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 insurance demand. Using data on credit ratings matched with unique contract-level insurance data from around 34,000 firms in Sweden, we find that financing constraints lead to higher insurance spending. We adopt a regression discontinuity approach and show that financially constrained firms spend 5–14% more on insurance than similar less or unconstrained firms. These findings shed light on risk management in smaller, mostly private firms and unveil a previously undocumented causal channel between financing frictions and insurance demand.

Keywords: Financing Constraints, Risk Management, Insurance Demand, Credit Scores, Unlisted 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 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) engage *more* in risk management, such as hedging (e.g., Nance et al., 1993, Rampini et al., 2014). But the most common, less studied, form of corporate risk management is insurance (Servaes et al., 2009). And, although several studies focus on why firms purchase insurance (e.g., Aunon-Nerin and Ehling, 2008), there is little causal evidence on the role of financing constraints.

We fill this gap in the literature by employing the novel measure of financing constraints from Caggese et al. (2019) and the most comprehensive panel to date on firms' insurance purchases (provided by a large insurer in Sweden). Our main idea is that when a firm experiences a tightening in financing constraints (i.e., as the wedge between the cost of external and internal finance widens) it becomes more sensitive to variability in cash flows and therefore demands more risk management through insurance (e.g., Froot et al., 1993).

To test these ideas we estimate how firm-level financing constraints (measured by credit scores) affect the demand for insurance (measured as total premiums over assets). We merge comprehensive administrative data on Swedish firms with data on credit scores from the main credit information agency in Sweden and proprietary contract-level data on firms' insurance purchases from a large Swedish insurer. Our population of insured firms are of similar size to and similarly distributed across industries as the universe of Swedish firms. Our sample totals around 34,000 firms spanning the years 2008–2017. We begin by documenting that the typical firm in our sample is small (employing on average 24 workers). Furthermore, we show that our credit rating measure, which is used to classify firms in to three categories (1–3) from less to more constrained, indeed seems to capture financing constraints.[1] 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.

Next, we estimate panel regression models, where we include firm and industry times year fixed effects, and find a positive, and highly statistically significant relationship between 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) banks demanding firms to carry insurance (covenant requirements), ii) that firms may manage risk using credit lines instead of insurance and, iii) the effect that tax rules may have on insurance demand when considering firms 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 exploiting the thresholds around the credit rating categories. 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. Estimating our regression discontinuity model, we find that firms that are just above a cutoff, and

[1]This classification is made by the credit rating agency, from an underlying continuous measure which they use to estimate the probability of default, and divides all Swedish firms in to 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).

thus are more constrained, have 0.030–0.056% higher premium-to-assets. This causal effect is sizable and corresponds to 5–14% of the sample average.

We perform three additional tests to further understand our mechanism. First, as financially constrained firms are more sensitive to variability in internally generated funds, we test if the financing constraints-insurance demand channel is affected by industry-level cash flow volatility (e.g., Bates et al., 2009, Favara et al., 2021). Exploiting our regression discontinuity approach, we document that financially constrained firms in high cash flow volatility sectors spend over 50% more on insurance than similar firms in low cash flow volatility sectors. We also find that more constrained firms in our setting save a higher proportion of their cash flows than less constrained firms (following Almeida et al., 2004).

Second, we consider to what extent our proposed financing constraints mechanism is affected by financial distress. We follow Purnanandam (2008) and consider a highly leveraged firm located in a concentrated industry to be more likely to be financially distressed. Based on this approach, our results are not driven by firms more likely to be financially distressed. Furthermore, as described above, the firms that are most likely in distress (firms in the two worst credit rating categories) are already excluded from the sample. Finally, we show that our findings are not driven by insurers charging higher prices as firms become more constrained.

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 provide causal evidence on the role of financing constraints and risk management in a comprehensive sample of private firms. Given that insurance policies represent both the most widely cited direct cost of risk management, as well as the most common such product (Servaes et al., 2009), these findings provide important insights connecting financing 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.[2] While the role of financing opportunities and risk management have been studied, our findings show that there is a causal relationship from financing constraints on the demand for insurance.

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, Asai, 2019). Our comprehensive sample of private firms spanning a decade shed novel insight into the risk management of a, due to data constraints, 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,[3] we provide causal evidence of how financing constraints impact one of the most important elements of corporate risk management, namely insurance demand. Also, our sample of typically small, private firms allow us to focus on firms who are truly constrained (e.g., Farre-Mensa and Ljungqvist, 2016).

[2] Smith and Stulz (1985), Nance et al. (1993), Froot et al. (1993), Mian (1996), Tufano (1996), Géczy et al. (1997), Holmstrom and Tirole (2000), Guay and Kothari (2003), Rampini and Viswanathan (2010), Rampini et al. (2014), Doshi et al. (2018), Bodnar et al. (2019)

[3] Examples include capital investment (e.g., Fazzari et al., 1988), R&D investment (e.g., Brown et al., 2012), investment in inventory (e.g., Carpenter et al., 1998), accumulation of cash (e.g., Almeida et al., 2004), employment (e.g., Chodorow-Reich, 2014), labor misallocation (e.g., Caggese et al., 2019), total factor productivity (e.g., Krishnan et al., 2015), advertising (e.g., Fee et al., 2009), entrepreneurship (e.g., Kerr and Nanda, 2009), workplace safety (e.g., Cohn and Wardlaw, 2016), pollution (e.g., Xu and Kim, 2022).

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. This data contain information on firms' premiums and losses (see subsection A.1 for a background on corporate insurance). Second, we have balance sheet and income statement data based on firms' annual filings with the Swedish Companies Registration Office (Bolagsverket) from the Bisnode Serrano database. This data also contain information on number of workers, corporate structure, founding year, credit lines, collateralized debt, and NACE industry classification.

Third, we obtain tax return data provided by the Swedish tax agency which contain, among others, information on firms' net operating losses. Finally, we use data on firms' credit scores from the credit information agency, *Upplysningscentralen* (UC). UC provides credit ratings on all Swedish limited liability companies and their 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, iii) have non-missing data in 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 rating in the worst two rating categories (we describe this more below).[4] After merging the four data sources and applying the sample selection criteria

[4]Specifically we drop firms from sectors with NACE code 64–66. The sample selection rules are similar to other studies using similar data (Bach, 2014, Brown et al., 2021).

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 are reported in Table 2. We begin by noting that the typical firm in our sample is quite small. Average (median) number of workers is 24 (11).[5] The key outcome variable in our study is insurance demand which we measure as total premiums paid in year t divided by the end of period book value of total assets in year t (*Premium*).[6] 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%).

2.2 Measuring Financing Constraints

2.2.1 Data and Measurement

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 a given year. 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.[7] The *Risk forecast* measure is then used to create five risk classes:[8]

[5] 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 similar capital structure to the typical Swedish firm (median debt-to-assets and cash-to-assets is 57% and 15% compared to 64% and 14%). The industry distribution in our sample is similar to the Swedish economy's.

[6] This is in line with the literature, that typically normalizes by insured assets (Hoyt and Khang, 2000, Regan and Hur, 2007, Asai, 2019).

[7] 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).

[8] 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.

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 credit rating categories is equivalent to removing speculative debt and only focusing on investment grade borrowers.[9] Based on UC's three rating categories spanning from normal to very low 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) is 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 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 note that there is substantial within-firm variation in our financing constraints indicator. Around 70% of all firms experience at least one up- or downgrade during the sample period, a feature we exploit in our tests below.

[9] 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).

2.2.2 Characteristics of the Financing Constraint Measure

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) spend 0.40% relative to assets on insurance, compared 0.61% among the most constrained (category 3). However, the largest difference in premium to assets is between category 1 and 2. Average *Premium* is significantly higher in category 2 and 3 relative to 1. The difference between category 2 and 3 is statistically indistinguishable from zero.

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 size and age (e.g., Hadlock and Pierce, 2010), and how they vary across our constraints measure. Average firm age and size in the least constrained group is 25 years and 32 workers. Average age of firms in categories two and three is 20 and 16 years respectively. In terms of firm size, category two and three firms employ around 20 workers, implying that category one firms are 50% larger.

We move on to consider growth options (proxied by sales growth and the capital investment to asset ratio). Average sales growth increases from 2.9% to 4.0% from category one to two to 5.1% in category three. 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%). There is also increasing debt to assets 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, smaller, generate less internal cash flow, pay lower dividends, hold less cash and 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:

$$Premium_{it} = \beta Constrained_{it} + \eta_i + \eta_{jt} + \epsilon_{it}. \tag{1}$$

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 the value 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, Scharfstein, and Stein, 1993). In other words, we predict a positive relationship between *Constrained* and *Premium*, $\beta > 0$.

