IFN Working Paper No. 1463, 2023

# The Effect of Financial Constraints on Inventory Holdings

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May 24, 2023

**Abstract**

This paper investigates the impact of financial constraints on firms' inventory holdings, an area of significant interest given that inventories are volatile over the business cycle. I use detailed data on Swedish firms' balance sheets, income statements, and credit scores. I employ a regression discontinuity design and a difference-in-differences analysis to examine the causal effects of financial constraints on inventory management. Firms with relaxed financing constraints increase their inventories by 20% when they get a better credit score, yet there is no robust effect on inventories relative to firm size. This study offers new insights into the influence of financial constraints on firms' inventory strategies amidst changing economic conditions.

**Keywords:** Financial Constraints, Risk Management, Inventories, Credit Scores, Private Firms

**JEL Codes:** D22, D25, G32, G32

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*Research Institute of Industrial Economics, emil.bustos@ifn.se. This is a revised version of a chapter in my doctoral dissertation. I want to thank Johan Cassel, Olle Engdegård, Oliver Engist, Richard Friberg, Gustav Martinsson, Barbro Olsson, Christian Thomann and Pehr Wissén. In addition, I want to thank seminar participants at the 10th National PhD Workshop in Finance (SHoF, 2021). Moreover, I would also like to thank Statistics Sweden, the Swedish House of Finance Insurance Data Initiative, Upplysningscentralen and an anonymous insurance company for access to data. Financial support by the Jan Wallander and Tom Hedelius fund and the Marianne and Marcus Wallenberg foundation (Grant 2020.0049) is gratefully acknowledged.

# 1 Introduction

**Motivation** This paper examines the impact of economic conditions on firms' inventory holdings, a topic of particular importance given that inventories account for nearly 90% of the decline in production during post-World War II recessions in the United States. While theory suggests that the cost of capital and financing conditions should be critical determinants, empirical research has struggled to find evidence supporting this view (Blinder and Maccini, 1991; Maccini et al., 2004; Jones and Tuzel, 2013).

In response, a new strand of literature has emerged, focusing on changes in monetary policy or cash flow volatility.[1] More recent studies have employed natural experiments to investigate the effects of changes in financing constraints (Barrot, 2016; Kim, 2021).

Concurrently, other research has emphasized the role of non-financial risks in driving inventory holdings (Aktas et al., 2015; Chen and Kieschnick, 2018). This paper contributes to the ongoing discussion by examining the interplay between these factors and their influence on firms' inventory management strategies in the context of changing economic conditions.

**This Paper** In this paper, I study how financial constraints affect the levels of inventory holdings I do this by using detailed Swedish firm-level data on credit scores as a measurement of financial constraint. I explore the causal effects both through using a regression-discontinuity design around the cutoff between two credit scores and through comparing firms with different credit scores around the time of a large monetary policy relaxation.

**Setting** To study this, I combine data on firms' inputs and outputs, as well as their credit scores. I use balance sheet and profit-and-loss information for Swedish limited liability firms, as well as credit score data. All limited liability firms in Sweden have a credit score

[1] Kashyap et al. (1992, 1994); Carpenter et al. (1994, 1998); Maccini et al. (2004); Guariglia and Mateut (2006); Jones and Tuzel (2013); Dasgupta et al. (2019); Bianco and Gamba (2019).

based on their estimated risk of default during the coming twelve months. This score is based on board member information, firm-level data and industry characteristics.

**Empirical Strategy** I compare firms around the cutoff between two credit scores. The credit score is based on an underlying continuous estimated risk forecast. Firms around the cutoff are similar on variables unrelated to credit conditions. I then do a regression-discontinuity analysis to estimate the causal effect. Moreover, I complement this analysis by doing a difference-in-differences analysis comparing firms with different credit scores when the Riksbank introduced near-zero interest rates. Furthermore, I supplement this approach with a difference-in-differences analysis, comparing firms with different credit scores when the Riksbank introduced a near-zero interest rate.

**Results** I find that relaxed financing constraints make firms increase thier inventories. In the regression-discontinuity study, the effect is roughly 20%. In the difference-in-differences setup, the effect is 5%. However, I find no robust effect on inventories relative to firm size. These results are robust across various sample and treatment variations.

**Model** To understand these results, I build a model where firms can invest in physical capital and hold inventories. However, both of these are subject to convex financing costs. Thus, while financial constraints depress both inventories and physical capital in absolute terms, it is unclear if their ratio is affected. In the model, this depends on how financial constraints affect inventories and physical capital. If they are affected similarly, the ratio will decline since only new capital (investment) is affected by the constraint. However, if they are affected in different ways, the net effect is ambiguous.

**Contribution** This study advances our understanding of the real effects of credit supply by investigating the role of financing constraints on firms' inventory holdings. While the literature has demonstrated that firms adjust their employment and investment decisions in response to changes in credit supply[2], we know less about the impact of financing constraints on inventory decisions (Guariglia and Mateut, 2006; Barrot, 2016; Dasgupta et al., 2019; Bianco and Gamba, 2019; Kim, 2021). This article contributes to the literature on inventory holdings by providing causal evidence on the effect of financing constraints on inventory investment.

Furthermore, this study contributes to the literature using credit scores as a proxy for financial constraints.[3] While prior research has used credit scores to examine the real effects of credit supply on employment and investment decisions, this study employs credit scores to explore their impact on inventory investment, a new setting in the literature.

I also explore the interaction between monetary policy and financing constraints, specifically credit ratings.[4] It is still being determined whether more or less financially constrained firms react more strongly to changes in financing conditions. While the financial accelerator model suggests that financially constrained firms should respond more to changes in financing[5], recent research by Ottonello and Winberry (2020) has found that more unconstrained firms react more strongly to changes in credit conditions. An upward-sloping marginal cost curve of external finance rationalizes this result.

Overall, this study offers novel contributions to the literature on the real effects of credit supply, using credit scores as a proxy for financial constraints and the interaction between monetary policy and financing constraints.

**Roadmap** This paper continues as follows. In Section 2, I provide a model that relates financial constraints to sales and inventory holdings. Next, Section 3, discusses the data and the institutional setting. In Section 4, I discuss my regression discontinuity setup. The results are then presented in Section 5. I present my difference-in-differences analysis of a monetary policy loosening in Section 6. Finally, Section 7 concludes.

[2] Campello et al. (2010); Chodorow-Reich (2014); Cingano et al. (2016); Berton et al. (2018); Amiti and Weinstein (2018); Huber (2018); Chen and Kieschnick (2018); Hviid and Schroeder (2021).

[3] Almeida et al. (2017); Caggese et al. (2019); Bustos et al. (2022); Engist (2021)

[4] (Cloyne et al., 2018; Ottonello and Winberry, 2020; Brabant et al., 2022; Rezghi, 2022).

[5] (Bernanke et al., 1996; Brabant et al., 2022; Cloyne et al., 2018)

# 2 Conceptual Framework

## 2.1 Setup and Related Literature

To help understand my empirical results, I provide a conceptual framework where a firm faces a two-period problem of choosing capital and inventories. In the first period, the firm chooses how much to sell and how much to keep in inventories for the next period. In addition, the firm chooses how much to invest into production the next period.

There are several papers modeling the role of financial constraints. Froot et al. (1993) show that hedging can increase firm value if external financing is costlier than internal finance. Several authors link collateral requirements and financing constraints to trade-offs between investment and risk management (Rampini and Viswanathan, 2010, 2013; Rampini et al., 2014). This papers relates to this literature by relating the size of financing frictions to firm size, by assuming that the cost of financing is lower for larger firms. However, given that risk comes from output prices, inventories work not as a hedge, but as a means to take advantage of better economic conditions.

This paper also relates to the literature that models inventory behavior. The classic work by Blinder (1986) shows that there is a positive correlation between sales and changes in inventories. That is, that inventories are pro-cyclical. I let my model capture these facts by having both inventories and production increase in booms, modeled as higher expected prices tomorrow.

The papers closest to my model are Bianco and Gamba (2019) and Dasgupta et al. (2019). The key difference from Bianco and Gamba (2019) is that I model inventories of the final good, rather than an input good, and thus the motive for holding inventories is to take advantage of fluctuations in the price of the output good. Moreover, they model financing constraints as a cost on issuing equity, while I model it as a convex cost of financing investments and inventories and allow them to differ between the two. Similarly, Dasgupta et al. (2019) model financing constraints as a condition on non-negative dividends. In addition, they include a penalty for low levels of inventories (so-called stockout avoidance costs Blanchard (1983)), which makes it optimal for firms to have larger inventories. In contrast, I include a non-negativity constraint on inventories and endogenize positive inventories through expectations of future prices.

The firm faces an upwards-sloping curve of financing costs (Stiglitz and Weiss, 1981; Almeida and Campello, 2001; Whited and Wu, 2006; Farre-Mensa and Ljungqvist, 2016). I model the reduced form of financing costs as a convex cost function in the inventories and investment to assets ratio. Notably, I allow the financing costs to differ between the two types of variables. This represents that the firm might use less risky short-term debt to finance inventories, while loans to finance capital might be more long-term and riskier.

