Snow and Leverage*

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Abstract

Both in development economics and corporate finance, the argument has been made that reducing a debt overhang improves incentives and thus performance. This paper provides empirical evidence supporting this argument using a sample of distressed and highly overleveraged Austrian ski hotels undergoing debt restructurings. The vast majority of the hotels experienced substantial debt forgiveness, resulting in significant reductions in leverage of about 23% on average. The reductions in leverage, in turn, caused statistically and economically significant improvements in operating performance of about 28% on average. Changes in leverage are instrumented with the level of snow prior to the debt restructuring. The effect of snow is both statistically and economically significant: A one-standard deviation increase in snow is associated with a reduction in leverage of about 23% on average.

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1 Introduction

Does too much debt impair incentives? And if borrowers are highly (over-)leveraged, does a reduction in debt improve incentives, and thus also performance? These questions are at the core of any debate about debt restructuring, be it in the context of sovereign lending or corporate lending. In the context of sovereign lending, Krugman (1988) and Sachs (1989) have argued that adverse incentive effects caused by a debt overhang may give rise to a "debt Laffer curve," with the implication that debt forgiveness may constitute a Pareto improvement that benefits both the borrowing country and its lender(s). In the corporate finance literature, Myers (1977) was the first to argue that a debt overhang may distort incentives at the firm level, an argument that has since been used in many theory models (e.g., Holmström and Tirole, 1993; Hart and Moore, 1995).

Given its importance both for policy and practice, the debt overhang problem has spurred a large empirical literature, mainly in development economics, but also in corporate finance.[1] An important concern with many of these studies is that they rely on variation in debt levels, or variation in changes in debt levels (e.g., due to a wide-scale debt relief, such as the "Brady plan") that is unlikely to be exogenous, making it difficult to establish causality. The objective of this paper is to provide evidence on the debt overhang problem using plausibly exogenous variation in leverage changes based on a sample of distressed Austrian ski hotels that undergo debt restructurings. All of the hotels in our sample are highly overleveraged; the average (book) leverage ratio prior to the debt restructuring is 2.40. In the course of the debt restructuring, the vast majority of the hotels experienced substantial debt forgiveness, resulting in a significant decrease in leverage of about 23% on average.

While there is substantial debt forgiveness in the aggregate, there is considerable cross-sectional variation. Since changes in leverage are endogenous, we need a theory of what determines leverage changes in debt restructurings. In a simple model, Krugman (1988) argues that one determinant is the extent to which future cash flows depend on the borrower's effort. If cash flows are completely exogenous, then it is optimal for the lender not to forgive any debt. On the other hand, if cash flows depend (exclusively) on the borrower's effort, then it may be optimal

[1] Empirical studies in development economics include, e.g., Cohen (1993), Deshpande (1997), Patillo, Poirson and Ricci (2003), Arslanalp and Henry (2005), and Cordella, Ricci, and Ruiz-Arranz (2005). Empirical studies in corporate finance include, e.g., Lang, Ofek, and Stulz (1996), Parrino and Weisbach (1999), and Hennessy (2004).

to forgive some of the debt to improve effort incentives. In the Appendix of this paper, we provide a simple extension of Krugman's model that also includes intermediate cases in which effort matters to varying degrees. The main empirical prediction of our model is that lenders should only forgive debt if the borrower's effort is sufficiently "important," in which case it is optimal to forgive more debt the more important is effort.

In reality, it is unlikely that lenders can directly observe how important effort is. This is also true in our sample of Austrian ski hotels, where lending banks must decide whether, and how much, debt they should forgive. However, the banks can apply the following reasoning. If a hotel had relatively little snow in the years prior to the debt restructuring, then it is more likely that the causes for the distress are exogenous. On the other hand, if a hotel got into distress even though it had relatively ample snow in the years prior, then it is more likely that the causes for the distress are incentive problems. Note that this reasoning does not address why the hotels got into distress in the first place. It merely argues that, conditional on being in distress, the causes are more likely exogenous if a hotel had little snow.

There is empirical support for this reasoning. Austrian Census data show a strong positive correlation between snow and the number of nights stayed at hotels, suggesting that hotels with more snow have more bookings and should thus perform better. In our sample of distressed hotels, however, the correlation between snow and return on assets in the year before the debt restructuring is virtually zero. Hence, while we would expect hotels with little snow to perform poorly, those with ample snow did not perform better, despite having ample snow, suggesting that the causes for their distress might be incentive problems.

This reasoning lends itself to a testable hypothesis, which we test in our first-stage regression: In our sample of hotels undergoing debt restructurings, those with relatively little snow in the years prior to the debt restructuring should experience smaller reductions in leverage than hotels with relatively ample snow. The results of the first-stage regression support this hypothesis. When we regress changes in leverage on snow in the years prior to the debt restructuring plus controls, we find that snow has a significant negative effect on changes in leverage. The effect is also economically significant: A one-standard deviation increase in snow is associated with a reduction in leverage of about 23% on average.