While the firm fixed-effects remove potential unobserved confounding, 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 firms' insurance demand might be correlated with constraints if the firm is purchasing insurance in anticipation of more profitable investment opportunities. In order to circumvent these concerns and investigate the causal relationship between financing constraints and insurance demand we adopt a regression discontinuity design.

We follow Caggese et al. (2019) and exploit a discontinuity in the underlying *risk forecast* measure. We analyze firms around either the cutoff between categories 1 and 2, or the cutoff between categories 2 and 3. Theoretically, firms around the cutoff between the two categories are almost identical but differ in their discrete credit score (random assignment).

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 closet cutoff (Engist et al., 2021). We calculate the bandwidth using the method of Calonico et al. (2014).

We denote the outcome of firm i in year t by y_{it} (most of often measured as *Premium*). Let s_{igt} be the *risk default* 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 regression discontinuity model (Lee and Lemieux, 2010). This model is characterized by local linear regressions which allow slopes above and below the threshold to differ:

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

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. We follow Gelman and Imbens (2019) and primarily use a linear specification since higher order polynomial have been shown to be sensitive to changes in the specification. Furthermore, we follow Calonico et al. (2017) and use a data-driven bandwidth selection for which a simple linear regression can provide a consistent estimate. See subsection A.2 and subsection A.3 for detailed descriptions of the underlying assumptions for estimating Equation 2.

3.2 Baseline 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 demand more 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* generate a β of 0.012.

Many risk management studies focus on the differential effect based on firm size (Mian, 1996, Géczy, Minton, and Schrand, 1997). We therefore control for firm size (log of number of workers) 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 financing constraints is associated with higher demand for insurance.

Next we proceed and exploit how firm-years just around the cut-offs behave and estimate Equation 2. We consider 0.10 (0.60) to 0.40 (0.90) around the first (second) discontinuity. We report results with different polynomials in columns (4)–(6). Using a pooled regression discontinuity approach, the coefficients are all highly statistically significant and fall between 0.040–0.054 depending on the choice of polynomial. These represent large effects and implies 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.

Next, we focus on the discontinuities around category 1–2 and 2–3 separately. We begin in Figure B.3 and show that around the (0.25%) cutoff between constraints category 1 and 2 there is a sharp difference in premium-to-assets. 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 B.3 underscores that more constrained firms have a higher premium to asset ratio. We report the same graph around the (0.75%) cutoff between the second and third category in the same figure. While there is a jump in premium-to-assets, it is visibly smaller than in Figure B.4.

We proceed and 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 from Calonico et al. (2017) (a fixed bandwidth of 0.15). The point estimates around the first cutoff are 0.055 and 0.053 respectively and highly statistically significant. The estimated coefficients for the second change are 0.026 and 0.021 and are statistically insignificant.

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%) more in premium-to-assets relative to a firm just below the first (second) cutoff. If we instead evaluate the economic magnitude of our results relative to the relevant category (i.e., a firm just above category 1 (2) should be compared with average premium to assets in category 1 (2)) 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 ways of 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 and financial assets from the book value of assets when scaling total premiums.

Next, we consider that Swedish tax and accounting rules enable fixed assets (excluding 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 five and six 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. 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 banks demanding firms to purchase insurance in order to access (collateralized) debt. Since the bank would lose seniority rights if the insured asset is destroyed, the bank 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. In order to rule out that our mechanism is driven by banks' covenant requirements we augment Equation 1 with an indicator variable taking on the value one if a firm has collateralized debt and present the result in column 1 (using similar data as Cerqueiro et al., 2016). If our mechanism in fact 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 results we also control for the ratio of collateralized debt to assets and find similar results. In the appendix we also report results from studying the collateralized debt to asset ratio around the cutoff between the best and the second-best constraints category. In Figure B.6 we see that there is no jump in the collateralized debt to asset ratio at the cutoff.

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 affect 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. 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 stronger incentive to purchase insurance. Specifically, following Tufano (1996), Géczy et al. (1997), 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 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 Additional Tests: Cash Flow Volatility, Financial Distress and Insurance Supply

Our findings support the idea that financing constraints lead firms to purchase more insurance. To further evaluate this mechanism we carry out four additional sets of tests.

4.1 Cash Flow Volatility

Central to the main mechanism of this study is that a tightening of financing constraints, increasing the wedge between the cost of external and internal funds, makes a firm more sensitive to fluctuations in internally generated funds. Therefore, if the channel we study is truly operational there should be a stronger effect of financing constraints for firms in sectors with more volatile cash flows. To test this potential channel, we measure cash flow volatility by taking the standard deviation in cash flow over assets over the sample period for each firm (similarly as Bates et al., 2009) and construct an indicator variable taking on the value one (zero) if the firm is above (below) the median in industry cash flow volatility (*High industry cash flow volatility*).[10]

In column 1 in Table 8 we report estimates where we augment Equation 1 with the interaction term between *Constrained* and *High industry cash flow volatility* (the uninteracted *High industry cash flow volatility* is absorbed by the firm fixed effect). In column 1, the coefficient for *Constrained* captures how firms with lower cash flow volatility respond. The estimate is slightly smaller than in the baseline case in Table 4 (0.010 compared to 0.012). More importantly, the interaction term with industry cash flow volatility is positive and (marginally) statistically significant. The effect of financing constraints on the demand for insurance is 0.014 in high cash flow volatility sectors compared to 0.010 in low.

Finally, in columns 2 and 3 we we turn to our regression discontinuity framework and split the sample in to high and low cash flow volatility sectors using the same indicator variable as in column 1 and estimate Equation 2. This way we explore a causal interpretation based of the differential cash flow volatility result in columns

[10]Specifically, we consider four digit NACE industries with at least 100 firms. Furthermore, mitigating the impact of cash flow volatility is an important motivation for risk management (Smith and Stulz, 1985, Froot et al., 1993, Servaes et al., 2009).

1 and 2. Indeed, the coefficient in the high relative to the low volatility sub-sample is higher (0.060 compared to 0.025). This differential result across firms operating in industries with different levels of cash flow volatility is indeed economically meaningful. Financially constrained firms in high volatility sectors demand more insurance than similarly constrained firms in low volatility sectors.

4.2 Financing Constraints and Saving Cash

Financially constrained firms have been shown to have a higher propensity to save cash from its cash flows (Almeida et al., 2004). Given the centrality of the sensitivity of internal finance in our mechanism we follow Almeida et al. (2004) and examine if more financially constrained firms in our sample save more of their internally generated cash flows than less constrained firms. This test also provides a robustness test of our interpretation that we are capturing financing constraints and also serves as an important evaluation of our financing constraints measure.

We follow the baseline specification in Almeida et al. (2004) as close as possible and report the results in Table 9. Change in cash holdings to assets is the dependent variable and the key explanatory variables are the cash flow to assets ratio, our financing constraints measure and the product of the two. If our measure captures financing constraints as in Almeida et al. (2004) we expect a positive and significant coefficient on the interaction term. As predicted, we do retrieve a positive and highly significant coefficient on the interaction between cash flow to assets and *Constrained*.

4.3 Financing Constraints or Financial Distress?

Next, we address whether our findings capture financing constraints or rather financial distress. We already have addressed this tension in our main approach by i) dropping the two categories of firms with the highest default probability, and ii) showing in section 2 that firms with higher values in *Constrained* appear to be financially constrained rather than distressed. However, we still carry out a more direct test here.[11]

We follow Opler and Titman (1994) and Purnanandam (2008) and measure a firm's likelihood to be in financial distress if it has high leverage and operates in a concentrated industry. An industry's concentration proxies for the likelihood of distress as firms in more concentrated industries tend to, e.g., be more likely to produce specialized products (leading to higher financial distress costs) and more vulnerable to losing their competitive position. These factors lead Purnanandam (2008) to predict a higher demand for risk management in firms more likely to be distressed. We measure high leverage as a firm having a debt-to-assets ratio above the median (*High leverage*) and we capture the impact of industry concentration if the firm is located in an industry above the median in concentration measured as a Herfindahl Index at the four digit industry level (*High concentration*).

We split our sample in to firms more (less) likely to be financially distressed in columns 1–2 (3–4) and estimate Equation 1 and Equation 2 in Table 10. Firms classified as both high leverage and operating in a highly concentrated industry are classified as distressed. The financing constraints channel on insurance demand is still important in the sub-group of firms with a higher probability to be in financial distress. Most importantly, among the firms less likely to be financially distressed, i.e., with below median leverage and operating in a more competitive industry, our baseline findings from section 3 are robust.[12]

[11]Financial distress has been studied in the corporate insurance literature (e.g., Mayers and Smith, 1982, Hoyt and Khang, 2000, Regan and Hur, 2007, Aunon-Nerin and Ehling, 2008, Dong and Tomlin, 2012, Asai, 2019)

[12]The findings here are robust to considering alternative cutoffs for high leverage and concentration and to consider another widely used proxy for bankruptcy costs in the insurance demand finance literature, namely, working capital-to-assets instead of leverage.