Sales are given by the difference between production $zk_1$ and inventory investments $n_2 - n_1$ in the first period and as production plus remaining inventories in the second period. For simplicity, I assume that production is linear in the capital stock, with a productivity parameter $z > 0$,

$$zk_1 - n_2 + n_1,$$

$$zk_2 + n_2.$$

The cost functions are convex in $\frac{n_2}{k_1}$ and $\frac{i_1}{k_1}$, representing both that financing gets more expensive, but can also include adjustment costs. There are two positive scaling parameters $c^K, c^N$. Financing costs are given by $\frac{k_1+\theta^K(\theta)}{k_1}$ and $\frac{k_1+\theta^N(\theta)}{k_1}$, where $\theta$ is a parameter common to both inventories and capital, and $\theta^K(\theta)$ and $\theta^N(\theta)$ are positive and increasing functions. I thus allow for financing constraints to affect capital and inventories differently. This is important, since financing constraints would otherwise only affect new investments but all of inventories, and thus mechanically depress the inventories to assets ratio. This functional form also means that larger firms have lower financing constraints (see Farre-Mensa and

Ljungqvist (2016)):

$$\Big(\frac{c^K}{2}\Big)\Big(\frac{k_1+\theta^K(\theta)}{k_1}\Big)\Big(\frac{i_1}{k_1}\Big)^2 k_1,$$
$$\Big(\frac{c^N}{2}\Big)\Big(\frac{k_1+\theta^N(\theta)}{k_1}\Big)\Big(\frac{i_1}{n_2}\Big)^2 k_1.$$

Capital depreciates by a factor $\delta \in (0,1)$, which gives capital in the second period by

$$k_2 = k_1(1-\delta) + i_1.$$

Finally, the firm cannot run negative inventories or have inventories larger than the initial stock plus production. I thus add two inequality constraints, and add their associated Lagrange multipliers:

$$(\mu) \qquad\qquad n_2 \geq 0,$$
$$(\lambda) \qquad\qquad zk_1 + n_1 \geq n_2.$$

## 2.2 Program and First-Order Conditions

The firm's Lagrangian is

$$L = p_1\Big(zk_1 - n_2 + n_1\Big) - \Big(\frac{c^K}{2}\Big)\Big(\frac{k_1+\theta^K(\theta)}{k_1}\Big)\Big(\frac{i_1}{k_1}\Big)^2 k_1 - \Big(\frac{c^N}{2}\Big)\Big(\frac{k_1+\theta^N(\theta)}{k_1}\Big)\Big(\frac{n_2}{k_1}\Big)^2 k_1$$
$$+ \mu n_2 + \lambda(zk_1 + n_1 - n_2)$$
$$+ \beta E\Big(p_2[n_2 + z(k_1(1-\delta) + i_1)]\Big),$$

$n_1, k_1$ given.

The associated first-order conditions are:

$$
\begin{aligned}
&(n_2) && p_1 + c^N\Big(\frac{k_1+\theta^K(\theta)}{k_1}\Big)\Big(\frac{n_2}{k_1}\Big) = \mu - \lambda + \beta E[p_2], \\
&(i_1) && c^K\Big(\frac{k_1+\theta^N(\theta)}{k_1}\Big)\Big(\frac{i_1}{k_1}\Big) = \beta z E[p_2], \\
&(\mu) && \mu \geq 0 \text{ and } \mu n_2 = 0, \\
&(\lambda) && \lambda \geq 0 \text{ and } \lambda(z k_1 + n_1 - n_2) = 0.
\end{aligned}
$$

## 2.3 Solution

First, I solve for the inventories to assets ratio

$$\frac{n_2}{k_1} = \frac{1}{c^N}\frac{k_1}{k_1+\theta^N(\theta)}\Big(\mu - \lambda + \beta E[p_2] - p_1\Big).$$

Optimal inventories are increasing in the difference between the expected next-period price and the current price. In addition, it is decreasing in financing costs $\theta^N(\theta)$ and increasing in initial size $k_1$.

To focus on the interesting case, I assume that inventories are strictly positive and less than the sum of initial inventories and first-period production. That is, none of the constraints are binding ($\mu = 0$ and $\lambda = 0$). This holds if the expected price increase is sufficiently large $\beta E[p_2] - p_1 > 0$, but not too large $\frac{k_1}{c^N}\frac{k_1}{k_1+\theta^N(\theta)}(\beta E[p_2] - p_1) < z k_1 + n_1$

Next, I solve for investment to assets ratio

$$\frac{i_1}{k_1} = \frac{1}{c^K}\frac{k_1}{k_1+\theta^K(\theta)}\beta z E[p_2].$$

Similar to inventories, optimal investment is increasing in expected future prices. In addition, it is increasing in productivity and initial size, and decreasing in financing costs.

Finally, we study the effect on the inventories to current assets ratio, $\frac{n_2}{k_2}$,

$$\frac{n_2}{k_2} = \frac{\frac{1}{c^N}\frac{k_1}{k_1+\theta^N(\theta)}\Big(\beta E[p_2]-p_1\Big)}{1-\delta+\frac{1}{c^K}\frac{k_1}{k_1+\theta^K(\theta)}\beta E[p_2]} =$$
$$\Big(\frac{c^K}{c^N}\Big)\Big(\frac{k_1+\theta^K(\theta)}{k_1+\theta^N(\theta)}\Big)\Big(\frac{k_1(\beta E[p_2]-p_1)}{c^K(k_1+\theta^K(\theta))(1-\delta)+k_1\beta z E[p_2]}\Big).$$

## 2.4 Predictions: Effects of Tightened Financial Constraints

The effect of tighter financial constraints can be seen as an increase in $\theta^N, \theta^K$. Assuming the firm still has positive inventories, we have

$$\frac{\partial n_2}{\partial \theta} = -\frac{\frac{\partial \theta^N(\theta)}{\partial \theta}}{c^N}\Big(\frac{k_1}{k_1+\theta^N(\theta)}\Big)^2\Big(\beta E[p_2]-p_1\Big) < 0,$$
$$\frac{\partial i_1}{\partial \theta} = -\frac{\frac{\partial \theta^N(\theta)}{\partial \theta}}{c^K}\Big(\frac{k_1}{k_1+\theta^K(\theta)}\Big)^2\beta E[p_2] < 0.$$

Higher financial constraints reduce both inventories and investment in physical capital. This gives our first hypothesis:

**Hypothesis 1:** Financially constrained firms have less assets and inventories.

Finally, we study the effect on the inventories to current assets ratio $\frac{n_2}{k_2}$,

$$\frac{\partial \frac{n_2}{k_2}}{\partial \theta} =$$
$$\frac{c^K}{c^N}k_1\Big(\beta E[p_2]-p_1\Big)\frac{k_1+\theta^K(\theta)}{k_1+\theta^N(\theta)}\frac{1}{c^K(k_1+\theta^K\theta)(1-\delta)+k_1\beta z E[p_2]}$$
$$\Big\{\frac{\frac{\partial \theta^K(\theta)}{\partial \theta}}{k_1+\theta^K(\theta)} - \frac{\frac{\partial \theta^N(\theta)}{\partial \theta}}{k_1+\theta^N(\theta)} - \frac{c^K(1-\delta)\frac{\partial \theta^K(\theta)}{\partial \theta}}{c^K(k_1+\theta^K(\theta))(1-\delta)+k_1\beta z E[p_2]}\Big\}.$$

Rewrite this as the elasticity of the inventories to current assets ratio, and denote the elasticities $\epsilon = \frac{\partial \frac{n_2}{k_2}}{\partial \theta} \frac{\theta}{\frac{i_1}{k_2}}$, $\varepsilon^N = \frac{\partial \theta^N(\theta)}{\partial \theta} \frac{\theta}{\theta^N(\theta)}$ and $\varepsilon^K = \frac{\partial \theta^K(\theta)}{\partial \theta} \frac{\theta}{\theta^K(\theta)}$,

$$\begin{aligned}
\epsilon &= \varepsilon^K \frac{\theta^K(\theta)}{k_1 + \theta^K(\theta)} - \varepsilon^N \frac{\theta^N(\theta)}{k_1 + \theta^N(\theta)} - \varepsilon^K \frac{c^K(1-\delta)\theta^K(\theta)}{c^K(k_1 + \theta^K(\theta))(1-\delta) + k_1\beta z E[p_2]} \\
&= \varepsilon^K \frac{\theta^K(\theta) k_1 \beta z E[p_2]}{(k_1 + \theta^K(\theta))(c^K(k_1 + \theta^K(\theta))(1-\delta) + k_1\beta z E[p_2])} - \varepsilon^N \frac{\theta^N(\theta)}{k_1 + \theta^N(\theta)}
\end{aligned}$$

This expression is negative if

$$\begin{aligned}
&\varepsilon^K \frac{\theta^K(\theta) k_1 \beta z E[p_2]}{(k_1 + \theta^K(\theta))(c^K(k_1 + \theta^K(\theta))(1-\delta) + k_1\beta z E[p_2])} - \varepsilon_N \frac{\theta^N(\theta)}{k_1 + \theta^N(\theta)} < 0 \\
&\frac{\varepsilon^N}{\varepsilon^K} > \Big(\frac{\theta^K(\theta)}{\theta^N(\theta)}\Big)\Big(\frac{k_1 + \theta^N(\theta)}{k_1 + \theta^K(\theta)}\Big)\Big(\frac{k_1 \beta z E[p_2]}{c^K(k_1 + \theta^K(\theta))(1-\delta) + k_1\beta z E[p_2]}\Big).
\end{aligned}$$

In other words, the inventories to current assets ratio declines if the effect of tighter financial constraints is sufficiently larger for inventories, compared to physical assets. This threshold value is lower because of depreciation, since then only a fraction of the capital stock is affected by the financing constraint.

