An Analysis of Liquidity Risk Drivers for Single Credit Facilities

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Abstract

In order to manage the liquidity risk associated with single credit facilities, it is important for financial institutions to clearly understand the drivers for their utilization. We apply a data set from a large Europe-based bank to analyze factors driving the utilization of single credit facilities. We find that the capacity utilization for single credit lines is inversely related to a customers' credit worthiness for collateralized credit lines. However, for uncollateralized credit lines the relation only applies up to a critical credit rating threshold. Beyond the critical threshold, the utilization of uncollateralized credit lines is a decreasing function of the credit worthiness. Further, we find that collateralized credit lines are generally more heavily utilized than uncollateralized credit lines. However, this effect is impacted both by the granted volume of the credit line and the credit worthiness of the customer. Within the sample of credit lines exceeding a critical granted volume, collateralized credit lines are more heavily utilized than uncollateralized credit lines with identical credit worthiness. The critical credit line volume is inversely related to the credit worthiness, suggesting that the positive utilization effect of collateral is most pronounced for large credit lines with relatively bad credit worthiness.

Key words: Credit Facility, Line of Credit, Credit line, Liquidity Risk, Funding Risk

JEL Classification: C33, C36, G21, G32.

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1 Introduction

Financial institutions around the world grant credit facilities to their customers as part of their day to day business.[1] Such products constitute a relevant liquidity source for the financial sector as well as the real economy.[2] However, since the beginning of the financial crisis in 2007, financial institutions themselves are facing significant liquidity shortcomings.[3]

Under such tense environmental circumstances, the liquidity situation for banks may therefore turn even worse if customers decide to draw heavily on their credit lines.[4] Consequently regulators emphasize the importance of an adequate liquidity risk[5] management framework regarding these products.[6]

A clear understanding of the *drivers* for (single) credit line utilization constitutes the basis for a robust liquidity management framework for credit facilities. The body of literature regarding this topic is extensive and can be broadly divided into theoretical models on credit facilities[7] and (empirical) literature on (single) credit line utilization. The latter focuses on (i) credit worthiness as the major driver of product utilization; (ii) credit facilities as a potential substitute for cash within a liquidity risk management framework of corporate customers or (iii) credit line utilization as a credit worthiness indicator.[8]

To complement current (empirical) literature, we analyze *further* factors driving the utilization of single credit lines. Therefore we utilize a data set from a large Europe-based

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[1] See Ergungor (2001), p. 2.

[2] See Sufi (2009), p. 1057.

[3] See BIS (2008).

[4] Financial Services Authority (2011) states that the risk exposure of the Royal Bank of Scotland during the financial crisis resulted partly from liquidity facilities. The UK government subsequently injected a total of £45.5 bn. of equity capital into the Royal Bank of Scotland to prevent its collapse.

[5] It is very common to distinguish *funding liquidity risk* and *market liquidity risk*. "Funding liquidity risk is the risk that the firm will not be able to meet efficiently both expected and unexpected current and future cash flow and collateral needs without affecting either daily operations or the financial condition of the firm. Market liquidity risk is the risk that a firm cannot easily offset or eliminate a position at the market price because of inadequate market depth or market disruption." (BIS (2008)). For the purpose of this paper, we will exclusively refer to funding liquidity risk. The term *liquidity risk* is therefore applied synonymously to *funding liquidity risk*.

[6] See e.g. BIS (2008) for general principles regarding liquidity risk as well as first details regarding credit facilities. Furthermore CEBS (2009) and CEBS (2010a) stress the importance of these facilities while implementing a robust liquidity risk management framework.

[7] E.g., literature regarding the existence of credit lines.

[8] We will give a brief overview on the current body of literature in Section 2.

bank including more than 220,000 credit lines and in total more than 1,100,000 observations.

In consistency with the existing body of literature, we confirm that the capacity utilization for single credit lines is related to a customers' credit worthiness. The relation is inverse for collateralized credit lines, i.e. a decreasing credit worthiness results in a higher line utilization.[9] For uncollateralized credit lines we find the same relationship up to a critical credit rating threshold.[10] Beyond this critical threshold, the utilization of unsecured credit lines is a decreasing function of the credit worthiness. In our analysis we will point out that the different utilization behavior for unsecured versus secured credit lines may result from the fact that the bank is in a position to cut-down credit lines. Thereby a customer may mitigate the risk of a cut-down of her credit line by *pledging* collateral, whereas customer holding an unsecured credit line are still facing the risk of a line cut-down.

In addition we find that collateralized credit lines are utilized differently from uncollateralized credit lines. We are the first to show that collateralized credit lines are generally more heavily utilized than uncollateralized credit lines, *but* that this effect is impacted both by the granted volume of the credit line and the credit worthiness of the customer. Within the sample of credit lines exceeding a critical granted volume, collateralized credit lines are more heavily utilized than uncollateralized credit lines with identical credit worthiness. Thereby the critical credit line volume is inversely related to the credit worthiness. We will point out that these results may again be driven by the effect that *pledging collateral* may mitigate the risk of a credit line cut-down for customers under specific circumstances.

The remainder of the paper is structured as follows: First we give a short overview of the body of literature related to our work in Section 2. We examine factors driving the utilization of credit lines on a single deal level in Section 3. Therefore we develop respective hypotheses in Section 3.1 and describe the unique data set from the large Europe-based bank in Section 3.2. Afterwards we perform a multivariate analysis in Section 3.3. The applied dynamic panel estimator is described in Section 3.3.1 and the corresponding results are presented in Section 3.3.2. We complement our analysis via a sample split of the data and further robustness checks in Section 3.3.3. The results are summarized in Section 4.

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[9] We attribute a credit line as *uncollateralized* if there is no collateral pledged to mitigate the loss for the bank in case the customer defaults. Otherwise we label a credit line as *collateralized*. The terms are defined in a more formal way in Section 3.2. The notation "collateralized" and "secured" are used synonymously throughout the paper.

[10] We use the expressions "credit rating", "rating" and "credit worthiness" synonymously throughout the paper. Thereby the credit rating refers to the (internal) rating determined by a bank, which might only be a rather poor proxy for the real credit worthiness of a customer.

2 Literature overview

Early works regarding credit lines mainly focus on *stylized facts* or give an *overview of theories* regarding credit lines and their existence.

Avery and Berger (1991) analyze the risk exposure for banks with respect to credit lines. They present a theoretical model which focuses on a bank's risk resulting from credit lines and explains how this risk is related to the process of determining *which* borrowers receive a credit line. They find that, all else being equal, credit lines increase the risk exposure of a bank and that these credit lines may generate adverse selection and moral hazard problems, which introduce additional risk. In addition Avery and Berger (1991) perform an empirical analysis. Utilizing a Federal Reserve Board survey of activity regarding commitments, they find evidence that loans issued under a commitment perform better than other loans.

Shockley and Thakor (1997) theoretically and empirically analyze stylized facts of credit lines in particular with regard to the fee structure[11] attached to a credit facility. Their empirical part of the analysis is based on credit lines granted to publicly traded U.S. firms.[12] Shockley and Thakor (1997) describe common features of varying credit line types and describe a model explaining the existence of complex structures within various credit line contracts. However, they do not analyze the factors driving the utilization of credit lines in detail.

Ergungor (2001) gives an overview of theories of bank loan commitments. He focuses on three main bodies of literature. First, he reviews papers (a) explaining the existence of credit lines and/or (b) deriving pricing schemes for corresponding products. Second, he discusses how such contracts affect the bank's risk exposure. Third, he reviews how loan commitments affect the interest rate and rationing channels of monetary policy. While Ergungor (2001) provides an overview of the aforementioned body of literature, he does not offer many details on explanatory models and/or factors for single credit line utilization.

Various papers analyze the link between the *credit worthiness* of a customer and the *utilization* of her credit line.

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[11] See also Loukoianova *et al.* (2006), who try to derive a pricing approach for a specific type of credit lines.

[12] The data set includes data points only for the years 1989 and 1990.

Marker (1997) uses a data set of rolling credit facilities from a large financial institution to analyze the (medium) utilization of these lines for varying rating classes. He concludes that the (medium) utilization of rolling credit facilities is inversely related to the credit worthiness. However, Marker (1997) relies purely on descriptive statistics. We will explicitly use multivariate analyses to assess the impact of the credit worthiness on credit line utilizations in Section 3.

Agarwal *et al.* (2006) analyze the link between a customer's credit worthiness and the associated utilization of credit lines via multivariate analyses. They use a data set from a large financial institution that originates home equity lines. These lines are 'open' for a fixed period (usually five years) and can be freely utilized during that time.[13] Agarwal *et al.* (2006) conclude that the initial credit utilization is lower for those customers associated to a higher a priori probability for a future decrease in credit worthiness. They further observe an inverse relationship between the utilization of a credit line and the credit worthiness. While these results indicate a link between credit line utilization and credit worthiness for credit lines in general, Agarwal *et al.* (2006) only consider home equity lines. The link between credit line utilization and credit worthiness is therefore not clear for all types of credit facilities (e.g. credit lines which can be repaid and utilized again during the lifetime). In Section 3 we utilize a data set containing mainly credit facilities which *can* be repaid during their lifetime. We will therefore assess whether similar effects are observable for these credit line types.

