are more likely to be restructured, Table 1 shows that restructured hotels are 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*

Table 9
Heckman (1979) correction

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 [1]	Δ ROA (Loc. Adj.) [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 Mils 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

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 2. In Panel B, the regression specification is the same as in Table 2 (column 2 of Panel B) and Table 7 (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 *** denote significance at the 10%, 5%, and 1% levels, respectively.

Share in Equation (3). Compared to (control) hotels in non-restructuring districts, however, restructured hotels are relatively smaller.[28]

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 ski hotels with non-missing bed data are indeed representative of our original sample of 115 ski hotels. For this purpose, we have re-estimated Equation (1) using only the 74 ski hotels with non-missing bed data. The results (not reported) are very similar to those in Table 2 (column 2 of Panel B). Specifically, the coefficient

[28] 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 1). 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 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.

on Δ leverage is -0.055 ($t = 2.39$), while the corresponding coefficient in Table 2 is -0.052 ($t = 2.48$).

In Panel B of Table 9, 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, while column 2 shows the results with locally adjusted Δ ROA as the dependent variable. In both cases, the coefficient on Δ leverage is very close to the coefficients in Table 2 (column 2 of Panel B) and Table 7 (column 2), respectively. Moreover, the *Inverse Mills Ratio*, although positive, is not significant. Overall, this evidence suggests that our results are unlikely to be driven by selection bias.

8. Literature Review

Our article is broadly related to empirical studies of debt overhang, debt renegotiations, and more generally, resolutions of financial distress. Gilson, John, and Lang (1990) consider 169 publicly traded U.S. companies that are in financial distress. The authors examine which of these companies successfully restructure their debt outside 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.[29]

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 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. Finally, our article is related to Melzer’s (2010) study of household debt overhang, which has been cited above.

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

Perhaps most closely related to our article, in terms of both research question and empirical design, 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. Had the gold clauses been enforced, the debt burden of borrowers would have increased by 69%, which implies that "the Supreme Court decision is effectively a debt forgiveness equivalent to 69% of the value of a firm's debt" (p. 20). Kroszner finds that both equity prices and corporate bond prices rise upon the announcement of the Supreme Court's decision, which is consistent with the view that debt forgiveness constitutes a Pareto-improvement that benefits both equityholders and debtholders.

9. Conclusion

This article provides empirical support for Myers's (1977) argument that debt overhang impairs firm performance using a sample of highly leveraged Austrian ski hotels undergoing debt restructurings. Debt restructurings are an ideal setting for the study of debt overhang: By definition, any (ex-post) solution must necessarily involve renegotiations with creditors.[30] Moreover, the specific nature of our data allows us to identify plausibly exogenous variation in leverage changes in the debt restructurings and thus to address whether—for highly leveraged borrowers—reducing a debt overhang leads to a subsequent improvement in operating performance.

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* thus provides lending banks with the counterfactual of what would have been the ski hotel's operating performance in the absence of strategic default, allowing them to distinguish between ski hotels that are in distress due to negative demand shocks (liquidity defaulters) and those that are in distress due to debt overhang (strategic defaulters). We find that ski hotels with higher (i.e., more positive) *Unexpected Snow* receive significantly larger reductions in leverage, which is consistent with lending banks perceiving these hotels as being in distress due to debt overhang. When instrumenting changes in leverage in the debt restructurings with *Unexpected Snow*, we find that a reduction in leverage leads to a significant increase in ROA.

To understand better why a reduction in leverage leads to an increase in ROA, we examine separately the effects 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

30 See Tirole (2006, pp. 125-26). Accordingly, what gives the debt overhang problem its bite is the absence of renegotiation, not excessive leverage per se.

our sample are small, family-owned 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 may also be interpreted as evidence of the owners' willingness to keep cash in the firm rather than to pay it out to themselves.

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 $t-1$. Denote by T_i the (end of the) fiscal year in which the debt restructuring of hotel i takes place. We have that

$$\Delta\ \mathrm{ROA}_i := \left(\frac{1}{3}\sum_{t=T_i}^{T_i+2}\frac{\mathrm{EBITDA}_{i,t+1}}{\mathrm{assets}_{i,t}}\right) - \frac{\mathrm{EBITDA}_{i,T_i}}{\mathrm{assets}_{i,T_i-1}}. \tag{A1}$$

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

$$\Delta\ \mathrm{NPM}_i := \left(\frac{1}{3}\sum_{t=T_i}^{T_i+2}\frac{\mathrm{EBITDA}_{i,t+1}}{\mathrm{sales}_{i,t+1}}\right) - \frac{\mathrm{EBITDA}_{i,T_i}}{\mathrm{sales}_{i,T_i}}. \tag{A2}$$

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

$$\Delta\ \mathrm{leverage}_i := \left(\frac{1}{3}\sum_{t=T_i}^{T_i+2}\frac{\mathrm{debt}_{i,t}}{\mathrm{assets}_{i,t}}\right) - \frac{\mathrm{debt}_{i,T_i-1}}{\mathrm{assets}_{i,T_i-1}}. \tag{A3}$$

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

$$\Delta\ \mathrm{snow}_i := \left(\frac{1}{3}\sum_{t=T_i}^{T_i+2}\mathrm{snow}_{i,t+1}\right) - \mathrm{snow}_{i,T_i}, \tag{A4}$$

where "$\mathrm{snow}_{i,t}$" 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 3.1. 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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