Financial Constraints and Insurance Demand in Small and Medium-Sized Enterprises *

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Abstract

We study the impact of financing constraints on small and medium firms' risk management through insurance using a panel data on 20,000 firms from a large insurance company. We measure financing constraints using credit scores. We find that financially constrained firms purchase more insurance. Smaller firms purchase more insurance at the intensive margin. A regression-discontinuity design that isolates credit constraints from other confounding variables supports that credit constraints influence firm's demand for insurance.

Keywords: Financial Constraints, Risk Management, Insurance Demand, Credit Scores, Unlisted Firms

JEL Codes: D22, D25, G22, G32

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1 Introduction

Risk management is particularly important for firms facing financing constraints. These firms face a wedge between the opportunity cost of internal funds and funds raised externally [Fazzari et al., 1988]. By managing risks, financially constrained firms can avoid having to access costly external funding or forgoing profitable investments when internal funds are low [Froot et al., 1993]. Smaller, unlisted firms or firms without access to public debt markets are typically more constrained than large, listed firms [Kaplan and Zingales, 1997, Farre-Mensa and Ljungqvist, 2016, Faulkender and Petersen, 2006]. The former typically rely on external capital such as bank loans and business credit lines for financing their growth [Robb and Robinson, 2014]. Furthermore, their owners cannot easily diversify firm-specific risk. All of these factors suggest that smaller firms should engage more in risk management. However, we know little about the risk management of small firms. Most of the literature has focused on the risk management via derivatives of large, publicly listed firms [Tufano, 1996, Nance et al., 1993, Rampini et al., 2014]. Even the empirical literature on insurance demand, with the exception of the survey study by Asai [2019], is centered large listed firms (eg Aunon-Nerin and Ehling [2008]).

One reason why so little is known about the risk management of small firms is a lack of data. Access to firm-level data on risk management is a challenge and it is particularly difficult for small and unlisted firms [Bodnar et al., 2019, Rampini and Vuillemey, 2020]. In addition, financing constraints are notoriously difficult to measure. The literature has tried to capture financing constraints by looking at the cash-flow sensitivity of investments [Fazzari et al., 1988], statements in firms' annual reports indicating financing constraints [Kaplan and Zingales, 1997], or firms' ability to increase debt in response to tax increases [Farre-Mensa and Ljungqvist, 2016]. All of these variables have in common that they build on observable information from firms' stock price, debt, age or size. Most of these indices are derived from analyses of listed firms. Unfortunately, small firms are rarely listed, which makes these measures less relevant.

Insurance is a common risk management tool. It covers firm-specific risks and is readily available to firms of all sizes, in contrast to trading in derivatives which demand financial sophistication. Buying insurance allows firms to weather large real shocks that would potentially threaten their existence.[1] Another positive aspect for studying insurance as a means of risk management is that it cannot be used for speculation. In Sweden, commercial non-life premiums amounted to 3.1 percent of the corporate sector's total earnings before interests and taxes.[2]

In our study, we focus on Swedish firms for which we access to administrative data on on firm characteristics (such as industry and number of employees) and profit-and-loss and balance sheet filings, including credit lines. Furthermore, we cooperate with a large Swedish insurer. From the insurer, we obtain proprietary data on the insurance purchases and losses under these contracts of roughly 20,000 firms over 10 years from all industries of the Swedish economy.

Finally, we measure financial constraints using credit scores. We obtain credit scores for the insured firms from Upplysningscentralen AB (UC). Recent studies, such as Caggese et al. [2019] or Bronzini and Iachini [2014], have used such proprietary credit scores calculated for loan providers as an approximation of financing constraints.[3] These measures are readily available for most firms and are used by banks in the loan application process.[4] We follow Caggese et al. [2019] and use credit scores for Swedish firms as a measure of financing constraints.

We investigate the relationship between insurance demand and financial constraints using two approaches. First, we compare the relationship between credit score and insurance demand in the cross-section and within firms over time. We also relate insurance demand to firm size. Thanks to the panel structure of our data, we can control for factors that are constant within the firm and that correlate within industries on annual levels, such as technological factors and owner-specific risk aversion [Roberts and Whited, 2013, Wooldridge, 2010].

Moreover, we use a regression discontinuity design to investigate the causal effect of

[1] This contrasts the observation of Guay and Kothari [2003] which find that most risk management strategies cover rather small risks.

[2] Years 2014-2018, Source: Statistics Sweden (SCB) and Swedish Insurance Association

[3] This contrasts the use of credit scores as a measure of a firm's riskiness by Asai [2019].

[4] This is documented for Sweden by Jacobson, Tor and Lindé, Jesper [2000].

credit constraints on insurance demand. We thereby also contribute to the literature that uses regression-discontinuity designs to estimate the causal impact of eligibility for financing. Caggese et al. [2019] study how financial constraints affect layoff decisions. Keys et al. [2010] uses a cutoff in the credit score for non-commercial borrowers to study moral hazard in the market for securitized loans. Bronzini and Iachini [2014] exploit a credit score cutoff in the application system for R&D grants in Italy to estimate the effects of financing constraints on innovation.

We find that that firms with better access to finance demand less insurance relative to their assets. A firm with the best credit score have roughly 0.024 percentage points less premium to assets compared to a firm with the third-highest credit score. This is a large effect as the median premium to asset ratio is equal to 0.38%. Our results hold both when we replace the credit score data with alternative measures of financial constraints in the literature [Whited and Wu, 2006, Hadlock and Pierce, 2010, Farre-Mensa and Ljungqvist, 2016] or when we change the dependent variable from assets to assets minus cash.

When running separate panel regressions by firm size category, we find that financing constraints are most important for the very smallest firms. Furthermore, the results indicate that firms from sectors with high cash flow volatility are more responsive to change in their credit rating. Firms that have a credit line are less responsive to changes in their credit rating.

Using the regression-discontinuity design, we find that firms with the best credit score demand less insurance. Around the cutoff between the top and second-best credit score, we find that firms have around 0.05 percentage point less insurance to assets. Moreover, they have more assets and more debt. This confirms that an upgrade in a firm's credit score indeed relaxes financial constraints.

Our paper continues as follows. Below, we present a first look at our data. Figure 1 suggests that firms that have a better credit rating (less constrained) demand less insurance. It also shows that insurance demand declines at the intensive margin as firms grow in size. In Section 2, we present the theory around financial constraints and insurance demand. Section 3 develops the setting and the data. In Section 4, we develop our empirical strategy. We present our results in Section 5 and additional results in Section 6. Finally, Section 7 concludes.

1.1 Motivating Evidence

We explore the cross-sectional relationship between insurance demand (measured as the ratio of insurance premiums to total assets), firm size (measured as number of employees) and the two best and most common credit ratings. In Figure 1, panel 1 and 2, we show these relationships. We see that larger firms purchase less insurance.[5] Firms with better credit rating (less affected by financial constraints) purchase less insurance. These relationships are stable even if account for differences in the level of cash holdings, by using premium divided by assets minus cash (see Figure A.1).

[Figure 1 Here]

2 Background and Theory

2.1 Setting: Insurance

We study firms' demand for commercial insurance[6]. The policies that we look at provide coverage against the most common damages to property, buildings, machinery, and, in our case, even liability risks (see Mayers and Smith [1982], for a more detailed description). Insured losses to buildings and machinery include such that are caused by fire, explosion, 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.[7]

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.[8] These choices impact insurance premiums. Insurers help policyholders to

[5] This is consistent with the cross-sectional evidence found by [Hoyt and Khang, 2000, Cole and McCullough, 2006, Regan and Hur, 2007].

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

[7] 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.

[8] Aunon-Nerin and Ehling [2008] investigate empirically how firms choose upper limits and deductibles for their insurance contracts.

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, 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, it cannot be used for speculation and policyholders are not required to post collateral in order to engage in risk management.[9] 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.

2.2 Theory and Hypotheses

Froot et al. [1993] show that costly external finance motivates firms to engage in costly risks risk management. In their model, shareholders can benefit from a firm's risk management if capital markets are not perfect. Risk management reduces the expected costs of having to access costly external finance or having to forego investments in the presence of adverse shocks.[10] In this context, risk management increases the value of the firm. Firms that face larger financial constraints benefit more from risk management since they face a larger wedge between internal and external financing costs. 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 firms 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 de-

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

[10]This is similar to the pecking order theory of Myers and Majluf [1984]. In a world with perfect capital markets, in the sense of Modigliani and Miller [1958] and Modigliani and Miller [1963], there would be no need for risk management or insurance. A profitable firm could always secure funding regardless of whether it had just incurred a loss.

stroyed.[11] However, purchasing insurance is costly and firms will consequently trade off costs and benefits and buy partial insurance [Holmstrom and Tirole, 2000]. This leads us to our first hypothesis.