We can look at some special cases. First, if inventories are not affected by financial constraints ($\varepsilon^N = 0$), then the entire effect is driven by depressed physical capital

$$\epsilon = \varepsilon^K \frac{\theta^K(\theta) k_1 \beta z E[p_2]}{(k_1 + \theta^K(\theta))(c^K(k_1 + \theta^K(\theta))(1-\delta) + k_1\beta z E[p_2])} > 0.$$

Secondly, if there is full depreciation ($\delta = 1$), the effect is entirely driven by the relative importance of the financial constraints on inventories and capital,

$$\epsilon = \varepsilon^K \frac{\theta^K(\theta)}{k_1 + \theta^K(\theta)} - \varepsilon^N \frac{\theta^N(\theta)}{k_1 + \theta^N(\theta)}.$$

In the end, we are left with an ambiguous case.

**Hypothesis 2:** The effect of financial constraints on the inventories to assets ratio is ambiguous.

# 3 Credit Scores and Firm Data

## 3.1 Balance Sheet and Income Statement Data

I combine data on firms' inventory holdings and credit scores to estimate the relationship between financial constraints and inventories. Moreover, I use data on Swedish limited liability companies provided by the Serrano database. The Serrano database is based on the administrative records held by Statistics Sweden and the Swedish Companies Registration Office. To also obtain data on credit scores, I have to limit the sample to those used in Bustos et al. (2022). They study the relationship between financial constraints and insurance demand, and thus the data is limited to the customers of one of Sweden's largest insurance companies. In addition, I use data on industry codes.[6]

The sample covers annual data between 2008 and 2017 on firms' balance sheets and profit-and-loss statements, as well as insurance and credit score data.[7] My sample covers firms around the cutoff between the top and the second-best rating. This cutoff is at a risk forecast of 0.25% and I extend the bandwidth by 0.145% on each side. This is by far the cutoff with the largest mass of firms.

Table 1 presents the summary statistics of the sample, providing a glimpse into the essential characteristics of firms in the study. These results shed light on the heterogeneity of firms, allowing for a more nuanced understanding of how credit supply and financing constraints impact firms of different sizes and industries.

The findings indicate that the average firm in the sample has relatively modest sales of SEK 55 million, roughly equivalent to USD 5.5 million. However, considerable variation, with the largest firms boasting nearly SEK 100 billion in sales, highlights the diverse range of firms in the Swedish economy. These results reveal the importance of studying the

[6] The codes are the level 1 SNI codes from Statistics Sweden. These are the Swedish version of the European NACE Revision 2.

[7] The sample is restricted to privately-owned, limited liability firms. Moreover, firms in the financial sector are excluded. Similarly, firm-years are only included if the firm has more then five employees, positive assets, debt, labor cost, sales and cash, as well as an interest rate below 100%.

impact of financing constraints and credit supply on firms of various sizes and operating in different industries.

The study also provides insights into the inventory management practices of firms. The findings indicate that the average firm holds slightly over SEK 2 million in inventories. Looking at ratios, the average firm has 13% of total assets and 3 times fixed assets. These results provide valuable insights into how financing constraints and credit supply can affect inventory management decisions and how firms may adjust their inventory holdings to overcome these constraints.

Regarding industry distribution, the results show that the retail and wholesale industry accounts for the largest share of firms in the sample, with 23% of the firms operating in this sector. The manufacturing industry comes in second, with 19% of the firms, while 18% are in the construction industry.

**Table 1:** Summary Statistics

| | Obs | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|---|
| Sales | 65,986 | 55,045 | 634,816 | 15,435 | 58 | 95,000,000 |
| Total Assets | 65,987 | 43,844 | 602,120 | 8,327 | 81 | 70,000,000 |
| Physical Assets | 65,985 | 9,768 | 151,641 | 660 | 0 | 15,000,000 |
| Total Debt | 65,986 | 25,218 | 402,645 | 3,745 | 2 | 50,000,000 |
| Long Debt | 65,986 | 10,246 | 243,212 | 0 | -1,767 | 25,000,000 |
| Inventories | 65,984 | 2,278 | 4,415 | 271 | 0 | 15,000 |
| Inventories to Assets | 65,984 | 13 | 18 | 5 | 0 | 85 |
| Inventories to Fixed Assets | 64,387 | 325 | 1,096 | 20 | 0 | 8,500 |
| Inventories to Physical Assets | 62,966 | 584 | 1,901 | 32 | 0 | 14,096 |
| Inventories to Assets - Inventories | 65,984 | 25 | 58 | 5 | 0 | 627 |
| Manufacturing | 65,987 | 19 | 39 | 0 | 0 | 100 |
| Construction | 65,987 | 18 | 39 | 0 | 0 | 100 |
| Retail | 65,987 | 23 | 42 | 0 | 0 | 100 |
| Professional | 65,987 | 9 | 28 | 0 | 0 | 100 |
| Stockholm | 65,933 | 16 | 36 | 0 | 0 | 100 |

*Notes.* The table shows summary statistics for the sample firms. The unit of observation is the firm-year. The inventory ratios, industry variables, and Stockholm dummy are expressed as percentages. The monetary values are in SEK 2010 and expressed in SEK 1,000. The maximum values are censored to provide confidentiality.

## 3.2 Credit Scores

I use credit scores to measure financial constraints. The data comes from Upplysningscentralen AB ("UC"), which rates all Swedish limited liability companies. UC uses board member, company, and industry information to estimate the risk of default within the next 12 months. This variable is denoted the risk forecast. I have data on the risk forecast of January 1 each year. Notably, UC could update the rating during the year.

Furthermore, UC converts the risk forecast into discrete credit scores. In this paper, due to sample size concerns, I focus on the top rating, which has a cutoff at 0.25% risk forecast.

This is a similar setup to Caggese et al. (2019); Bustos et al. (2022).

Table 2 shows summary statistics for different types of firms in my sample. The sample is restricted to firms with a risk forecast between 0.105% and 0.395%. The average risk forecast in the sample is 0.23%, and the median is 0.22%. We thus have some more firms to the left of the cutoff. We then split the sample into different types. First, small firms (less than 10 employees) and large firms (more than 50 employees) have a similar mean and median risk forecasts. Next, we see the same pattern when splitting the sample into industry groups (manufacturing, construction, professional services, retail, and repair). These numbers suggest that risk forecasts are similar within the chosen bandwidth for different types of firms.

**Table 2:** Summary Statistics (Risk Forecast)

| | Observations | Mean | Median |
|---|---|---|---|
| All | 65,987 | 0.23 | 0.22 |
| Below 10 Employees | 32,579 | 0.23 | 0.22 |
| Above 50 Employees | 4,565 | 0.22 | 0.21 |
| Manufacturing | 12,280 | 0.23 | 0.22 |
| Construction | 12,183 | 0.23 | 0.22 |
| Professional Services | 5,644 | 0.22 | 0.21 |
| Retail and Repair | 14,922 | 0.23 | 0.22 |

*Notes.* The table shows the mean and median estimated risk of default as of January 1 for each firm and year (between 0 and 100) for firms in different groups. The unit of observation is the firm-year.

## 3.3 Inventories

This study hones in on the critical role of inventory holdings for firms, consisting of products available for sale and inputs utilized in future production. Table 3 presents the average inventory values for various subsamples, offering insights into the inventory management practices of firms and the potential effects of financing constraints and credit supply on these practices.

The results reveal that small and large firms have relatively similar inventory values. Small firms have 13% of assets in inventories and almost 4 times their fixed assets. For large firms, these figures correspond to 14% and 155%, respectively. Looking at different industries, we see that retail and repair firms have the most inventories: they have 30% of assets and almost 9 times their fixed assets. In contrast, firms in professional services, have 3% of their total assets and 94% of their fixed assets. These findings suggest that the inventory management practices of firms may be more affected by their industry and financing constraints rather than their size.

**Table 3:** Summary Statistics (Inventory Variables)

| | Log Inventories | $\frac{\text{Inventories}}{\text{Assets}}$ | $\frac{\text{Inventories}}{\text{Fixed Assets}}$ | $\frac{\text{Inventories}}{\text{Physical Capital}}$ | $\frac{\text{Inventories}}{\text{Assets Minus Inventories}}$ |
|---|---|---|---|---|---|
| All | 6.81 | 0.13 | 3.25 | 5.84 | 0.25 |
| Below 10 Employees | 6.20 | 0.13 | 3.74 | 6.66 | 0.26 |
| Above 50 Employees | 8.96 | 0.14 | 1.55 | 2.82 | 0.24 |
| Manufacturing | 7.51 | 0.20 | 2.97 | 4.67 | 0.32 |
| Construction | 5.89 | 0.07 | 2.23 | 4.02 | 0.11 |
| Professional Services | 5.86 | 0.03 | 0.94 | 1.77 | 0.04 |
| Retail and Repair | 7.88 | 0.30 | 8.68 | 16.03 | 0.67 |

*Notes.* The table shows summary statistics for the sample firms with regards to inventory variables and different subsamples. The unit of observation is the firm-year. The monetary values are in SEK 2010 and expressed in SEK 1,000.

# 4 Estimating the Effects of Financial Constraints

## 4.1 Regression Discontinuity

I leverage the discontinuous nature of credit scores, to identify the effect of financing constraints, Specifically, I compare firms close to the cutoff between the first and second credit scores. We can use this approach to identify the causal effect if firms cannot perfectly manipulate their credit score.

**Estimating Equation** I do a standard regression discontinuity analysis and study the difference in inventory holdings for firms around the cutoff, controlling linearly ($\gamma_L$ to the left and $\gamma_L$ to the right of the cutoff) for the running variable (Lee and Lemieux, 2010). I estimate a linear polynomial around the cutoff, following (Gelman and Imbens, 2019), since previous work suggest that results might be sensitive to the choice of the exact number of higher-order polynomials. As baseline, I have a bandwidth of $[0.105, 0.395]$.

