IFN Working Paper No. 1493, 2024

Financial Constraints and Cash Holdings in Private Firms: Evidence from Discontinuous Credit Ratings

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June 24, 2024

Abstract

We study how financing constraints affect the cash holdings of small and medium-sized enterprises. There has been little empirical work on this topic, even though these firms often face financial constraints. We contribute by using detailed data on credit ratings in Sweden as a measure of financial constraints. We then use panel regressions and a regression-discontinuity analysis to estimate the relationship between access to credit and cash holdings. Our analysis finds no causal effect of credit ratings on cash holdings.

Keywords: Financial Constraints, Cash, Private Firm, Credit Score

JEL Codes: D22, D25, G32

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1 Introduction

Firms hold more cash now compared to previous decades. Many papers explore the motives for corporate cash holdings (Opler et al., 1999; Bates et al., 2009; Foley et al., 2007; Kalcheva and Lins, 2007). Most of these focus on large firms and few on small firms. However, financing constraints should be more relevant for small firms.

We study how financing constraints affect small firms' cash holdings. We combine detailed data on firms' credit ratings with data on their financial statements. The credit ratings allow us to exploit a regression-discontinuity design where firms with similar risk profiles vary in their discrete rating. We find no causal effect of financing constraints on firms' cash holdings. Firms around the cutoff hold more assets but no more cash, which decreases the cash-to-assets ratio.

Our paper contributes to a growing literature on the cash-holding motives of small and private firms (Bigelli and Sánchez-Vidal, 2012; Gao et al., 2013; Robb and Robinson, 2014; Potì et al., 2020; Mortal et al., 2020). We provide causal evidence on how financing constraints affect cash holdings. Khieu and Pyles (2012) find that credit rating downgrades are associated with increased cash holdings. We use the same data as Bustos et al. (2022); Bustos (2023), and do similar analyses.

2 Credit Ratings and Financial Data

Our key variables are cash, debt, and cash scaled by total assets net of cash. These variables come from the Serrano database covering the universe of Swedish firms. We winsorize all key dependent variables at the 99^{th} percentile.

We have data on start-of-year credit scores from a major Swedish rating firm, Upplysnings-centralen AB (UC).[1] The rating firm estimates the firm's default probability over the

[1] See, for example, Jacobson and Lindé (2000); Caggese et al. (2019); Bustos et al. (2022)

coming year. The risk forecast is based on a proprietary algorithm, which includes variables such as financial indicators and payment history. The risk forecast is then binned into five discrete ratings with cutoffs at 0.24%, 0.74%, 3.04%, and 8.04%.

We remove observations without an identifier, with less than six employees (no observed credit rating), zero or negative assets, revenues, labor costs, cash, or interest payments exceeding total debt, in the financial sector, not privately owned, or not a limited liability firm. We only include the three best ratings (to rule out financial distress). Monetary values are converted to SEK 2010. Our final sample consists of 208,607 firm-year observations from 37,449 firms from 2008 to 2017.

Table 1 shows summary statistics for the main sample. Average cash holdings are SEK 2.5 million or 43% of non-cash assets. Moreover, the average risk forecast is 0.64%, which translates into an average credit rating of 1.87

Table 1: Summary Statistics

	Observations	Mean	Median	Std Dev
Cash	208,600	2,472.35	1,078.01	3,500.00
Cash to Assets	208,593	0.43	0.17	1.25
Total Debt	208,605	12,620.48	4,421.88	25,000.00
Risk Forecast	208,607	0.64	0.39	0.69
Credit Rating	208,607	1.87	2.00	0.80

Notes: The table shows summary statistics for the sample. The variables cash, cash to assets, and debt are winsorized on the 1% level

3 Empirical Strategy

3.1 Panel Models

First, we use the temporal variation in firms' credit ratings. We regress a cash variable on dummies for the credit ratings, using the middle rating (2) as the baseline, on firm (μ_i)

and year (μ_t) fixed effects. We estimate the following model using ordinary least squares.

$$\text{Cash}_{it} = \beta' \text{Credit Rating}_{it} + \gamma' \mathbf{X}_{it} + \mu_i + \mu_t + \epsilon_{it} \tag{1}$$

The coefficients β measure differences in cash holdings for firms with different credit ratings. We cluster standard errors on the firm level.

3.2 Regression-Discontinuity Design

Next, we do we exploit the discontinuity in the credit rating system. Under the assumption that firms just above and below the cutoff are comparable in unobserved characteristics, having a better credit rating can be seen as a randomly assigned relaxation of financing constraints.