The broader objective of our study, which we pursue in our second-stage regression, is to examine how changes in leverage affect changes in operating performance. Our measures of operating performance are return on assets (ROA) and net profit margin. While OLS regressions yield a significant positive association between changes in leverage and changes in operating performance, it is not difficult to think of a reverse causality explanation. For instance, hotels with larger *anticipated* improvements in operating performance might receive less debt forgiveness, resulting in smaller reductions in leverage. When changes in leverage are instrumented with snow in the years prior to the debt restructuring, we obtain the opposite result: changes in leverage have a significant negative effect on changes in operating performance. The effect is also economically significant. For instance, when operating performance is measured using ROA, we find that ROA increases by about 28% on average. Thus, consistent with the arguments by Myers (1977), Krugman (1988), Sachs (1989), and others, our IV results suggest that reductions in leverage lead to statistically and economically significant improvements in operating performance, at least in our (selected) sample of highly overleveraged Austrian ski hotels.

While we control for *changes* in snow to account for any contemporaneous effect of snow on operating performance, an important concern is that snow in the years prior to the debt restructuring might have a direct effect on (future) changes in operating performance. Suppose, for instance, that ski tourists book one year ahead, especially if they had a good skiing vacation with ample snow. In that case, past snow might predict future changes in operating performance, violating the exclusion restriction. While this is an important concern, we believe it is minimized here, for several reasons.

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

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

Third, there is a strong correlation between snow in the years before the debt restructuring and deviations of this variable from long-run average snow levels. Much of this correlation is driven by the left tail of the distribution, i.e., hotels that had little snow in the years prior to the debt restructuring also had little snow by their own historical standards. Given this strong correlation, it is not surprising that we obtain similar results if we use deviations from long-run average snow levels as our instrument. In that case, the argument with respect to a possible violation of the exclusion restriction would have to be that ski tourists make their bookings not based on whether snow in their last vacation was plenty, but instead based on the extent to which observed snow levels deviate from long-run historical averages. This is arguably unlikely, especially since deviations from long-run average snow levels are uncorrelated over time, i.e., there is no reason to expect that abnormally high snow in one year would predict abnormally high snow in the next year.

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

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

In addition to being related to the debt overhang literature, and the literature examining the relationship between leverage and incentives in general, our paper is also related to the literature on debt restructurings and debt renegotiations. Empirical studies in this literature include, e.g., Gilson, John, and Lang (1990) and Asquith, Gertner, and Scharfstein (1994), who both examine which types of firms are more likely to restructure their debt privately rather than through Chapter 11. More recently, Roberts and Sufi (2009) examine debt renegotiations outside of default or bankruptcy, showing that the accrual of new information pertaining to credit quality, investment opportunities, and collateral, as well as fluctuations in credit market conditions, are strong predictors of the incidence and outcomes of debt renegotiations.

The rest of this paper is organized as follows. Section 2 describes institutional details that are helpful to better understand the data. Section 3 discusses sample selection, empirical methodology, and summary statistics. Section 4 presents our main results, including robustness checks. Section 5 addresses issues related to identification, including the validity of our instrument. Section 6 addresses sample selection bias. Section 7 concludes. The Appendix contains a simple extension of Krugman's (1988) model to motivate our first-stage regression.

2 Institutional Background

As is common in many countries, Austrian firms may attempt to restructure their debt prior to filing for bankruptcy. Typically, debt restructurings are the outcome of direct negotiations between borrowers and lenders. In the Austrian tourism industry, however, debt restructurings often involve the participation of the Austrian Hotel- and Tourism Bank (AHTB).[2] Founded in 1947, the AHTB is a development bank that administers funds provided by the ERP (European Recovery Program, or "Marshall Plan"). While the AHTB also provides limited financial support, its role in debt restructurings is primarily that of a mediator, as it does not take on any credit risk.[3] Mediation by the AHTB is desirable as it brings all lending banks together at one table, ensuring that the negotiations take place in a centralized 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 lead to a breakdown of the negotiations (Cline, 1983; Gertner and Scharfstein, 1991). In our sample of 115 debt restructurings, 70 cases involve at least two lending banks, and 33 cases involve at least four lending banks.

As part of its role as a mediator, the AHTB collects data on the distressed hotels, including P&L and balance sheet data, as well as "soft" information gathered from on-site visits by the

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

[3] 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.

AHTB's loan officers. The first main data collection takes place prior to the debt restructuring. These data are compiled into a restructuring report, which provides a snapshot of the distressed hotel prior to the restructuring. In our empirical analysis, they constitute our "before" data. The AHTB also collects post-restructuring data, with varying frequency, to monitor the success of the debt restructuring. These data typically involve only "hard" (financial) information, which are compared against ex-ante P&L and balance-sheet projections. In our empirical analysis, these data constitute our "after" data.

For the AHTB to be involved in the restructuring negotiations, certain eligibility criteria must be met. For instance, the AHTB's mandate is restricted to "structurally important firms" whose operations have positive external effects on the local tourism industry. While this criterion is rather "soft," it is usually satisfied if a hotel is the largest hotel among all hotels in the same municipality and total sales exceed Euro 360,000. In addition, a number of necessary conditions must be met. For instance, the book value of the hotel's debt must be at least 15 times its total sales, the book value of equity must be smaller than eight percent of total assets, and the restructuring must not involve investments into assets that are not deemed absolutely necessary for regaining profitability. This rules out, e.g., investments in land, investments to complete projects already under way, and investments in capacity expansion in markets with excess capacity. There are also restrictions imposed by the EU. For instance, the hotel must be a small- or medium-sized enterprise, and it must have been founded more than three years ago.