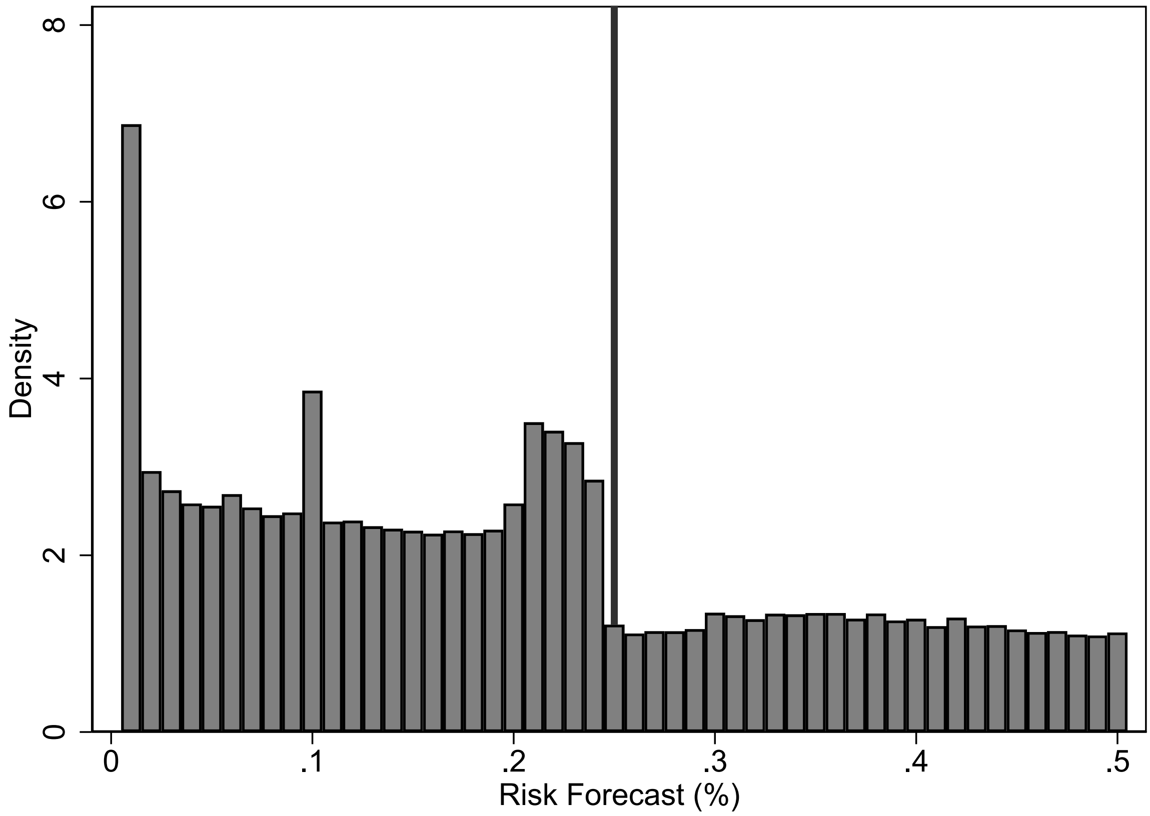
$$\text{Inventories}_{it+3} = \alpha + \beta \mathbb{1}\{x_{it} \geq 0.25\} + \gamma_L(x_{it} - 0.25) + \gamma_r \mathbb{1}\{x_{it} \geq 0.25\}(x_{it} - 0.25) + u_{it} \tag{1}$$

The coefficient of interest is $\beta$, which measures the average difference in inventory holdings for firms above and below the cutoff. The exact interpretation depends on the choice of inventory measures. If we have the log of inventories, then the interpretation is the difference in percentages. If we instead have inventories to assets, the interpretation is the average difference in percentage points. Finally, I cluster standard errors on the firm level, to account for correlation in the error term within the firm.

**Validating the Research Design** To identify the effect of credit scores on financing constraints, we have to assume that firms cannot perfectly manipulate their scores around the cutoff. While it's impossible to test this assumption directly, we can assess its plausibility.

To do so, I first check if the distribution of credit scores is continuous around the cutoff. Any clustering of scores would suggest manipulation. I plot the distribution of credit scores around the 0.25% risk forecast cutoff in Figure 1. There is excess mass just to the left of the cutoff at 0.25% risk forecast. This fact is due to an institutional setting where it's difficult for firms to be downgraded within the same year once they cross the threshold, as noted by Bustos et al. (2022). This suggests that the assumption of no manipulation is reasonable.

**Figure 1:** Histogram of the Risk Forecast around the Credit Score Cutoff




*Notes:* The figure shows a histogram of the distribution of risk forecasts around the first cutoff, at 0.25%.

To further assess the plausibility of the assumption that firms cannot perfectly manipulate their credit scores around the cutoff, I examine whether background variables respond to the cutoff. Many variables, such as size or capital structure, are potentially affected by the credit score. I thus focus on industry and geographical location, which should not be affected by the credit score. Table 4 shows that there are no systematic differences with sepect to industry distribution or the share located in Stockholm. Notably, firms to the right of the cutoff are somewhat more likely to be in the retail sector.

Taken together, these auxiliary tests suggest that firms just to the left and to the right of the cutoff are similar in many respects. Thus, differences in inventory behavior is likely only caused by different credit scores.

**Table 4:** Balance Check: Regression Discontinuity Estimates of Credit Score Change

| | (1)<br>Manufacturing | (2)<br>Construction | (3)<br>Retail | (4)<br>Professional Services | (5)<br>Stockholm |
|---|---|---|---|---|---|
| Effect of Lower Credit Score | -0.012 | 0.006 | -0.020** | -0.003 | -0.000 |
| | (0.008) | (0.008) | (0.009) | (0.006) | (0.007) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.109 | 0.339 | 0.013 | 0.508 | 0.904 |
| Observations | 228,559 | 228,559 | 228,559 | 228,559 | 228,398 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are dummies if the firm is in the manufacturing sector, in the construction sector, in the retail sector, in the professional services sector, and located in Stockholm. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

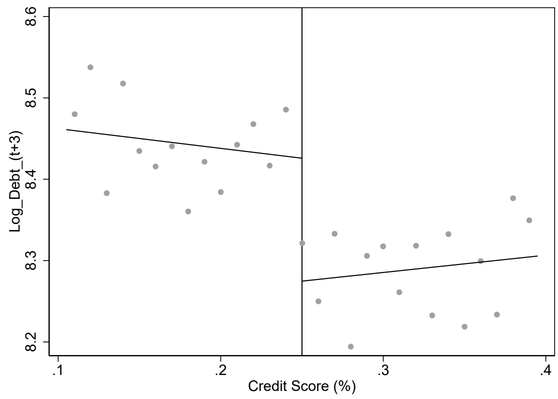
# 5 Effects of Financial Constraints: Credit Score Assignment Regression Discontinuity

## 5.1 First Stage: Credit Scores and Financing Choices

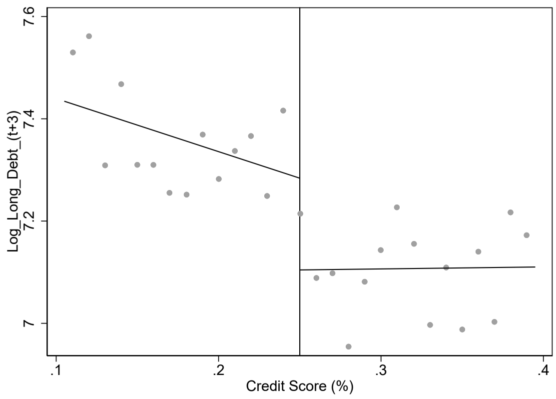
I study whether credit scores accurately predict financing constraints. I illustrate this relationship in Figure 2 by examining the impact of being near the cutoff point between the highest and second-highest credit scores. Companies just to the right of the cutoff indeed seem to have stronger financial constraints. These results are also shown in Table A1. We see that they have less total debt as well as long-term debt. The effects are roughly -20% to -15% for both variables. Similarly, we see that this gets translated into lower total assets and sales as well. The effects are roughly -10% to -20% for these variables. These results also show that financing constraints indeed impact firms' financing and growth opportunities (Campello et al., 2010; Chodorow-Reich, 2014; Cingano et al., 2016; Berton et al., 2018; Amiti and Weinstein, 2018; Huber, 2018; Chen and Kieschnick, 2018; Hviid and Schroeder, 2021).