We assign each observation to the closest cutoff (0.25% or 0.75%) and calculate the distance to this cutoff as the running variable. Following Lee and Lemieux (2010), we estimate:

$$y_{it} = \alpha + \beta \mathbb{1}(s_{it} \geq c) + f_1(s_{it} - c) + \mathbb{1}(s_{it} \geq c) f_2(s_{it} - c) + \epsilon_{it}, \tag{2}$$

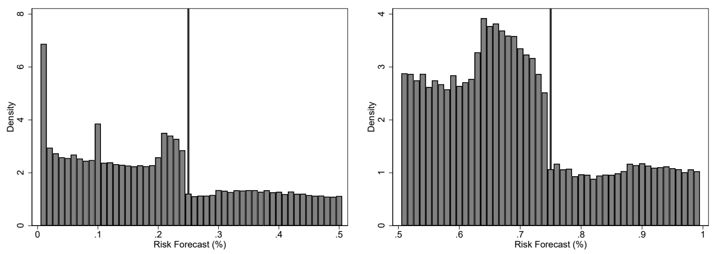
where c is the cutoff (0.25 or 0.75), f is a polynomial of the running variable, and y_{it} is an outcome. We include a linear control to the distance from the cutoff (Gelman and Imbens, 2019) and use the optimal bandwidths from Calonico et al. (2014, 2017).

3.3 Additional Validations

In Figure 1, the credit rating density is smooth except right above the cutoff. However, firms bunch because those above the cutoff are assessed less critically and somewhat shielded from a downgrade. This feature ensures that firms do not change credit ratings too often.

Figure 1: Risk Forecast Density

Panel A: First Cutoff **Panel B:** Second Cutoff



The figure shows the density of the risk forecast around either the first cutoff (0.25%) or the second cutoff (0.75%). Similar figures appear in Bustos et al. (2022).

To further validate our design, we show in Table 2 that firms are comparable across the cutoffs by comparing the industry and geographical characteristics that should be unaffected by the credit rating.

Table 2: Credit Rating and Non-Financial Variables

	Effect of Lower Credit Score	Robust P-Value
Agriculture, Forestry, and Fishing	0.00	0.75
Mining and Quarrying	0.00	0.88
Manufacturing	-0.02	0.01
Electricity, Gas, and Steam	-0.00	0.18
Water Supply and Waste Management	-0.00	0.73
Construction	0.00	0.52
Wholesale and Retail	-0.01	0.05
Transportation and Storage	-0.01	0.08
Accommodation and Food Services	0.02	0.00
Information and Communication	0.00	0.95
Real Estate	0.00	0.33
Professional, Scientific, and Technical Activities	-0.00	0.83
Administration and Support	0.00	0.38
Education	0.01	0.01
Human Health and Social Work	0.00	0.46
Arts and Entertainment	0.00	0.24
Other Services	0.00	0.27
In Stockholm	0.00	0.53

Notes: The table shows regression discontinuity estimates around the credit rating cutoffs. These are estimated using the optimal bandwidth from Calonico et al. (2014, 2017) and a local linear polynomial. A similar table appears in Bustos et al. (2022).

4 Results

We estimate the relationship between cash holdings and credit ratings. Figure 2 visually represents the regression-discontinuity results.

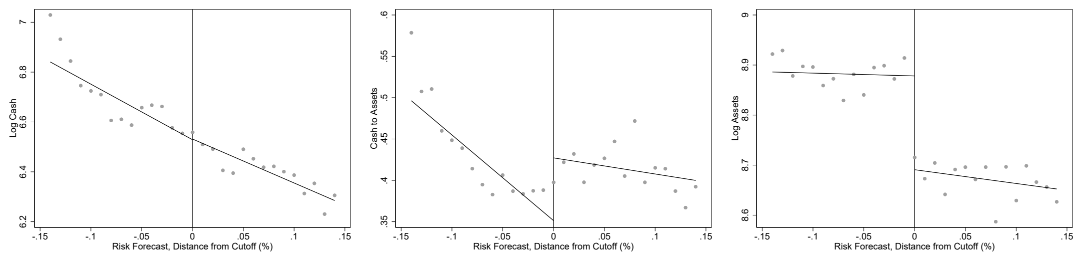
Table 3, columns (1) and (2) show that cash holdings increase with a better credit rating in the panel analysis. This relationship holds both with and without firm and year fixed effects. In contrast, in column (3), the relationship is small (0.022) and statistically insignificant in the regression-discontinuity setup.

We then turn to cash scaled by total assets minus cash holdings (columns 4-6). We see a positive relationship both in the panel and the regression-discontinuity analyses. The jump at the cutoff is estimated to be around 4.7 percentage points.

Finally, we study the effect on log non-cash assets. We then see the same pattern in the panel analysis. Firms with better ratings also have more assets. Finally, in column (9), we see that the regression-discontinuity estimate is 20%.

Figure 2: Regression Discontinuity Results:

Panel A: Log Cash **Panel B:** Cash to Assets **Panel C:** Log Assets



The figure shows regression discontinuity results using the optimal bandwidth from Calonico et al. (2014, 2017), but only within 0.15 percentage points around the two cutoffs (0.25% and 0.75%), and a local linear polynomial.