4.4 Insurance Supply Effects

We conclude by addressing whether we are in fact picking up that insurers use credit scores to continuously alter premiums for their customers. Our results so far make such an interpretation challenging for a variety of reasons. First, we remove firms classified as having above normal risk (categories 4 and 5) 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 increase prices for a firm that goes from "Very low default risk" to "Low default risk".

Second, there is some support that insurers use the firms' financial conditions when set prices. However, this is primarily done to capture financial distress (e.g., Regan and Hur, 2007). Again, we have removed the firms most likely to be financially distressed and we show above that accounting for financial distress in our baseline regressions does not change our findings. Thus, it seems unlikely that insurers purposefully hike prices for firms with low default risk. Still, we proceed with a few additional tests and compile the results in Table 11.

We begin and consider whether the insurer places a greater weight on credit ratings in 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 rating may decrease. As a result, credit ratings can be an important factor for the pricing of insurance but its importance would decline over time. We therefore investigate if the importance of credit ratings falls over time as the insurer-client relationship matures by excluding the first two years that a firm is in the sample (Morris et al., 2017) as these years may allow the insurer to learn about its policyholder. We find similar results when we exclude the first two years (results compiled in columns 1 and 2).

Next, we design a test to explore how sensitive premiums are to changing conditions for the firm. As premiums reflect discounted expected losses we remove all firms that have a loss during our sample period and re-estimate our baseline specifications. The idea is that firms without a loss should be the least likely to receive a pricing change from the insurer. Thus, if our baseline findings also show up in this sub-sample it is unlikely to be due to insurer pricing reasons. Our main findings are unchanged from removing all firms with a reported loss.

Finally, in columns 5–6 in Table 11 we address pricing power of the insurers. For an insurance company to be able to hike prices on existing customers (and also retain these customers), when they go from being rated as having a very low to a low default risk, would imply considerable market power. First, the Swedish insurance market is among the least concentrated (thus higher level of competition) in Europe (European Insurance and Occupational Pension Authority, 2020). In order to capture the fact that level of insurance competition can vary across regions we create an indicator variable taking on the value one if the firm is located in any of the three largest cities (Stockholm, Gothenburg and Malmö). If our findings are impacted by insurers changing prices we expect that outside the most competitive regions in Sweden there to be a larger effect. The interaction term between *Constrained* and the big city indicator variable is insignificant and close to zero.

Finally, we examine how claims and losses behave around ratings cutoffs. We find that claims to assets are similar above and below the cutoff (Figure B.7), the probability of having a loss is also similar around the cutoff (Figure B.8) and finally, total claims are similar across the cutoff as well (Figure B.9). This suggests that the insurer's expected costs do not change for firms when they cross the cutoff. Based on the findings here, we expect supply effects not to be driving our results.

5 Conclusion

We examine the causal connection between financing constraints and corporate insurance demand. We find that as financing constraints tightens, firms purchase more insurance. Our findings are based on within firm panel regression estimates and using a regression discontinuity design. The underlying logic for our findings is that as a firm becomes financially constrained, the wedge between the cost of external and internal sources of finance widens, making the firm more sensitive to variability in cash flows. Consistent with this mechanism we find that financially constrained firms i) located in high cash flow volatility sectors demand more insurance than similar firms in low volatility sectors and, ii) save more cash out of their cash flows. Our study has implications for a number of related and important literatures.

The evidence is particularly relevant for the literature on the risk management of financially constrained firms starting with Froot et al. (1993). Studies focusing on narrower samples of firms, where risk management is measured through hedging, typically finds that *ex-ante* less constrained firms (often measured as large firms) do more risk management (e.g., Nance et al., 1993, Rampini et al., 2014). Our work shows financially constrained firms, using a large, representative sample of the economy, do purchase 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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5.1 Tables

Table 1: Description of Variables

Variable Name	Description	Source
Premium	Total premium divided by book value of end-of-year total assets	Serrano and Insurance Company
Premium Less Cash	Total premium divided by book value of end-of-year total assets minus cash holdings	Serrano and Insurance Company
Premium Less Financial Assets	Total premium divided by book value of end-of-year total assets minus book value of financial assets	Serrano and Insurance Company
Premium Adjusted for Age	Total premium divided by book value of total assets for the last three calendar years	Serrano and Insurance Company
Constrained	Credit rating of January 1 from Upplysningscentralen, where 1 is the best score, 2 is the second-best score and 3 is the worst score.	Upplysningscentralen
Collateralized Debt	Book value of end-of year secured debt	Serrano
Credit Line	Total credit limit	Serrano
Net Operating Losses	Value of taxable accumulated losses	Serrano
High Cash Flow Volatility	Dummy if cash flow exceeds the 4-digit industry median	Serrano
Firm Age	Years since firm foundation	Serrano
Number of Workers	Number of employees	Serrano
Sales Growth	Change in sales between two years divided by sales of the previous year	Serrano
Investment to Assets	Change in physical capital plus depreciation divided by book value of total assets	Serrano
Cash Flow to Assets	Profits plus depreciation divided by book value of total assets	Serrano
Dividends to Assets	Dividends paid out divided by book value of total assets	Serrano
Debt to Assets	Total debt divided by book value of total assets	Serrano
Cash to Assets	Cash holdings divided by book value of total assets	Serrano
High Leverage	Dummy if total debt to assets XXXXX	Serrano
High Concentration Industry	Dummy if 4-digit industry sales Herfindahl–Hirschman index exceeds XXXXXX	Serrano
Distressed Firm	Dummy if the firm is both high leverage and if the industry is highly concentrated	Serrano

Notes. Table 1 shows the variables used in the paper, description and source. The sources are Serrano, Statistiska centralbyrån (SCB), Upplysningscentralen (UC) or and an unnamed insurance company. Nominal variables are deflated using the 2010 CPI deflator from SCB. All variables are on an annual basis.

Table 2: Summary Statistics of Sample Firms

	Observations	Mean	Median	Std Dev	Min	Max
Premium	158,836	0.52	0.38	0.48	0.01	2.59
Premium to Assets Minus Cash	158,826	0.73	0.50	0.78	0.01	4.56
Premium to Nonfinancial Assets	158,833	0.55	0.41	0.51	0.01	2.79
Premium to Age-Adjusted Assets	142,569	0.52	0.39	0.46	0.01	2.42
Constrained	158,836	1.87	2.00	0.80	1.00	3.00
Risk Forecast	158,836	0.64	0.39	0.69	0.01	3.04
Has Collateralized Debt	142,695	77.46	100.00	41.78	0.00	100.00
Has Credit Line	158,836	47.87	0.00	49.95	0.00	100.00
Has Net Operating Loss	158,836	9.72	0.00	29.63	0.00	100.00
High Cash Flow Volatility	151,994	53.47	100.00	49.88	0.00	100.00
Firm Age	158,836	20.83	18.00	15.01	1.00	100.00
Employees	158,836	24.37	11.00	167.08	6.00	10,000.00
Sales Growth	122,216	3.76	2.29	18.37	-46.24	77.80
Investment to Assets	122,221	3.87	1.21	7.41	-13.94	36.56
Cash Flow to Assets	158,790	10.98	10.19	11.25	-30.69	45.61
Dividends to Assets	158,836	4.86	0.00	8.21	0.00	40.58
Debt to Assets	158,834	56.53	57.08	21.93	9.71	99.46
Cash to Assets	158,831	20.66	15.49	19.54	0.01	79.09
High Leverage	158,836	50.00	0.00	50.00	0.00	100.00
High Concentration	158,836	48.08	0.00	49.96	0.00	100.00
Distressed	158,836	24.04	0.00	42.74	0.00	100.00

Notes. Table 2 reports summary statistics for the key variables included in this study. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The sample is restricted to insured non-financial non-governmental limited liability companies with more than five employees, positive sales, assets, debt, cash, number of establishments and labor costs, as well as average financial expenses to debt below 100%. We convert all monetary values to 2010 SEK using the consumer price index from Statistics Sweden. The maximum values for firm age and employees are censored to ensure confidentiality. Table 1 provides detailed variable definitions.