**Figure 2:** First Stage: Regression Discontinuity Estimates of Credit Score Change

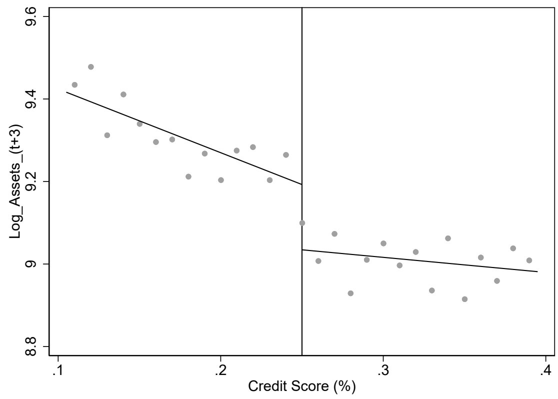
**Panel A:** Log Total Debt



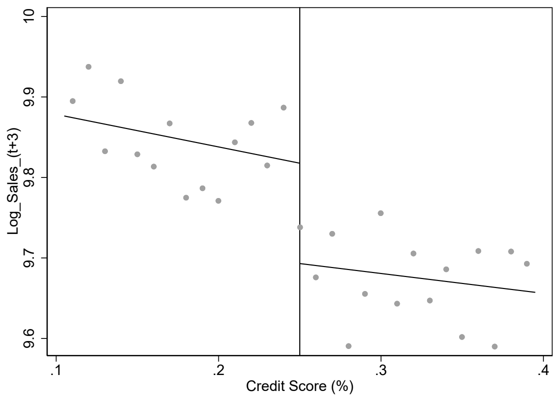

**Panel B:** Log Long Debt




**Panel C:** Log Total Assets




**Panel D:** Log Sales




*Notes:* The figure shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are log total debt, log long debt, log total assets, and log sales. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

## 5.2 Credit Scores and Inventories

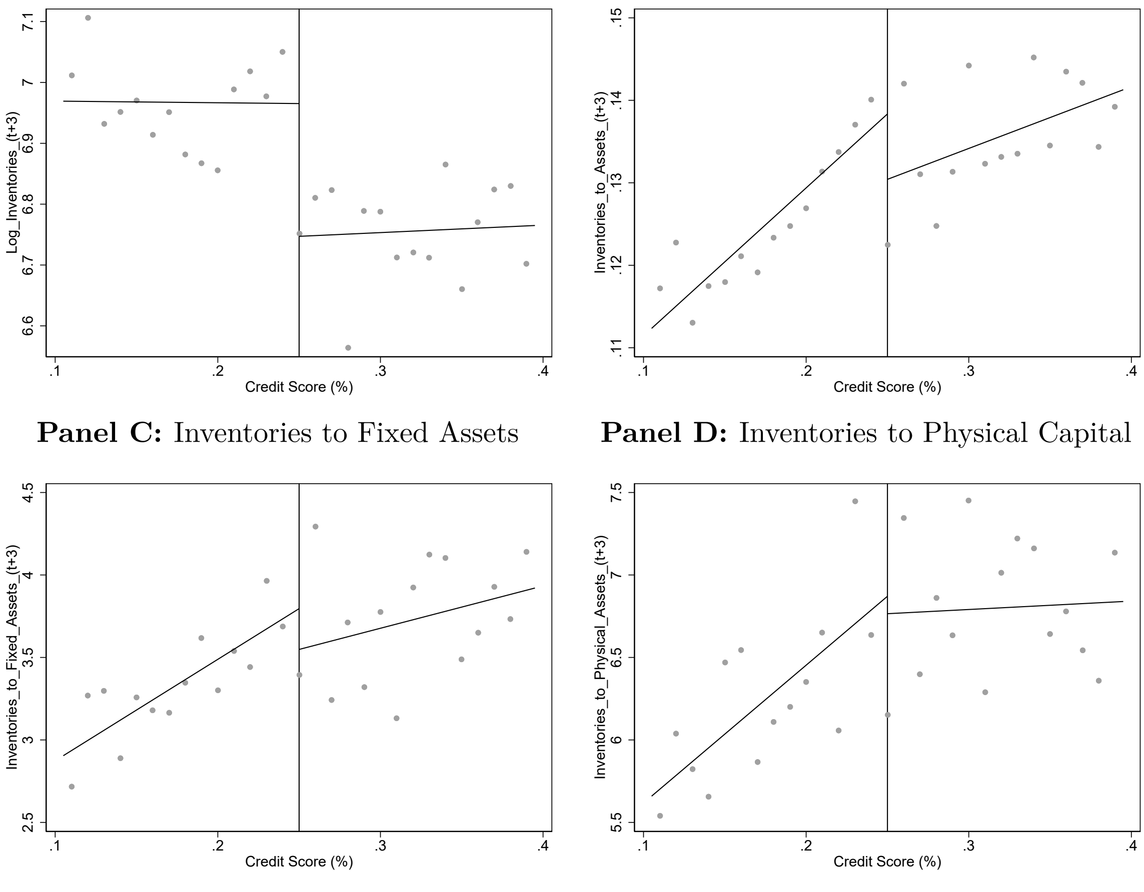
Next, I examine the effect of credit scores and inventory holdings. I present the regression discontinuity results in Figure 3 to investigate this relationship. These results are shown in Table A2. The figure shows firms just to the left and right of the cutoff between credit scores one and two. First, we see that firms just to the right of the cutoff have less inventories. The estimated coefficient is around - 25%, which is similar in magnitudes to the overall effect on firm size.

Next, we see if the more financially constrained firms also change their inventory holdings relative for firm size, as in Barrot (2016). We see that there is a marginally statistically significant effect on inventories to total assets of -0.011. However, the effect disappears if we scale by either fixed asses, physical assets, or total assets minus inventories. Taken together, these results suggest that there is no effect on inventories once we take into account changes in firm size.

**Figure 3:** Regression Discontinuity Estimates of Credit Score Change and Inventory Variables

**Panel A:** Log Inventories **Panel B:** Inventories to Total Assets

**Panel C:** Inventories to Fixed Assets **Panel D:** Inventories to Physical Capital




*Notes:* The figure shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are log inventories, inventories to total assets, inventories to fixed assets, and inventories to physical capital. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

## 5.3 Robustness Checks

I complement the analysis with additional robustness tests. First, we study changes in the bandwidth used to estimate the effects. We see in Table A3, Table A4, Table A5, Table A6, and Table A7, that the results are robust to varying the bandwidth between 0.05 percentage points to 0.25 percentage points, in addition to the optimal bandwidth from (Calonico et al., 2014, 2017).

Next, we study variations in the sample used. I provide six sample variations: excluding firm-years with less than 10 employees, firm-years with more than 100 employees, excluding small regions (län), excluding the larges region, excluding small sectors, and excluding the largest sector. Table A8, Table A9, Table A10, Table A11, and Table A12 show the results. We see that the results are broadly robust across these specifications.

Finally, I study alternative cutoffs. In particular, I use the 0.25% cutoff but use a donut setup where I exclude the firms closest to the cutoff. I thus only include firms with risk forecasts below 0.24% and above 0.25%. Next, I study the second and third cutoffs at 0.75% and 3.05% cutoffs, respectively. I use the optimal bandwidths in these setups. These results are shown in Table A13, Table A14, Table A15, Table A16, and Table A17. We see that the effects are similar across cutoffs.

## 5.4 Heterogeneity Analysis

**Heterogeneity by Cash Flow Volatility** We expect systematic differences between firms in different industries. For instance, a large literature suggests that cash flow volatility matters for risk management and cash holdings (Froot et al., 1993; Minton and Schrand, 1999; Opler et al., 1999; Bates et al., 2009). Thus, I split the sample into high and low cash flow volatility sectors.[8]

[8] I define cash flow as EBIT plus depreciation. I then take the ratio of the standard deviation of cash flow and the mean cash flow for each three-digit SNI industry. I then separate firms into industries above and below the median.

We see in Table 5 that there is a strong effect for firms in sectors with high cash flow volatility. For instance, we see in column (1) that firms in low-volatility sectors have about 17% less inventories but 38% less in industries with high volatility. We also see that there are marked effects on the scaled measures.

**Table 5:** Regression Discontinuity Estimates for Firms in Industries with High and Low Cash Flow Volatility

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Log Inv (1) | Log Inv (2) | Inv/Assets (1) | Inv/Assets (2) | Inv/FA (1) | Inv/FA (2) | Inv/Phys (1) | Inv/Phys (2) |
| Effect of Lower Credit Score | -0.167** | -0.378*** | -0.004 | -0.022*** | 0.564* | -1.357*** | 1.104* | -2.205** |
| | (0.074) | (0.091) | (0.005) | (0.007) | (0.340) | (0.495) | (0.575) | (0.890) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.102 | 0.000 | 0.407 | 0.003 | 0.042 | 0.004 | 0.080 | 0.005 |
| Observations | 58,467 | 44,442 | 83,559 | 65,873 | 80,536 | 62,478 | 78,569 | 59,586 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are log total debt, log long debt, log total assets, and log sales. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