Jiménez *et al.* (2009) analyze the utilization of credit lines for Spanish corporates. Their analysis is based on the Spanish Credit Register, which includes Spanish bank lending over the past twenty years. Their main findings are again related to the credit worthiness of a customer. They find that credit lines are more heavily utilized by firms that potentially default on these lines in the future compared to firms that do not default (in their data set). Their analysis also suggest that a wide variety of factors may determine credit line usage. Amongst others, they also include the collateralization of credit lines as a control variable in their analysis. They conclude that collateralized credit lines are attached to slightly higher utilization levels compared to uncollateralized credit lines. However, they do not allow for interaction effects between the collateralization and further explanatory variables. We will analyze the effect of collateralization of credit lines in a clearly more detailed manner in Section 3 and will explicitly include interaction effects.

[13] However, repayment of these credit facilities is not allowed during the contractual time-frame. Home equity lines are repaid in full at period end.

Norden and Weber (2010) analyze the link between checking account activity and the respective customer's credit quality via a unique data set that includes more than three million account-month observations over a four year horizon. They find that in particular customers, who default during the observed time horizon, increase their line utilization (prior to default) heavier than non-defaulters, violate the credit limits more often than non-defaulters and exhibit a higher median line utilization than non-defaulters. While the results of Norden and Weber (2010) are not directly linked to liquidity risk and are based on checking accounts only, they again confirm that the line utilization and the credit quality of customers are linked.

Schertler *et al.* (2010) analyze a data set of credit lines from a universal bank in Germany, which covers more than one million account-month observations from October 2002 to December 2008. In their case, the data set corresponds to a bank, which has the right to recall these lines upon short notice but does neither require an upfront provision fee nor a fee on the unutilized proportion of the credit line. Further, the data set includes (only) credit lines of German small and medium enterprises who mainly rely on bank funding as these customers rarely have direct access to capital markets. Schertler *et al.* (2010) find that customers with low recall risk for their credit lines have lower cash holdings and utilize their lines more heavily compared to customers with medium recall risk. Furthermore, customers with high recall risk have lower cash holdings but highly utilize their credit facilities compared to customers with medium recall risk. Schertler *et al.* (2010) clearly point out the importance of recall risk on credit line utilization.

Hardin and Hill (2011) analyze a specific type of credit lines. They dissect credit line availability and utilization in real estate investment trust lines (REITs). According to their multivariate analysis, credit line *availability* is (amongst other factors) related to cash flow uncertainty, dividend distributions and capital market access.[14] Further, results suggest that credit line *utilization* depends (amongst other factors) on operating cash flows as well as capital market access. Their results for the utilization of REITs are consistent with the results of Agarwal *et al.* (2006). We will show in Section 3 that comparable results hold for our data set as well.4

Further empirical papers focus on *other drivers* than the credit worthiness for the utilization of credit lines.

[14] Capital market access is in some cases approximated via the customers' rating, since a bad rating quality indicates less reliable access to capital markets.

Klapper (2001) analyzes the effect of short-term collateralization (by accounts receivable) on credit line utilization. She uses a stylized theoretical model to demonstrate that the value of a secured line of credit is associated with the business risk of the borrower and the quality of the customers of the borrower. She examines a sample of firms to conclude that firms with secured credit lines are more risky and have fewer expected growth opportunities. Klapper (2001) focuses on publicly traded manufacturing firms. However, she only examines characteristics driving credit line collateralization by accounts receivable. Klapper (2001) does not analyze the *utilization* of credit lines of secured versus unsecured credit lines. We will analyze the impact of collateral on the utilization of a credit line including the consideration of interaction effects in detail in Section 3.

Sufi (2009) examines under which circumstances firms use credit lines or cash to manage corporate liquidity. He finds that maintenance of high cash flows is a very important factor in determining whether corporate customers prefer to use credit lines or cash in their liquidity management. The results are explained by Sufi (2009) via cash flow based covenants widely applied on customers within his data set. Given, that his data set of credit lines is contingent on maintenance of cash flow based covenants, credit lines are a poor substitute for liquidity for corporate firms with low cash flows. The results suggest that the cash flows or at least a proxy for cash flows of corporate firms needs to be considered if the utilization of credit lines is analyzed.[15]

The work of Yun (2009) is related to the work of Sufi (2009). He uses data from dealscan[16] and states that credit lines constitute a major source of liquidity for U.S. firms. However, he finds support that poorly-governed firms increase their cash reserves relative to their volume of loan commitments, whereas this hypothesis does not hold for well-governed firmes.

Lins *et al.* (2010) chose a completely different approach to analyze credit line utilization. Rather than analyzing a specific data set of credit lines, they survey chief financial officers from various countries and examine causes for as well as the extent of credit line versus cash utilization as liquidity sources. Lins *et al.* (2010) find that credit lines are used to seize business opportunities in good times while cash guards potential cash flow (outflows) of the firms in bad times. Further, they also conclude from their surveys that firms value credit line availability especially high under circumstances exacerbating alternative

15 As we do not have any information on cash flows for the customers in our data set, we will apply the turnover in relation to the balance sheet volume to approximate the cash flow of firms in Section 3.

16 He uses commitment contracts for future loans between 1987 and 1996.

funding (in particular if it is hard for firms to attract bank funds on the spot markets in specific regions or markets).

Most of the literature presented in this section links the credit worthiness of a customer to the utilization of her credit line. Furthermore Klapper (2001) links the collateralization to credit line *availability* and Jiménez *et al.* (2009) consider the collateralization of credit lines at least as a control variable in their analysis. To the best of our knowledge no literature exists, which links credit line *utilization* to collateralization *and* combines these facts with e.g. the credit worthiness of customers holding credit lines. We will close this gap in the literature and examine the individual impact of these factors as well as their combined impact on the utilization of single credit lines via a multivariate analysis. Furthermore, we will also have a closer look on the impact of the credit worthiness on the utilization of a credit line.

3 Analysis

3.1 Development of hypotheses

As outlined in Section 2, the link between a customer's credit worthiness and the utilization of credit lines associated with that customer, is well established in academic literature. It is commonly argued that *holding* a line of credit is a viable insurance against potential declines in credit worthiness, in particular for risk-averse customers.[17] While a good rating quality is generally associated with a broad availability of various funding sources, these may dry up or respective fees may increase in case the credit worthiness decreases. In the most extreme case, no other sources of funding may remain available, turning existing credit lines into a 'funding source of last resort'.[18] Consequently, if customers hold credit lines as an insurance against a decline in credit worthiness, one should observe higher utilizations for customers at the lower end of the rating scale.[19] This line of argumentation would support the inverse relation between a customers credit worthiness and the utilization of the respective credit lines.

However, there are various effects which might overlay, mitigate or enforce this common hypothesis. First of all, banks often attach lines of credit with material adverse clauses (MACs) and/or covenants.[20] Furthermore, credit lines may only be equipped with a short-term maturity, which leaves customers with the risk that these lines may not be rolled over at maturity. Hence, banks granting lines of credits may be in a position to cut-down existing credit lines if such clauses or covenants apply or do not roll over (short-term) maturity credit lines. Considering that a cut-down of credit lines should usually appear in times of a customer's financial distress, such a line of credit is only an imperfect

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[17] See e.g. Avery and Berger (1991), p. 176.

[18] Gao and Yun (2010) analyze the interplay between the use of credit lines and the commercial paper markets. They find that after the collapse of Lehman Brothers especially riskier firms (measured via the expected default frequency) drew heavily on their credit lines as they suffered severe declines in their commercial paper programs.

[19] See e.g. Agarwal *et al.* (2006). Of course the same line of argumentation may hold in case the macroeconomic changes result in increased credit risk in the markets, leading to an systemic crisis rather than solely an idiosyncratic crisis of the specific customer (see Kanatas (1987)). As it is quite common to compose the interest rate for drawings on a credit line as a *fixed* add-on onto a reference rate (e.g. the Libor), such a credit line would be an insurance against changes to idiosyncratic risk for a customer as well as systemic risks not reflected within the reference rate. However, the risk of a change in the reference rate is mainly handed over to the customer (see Demiroglu and James (2011)).

[20] See Sufi (2009), p. 1065 and Hawkins (1982), p. 63.

insurance against a deterioration of (future) credit ratings.[21] Consequently, customers finding themselves in faced with the threat of large rating downgrades may react in different ways. They might (fully) draw-down on their lines even *before* a material adverse clause or a covenant break recalls their right to do so.[22]

However, if customers anticipate a cut-down of their credit lines in times of economic distress, they may be more inclined to a priori build additional provisions against credit downgrading, which are then utilized in preference of existing credit lines. One flexible substitute for credit lines may be solid cash reserve for firms. Sufi (2009) finds, that firms with either current or expected cash flow needs maintain high cash balances if credit line availability is contingent on cash flow-based covenants. Campello *et al.* (2010) underpinned this result surveying $1,050$ CFOs. They find that constrained[23] firms had more issues using their lines of credit[24] during the financial crisis compared to unconstrained firms. Hence, constrained firms may broadly use their cash reserves to obtain a sound liquidity situation. These arguments *mitigate* the expected *inverse relation* between credit worthiness and utilization of respective credit lines, especially for customers with a very weak credit rating.