Table 3: Summary Statistics of Sample Firms by Credit Rating

	All	1	2	3	1 vs 2	P 1-2	2 vs 3	P 2-3
Premium	0.52	0.40	0.57	0.61	-0.17	0.00	-0.04	0.00
Firm Age	20.83	24.88	19.78	16.19	5.10	0.00	3.59	0.00
Employees	24.37	31.75	19.61	19.45	12.14	0.00	0.16	0.76
Sales Growth	3.76	2.88	3.95	5.09	-1.07	0.00	-1.14	0.00
Investment to Assets	3.87	3.37	4.02	4.58	-0.65	0.00	-0.57	0.00
Cash Flow to Assets	10.98	12.72	10.70	8.75	2.02	0.00	1.95	0.00
Dividends to Assets	4.86	6.69	4.43	2.68	2.27	0.00	1.74	0.00
Debt to Assets	56.53	44.38	59.75	70.44	-15.38	0.00	-10.69	0.00
Cash to Assets	20.66	27.08	18.86	13.43	8.22	0.00	5.43	0.00
Has collateralized Debt	77.46	68.41	81.24	85.37	-12.83	0.00	-4.13	0.00
Has Credit Line	47.87	34.27	53.40	60.98	-19.13	0.00	-7.57	0.00
Has Net Operating Loss	9.72	4.75	9.03	17.95	-4.28	0.00	-8.92	0.00
High Cash Flow Volatility	53.47	53.15	53.91	53.38	-0.77	0.01	0.53	0.11
High Leverage	50.00	26.50	55.54	77.77	-29.04	0.00	-22.22	0.00
High Concentration	48.08	50.95	46.22	46.20	4.73	0.00	0.01	0.97
Distressed	24.04	14.12	26.19	36.02	-12.07	0.00	-9.83	0.00

Table 3 reports averages the key variables included in this study for the first three credit scores. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The sample is restricted to insured non-financial non-governmental limited liability companies with more than five employees, positive sales, assets, debt, cash, number of establishments and labor costs, as well as average financial expenses to debt below 100%. Column (5) shows the mean difference between credit score two and one, while columns (6) show the mean difference between credit score three and two. We convert all monetary values to 2010 SEK using the consumer price index from Statistics Sweden. Table 1 provides detailed variable definitions.

Table 4: Insurance Demand and Credit Scores

	Premium to Assets						
	OLS			RDD			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constrained	0.096***	0.012***	0.011***	0.054***	0.044**	0.040**	0.047***
	(0.002)	(0.001)	(0.001)	(0.012)	(0.018)	(0.020)	(0.014)
Log Employees			-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	0.013
Observations	158,834	152,193	152,193	158,836	158,836	158,836	76,883

Table 4 reports ordinary least squares (OLS) estimates of Equation 1. Premium to total assets is the dependent variable. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. Column (1) has the credit score between 1–3 as the independent variable and includes industry-year fixed effects, column (2) also includes firm fixed effects, column (3) includes the log of number of workers, column (4) shows the regression-discontinuity (RDD) estimate around the pooled cutoffs between the first and second credit score cutoffs, using a polynomial of order one and the optimal bandwidth from Calonico et al. (2014, 2017), column (5) shows the RD estimate using a polynomial of order two, column (6) shows the RD estimate using a polynomial of order three and column (7) shows the RDD estimate using a polynomial of order one and a bandwidth of 0.15 percentage points around each cutoff. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Insurance Demand and Credit Scores (Both Cutoffs)

	Around 0.25%		Around 0.75%	
	(1)	(2)	(3)	(4)
Lower Credit Score	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 regression discontinuity estimates (RDD) of Equation 2. Premium to total assets is the dependent variable. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. Columns (1) and (2) show RDD estimates from the first credit score cutoff (0.25%), while columns (3) and (4) show the estimates from the second cutoff (0.75%). Columns (1) and (3) use the optimal bandwidth from Calonico et al. (2014, 2017) while columns (2) and (4) use a bandwidth of 0.15 percentage points. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Robustness Checks

	Premium / Assets-Cash		Premium / Assets-Financial Assets		Premium / Age-Adjusted Assets	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	RDD	OLS	RDD	OLS	RDD
Constrained	0.012***	0.086***	0.011***	0.057***	0.022***	0.050***
	(0.002)	(0.018)	(0.001)	(0.013)	(0.001)	(0.012)
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	136,354	142,569

Table 6 reports ordinary least squares (OLS) and Regression Discontinuity Design (RDD) estimates. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The dependent variable is premium divided by total assets minus cash in columns (1) and (2), premium divided by non-financial assets in columns (3) and (4), and premium divided by the average of total assets between years t, t-1 and t-2 in columns (5) and (6). Columns (1), (3) and (5) have the credit score between 1–3 as the independent variable and include controls for firm and industry-year fixed effects. Columns (2), (4) and (6) have the distance from the nearest credit score cutoff (0.25% or 0.75%) as the running variable. The estimations include polynomials of order one and use the optimal bandwidth from Calonico et al. (2014, 2017). Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Channels

	Premium to Assets		
	(1)	(2)	(3)
	Collateralized Debt	Credit Lines	Net Operating Loss
Constrained	0.011***	0.012***	0.011***
	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes
R-Squared	0.842	0.836	0.836
Observations	136,473	152,193	152,193

Table 7 reports ordinary least squares (OLS) estimates of Equation 1. Premium to total assets is the dependent variable. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. All specifications control for firm and industry-year fixed effects. Column (1) includes a dummy if the firm has collateralized debt, column (2) includes a dummy if the firm has a credit line, and column (3) includes a dummy if the firm has net operating losses. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Cash Flow Volatility

	Premium to Assets		
	(1)	(2)	(3)
	Indicator	High Cash Flow Volatility	Low Cash Flow Volatility
Constrained	0.010***	0.060***	0.025*
	(0.002)	(0.018)	(0.015)
High Volatility × Constrained	0.004*		
	(0.002)		
Polynomials		1	1
Firm Fixed Effects	Yes	No	No
Industry-Year Fixed Effects	Yes	No	No
Robust p-Value		0.005	0.193
Observations	145,583	75,849	76,145

Table 8 reports ordinary least squares (OLS) and Regression Discontinuity Design (RDD) estimates. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The dependent variable is premium divided by total assets. Column (1) has the credit score between 1–3 as the independent variable and include controls for firm and industry-year fixed effects. Columns (2) and (3) have the distance from the nearest credit score cutoff (0.25% or 0.75%) as the running variable. Column (1) includes a dummy if the firm is in an industry with high cash flow and its interaction with the constrained variable, firm and industry-year fixed effects. Column (2) shows the RD estimates, with the sample restricted to firms in industries with high cash flow volatility, while column (3) restricts the sample to firms in industries with low cash flow volatility. The estimations include polynomials of order one and use the optimal bandwidth from Calonico et al. (2014, 2017). Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Cash Flow Sensitivity

	Cash to Assets		
	(1)	(2)	(3)
	Industry-Year FE	Firm FE	Additional Controls
Cash Flow	0.086***	0.198***	0.182***
	(0.009)	(0.015)	(0.015)
Constrained	0.008***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)
Cash Flow × Constrained	0.033***	0.030***	0.029***
	(0.005)	(0.007)	(0.007)
Sales Growth			0.043***
			(0.003)
Log Employees			-0.013***
			(0.002)
Firm Fixed Effects	No	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes
R-Squared	0.030	-0.034	-0.029
Observations	117,793	112,567	112,564

Table 9 reports ordinary least squares (OLS) estimates. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The change in the cash to total assets ratio is the dependent variable. All columns have the credit score between 1–3 as the independent variable and include industry-year fixed effects. Column (1) includes cash flow and the interaction with credit score, column (2) also includes firm fixed effects and column (3) also control for sales growth, the log of the number of employees and firm fixed effects. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Distress

	Premium to Assets			
	High Concentration and Leverage		Low Concentration and Leverage	
	(1)	(2)	(3)	(4)
	OLS	RDD	OLS	RDD
Constrained	0.007***	0.034*	0.006***	0.032*
	(0.002)	(0.019)	(0.002)	(0.019)
Polynomials		1		1
Firm Fixed Effects	Yes	No	Yes	No
Industry-Year Fixed Effects	Yes	No	Yes	No
Robust p-Value		0.057		0.078
Observations	34,111	38,191	37,923	41,236

Table 10 reports ordinary least squares (OLS) and Regression Discontinuity Design (RDD) estimates. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The dependent variable is premium divided by total assets. Columns (1) and (3) have the credit score between 1–3 as the independent variable and include controls for firm and industry-year fixed effects. Columns (2) and (4) have the distance from the nearest credit score cutoff (0.25% or 0.75%) as the running variable. The estimations include polynomials of order one and use the optimal bandwidth from Calonico et al. (2014, 2017). Columns (1) and (2) restrict the sample to firms that have high leverage and are in industries with high concentration, while columns (3) and (4) exclude those observations. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Demand Channels

	Premium to Assets					
	Without First Two Years		Firms Without Losses		Large Cities	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	RDD	OLS	RDD	OLS	Only Large Cities (RDD)
Constrained	0.010***	0.047***	0.013***	0.063***	0.014***	0.038**
	(0.002)	(0.014)	(0.002)	(0.016)	(0.002)	(0.016)
Big City					0.001	
					(0.016)	
Big City × Constrained					-0.003	
					(0.002)	
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		0.004		0.074
Observations	93,023	97,058	93,892	100,059	152,193	88,209