# 6 Effects of Financial Constraints: Monetary Policy Loosening Difference-in-Differences

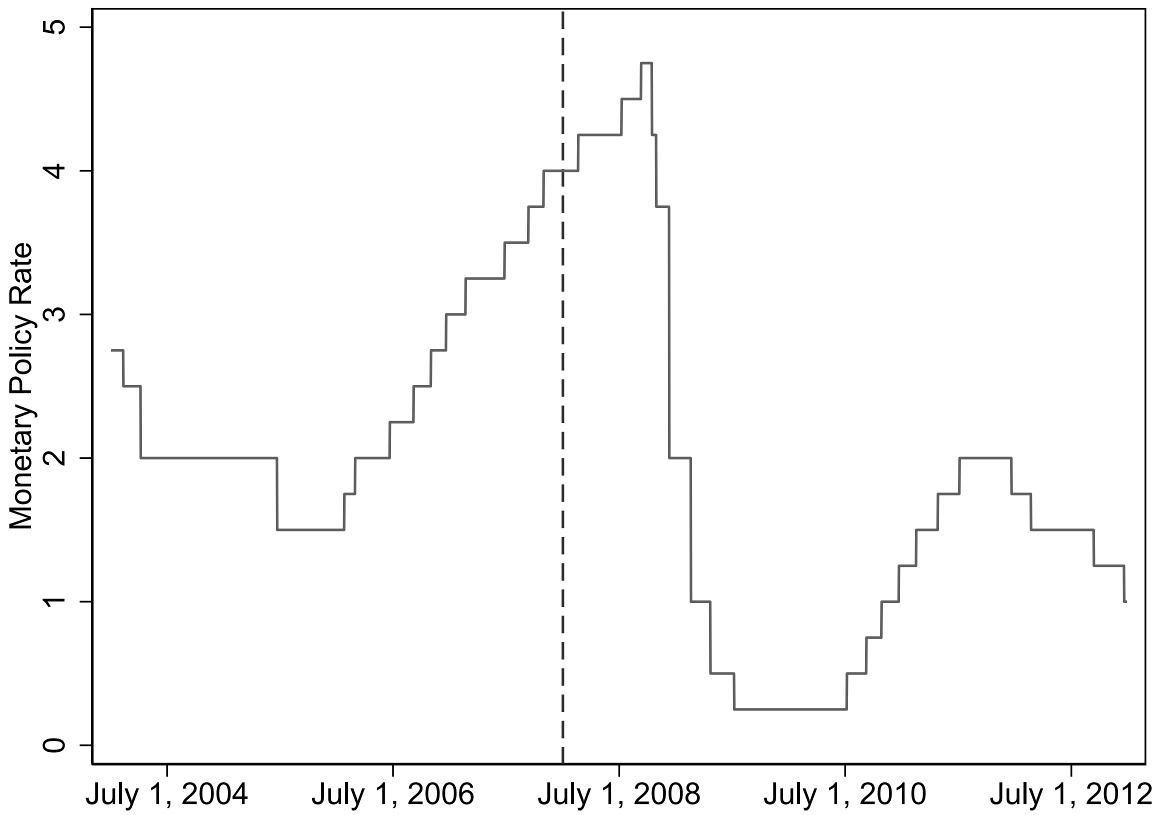
## 6.1 Event Study

I complement the regression discontinuity analysis with an event study around the large drop in the monetary policy rate in 2008–2009. Figure 4 shows the Riksbank monetary policy rate between 20023 and 2012. We see that interest rates increased in 2006, and then sharply declines during 2008. In early 2008, the rate was at 4%, and then declines to 0.25% in the summer of 2009.

I compare firms with the second-best score with those that had the best score. The former group should benefit more from the better credit conditions following the change in monetary policy. The key identification assumption is that firms with the best and second-best rating were on similar trends before the monetary policy change.

The paper closest to this is Rezghi (2022). He uses measures of monetary policy surprises in the United States and study how American firms in Compustat change their investment, but also inventory, policies. He finds that firms with poor credit ratings reduce inventories after a surprise reduction of interest rates, while firms with good rating instead increase them. In particular, he compare investment-grade versus junk-grade firms. Notably, his sample consists of larger firms: the investment-grade (junk) firms have median sales of 7,300 million dollars (1,000 million dollars). In contrast, the median in my sampe is roughly 1.6 million dollars. In contrast, my sample focuses on small and private firms.

**Figure 4:** Monetary Policy Rates




*Notes:* The figure shows monetary policy rates by the Swedish Riksbank (Riksbank, 2023).

**Defining Treatment and Control** Since I use data on the January 1 credit scores, I define treated firms as those with the second score in 2008, and the control firms as those with the best score. However, I impose a bandwidth restriction, since very good firms might behave systematically differ from firms with worse ratings. Treated firms need a

**Table 6:** Summary Statistics: Event Study Sample

| | Observations | Mean | Median | Std Dev | Min | Max |
|---|---|---|---|---|---|---|
| Revenues | 11,430 | 76,675 | 15,561 | 1,276,085 | 27 | 110,000,000 |
| Employees | 11,430 | 28 | 10 | 254 | 6 | 17,000 |
| Total Assets | 11,430 | 66,151 | 7,722 | 1,196,578 | 226 | 70,000,000 |
| Inventories | 11,428 | 2,449 | 447 | 4,469 | 0 | 17,000 |
| Inventories to Assets (%) | 11,428 | 15 | 7 | 19 | 0 | 85 |
| Inventories to Fixed Assets (%) | 11,355 | 297 | 29 | 956 | 0 | 8,500 |
| Inventories to Physical Capital (%) | 11,314 | 454 | 39 | 1,460 | 0 | 14,000 |
| Inventories to Assets - Inventories | 11,428 | 30 | 8 | 61 | 0 | 620 |

Notes: The table shows summary statistics for the event study sample firms. The unit of observation is the firm-year. The monetary values are in SEK 2010 and expressed in SEK 1,000. The maximum values are censored to provide confidentiality.

risk forecast no larger than 0.50%. while control firms need a forecast no smaller than 0.05%.

**Estimating Equation** Similar to above, we regress some measure of inventories on a dummy if the firm has the second-best rating in 2008 and interact this with year dummies for the years 2004–2011, with 2007 as the base year. I also include firm fixed effects ($\mu_i$) and three-digit industry by year fixed effects ($\mu_{jt}$). The estimating equations look like follows:

$$\text{Inventories}_{it} = \alpha + \sum_{k=2004,\neq 2008}^{2011} \beta_k \text{Treated}_i \times \mathbb{1}\{\text{Year}_t = k\} + \mu_i + \mu_{jt} + \varepsilon_{it} \tag{2}$$

The coefficients of interest are the $beta_k$, which measure the average difference between firms with the second-best and the best credit score relative to 2007. I cluster standard errors on the firm level.

**Summary Statistics** Table 6 shows summary statistics for the event study sample. We see that the average firm has 28 employees and a median of 10, as well as a large range between 6 and 15,000 employees. Similarly, average revenues are SEK 2.5 million, with a median of almost SEK 500,000. Inventories to assets are instead 15% on average, with a median of 7%.

## 6.2 Results

Next, I turn to the difference-in-differences estimates. These are shown in Figure 5 and Table 7. We see that firms with the second credit score just before the monetary policy loosening indeed increased their inventories more in the years from 2008 to 2010. The estimated effect sizes on log inventories start off at 0.022 in 2008, and then steadily grows to 0.050 in 2011. This suggests that treated firms increase their inventory holdings by roughly five percent. Moreover, we see that treated and control firms were on parallel trends in the years before, 2004–2006.

At the same time, there are no discernible effects for inventories scaled by total assets, fixed assets, or physical assets. This suggests that firms only change their size when monetary financing constraints are changed, and not how much inventories they need in relative terms.

My results thus suggest that more financially constrained firms indeed change their inventories more when facing relaxed financing conditions, similar to Bernanke et al. (1996); Cloyne et al. (2018); Brabant et al. (2022). However, this effect seens to be entirely a scale effect: the role of inventories in firms' operations seem to be unchanged.

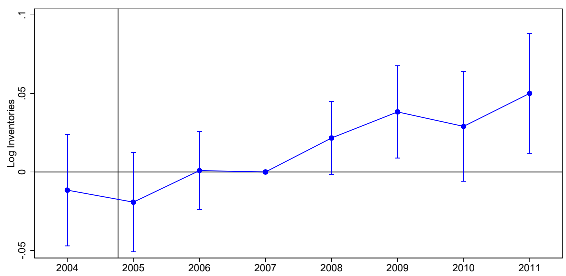
**Table 7:** Difference-in-Differences Estimates of High and Low Credit Score Around Monetary Policy Loosening

| | Difference-in-Differences Estimates | | | | |
|---|---|---|---|---|---|
| | (1) Log Inventories | (2) Inventories to Assets | (3) Inventories to Fixed Assets | (4) Inventories to Physical Capital | (5) Inventories to Assets Minus Inventories |
| Second Score × 2004 | -0.012 | 0.001 | -0.185 | -0.469 | 0.002 |
| | (0.018) | (0.002) | (0.185) | (0.287) | (0.008) |
| Second Score × 2005 | -0.019 | 0.000 | -0.073 | -0.304 | 0.002 |
| | (0.016) | (0.002) | (0.152) | (0.245) | (0.006) |
| Second Score × 2006 | 0.001 | 0.002** | 0.141 | -0.058 | 0.008* |
| | (0.013) | (0.001) | (0.114) | (0.179) | (0.005) |
| Second Score × 2007 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| Second Score × 2008 | 0.022* | -0.001 | 0.072 | 0.259 | 0.004 |
| | (0.012) | (0.001) | (0.120) | (0.186) | (0.005) |
| Second Score × 2009 | 0.038** | 0.001 | 0.077 | 0.167 | -0.003 |
| | (0.015) | (0.002) | (0.164) | (0.268) | (0.007) |
| Second Score × 2010 | 0.029 | -0.000 | -0.211 | -0.148 | -0.005 |
| | (0.018) | (0.002) | (0.195) | (0.319) | (0.007) |
| Second Score × 2011 | 0.050** | -0.002 | -0.177 | -0.140 | -0.007 |
| | (0.019) | (0.002) | (0.229) | (0.371) | (0.008) |
| Firm Effects | Yes | Yes | Yes | Yes | Yes |
| Industry-Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| R-Squared | 0.939 | 0.919 | 0.679 | 0.674 | 0.877 |
| Observations | 63,201 | 83,846 | 83,162 | 82,710 | 83,846 |

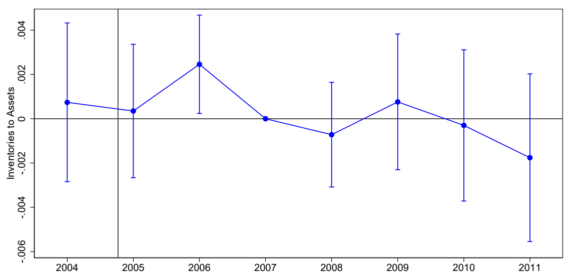
Notes: The table shows difference-in-differences estimates where firms with the second-best credit score are compared with firms with the best credit score around the sharp reduction in the monetary policy rate in 2009. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