Summarizing this line of argumentation, we formulate the following two hypotheses:

Hypothesis 1. *The utilization of a credit line is driven by the rating of the customer.*

Hypothesis 2. *Up to a critical threshold, a customers' creditworthiness has a positive impact on credit line utilization. Beyond this critical credit worthiness, the line utilization is a decreasing function of the credit rating.*

We also want to assess the link between collateralization and utilization of a credit line. It is theoretically well established that the existence of collateral for a *specific* loan decreases the riskiness of that loan, since the granting bank receives a claim on the collateral without reduction of its claim against the borrower.[25] Admittedly, the riskiness of a customer and

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[21] See Kanatas (1987).

[22] Norden and Weber (2010) find that in particular customers, who default in the future, increase their line utilization heavier than non-defaulters and the median line utilization of their credit lines is higher than for non-defaulters. Schertler *et al.* (2010) use a comparable line of argumentation for credit lines, where the bank can opt to cut-down the credit lines completely at its own discretion. They find, that in particular credit line holders associated with a high risk of getting their lines recalled utilize these lines more heavily than customers with moderate recall risk.

[23] *Constrained* refers in particular to risky and less profitable firms.

[24] These firms in particular feared that banks would restrict their access to credit lines in the future.

[25] See Stiglitz and Weiss (1981) and Berger and Udell (1990), p. 22.

the collateral status[26] may affect each other. In particular if only risky borrowers pledge collateral, the secured loans may be more risky than unsecured loans from less-riskier borrowers.[27]

However, low-risk firms may (ex ante) signal their quality by pledging collateral to obtain sufficient funds (i.e. to assure credit *availability*).[28] Extensive literature discuss the 'sorting-by-private information' paradigm, i.e. the effectiveness of collateral to mitigate informational disadvantages of the bank regarding the credit worthiness of the borrower. Besanko and Thakor (1987) analyze this effect in markets, where the bank has an informational disadvantage and finds that collateral may mitigate problems regarding credit-rationing.[29] Furthermore, also observably riskier borrowers are willing to pledge collateral to obtain funds but may be required to pledge even more collateral compared to low-risk firms.[30] In fact, pledging collateral may actually be the only opportunity for high-risk borrowers to obtain any funds.[31] Klapper (2001) support this hypothesis for credit lines. Firms associated with a high degree of borrowing risk are permitted to borrow larger amounts through credit lines if they offer collateral.[32] Berger and Udell (1990) call the mechanism to obtain funds via pledging collateral for high-risk borrowers the 'sorting-by observed-risk paradigm'.

We will combine the aforementioned body of literature on *credit availability* with the literature discussing that customers may fear a possible *cut-down of their credit lines*.[33]

Consider a customer with an existing credit line who is in need of liquidity and may choose between drawing the credit line or utilizing alternative funding sources. The customer may

[26] The "Collateral Staus" denotes whether a credit line is collateralized or uncollateralized.

[27] See Berger and Udell (1990).

[28] Peltoniemi (2007) find support for this line of argumentation via their empirical analysis. See also Barclay and Smith (1995) for a comparable line of argumentation.

[29] Berger *et al.* (2011) employ a data set containing small business loans, where lenders utilize different technologies to obtain information regarding the borrowers over time. Using a more advanced technology to obtain information regarding the borrower (and therefore a reduction of informational asymmetries) is associated with a reduction in collateral requirements.

[30] Boot *et al.* (1991) obtain conditions, where more collateral is pledged by riskier borrowers.

[31] See Elsas and Krahnen (2000), p. 33.

[32] Sufi (2009) also states that firms, who can pledge a higher degree of collateral, can obtain more debt. Chakraborty and Hu (2006) analyze how the duration of a lender-borrower relationship affects the decision to collateralize credit lines. They find that the likelihood to collateralize a credit line decreases with the duration of the relationship and conclude that collateral requirements may over time be substituted with additional private information.

[33] Again we assume that the bank can draw a MAC, opts out covenants or does not roll over a credit line at maturity.

then consider the probability of future line cut-downs (i.e. the recall risk) and therefore assess *future credit availability*, to decide on the optimal funding source.[34] In case she already signaled her good quality via pledging collateral for the credit line, or was already required to pledged collateral to mitigate her riskiness, the future credit availability for that line should be higher (and the recall risk lower). This is in line with the theory of credit availability. Therefore, collateralized credit lines may serve as a *more reliable* liquidity source compared to unsecured credit lines for customers of the same riskiness. Hence, collateralization may allow customers to lower recall risk (in case they already have a credit line) or even allow them to attract a credit line in the first place. In addition, the costs for pledging collateral may drive a customers future funding decisions (for high-risk as well as low-risk customers). In case the secured credit line is a reliable source of funding, the customer will draw on this credit line if comparative costs for alternative reliable unsecured funding sources are higher.[35]

However, secured lines may not necessarily be more heavily drawn than unsecured credit lines. In particular for observably (very) low-risk customers there is no need to pledge collateral to assure *current and/or future credit availability.* Consequently, the 'sorting-by observed-risk paradigm' should lead to a situation where the collateralization effect (i.e. higher utilization for secured credit lines) is less significant or even nonexistent for very low-risk customers. Certainly, turning this line of argumentation the other way round, for observably high-risk customers, the collateralization effect should be highly significant.

Combining the line of argumentation as above, we formulate the following two hypotheses:

Hypothesis 3. *The utilization of a credit line is driven by the collateral status of a credit line.*

Hypothesis 4. *Customers with an uncollateralized credit line tend to utilize their lines less compared to customers having access to a collateralized credit line. However, the effect depends again on the credit worthiness of a customer and is more pronounce for high-risk clients but less pronounce for low-risk clients.*

Last, we analyze the influence of granted credit line *volume* on the utilization of secured credit lines. Stiglitz and Weiss (1981) argue that generally the credit rating of customers decreases as they borrow more (i.e. request larger loans). If we consign this line of argumentation from loans to credit lines, customers with larger credit lines may exhibit

34 See Schertler *et al.* (2010) for a comparable line of argumentation.

35 This effect should also be expressed in the interest rate for drawings of the credit line.

higher default risk. More risky clients would therefore be attached to a higher recall risk of their credit lines. According to the 'sorting-by observed-risk paradigm' stated above, a collateralized credit line, all else being equal, would lower the recall risk and utilization of the credit line does only to a lesser extend affect future credit availability. In short, for credit lines with a large volume the difference in utilization of secured credit lines vs. unsecured credit lines should be even more pronounced.

Other effects may mitigate or realign this effect as it is a priori not clear whether or not the economic aftermath of the cut-down of credit lines with different granted volumes is comparable for *one* specific customer. From a marginal funding perspective, there should be no difference. However (i) large credit lines contribute to a larger extent to the funding and liquidity mix of a customer and (ii) the cut-down of a large credit line may severely weaken the customer's financial strength as well as damage the reputational strength in case she is required to report the overall volume of granted credit lines externally (e.g. as part of the annual report). Furthermore, setting up a collateral agreement for large credit lines may be on average (per unit credit line) less costly than for small credit lines, as administrative costs may not rise in proportional to the collateral value and the granted line volume.

This leads to the following hypothesis:

Hypothesis 5. *The impact of the collateral status on the utilization of a credit line increases in the size of the granted volume.*

3.2 Data set and descriptive statistics

We employ a data set of credit lines of a large Europe-based bank to test Hypotheses 1-5. The data set mainly contains single deal information for *revolving* lines of credit.[36] Most of these lines have a short-term maturity or are granted 'until further notice', i.e. the credit line may generally be terminated by the bank without further notice.[37] The *vast majority* (approximately 96%) of the credit lines are granted 'until further notice' in our data set, which underpins the position of the bank to *cut-down* these lines *upon their discretion.*

The data set contains end of month data points with data availability starting from June 2009 up to August 2010. End of month data corresponds to credit line information for the last business day of each month. Given the enormous size of the data set (more than $200,000$ data points per month) we focus on quarterly analysis of our data, i.e. we use end of month data points for June 2009, September 2009, December 2009, March 2010 and June 2010. We use the subscripts (i, t) to identify information regarding credit line i at time $t \in \{06/2009, 09/2009, 12/2009, 03/2010, 06/2010\}$. Each credit line is attached to *one specific* customer of the bank.

We omit approximately 3.7 % of the exploitable data points due to the following data cleansing steps: Credit lines with a total granted volume ($Vol_{i,t}$) of less than 500 € or more than $100,000,000$ € are omitted. Additionally, all credit lines with a relative utilization $Util_{i,t}$ of more than 250% (i.e. lines, where the fraction of utilized and granted volume exceed 250%) or a collateral status $\hat{Col}_{i,t}$ exceeding 250% (i.e. where the fraction of the collateral value and the granted volume exceeds 250%) are deleted.[38] Furthermore, we delete all credit lines which are attached to interest rates $Interest_{i,t}$ above 100%. Thereby $Interest_{i,t}$ is the rate agreed between the bank and the customer for the utilized amount of the credit line.

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[36] The term revolving lines of credit corresponds to the fact, that customers are able to continuously draw or repay their credit lines upon their discretion. There are no contractual repayment schedules *during the lifetime* of the credit lines.