Table 11 reports ordinary least squares (OLS) and Regression Discontinuity Design (RDD) estimates. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The dependent variable is premium divided by total assets. Columns (1), (3) and (5) have the credit score between 1–3 as the independent variable and include controls for firm and industry-year fixed effects. Columns (2), (4) and (6) have the distance from the nearest credit score cutoff (0.25% or 0.75%) as the running variable. The estimations include polynomials of order one and use the optimal bandwidth from Calonico et al. (2014, 2017). Columns (1) and (2) exclude the first two years a firm is in our sample, columns (3) and (4) only include firms that do not experience a loss in our sample, column (5) include a dummy if the firm is in one of the three major cities in Sweden and its interaction with the constrained variable and column (6) restricts the sample to firms in the three major cities. Table 1 provides detailed variable definitions. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

A.1 Corporate insurance

A particular form of risk that firms face are risks to its physical capital. Such losses can be of considerable size. They may also reduce a firm's ability to use its assets as collateral. By purchasing insurance a firm will be able to follow through with its planned investments and finance these from the insurer's compensation, even in the case that its physical assets are destroyed.[13] To study firms' demand for commercial insurance[14], we look at policies 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, leakage but also theft and robbery. In addition, firms can purchase business interruption insurance that covers the loss of income following an insured event.[15]

Insurance premiums are set to reflect an individual firms' assets and risks for incurring an insured claim. Furthermore, policyholders can decide on deductibles and limits to coverage.[16] These choices impact insurance premiums. Insurers help policyholders to minimize losses by advising them with respect to loss prevention. 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. Insurance is tightly regulated to reduce fraud and abuse. In contrast to other risk management products, for instance currency derivatives, insurance policies cover firm-specific risk; cannot be used for speculation; and policyholders are not required to post collateral in order to engage in risk management.[17] 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 a compensation to equal time 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). We expect firms that face greater financial constraints purchase more insurance.

[13]Insurance may even impact the willingness of investing into risky projects as Cole et al. (2017) shows in the context of agricultural insurance.

[14]This type of insurance is also referred to as property and casualty insurance

[15]The policies that are part of this study have exemptions for vehicles or losses caused by natural catastrophes (such as flooding and earthquakes), terrorism or cyber risk.

[16]Aunon-Nerin and Ehling (2008) investigate empirically how firms choose upper limits and deductibles or coinsurance for their insurance contracts. Firms may also invest in loss reduction or loss prevention.

[17]Rampini and Viswanathan (2010), Rampini et al. (2014) discuss risk management under financing constraints if collateral has to be posted.

A.2 The Distribution of Risk Forecasts

Figure B.5 shows the distribution of the risk forecast, as probabilities between 0% and 0.5%. The thick line at 0.25% shows the cutoff between credit scores 1 and 2. We see that there are more firms with the best credit score compared to firms that have the second best in this interval.

Figure B.5 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. 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 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.[18] The pure number of factors and their unknown weighing makes strategic manipulation very difficult. Secondly, the frequent changes in a firm's credit rating, about 70% of firms change their credit rating while they are in our sample, suggest that strategic manipulation, if possible, is far from perfect. Third, the rules for creating the risk forecast, for instance, the weighing of different variables, is not public information.

Instead, the observed bunching can be explained by the details in 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 continuous of top-rated firms is updated less frequently, which means it is somewhat harder to be downgraded than upgraded. This explains the greater density above the cutoff between the first and second best credit rating.

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 firm's propensity

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

to manipulate and 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 which should be unaffected. We focus on industry, age and location. 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 and that our analysis not valid.

Table B.4 in the Appendix shows the fraction of firms in each industry to the left and to the right of the cut-off for the best credit rating (1). Firms to the left of the cut-off have the best credit rating while firms to the right of the cut-off have the second best credit rating. The table indicates that the distribution across industries is very similar, suggesting no clustering of particular industries on either side of the cutoff.

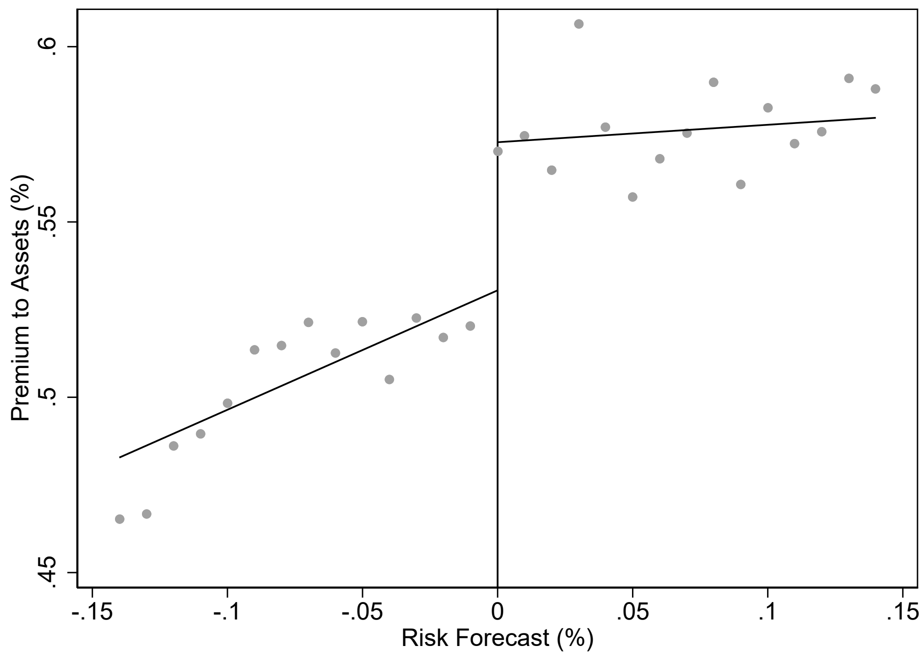
In addition, we look at firms by age at the cutoff. Since older firms have survived and thus are more likely to be of better financial health, we would be worried if firms to the left of the cutoff were much older than firms to the right. We see that this is not the case. Firms to the left are 22.38 years on average, while those to the right are 20.47 years old.

Another concern is that might be a systematic difference in firms' location, for instance firms that have better credit ratings may be more likely to be located in the capital city, Stockholm. We thus compare the share of firms located in the Stockholm region. We see that 14.40% of the firms to the left are in Stockholm, while 14.48% of those to the right are in Stockholm. We conclude that a similar fraction of firms are located in Stockholm.

Taken together, our balance checks further support that there are no systematic differences in firms to the left and to the right of the cutoff with respect to industry, age and location and that we do not expect our results invalidated due to what Lee and Lemieux (2010) call precise manipulation of the assignment variable.

A.4 Figures

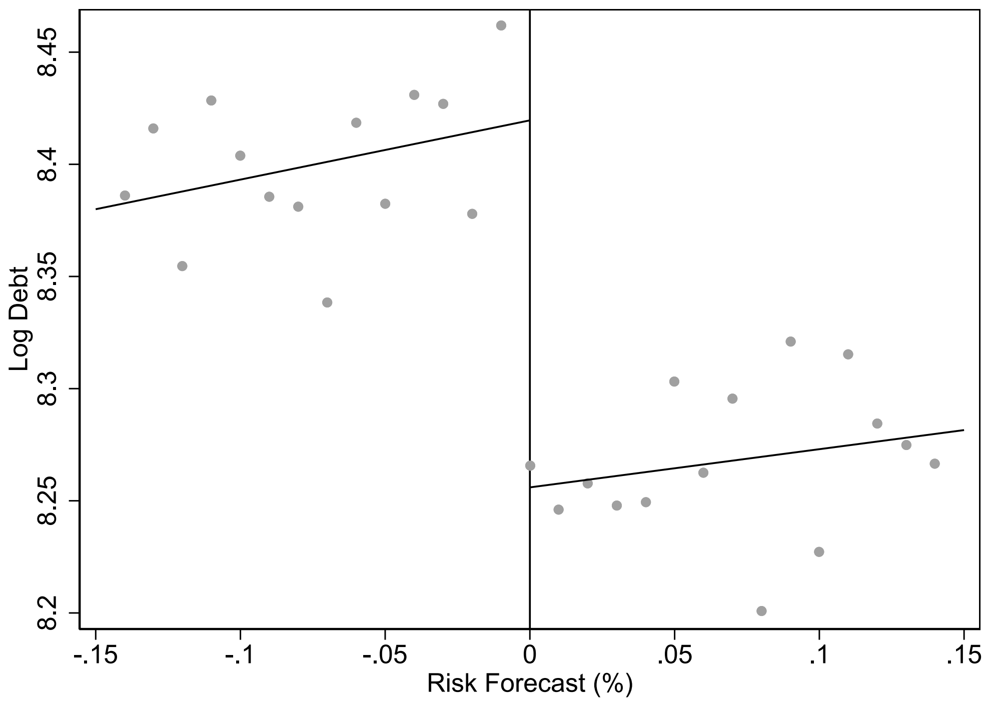
Figure B.1: Regression Discontinuity Plot, Premium to Asset Ratio



