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Financing Constraints and Risk Management: Evidence From Micro-Level Insurance Data

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Abstract

We study the impact of financing constraints on corporate risk management. Using data on credit scores matched with unique information on firm level commercial insurance purchases, we find that financing constraints lead to higher insurance spending. We adopt a regression discontinuity design and show that financially constrained firms spend 5–14% more on insurance than otherwise similar unconstrained firms. Our findings add new insights to the longstanding empirical puzzle whether financially constrained firms engage more in risk management. Furthermore, our results, shed light on risk management in smaller, mostly private firms.

Keywords: Financing Constraints, Risk Management, Insurance Demand, Credit Scores, Private Firms

JEL codes: D22, D25, G22, G32

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1 Introduction

Financing frictions creating a wedge between the cost of externally and internally generated funds can motivate corporate risk management (e.g., Holmstrom and Tirole, 2000). Such capital market imperfections induce financially constrained firms to invest more in managing risk (Froot et al., 1993). While this prediction has stimulated a sizable empirical literature, the evidence is mixed (Bodnar et al., 2019). If anything, the findings suggest that less constrained firms (often proxied by firm size) hedge *more* (e.g., Nance et al., 1993, Mian, 1996, Rampini and Viswanathan, 2010, Rampini et al., 2014). We revisit this risk management puzzle empirically.

Focusing on the most common form of corporate risk management (Servaes et al., 2009), we provide new insights on the role of costly external finance. We explore how financing constraints, in a large sample of mostly privately held firms, affect the demand for commercial insurance.[1] Our main idea is based on the literature emphasizing the role of risk management in mitigating the effect of financial frictions on firm investment (e.g., Froot et al., 1993, Holmstrom and Tirole, 2000). Financing constraints reinforce the importance of internally generated funds, and, as a consequence, constrained firms become more sensitive to sudden changes in the supply of internal finance, and thus, demand more risk management.

To test this idea, we combine detailed and unique data on both credit scores (from the main national credit information agency) and insurance purchases (provided by a large insurer in Sweden) and analyze how firm-level financing constraints affect the demand for insurance in a large sample of private firms. We merge comprehensive administrative data on Swedish limited liability companies with information on credit scores and proprietary information on 34,000 firm level insurance purchases over the period 2008–2017. We use the credit scores to sort firms into different financing constraints categories, from low to high,

[1]This difference in focus matters. Insurance is readily available to firms of all sizes and ownership structures and does not demand financial sophistication or collateral requirements, and, our focus on generally smaller, unlisted companies allows us to study truly financially constrained firms (Farre-Mensa and Ljungqvist, 2016). Furthermore, corporate derivatives commonly cover only smaller, less substantial risks (Guay and Kothari, 2003) and can be used for non-risk management purposes (Géczy et al., 1997), whereas insurance contracts can only be used for managing risk and cover firm-specific risks that can potentially threaten the firm's existence.

and test the impact on insurance purchases (measured as total premium divided by total assets).

We begin by documenting that the typical firm in our sample is small (employing on average 24 workers).[2] Next, we show that our financing constraints measure, which is used to classify firms into three categories (1–3) from less to more constrained, indeed seems to capture financing constraints.[3] Firms classified as more constrained using our measure are younger, smaller, generate less internal cash flow, and have less cash while also having higher leverage, growing faster, and investing more.

In our initial empirical approach, we estimate panel regression models, where we include firm and industry times year fixed effects. We find a positive, and highly statistically significant relationship between (higher) financing constraints and the demand for insurance. This relationship is robust to different ways of normalizing premiums. Furthermore, in additional tests, we rule out that our financing constraints channel is driven by i) lenders demanding firms to carry insurance (covenant requirements), ii) that firms may manage risk using credit lines instead of insurance and, iii) firms using insurance to protect the value of deferred tax assets resulting from carrying forward net operating losses.

While our first set of results document a robust within-firm relationship between financing constraints and insurance demand it does not offer a causal interpretation. We therefore proceed and use a regression discontinuity design (RDD) exploiting the discrete nature of our credit score measure. By construction, small differences in the underlying default probabilities lead to upgrades or downgrades in a publicly visible credit rating, which affect the perception of a firm's creditworthiness. In other words, a firm with a default probability of 0.24% (0.74%) ends up with the best (middle) credit score whereas a firm with 0.25% (0.75%) receives a score of two (three). We exploit this characteristic in our data, comparing firms just to the left and right of each cutoff, using a formal RDD.

[2] The industry distribution, firm size, and other relevant firm characteristics are representative of the universe of Swedish firms.

[3] This classification is made by the credit rating agency, from an underlying continuous measure that they use to estimate the probability of default, and divides all Swedish firms into five categories. We remove the two categories of firms with the highest default probabilities (i.e., worst ratings), corresponding to about 9% of the firms since our focus is on financing constraints and not financial distress (following the approach in Caggese et al., 2019).

The RDD results show that firms just above any of the two cutoffs, and thus are more constrained, display a 0.040–0.054% higher premium-to-assets ratio compared to an otherwise similar firm just below. We proceed and analyze the two cutoffs separately, and find that the result is predominantly driven by firms around the 0.25% cutoff (i.e., crossing from the best to second best rating category). A firm just to the right of the first cutoff spends 0.055 more on insurance than a firm just to the left (or 14% more compared to in the lowest financing constraints category). This effect is also highly statistically significant. Around the cutoff between categories 2 and 3, the effect is both smaller economically (0.021–0.026% or around 5% relative to average premium-to-assets) as well as being less precisely estimated. To summarize: the estimated financing constraints-to-insurance demand effect based on the RDD is sizable. A tightening in constraints leads to between 5–14% higher demand for insurance.

We now turn to explore whether the results reported so far in fact stem from financially constrained firms demanding more insurance (which is the mechanism we put forward) or the insurer changing premiums in response to changing credit scores. We test this in four different ways. First, we address so-called *experience rating* which could imply that insurance companies place greater weight on credit scores for a new policyholder (e.g., Werner and Modlin, 2016). We find similar results if we exclude new policyholders from the sample which suggests it is unlikely that we are spuriously picking up that the insurer is employing experience rating strategies.

Next, we consider if the potential pricing power of the insurer is driving our results. Premiums should broadly reflect the discounted expected losses of a firm. For an insurance company to increase premiums by over 10% for a firm going from being rated as having very low default risk (rating category 1) to low default risk (category 2) would suggest considerable market power. To address pricing power, we sort firms based on local insurance market competition. We use local competition as a proxy for insurer pricing power. Then, if the mechanism we study is in fact due to increases in insurance prices, we would expect the result to be strongest in areas outside large urban areas with low competition (i.e., higher pricing power). We find very similar results across firms facing different local insurance market competition.

Third, we consider if we are spuriously picking up that firms around the cutoffs actually are worse from an insurer's perspective. If firms with more reported insurance claims also receive worse credit scores then we might simply capture an increase in premiums, reflecting greater expected losses, rather than changing firm behavior due to financing constraints. We therefore study the subset of firms that do not report any claims to the insurer (and which might be extra careful in avoiding losses), and thus would be the least likely to receive an increase in premiums. Again, we find results similar to the main findings reported above when we exclude firms that have reported a claim.

Finally, we analyze in more detail if firms just above a cutoff indeed do report more insurance claims than firms just below. If this is the case, then it would be rational for the insurer to charge higher premiums. However, we find no evidence that claims relative to total assets differ around the credit score cutoffs. In total, the results from the four additional tests represent strong evidence against the alternative explanation (that the insurer changes premiums in response to changing credit scores) and provide support for our proposed channel that financially constrained firms demand more insurance.

Overall, our findings provide robust evidence that capital market imperfections, increasing the wedge between the cost of external and internal sources of finance, have a substantial impact on corporate insurance demand. We are not aware of any other study that provides causal evidence on the role of financing constraints and risk management in a comprehensive sample of primarily private firms. Given that commercial insurance represents both the most widely cited direct cost of risk management, as well as the most common such product (e.g., Servaes et al., 2009), these findings, provide important insights connecting financial frictions and corporate risk policy.