## **Figure 5:** Difference-in-Differences Estimates of High and Low Credit Score Around Monetary Policy Loosening

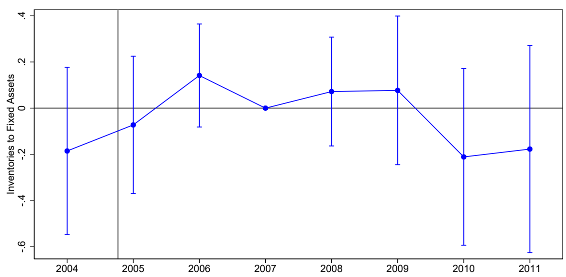
### **Panel A:** Log Inventories



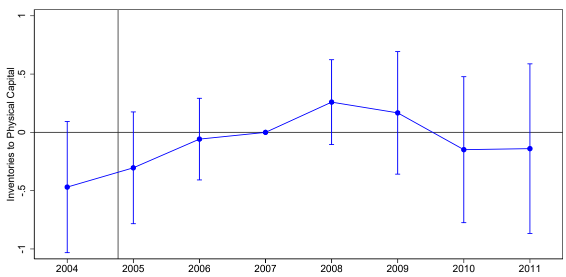

### **Panel B:** Inventories to Assets




### **Panel C:** Inventories to Fixed Assets




### **Panel D:** Inventories to Physical Capital




*Notes:* The figures show difference-in-differences estimates where firms with the second-best credit score are compared with firms with the best credit score around the sharp reduction in the monetary policy rate in 2009. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

# 7 Conclusion

Inventories play a crucial role in firms' risk management strategies. However, the interaction between inventory management and financial constraints remains underexplored. In this study, I present a model demonstrating that financial constraints decrease inventory holdings. However, the impact on the inventories-to-assets ratio is contingent upon how financing constraints bind.

I utilize comprehensive Swedish administrative data and credit score information to investigate financial constraints' effect on inventory management. I exploit a discontinuity in the translation of the continuous risk forecasts into discrete credit scores, allowing me to compare similar firms with differing access to credit.

My findings reveal that firms with better credit scores increase their inventory holdings by approximately 20%. However, these firms do not increase their inventories relative to sales or assets. Moreover, I demonstrate that these results are consistent across various samples, suggesting that inventories primarily follow changes in assets without serving an independent risk management function. Additionally, I show that the results look similar in an alternative setting where I compare how firms with different credit scores adjust their inventories following the Riksbank's introduction of a zero interest rate policy.

Collectively, these results provide new insights into the role of financing constraints in shaping firms' inventory management practices. Specifically, they suggest inventories primarily serve as a hedge against operational risk, with financial risk playing a comparatively limited role in determining inventory holdings.

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# A Appendix

## A.1 Main Tables

**Table A1:** First Stage: Regression Discontinuity Estimates of Credit Score Change

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Debt | Long Debt | Total Assets | Sales |
| Effect of Lower Credit Score | -0.160*** | -0.208*** | -0.170*** | -0.141*** |
| | (0.036) | (0.068) | (0.032) | (0.032) |
| Bandwdith (Left) | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.000 | 0.004 | 0.000 | 0.000 |
| Observations | 149,176 | 81,791 | 149,435 | 147,235 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are log total debt, log long debt, log total assets, and log sales. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A2:** Regression Discontinuity Estimates of Credit Score Change and Inventory Variables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Log Inventories | $\frac{\text{Inventories}}{\text{Assets}}$ | $\frac{\text{Inventories}}{\text{Fixed Assets}}$ | $\frac{\text{Inventories}}{\text{Physical Capital}}$ | $\frac{\text{Inventories}}{\text{Assets Minus Inventories}}$ |
| Effect of Lower Credit Score | -0.255*** | -0.011** | -0.235 | -0.227 | -0.023 |
| | (0.057) | (0.004) | (0.287) | (0.502) | (0.015) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.000 | 0.008 | 0.502 | 0.401 | 0.087 |
| Observations | 102,909 | 149,432 | 143,014 | 138,155 | 149,432 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. The dependent variables are log inventories, inventories to total assets, inventories to fixed assets, inventories to physical capital, and inventories to assets minus inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

## A.2 Bandwidth Robustness

**Table A3:** Regression Discontinuity Estimates of Credit Score Change and Log Inventories (Varying Bandwidths)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | Optimal |
| Effect of Lower Credit Score | -0.267*** | -0.292*** | -0.255*** | -0.191*** | -0.145*** | -0.205*** |
| | (0.092) | (0.067) | (0.057) | (0.051) | (0.048) | (0.053) |
| Bandwidth (Left) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.179 |
| Bandwidth (Right) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.179 |
| Robust p-Value | 0.025 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 102,909 | 102,909 | 102,909 | 102,909 | 102,909 | 102,909 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regressions use bandwidths of 0.05, 0.10, 0.15, 0.20, and 0.25 percentage points, as well as the optimal bandwidth from Calonico et al. (2014, 2017) and a linear local polynomial. The dependent variable is log inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A4:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets (Varying Bandwidths)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | Optimal |
| Effect of Lower Credit Score | -0.014** | -0.013*** | -0.011** | -0.010** | -0.008** | -0.010** |
| | (0.007) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) |
| Bandwidth (Left) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.194 |
| Bandwidth (Right) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.194 |
| Robust p-Value | 0.135 | 0.032 | 0.008 | 0.010 | 0.006 | 0.006 |
| Observations | 149,432 | 149,432 | 149,432 | 149,432 | 149,432 | 149,432 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regressions use bandwidths of 0.05, 0.10, 0.15, 0.20, and 0.25 percentage points, as well as the optimal bandwidth from Calonico et al. (2014, 2017) and a linear local polynomial. The dependent variable is inventories to total assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A5:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Fixed Assets (Varying Bandwidths)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | Optimal |
| Effect of Lower Credit Score | -0.206 | -0.257 | -0.235 | -0.236 | -0.235 | -0.234 |
| | (0.466) | (0.336) | (0.287) | (0.257) | (0.239) | (0.255) |
| Bandwidth (Left) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.205 |
| Bandwidth (Right) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.205 |
| Robust p-Value | 0.955 | 0.725 | 0.502 | 0.449 | 0.420 | 0.410 |
| Observations | 143,014 | 143,014 | 143,014 | 143,014 | 143,014 | 143,014 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regressions use bandwidths of 0.05, 0.10, 0.15, 0.20, and 0.25 percentage points, as well as the optimal bandwidth from Calonico et al. (2014, 2017) and a linear local polynomial. The dependent variable is inventories to fixed assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A6:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Physical Assets (Varying Bandwidths)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | Optimal |
| Effect of Lower Credit Score | -0.531 | -0.445 | -0.227 | -0.225 | -0.202 | -0.221 |
| | (0.809) | (0.583) | (0.502) | (0.449) | (0.417) | (0.470) |
| Bandwidth (Left) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.174 |
| Bandwidth (Right) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.174 |
| Robust p-Value | 0.942 | 0.472 | 0.401 | 0.582 | 0.529 | 0.642 |
| Observations | 138,155 | 138,155 | 138,155 | 138,155 | 138,155 | 138,155 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regressions use bandwidths of 0.05, 0.10, 0.15, 0.20, and 0.25 percentage points, as well as the optimal bandwidth from Calonico et al. (2014, 2017) and a linear local polynomial. The dependent variable is inventories to physical capital. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A7:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets Minus Inventories (Varying Bandwidths)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 0.05 | 0.10 | 0.15 | 0.20 | 0.25 | Optimal |
| Effect of Lower Credit Score | -0.031 | -0.028* | -0.023 | -0.021 | -0.021* | -0.021 |
| | (0.023) | (0.016) | (0.015) | (0.013) | (0.012) | (0.013) |
| Bandwidth (Left) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.196 |
| Bandwidth (Right) | 0.050 | 0.100 | 0.145 | 0.200 | 0.250 | 0.196 |
| Robust p-Value | 0.338 | 0.254 | 0.087 | 0.124 | 0.137 | 0.156 |
| Observations | 149,432 | 149,432 | 149,432 | 149,432 | 149,432 | 149,432 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regressions use bandwidths of 0.05, 0.10, 0.15, 0.20, and 0.25 percentage points, as well as the optimal bandwidth from Calonico et al. (2014, 2017) and a linear local polynomial. The dependent variable is inventories to total assets minus inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