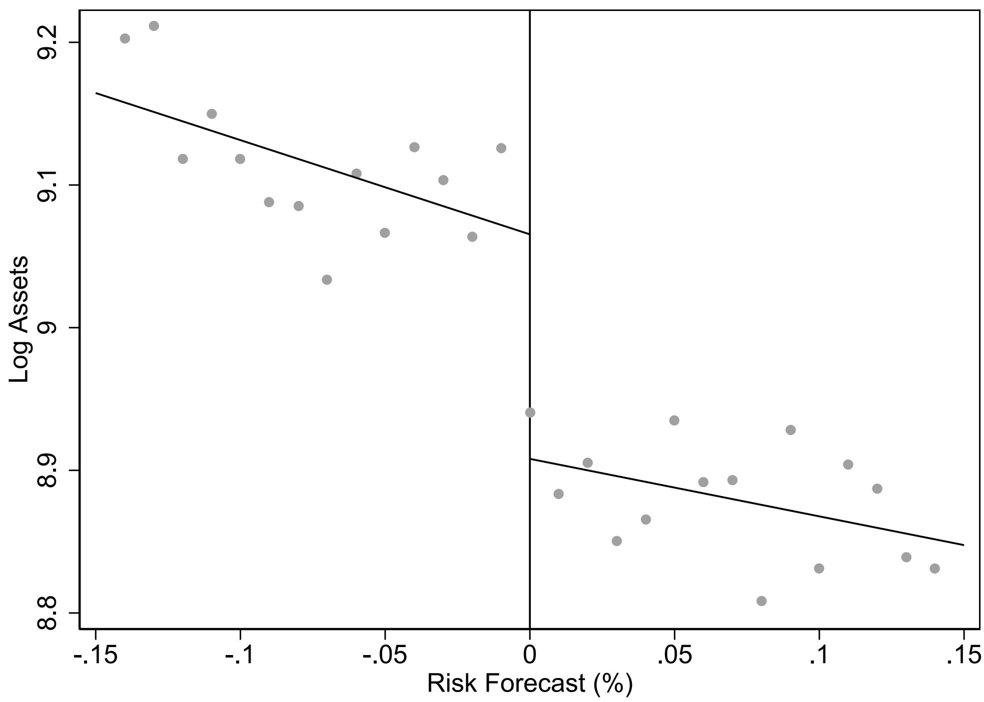
Notes. Figure B.1 shows regression-discontinuity estimates of Equation 2. Premium to total assets is the dependent variable. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.2: Regression Discontinuity Plots: Debt and Total Assets

(a) Log Debt



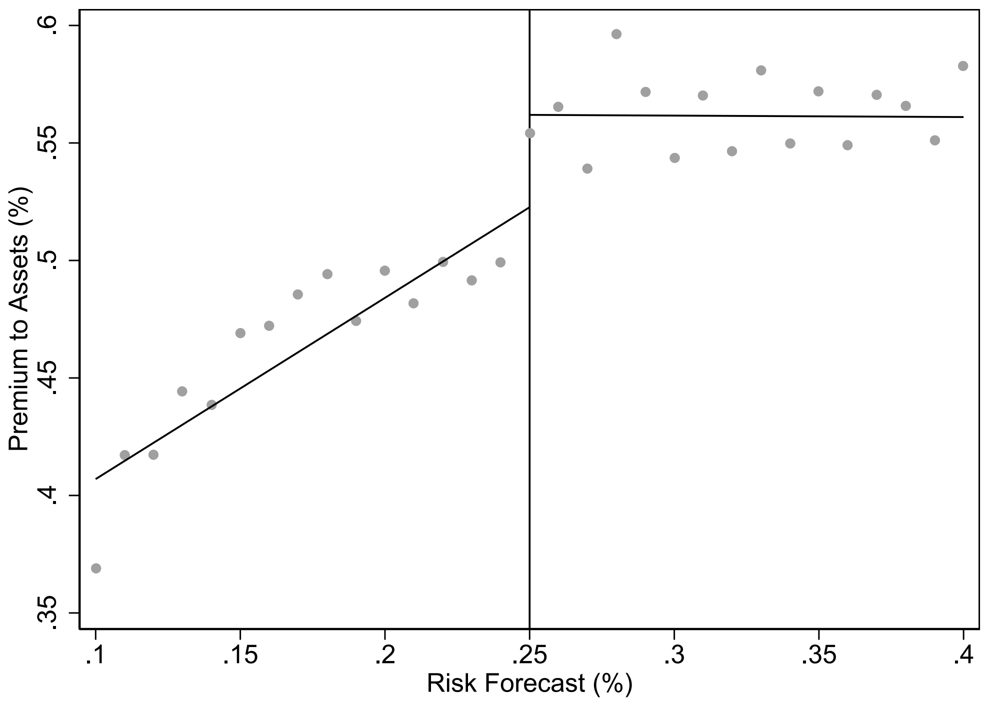
(b) Log Assets



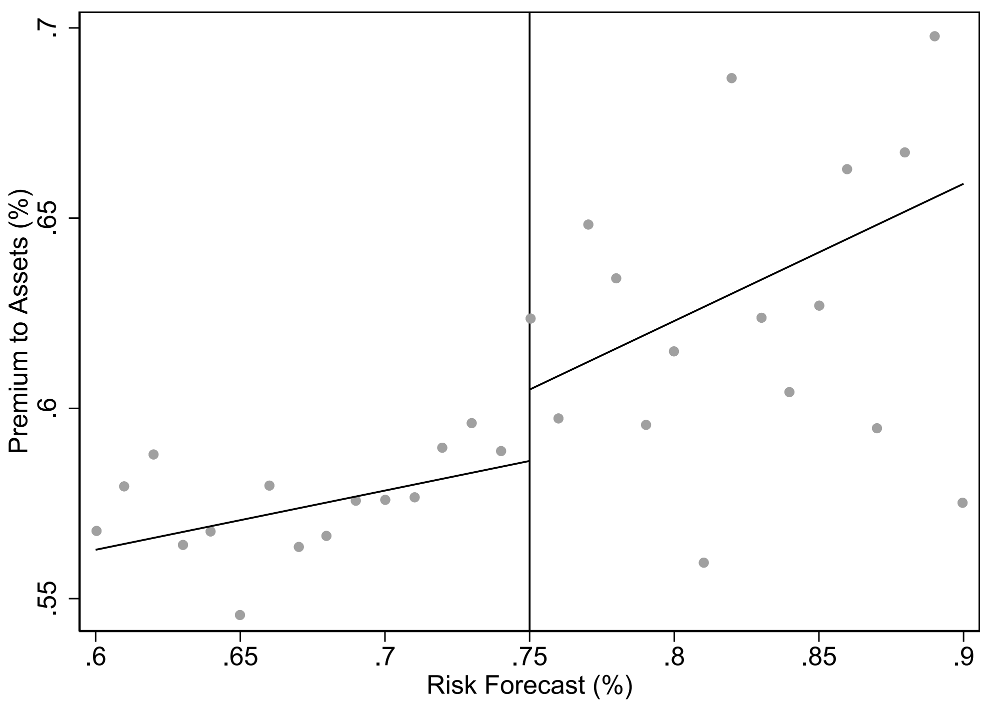
Notes. Figure B.2 shows regression-discontinuity estimates of Equation 2. Log debt and log assets are the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.3: Regression Discontinuity Plot, Premium to Asset Ratios