Our findings are especially relevant for a set of related literatures that study how risk management depends on the nature of investment and financing opportunities. First, the evidence showing that financing constraints lead to higher insurance demand adds to the large body of evidence on corporate risk management (e.g., Mayers and Smith, 1982, Nance et al., 1993, Froot et al., 1993, Mian, 1996, Tufano, 1996, Géczy et al., 1997, Rampini and

Viswanathan, 2010, Bodnar et al., 2019, Ge and Weisbach, 2021). While the role of financing opportunities and risk management has been studied, our findings show that there is a positive, causal relationship between financing constraints and demand for insurance. These results provide empirical support for theories suggesting that financing constraints lead firms to engage more in risk management (to protect internal financial resources and thus maintain investment) (e.g., Froot et al., 1993).

Second, an important part of the risk management literature specifically focuses on insurance demand (e.g., Mayers and Smith, 1982, Hoyt and Khang, 2000, Regan and Hur, 2007, Aunon-Nerin and Ehling, 2008, Dong and Tomlin, 2012). These studies typically focus on large listed firms and test which characteristics are correlated with the demand for insurance. In contrast, our study is based on a comprehensive sample of private firms and we employ a causal identification strategy. Thus our findings provide novel insights into corporate risk management of an understudied part of the economy.

Finally, our findings add to the vast literature on financing constraints (e.g., Whited and Wu, 2006, Hadlock and Pierce, 2010). While there is evidence that financing constraints matter for many real outcomes (e.g., Whited, 2006, Kerr and Nanda, 2009, Krishnan et al., 2015, Steri et al., 2021), we provide causal evidence that financing constraints positively impact one of the most important elements of corporate risk management, namely insurance demand. Also, our sample of typically small, private firms allows us to focus on firms who are truly constrained (e.g., Farre-Mensa and Ljungqvist, 2016).

2 Data, Measurement, and Sample Characteristics

2.1 Sample Construction

We combine data from four sources to construct our sample. First, we have proprietary data on insurance purchases from one of the largest insurance companies operating in Sweden for the years 2008–2017. The data contain information on firm level premiums and losses (see subsection A.1 for a background on corporate insurance). Second, we have balance sheet and income statement data based on firm annual filings with the Swedish Companies Registration

Office (Bolagsverket) from the Bisnode Serrano database. This data also contains information on the number of workers, corporate structure, founding year, credit lines, collateralized debt, and NACE industry classification.

Third, we obtain data on corporate income tax filings from the Swedish tax agency which contains, among others, information on firm net operating losses. Finally, we use data on firm level credit scores from the credit information agency, *Upplysningscentralen* (UC). UC provides ratings on all Swedish limited liability companies and their credit scores are broadly used in the financial industry as well as by the Swedish central bank (Jacobson and Lindé, 2000). The merging of the four data sources is made possible since all Swedish firms are assigned a unique firm identifier.

We apply the following sample selection criteria. We require that a firm i) has more than five workers, ii) operates outside the financial sector (i.e., excluding firms with industry NACE codes 64–66), iii) have positive values for the book value of total assets, total debt, labor costs, cash holdings, number of establishments, and has an average interest cost-to-debt ratio below 100%, and iv) does not have a credit score in the worst two rating categories (we describe this more below). After merging the four data sources and applying the sample selection criteria our sample includes about 34,000 unique firms during the years 2008–2017.

We report complete definitions of all variables used in the study in Table 1 and summary statistics in Table 2. We begin by noting that the typical firm in our sample is quite small. The average (median) number of workers is 24 (11).[4] The key outcome variable in our study is insurance demand which we measure as total premium paid in year t divided by the end-of-period book value of total assets in year t (*Premium*).[5] Standardizing by end-of-period assets reflects that supply and demand factors might vary between sectors and the fact that policyholders need to update their insurance policies if they purchase new assets. Average *Premium* is 0.52% (median 0.38%).

[4]The median firm covered in our insurance sample has 11 workers compared to 12 for the median Swedish limited liability firm. Our sample firms also have a similar capital structure to the typical Swedish firm (median debt-to-assets and cash-to-assets are 57% and 15% compared to 64% and 14%). The industry distribution in our sample is also similar to the Swedish economy.

[5]This is in line with the literature, that typically normalizes by insured assets (Hoyt and Khang, 2000, Regan and Hur, 2007).

2.2 Measuring Financing Constraints

We follow Caggese et al. (2019) and use data on firms' credit scores from the credit information agency Upplysningscentralen AB (UC). UC creates a continuous measure (Risk forecast) with an estimate of a firm's default risk in the coming twelve months. This measure is based on 52 sources including balance sheet and income statement items, records on owners and board members, previous defaults, late payments, etc.[6] The risk forecast measure is then used to create five risk classes:[7]

1. Very low risk (default probability within one year is less than 0.25%)
2. Low risk (0.25%–0.74% default probability)
3. Normal risk (0.75–3.04%)
4. High risk (3.05%–8.04%)
5. Very high risk (>8.04%)

As mentioned above, we remove firms with the two worst credit scores (representing about 9% of the firms). We do this to make sure we capture financing constraints rather than financial distress (as in Caggese et al., 2019). Removing firms in the two riskiest rating categories is equivalent to removing speculative debt and only focusing on investment grade borrowers.[8] Based on UC's three rating categories spanning from very low to normal risk of default, we create our financing constraints variable, *Constrained*, where firms with an estimated risk forecast below 0.25% (i.e., the least financially constrained) are categorized as one. Firms with a risk forecast between 0.25% and 0.74% are categorized as two, and finally, firms with a risk forecast between 0.75% and 3.04% are categorized as three, or most

[6] The sources that are considered for this score can be found here: (https://www.uc.se/en/about-uc/ucs-sources/. Similarly, the credit scores are described here: https://www.uc.se/hjalp–kontakt/riskklass/hur-beraknas-riskprognos-och-riskklass/. The measures are similar to the systems found in other countries and described in Berger and Udell (2006).

[7] The original credit categories go from 1 (very high risk) to 5 (Very low risk). In line with Caggese, Cuñat, and Metzger (2019), we have reversed the score.

[8] Having a risk forecast of under 0.25% (between 0.25%–0.74%) is roughly equal to having a AAA (BBB) credit rating at the major credit rating agencies (Langohr and Langohr, 2010).

financially constrained. Around 40% of the firms are in the first category in *Constrained* (i.e., least constrained) (Table B.1). Another 34% are in the second and finally, 27% are in the third category in *Constrained* (i.e., most constrained). We discuss the distribution of risk forecasts in subsection A.2.

2.3 The Financing Constraints Measure and Firm Characteristics

In Table 3, we present summary statistics across the different constraints categories. We begin by noting that *Premium* is higher for more constrained firms. The least constrained firms (category 1) dislay a premium to assets ratio of 0.40%, compared 0.61% among the most constrained (category 3). However, the largest difference in premium-to-assets is between categories 1 and 2. Average *Premium* is significantly higher in categories 2 and 3 relative to 1.

Next, we compare how our financing constraints measure compares with commonly used predictors of firm financing constraints (Table 3). We begin and check two of the most commonly used proxies for financing constraints, firm age and size (e.g., Hadlock and Pierce, 2010), and how they vary across our constraints measure. The average firm age and size in the least constrained group are 25 years and 32 workers. The average age of firms in the next two categories is 20 and 16 years respectively. In terms of firm size, firms in these categories employ around 20 workers, implying that the least constrained firms (category 1) are 50% larger.

We move on to consider growth options (proxied by sales growth and the investment-to-asset ratio). Average sales growth increases from 2.9% to 4.0% from the least to the middle category to 5.1% in the most constrained category. In terms of capital investment to assets, the least constrained firms display a ratio of 3.4% compared to 4.0% and 4.6% for the more constrained groups of firms. These results are important for a couple of reasons. First, they are generally in line with previous findings of the characteristics of financially constrained firms. Second, this provides us with confidence that our constraints measure indeed captures financing constraints (rather than financial distress).

In the final part of Table 3, we evaluate various financial variables. Average cash flow to assets goes from 13% in the least constrained category to 11% (in the middle group) to 9% in the most constrained group. Another commonly used proxy of financing constraints is dividend payments. Again we find that the least constrained group of firms pay more dividends in relation to assets than the more constrained firms (6.7% vs 4.4% and 2.7% respectively). There is also increasing leverage ratios across constraints categories (from 44% to 60% to 70%).

To summarize: our financing constraints measure (*Constrained*) lines up well with commonly used proxies in the literature. More constrained firms are younger, and smaller, generate less internal cash flow, have lower dividends, hold less cash and display higher leverage. More constrained firms also grow faster and invest more than less constrained firms.