Hypothesis 1: Firms that face greater financial constraints purchase more insurance.

Next, we investigate if firms that face a greater volatility of their cash flows demand more insurance. These firms are more likely to face internal funding shortfalls and as such they have to forgo investments or access external finance. The relevance of cash flow volatility for firms' investment is underscored by Minton and Schrand [1999]. They show that firms with high cash flow volatility are more likely to permanently forgo investments. Insured losses may occur at any time and for Sweden these losses can be expected to be largely uncorrelated with investment opportunities.[12] Consequently, a firm may at the same time be confronted by a loss to a physical asset and a state of low cash flow from its operations. These arguments suggest that firms that both face a greater wedge between internal and external finance and that have more volatile cash flows can benefit more from risk management through insurance. Cash flow volatility is, however, endogenous. It is impacted by firms' investment choices that take into account financing constraints [Faulkender and Wang, 2006]. We consequently revert to using differences in cash flow volatility between sectors. Unfortunately, given that expected losses are highly correlated with production technology we cannot directly measure if firms in more volatile sectors purchase more insurance. Instead, we investigate if firms that are in sectors characterized by cash flow high volatility are more sensitive to changes in their credit rating. This motivates the next hypothesis:

Hypothesis 2: The demand for insurance demand is more sensitive to financing constraints for firms in more volatile sectors.

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

[12] Sweden is largely spared from catastrophe losses, for instance hurricanes or earthquakes, that might impact investment opportunities.

By buying insurance firms are able to avoid some situations when internal resources are low and there are profitable investment opportunities. Risk management through insurance is only one way firms can ensure that they may have sufficient resources when investment opportunities arise. Another way that firms can ensure sufficient liquidity may be to build cash reserves or to obtain a credit line. Credit lines are a promise by a financial institution that it will allow its client to borrow a certain amount funds of funds if certain requirements are full filled. Financing constraints can motivate the use of credit lines [Holmström and Tirole, 1998]. The findings of Lins et al. [2010] suggest that credit lines are important source of funding of growth opportunities. Brown et al. [2021] suggests that credit lines function as liquidity insurance for small firms that are confronted with a weather shock which is not directly related to fundamentals. Sufi [2009] shows that firms, on average, pay a commitment fee of 25 basis points for their unused credit lines. Once a firm has a credit line it can be assumed to be less financially constrained than a similar firm without a credit line [Sufi, 2009]. Following this argument we investigate if the demand for insurance is less responsive to changes in credit ratings for firms that have a credit line.

Hypothesis 3: The demand for insurance demand is less sensitive to changes in credit ratings for firms that have a credit line.

3 Data Construction and Sample Descriptive Statistics

3.1 Sample Overview

We combine micro data from three sources to construct our panel of Swedish firms: administrative data on private sector limited liability firms, insurance purchases from one of Sweden's largest insurers, and credit scores for these firms.[13] Matching data

[13]The data is provided through Statistics Sweden (SCB). SCB hosts the data and ensures confidentiality.

from three different sources is possible because all Swedish firms are assigned a unique and time-invariant firm-identifier. To create our sample we introduce some restrictions on firms covered for years 2008–2017. We keep firm-years where firms have six or more employees, positive sale and positive assets, and positive labor costs. Moreover, we require the firm to be at least two years in our sample. We also remove firms belonging to the financial sector. Furthermore, we follow Caggese et al. [2019] and drop firms that might be in financial distress, as measured by the two lowest credit scores. We winsorize the variables denoting ratios of insurance demand or financials at the 1% level. Combining the three data sets and restricting our data leaves us with 99,286 firm-year observations from 16,067 firms, for the years 2008–2017. Our sample covers around 50% of the firms that satisfies our sample restrictions. We provide the variables used in our analysis in Table **??** in the Appendix.

3.2 Balance Sheet and Profit-and-Loss Items

Data on firms' annual reports for years 2008–2017 comes from the Bisnode Serrano database. It is based on firms' annual filings with the Swedish Companies Registration Office (Bolagsverket). The data contains information on firms' sales, depreciation, assets and debt. It also holds information on number of employees and industry classifications (NACE rev 2)[14] and firm age. The data also contains information on firms' corporate structures. The data is harmonized to calendar years.[15]

Table 1 shows summary statistics for all insured firms after application of the sample restrictions. The data shows that most firms in our sample are small. For instance, the median (mean) firm has 11 (26) employees. However, there are some very large firms in the sample (we have 310 firm-years were we record more than 500 employees). Similarly, the mean firm has SEK 65 million (median 17 million) in sales and 57 million in assets (9 million). Similarly, the median firm has one establishments. The mean firm has a cash to asset ratio of 21%. Moreover, mean premium is SEK 62,000, while median is 33,000.

[14]The NACE system is similar to the North American Industry Classification System (NAICS). NACE is short for "Statistical Classification of Economic Activities in the European Community"

[15]The data starts in 1998. We make use of pre-period data to obtain estimates of sector level cash flow volatility.

The mean firm has premium to assets of 0.51% (median 0.38%). In addition, 49% of our firms are independent, that is do not belong to a corporate group. 52% percent of the firms year observations show positive dividend payments. Roughly half of the firms have a credit line.

The skewness of the data is underscored by the difference between the mean and the median of the variables related to number employees and sales. All monetary values are expressed in 2010 constant prices, using the consumer price index from Statistics Sweden. We winsorize premium to assets and premium to assets minus cash at the 1^{st} and 99^{th} percentile to mitigate the effect of outliers.

[Table 1 Here]

3.3 Premium Data

Our second data source contains proprietary data on insurance purchases by one of the largest insurance firms operating in Sweden.[16] This data contains information on firms' premiums and losses. Average premiums are, as Table 1 shows, equal to SEK 63,000 (median SEK 33,000). The mean premium to asset ratio is 0.51% (median 0.38%) with a standard deviation of 0.48%. The ratio of premiums to assets minus cash is on average 0.73%. Insurance premiums are not only mechanically impacted by a firm's assets. Instead, a firm can choose its deductible, coinsurance rates, limits of coverage and included types of losses.[17]

In our empirical analysis, insurance demand acts as our dependent variable. Given that supply and demand factors might vary between sectors, we normalize insurance demand as total premium for t divided by the end of period t book value of total assets. Standardizing by end of period assets reflects the fact that policyholders need to update their insurance policies if they purchase new assets. This line of reasoning is in lie with the literature, that often normalizes by insured assets [Hoyt and Khang, 2000, Regan and

[16] Data by the Swedish Insurance federation shows that there are at least 8 insurers that each have premium income of more than 1 % of the aggregate premium income in commercial insurance. https://www.svenskforsakring.se/en/

[17] Firms may also invest in loss reduction or loss prevention.

Hur, 2007, Asai, 2019]. For robustness, for our results not to be driven by differences in cash holdings, we re-estimate our models and normalize premiums by assets minus cash.

3.4 Credit Scores

Finally, we add data on firms' credit scores from one of Sweden's largest rating companies, Upplysningscentralen (henceforth UC). UC provides credit ratings on all Swedish limited liability companies and their scores are broadly used in the financial industry and the Swedish central bank [Jacobson, Tor and Lindé, Jesper, 2000]. Until 2018 the four largest Swedish banks owned 97 % of UC's shares.

UC creates an continuous measure that estimates a firm's default risk in a given year. We follow Caggese et al. [2019] and refer to this continuous measure as the "risk forecast". The risk forecast varies even depending on macroeconomic conditions. To produce the risk forecast UC uses data from 52 sources. Among these are balance sheet and income statement items, records on owners and board members, previous defaults, late payments, as well as the number of times a financial institution checks a firm's credit score.[18] The risk forecast is used to produce a discrete credit rating which we refer to as "credit score".[19] Firms with an estimated risk forecast of no more than 0.25% receive the top score. This is roughly equivalent with AAA rating by the major rating agencies. Firms with a risk forecast of between 0.25 % and 0.74 % receive the next best credit score.[20]. Firms with a risk forecast between 0.75 % and 3.04% receive the credit score "3". Following Caggese et al. [2019] and given that our study focuses on firms that are financially constrained but not in distress we remove firm-year observations where the risk forecast is higher than the cut-off for this final category.[21] We find that there is some

[18]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 desrcibed 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 by Berger and Udell [2006].