[37] Whether terminating these lines is feasible in times of stress for a huge portfolio of credit lines, given the possible impact on the reputation of the bank, is at least questionable. Furthermore, regulators require banks to price (and consequently model) uncommitted credit lines in a comparable manner (see CEBS (2010b), p. 8).

[38] Credit lines could have a utilization level beyond 100%. The bank may tolerate such overdrafts on a case-by-case basis and/or charge additional fees to the customer. Dependent on the overdraft, a specific approval of the overdraft could be necessary.

The cleaned data set contains more than $1,100,000$ data points which correspond to more than $220,000$ observations for each quarter-end. The total granted volume of credit lines roughly fluctuates between €16 bn. and €17 bn. The mean of $Util_{i,t}$ for each quarter fluctuates less than 2 percentage points over time.

With regard to the hypotheses formulated in Section 3.1, the *credit worthiness* of customers and the *collateral status* of credit lines are of major importance for all subsequent analyses. The large Europe-based bank providing the data uses a rating master scale with more than ten rating classes.[39]

In the following we apply the categorial variable $Rat_{i,t}$ to describe the credit worthiness of the customer associated with credit line i, at time t. A rating $Rat_{i,t} = 1$ corresponds to the best credit worthiness. For the duty of secrecy, we mainly present statistics for rating classes 1 through 6 and summarize the *results* for the remaining rating classes. In addition, all credit lines with no available rating information are summarized in a segregated rating category, which we call NR.[40] An overview of the rating distribution of our data set is provided in Table 1:

Table 1: Relative frequency of data points with respect to rating classes

$Rat_{i,t}$	Frequency
1	0.04%
2	15.09%
3	18.38%
4	21.81%
5	20.45%
6	12.26%
> 6	11.14%
NR	0.83%

For a first indication regarding Hypotheses 1-5, we compute the mean of $Util_{i,t}$ for all combinations of rating class and collateral status. Considering that the vast majority of credit lines is either completely uncollateralized or fully collateralized[41], we define the

[39] We use the rating according to the rating *master scale* as a credit worthiness proxy as these (internal) rating classes are *comparable to each other*. This may not be valid for other credit worthiness proxies provided along with our data set, as they may not be mapped to a *comparable master scale* beforehand.

[40] We will exclude these data points in our multivariate analysis in Section 1.

[41] It is worth noting, that customers may explicitly pledge collateral for a specific credit line (especially large companies associated with large credit lines). However, if the customer has a broader relationship with the bank, she may also pledge a pool of collateral for various loans, credit lines etc., where the collateral is suballocated to the various products. Unfortunately we are not able to differentiate between these type of customers.

dummy-variable $Col_{i,t} \in \{0,1\}$ with $Col_{i,t} = 0$ if $\hat{Col}_{i,t} = 0$ and $Col_{i,t} = 1$ otherwise.[42] Bi-variate statistics for the dummy variable $Col_{i,t}$ are illustrated in Table 2:

Table 2: Mean utilization of $Util_{i,t}$ based on rating classes and collateral status

Mean of $Util_{i,t}$	$Col_{i,t} = 0$	$Col_{i,t} = 1$
$Rat_{i,t} = 1$	16.15%	0.00%
$Rat_{i,t} = 2$	0.50%	1.17%
$Rat_{i,t} = 3$	3.44%	5.90%
$Rat_{i,t} = 4$	10.58%	14.26%
$Rat_{i,t} = 5$	26.45%	35.37%
$Rat_{i,t} = 6$	49.10%	55.73%
$Rat_{i,t} > 6$	70.44%	74.49%
$Rat_{i,t} = NR$	31.65%	57.89%

Generally, mean utilization increases (starting from $Rat_{i,t} = 2$) if credit quality worsens. The mean utilization is higher for collateralized credit lines, as compared to uncollateralized credit lines. These observations are consistent with Hypotheses 1 and 3 and more or less consistent[43] with Hypotheses 2 and 4. For a clear indication regarding Hypothesis 4 we apply an interaction term ($ColRat_{i,t}$) between the (categorial) variable $Rat_{i,t}$ and the binary variable $Col_{i,t}$ of the following form for the multivariate analysis in Section 3.3:

$$ColRat_{i,t} = \begin{cases} Rat_{i,t} & \text{if } Col_{i,t} = 1 \\ 0 & \text{else.} \end{cases}$$

In addition, we will apply $Rat_{i,t}^2$ as non-linear explanatory variable for the multivariate analysis to assess the shape of the relation between $U_{i,t}$ and the credit worthiness (here measured via the linear term $Rat_{i,t}$ and the non-linear term $Rat_{i,t}^2$).

For first indications regarding Hypothesis 5, we segment the data set according to the $0\% - 33.33\%$, $33.33\% - 66.66\%$ and $66.66\% - 100\%$ quantile of $Vol_{i,t}$.[44] We compute the difference between the means of $Util_{i,t}$ for $Col_{i,t} = 0$ and $Col_{i,t} = 1$, according to this segmentation. An increase in these differences is a first indicator for the increasing impact of the collateral status with regard to $Vol_{i,t}$.

42 We will use this dummy-variable consistently throughout the paper.

43 However, the mean utilization is significantly higher for uncollateralized credit lines with $Rat_{i,t} = 1$ compared to secured credit lines with $Rat_{i,t} = 1$ as well as credit lines with $Rat_{i,t}$=2.

44 Thereby we denote the α-quantile by q_α.

Consistent with Hypothesis 5, these differences increase (in particular for credit lines attached to a large granted volume) suggesting that large secured credit lines are more heavily utilized (compared to unsecured credit lines). The results are summarized in Table 3:

Table 3: Differences of mean of $U_{i,t}$ for $Col_{i,t} = 0$ and $Col_{i,t} = 1$

Mean of $Util_{i,t}$	$Col_{i,t} = 0$	$Col_{i,t} = 1$	Δ
$q_{0\%}$ up to $q_{33,33\%}$	15.49%	19.37%	3.88%
$q_{33.33\%}$ up to $q_{66.66\%}$	20.69%	26.14%	5.45%
$q_{66.66\%}$ up to $q_{100\%}$	31.57%	38.39%	6.82%

This analysis has various disadvantages, e.g. we completely ignore interaction effects. Therefore we will analyze Hypothesis 5 in more detail in the next section. We use $\hat{Vol}_{i,t} = log(Vol_{i,t})$ as metric control variable in the multivariate analysis and additionally define the *interaction effect* between $\hat{Vol}_{i,t}$ and $Col_{i,t}$ as a new metric variable $ColVol_{i,t}$.[45]

We introduce further control variables for conducting the multivariate analyses in Section 3.3. To account for all credit lines granted 'until further notice', we introduce a binary variable $baw_{i,t}$, which denotes 1 in case the credit line is granted 'until further notice' and 0 otherwise.[46]

As Sufi (2009) identified the cash flows of a firm as a major driver for the utilization of single credit lines, we need to control for this effect. However, we do not have detailed information on the cash flows of the customers. We therefore apply the turnover of the respective customer as a proxy. We include the ratio of (year-end) turnover to the (year-end) balance sheet volume ($Turn_{i,t}$).[47]

Furthermore, the bank reports for each customer a categorial variable ($Size_{i,t}$), which clusters all customers in light of § 273 Basler Ausschuss für Bankenaufsicht (2006) and thereby also reflects the annual turnover of a customer. Generally private persons and very small entities are allocated to the lowest category, whereas large companies are assigned to the highest category. For confidentiality reasons, we do not describe the composition of the variable in a more detailed manner.

[45] Naturally, the variable $ColVol_{i,t}$ is the product of $\hat{Vol}_{i,t}$ and $Col_{i,t}$.

[46] As mentioned earlier, approximately 96% of the credit lines are granted 'until further notice'.

[47] We have to use year-end information, as generally balance sheet data is only available on an annual basis. As not *all* customers are required to report balance-sheet information and the bank does not have these information readily available in the data set for the majority of customers, we prefer setting $Turn_{i,t} = 0$ under such circumstances, rather than annihilating the relevant credit lines. However, we introduce a further variable containing information on the turnover next.

Since the portfolio is quite heterogenous regarding the customers' industries, we additionally control for these via dummy variables $C^j_{i,t}$. $C^j_{i,t}$ equals 1, if credit line i at time t corresponds to a customer in industry j. Otherwise $C^j_{i,t}$ is zero.[48] However, we are from a technical perspective[49] not able to process all information regarding the industries processed by the bank. We therefore merge all industries including less than 3% of the data points into the industry class 'others'.

Last, we introduce time-dummies for each quarter ($Time^k_{i,t}$). $Time^k_{i,t}$ equals 1 in case $t = k$ and is otherwise zero.

Before we start the multivariate analyses, we complement our descriptive statistics by reporting all major correlation coefficients in Table 4. In particular the correlations between the dependent variable $Util_{i,t}$ and the explanatory variables $Rat_{i,t}$, $Col_{i,t}$, $ColRat_{i,t}$ and $ColVol_{i,t}$ for Hypotheses 1-5 are in line with our expectations.