3 Financing Constraints and Insurance Demand

3.1 Baseline Specifications

To examine how firm financing constraints affect insurance demand we estimate the following (baseline) specification:

$$Premium_{it} = \beta\, Constrained_{it} + \eta_i + \eta_{jt} + \epsilon_{it}. \quad (1)$$

In Equation 1, *Premium* measures insurance demand as the premium-to-asset ratio of firm i in year t. *Constrained* is a categorical variable taking on values from 1 (least constrained) to 3 (most constrained). The specification includes firm (η_i) and industry-year fixed effects (η_{jt}). The firm fixed effects account for any unobserved, time-invariant firm characteristics that may impact insurance demand, and the industry-year fixed effects control for time-varying shocks common to firms in the same industry. We cluster standard errors at the firm level. Our baseline prediction is that firms with more costly external finance demand more insurance (Froot et al., 1993). In other words, we predict a positive relationship between

Constrained and *Premium*, $\beta > 0$. The statistical precision and magnitude of β is ultimately an empirical question.

While the firm fixed effects remove potential unobserved confounding and time-invariant factors, financing constraints might still correlate with the error term. Transitory shocks to the firm's productivity might improve its financial conditions and increase insurance demand simultaneously. For example, a firm's insurance demand might be correlated with constraints if the firm is purchasing insurance in anticipation of more profitable investment opportunities. To circumvent these concerns and investigate the causal relationship between financing constraints and insurance demand we adopt a regression discontinuity design (RDD).

We follow Caggese et al. (2019) and exploit a discontinuity in the underlying risk forecast measure. We analyze firms around both the 0.25% (between rating categories 1 and 2) and the 0.75% (between 2 and 3) cutoffs. This approach crucially depends on two assumptions. We assume that firms are virtually identical with respect to the running variable around the cutoffs and that they are unable to manipulate their credit scores (random assignment). UC computes the running variable from 52 underlying variables whose weighting scheme is unknown to the firms. The sheer number of factors that affect the running variable and the unknown weights makes it next to impossible for the firm to strategically manipulate the credit score. Also, as UC explicitly states on its website, they do not accept or factor in any subjective information sent to them or statements made by accounting firms or the firm itself aiming to affect the credit score. The credit score is strictly based on changes in the 52 variables in their model. UC regularly runs its credit scoring model against official registries up to five times per week which further complicates manipulation. For a comprehensive discussion on this identifying assumption see the appendix (subsection A.2 and subsection A.3).

Also, it is critical for our identification strategy that external suppliers of finance do in fact respond to changes in credit scores. This critical assumption is likely to hold. UC is widely adopted and well-known throughout Sweden. The Swedish Central Bank relies on UC for their calculations of default probabilities (Jacobson and Lindé, 2000) and firms typically display their UC rating category either in the physical workplace or on their website. Firms get "Gold", "Silver" or "Bronze" badges for rating categories one, two, and three respectively.

To identify the effect of financing constraints we compare firms close to the cutoff in the underlying risk forecast measure. Since we use two cutoffs, we assign firms to the closest cutoff. Let s_{igt} be the risk forecast of firm i in group g (first or second cutoff) and year t, and c_g the relevant cutoff (0.25% or 0.75%). We compare firms just to the left and to the right of the cutoff and allow for different intercepts and slopes. Formally, we estimate a standard RDD model. The model is characterized by local linear regressions which allow slopes above and below the threshold to differ (Lee and Lemieux, 2010):

$$Premium_{it} = \alpha + \beta \mathbb{1}(s_{igt} \geq c_g) + f_1(s_{igt} - c_g) + \mathbb{1}(s_{igt} \geq c_g) f_2(s_{igt} - c_g) + u_{it} \qquad (2)$$

Where $f_1(\cdot)$ is a function to control for the distance from the cutoff on the left side; $f_2(\cdot)$ is the same but to the right of the cutoff; and $\mathbb{1}(s_{igt} \geq c_g)$ is an indicator function that is equal to one whenever the risk forecast exceeds the cutoff. In line with Gelman and Imbens (2019) we primarily use a linear specification (as well as some lower-order polynomials) since higher-order polynomials have been shown to be sensitive to changes in the specification. Furthermore, we follow Calonico et al. (2014, 2017) and use a data-driven bandwidth selection for which a simple linear regression can provide a consistent estimate.

3.2 Baseline Results

3.2.1 Panel Regression Results

We begin and present estimates of Equation 1 without firm fixed effects and report the results in column 1 in Table 4. The coefficient is 0.096 and highly statistically significant, indicating that more financially constrained firms have higher premium to assets (consistent with a higher demand for insurance). This estimate suggests that a one unit increase in *Constrained* is associated with a 0.096% increase in premium-to-assets. Since average premium to assets is 0.52% this effect is sizable.

We continue in column 2 and report results from estimating the full Equation 1 including firm fixed effects. This leads to a drastic decline in the magnitude of β. But, the coefficient is still highly statistically significant. The within-firm response to a one unit increase in *Constrained* generates a β of 0.012.

Many risk management studies focus on the differential effect based on firm size (e.g., Mian, 1996, Géczy et al., 1997). We, therefore, control for firm size (log of the number of employees) and present the results in column 3. The estimated coefficient on firm size is negative and highly statistically significant implying that smaller firms demand more insurance. Most importantly for our purposes, the relationship between *Constrained* and *Premium* is left unchanged from the inclusion of firm size. Overall, in the first three columns, we find strong support for our main prediction that firm-level financing constraints are associated with higher demand for insurance.

3.2.2 Regression Discontinuity Design Results

Next, we proceed and examine how firm-years just around the cutoffs behave and estimate Equation 2. We report results using the optimal bandwidth selection with different polynomials from Calonico et al. (2014, 2017) in columns 4–6 in Table 4. Using a pooled RDD approach, the coefficients are all highly statistically significant and fall between 0.040–0.054 depending on the choice of polynomial. These are large effects and imply that financing constraints have a causal impact on insurance demand. Finally, in column 7 we report the pooled regression discontinuity specification with a tighter bandwidth and again find a highly significant and large effect. Figure 1 illustrates the results from column 4, where the dots represent the sample averages within the bins while the lines present the fitted lines of the local linear regressions on each side of the cutoff. Figure 1 underscores that more constrained firms have a higher premium-to-asset ratio.

Next, we focus on the discontinuities around categories 1–2 and 2–3 separately. We report the coefficient estimates from estimating Equation 2 around the 1 to 2 (2 to 3) cutoff in columns 1 and 2 (3 and 4) in Table 5. Odd (Even) numbered columns use the optimal bandwidth approach cited above (a fixed bandwidth of 0.15). The point estimates around the first cutoff are 0.055 and 0.053 respectively and are highly statistically significant. The estimated coefficients for the second change are 0.026 and 0.021 and are statistically insignificant.

We also provide graphical evidence of the RDD results in Figure 2. It is evident there is a sharp difference in premium-to-assets at the 0.25% cutoff (panel A). Figure 2 underscores that more constrained firms have a higher premium to asset ratio. In panel B, we can see that there is a smaller increase in premium-to-assets around the 0.75% point. While there is a jump in premium-to-assets, it is visibly smaller than in panel A.

Our results imply that a firm just below the category 2 (3) cutoff and a firm just above differ in their premium-to-asset ratio by 0.055 (0.026). If we compare with sample average *Premium*, the estimated result in Table 5 implies that a firm just above the first (second) cutoff pays 11% (5%) higher premium relative to assets compared to a firm just below the first (second) cutoff. If we instead evaluate the economic magnitude of our results relative to the different constraints categories, the magnitude around the first (second) cutoff implies 14% (5%) higher premium-to-assets.

3.3 Robustness

The positive association between financing constraints and premium-to-assets is robust to numerous measurement and modeling choices. We compile some of the most important robustness checks in Table 6. We begin in the first four columns in Table 6 and report results with alternative normalization of the premium to assets variable. In the first two columns we subtract cash holdings and in the next two columns all financial assets from the denominator and re-scale our dependent variable. Results from estimating both Equation 1 and Equation 2 are virtually unchanged from removing cash or financial assets from the book value of assets when scaling total premium. In Figure 3 we plot the RDD result when we have subtracted cash from the denominator which underscores the robustness with respect to alternative scaling of the dependent variable.