[19]UC offers firms to purchase the right to publicly display their credit rating for marketing purposes. Furthermore, interested parties can purchase information on a firm's credit rating via UC's website.

[20]Similarly, a default probability of 0.75% (the second-highest score) is roughly equivalent to BBB [Langohr and Langohr, 2010]

[21]Removing firms in distress reflects the findings of Purnanandam [2008], who shows that that incentives for hedging decline for firms in distress. Even Asai [2019] who does not remove firms in distress and uses credit ratings as a measure for the risk of default finds that a firm's riskiness decreases its demand for insurance.

considerable within firm variation of credit scores. Indeed, in our final sample we observe that 70% of all firms in our final sample experience at least one up- or downgrade of the their credit rating.

In Table 2, we also see the distribution of credit scores in our sample after removing 6% of firm-year observations have the two lowest scores. Credit score data and the corresponding risk forecast is from January 1 of each year t. We see that 44% of firms have the best score (1). Then, 34% have the second-best score. Remaining firms have the third best score.

[Table 2 Here]

Going forward we use the UC credit scores and risk forecast to measure financing constraints. Firms that have a worse credit rating are considered to be more financially constrained. These firms face a greater wedge between internal and external finance. We exploit the frequent changes in the discrete credit rating for our panel regressions and for the cut-off for our regression discontinuity approach.

4 Empirical Strategy

4.1 Cross-Section and Panel Analyses: Main Model

We study the relationship between insurance demand and financial constraints. Insurance demand is measured as the premium-to-asset ratio of firm i in year t, $\frac{Premium_{it}}{Assets_{it}}$. We then use two dummy variables as our measures for financial constraints: T_{it} if the firm has the best UC credit score in year t, and S_{it} if the firm has the second best UC credit score. Our baseline is a firm with the third best credit rating. Moreover, π_i is the firm-fixed effect, μ_{jt} are industry-year fixed effect[22], and X_{it} is a vector of firm-level controls, such as size and number of establishments. The error term is denoted by ϵ_{it}. We cluster standard errors on the firm level to account for serial correlation in the relationship between error

[22]We use a the 21 level one codes A-U (NACE rev2) to categorize firms in the Swedish economy.

terms and the risk forecast. Our main model is:

$$\frac{Premium_{it}}{Assets_{it}} = \beta_T T_{it} + \beta_S S_{it} + \pi_i + \mu_{jt} + \gamma' X_{it} + \epsilon_{it} \tag{1}$$

The coefficients β_T and β_S measure the difference in average premium-to-assets for a firm that has the top credit score, alternatively the second best score, compared to a firm with the third best score.

We have four basic specifications. All specifications include controls for firm size (log employment) and industry-year fixed effects. We control for firm size to account for differences in insurance demand and pricing related to size. Industry-year fixed effects control for systematic and time-varying differences between industries. For instance, they capture differences in insurance prices that may be caused by the well-documented cyclical price developments on the reinsurance market [Gron, 1994, Froot, 2001].

Specifications two to four include firm fixed effects, which control for time-invariant unobservable firm characteristics. We thus use within-firm effects of changes in credit score and size. Our third specification also controls for a firm's number of physical establishments. Establishments mark the number of locations that firms operate from. By controlling for establishments we reflect that there may be a physical diversification of a firm's assets. Finally, we restrict the sample to independent firms in the fourth specification. While this decreases the sample size it allows us to get a better understanding of how a firm's demand for insurance reacts quantitatively to a change in its credit rating. Independent firms are not able to benefit from diversification within corporate groups.

While the firm fixed-effects remove potential unobserved confounding variables that are time-invariant, the measured risk forecast 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 the risk forecast if the firm is purchasing insurance in anticipation of more profitable investment opportunities. To investigate the causal effect of financing constraints on insurance demand, we also use a regression discontinuity design.

4.2 Regression Discontinuity Design

Since the access to external finance for firms is endogenous, it is difficult to identify identical firms that only differ in their access to credit. The literature has developed a range of measures that build on financial choice variables, such as the decision to pay dividends or the firms' size to identify financing constraints [Kaplan and Zingales, 1997, Hadlock and Pierce, 2010, Farre-Mensa and Ljungqvist, 2016]. However, Farre-Mensa and Ljungqvist [2016] show in a natural experiment that firms that appear to be financially constrained, if judged by these traditional measures, often show behavior that is inconsistent with being financially constrained. To use exogenous variation in financial constraints, we follow Caggese et al. [2019] and exploit a discontinuity in the Swedish credit scores provided by UC. We focus on the two highest credit score: 2 (good creditworthiness), which is for firms with risk forecasts from 0.25% and including 0.74% and 1 (maximum creditworthiness), which is for firms with risk forecasts below and including 0.25%. [23]

In theory, firms on different sides of the cutoff between the two ratings are almost identical but differ in their discrete credit score (random assignment). We show that a discrete jump in the credit score is in fact predictive of capital structure choices and therefore imposes a binding constraint for the firm. To identify the effect of higher credit score we compare firms close to the cutoff in the underlying continuous measure ($s = 0.25\%$) between the highest and second-highest rating.

We denote the outcome of firm i in year t by y_{it}, for instance the premium to asset ratio. s_{it} denotes the risk forecast for a firm in in year t. 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

[23] https://www.uc.se/hjalp–kontakt/riskklass/vad-ar-uc-riskklass-och-riskprognos/. This is summarized in Table 2.

threshold to differ:

$$y_{it} = \alpha + \beta \mathbb{1}(s_{it} \geq 0.25) + f(s_{it} - 0.25) + \mathbb{1}(s_{it} \geq 0.25) f(s_{it} - 0.25) + u_{it} \qquad (2)$$

Where $f(\cdot)$ is a function to control for the distance from the cutoff and $\mathbb{1}(s_{it} \geq 0.25)$ is an indicator function that is equal to one whenever the risk forecast exceeds 0.25. We follow Gelman and Imbens [2019] and use 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 also use a data-driven bandwidth selection for which a simple linear regression can provide a consistent estimate.

4.2.1 The Distribution of Risk Forecasts

Figure 2 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 2 Here]

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.

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. 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 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.

4.2.2 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, we 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 to manipulate and other characteristics (see 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 A.1 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.

Table A.1 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 25.82 years on average, while those to the right are 22.93 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 13.17% of the firms to the left are in Stockholm, while 13.33% 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.

5 Results: Insurance Demand and Financial Constraints

5.1 Panel Evidence

In Table 3, we estimate the relationship modelled by equation 1. In all columns, we control for log employment and industry-year fixed effects. Our model thus captures the general relationships between firm size and demand, as well as for time-varying shocks at the industry level.

All of our specifications show that firms with better credit ratings purchase less insurance. In column (1), we see that the estimated coefficients β_T and β_S are negative and statistically significant at the 1% level. The coefficients imply that, conditional on firm size, firms with the top score (second score) pay, on average, 0.169 (0.034) percentage points less premium per unit of assets. Looking at the coefficient for firm size, we see that a 1% increase in the number of employees is associated 0.00133 percentage points lower premium to asset ratio.

We see that the magnitudes of β_T and β_S are reduced when we introduce firm fixed effects (column 2). However, a firm with the top (second) credit score still has a 0.024 (0.009) percentage points lower premium to asset ratio than a firm that has a credit rating of three. These estimates are statistically significant at the one percent level. Given that the mean level of premium to asset is 0.50%, this represents roughly a decrease in insurance by five percent. Interestingly, the coefficient for firm size is close to the coefficient that we obtain without firm-fixed effects (-0.133 and -0.123). This suggests that the effect of firm size on the premium to asset ratio is uncorrelated with firm-specific factors.

We then show that controlling for the number of establishments does not affect our results. We note that the coefficients in column (3) are similar to those in column (2). The coefficient for the number of establishments is positive (0.004) and statistically significant. An increase in the number of establishments is thus associated with increased insurance demand. This suggests that physical diversification, above and beyond firm size, does not affect the relationship between credit scores and insurance demand. It also indicates that the risks associated with opening of an additional establishment seem to dominate possible effects on diversification.

Finally, in column (4), we show that the sample is robust to only using independent firms. Notably, the sample size drops from 99,000 to 48,000 firm-year observations. The coefficients denoting a firm's credit rating increase by 50% in comparison to column (2). Even the coefficient for size increases in magnitude. This suggests that independent firms are more responsive to changes in their credit rating and size.