Table 4: Pearson's correlation coefficients

Variables	$Util_{i,t}$	$Rat_{i,t}$	$Rat^2_{i,t}$	$ColRat_{i,t}$	$Col_{i,t}$	$ColVol_{i,t}$	$\hat{Vol}_{i,t}$
$Util_{i,t}$	1.0000						
$Rat_{i,t}$	0.5657	1.0000					
$Rat^2_{i,t}$	0.5385	0.9694	1.0000				
$ColRat_{i,t}$	0.1854	0.2425	0.2257	1.0000			
$Col_{i,t}$	0.1086	0.1193	0.0918	0.9399	1.0000		
$ColVol_{i,t}$	0.1249	0.1354	0.1084	0.9411	0.9841	1.0000	
$\hat{Vol}_{i,t}$	0.2053	0.2598	0.2283	0.2883	0.2650	0.3375	1.0000
$baw_{i,t}$	-0.1568	-0.1484	-0.1469	-0.0617	-0.0404	-0.0616	-0.2235
$Size_{i,t}$	0.1227	0.2316	0.2162	0.1705	0.1325	0.1727	0.5460
$Interest_{i,t}$	-0.0305	-0.0443	-0.0356	-0.1387	-0.1479	-0.1731	-0.4081
$Turn_{i,t}$	0.0035	0.0015	0.0012	0.0020	0.0012	0.0017	0.0191

Variables	$baw_{i,t}$	$Size_{i,t}$	$Interest_{i,t}$	$Turn_{i,t}$
$baw_{i,t}$	1.0000			
$Size_{i,t}$	-0.1838	1.0000		
$Interest_{i,t}$	0.2309	-0.3086	1.0000	
$Turn_{i,t}$	-0.0009	0.0237	-0.0110	1.0000

[48] Acharya *et al.* (2009) finds that a customers' exposure to systemic risk is important to determine whether she manages liquidity primarily via credit lines or cash. We control for these effects via the control variables $C^j_{i,t}$, $Turn_{i,t}$ and $Size_{i,t}$.

[49] We would end up with a large number of dummy-variables (highly unpreferable in regression models). Furthermore, the IT requirements to estimate a model with a very large number of dummy-variables are very steep.

3.3 Multivariate Analyses

This section provides multivariate analyses regarding our Hypotheses 1 - 5 on the basis of the data set described in Section 3.2.

First we formulate our econometric model in Section 3.3.1. The corresponding results are presented in Section 3.3.2. Finally, we complement our analysis via an application of our multivariate analysis on two sub-samples of our data and further robustness checks in Section 3.3.3.

3.3.1 Econometric model

We apply the following model to test Hypotheses 1-5:

$$\begin{aligned} Util_{i,t} &= \beta_0 + \beta_1 \cdot Rat_{i,t} + \beta_2 \cdot Rat_{i,t}^2 + \beta_3 \cdot Col_{i,t} + \beta_4 \cdot ColRat_{i,t} \\ &+ \beta_5 \cdot ColVol_{i,t} + \beta_6 \cdot \hat{Vol}_{i,t} + \beta_6 \cdot Interest_{i,t} + \beta_7 \cdot baw_{i,t} \\ &+ \beta_8 \cdot Size_{i,t} + \beta_9 \cdot Turn_{i,t} + \beta_{10} \cdot Util_{i,t-1} \\ &+ \sum_{j=11}^{n_C} \beta_j C_{i,t}^j + \sum_{k=n_c+1}^{n_c+5} \beta_k \cdot Time_{i,t}^k + \mu_i + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where μ_i denotes a customer-specific effect and $\epsilon_{i,t}$ a disturbance term. All other variables have already been introduced in Section 3.2.

We will use a dynamic panel estimator introduced by Arellano and Bover (1995) and further developed by Blundell and Bond (1998) with a finite sample correction for the variance, as proposed by Windmeijer (2005). We use the dynamic panel estimator following Blundell and Bond (1998) for mainly two reasons.

First, we include $Util_{i,t-1}$ in the estimation, as it seems intuitive that the lagged utilization $Util_{i,t-1}$ serves as an anchoring point for the utilization at t: The line utilization at t simply calculates as the utilization change during the period from $t-1$ to t added on top of $Util_{i,t-1}$.[50] Additionally, we can control for further time-dependent customer-specific individual effects in equation (1). Standard OLS models[51] are inconsistent in case past

[50] Moreover, a standard fixed effects model also suggest the relevance of $Util_{i,t-1}$ (see Section 3.3.3).

[51] See e.g. Kohler and Kreuter (2008) for a short introduction to standard OLS models.

realizations of the dependent variable are included in the regression,[52] but the dynamic panel estimator following Blundell and Bond (1998) can deal with this problem.[53] Second, the estimator is designed for panel data sets with a very limited number of observations across the time dimension and a large number of observations per point in time.[54] As the data set contains observations for *only* T=5 quarters, but a large number of observations per quarter (more than $220,000$), the model seems to be suitable for our data set.

The estimations for the model following Blundell and Bond (1998) will be consistent if we use reasonable instruments for the lagged dependent variable $Util_{i,t-1}$ and if there is no autocorrelation of second-order in the data.[55]

To assess the validity of the applied instruments, the test of overidentifying restrictions by Hansen[56] is used. However, the Hansen test can be weakened by many instruments.[57] Therefore we restrict ourself to only a very limited number of instruments and use only explanatory variables already included in the model to instrument the lagged dependent variable. Furthermore, a standard test for autocorrelation is used, to analyze whether no autocorrelation of second-order is present in our data.

3.3.2 Results for the full data set

Table 5 summarizes the estimation results for equation (1) using the dynamic panel estimator following Blundell and Bond (1998). Further, Table 5 states the results of the Hansen test, the number of instruments[58] used and the results of the test on autocorrelation.

The Hansen test for overidentifying restrictions indicates that we use valid instruments for the model and the tests on autocorrelation confirm that no second-order autocorrelation is given for the full data set.

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[52] See Nickell (1981) for the discussion of the biases in dynamic models with fixed effects. The bias may be ignorable if T is rather large. As T equals *five* in the present case, it is not feasible to completely ignore the bias and rely on standard OLS. Therefore we only use a standard fixed effects OLS model as robustness check in Section 3.3.3.

[53] See Roodman (2009a).

[54] See Mileva (2007).

[55] See Bornemann *et al.* (2012) and Roodman (2009a).

[56] See Arellano and Bond (1991) and Blundell and Bond (1998).

[57] See Roodman (2009b) and Bornemann *et al.* (2012).

[58] We use 25 instruments for the estimation of equation (1).

Table 5: Dynamic panel estimation for $Util_{i,t}$

	Dependent variable: $Util_{i,t}$	
Explanatory variables:	Coefficient	Corrected SE
$Rat_{i,t}$	0.62499^{***}	0.21262
$Rat^2_{i,t}$	-0.05107^{***}	0.01750
$Col_{i,t}$	-9.50610^{**}	3.78073
$ColRat_{i,t}$	0.49085^{***}	0.14800
$ColVol_{i,t}$	0.76849^{**}	0.34134
$\hat{Vol}_{i,t}$	-0.47772^{***}	0.16836
$Interest_{i,t}$	-4.14787^{**}	1.96745
$baw_{i,t}$	-1.51039^{*}	0.86152
$Size_{i,t}$	0.34773^{**}	0.14412
$Turn_{i,t}$	0.00054	0.00658
$Util_{i,t-1}$	-0.25553	0.40307
Industry dummies	included without being reported	
Time dummies	included without being reported	
Const. $[\theta]$	4.30410^{**}	1.84327
No. of obs.	880,366	
No. of customer	237,614	
No. of instruments	25	
AR(1) test (p-value)	0.072	
AR(2) test (p-value)	0.381	
Hansen test (p-value)	0.143	

Note: We use a dynamic generalized method of moments (GMM) estimation following Blundell and Bond (1998) with finite sample correction proposed by Windmeijer (2005). The robust standard errors are given in the Column 'Corrected SE'. *, ** and *** indicate significance at the 10%, 5% and 1% level based on the robust standard errors. Only explanatory variables for the regression are used as instruments for the lagged variable $Util_{i,t-1}$. The functional form of the estimation model is given by equation (1). The variables are described in detail in Section 3.2.

The coefficients for $Rat_{i,t}$ and $Rat^2_{i,t}$ are strongly significant.[59] Furthermore, the coefficient for $ColRat_{i,t}$ is significant. Hence, we can confirm the first Hypothesis as the utilization of the credit line is significantly driven by the rating of the customer.