Next, we consider that Swedish tax and accounting rules enable fixed assets (except buildings) to be fully depreciated within five years which can lead to differences in the book value of the assets (which we observe) and the insured value. As a result, there might be systematic differences across industries based on their capital investment intensity. To ensure that changes in the premium-to-asset ratio caused by firms' fixed assets spending are not driving our results we replace the annual book value of assets in the denominator with the average of a firm's assets in $t = 0$ to $t = -2$. In Table 6 columns 5 and 6, we find that our baseline result is left largely unchanged.

3.4 Alternative Firm-Level Channels

Here, we focus on the interplay between insurance demand and three other factors previously studied in the literature, namely that insurance purchases are driven by lender demands (e.g., Nini, 2020), access to credit lines (e.g., Holmstrom and Tirole, 2000) or tax motivations (e.g., Mayers and Smith, 1982). The estimation results are compiled in Table 7.

A potential concern is that our results are not driven by financing constraints directly, but rather by lenders demanding firms to purchase insurance to access (collateralized) debt. Since a lender would lose seniority rights if the asset used as collateral is destroyed, the lender has strong incentives to demand insurance in the loan covenant. In fact, Nini (2020) shows that insurance covenants are found in as many as 98% of private loan contracts. To rule out that our mechanism is driven by lender covenant requirements we augment Equation 1 with an indicator variable taking on the value one if a firm has collateralized debt and zero otherwise (using similar data as Cerqueiro et al., 2016). We report the results in column 1 of Table 7. If our mechanism is driven by such loan covenants we expect a positive and significant collateralized debt indicator variable. However, our baseline result is unchanged from the inclusion of the collateralized debt indicator. In unreported regressions, we also control for the ratio of collateralized debt to assets and find similar results. We also report results from studying the collateralized debt-to-asset ratio around the credit score cutoffs in Figure 4. There is no significant change in the collateralized debt-to-asset ratio around the cutoffs.

Next, we consider the substitution between liquidity and risk management (Holmstrom and Tirole, 2000). We compare firms with and without access to a credit line and test whether this affects our proposed financing constraints-insurance demand channel. We construct an indicator variable taking on the value one if the firm has a credit line and zero otherwise.

Our baseline result is left unchanged (column 2 in Table 7). We get similar results if we instead include the ratio of unused credit lines to assets.

Third, we consider tax incentives for risk management and how this might affect our mechanism. As profits are taxed immediately, net operating losses, on the other hand, must be carried forward. As a consequence, firms that carry forward net operating losses may be more sensitive to adverse events and thus have a stronger incentive to purchase insurance. Specifically, following, e.g., Nance et al. (1993), we test whether our results are driven by firms with net operating losses demanding more insurance. Here we define a dummy variable taking on the value one if the firm has a net operating loss that it is carrying forward and zero otherwise. The result is displayed in Table 7, column 3. Our baseline findings are left largely unchanged. We obtain very similar inferences if we instead use net operating losses divided by total assets.

4 Financing Constraints and Insurance Demand vs The Insurer Changing Premiums

Are the results reported above driven by the insurer offering coverage at higher (lower) premiums to policyholders as they get worse (better) credit scores? If firms with worse credit scores also have higher expected losses, the insurer might rationally hike premiums in response to a deteriorating credit score. Indeed, there is a debate on insurers using credit scores or, closely related, credit-based insurance ratings to determine insurance premiums, as they may be predictive of claims (Morris et al., 2017, Powell, 2020). Our findings so far support the idea that financing constraints lead firms to purchase more insurance. But, to rule out that we, instead, are picking up that it is the insurer that is changing premiums based on changes in credit scores we design four additional tests.

We first note that such an alternative interpretation of our results so far is challenging for a variety of reasons. First, we exclude firms classified as having above-normal risk (categories 4 and 5) from the sample and the strongest effect is found around the cutoff for categories 1 and 2. While a change between these categories indeed can serve as a sign of tightening financing constraints, it is unlikely that insurance companies would raise prices for a firm that goes from "Very low default risk" to "Low default risk". Second, there is some support that insurers consider the firms' financial conditions when setting prices. However, this is primarily a way to capture the risk of financial distress (e.g., Regan and Hur, 2007). Again, we have removed the firms most likely to be financially distressed. Thus, it seems unlikely that our results are driven by the insurer purposefully hiking prices for firms with relatively low default risk. Still, we proceed with a few additional tests and compile the results in Table 8, Table 9, and Figure 5.

4.1 Experience Rating

We begin and consider whether the insurer places a greater weight on credit scores at the beginning of the policyholder-insurer relationship. A well-known premium setting strategy is so called *experience rating*. This implies that the insurer's premium offer depends on its loss experience with a specific policyholder to set its premium (Werner and Modlin, 2016). As the insurer learns more about its client (e.g., from losses incurred) the weight that is placed on a credit score may change during the insurer-policyholder relationship. As a result, the credit score can be an important factor for the pricing of insurance but its importance would decline over time.

In order to test whether experience rating strategies are spuriously causing our results we investigate if the importance of credit scores falls over time as the insurer-client relationship matures. Specifically, we exclude the first two years that a firm is in the sample (Morris et al., 2017) (and thus the first two years that a firm is insured by the insurer) as these years may allow the insurer to learn about its policyholder. We compile results using the panel approach and RDD respectively in columns 1 and 2 in Table 8. Even after excluding the first two years of the firm-insurer relationship we retrieve very similar results as in the baseline case. Based on these findings, it is unlikely that we are picking up that the insurer uses credit scores to practice experience rating.

4.2 Pricing Power of the Insurer

Here we further examine the potentiality that it is the insurer that increases the premium in light of changing credit scores. We begin and note that it would require considerable pricing power of the insurer to be able to change prices (and also retain these customers) for creditworthy firms (given our result is driven around the 0.25% threshold). Even more so as the Swedish insurance market is among the least concentrated (thus high level of competition) in Europe (European Insurance and Occupational Pension Authority, 2020) which suggests that the pricing power of an individual insurance company is reasonably limited.

However, pricing power can vary across regions. There is likely more competition among insurers for customers in the large city regions in Sweden, and, we therefore, assume the pricing power among insurers is weaker in any of the three largest urban areas (Stockholm, Gothenburg, and Malmö) compared to the rest of Sweden. In other words, if our proposed financing constraints-insurance demand channel instead is driven by insurers raising prices for reasonably financially healthy firms we expect the channel to be strongest in the sub-sample of firms located in areas where we assume there is less insurance market competition (outside the major economic regions as proxied by the three large urban areas).

We, therefore, create an indicator variable (*Big City*) taking on the value one if the firm is located in any of the three large city areas and zero otherwise. If our findings are impacted by the insurer changing prices we expect a larger effect in the less competitive regions in Sweden (i.e., outside the big cities). For the panel approach, we interact *Constrained* with *Big City* and report the results in column 3 in Table 8. The interaction term is close to zero and the original, un-interacted *Constrained* estimate is unchanged compared to in Table 4. In column 4, for the RDD, we restrict our sample to only contain firms that are located in the largest cities and assume that if we continue to find a large and statistically significant effect in the most competitive region it is unlikely that it will be driven by the insurer changing prices. Again, the result considering firms located in any of the three big city regions is very similar to the baseline RDD results in Table 5.

4.3 Credit Scores and Reported Insurance Claims

Premiums should reflect the discounted expected losses of the policyholder. If changes in credit scores in part are caused by, or coincide with, changes in reported insurance claims then we should expect the insurer to change premiums. Therefore, it could be that we are picking up that it is the insurer that rationally charges firms higher premiums around discrete rating category changes. We address this concern in two ways.

4.3.1 Excluding Firms with Reported Claims

To begin we simply exclude all firms that report an insurance claim during the sample period and re-estimate our baseline specifications. The idea is that if our baseline finding also shows up in this subset of firms (which due to unobservable characteristics might be particularly careful in avoiding losses), it would go a long way in ruling out that we mistakenly are picking up premium changes by the insurer. This admittedly crude way of addressing the potential difference in claims around changes in credit scores excludes about 50–60,000 firm-years. We report virtually unchanged results from removing all firms with a reported insurance claim (columns 5 and 6) in Table 8.

4.3.2 Credit Scores and Reported Claims

We conclude by examining directly, again using our panel regression and RDD approaches, whether there is a significant difference in claims around the different credit score cutoffs. If firms do report more claims just above a credit score threshold compared to a firm just below, then it would be completely rational for the insurer to charge higher prices (since premiums should reflect the expected losses of the firm). We, therefore, consider the ratio of claims to total assets and plot the RDD result in Figure 5. While claims (relative to assets) are increasing along the risk forecast variable, they, if anything, are lower for firms just above the cutoff.