The results shown in Table 3 support Hypothesis 1 and, more importantly, the theory suggested by Froot et al. [1993] and Holmstrom and Tirole [2000]. Firms that face higher costs of external finance, as measured by a widely-used credit rating, purchase more insurance. Given that we drop firms that are likely to be distressed these results are unlikely to be driven by bankruptcy costs.[24] Furthermore, in line with other papers on insurance demand Asai [2019], Regan and Hur [2007], Hoyt and Khang [2000] and Yamori [1999] we record that larger firms purchase less insurance. Larger firms can be expected to benefit from, for instance, operational diversification and economies of scale when coordinating internal funds and investments. This finding contrasts findings from the literature on firm's risk management via derivatives, for instance Nance et al. [1993], Giambona and Bodnar [2018].

[Table 3 Here]

5.2 Regression-Discontinuity Results

We now study differences in the demand for insurance at the cut-off for the top credit rating. We expect firms just around the cut-off to be very similar, except that some firms happen to get a slightly better risk forecast and thus a better credit score. In addition to studying the premium to asset ratio, we also investigate if credit scores affect other outcomes commonly associated with financing constraints and their impact on investments. The outcomes we study are log debt and log assets. [25]

Figure 3 shows that firms with the second best credit score indeed demand more insurance relative to their assets. We show the regression discontinuity plots for the premium to asset ratio at the risk forecast cutoff of 0.25%. The dots present the sample averages within the bins while the lines present the fitted lines of the local linear regressions on each side of the cut-off. Figure 3 underscores that firms with a better credit score indeed have a lower premium to assets ratio. This is result is in line with Hypothesis 1.

We complement the graphical result with regression estimates. Table A.5 shows the estimates for different bandwidths. First, we have the 0.15 bandwidth, the one shown in Figure 3. The estimated effect is 0.047 and statistically significant at the 1% level. This shows that firms with a worse credit score have 0.05 percentage points more premium

[24] UC refers to the three categories as (maximum creditworthiness, good creditworthiness, creditworthy). https://www.uc.se/en/seal-and-certificate/

[25] Note that the timing of our variables allows firms to adjust their financing and investment plans after receiving their credit score. The credit scores are from the being of year t, the accounting variables are from the end of year t and the insurance data marks the whole year t.

to assets.[26] Thus, our regression discontinuity analysis complements the panel analysis and confirms that firms with relaxed financial constraints purchase less insurance. The regression discontinuity approach establishes that there is a causal link between financing constraints and insurance demand.

[Figure3 Here]

Next, we validate that firms with lower credit scores are actually more constrained by looking at log debt and log total assets. In Figure 4, we show graphically the results, using the same analysis as before. We see that firms with better credit scores have more debt and assets. In Tables A.6 and A.7, we see that the estimated effects are around -0.20 and statistically significant at the 1% level. This means that firms with a better credit score have around 20% more debt and assets. In the same Tables, we show that the results are robust to different bandwidths.

[Figure4 Here]

In Table A.8, we confirm that the effect is driven by an increase in physical capital and machinery, and not in financial assets. The estimated effects are close to -0.20, suggesting that this explains the effect on total assets.

Taken together, these results show that credit scores play a large role in firms' financing and investment decisions. This is in line with the reasoning in Caggese et al. [2019] and also in line with the literature studying the real effects of financing constraints [Chodorow-Reich, 2014, Duygan-Bump et al., 2015, Giroud and Mueller, 2015, Cingano et al., 2016, Berton et al., 2018, Amiti and Weinstein, 2018, Hviid and Schroeder, 2021].

6 Extensions and Robustness

6.1 Heterogeneity: Sensitivity of the Demand for Insurance

We now test if the demand of certain types of firms is particularly sensitive to changes in their credit score. We focus on firms in industries with more volatile cash flows (Hy-

[26] In addition, we show the result for the optimal bandwidth [Calonico et al., 2017].

pothesis 2), firms with credit lines (Hypothesis 3). We also investigate if smaller firms which can be expected to be particularly affected by credit constraints are more sensitive to changes in their credit ratings.

First, we study if firms in industries with more volatile cash flows have a higher sensitivity of insurance with respect to credit scores. The demand for insurance should be larger for firms with higher cash flow volatility, because they have a larger risk to be in need of costly external finance when they are hit by an adverse insured shock. Indeed, Minton and Schrand [1999] shows that high volatility firms invest less.

We define firms to have high cash flow volatility if they belong to an industry with a high coefficient of variation in their earnings before interest, taxes, depredations and amortizations (EBITDA). Once we have calculated this measure at the firm level we take the unweighted average for each two-digit sector.[27] We then split our sample for in half at the median of our cash-flow volatility measure. We run separate panel regressions including firm fixed effects to investigate whether firms in high volatility sectors are more responsive to improvements in their credit score.

In Table 4, columns (1) and (2), we see the results. Firms in industries with high cash flow volatility have 0.025 (0.011) percentage point lower premium to assets if they have the top compared to the third-best credit score. For firms with low credit scores, the coefficient is 0.021 (0.006). Both coefficients are statistically significant on the 1 % level. We thus see that firms with high cash flow volatility are more sensitive to changes in their credit score.

Next, we move on to analyse firms with or without a credit line during their first year of observation. Credit lines provide alternative access to funds, which should reduce the demand for insurance. We thus compare the sensitivity of firms with and without credit lines. In Table 4, columns (3) and (4), we see that the coefficient estimates are larger (in absolute value) for firms without initial credit lines.

[27] We identify the first group by calculating cash flow volatility for all incorporated firms in the Swedish economy for the years 2000-2007. Our approach follows Minton and Schrand [1999]. We exclude firms with less than 10 employees to limit the role of very small firms in certain sectors. Furthermore, we require firms to have six years' worth of observations for cash flow. We drop industries for which we have less than 30 firm-year observations.

Finally, we study firms in high-volatility sectors and without credit lines, and firms in low-volatility sector and with credit lines. We expect firms in the former group to be the most sensitive to changes in credit scores, and the latter group to be the least sensitive. These relationships are indeed confirmed in Table 4, columns (5) and (6).

Taken together, our results provide support for Hypotheses 2 and 3. Firms in more volatile sectors and without initial access to credit lines have a more sensitive insurance demand with respect changes in their credit scores.

[Table 4 Here]

Next, we investigate if smaller firms' demand for insurance is more sensitive to changes in credit ratings. Small firms are often assumed to be more financially constrained than larger firms [Kaplan and Zingales, 1997, Farre-Mensa and Ljungqvist, 2016]. In Table 5 we divide our sample by size according to the EU definition for small and medium sized firms by number of employees. Column (1) includes micro firms (less than 10 employees). Column (2) holds the results for small firms (10 to 49 employees) and column (3) all other firms (medium-sized and large firms).

We find that micro firms are most responsive to changes in their credit rating. For this group, a firm with the top credit score has 0.032 less premium to assets compared to firms with the third-best credit score. Moving on to firms with 10–50 employees, the coefficient is -0.012. Finally, for firms with more than 50 employees, the coefficients is -0.005. The estimated coefficients are statistically significant on the 1 % level in the first two cases, but not in the third. Moreover, the effect of size on the premium to asset ratio is significant for all sub-samples and the coefficient decreases in absolute terms when moving from the smallest firms towards larger firms. Also the coefficient for size (log employees) declines as we look at firms that are larger. The results presented in 5 suggest that financing constraints are more pronounced for the smallest firms.

[Table 5 Here]

6.2 Robustness Checks

To check the robustness of our results we first replace the discrete credit ratings with the continuous risk measure from UC. Next, we measure financing constraints using measures that are commonly used in the literature. Thereafter, we employ the ratio of premiums to assets minus cash as our dependent variable and re-estimate our main regressions. Finally, we investigate if our results may be driven by supply side factors.

In a first step we investigate if the results are robust to marginal changes that do not necessarily lead to a firm going from one credit score to another. To do this we replace the discrete credit scores with the continuous measure from our rating agency. We then re-estimate our basic specification from Table 3. We show the results from this exercise in A.2. As expected, we find that the results are qualitatively very similar to the results shown for the discrete measure. This holds both for the coefficients denoting risk forecast and credit rating and the size coefficient.

Next, we use an alternative measure of insurance demand. Instead of measuring insurance demand as insurance premiums to total assets we measure insurance demand as premiums to assets minus cash. Using this alternative formulation we ensure that our results are not driven by differences in cash between firms that have a higher credit rating and such that have a lower credit rating. We return to the main specification, the regression discontinuity specification, and the heterogeneity analyses. In Tables A.3, A.9, and A.4, we see that the results are very similar and that the results are not driven by differences in cash between firms.