(a) 0.25% Cutoff

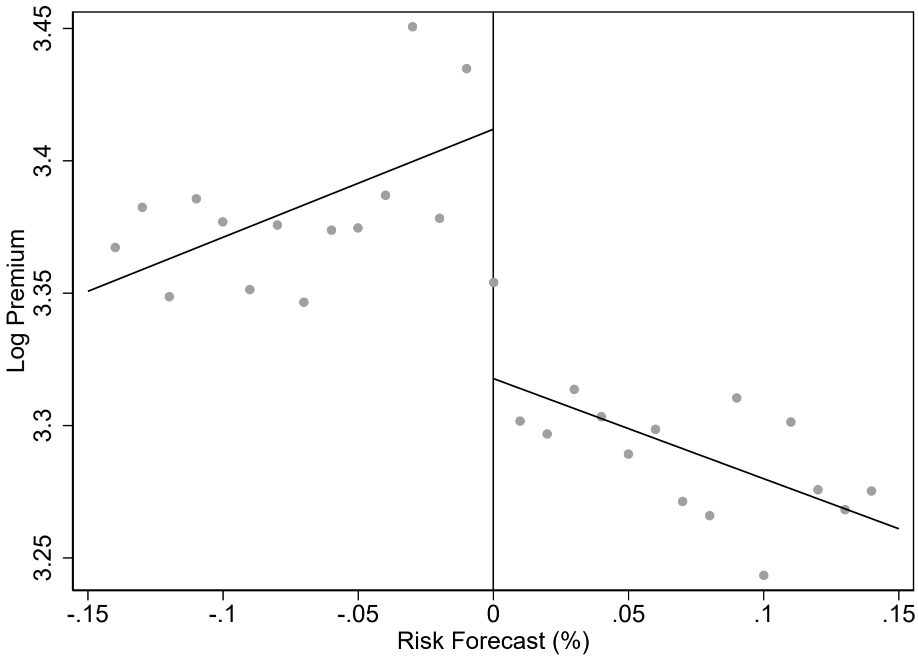


(b) 0.75% Cutoff



Notes. Figure B.3 shows regression-discontinuity estimates of Equation 2. Premium to total assets is the dependent variable. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. In panel (A), firms to the left (right) of the vertical line at 0.25% have the best (second-best) credit score, while in panel (B) firms to the left (right) of the vertical line at 0.75% have the second-best (third-best) credit score.

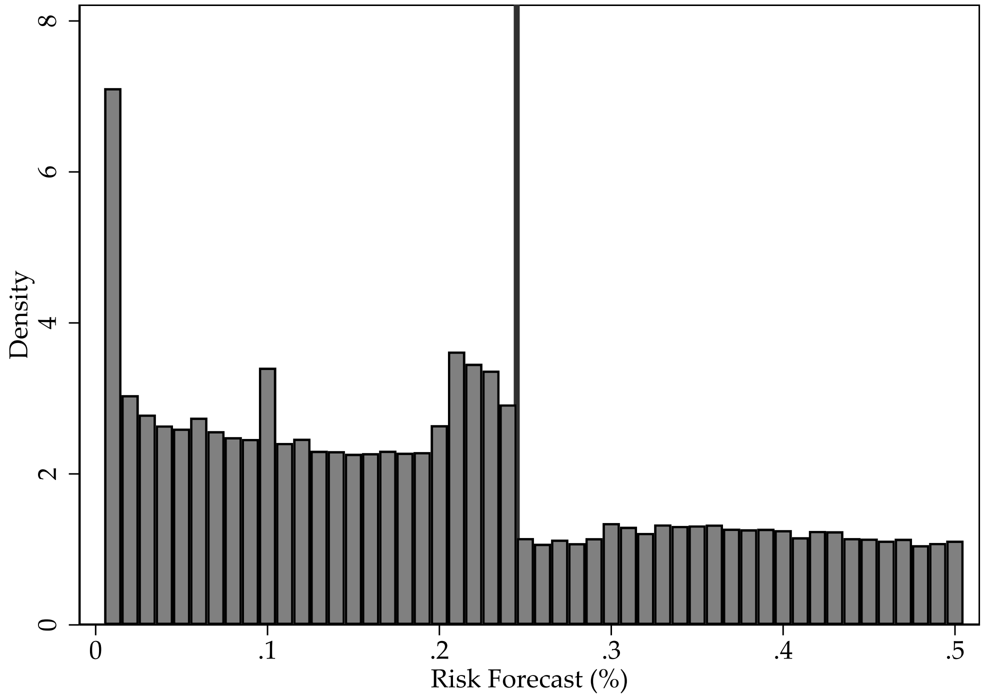
Figure B.4: Regression Discontinuity Plots: Premium



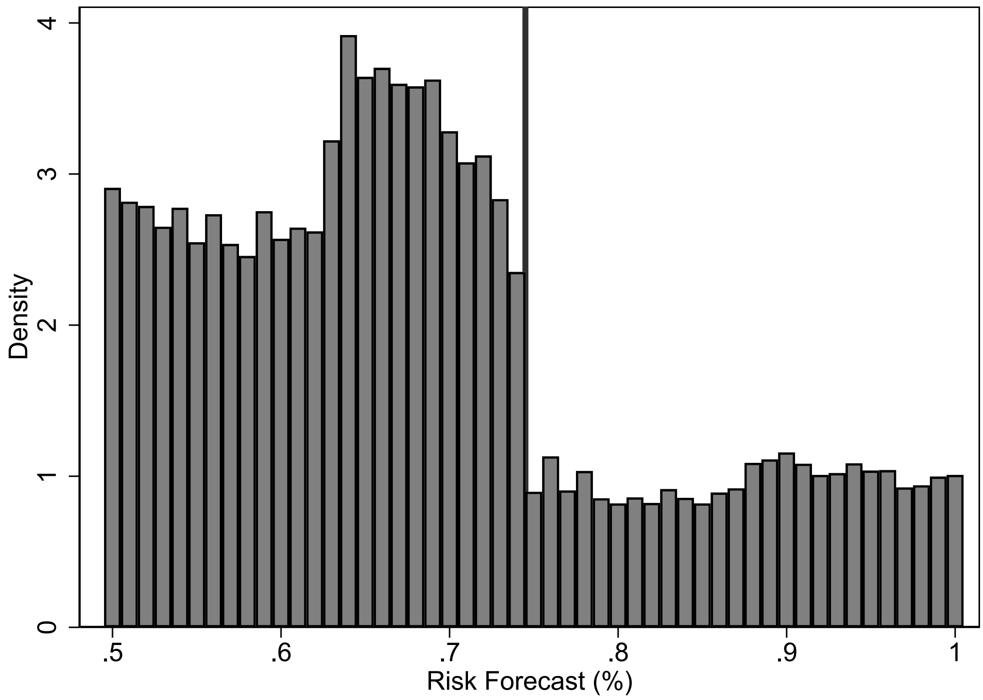
Notes. Figure B.4 shows regression-discontinuity estimates of Equation 2. Log premium is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.5: Distribution of Risk Forecast

(a) 0.25% Cutoff

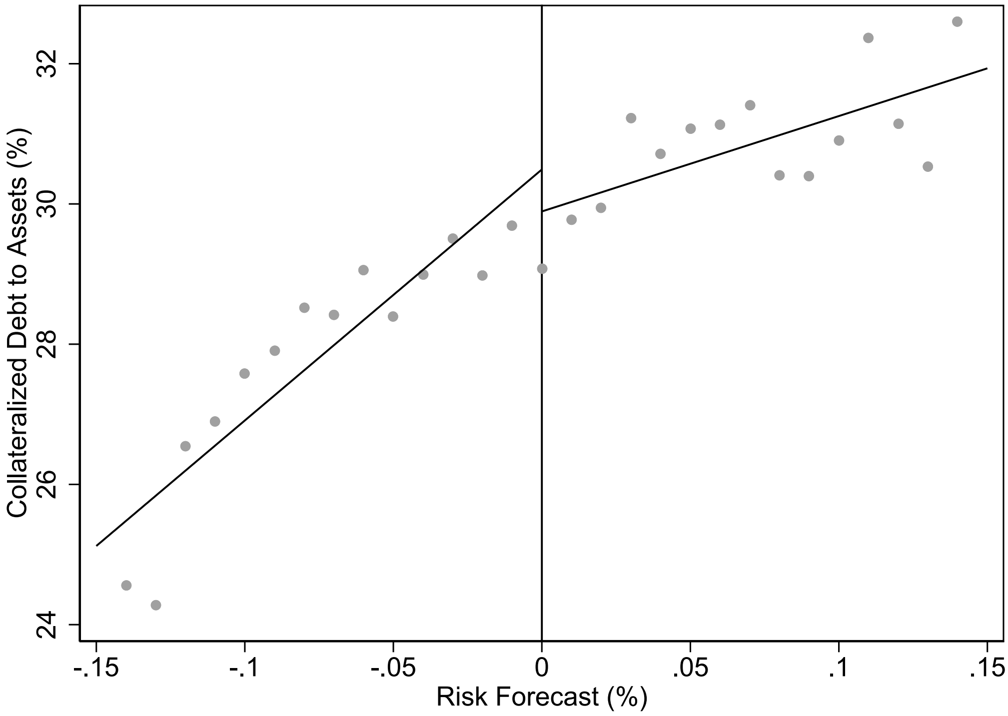


(b) 0.75% Cutoff



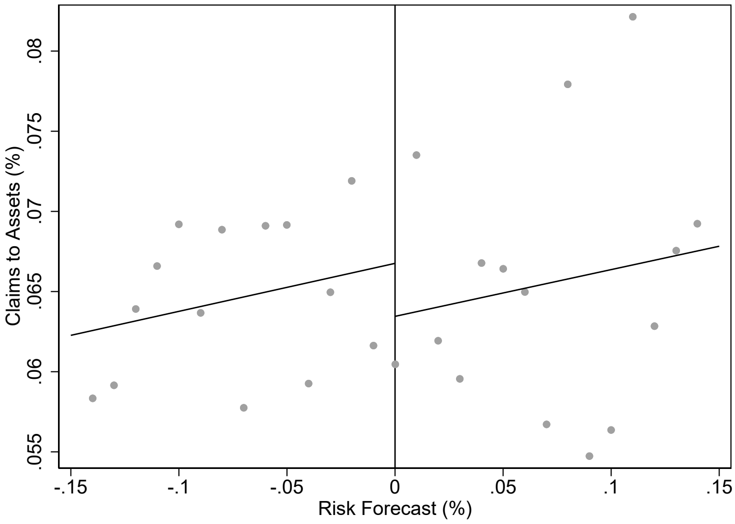
Notes. Figure B.5 shows the distribution of the risk forecast around between 0 and 0.5% (the first cutoff), as well as around 0.5% to 1% (the second cutoff). The risk forecast data is from Upplysningscentralen AB.