Next we report results using claims to assets as the dependent variable, using both Equation 1 and Equation 2, in the first two columns in Table 9. The coefficients are close to zero and far from statistically significant. Finally, in columns 3 and 4 we test the two cutoffs separately, and again find no impact on changes in credit scores leading to changes in the claims-to-assets ratio.

5 Conclusion

We study financial frictions and corporate risk management and find that financing constraints lead firms to purchase more insurance. Our findings are based on both within-firm panel regression estimates and a regression discontinuity design. The mechanism we study is based on the theory that a key motivation for risk management is to protect internal financial resources in order to maintain investment levels (e.g., Froot et al., 1993, Holmstrom and Tirole, 2000). Our study has implications for a number of related and important literatures.

Our evidence is particularly relevant for the literature on the risk management of financially constrained firms. Studies focusing on large, listed firms, where risk management is measured through hedging, using derivatives, typically find that *ex-ante* less constrained firms engage more in risk management (e.g., Nance et al., 1993, Rampini et al., 2014). Our work, using a comprehensive sample of predominantly unlisted firms, shows that financially constrained firms demand more insurance. In this way, we provide novel evidence on the risk management of smaller, private firms previously left under-examined due to data constraints.

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Figure 1: Financing Constraints and Insurance Demand (Pooled Across Both Cutoffs)

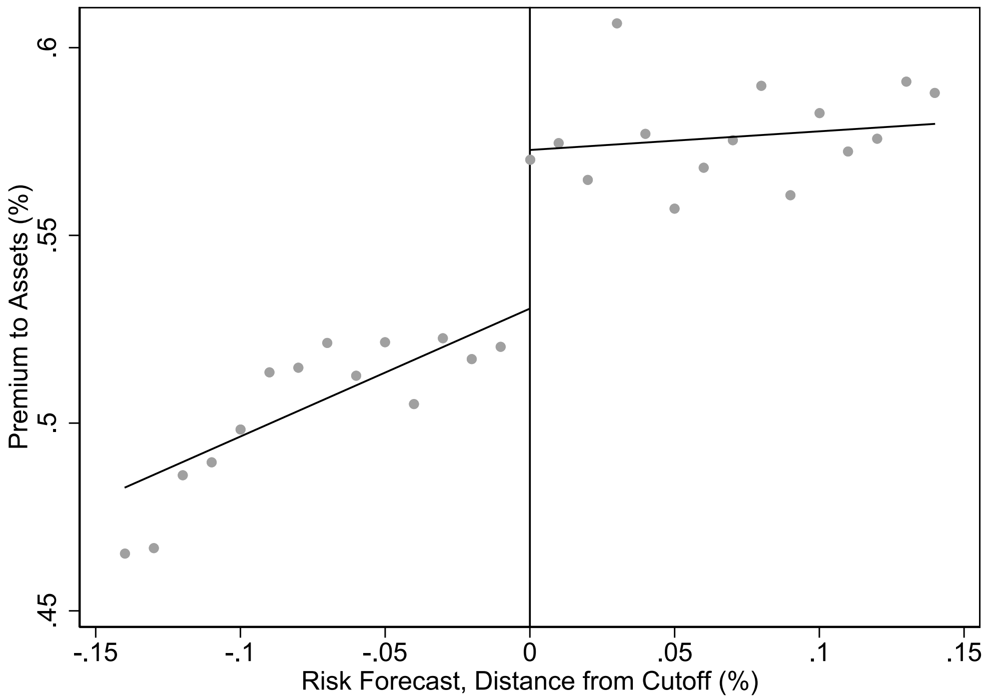

Figure 1 displays RDD estimates of Equation 2 with *Premium* as the dependent variable across both cutoffs. For estimation details see Table 4.

Figure 2: Financing Constraints and Insurance Demand (Around Each Cutoff Separately)

(a) 0.25% Cutoff

(b) 0.75% Cutoff

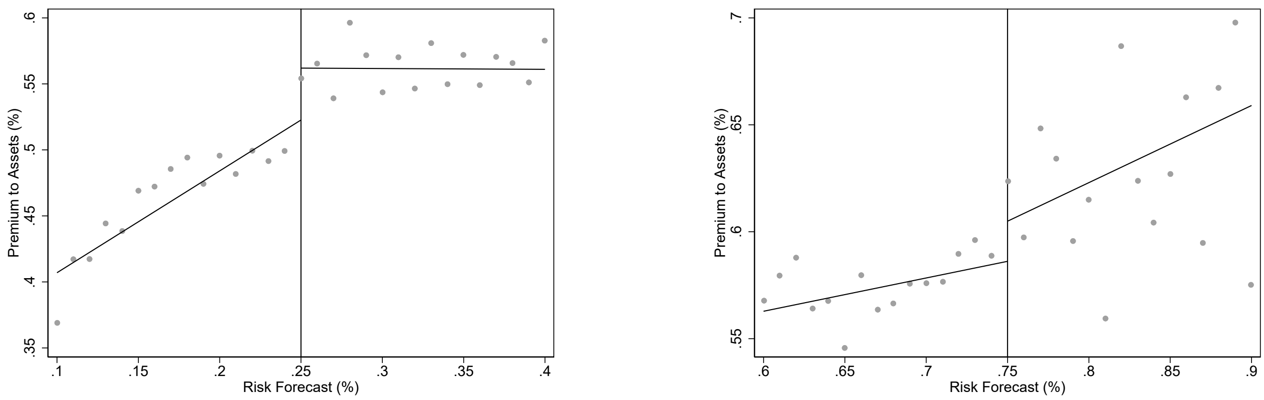

Figure 2 displays RDD estimates of Equation 2 with *Premium* as the dependent variable across the 0.25% cutoff in panel A and the 0.75% cutoff in panel B. For estimation details see Table 5.

Figure 3: Financing Constraints and Insurance Demand (Less cash and Pooled Across Both Cutoffs)

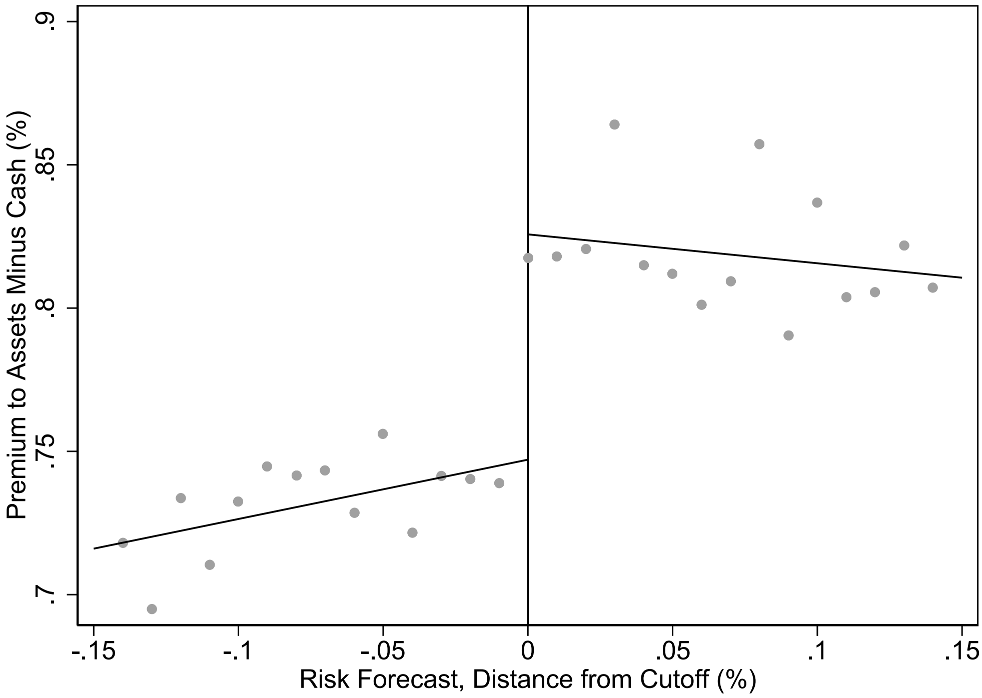

Figure 3 displays RDD estimates of Equation 2 with *Premium less cash* as the dependent variable across both cutoffs. For estimation details see Table 6.