Having established that there is a link between our measures of financial constraints and insurance demand we explore if firms' demand for insurance can be explained by the measures traditionally used in the literature to denote financing constraints. We follow the analysis by Farre-Mensa and Ljungqvist [2016], but translate the measures to the Swedish registry data.[28] First, we use the Whited-Wu (WW) index from Whited and Wu [2006] and Hennessy and Whited [2007]. Next, we use the Hadlock-Pierce (HP) index from Hadlock and Pierce [2010]. Finally, we follow Fazzari et al. [1988] and mark all

[28]Notably, given that basically all of our firms are unlisted we cannot use measures based on stock market capitalization, like the Kaplan-Zingales index.

firms that pay dividends in a given year as being not financially constrained. We describe these in detail in Subsection 9.9. Table A.10 in the Appendix provides for correlations between these traditional measures of financing constraints and the continuous measure of financing constraints from UC. We find that the traditional measures of financing constraints and the UC measure is highly correlated.

In Table 6, we regress premium to assets on the WW and HP indices, as well as a dummy if the firm does not pay dividends. Again, we control for firm and industry fixed effects and log employment. We find more financially constrained firms also also have more premium to assets. The associations are statistically significant for all three measures. The results presented in Table 6 provide additional support for Froot et al. [1993]. It also shows that our results are not driven by our specific measure of financing constraints.

[Table 6 Here]

Another concern is that our results are driven by supply-side factors. An insurance company might reduce premium when they deem a firm to be less risky. If firms with better credit scores also have lower loss risk, the insurer might rationally reduce premiums in response to a higher credit score. To investigate this question we extend our regression discontinuity design to look at the claims to assets ratio, the probability of having a loss and the average claim. We find that claims to assets are similar above and below the cutoff (Figure A.4), the probability of having a loss is also similar around the cutoff (Figure A.3) and finally, total claims are similar across the cutoff as well (Figure A.2). This suggests that the insurer's expected costs change for firms when they cross the cutoff. Accordingly, we expect supply effects to be unlikely.

7 Conclusion

We use a unique data set to study how financing constraints impact the demand for insurance in small and medium-sized firms. We complement the existing literature by providing a detailed analysis of the demand for insurance by 20,000 Swedish firms. Small and medium sized firms are more likely to be financially constrained than their larger peers. In difference to risk management via derivatives insurance is a risk management tool that smaller firms can use.

We employ a credit score that is provided by a rating agency and used by banks and financial intermediaries. In contrast to standard measures of financial constraints, this score which is used by banks to determine a company's credit worthiness is not directly estimated from firms' balance sheet and income statement data. We find that firms with larger estimated financial constraints demand more insurance measured as premium paid in relation to their assets. We obtain this result in our panel and cross section regressions. We establish a causal link between financing constraints and insurance demand using a regression discontinuity design. Furthermore, at the intensive margin insurance demand is falling in size. Looking at different categories of firms we find that insurance demand of the smallest firms, firms without a credit line and firms that are operating in highly volatile sectors is most sensitive to changes financing constraints. Additional tests show that using alternative measures of financial constraints yield similar results. We present evidence showing that the finding that better rated firms have lower insurance premium is not due to lower expected losses.

Our results which are in line with Froot et al. [1993] suggest that risk management is more important for smaller and more financially constrained firms.

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8 Appendix

8.1 Tables

Table 1: Summary Statistics of Insured Firms

	Observations	Mean	Median	Std Dev	Min	Max
Revenues	99,294	64,758	16,884	1,033,807	11	120,000,000
Employees	99,297	26	11	192	6	18,000
Total Assets	99,297	57,190	8,953	1,109,099	81	100,000,000
Establishments	99,297	1.34	1	2.97	1	100
Premium	99,297	62	33	168	0	9,000
Premium to Assets (%)	99,297	0.51	0.38	0.46	0.01	2.20
Cash to Assets (%)	99,296	20.57	15.63	19.33	0.00	100.99
Pays Dividends (%)	99,297	52.46	100	40.94	0.00	100.00
Independent (%)	99,297	48.80	0.00	49.99	0.00	100.00
Has Credit Line (%)	99,297	49.54	0.00	49.99	0.00	100.00

Notes. The Table shows summary statistics for insured firms in our sample. Monetary values are given in 1,000 SEK and deflated to the 2010 consumer price index. The years are from 2008 to 2017. Maximum values are censored to preserve confidentiality.

Table 2: Credit Score and Risk Forecast

Score	Risk Forecast (Lower)	Risk Forecast (Upper)	Frequency	%
1	0	0.24	43,479	43.79
2	0.25	0.74	33,329	33.57
3	0.75	3.04	22,479	22.64
Total			99,287	100

Notes. Table shows credit scores, the range of risk forecasts as well as the number of firm-year observations with each score. The table only includes the top three credit scores. We remove firm-year observations that belong to the two lowest credit scores and for which the risk forecast is 3.05% or higher. This group consists of around 6% of the firm-year observations of the initial sample.

Table 3: Insurance Demand and Credit Scores

	Premium to Assets			
	(1)	(2)	(3)	(4)
	No Firm FE	Firm FE	Establishments	Independent
Top Score	-0.169***	-0.024***	-0.024***	-0.036***
	(0.006)	(0.003)	(0.003)	(0.005)
Second Score	-0.034***	-0.009***	-0.009***	-0.013***
	(0.005)	(0.002)	(0.002)	(0.004)
Log Employees	-0.133***	-0.123***	-0.125***	-0.176***
	(0.003)	(0.006)	(0.006)	(0.011)
Establishments			0.004***	
			(0.001)	
Firm	No	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
R-Squared	0.217	0.845	0.845	0.854
Observations	99,286	99,286	99,286	47,781

Notes. The Table shows regressions of premium to assets on the UC credit score. (1)-(3) are the full sample. (4) is the sample restricted to independent firms. Firm and Industry-Year mark fixed effects included in the regressions. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Insurance Demand and Credit Scores: Sample Splits

	Premium to Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash Flow Volatility		Credit Line First Year?		Volatility and Credit Line	
	Above Median	Below Median	No	Yes	Above and No	Below and Yes
Top Score	-0.025***	-0.021***	-0.028***	-0.020***	-0.028***	-0.016***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.008)	(0.005)
Second Score	-0.011***	-0.006*	-0.011**	-0.007**	-0.015**	-0.006
	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)	(0.004)
Log Employees	-0.113***	-0.141***	-0.100***	-0.142***	-0.102***	-0.166***
	(0.009)	(0.009)	(0.010)	(0.008)	(0.013)	(0.012)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes
Significant Difference?		No		No		No
R-Squared	0.840	0.852	0.837	0.850	0.842	0.860
Observations	49,681	49,453	42,768	56,514	23,021	29,772

Notes. The Table shows regressions of premium to asset ratio on the UC credit score and controls. The cash flow volatility measure in columns (1) and (2) refer to firms in industries above and below the median level of the coefficient of variation for cash flows. The credit line measure in columns (3) and (4) is a dummy if the firm has a credit line during the first year it is observed. Columns (5) and (6) refer to firms with high volatility and no credit line or firms with low volatility and credit lines. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Insurance Demand and Credit Scores (by Number of Employees)

	Premium to Assets		
	(1)	(2)	(3)
	6-9	10-49	≥ 50
Top Score	-0.032***	-0.012***	-0.005
	(0.005)	(0.004)	(0.007)
Second Score	-0.014***	-0.000	-0.004
	(0.004)	(0.003)	(0.006)
Log Employees	-0.208***	-0.122***	-0.032***
	(0.014)	(0.009)	(0.011)
Firm	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes
P-Value (Against Baseline)		(Yes,Yes)	(Yes,Yes)
R-Squared	0.855	0.833	0.832
Observations	44,677	45,826	6,876

Notes. The Table shows regressions of premium to asset ratio on the UC credit score and controls. Standard errors clustered at the firm level in parentheses. The p-value denotes the statistical significance of pairwise tests of each coefficient against the coefficient in column (1). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

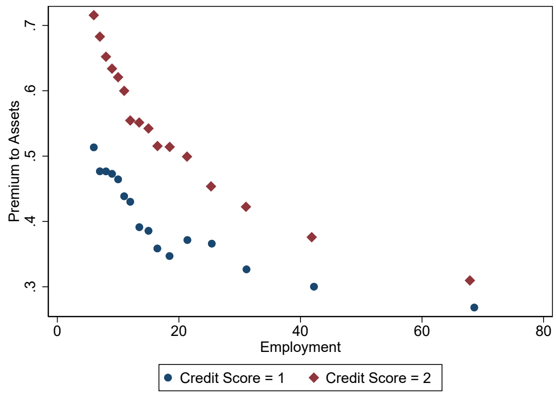
Table 6: Insurance Demand and Traditional Measures of Financial Constraints