The coefficients for the linear terms ($Rat_{i,t}$ and $ColRat_{i,t}$) are positive, whereas the non-linear term exhibits a negative $Rat^2_{i,t}$. If we omit the effect of the coefficient $ColRat_{i,t}$ (and of all other variables as well) and just analyze the coefficients for $Rat_{i,t}$ and $Rat^2_{i,t}$, the highest utilization is estimated for the rating class $Rat_{i,t} = 6$.[60] Customers *exceeding* this rating class utilize their credit lines less. The effect is visualized in Figure 1 and basically illustrates, all else being equal, the impact of the credit worthiness on $Util_{i,t}$ for *unsecured* credit lines.[61]

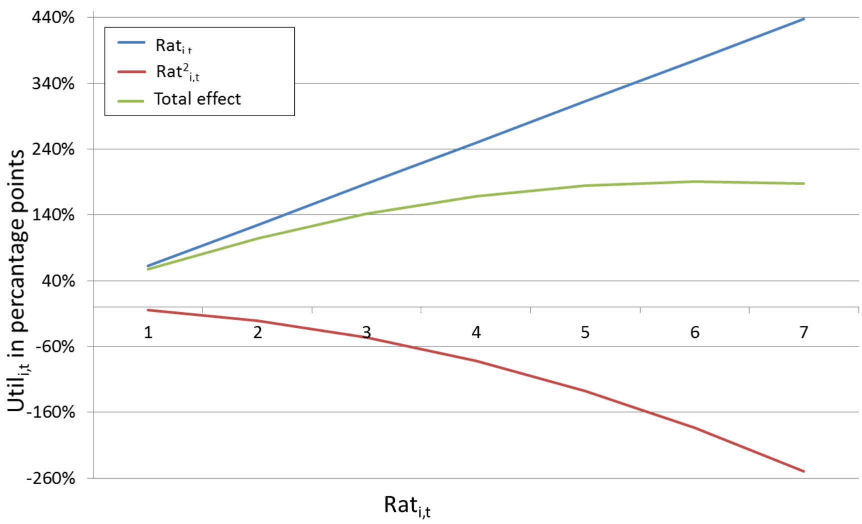

Figure 1: Impact of $Rat_{i,t}$ and $Rat^2_{i,t}$ on $Util_{i,t}$ of unsecured (i.e. $Col_{i,t} = 0$) credit lines

However, if we analyze this effect solely for secured credit lines (i.e. $Col_{i,t} = 1$), we need to take the linear effect of $ColRat_{i,t}$ into account. The non-linear effects of $Rat^2_{i,t}$ unfold their full potential only for customers with a very bad credit rating. Hence, from a practical perspective there exists no reasonable critical credit worthiness beyond which we can observe a negative correlation between credit rating and utilization of a credit line. Pledging collateral may *mitigate* the recall risk regarding credit lines of high-risk

[59] We refer to a coefficient being "strongly significant", "significant" or "weakly significant" if the level of significance is "1%","5%" or "10%".

[60] Basically, we analyze the functional form of $Util_{i,t} = \beta_1 \cdot Rat_{i,t} + \beta_2 \cdot Rat^2_{i,t}$ and connect the discrete realizations for each rating class via linear splines.

[61] As already discussed in Section 3.2 we do not show *all* rating classes for confidentiality reason. The graph illustrates the effects up to rating class 7.

customers, whereas comparable high-risk customer holding uncollateralized credit lines are still facing high recall risk leading to the fact that the utilization is a decreasing function in the credit rating beyond the critical credit worthiness. Summarizing, we can fully confirm our Hypothesis 2 for unsecured credit lines, whereas for secured credit lines we can only confirm the inverse relation between the utilization of a credit line and the credit worthiness of a customer.

The coefficients $Col_{i,t}$ and $ColVol_{i,t}$ are significant. In addition the coefficient $ColRat_{i,t}$ is strongly significant. As the utilization of a credit line is significantly driven by the collateral status of a credit line, we can confirm Hypothesis 3.

The coefficient for $ColVol_{i,t}$ is positive, which confirms Hypothesis 5 (i.e the impact of the collateral status on the utilization of a credit line increases in the size of the granted volume of a credit line).

To confirm the Hypothesis 4, we need to analyze the levels and signs of the relevant coefficients *in combination*. First, we analyze for the *fixed* rating class *five* the utilization for secured ($Col_{i,t} = 1$) versus unsecured ($Col_{i,t} = 0$) credit lines under *varying* levels for $\hat{Vol}_{i,t}$. The effect is visualized in Figure 2.[62]

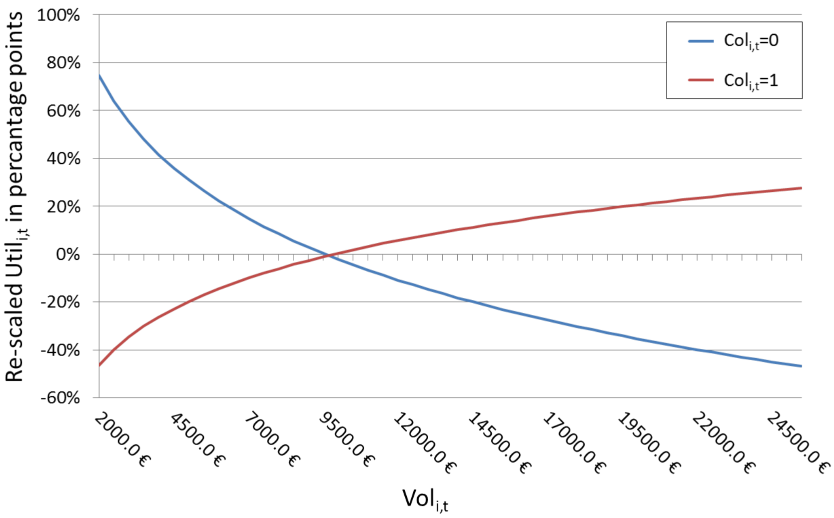

Figure 2: Impact of $Col_{i,t} = 1$ vs. $Col_{i,t} = 0$ on $Util_{i,t}$ on credit line

62 The absolute level of utilization can not be interpreted reasonably. We analyze the functional form of the two curves $Util_{i,t} = \beta_3 \cdot Col_{i,t} + \beta_4 \cdot ColRat_{i,t} + \beta_5 \cdot ColVol_{i,t} + \beta_6 \cdot \hat{Vol}_{i,t} + \tau$ for $Col_{i,t} = 0$ and $Col_{i,t} = 1$. Only data points with associated rating $Rat_{i,t} = 5$ are considered. Furthermore, we set τ in such a way that the curves for $Col_{i,t} = 0$ and $Col_{i,t} = 1$ intercept at an utilization level of approximately 0%.

Figure 2 shows that customers with a credit line volume of more than approximately €9,500 draw more heavily on their credit lines if these are secured. The median and the mean of secured credit line volumes for this rating class far exceeds the critical $\hat{Vol}_{i,t}$ of approximately €9,500, which supports Hypothesis 4 for *rating class five.*

For each rating class there *exists one unique* critical value for $\hat{Vol}_{i,t}$, at which the curves for secured vs. unsecured credit lines intercept. Beyond the critical value of $\hat{Vol}_{i,t}$, secured credit lines are more heavily utilized than unsecured credit lines. As the coefficient for $ColRat_{i,t}$ is positive, the critical value for $\hat{Vol}_{i,t}$ is *higher* for a good credit worthiness of customers and *lower* for customers with a bad credit worthiness. This effect is in line with Hypothesis 4 as the effect depends on the credit worthiness of the customers.

To understand, whether secured credit lines are *generally* utilized more heavily than unsecured credit lines, we contrast the critical credit line volume $\hat{Vol}_{i,t}$ for each credit worthiness with the median credit line volume of secured credit lines for this specific rating class. We find that for high credit worthiness (e.g rating class 2 and 3)[63], the median credit line volume is lower than the critical credit line volume $\hat{Vol}_{i,t}$.

Consequently, we can confirm Hypothesis 4 except for customers attached to a high credit worthiness. Whereas the collateralization effect (i.e. higher utilization for secured credit lines) is obvious for high-risk clients, for low-risk customers the collateralization effect is nonexistent. As pointed out in Section 3.2 in particular for (very) low-risk customers there is no need to pledge collateral to assure *current and/or future credit availability.* Consequently, the 'sorting-by observed-risk paradigm' may lead to exactly this situation for customers with a good credit worthiness. Furthermore, customers with a broader bank relationship may already be required to pledge collateral for other banking products. In case there is a collateral surplus from other products, the bank may allocate the collateral surplus to other (uncollateralized) transactions. This will lead to a situation, where in particular some credit lines might be collateralized although the bank neither explicitly required collateralizing (given the riskiness of the customer) nor the customer explicitly wanted to pledge collateral to safeguard her access to the credit line. Hence, these processes may pollute the results for customers with a high credit rating.

We comment briefly on the most relevant control variables. The coefficient for $Interest_{i,t}$ is significant and negative. The negative sign is in line with common expectations for

[63] This effect does not hold for the best credit worthiness (i.e. rating class 1). However, given the low frequency of customers with the best credit worthiness (see Table 1) and in particular of customers with secured credit lines, we do not further stress these cases.

customers, who have a broad access to funding sources. Under such circumstances a customer would compare the funding conditions for *all* her funding sources. Therefore a *higher* interest rate should, all else being equal, result in a lower utilization of her credit line. However, the impact on $Util_{i,t}$ is not extremely high, as an increase of the interest rate of 1 percentage point would only result in a decrease of utilization of 4 percentage points.[64]

The coefficient for $baw_{i,t}$ is weakly significant and negative. Especially for credit lines granted 'until further notice', the committing bank can terminate the unutilized amount without further notice. For credit lines *not* granted 'until further notice', the bank is not allowed to react in the same way. Consequently, if the line is *not* granted 'until further notice', customers do not have to fear a cut-down of their lines in case they heavily utilize these lines in the same manner as customers holding a line granted 'until further notice'. This should in fact result in *higher* utilization levels for lines where $baw_{i,t} = 0$ and explains the negative sign of $baw_{i,t}$.