If these eligibility criteria are met, the mediation starts with an on-site inspection by the AHTB's loan officers. The AHTB then produces a restructuring 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 with the purpose of discussing restructuring options. The restructuring report includes, besides "hard" financial information, also other (including "soft") information, such as information about the hotel itself, e.g., the date of the last renovation, number of employees, star category, banking relationships, number of beds, price per night, whether it is a "leading" hotel (Leitbetrieb), and legal form, but also 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, when the current management took over, and the date of the license granted to the current owner. The restructuring report often also includes an assessment by the AHTB's loan officers as to the causes of the hotel's financial distress. Unfortunately, the quality of the information contained in the restructuring report varies considerably. While "hard" financial information is available for most hotels in our sample, other information, including "soft" information, is frequently only available for a small subset.

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

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

Once formal bankruptcy proceedings are initiated, there are two typical outcomes: liquidation or the hotel's reorganization. An Austrian credit rating agency, the KSV 1870, provided us with data about insolvency cases in the tourism industry. The data are mostly count variables and include only one balance-sheet variable, namely, the sales of the bankrupt firm. Between 1999 and 2006, there were 333 bankruptcies, of which 280 cases were closed by June 2008. 110 of these cases resulted in a compulsory composition under the BC, seven cases ended with a composition under the CC, and the remaining cases ended with the firm's liquidation.

3 Data

3.1 Sample Selection

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

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

All 115 hotels are open during the winter season, and most of them are open all year round. In each individual case, we match hotel data to weather data provided to us by the Austrian Central Institute for Meteorology and Geodynamics.[4] We have monthly weather data for all Austrian weather stations. We match hotels to nearby weather stations by locating the weather station with the minimal Euclidean distance from the co-ordinates of the surface-weighted center of the area spanned by the ZIP code of the hotel. To ensure that the weather conditions reflect those in the hotel's vicinity, we further impose the constraint that the altitudinal distance between the weather station and the hotel must not exceed 500 meters. This constraints binds only in

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

a few cases, and our results are virtually identical if the constraint is dropped. Arguably, the weather conditions measured by the closest weather station will be a noisy proxy of the weather conditions that are truly relevant for the hotel (e.g., the snow conditions at a nearby ski slope). While this is unlikely to introduce a systematic bias, it introduces noise into the regression, making it harder for us to find any significant results.

3.2 Empirical Methodology

We examine whether changes in leverage around debt restructurings lead to changes in operating performance. We estimate:

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

where i indexes hotels, Δ is the difference operator ("after" minus "before"), and $\mathbf{X}$ is a vector of control variables, which includes size, age, altitude, Δ snow, and status-year dummies. Altitude captures persistent differences across hotels—e.g., it correlates highly with long-run average snow levels—which is important as our sample is a pure cross-section and hotel-fixed effects cannot be included. For example, the correlation between altitude and 10-, 15-, and 20-year average snow levels is between 67.6% and 69.3%.[5] Altitude may also capture unobservable differences across hotels. For instance, hotel owners and managers with different qualities may optimally choose different altitudes.

Including Δ snow in equation (1) controls for any *direct* (contemporaneous) effect of snow on operating performance. Thus, if operating performance improves after the restructuring, it is not because snow conditions have improved. The status-year dummies capture any effect that is common to all hotels that are restructured in the same year. While our sample period is from 1998 to 2005, the majority of the 115 debt restructurings took place between 1999 and 2003. There are two events in 1998, 20 events in 1999, 31 events in 2000, 27 events in 2001, 13 events in 2002, 12 events in 2003, four events in 2004, and six events in 2005. We cluster standard errors at the district level in all our regressions.[6]

[5] All correlations are significant at the 1% level. That the correlations are not (even) higher might be due to the fact that snow accumulation depends—in addition to altitude—also on whether a location has Northern or Southern exposure.

[6] Districts ("Bezirk" 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

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

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

In reality, it is unlikely that lenders can directly observe how important effort is. This is also true in our sample of Austrian ski hotels, where lending banks must decide whether, and how much, debt they should forgive. However, the banks can apply the following reasoning. If a hotel had relatively little snow in the years prior to the restructuring, then it is more likely that the causes for the distress are exogenous. On the other hand, if a hotel got into distress even though it had relatively ample snow in the years prior, then it is more likely that the causes for the distress are incentive problems. Note that this reasoning does not address why the hotels got into distress in the first place. It merely argues that, conditional on being in distress, the causes are more likely exogenous if a hotel had little snow. Note also that "more likely" and "less likely" are not meant in an absolute sense, but in a relative sense, i.e., relative to other hotels in distress. After all, the (narrow) objective is to explain cross-sectional variation in debt restructuring outcomes for a sample of ski hotels that are all in distress.

There is empirical support for this reasoning. Austrian Census data show a strong positive correlation between snow and bookings made by tourists. The data span 37 years from 1971 to 2007. For each year, the data show the total number of nights stayed at hotels in each of the 611 "tourism regions" in Austria. There are thus $37 \times 611 = 22,607$ region-year observations, where an observation indicates the total number of nights stayed at hotels per region and year.

population per political district is 67.5 thousand. The 115 hotels in our sample are located in 42 different districts.