	Premium to Assets		
	(1)	(2)	(3)
	Whited-Wu	Hadlock-Pierce	No Dividends
Constraint	1.638***	0.062***	0.060***
	(0.037)	(0.024)	(0.004)
Log Employees	-0.072***	-0.126***	-0.175***
	(0.006)	(0.006)	(0.011)
Firm	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes
R-Squared	0.879	0.845	0.856
Observations	76,604	99,286	47,781

Notes. The Table shows the relationship between premium to assets and various measures of financial constraints. The analysis in column (3) is done with only independent firms. Withed-Wu stands for measure from Whited and Wu [2006]. Hadlock-Pierce uses Hadlock and Pierce [2010]. No Dividends follows Fazzari et al. [1988]. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

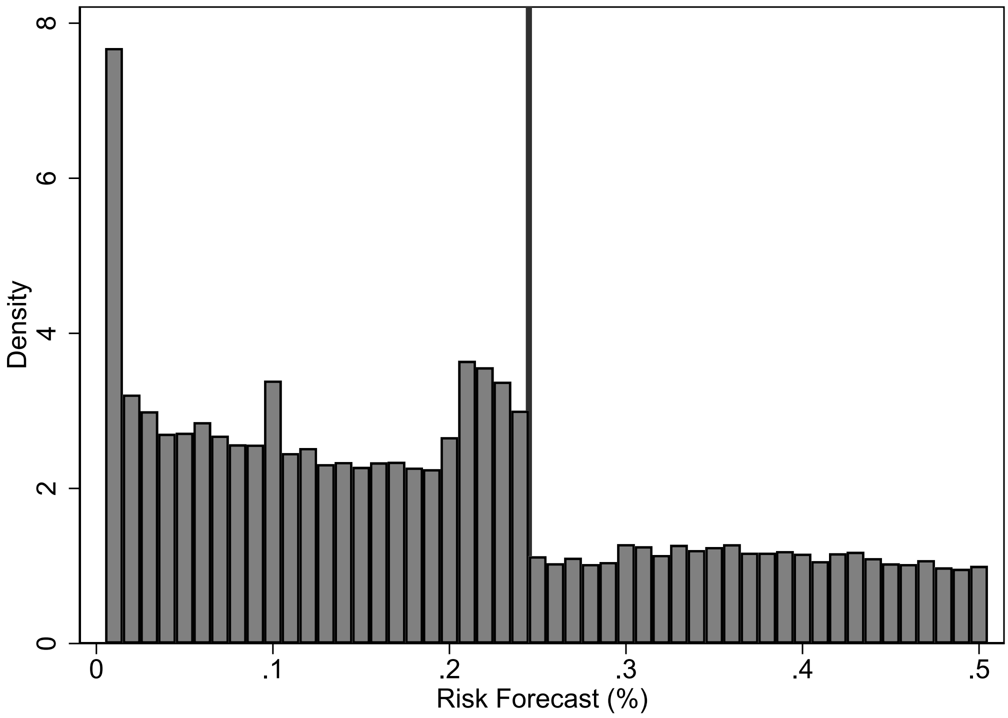
8.2 Figures

Figure 1: Insurance Demand, Firm Size and Financial Constraints



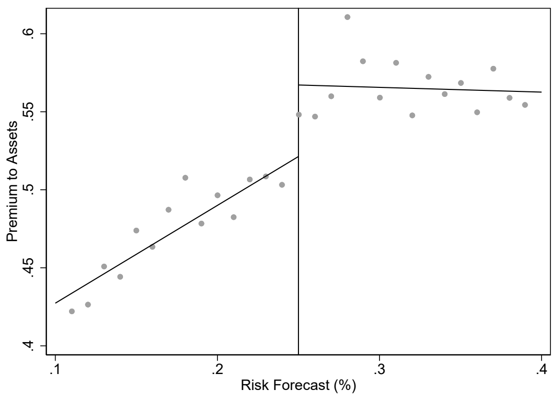
Notes. The Figure shows the relationship between premium to assets, number of employees and credit scores. The sample is restricted to firms with less than 100 employees. Credit Score=1 (=2) marks the best (second best) credit score. For these firms the risk of default is estimated at less than 0.25 % (between 0.25 % and 0.74 %)

Figure 2: Distribution of Risk Forecast



Notes. The figure shows the distribution of credit scores for insured firms for years 2008 to 2017. The thick line at 0.25 % shows the cutoff between credit score 1 (=best) and 2 (second best). Firms to the left (right) of the cutoff have the best (second best) credit score.

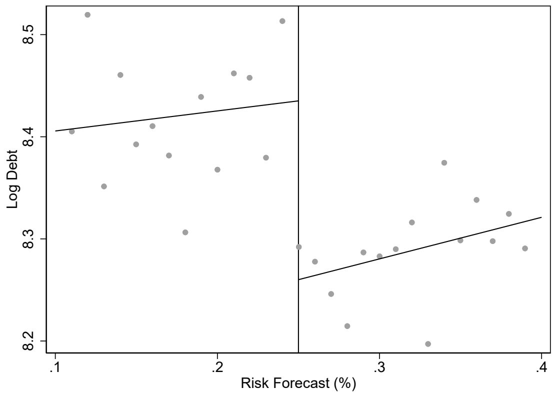
Figure 3: Regression Discontinuity Plots: (Premium to Asset Ratio)



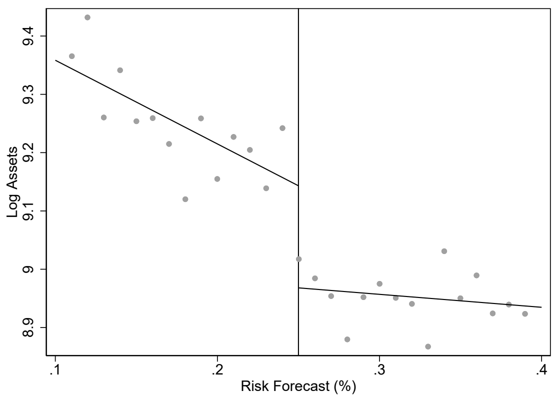
Notes. The figure shows how the premium to asset ratio responds close to the cutoff between the best credit score and the second best. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. Firms to the left (right) of the vertical line at 0.25% have the best (second best) credit score.

Figure 4: Regression Discontinuity Plots: Debt and Total Assets

(a) Log Debt



(b) Log Assets



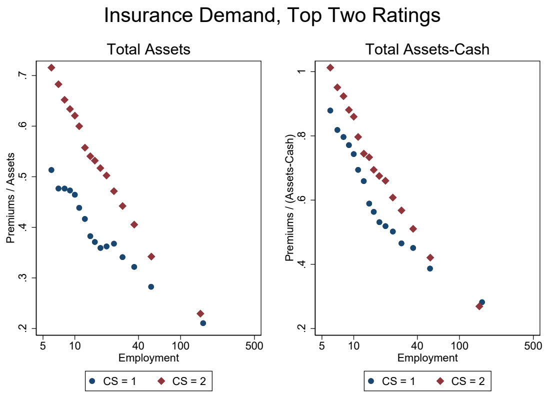
Notes. The figure shows how log debt and log assets respond close to the cutoff between the best credit score and the second best credit score, together with local linear regressions on each side of the cutoff. Firms to the left (right) of the cutoff at 0.25% have the best (second best) credit score.

9 Appendix: Supplemental Material

9.1 Figure

Alternative measures of insurance demand: premium to assets-cash.