## A.3 Sample Robustness

**Table A8:** Regression Discontinuity Estimates of Credit Score Change and Log Inventories (Sample Variations)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Excluding... | $\leq$ 10 Employees | $\geq$ 100 Employees | Small Regions | Large Regions | Small Sectors | Largest Sector |
| Effect of Lower Credit Score | -0.217*** | -0.273*** | -0.230*** | -0.217*** | -0.238*** | -0.297*** |
| | (0.077) | (0.057) | (0.060) | (0.063) | (0.058) | (0.067) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.012 | 0.000 | 0.000 | 0.002 | 0.000 | 0.000 |
| Observations | 61,427 | 100,178 | 93,232 | 80,227 | 101,055 | 71,732 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. Column (1) excludes firm-years with less than 10 employees, column (2) excludes those with more than 100 employees, column (3) excludes small regions, column (4) excludes large regions, column (5) excludes small sectors, and column (6) excludes large sectors. The dependent variable is log inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A9:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets (Sample Variations)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\leq$ 10 Employees | $\geq$ 100 Employees | Small Regions | Large Regions | Small Sectors | Largest Sector |
| Effect of Lower Credit Score | -0.015*** | -0.012** | -0.011** | -0.010** | -0.011** | -0.005 |
| | (0.006) | (0.004) | (0.005) | (0.005) | (0.004) | (0.004) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.009 | 0.007 | 0.018 | 0.011 | 0.013 | 0.361 |
| Observations | 89,011 | 145,351 | 136,275 | 116,941 | 146,745 | 115,151 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. Column (1) excludes firm-years with less than 10 employees, column (2) excludes those with more than 100 employees, column (3) excludes small regions, column (4) excludes large regions, column (5) excludes small sectors, and column (6) excludes large sectors. The dependent variable is inventories to total assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A10:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Fixed Assets (Sample Variations)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Excluding... | $\leq$ 10 Employees | $\geq$ 100 Employees | Small Regions | Large Regions | Small Sectors | Largest Sector |
| Effect of Lower Credit Score | 0.247 | -0.210 | -0.277 | -0.149 | -0.228 | 0.180 |
| | (0.354) | (0.294) | (0.298) | (0.320) | (0.292) | (0.230) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.501 | 0.597 | 0.475 | 0.759 | 0.542 | 0.338 |
| Observations | 86,167 | 139,013 | 130,308 | 112,100 | 140,408 | 110,080 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. Column (1) excludes firm-years with less than 10 employees, column (2) excludes those with more than 100 employees, column (3) excludes small regions, column (4) excludes large regions, column (5) excludes small sectors, and column (6) excludes large sectors. The dependent variable is inventories to fixed assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A11:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Physical Assets (Sample Variations)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Excluding... | $\leq$ 10 Employees | $\geq$ 100 Employees | Small Regions | Large Regions | Small Sectors | Largest Sector |
| Effect of Lower Credit Score | 1.079 | -0.183 | -0.303 | 0.074 | -0.175 | 0.413 |
| | (0.662) | (0.514) | (0.526) | (0.563) | (0.509) | (0.404) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.227 | 0.495 | 0.340 | 0.808 | 0.491 | 0.438 |
| Observations | 83,898 | 134,209 | 125,765 | 108,383 | 135,598 | 106,387 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. Column (1) excludes firm-years with less than 10 employees, column (2) excludes those with more than 100 employees, column (3) excludes small regions, column (4) excludes large regions, column (5) excludes small sectors, and column (6) excludes large sectors. The dependent variable is inventories to physical capital. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A12:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets Minus Inventories (Sample Variations)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Excluding... | $\leq$ 10 Employees | $\geq$ 100 Employees | Small Regions | Large Regions | Small Sectors | Largest Sector |
| Effect of Lower Credit Score | -0.039** | -0.024 | -0.023 | -0.014 | -0.022 | -0.008 |
| | (0.018) | (0.015) | (0.015) | (0.016) | (0.015) | (0.009) |
| Bandwidth (Left) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Bandwidth (Right) | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 | 0.145 |
| Robust p-Value | 0.028 | 0.081 | 0.123 | 0.192 | 0.115 | 0.642 |
| Observations | 89,011 | 145,351 | 136,275 | 116,941 | 146,745 | 115,151 |

Notes: The table shows regression discontinuity estimates around the threshold between the first and second credit score, at a risk forecast of 0.25%. The regression is estimated using a bandwidth of $[0.105, 0.395]$ and a linear local polynomial. Column (1) excludes firm-years with less than 10 employees, column (2) excludes those with more than 100 employees, column (3) excludes small regions, column (4) excludes large regions, column (5) excludes small sectors, and column (6) excludes large sectors. The dependent variable is inventories to total assets minus inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

## A.4 Heterogeneity Around Cutoffs

**Table A13:** Regression Discontinuity Estimates of Credit Score Change and Log Inventories (Cutoff Variations)

| | (1) | (2) | (3) |
|---|---|---|---|
| | 1st (0.25%, Donut) | 2nd (0.75%) | 3rd (3.05%) |
| Effect of Lower Credit Score | -0.222*** | -0.307*** | -0.198* |
| | (0.065) | (0.069) | (0.115) |
| Bandwidth (Left) | 0.145 | 0.250 | 0.917 |
| Bandwidth (Right) | 0.145 | 0.250 | 0.917 |
| Robust p-Value | 0.007 | 0.000 | 0.097 |
| Observations | 100,699 | 102,909 | 102,909 |

Notes: The table shows regression discontinuity estimates around the threshold between different credit scores. Column (1) shows estimates around the first cutoff, using the optimal bandwidth of Calonico et al. (2014, 2017), but only including risk forecasts below 0.24% and above 0.25%. Columns (2) and (3) show estimates around the second and third cutoffs, using the optimal bandwidth of Calonico et al. (2014, 2017). All regressions estimate linear local polynomials. The dependent variable is log inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A14:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets (Cutoff Variations)

| | (1)<br>1st (0.25%, Donut) | (2)<br>2nd (0.75%) | (3)<br>3rd (3.05%) |
|---|---|---|---|
| Effect of Lower Credit Score | -0.007 | -0.029*** | -0.025** |
| | (0.005) | (0.006) | (0.011) |
| Bandwidth (Left) | 0.145 | 0.238 | 0.856 |
| Bandwidth (Right) | 0.145 | 0.238 | 0.856 |
| Robust p-Value | 0.284 | 0.000 | 0.018 |
| Observations | 146,215 | 149,432 | 149,432 |

Notes: The table shows regression discontinuity estimates around the threshold between different credit scores. Column (1) shows estimates around the first cutoff, using the optimal bandwidth of Calonico et al. (2014, 2017), but only including risk forecasts below 0.24% and above 0.25%. Columns (2) and (3) show estimates around the second and third cutoffs, using the optimal bandwidth of Calonico et al. (2014, 2017). All regressions estimate linear local polynomials. The dependent variable is inventories to total assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A15:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Fixed Assets (Cutoff Variations)

| | (1)<br>1st (0.25%, Donut) | (2)<br>2nd (0.75%) | (3)<br>3rd (3.05%) |
|---|---|---|---|
| Effect of Lower Credit Score | -0.176 | -0.665** | -0.298 |
| | (0.331) | (0.336) | (0.572) |
| Bandwidth (Left) | 0.145 | 0.395 | 1.259 |
| Bandwidth (Right) | 0.145 | 0.395 | 1.259 |
| Robust p-Value | 0.770 | 0.137 | 0.460 |
| Observations | 139,936 | 143,014 | 143,014 |

Notes: The table shows regression discontinuity estimates around the threshold between different credit scores. Column (1) shows estimates around the first cutoff, using the optimal bandwidth of Calonico et al. (2014, 2017), but only including risk forecasts below 0.24% and above 0.25%. Columns (2) and (3) show estimates around the second and third cutoffs, using the optimal bandwidth of Calonico et al. (2014, 2017). All regressions estimate linear local polynomials. The dependent variable is inventories to fixed assets. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$.

**Table A16:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Physical Capital (Cutoff Variations)

| | (1)<br>1st (0.25%, Donut) | (2)<br>2nd (0.75%) | (3)<br>3rd (3.05%) |
|---|---|---|---|
| Effect of Lower Credit Score | -0.062 | -1.309** | 0.055 |
| | (0.590) | (0.654) | (1.144) |
| Bandwidth (Left) | 0.145 | 0.288 | 1.093 |
| Bandwidth (Right) | 0.145 | 0.288 | 1.093 |
| Robust p-Value | 0.510 | 0.120 | 0.833 |
| Observations | 135,174 | 138,155 | 138,155 |

Notes: The table shows regression discontinuity estimates around the threshold between different credit scores. Column (1) shows estimates around the first cutoff, using the optimal bandwidth of Calonico et al. (2014, 2017), but only including risk forecasts below 0.24% and above 0.25%. Columns (2) and (3) show estimates around the second and third cutoffs, using the optimal bandwidth of Calonico et al. (2014, 2017). All regressions estimate linear local polynomials. The dependent variable is inventories to physical capital. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.

**Table A17:** Regression Discontinuity Estimates of Credit Score Change and Inventories to Assets Minus Inventories (Cutoff Variations)

| | (1)<br>1st (0.25%, Donut) | (2)<br>2nd (0.75%) | (3)<br>3rd (3.05%) |
|---|---|---|---|
| Effect of Lower Credit Score | -0.009 | -0.098*** | -0.104*** |
| | (0.017) | (0.023) | (0.039) |
| Bandwidth (Left) | 0.145 | 0.242 | 0.806 |
| Bandwidth (Right) | 0.145 | 0.242 | 0.806 |
| Robust p-Value | 0.685 | 0.000 | 0.006 |
| Observations | 146,215 | 149,432 | 149,432 |

Notes: The table shows regression discontinuity estimates around the threshold between different credit scores. Column (1) shows estimates around the first cutoff, using the optimal bandwidth of Calonico et al. (2014, 2017), but only including risk forecasts below 0.24% and above 0.25%. Columns (2) and (3) show estimates around the second and third cutoffs, using the optimal bandwidth of Calonico et al. (2014, 2017). All regressions estimate linear local polynomials. The dependent variable is inventories to assets minus inventories. Monetary values are deflated to 2010 Swedish crowns. Standard errors clustered on the firm level in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$ and $^{***}$ $p < 0.01$.