Table 3: Credit Rating and Cash Holding Results

	Log Cash			Cash to Assets			Log Assets		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	RDD	OLS	OLS	RDD	OLS	OLS	RDD
Best Credit Score	1.249***	0.163***		0.248***	0.021***		0.460***	0.032***	
	(0.015)	(0.010)		(0.010)	(0.007)		(0.012)	(0.003)	
Worst Credit Score	-0.706***	-0.149***		-0.115***	-0.019***		0.017*	-0.024***	
	(0.015)	(0.011)		(0.006)	(0.006)		(0.009)	(0.003)	
Lower Credit Score			0.022			0.047***			-0.213***
			(0.046)			(0.018)			(0.029)
Polynomials			1			1			1
Firm Fixed Effects	No	Yes	No	No	Yes	No	No	Yes	No
Year Fixed Effects	No	Yes	No	No	Yes	No	No	Yes	No
Robust p-Value			0.401			0.042			0.000
Observations	208,600	203,076	208,600	208,593	203,068	208,593	208,591	203,066	208,591

Notes: The table shows panel and regression discontinuity estimates. The regression-discontinuity models are estimated using the optimal bandwidth from Calonico et al. (2014, 2017) and a local linear polynomial. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

5 Conclusion

Few studies focus on the cash holdings of small firms, even though they are likely to have strong motives due to precautionary savings or transaction costs. We use data on Swedish firms and their credit ratings to study this question. The rating agency estimates an underlying continuous risk forecast and converts this into discrete credit ratings. This value is then mechanically converted into a credit rating. We can thus compare firms right at the cutoff.

We find that firms with different credit ratings have different cash holdings in the panel analyses. However, we find no differences in total cash holdings when we look at the cutoff. The cash-to-asset ratio increases for firms with a worse credit rating, entirely driven by lower assets. This result contrasts large parts of the literature that find higher financial constraints associated with higher cash holdings.

References

Bates, T. W., K. M. Kahle, and R. M. Stulz (2009). Why Do US Firms Hold So Much More Cash Than They Used To? *The Journal of Finance 64*(5), 1985–2021.

Bigelli, M. and J. Sánchez-Vidal (2012). Cash Holdings in Private Firms. *Journal of Banking & Finance 36*(1), 26–35.

Bustos, E. (2023). The Effect of Financial Constraints on Inventory Holdings. *IFN Working Paper 1463*.

Bustos, E., O. Engist, G. Martinsson, and C. Thomann (2022). Financing Constraints and Risk Management: Evidence From Micro-Level Insurance Data. *IFN Working Paper 1452*.

Caggese, A., V. Cuñat, and D. Metzger (2019). Firing the Wrong Workers: Financing Constraints and Labor Misallocation. *Journal of Financial Economics 133*(3), 589–607.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2017). Rdrobust: Software for Regression-Discontinuity Designs. *The Stata Journal 17*(2), 372–404.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. *Econometrica 82*(6), 2295–2326.

Foley, C. F., J. C. Hartzell, S. Titman, and G. Twite (2007). Why Do Firms Hold So Much Cash? A Tax-Based Explanation. *Journal of Financial Economics 86*(3), 579–607.

Gao, H., J. Harford, and K. Li (2013). Determinants of Corporate Cash Policy: Insights From Private Firms. *Journal of Financial Economics 109*(3), 623–639.

Gelman, A. and G. Imbens (2019). Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. *Journal of Business & Economic Statistics 37*(3), 447–456.

Jacobson, T. and J. Lindé (2000). Credit Rating and the Business Cycle: Can Bankruptcies Be Forecast? *Sveriges Riksbank Economic Review 4*, 11–33.

Kalcheva, I. and K. V. Lins (2007). International Evidence on Cash Holdings and Expected Managerial Agency Problems. *The Review of Financial Studies 20*(4), 1087–1112.

Khieu, H. D. and M. K. Pyles (2012). The Influence of a Credit Rating Change on Corporate Cash Holdings and Their Marginal Value. *Financial Review 47*(2), 351–373.

Lee, D. S. and T. Lemieux (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature 48*(2), 281–355.

Mortal, S., V. Nanda, and N. Reisel (2020). Why Do Private Firms Hold Less Cash Than Public Firms? International Evidence on Cash Holdings and Borrowing Costs. *Journal of Banking & Finance 113*, 105722.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson (1999). The Determinants and Implications of Corporate Cash Holdings. *Journal of Financial Economics 52*(1), 3–46.

Potì, V., P. Pattitoni, and B. Petracci (2020). Precautionary Motives for Private Firms' Cash Holdings. *International Review of Economics & Finance 68*, 150–166.

Robb, A. M. and D. T. Robinson (2014). The Capital Structure Decisions of New Firms. *The Review of Financial Studies 27*(1), 153–179.