The correlation with snow is 19.6% ($p = 0.000$). Given that the data include *all* tourism regions in Austria, it is likely that the correlation is (even) higher in regions that are primarily winter tourism regions. Overall, the Census data results suggest that hotels with more snow have more bookings and should thus perform better. In our sample of 115 distressed hotels, however, the correlation between snow and return on assets (ROA) in the year before the debt restructuring is 0.7% ($p = 0.942$), which means it is virtually zero. Hence, while we would expect hotels with little snow to perform poorly, those with ample snow did not perform better, despite having ample snow, suggesting that the causes for their distress might be incentive problems.

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

While the results of the first-stage regression support the main prediction of our model, it should be noted that only snow in the *two* years prior to the restructuring is a good predictor of Δ leverage. In contrast, snow three and four years prior are poor predictors. From a theoretical perspective, this is reassuring, as it suggests that lending banks look at the level of snow when the hotel likely got into distress, not at the level of snow several years before. Also noteworthy is that snow in the two years prior to the debt restructuring is highly correlated with deviations from long-run historical averages. Much of this correlation is driven by the left tail of the distribution, i.e., hotels that had little snow in the two years prior to the debt restructuring also had little snow by their own historical standards. This is not entirely surprising, given that "two years prior" is not just any random time period, but it is precisely the period when the hotels likely got into distress. Indeed, instead of using snow in the two years prior as an instrument, we can use deviations from long-run average snow levels as our instrument, and the results remain qualitatively similar.

While we control for Δ snow in equation (1) to account for any contemporaneous effect of snow on operating performance, an important concern is that snow in the two years prior to the restructuring might have a *direct* effect on Δ operating performance. Suppose, for instance, that ski tourists book one year ahead, especially if they had a good skiing vacation with ample snow. In that case, past snow might predict future operating performance, violating the exclusion restriction. While this is an important concern, we believe it is minimized here, for several reasons.

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

2. We obtain similar results if instead of using the average snow in the two years prior to the restructuring as an instrument, we exclusively use snow two years prior (i.e., not including snow in the year before) as our instrument. Arguably, only few ski tourists book two years ahead.

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

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

3.3 Definition of Variables and Summary Statistics

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

Given that all hotels in our sample are privately held, market values are not available. Accordingly, "leverage" is the book value of debt divided by the book value of assets. "Size" is the book value of assets (in Euros) in the year before the debt restructuring. "Age" is the number of years since the hotel was granted its license, measured in the year before the debt restructuring. This information is missing for 28 hotels in our sample. For these hotels, we use instead the number of years with available accounting data.[7] In all our regressions, we use the logarithms of size and age. Finally, "altitude" is the surface-weighted average altitude of the area associated with 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, March) with more than 10 centimeters of snow on the ground, as measured by the closest weather station. (Recall that our instrument is the average "snow" in the two years prior to the debt restructuring.) winter months are matched to firm-year observations based on hotels' fiscal year ends. For instance, if the fiscal year ends in December 1999, then the relevant winter season includes the months of January 1999, February 1999, March 1999, and December 1999.[8] This matching ensures that when controlling for any contemporaneous effect of snow on EBITDA, we indeed capture the relevant snow during the *fiscal year* in which EBITDA was generated.

It should be noted that our results are not sensitive to the choice of snow variable. For

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

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

instance, we obtain virtually identical results if we use a 5 or 20 centimeter threshold in place of a 10 centimeter threshold. This is not surprising, given that the correlation between our snow variable and snow variables based on either a 5 or 20 centimeter threshold is 98.6% and 95.5%, respectively. Our results are also similar if we use entirely different snow variables, such as the number of days with fresh snowfall, or if we use entirely different weather variables altogether, such as the average temperature during the winter season. In all these cases, the correlation with our snow variable is very high.

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

Table I provides summary statistics. "Restructuring sample" refers to the 115 distressed hotels that underwent debt restructurings. "Control sample" refers to the 2,095 hotels in the control group that did not undergo debt restructurings. In the restructuring sample, "Mean" and "Median" refer to the value in the year before the debt restructuring. In the control sample, "Mean" and "Median" refer to firm averages across all firm-years. As can be seen, restructured hotels are smaller than control hotels (smaller book value of assets, fewer beds, fewer employees), which is consistent with the notion that smaller hotels are more likely to get into distress. Also, restructured hotels are located at slightly lower altitudes and have slightly lower levels of snow than control hotels, though conditional on altitude the snow levels are comparable.[9] The "quality" of hotels, as measured by their star rating (five stars being the highest), is the same across both samples.

Perhaps most important for our study, restructured hotels are highly overleveraged. The average leverage ratio in the year before the debt restructuring is 2.40 (median 1.77), which is roughly twice as large as the corresponding number for control hotels (mean 1.26, median 0.99).

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

When comparing these numbers to other samples, (e.g., Compustat firms), it is useful to bear in mind that practically all hotels, including those in the control sample, are small privately held family-run hotels, which tend to rely heavily on debt financing. Moreover, it is important to remember that leverage is based on book values. Finally, restructured hotels are less profitable than control hotels, which is not surprising. While the average ROA of control hotels is 13.0% (median 12.0%), the average ROA of restructured hotels in the year before the debt restructuring is 10.9% (median 9.3%).

As mentioned earlier, the restructuring reports show that the vast majority of the restructured hotels experienced substantial debt forgiveness. As a consequence, the average leverage ratio after the restructuring dropped to 1.85 (median 1.56) (not reported in Table I), which implies a reduction in leverage of about 23%. At the same time, the average ROA increased to 11.9% (median 10.9%). It should be noted that, to the extent that it takes several years to improve performance, these numbers—which are based on averages in the three years after the restructuring—are likely to understate the true long-run improvements in operating performance.