Figure 4: Financing Constraints and Collateralized Debt To Assets (Pooled Across Both Cutoffs)

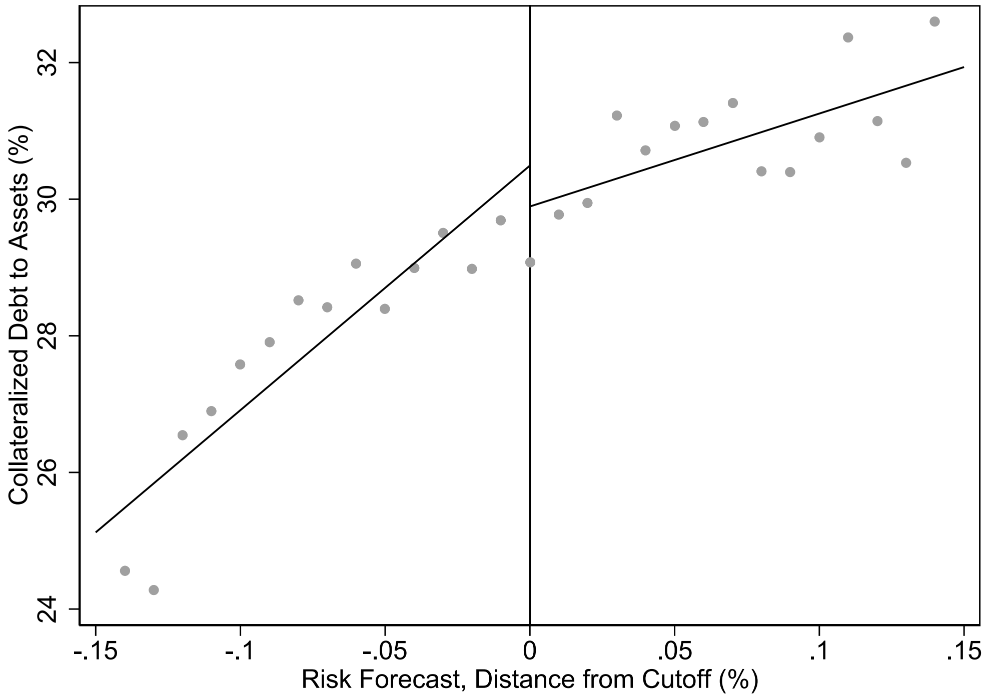

Figure 4 displays RDD estimates of Equation 2 with *Collateralized debt-to-assets* as the dependent variable across both cutoffs. For background details around the estimation of Equation 2 see Table 4.

Figure 5: Financing Constraints and Insurance Claims (Pooled Across Both Cutoffs)

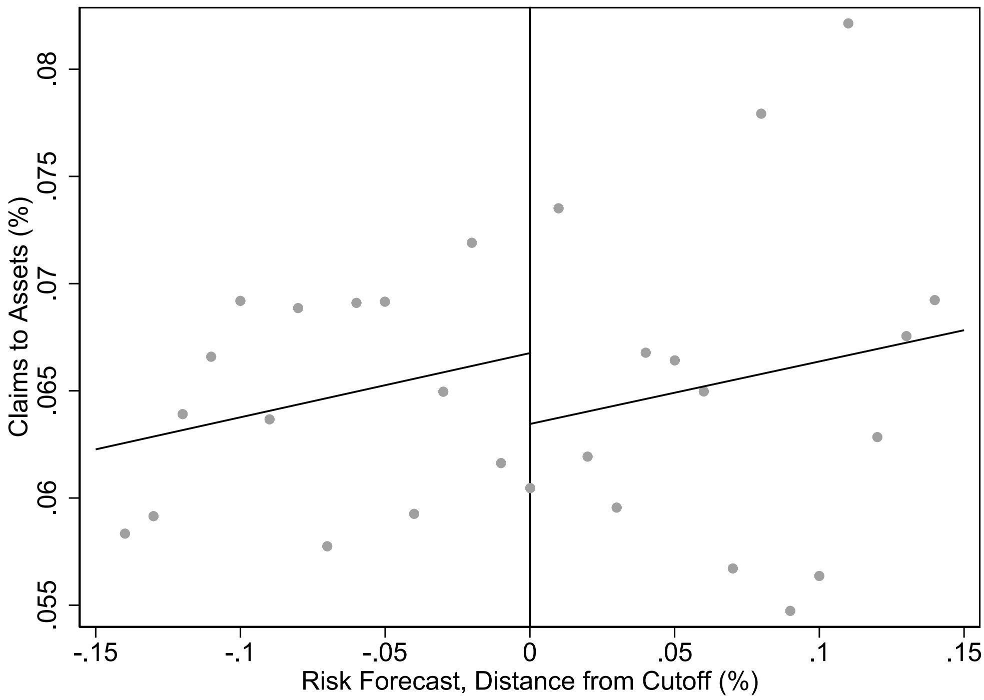

Figure 5 displays RDD estimates of Equation 2 with *Claims* as the dependent variable across both cutoffs. For estimation details see Table 9.

Table 1: Description of Variables

Variable Name	Description	Source
Premium	Premium divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano and Insurance Company
Premium less cash	Premium divided by the book value total assets less cash holdings (in %) and Winsorized at the 1% level.	Serrano and Insurance Company
Premium less financial	Premium divided by the book value total assets less financial assets (in %) and Winsorized at the 1% level.	Serrano and Insurance Company
Premium Age-Adjusted	Premium divided by the book value of total assets for t to t-2 (in %) and Winsorized at the 1% level.	Serrano and Insurance Company
Constrained	A categorical variable taking on values from 1 to 3 where 1 is the best credit score (least constrained) and 3 is the worst credit score (most constrained).	Upplysningscentralen
Collateralized debt	An indicator variable taking on the value one if the firm has collateralized debt and zero otherwise.	Serrano
Credit line	An indicator variable taking on the value one if the firm has a credit line and zero otherwise.	Serrano
Net operating losses	An indicator variable taking on the value one if the firm has a net operating loss to carry forward and zero otherwise.	Statistics Sweden and the Tax Agency
Firm age	Number of years since incorporation.	Serrano
Firm size	Number of employees and Winsorized at the 1% level.	Serrano
Sales growth	Annual change in net sales and Winsorized at the 1% level.	Serrano
Investment	Annual change in fixed assets plus depreciation divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano
Cash flow	Cash flow divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano
Dividend	Dividend payments divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano
Leverage	Total debt divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano
Cash	Cash holdings divided by the book value of total assets (in %) and Winsorized at the 1% level.	Serrano

Table 2: Summary Statistics

	Observations	Mean	Median	Std Dev
Premium	158,836	0.52	0.38	0.48
Premium less cash	158,826	0.73	0.50	0.78
Premium less financial	158,833	0.55	0.41	0.51
Premium Age-adjusted	158,774	0.52	0.39	0.46
Constrained	158,836	1.87	2.00	0.80
Collateralized debt	142,695	77.46	100.00	41.78
Credit line	158,836	47.87	0.00	49.95
Net operating losses	158,836	9.72	0.00	29.63
Firm age	158,836	20.83	18.00	15.01
Firm size	158,836	24.37	11.00	167.08
Sales growth	122,216	3.76	2.29	18.37
Investment	122,221	3.87	1.21	7.41
Cash flow	158,790	10.98	10.19	11.25
Dividend	158,836	4.86	0.00	8.21
Leverage	158,834	56.53	57.08	21.93
Cash	158,831	20.66	15.49	19.54

The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. Table 1 provides detailed variable definitions.

Table 3: Descriptive Statistics Sorted by Financing Constraints Category

		Constrained category			Test of Difference in Means (p-values)	
	All	1	2	3	1 vs 2	2 vs 3
Premium	0.52	0.40	0.57	0.61	0.00	0.00
Firm age	20.83	24.88	19.78	16.19	0.00	0.00
Firm size	24.37	31.75	19.61	19.45	0.00	0.76
Sales growth	3.76	2.88	3.95	5.09	0.00	0.00
Investment	3.87	3.37	4.02	4.58	0.00	0.00
Cash flow	10.98	12.72	10.70	8.75	0.00	0.00
Dividend	4.86	6.69	4.43	2.68	0.00	0.00
Leverage	56.53	44.38	59.75	70.44	0.00	0.00
Cash	20.66	27.08	18.86	13.43	0.00	0.00

The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. Column 1 presents the sample mean across variables. Columns 2–4 report the mean for each category of *Constrained* from 1 to 3 (least to most constrained). Columns 5 and 6 present the p-values of the difference in means between *Constrained* categories 1 vs 2 and 2 vs 3 respectively. Table 1 provides detailed variable definitions.