Figure B.6: Regression Discontinuity Plot, Collateralized Debt to Asset Ratio



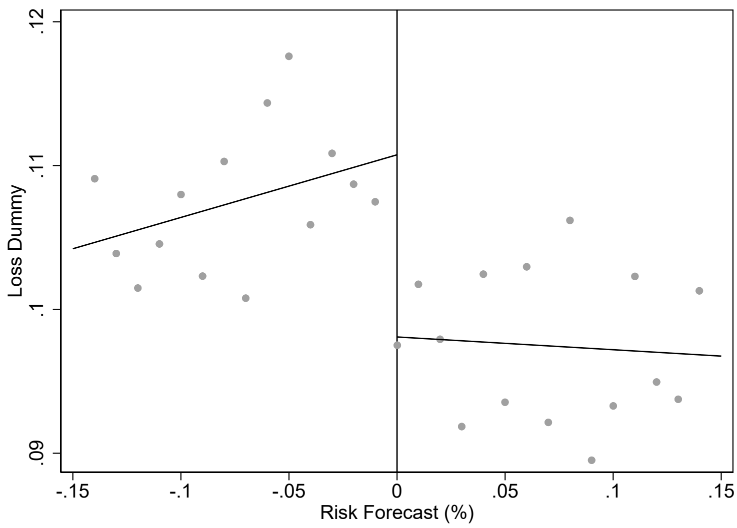
Notes. Figure B.6 shows regression-discontinuity estimates of Equation 2. Collateralized debt to assets is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.7: Regression Discontinuity Plots (Claims to Assets)



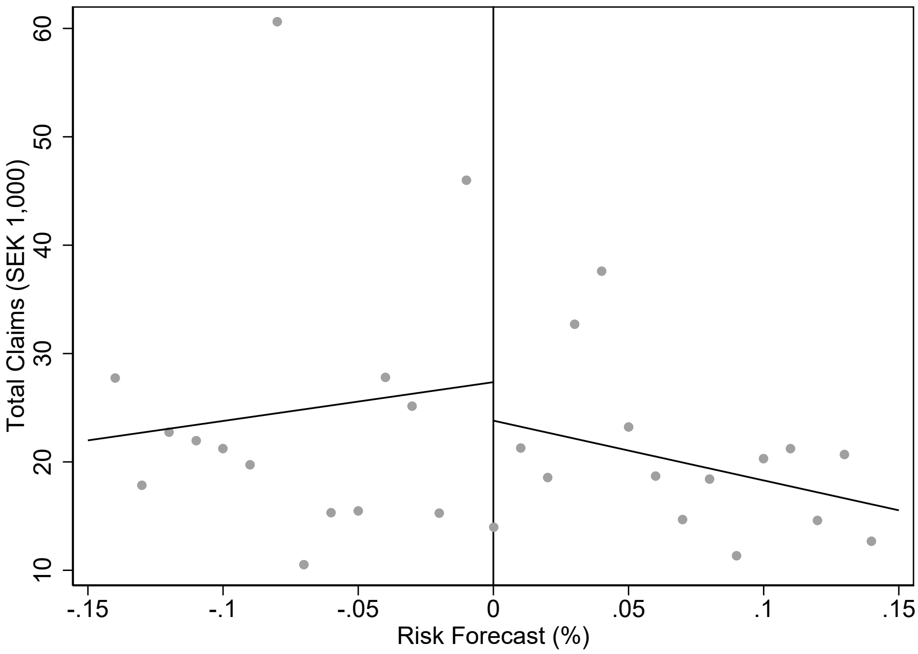
Notes. Figure B.7 shows regression-discontinuity estimates of Equation 2. Total claims to assets is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.8: Regression Discontinuity Plots (Loss Risk)



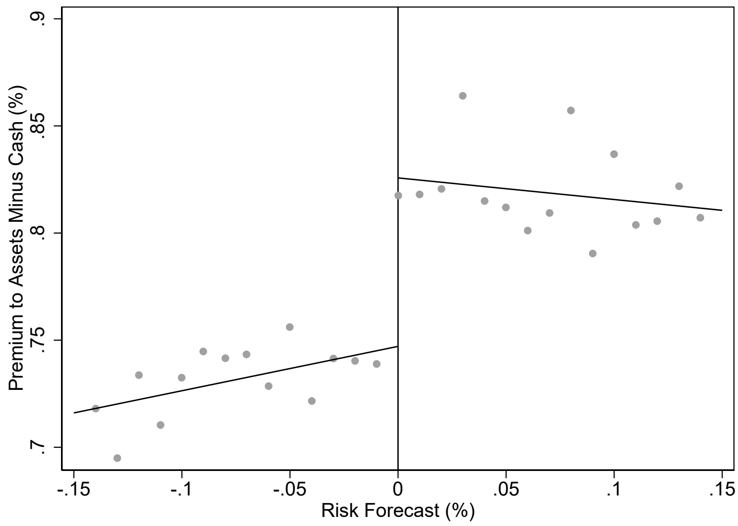
Notes. Figure B.8 shows regression-discontinuity estimates of Equation 2. A dummy if the firm has a loss is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.9: Regression Discontinuity Plots (Total Claims)



Notes. Figure B.9 shows regression-discontinuity estimates of Equation 2. Total claims is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

Figure B.10: Regression Discontinuity Plots (Premium to Assets Minus Cash)



Notes. Figure B.10 shows regression-discontinuity estimates of Equation 2. Premium to assets minus cash is the dependent variables. The accounting firm-level data are from Serrano, the insurance data is from an anonymous insurance company and the credit score data is from Upplysningscentralen AB. The estimates are done using the optimal bandwidth from Calonico et al. (2014, 2017) and a polynomial of order one. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. The risk forecast is normalized by the closest cutoff (0.25% or 0.75%), such that firms to the left (right) of the vertical line have a better (worse) credit score.

A.5 Tables

Table B.1: Financing constraints and Risk Forecast

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

Notes. Table B.1 displays the range of *Risk Forecast* as well as the number of firm-year observations for each category in *Constrained*.

Table B.4: Distribution of Firms Around the Cutoff at (%)

	First Cutoff (0.25%)		Second Cutoff (0.75%)	
	Left	Right	Left	Right
Sector (%)				
Agriculture, Forestry and Fishing	0.02	0.02	0.02	0.02
Mining and Quarrying	0.00	0.00	0.00	0.00
Manufacturing	0.19	0.18	0.18	0.17
Electricity, Gas and Steam	0.00	0.00	0.00	0.00
Water supply and Waste Management	0.01	0.01	0.00	0.00
Construction	0.18	0.20	0.21	0.21
Wholesale and Retail	0.22	0.22	0.23	0.22
Transportation and Storage	0.05	0.05	0.06	0.06
Accommodation and Food Services	0.05	0.07	0.07	0.09
Information and Communication	0.04	0.04	0.04	0.04
Real Estate Activities	0.02	0.01	0.01	0.01
Professional, Scientific and Technical Activities	0.09	0.08	0.07	0.06
Administration and Support	0.05	0.05	0.05	0.05
Education	0.02	0.02	0.02	0.02
Human Health and Social Work	0.04	0.03	0.02	0.01
Arts and Entertainment	0.01	0.01	0.01	0.01
Other Service Activities	0.01	0.01	0.01	0.01
In Stockholm (%)	0.15	0.15	0.15	0.15
Firm Age (Years)	23.77	20.55	19.20	17.26

Notes. Table B.4 shows the distribution of firms around the closest cutoff, 0.25% in column (1), and 0.75% in column (2). All measures are in percentages, except for firm age, which is given in years.