Figure A.1: PAC Scatter

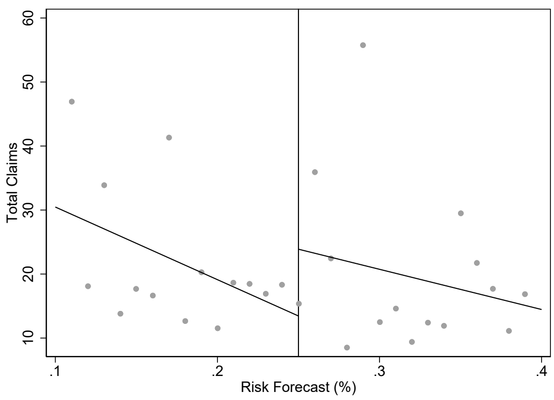


Notes. Alternative version of Figure 1,

9.2 Regression Discontinuity: Claims

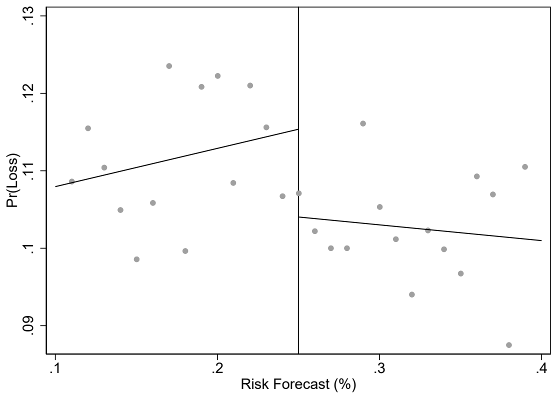
Figures show regression discontinuity design for total claims, probability of claims and claims to assets for the cutoff between the best and second best credit score.

Figure A.2: Regression Discontinuity Plots (Total Claims)



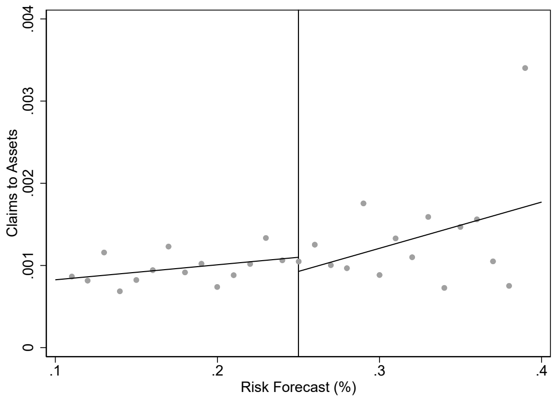
Notes. The figure shows how *total claims* respond close to the cutoff between credit scores 1 and 2, together with local linear regressions on each side of the cutoff. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. Firms to the left (right) of the vertical line at 0.25% have the best (second best) credit score.

Figure A.3: Regression Discontinuity Plots (Loss Risk)



Notes. The figure shows how *probability of loss* respond close to the cutoff between credit scores 1 and 2, together with local linear regressions on each side of the cutoff. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. Firms to the left (right) of the vertical line at 0.25% have the best (second best) credit score.

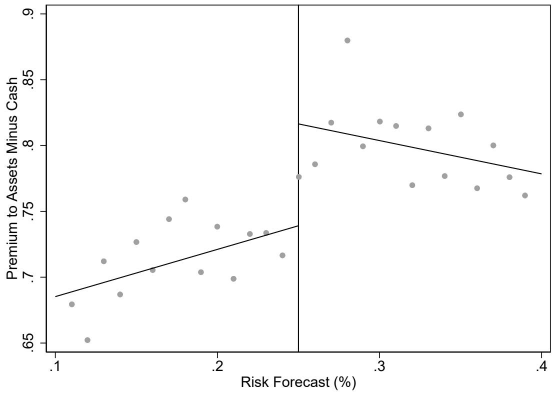
Figure A.4: Regression Discontinuity Plots (Claims to Assets)



Notes. The figure shows how *claims to assets* respond close to the cutoff between credit scores 1 and 2, together with local linear regressions on each side of the cutoff. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. Firms to the left (right) of the vertical line at 0.25% have the best (second best) credit score.

9.3 Regression Discontinuity: Alternative Measure of Insurance demand

Figure A.5: Regression Discontinuity Plots (Premium to Assets Minus Cash)

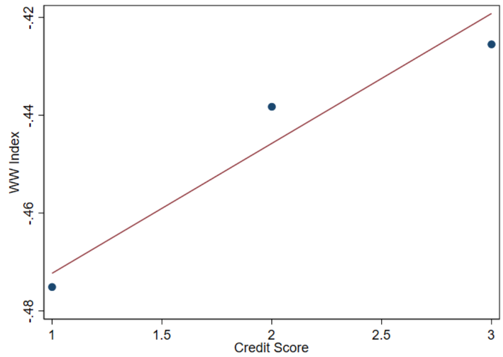


Notes. The figure shows how *premiums to assets minus cash* respond close to the cutoff between credit scores 1 and 2, together with local linear regressions on each side of the cutoff. Dots mark local sample means. Straight lines are derived by local linear regressions on each side of the cutoff. Firms to the left (right) of the vertical line at 0.25% have the best (second best) credit score.

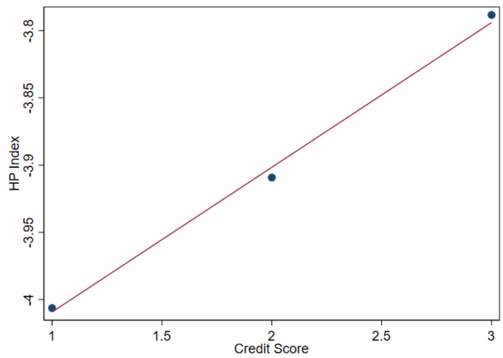
9.4 Traditional Measures of Financial Constraints

Figure A.6: Credit Score and Financial Constraints Measures

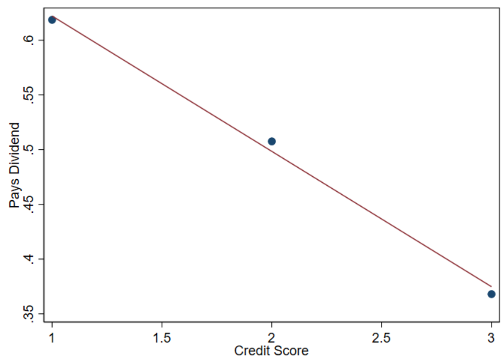
(a) WW Index



(b) HP Index



(c) Pays Dividends



Notes. The Figure shows binned scatter plots of financial constraint measures against credit scores 1 - 3. Dots mark local sample means. WW Index marks Index from Whited and Wu [2006], HP index marks Hadlock and Pierce [2010]. Panel (c): Y-axis shows fraction of firms paying dividends.

9.5 Regression Discontinuity Analysis: Balance Check

Table A.1: Distribution of Firms Around the Cutoff at 0.25 % (%)

	Left of Cutoff	Right of Cutoff
Distribution of Industries	(%)	(%)
Accommodation and food services	4.60	5.95
Administration and support	4.55	4.73
Agriculture, forestry and fishing	2.27	2.17
Arts and entertainment	0.61	0.74
Construction	19.81	21.91
Education	1.86	1.93
Electricity, gas, steam	0.04	0.00
Human health and social work	2.51	2.03
Information and communication	3.24	3.27
Manufacturing	20.76	19.84
Mining and quarrying	0.17	0.13
Other service activities	0.81	0.96
Professional, scientific and technical activities	7.69	6.68
Real Estate activities	1.38	0.88
Transportation and storage	5.45	5.61
Water supply, Waste Mgmt	0.56	0.49
Wholesale and retail, repair of motor vehicles	23.68	22.69
Age and Location		
Firm Age (Years)	25.82	22.93
Share in Stockholm (%)	13.17	13.33
N	22,964	10,813

Notes. The Table shows the distribution of industries around the cutoff in the UC measure. The left cutoff has firms with measures from 0.10 % to 0.24 %, while the right cutoff has firms with measures from 0.25 % to 0.40 %. All measures are in percentages, except for firm age, which is given in years.