Table 4: Panel Regression Results: Financing Constraints and Insurance Demand

	Premium						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	RDD	RDD	RDD	RDD
Constrained	0.096***	0.012***	0.011***	0.054***	0.044**	0.040**	0.048***
	(0.002)	(0.001)	(0.001)	(0.012)	(0.018)	(0.020)	(0.010)
Firm size (in logs)			-0.124***				
			(0.005)				
Polynomials				1	2	3	1
Firm Fixed Effects	No	Yes	Yes	No	No	No	No
Industry-Year Fixed Effects	Yes	Yes	Yes	No	No	No	No
Robust p-value				0.000	0.064	0.117	0.000
Observations	158,834	152,193	152,193	158,836	158,836	158,836	158,836

Table 4 reports estimates of Equation 1 (Equation 2) in columns 1–3 (4–7) with *Premium* as the dependent variable. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). Columns 2–3 include firm fixed effects and columns 1–3 industry-year fixed effects. Columns 4–6 contain RDD estimates across both cutoffs using the optimal bandwidth from Calonico et al. (2014, 2017) and column 7 has a fixed bandwidth of 0.15 percentage points around each cutoff. Columns 4 and 7 use a polynomial of order one and columns 5 and 6 a polynomial order of 2 and 3 respectively. Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Regression Discontinuity Design: Financing Constraints and Insurance Demand

	(1)	(2)	(3)	(4)
	Around 0.25% cutoff		Around 0.75% cutoff	
Constrained	0.055***	0.053***	0.026	0.021
	(0.011)	(0.011)	(0.018)	(0.019)
Polynomials	1	1	1	1
Robust p-value	0.000	0.000	0.341	0.497
Observations	158,836	158,836	158,836	158,836

Table 5 reports RDD estimates of Equation 2 with *Premium* as the dependent variable. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). Columns 1–2 (3–4) present estimates around the 0.25% (0.75%) cutoff. Columns 1 (2) and 3 (4) use the optimal bandwidth from Calonico et al. (2014, 2017) (a fixed bandwidth of 0.15 percentage points). Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Financing Constraints and Insurance Demand: Robustness Checks

	Premium less cash		*Premium less financial*		*Premium Age-adjusted*	
	(1) OLS	(2) RDD	(3) OLS	(4) RDD	(5) OLS	(6) RDD
Constrained	0.012***	0.086***	0.011***	0.057***	0.023***	0.050***
	(0.002)	(0.018)	(0.001)	(0.013)	(0.001)	(0.011)
Polynomials		1		1		1
Firm Fixed Effects	Yes	No	Yes	No	Yes	No
Industry-Year Fixed Effects	Yes	No	Yes	No	Yes	No
Robust p-value		0.000		0.000		0.000
Observations	152,182	158,826	152,190	158,833	152,138	158,774

Table 6 reports estimates of Equation 1 (Equation 2) in odd (even) numbered columns with *Premium less cash* as the dependent variable in columns 1–2, *Premium less financial* in columns 3–4, and *Premium Age-adjusted* in columns 5–6. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). Odd numbered columns include firm and industry-year fixed effects. Even numbered columns contain RDD estimates across both cutoffs using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Financing Constraints and Insurance Demand: Alternative Firm-Level Channels

	Premium		
	(1)	(2)	(3)
Constrained	0.011***	0.012***	0.011***
	(0.001)	(0.001)	(0.001)
Collateralized debt	-0.002		
	(0.004)		
Credit line		0.014***	
		(0.003)	
Net operating losses			0.034***
			(0.003)
Firm Fixed Effects	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes
Observations	136,473	152,193	152,193

Table 7 reports OLS estimates of Equation 1 with *Premium* as the dependent variable. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). *Collateralized debt* is an indicator variable taking on the value one if the firm has collateralized debt and zero otherwise. *Credit line* is an indicator variable taking on the value one if the firm has a credit line and zero otherwise. *Net operating losses* is an indicator variable taking on the value one if the firm has a net operating loss to carry forward and zero otherwise. All regressions include firm and industry-year fixed effects. Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Financing Constraints and Insurance Demand: Additional Tests

	Excl. first two years		Large urban areas		No insurance claims	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	RDD	OLS	RDD	OLS	RDD
Constrained	0.010***	0.047***	0.013***	0.065***	0.013***	0.063***
	(0.002)	(0.014)	(0.002)	(0.024)	(0.002)	(0.016)
Big City × *Constrained*			-0.002			
			(0.003)			
Polynomials		1		1		1
Firm Fixed Effects	Yes	No	Yes	No	Yes	No
Industry-Year Fixed Effects	Yes	No	Yes	No	Yes	No
Robust p-value		0.000		0.016		0.004
Observations	93,023	97,058	152,193	48,294	93,892	100,059

Table 8 reports estimates of Equation 1 (Equation 2) in odd (even) numbered columns with *Premium* as the dependent variable. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). Odd numbered columns include firm and industry-year fixed effects. Even numbered columns contain RDD estimates across both cutoffs using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Results in columns 1–2 exclude the first two years of a firm in the sample. *Big city* is an indicator variable taking on the value one if the firm is located in any of the three largest cities (Stockholm, Gothenburg and Malmö) and zero otherwise. Column 4 uses a restricted sample of when *Big city* is equal to one. Columns 5–6 use a restricted sample where all firms that report an insurance claim during the sample period are excluded. Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Financing Constraints and Insurance Claims

	Claims			
	(1)	(2)	(3)	(4)
			RDD	
	OLS	Pooled	0.25%	0.75%
Constrained	0.002	-0.001	-0.000	-0.012
	(0.002)	(0.007)	(0.006)	(0.009)
Polynomials		1	1	1
Firm Fixed Effects	Yes	No	No	No
Industry-Year Fixed Effects	Yes	No	No	No
Robust p-value		0.948	0.848	0.229
Observations	152,193	158,836	158,836	158,836

Table 9 reports estimates of Equation 1 (Equation 2) in column(s) 1 (2-4) with *Claims* as the dependent variable. *Claims* is measured as insurance claims divided by the book value of total assets. The firm-level data are from three sources. Accounting data is from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen (UC). The sample consists of non-financial, limited liability firms with more than five workers and covers the period 2008–2017. *Constrained* is a categorical variable taking one values from 1 to 3 (least to most constrained). Column 1 includes firm and industry-year fixed effects. Columns 2–4 contain RDD estimates using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Column 2 present estimates across both cutoffs and columns 3 and 4 around the 0.25% and 0.75% cutoff respectively. Table 1 provides detailed variable definitions. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

A.1 Commercial Insurance

To study firms' demand for risk management we focus on commercial insurance. We consider policies sold to Swedish limited liability firms (aktiebolag) by one of the largest Swedish insurers that provide coverage against the most common damages to property, buildings, machinery, and liability risks (see Mayers and Smith (1982), for a more detailed description). Insured losses to buildings and machinery include accidents that are caused by fire, explosions, water, storm and leakage but also theft and robbery. In addition, firms can purchase business interruption insurance that covers the loss of income following an insured event. The policies that are part of this study have exemptions for vehicles or losses caused by most natural catastrophes (such as flooding and earthquakes), terrorism, or cyber risk.

Insurance premiums are set to reflect an individual firm's assets and risks for incurring an insured claim. Furthermore, policyholders can decide on which risks they want to cover, on deductibles and limits to coverage. Insurers help policyholders to minimize losses by advising them with respect to loss prevention. Insurance is tightly regulated to reduce fraud and abuse. Insurance contracts can demand that firms invest in loss prevention or reduction (for instance installing sprinklers and alarms). To keep their coverage, policyholders need to pay their premium and inform their insurer if they invest in additional assets or if they decide to sell assets. In contrast to other risk management instruments, for instance, currency derivatives, insurance policies i) cover firm-specific risk, ii) cannot be used for speculation, and iii) policyholders are not required to post collateral in order to engage in risk management. By paying an insurance premium and following the requirements set out in the insurance contract, policyholders are compensated for their losses. In some pre-defined cases, the insurer will compensate a policyholder with a new machine or a new building (full value). In other cases, the policyholder will receive compensation to equal the value of the destroyed asset. Purchasing insurance is costly and firms will consequently trade off costs and benefits and buy partial insurance (Holmstrom and Tirole, 2000).