4 Results

4.1 Return on Assets (ROA)

Our main results are in **Table II**. The dependent variable is Δ ROA. In columns [1] and [2], equation (1) is estimated by OLS. In columns [3] and [4], it is estimated by IV, using snow as an instrument for Δ leverage. For both types of regressions, we report results both with and without control variables. The results of the first-stage regression are discussed separately in Section 4.2.

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

When Δ leverage is instrumented with snow, we obtain the opposite result: the coefficient on Δ leverage is now negative and significant. When control variables are not included, the coefficient is -0.037 ($t = 2.60$). When control variables are included, the coefficient is -0.055 ($t = 2.49$). Given that Δ leverage is -0.55 on average, this corresponds to an average increase in ROA of $-0.055 \times -0.55 = 0.03$, or three percentage points. In relative terms, given that ROA before the debt restructuring is on average 10.9%, this implies an average increase in ROA of about 28%. Thus, consistent with the arguments by Myers (1977), Krugman (1988), Sachs (1989), and others, the IV results suggest that a reduction in leverage leads to a (statistically and economically) significant improvement in operating performance, at least in our (selected) sample of highly overleveraged Austrian ski hotels. As for the control variables, size is positively associated with Δ ROA in both the OLS and IV regressions, though it is only significant in the latter. The other control variables are insignificant in both types of regressions.

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

4.2 Net Profit Margin (NPM)

In **Table III**, the dependent variable is Δ NPM. Columns [1] and [2] report OLS results, while columns [3] and [4] report IV results.[10] As is shown, the results are similar to our ROA results. OLS regressions yield a positive relationship between Δ NPM and Δ leverage, albeit this relationship is not significant. When Δ leverage is instrumented with snow, we again obtain a negative and significant coefficient on Δ leverage. When control variables are not included, the coefficient is -0.036 ($t = 2.18$). When control variables are included, the coefficient is -0.055 ($t = 2.59$). Remarkably, the coefficients are almost identical to those in our ROA regressions, suggesting that the scaling variable plays little role. The Hausman tests also yield similar results. Regardless of whether control variables are included, we can always reject the null of no endogeneity at high significance levels ($p = 0.033$ without controls, $p = 0.002$ with controls).

[10] The number of observations drops from 115 to 114 due to sales being missing for one hotel.

4.3 Median Regressions

To mitigate the effect of outliers, we winsorize both ROA and NPM at the 5th and 95th percentiles of their empirical distribution. As mentioned earlier, we obtain similar results if we winsorize at the 1st and 99th percentiles or at the 10th and 90th percentiles. In **Table IV**, we use non-winsorized values of ROA and NPM but instead of using OLS, we 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 in our OLS and IV regressions, we construct blocks at the district level, leaving us with 42 blocks. Precisely, we construct a large number (500) of 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.

In columns [1] and [2], the dependent variable is Δ ROA. In columns [3] and [4], the dependent variable is Δ NPM. In columns [1] and [3], Δ leverage is not instrumented. As is shown, the results are similar to our previous OLS results. In columns [2] and [4], Δ leverage is instrumented with snow. When Δ ROA is the dependent variable, the results are slightly weaker than before. The coefficient on Δ leverage is -0.044 ($t = 2.10$) compared to -0.055 ($t = 2.49$) in column [4] of Table II. On the other hand, when the dependent variable is Δ NPM, the results are similar to before. The coefficient on Δ leverage is -0.053 ($t = 2.51$) compared to -0.055 ($t = 2.59$) in column [4] of Table III. Overall, the evidence presented here suggests that our results are unlikely to be driven by outliers.

5 Identification

5.1 First-Stage Regression

At various points in the paper, we have referred to the results of the first-stage regression. In that regression, we regress Δ leverage on snow plus all control variables from equation (1). We estimate:

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

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

The results of the first-stage regression are presented in **Table V**. As is shown, snow is negatively associated with Δ leverage and significant at the 1% level. The coefficient on snow is -0.014 ($t = 3.15$), implying that a one-standard deviation (39.32) increase in snow is associated with a reduction in leverage of $-0.014 \times 39.32 = -0.55$. In relative terms, given that the average leverage ratio prior to the debt restructuring is 2.40, this corresponds to a reduction in leverage by about 23% on average. Overall, these results suggest that hotels with less snow in the years prior to the debt restructuring experienced relatively smaller reductions in leverage, which is consistent with the hypothesis formulated in Section 3.2. As for the control variables, size is significantly positively associated with Δ leverage, while all other control variables are insignificant.

A reassuring finding, at least from a theoretical perspective, is that while snow in the two years prior is a good predictor of Δ leverage, snow three and four years prior are poor predictors. This finding is reassuring as it suggests that lending banks look at the level of snow when the hotel likely got into distress, not at the level of snow several years before. If we replace "snow" in equation (2) with the corresponding "snow" variables pertaining to individual years, we find that the coefficient on snow becomes increasingly smaller (and less significant) as we move further away from the debt restructuring: The coefficient in the year prior to the restructuring is -0.014 ($t = 3.37$), the coefficient two years prior is -0.011 ($t = 2.98$), the coefficient three years prior is -0.004 ($t = 1.19$), and the coefficient four years prior is -0.003 ($t = 0.93$). Given that the coefficients in the first two years before the debt restructuring are similar both in magnitude and significance, we use the average snow in these two years as our instrument.