3.3.3 Sample split and further robustness analysis

In the following we analyze the robustness of our results derived in Section 3.3.2. Therefore we split the data set into two sub-samples. Sub-sample (1) contains only unsecured credit lines, i.e. we omit all credit lines with $Col_{i,t} = 1$. Sub-sample (2) contains only secured credit lines, i.e. we omit all credit lines with $Col_{i,t} = 0$. As there are by definition no interaction effects between the collateral status and other explanatory variables *within each* sub-sample, we adjust equation (1) and use the following model:

$$\begin{aligned} Util_{i,t} &= \beta_0 + \beta_1 \cdot Rat_{i,t} + \beta_2 \cdot Rat_{i,t}^2 + \beta_3 \cdot \hat{Vol}_{i,t} + \beta_4 \cdot Interest_{i,t} + \beta_5 \cdot baw_{i,t} \\ &\quad + \beta_6 \cdot Size_{i,t} + \beta_7 \cdot Turn_{i,t} + \beta_8 \cdot Util_{i,t-1} \\ &\quad + \sum_{j=9}^{n_C} \beta_j C_{i,t}^j + \sum_{k=n_c+1}^{n_c+5} \beta_k \cdot Time_{i,t}^k + \mu_i + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where μ_i denotes a customer-specific effect and $\epsilon_{i,t}$ a disturbance term. All other variables are already described in detail in Section 3.2.

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[64] We analyze the effects regarding $Interest_{i,t}$ in more detail in Section 3.3.3.

As before, we use the dynamic generalized method of moments (GMM) estimation following Blundell and Bond (1998) with finite sample correction proposed by Windmeijer (2005) for both sub-samples. Table 6 summarizes the results of the model:[65]

Table 6: Sample split for $Col_{i,t} = 0$ vs. $Col_{i,t} = 1$: Dynamic panel model for $Util_{i,t}$

	Dependent variable: $Util_{i,t}$			
	Sub-sample (1)		Sub-sample (2)	
Explanatory variables:	Coefficient	Corrected SE	Coefficient	Corrected SE
$Rat_{i,t}$	0.35817^{***}	0.05118	0.13845^{***}	0.04698
$Rat^2_{i,t}$	-0.02616^{***}	0.00472	-0.00849^{**}	0.00364
$\hat{Vol}_{i,t}$	-0.00817	0.00663	0.12892^{***}	0.04867
$Interest_{i,t}$	-2.43588^{*}	1.42097	4.28764^{***}	1.30901
$baw_{i,t}$	-0.96363^{***}	0.20631	-1.20034^{***}	0.34752
$Size_{i,t}$	-0.09503^{***}	0.01500	-0.17945^{***}	0.06903
$Turn_{i,t}$	0.00002^{***}	0.00000	0.00022	0.00021
$Util_{i,t-1}$	0.06337	0.06375	0.20677	0.15332
Industry dummies	included without being reported		included without being reported	
Time dummies	included without being reported		included without being reported	
Const. [θ]	0.59483	0.39763	-0.42623	0.38385
No. of obs.	722,924		157,442	
No. of customer	198,690		45,930	
No. of instruments	35		36	
AR(1) test (p-value)	0.000		0.000	
AR(2) test (p-value)	0.655		0.335	
Hansen test (p-value)	0.097		0.667	

Note: We use a dynamic generalized method of moments (GMM) estimation following Blundell and Bond (1998) with finite sample correction proposed by Windmeijer (2005) for both sub-samples. Sub-sample (1) contains only unsecured credit lines (i.e. credit lines with $Col_{i,t} = 0$) and sub-sample (2) contains only secured credit lines (i.e. credit lines with $Col_{i,t} = 1$). The robust standard errors are given in Column 'Corrected SE'. *, ** and *** indicate significance at the 10%, 5% and 1% level based on the robust standard errors. We only include as instruments for the lagged variable $Util_{i,t-1}$ explanatory variables also used for equation (1). The functional form of the estimation model for both sub-samples is given by equation (2). The variables are described in detail in Section 3.2.

First, we comment on the results for sub-sample (1). Although the significance levels for the main coefficients $Rat_{i,t}$, $Rat^2_{i,t}$ and $Vol_{i,t}$ slightly differ compared to the full data sample, the coefficient *signs* remain identical and still support Hypotheses 1 and 2 regarding

[65] The Hansen test for overidentifying restrictions indicates that we use valid instruments for the model on sub-sample (2). The test is less robust for sub-sample (1) compared to the results for the model on the full data set. No second-order autocorrelation is identified for both sub-samples.

unsecured credit lines.[66] Furthermore, the signs of the main control variables $Interest_{i,t}$ and $baw_{i,t}$ are also consistent with the estimates for the full data set and (at least weakly) significant.

Analyzing the coefficients of the model for sub-sample (2), we find consistent (and significant) results regarding the rating coefficients. Also the coefficient on $\hat{Vol}_{i,t}$ is strongly significant and has a positive sign (contradictory to the coefficient in sub-sample (1)). However, the positive sign is consistent to the results for the full data set regarding secured credit lines. We have to compare the sign of the coefficient on $\hat{Vol}_{i,t}$ in our sub-sample (2) with the sign of the sum of the coefficients $ColVol_{i,t}$ and $\hat{Vol}_{i,t}$ of the estimations for the full data set, as they both include information regarding secured credit lines. The sum of these two coefficients on the full data set has a positive sign. Hence, we conclude that the coefficient $\hat{Vol}_{i,t}$ is also consistent to the results on the full data set. The coefficient for $baw_{i,t}$ is also consistent with the results for the full data set. We do not want to conceal that contradictory to the regression on the full data set as well as on the unsecured credit lines, we estimate a strongly significant and *positive* coefficient for the control variable $Interest_{i,t}$.

We again have a closer look on the distribution of interest rates associated with the customers and find that customers with secured credit lines are associated with both a lower mean and median interest rate.[67] This follows economic intuition according to which secured credit lines are, all else being equal, less risky and customers should pay a lower interest rate. Of course this does not yet explain the positive coefficient in the regression model. Potentially customers with secured credit lines may have to a lesser extent access to other funding sources (outside the specific bank). Maybe they attracted their credit line at the bank only, *because* they pledged collateral or if they attract outside funding. In that case they should depend more strongly on bank funding and might even accept higher interest rates in case they are really required to attract funding. In such a case the bank could enforce its bargaining power and try to increase its interest profitability.[68]

In total, the estimation results on both of the sub-samples (1) and (2) support Hypotheses 1-5.

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[66] The coefficient regarding $\hat{Vol}_{i,t}$ is not of major interest for the analysis on *unsecured* credit lines. Consequently, we do not see any issues with the insignificance of the coefficient. As Hypotheses 3-5 deal with secured credit lines, we can not test for them on sub-sample (1).

[67] The standard deviation of interest rates for both sub-samples do not differ significantly.

[68] Also, the interest rate may reflect further characteristics about the customers, which we unfortunately do not capture adequately via the set of variables in equation (2).

In addition, we use a plain fixed effects regression (OLS) model for the estimation of equation (1) to check the robustness of the results.[69] As pointed out in Section 3, using a plain fixed effects model is questionable, given the "Nickell bias".[70] However, we are confident in using the model at least as a robustness check as we are *only* interested in the *sign* of the main coefficients regarding the credit worthiness of the customers and the collateral status rather than the exact magnitude of the coefficients. The results of the regression model are presented in Table 7:

Table 7: Fixed effects estimation for $Util_{i,t}$

	Dependent variable: $Util_{i,t}$	
Explanatory variables:	Coefficient	Corrected SE
$Rat_{i,t}$	0.01850^{***}	0.00204
$Rat^2_{i,t}$	-0.00048^{**}	0.00023
$Col_{i,t}$	-0.01058	0.01875
$ColRat_{i,t}$	0.00116	0.00149
$ColVol_{i,t}$	0.00195	0.00196
$\hat{Vol}_{i,t}$	0.03171^{***}	0.00392
$Interest_{i,t}$	0.09534^{***}	0.02353
$baw_{i,t}$	0.00481	0.00711
$Size_{i,t}$	0.00122	0.00455
$Turn_{i,t}$	0.00023	0.00024
$Util_{i,t-1}$	-0.05032^{***}	0.00238
Industry dummies	included without being reported	
Time dummies	included without being reported	
Const. $[\theta]$	-0.13006^{***}	0.03969
No. of obs.	880,366	
No. of customer	237,614	
No. of instruments	25	
R^2	0.027	

Note: We use a fixed effect estimator. Robust standard errors clustered on a customer level are given in Column 'Corrected SE'. *, ** and *** indicate significance at the 10%, 5% and 1% level based on the robust standard errors. The functional form of the estimation model is given by equation (1). The variables are described in detail in Section 3.2.