A.2 The Distribution of Risk Forecasts

Figure B.1 shows the distribution of the risk forecast, as probabilities between 0% and 0.5%, as well as between 0.5% and 1.0%. The thick line at 0.25% (0.75%) shows the cutoff between credit scores 1 and 2 (2 and 3). We see that there are more firms just to the left of the cutoff in both cases.

Figure B.1 underscores that the distribution of firms by risk forecast is not smooth. Instead, firms bunch just above the cutoff where the credit score jumps from 1 to 2 (2 to 3). Consequently, a standard density test, as proposed by McCrary (2008), would suggest that there might be some form of strategic selection at the cutoff. Such a deliberate manipulation by firms with higher incentives (for example those that intend to invest more) would be problematic for our study as it would lead to biased estimates (Imbens and Lemieux, 2008). In order for our results not to be impacted by the selection we investigate the assignment mechanism and provide for a balance check of firms just above and below the threshold.

Analyzing the way that credit scores are assigned we find evidence suggesting that the observed bunching is unlikely to be caused by strategic manipulation. First, the assignment mechanism used by the rating agency considers 52 different variables ranging from board members' personal credit history to the assessed property values.[9] The sheer number of factors and their unknown weighting makes strategic manipulation very difficult. Second, the frequent changes in a firm's credit rating, about 70% of firms experience changing credit scores during the sample period, which suggests that strategic manipulation is unlikely. Third, the rules for creating the risk forecast, for instance, the weighting of different variables, are not public information. Fourth, UC's credit score is absolute and is adjusted for the business cycle. Therefore, even when there are no material changes to the firm's balance sheet or income statement there still might be changes to the running variable and ultimately, the credit score. And, finally, companies cannot submit information to UC or makes statements aiming to affect the credit score. UC explicitly states on its website that they do not factor in or care about subjective statements from accounting firms or the company itself about the proposed financial health of the firm. The credit score is strictly based on changes in the 52 variables in their model.[10] UC regularly runs their credit scoring model against official registries between once to up to five times per week. To summarize: it is practically impossible for a firm to manipulate the running variable.

Instead, the observed bunching can be explained by the details of how the underlying risk assessment is updated. Notably, firms that cross the threshold at 0.25%, the jump from score 1 to 2, face fewer critical assessments. One example might be that a firm that has a risk score of just above 0.25% is negatively affected by the number of times a financial institution checks its status. A firm above the cutoff may however to some degree be immune to these checks. As a result, the consistently top-rated firms are updated less frequently, which suggests it is somewhat harder to be downgraded than upgraded. This, in part, explains the greater density above the cutoff between the first and second-best credit score.

A.3 Balance Check

We show that firms close to the cutoff are similar in variables that are not directly affected by the credit score. Given the observed bunching, there might be a risk that firms around the cutoff differ in ways related to their performance. We thus test if the firms above and below the threshold are similar. This test is warranted if there is a correlation between a firm's propensity to manipulate other characteristics (Urquiola and Verhoogen, 2009). Since most observable characteristics, such as profitability, size, or debt are affected by the credit score, we focus on variables that should be unaffected. We focus on the industry distribution. Given that firms in some industries might have an easier time sorting (see Palguta and Pertold (2017)), this test is indicative if there is sorting on observables. Finding a difference between the firms above and below the threshold would indicate that our treatment and control group are different in a way that invalidates our identification.

Table B.2 reports the fraction of firms in each industry to the left and to the right of the two cutoffs. Firms to the left of the 0.25% cutoff have the best credit score while firms to the right of the cutoff have the second-best credit score. Firms to the left of the 0.75% cutoff have the second best rating and the firms located to the right are in the third category. The table indicates that the distribution across industries is very similar at each of the cutoffs, suggesting no clustering of particular industries on either side of the respective cut-offs.

[9] An overview is presented here: https://www.uc.se/hjalp–kontakt/riskklass/hur-beraknas-riskprognos-och-riskklass/

[10] See here: https://www.uc.se/hjalp–kontakt

A.4 Additional Tables and Figures

Figure B.1: Distribution of Risk Forecast

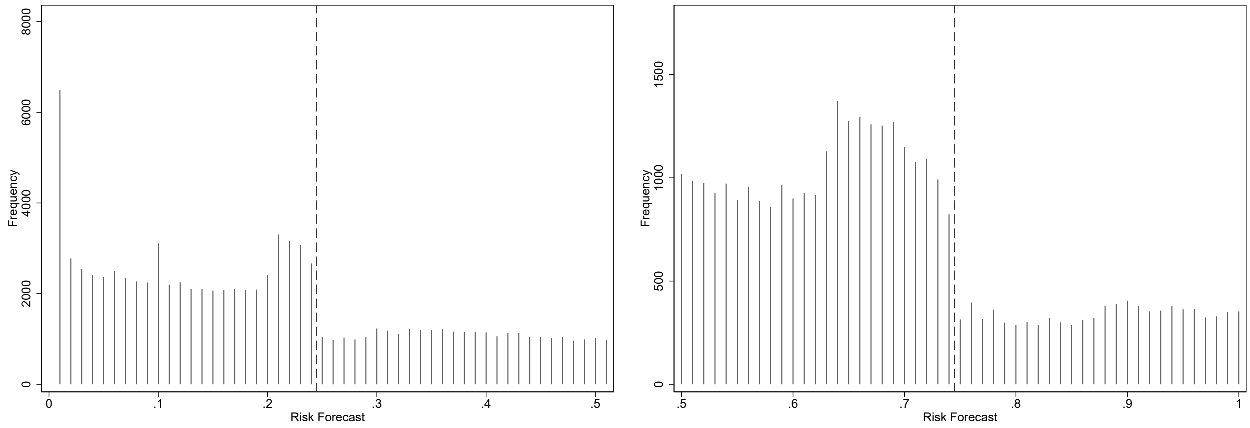

Figure B.1 shows the distribution of the risk forecast around between 0 and 0.5% (the first cutoff, shown in the left panel), as well as around 0.5% to 1% (the second cutoff, right panel). The risk forecast data is from Upplysningscentralen AB.

Table B.1: Sample Distribution Across Financing Constraints Categories

Credit Score	Risk Forecast (Lower)	Risk Forecast (Upper)	Frequency	%
1	0	0.24	62,755	39.51
2	0.25	0.74	53,677	33.79
3	0.75	3.04	42,404	26.70
Total			158,836	100.00

Table B.1 displays the range of Risk Forecast as well as the number of firm-year observations for each category in *Constrained*. Column 1 shows the lower bound for the risk forecast in that category, column 2 shows the upper bound, column 3 shows the number of firm-year observations in that category, and column 4 shows the share of observations in that category.

Table B.2: Distribution of Firms Around Each Cutoff

	First Cutoff (0.25%)		Second Cutoff (0.75%)	
Sector (%)	Left	Right	Left	Right
Agriculture, Forestry, and Fishing	2.23	1.90	1.85	1.82
Mining and Quarrying	0.21	0.13	0.17	0.09
Manufacturing	18.91	17.98	18.29	16.86
Electricity, Gas, and Steam	0.11	0.03	0.05	0.08
Water Supply and Waste Management	0.54	0.52	0.42	0.42
Construction	17.99	20.13	21.35	20.98
Wholesale and Retail	22.15	21.78	23.19	21.80
Transportation and Storage	4.97	5.06	5.79	5.76
Accommodation and Food Services	5.30	7.27	7.01	9.43
Information and Communication	3.74	3.69	3.54	3.79
Real Estate Activities	2.13	1.38	1.09	1.16
Professional, Scientific, and Technical Activities	9.19	8.24	7.05	6.46
Administration and Support	4.65	5.16	4.93	5.47
Education	2.30	2.15	1.78	2.29
Human Health and Social Work	3.54	2.59	1.50	1.23
Arts and Entertainment	0.92	0.89	0.88	0.95
Other Service Activities	1.11	1.10	1.10	1.42
Total	100.00	100.00	100.00	100.00

Table B.2 shows the industry distribution (in %) of firm years around the closest cutoff, 0.25% in columns (1 and 2), and 0.75% in column (3 and 4). Column 1 (Column 3) shows the distribution of firms for which the UC measure is slightly better than 0.25% (0.75%). Column 2 (Column 4) shows the distribution of firms for which the UC measure is slightly worse than 0.25% (0.75%). The interval around the first cutoff is [0.10,0.40] and the interval around the second cutoff is [0.60,0.90].