Consistency of IV estimation in a finite sample requires that the instrument be sufficiently "strong" (Staiger and Stock, 1997), meaning it must correlate "strongly" with the endogenous variable. In equation (2), the coefficient on snow has a t-statistics of 3.15 ($p = 0.003$), implying that weak identification is unlikely to be a concern. Likewise, the F-statistics for the null that $\beta = 0$ is 9.92, which lies above the 15% critical value in Table 5.2 of Stock and Yogo (2005, p. 101). (Formally, this implies that the maximum size of a 5% level Wald test based on the IV is at most 15%, so that the maximum size distortion is at most 10%.) Again, this suggests that weak identification is unlikely to be a concern here.

5.2 Exclusion Restriction

Validity of the instrument requires that the exclusion restriction be satisfied. The exclusion restriction is violated if snow has a *direct* effect on Δ ROA, i.e., if it has an effect other than through Δ leverage. Suppose, for instance, that ski tourists book one year ahead, especially if they had a good vacation with ample snow. In that case, past snow might predict future operating performance, violating the exclusion restriction. While this is an important concern, we believe it is minimized here, for several reasons:

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

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

leverage is -0.070 ($t = 2.86$) compared to -0.055 ($t = 2.49$) when "snow" was used as an instrument (cf., column [4] of Table II).

3. There is a strong correlation between "snow" and deviations of this variable from its long-run historical average. Depending on the time horizon (10, 15, or 20 years), the correlation is between 50.7% and 57.6%.[11] Much of this correlation is driven by the left tail of the distribution, i.e., hotels that had little snow in the two years prior to the debt restructuring also had little snow by their own historical standards. This is not entirely surprising, given that "two years prior" is not just any random time period, but it is precisely the period when the hotels likely got into distress. Accordingly, "snow" can be sensibly interpreted as capturing the extent to which snow in the two years prior to the debt restructuring was *abnormally* low.

   Given this strong correlation, it is not surprising that we obtain similar results when using deviations from long-run historical averages as our instrument. In this case, the argument with respect to a possible violation of the exclusion restriction would have to be that ski tourists make their bookings not based on whether snow in their last vacation was plenty, but instead based on the extent to which observed snow levels deviate from long-run historical averages. This is arguably unlikely, especially since deviations from long-run historical averages are uncorrelated over time, i.e., there is no reason to expect that abnormally high snow in one year would predict abnormally high snow in the next year.[12]

   In columns [3] and [4] of Table VI, we use the deviation of "snow" from its 15-year historical average as our instrument. Results based on deviations from 10- or 20-year historical averages are similar. Like above, we only report second-stage results when Δ ROA is the dependent variable. The results when Δ NPM is the dependent variable are again

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

[12] Deviations from long-run historical averages are also uncorrelated with altitude, or with the long-run historical averages themselves, suggesting they are truly random. For instance, the correlation between altitude and the deviation of "snow" from its 10-year historical average (i.e., the average snow in years -3 to -12) is 0.7% ($p = 0.945$), which means it is virtually zero. Likewise, the correlation between the 10-year historical average snow and the deviation of "snow" from this variable is 0.6% ($p = 0.950$), which is again virtually zero.

similar. As is shown, the coefficient on the instrument in the first-stage regression is -0.016 ($t = 2.11$), and the coefficient on Δ leverage in the second-stage regression is -0.060 ($t = 2.06$). Both results are statistically weaker than when "snow" was used as an instrument (cf., Table V and column [4] of Table II). In particular, that the first-stage results are weaker suggests that "snow" is a better—i.e., a less noisy—proxy of what lending banks take into account when choosing Δ leverage.[13]

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

   Table VII presents the results. (The adjustment only affects the second-stage regression.) In columns [1] and [2], the dependent variable is "locally adjusted" Δ ROA. In columns [3] and [4], the dependent variable is "locally adjusted" Δ NPM. In columns [2] and [4], we use median regressions, where the standard errors are computed using block boostrapping as described in Section 4.3. As is shown, the ROA results are slightly stronger than the ROA results using non-adjusted measures. In column [1], the coefficient on Δ leverage is -0.061 ($t = 2.68$) compared to -0.055 ($t = 2.49$) in column [4] of Table II. Likewise, in column [2] (median regression), the coefficient is -0.052 ($t = 2.41$) compard to -0.044 ($t = 2.10$) in column [2] of Table IV. The NPM results are also slightly stronger but statistically weaker than the NPM results using non-adjusted measures. In column [3], the coefficient on Δ leverage is -0.058 ($t = 2.35$) compard to -0.055 ($t = 2.59$) in column [4] of Table III. Likewise, in column [4] (median regression), the coefficient is -0.057 ($t = 2.26$) compared to -0.053 ($t = 2.51$) in column [4] of Table IV.

[13] Lending banks in our sample are typically small local institutions that are likely to have a good sense of whether snow in the two years prior to the debt restructuring was abnormally low or high without having to formally compute its deviation from long-run historical averages.