9.6 Robustness

9.6.1 Alternative Independent Variable: Risk Forecast

Table A.2: Insurance Demand and Risk Forecast

	Premium to Assets			
	(1)	(2)	(3)	(4)
	No Firm FE	Firm FE	Establishments	Independent
Risk Forecast	0.088***	0.011***	0.011***	0.015***
	(0.004)	(0.002)	(0.002)	(0.003)
Log Employees	-0.138***	-0.124***	-0.126***	-0.177***
	(0.003)	(0.006)	(0.006)	(0.011)
Establishments			0.004***	
			(0.001)	
Firm	No	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
R-Squared	0.206	0.845	0.845	0.854
Observations	99,286	99,286	99,286	47,781

Notes. The Table shows regressions of premium to assets on the UC risk forecast. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

9.6.2 Alternative Dependent Variable: Total Assets Minus Cash

Table A.3: Alternative Measure of Insurance Demand

	Premium to Assets Minus Cash			
	(1)	(2)	(3)	(4)
	No Firm FE	Firm FE	Establishments	Independent
Top Score	-0.063***	-0.017***	-0.017***	-0.039***
	(0.010)	(0.005)	(0.005)	(0.009)
Second Score	0.021***	-0.002	-0.002	-0.007
	(0.007)	(0.004)	(0.004)	(0.006)
Log Employees	-0.227***	-0.199***	-0.202***	-0.288***
	(0.005)	(0.010)	(0.010)	(0.019)
Establishments			0.004**	
			(0.002)	
Firm	No	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes
R-Squared	0.215	0.823	0.823	0.828
Observations	99,283	99,282	99,282	47,780

Notes. The Table shows regressions of premium to total assets minus cash on the UC risk forecast. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

9.6.3 Alternative Dependent Variable Heterogeneity: Total Assets Minus Cash

Table A.4: Premium to Assets Minus Cash and Credit Scores (Heterogeneity)]

	Premium to Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash Flow Volatility		Credit Line First Year?		Volatility and Credit Line	
	Above Median	Below Median	No	Yes	Above and No	Below and Yes
Top Score	-0.019**	-0.013*	-0.025**	-0.010*	-0.027*	-0.008
	(0.008)	(0.007)	(0.010)	(0.006)	(0.015)	(0.007)
Second Score	-0.002	-0.001	-0.000	-0.004	-0.003	-0.005
	(0.006)	(0.005)	(0.008)	(0.004)	(0.012)	(0.005)
Log Employees	-0.200***	-0.208***	-0.197***	-0.204***	-0.215***	-0.226***
	(0.016)	(0.013)	(0.017)	(0.012)	(0.025)	(0.016)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.822	0.824	0.806	0.839	0.811	0.844
N	49,695	49,453	42,781	56,515	23,033	29,771

Notes. The Table shows regressions of premium to asset ratio on the UC credit score and controls. The cash flow volatility measure in columns (1) and (2) refer to firms in industries above and below the median level of the coefficient of variation for cash flows. The credit line measure in columns (3) and (4) is a dummy if the firm has a credit line during the first year it is observed. Columns (5) and (6) refer to firms with high volatility and no credit line or firms with low volatility and credit lines. Standard errors clustered at the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

9.7 Regression Discontinuity

9.7.1 Insurance Demand

Table A.5: The Effect of Lower Credit Score on Insurance Demand

	(1)	(2)
	0.15%	Optimal
Lower Credit Score	0.047***	0.048***
	(0.013)	(0.014)
Robust p-Value	0.006	0.000
Observations	33,756	99,287

Notes. The Table shows regression discontinuity regressions around the cutoff where a firm gets downgraded from the highest to the second-highest credit score. We estimate local linear regressions on each side of the cutoff. Standard errors are clustered at the firm level. Below the standard errors, we show p-valued that are robust and bias-corrected.

9.7.2 Debt and Total Assets

Table A.6: The Effect of Lower Credit Score on Debt

	(1)	(2)
	0.15%	Optimal
Lower Credit Score	-0.196***	-0.213***
	(0.037)	(0.041)
Robust p-Value	0.000	0.000
Observations	33,756	99,287

Notes. The Table shows regression discontinuity regressions around the cutoff where a firm gets downgraded from the highest to the second-highest credit rating. We estimate local linear regressions on each side of the cutoff. Standard errors are clustered at the firm level. Below the standard errors, we show p-valued that are robust and bias-corrected.

Table A.7: The Effect of Lower Credit Score on Assets

	(1)	(2)
	0.15%	Optimal
Lower Credit Score	-0.197***	-0.215***
	(0.035)	(0.040)
Robust p-Value	0.000	0.000
Observations	33,756	99,287

Notes. The Table shows regression discontinuity regressions around the cutoff where a firm gets downgraded from the highest to the second-highest credit rating. We estimate local linear regressions on each side of the cutoff. Standard errors are clustered at the firm level. Below the standard errors, we show p-valued that are robust and bias-corrected.

9.7.3 Detailed Investment Outcomes

Table A.8: The Effect of Lower Credit Score on Different Investment Outcomes

	(1)	(2)	(3)
	Log Physical Capital	Log Machinery	Log Financial Assets
Lower Credit Score	-0.188***	-0.180***	-0.011
	(0.060)	(0.055)	(0.084)
Robust p-Value	0.011	0.010	0.544
Observations	32,472	32,227	20,193

Notes. The Table shows regression discontinuity regressions around the cutoff where a firm gets downgraded from the highest to the second-highest credit rating. The bandwidth is 0.15 and we restrict the sample to UC risk forecast between 0.1 and 0.4, with a cutoff at 0.25 %. We estimate local linear regressions on each side of the cutoff. Standard errors are clustered at the firm level. Below the standard errors, we show p-valued that are robust and bias-corrected.

9.8 Robustness: Regression Discontinuity, Assets Minus Cash

Table A.9: The Effect of Lower Credit Score on Premium to Assets Minus Cash

	(1)	(2)
	15%	optimal
RD_Estimate	0.079***	0.079***
	(0.022)	(0.022)
Robust p-Value	0.008	0.000
Observations	33,754	99,284

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes. The Table shows regression discontinuity regressions around the cutoff where a firm gets downgraded from the highest to the second-highest credit rating. We estimate local linear regressions on each side of the cutoff. Standard errors are clustered at the firm level. Below the standard errors, we show p-valued that are robust and bias-corrected.

9.9 Constructing Measures of Financial Constraints

Whited and Wu (2006) Index of Financial Constraints

We use the index from Whited and Wu [2006] and Hennessy and Whited [2007]:

$$WW = -0.091\frac{\text{Cash Flow}}{\text{Total Assets}} - 0.062 \times \mathbb{1}\{\text{Dividends} > 0\} + 0.021\frac{\text{Long Debt}}{\text{Total Assets}}$$
$$-0.044 \times \text{Log Assets} + 0.012 \times \text{Industry Sales Growth} - 0.035 \times \text{Sales Growth}$$

We define cash flows as income before extraordinary incomes and expenses plus depreciation and amortization. We follow the authors and use 3-digit industry codes and take the average sales growth in each industry.

Hadlock and Pierce (2010) Index of Financial Constraints

We use the index by Hadlock and Pierce [2010]:

$$0.737 \times \text{Log Assets} + 0.043 \times (\text{Log Assets})^2 - 0.040 \times \text{Age}$$

We follow the authors and cap age at 37 and assets at USD 4.5 billion. To convert this into SEK, we take the average exchange rate for 2012 (the middle year of our sample). According to the Riksbank, this eschange rate is 6.7871 SEK/USD[29].

[29] https://www.riksbank.se/sv/statistik/sok-rantor–valutakurser/arsgenomsnitt-valutakurser/?y=2012m=11s=Commaf=y

Table A.10: Relationship Between Risk Forecast and Other Measures of Financial Constraints

	Risk Forecast		
	(1)	(2)	(3)
	Whited-Wu	Hadlock-Pierce	Pays Dividend
Risk Forecast	0.026***	0.135***	-0.155***
	(0.000)	(0.004)	(0.003)
Industry=0.industry_21 Year=0.year Log Employment	Yes	Yes	Yes
R-Squared	0.399	0.123	0.057
Observations	78,933	99,291	99,291

Notes. Table shows regression of the measures used in the literature to denote financing constraints on the continuous risk forecast from UC. Column (1): Whited and Wu [2006], column (2) Hadlock and Pierce [2010] and (3) Fazzari et al. [1988]. Regression include industry-year fixed effects and log employment as control variables.

9.10 List of Variables

Table A.11: List of Variables

Variable Name	Description	Source
Identifiers etc		
Firm ID	Firm ID number	Company Registration Office
Year	Year (t)	-
Industry	NACE code (Section or 2-digit)	SCB
Age	Years since firm foundation	SCB
Basic Firm Variables (end of period t)		
Sales	Sales	Serrano
Value Added	Value added	Serrano
Employment	Annual full-time employees	Serrano
(Total) Assets	Book value of total assets	Serrano
(Total) Debt	Book value of total debt	Serrano
Cash	Cash and bank balances	Serrano
Credit Line	Maximum credit line	SCB
Interest Rate	Financial expenses divided by liabilities	Serrano
Cash Flow	Profits after financial expenses - depreciation	Imputed
R&D-to-Sales	R&D ????	SCB
Insurance and Credit Score Variables		
Premium	Annual premiums paid (t)	Insurance company
Risk Forecast	Estimated risk of default (beginning of period t)	UC
Credit Score	Discretized version of the risk forecast (beginning of period t)	UC

Notes. The table 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.