6 Selection Bias

The 115 hotels undergoing debt restructurings are a selected sample. To account for possible selection bias, we use Heckman's (1979) two-step correction method. The first step involves estimation of a selection equation. For this purpose, we extend our sample by including the 2,095 "control hotels" that did not undergo debt restructurings. As mentioned 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 be "structurally important," which means it must be large relative to other hotels in the same municipality. Based on this criterion, we construct a new variable, "local capacity share"—defined as the number of beds of a hotel divided by the number of beds of all hotels in the same district and year—which we use as an instrument in our selection equation. As "structurally important" hotels are more likely to have larger local capacity shares, we would expect to find a positive association between this variable and the likelihood of being selected. Importantly, local capacity share is based on the number of *available* beds, not the number of nights stayed. Hence, it does not capture aspects of performance and is therefore likely exogenous in equation (1).

We estimate the Probit selection equation

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

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

Panel (A) of **Table VIII** shows the results from estimating the selection equation (3). The coefficient on local capacity share is positive and significant ($t = 2.74$), implying that hotels with larger local capacity shares are more likely to be restructured. This result is not surprising, given that we have constructed this variable based on our knowledge that the AHTB's mandate is limited to "structurally important firms." What appears puzzling, on the other hand, is that hotels with larger local capacity shares are more likely to be restructured, yet the summary statistics in Table I show that restructured hotels are smaller than control hotels (smaller book value of assets, fewer beds, fewer employees). There is a simple explanation, which is that restructurings are concentrated in districts with smaller hotels. *Within* these districts, however, restructured hotels are relatively large, which explains the positive coefficient on local capacity share. In contrast, compared to (control) hotels located in districts in which no restructuring occurred, restructured hotels are relatively small.[14]

Using the estimates from equation (3), we can compute the Inverse Mills Ratio and include it as an explanatory variable in the second-stage regression. Before doing so, however, we want to verify that the 74 hotels with non-missing bed data are representative of our full sample of 115 hotels. In Panel (B) of Table VIII, we re-estimate the second-stage regression based on this smaller subsample. (We do not show the results of the first-stage regression for brevity. They are qualitatively similar to previous results but statistically weaker due to the smaller sample size.) As is shown, regardless of whether the dependent variable is Δ ROA or Δ NPM, and regardless of whether we use "locally adjusted" performance measures or non-adjusted measures, the results are similar to those based on our full sample of 115 hotels (cf., column [4] of Table II, column [1] of Table VII, column [4] of Table III, and column [3] of Table VII).

In Panel (C) of Table VIII, we finally estimate the second-stage regression when the Inverse Mills Ratio is included as an explanatory variable. (The results of the first-stage regression are again qualitatively similar but statistically weaker. Also, the Inverse Mills Ratio is not significant.) As is shown, the coefficient on Δ leverage is virtually identical to those in Panel

[14] The average number of beds of all (restructured and control) hotels located in districts in which a restructuring occured, as of the year before the restructuring, is 70.0. In contrast, the average number of beds of only the restructured hotels in the same year is 76.0 (see Table I). Thus, restructured hotels are large relative to control hotels located in the same district. On the other hand, the average number of beds of (control) hotels located in districts in which no restructuring occurred is 117.6. Consequently, control hotels located in "non-restructuring districts" are *much* larger than restructured hotels, which in turn are larger than control hotels located in the same ("restructuring") district. As a result, the average control hotel (including those located in "restructuring districts") is still significantly larger than the average restructured hotel. Using size or number of employees instead of number of beds yields similar results.

(B) in all regressions. Moreover, the Inverse Mills Ratio, while positive, is never significant.[15] Overall, the evidence suggests that our results are unlikely to be driven by selection bias.

7 Conclusion

We provide empirical support for the argument made both in development economics and corporate finance that reducing a debt overhang improves incentives and thus performance. Using a sample of distressed and highly overleveraged Austrian ski hotels undergoing debt restructurings, we find that reductions in leverage bring about statistically and economically significant improvements in operating performance. To identify the effect of changes in leverage on changes in operating performance, we instrument changes in leverage with the level of snow prior to the debt restructuring. The choice of instrument is motivated by the argument that if a hotel had relatively little snow in the years prior to the debt restructuring, then it is more likely that the causes for the distress are exogenous. On the other hand, if a hotel got into distress even though it had relatively ample snow in the years prior, then it is more likely that the causes for the distress are incentive problems, making it optimal to reduce leverage to improve effort incentives. Our results hold for different measures of operating performance (return on assets, net profit margin) as well as different snow instruments.

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

[15] Interestingly, while including the Inverse Mills Ratio has no impact on the coefficient on Δ leverage, it reduces the magnitude and significance of the coefficient on size. When Δ NPM is the dependent variable, size is even insignificant. Hence, at least part of the significant effect of size that we consistently find in our regressions might be driven by sample selection, which is not entirely surprising, given that restructured hotels are smaller than control hotels on average.

8 Appendix

In Krugman's (1998) model, a country is unable to repay its outstanding debt. Krugman considers two polar cases. If the country's future cash flows are completely exogenous, then it is optimal for the country's lender not to forgive any debt. In contrast, if future cash flows depend exclusively on the country's effort, then it may be optimal to forgive some of the outstanding debt to improve effort incentives.

This section provides a simple extension of Krugman's model. In addition to considering the two polar cases analyzed by Krugman, we also consider intermediate cases in which effort is "more or less important" for future cash flows. Krugman's model is arguably better suited for firms than it is for countries, given his (in the sovereign lending literature controversial) assumption that lenders can seize a country's assets upon default ("gunboat technology"). In the case of corporate lending, this assumption holds naturally, being an integral part of the law in most countries. Without loss of generality, and given our interest in corporate debt restructurings, we thus refer to the borrower as a firm rather than a country.

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

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

8.1 Exogenous Cash Flows

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

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

8.2 Cash Flows Depending Exclusively on Effort

In the other polar case, the probability of a high cash flow depends exclusively on the firm's effort, $p := \Pr(x_2 = x_G) = e$.[16] For simplicity, we assume that effort costs are quadratic, $c(e) = \frac{1}{2}e^2$. To ensure an interior first-best solution $e_{FB} < 1$, we need to assume that $x_G - x_B < 1$. As the second-best effort will always be less than e_{FB}, this assumption also ensures that the second-best solution is feasible, i.e., it ensures that $e^* \leq 1$. Given this assumption, it is straightforward to show that there is a unique interior first-best level of effort $e_{FB} = x_G - x_B$. As will become clear shortly, the condition for a debt overhang—i.e., the condition that the firm cannot raise funds from new investors to repay its outstanding debt—is $(\frac{x_G - x_B}{2})^2 + x_B < D_1$.

The question is, again, what is the lender's optimal strategy? Without loss of generality, we solve directly for the optimal second-period debt D_2^*, noting that $i^* = \frac{D_2^*}{D_1} - 1$. We can safely ignore any solution in which the interest rate is so high that $D_2 > x_G$. As the maximum the lender can obtain in the good state is x_G, any such solution would yield the same expected

[16]Krugman does not explicitly solve the model with effort, albeit he notes that the optimal solution if cash flows are exogenous would result in zero effort and is therefore not optimal.

payoff to the lender, and it would result in the same effort by the firm (namely, $e^* = 0$), as a solution in which $D_2 = x_G$. Likewise, we can ignore the case in which the interest rate is so low that $D_2 < x_B$. As the lender would then obtain D_2 for sure (i.e., in both states), he would always want to raise the interest rate further, implying there exists no solution in which $D_2 < x_B$ ("open set problem").

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

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

which has a unique solution $e^* = x_G - D_2$. Note that, if the lender were to extract all of the firm's cash flows, as was optimal in the case with exogenous cash flows, the firm's optimal response would be to provide zero effort.

The lender's problem is

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

subject to

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

which has a unique solution

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

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

8.3 Intermediate Cases

We now extend Krugman's framework to allow for intermediate cases in which effort affects future cash flows to varying degrees. In general, we might write $p := \Pr(x_2 = x_G) = p(e, \varphi)$, where φ is a parameter indicating how important the firm's effort is. Given that we wish to obtain a closed-form solution, however, we shall refrain from using a general specification and instead assume a specific functional form of $p(e, \varphi)$. In the two polar cases considered above, we obtained $D_2^* = x_G$ if future cash flows are completely exogenous and $D_2^* = \frac{x_B + x_G}{2} < x_G$ if future cash flows depend exclusively on the firm's effort. In intermediate cases, we would thus expect that D_2^* lies somewhere in between $\frac{x_B + x_G}{2}$ and x_G, and that D_2^* is larger the less important is the firm's effort. Interestingly, this intuitive result does not obtain for some "natural" specifications of $p(e,\varphi)$. For example, if $p(e,\varphi) = e\varphi$, the optimal second-period debt is *independent* of how important the firm's effort is.[17]

An additive specification of the form $p(e,\varphi) = e + \varphi$, where $\varphi < 1$, delivers the intuitive result. Under this specification, the marginal productivity of effort is $x_G - x_B$ for all $e < 1 - \varphi$ and zero otherwise.[18] Thus, while the marginal productivity of effort does not vary continuously with the parameter φ, it determines the range of effort levels over which effort is productive. For example, if $\varphi = 0.1$, effort can raise the success probability by up to 90 percent. On the other hand, if $\varphi = 0.9$, effort can only raise the success probability by up to 10 percent. It is in this sense that the parameter φ measures the importance of the firm's effort, with higher values of φ indicating that effort is less important.

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

We can again safely ignore cases in which either $D_2 > x_G$ or $D_2 < x_B$. Given that $x_G > D_2 \geq x_B$, the firm's problem is

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

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

The lender's problem is

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

subject to

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

which has a unique solution

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

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

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

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

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

To summarize, if the firm's effort is sufficiently important (φ is sufficiently small), the lender charges an interest rate that makes the firm the residual claimant in the good state, motivating it to exert effort. Krugman refers to this as *debt forgiveness*, as the lender voluntarily reduces the firm's debt below the maximum he could potentially obtain in the second period. On the other hand, if the firm's effort is not very important (φ is sufficiently large), the lender charges the maximum possible interest rate, in which case the firm optimally provides zero effort.

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Table I
Summary Statistics

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

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

Table II
Return on Assets (ROA)

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

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

Table III
Net Profit Margin (NPM)

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

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

Table IV
Median Regressions

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

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

Table V
First-Stage Regression

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

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

Table VI
Alternative Instruments

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

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

Table VII
Locally Adjusted Performance Measures

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

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

Table VIII
Sample Selection

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

Panel (A): Selection Equation

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

Panel (B): Regressions without Heckman Correction

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

Panel (C): Regressions with Heckman Correction

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