We restrict ourselves to comments regarding the main coefficients. The coefficient on $Rat_{i,t}$ ($Rat^2_{i,t}$) is strongly significant (significant). In addition, the signs of the coefficients

69 The usual Hausman-Test was performed beforehand to conclude that a random effects model cannot be applied appropriately on our data set (see Cameron and Trivedi (2005), chapter 21 for the requirement to perform such a test).

70 See Nickell (1981) for the discussion of the biases in dynamic models with fixed effects.

are in line with the results for the dynamic GMM estimation following Blundell and Bond (1998). The same holds for the signs of the other relevant coefficients $Col_{i,t}$, $ColRat_{i,t}$ and $ColVol_{i,t}$. However, these coefficients are not significant anymore.[71]

Last, we perform a regression of a small data subset (i.e. approximately 6,000 customer which show up to five credit line observations over the time horizon) of the full data set, where we could explicitly derive that the utilization of credit lines is no input for the rating calibration (i.e. the rating-model should not include any information regarding the credit line).[72] We re-performed the dynamic GMM estimation following Blundell and Bond (1998) on the small sub-sample as described in Section 3. The coefficient for $Rat_{i,t}$ is *still significant* and remains positive as in the main regression. Also the other relevant coefficients have mostly the same sign as the results for the main regression presented in Table 5.[73]

Summarizing the results of the robustness checks, we are confident that the hypotheses hold in the sense discussed in Section 3.3.2, because the sample split, the fixed effect model as well as the regression of the small data subset do not yield reasonable inconsistencies regarding the main coefficients relevant for the hypotheses.

71 This effect might be a result of the "Nickell bias".

72 Note, that it is highly likely that the rating does not include information on the line utilization for *most* of the credit lines in the data set. However, we suffer some data constrains on that analysis.

73 The results are available from the authors upon request. Other coefficients are mostly insignificant. However, as the robustness analysis focuses on the single risk driver *rating*, the other coefficients are of less importance. Respective rating effects may be mitigated through our estimation model (equation 1) anyway, as $Util_{i,t-1}$ is included as explanatory variable.

4 Conclusion

A thorough understanding of liquidity risk drivers for single credit lines is of major importance for financial institutions and constitutes a fundamental building block in a robust liquidity risk management framework.

We utilize a data set of credit lines from a large Europe-based bank to analyze factors driving credit line utilization via a dynamic panel estimator. Consistent to the current body of literature, we find that the credit worthiness of customers is an important driver of the utilization of single credit lines. However, we are the first to differentiate in that regard between collateralized and uncollateralized credit lines. For collateralized credit lines, we report an inverse relation between the credit line utilization and the customer's credit worthiness. For uncollateralized credit lines we find the same relationship up to a critical credit worthiness for the customer. Beyond this threshold, line utilization is a decreasing function of the credit rating. The different effects for uncollateralized versus collateralized credit lines may result from the risk that the bank is in the position to cut-down respective credit lines. Pledging collateral may mitigate the recall risk for high-risk customers, resulting in the observation that *only* the utilization of an uncollateralized credit line is a decreasing function in the credit rating beyond the critical credit worthiness.

We also show that the utilization of a single credit line is further driven by the collateral status of that line. We find that collateralized credit lines are generally more heavily utilized than uncollateralized credit lines. However, we newly find that the effect depends on the volume of the credit line as well as the credit worthiness of the customer. Beyond a critical credit worthiness, collateralized credit lines are more heavily utilized than uncollateralized credit lines. The critical credit line volume is inversely related to the credit worthiness, i.e. the worse the credit rating of customers, the lower the critical credit line volume. This suggests that collateral credit lines are more heavily utilized compared to unsecured credit lines in case the credit line is large and the credit worthiness of the customer is bad, whereas for small credit lines of customers attached to a good credit worthiness this effect is nonexistent.

Our results suggest a necessity to consider the credit worthiness *and* the collateral status when setting up a model to measure the liquidity risk for credit facilities as part of a sound liquidity risk management framework for financial institutions.

References

ACHARYA, V., PEDERSEN, L. H., PHILIPPON, T., AND RICHARDSON, M. (2009). Regulating Systemic Risk. In V. Acharya and M. Richardson, editors, *Restoring Financial Stability: How to Repair a Failed System*, chapter 13, pages 283–304. Wiley.

AGARWAL, S., AMBROSE, B. W., AND LIU, C. (2006). Credit Lines and Credit Utilization. *Journal of Money, Credit and Banking*, **38**(1), 1–22.

ARELLANO, M. AND BOND, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, **58**(2), 277–97.

ARELLANO, M. AND BOVER, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, **68**(1), 29–51.

AVERY, R. B. AND BERGER, A. N. (1991). Loan commitments and bank risk exposure. *Journal of Banking and Finance*, **15**(1), 173–192.

BARCLAY, M. J. AND SMITH, CLIFFORD W, J. (1995). The Maturity Structure of Corporate Debt. *Journal of Finance*, **50**(2), 609–31.

BASLER AUSSCHUSS FÜR BANKENAUFSICHT (2006). Internationale Konvergenz der Eigenkapitalmessung und Eigenkapitalanforderungen - Überarbeitete Rahmenvereinbarung. http://www.bis.org/publ/bcbs128ger.pdf (28.08.2012).

BERGER, A. N. AND UDELL, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, **25**(1), 21–42.

BERGER, A. N., ESPINOSA-VEGA, M. A., FRAME, W. S., AND MILLER, N. H. (2011). Why do borrowers pledge collateral? New empirical evidence on the role of asymmetric information. *Journal of Financial Intermediation*, **20**(1), 55–70.

BESANKO, D. AND THAKOR, A. V. (1987). Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets. *International Economic Review*, **28**(3), 671–89.

BIS (2008). Principles for Sound Liquidity Risk Management and Supervision. http://www.bis.org/publ/bcbs144.pdf (28.08.2012).

BLUNDELL, R. AND BOND, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, **87**(1), 115–143.

Boot, A. W. A., Thakor, A. V., and Udell, G. F. (1991). Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results. *Economic Journal*, **101**(406), 458–72.

Bornemann, S., Kick, T., Memmel, C., and Pfingsten, A. (2012). Are banks using hidden reserves to beat earnings benchmarks? Evidence from Germany. *Journal of Banking & Finance*, **36**(8), 2403 – 2415.

Cameron, A. C. and Trivedi, P. K. (2005). Microeconometrics: Methods and Applications. Cambridge University Press.

Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, **97**(3), 470–487.

CEBS (2009). Guidelines on Liquidity Buffers & Survival Periods. http://www.eba.europa.eu/documents/Publications/Standards-Guidelines/2009/-Liquidity-Buffers/Guidelines-on-Liquidity-Buffers.aspx (17.05.2012).

CEBS (2010a). CEBS Guidelines on the management of concentration risk under the supervisory review process. http://www.eba.europa.eu-/documents/Publications/Standards–Guidelines/2010/Concentration-risk-guidelines/Concentration.aspx (17.05.2012).

CEBS (2010b). Guidelines on Liquidity Cost Benefit Allocation. http://www.eba.europa.eu/cebs/media/Publications/Standards and Guidelines/-2010/Liquidity cost benefit allocation/Guidelines.pdf (17.05.2012).

Chakraborty, A. and Hu, C. X. (2006). Lending relationships in line-of-credit and nonline-of-credit loans: Evidence from collateral use in small business. *Journal of Financial Intermediation*, **15**(1), 86–107.

Demiroglu, C. and James, C. (2011). The use of bank lines of credit in corporate liquidity management: A review of empirical evidence. *Journal of Banking & Finance*, **35**(4), 775–782.

Elsas, R. and Krahnen, J. (2000). Collateral, default risk, and relationship lending: an empirical study on financial contracting. Discussion paper. Centre for Economic Policy Research.

Ergungor, O. E. (2001). Theories of loan commitments: a literature review. *Economic Review*, **37**(Q III), 2–19.

Financial Services Authority (2011). The failure of the Royal Bank of Scotland. http://www.fsa.gov.uk/rbs (28.08.2012).

Gao, P. and Yun, H. (2010). Commercial Paper, Lines of Credit, and the Real Effects of the Financial Crisis of 2008: Firm-Level Evidence from the Manufacturing Industry. Working Paper.

Hardin, W. G. and Hill, M. D. (2011). Credit Line Availability and Utilization in REITs. *Journal of Real Estate Research*, **33**(4), 507–530.

Hawkins, G. D. (1982). An analysis of revolving credit agreements. *Journal of Financial Economics*, **10**(1), 59–81.

Jiménez, G., Lopez, J. A., and Saurina, J. (2009). Empirical Analysis of Corporate Credit Lines. *Review of Financial Studies*, **22**(12), 5069–5098.

Kanatas, G. (1987). Commercial paper, bank reserve requirements, and the informational role of loan commitments. *Journal of Banking & Finance*, **3**, 425–488.

Klapper, L. (2001). The Uniqueness of Short-Term Collateralization. The world bank: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.17.8063&rep=rep1&-type=pdf (28.08.2012).

Kohler, U. and Kreuter, F. (2008). Datenanalyse mit Stata - Allgemeine Konzepte der Datenanalyse und ihre praktische Anwendung. Oldenbourg Wissenschaftsverlag GmbH.

Lins, K. V., Servaes, H., and Tufano, P. (2010). What drives corporate liquidity? An international survey of cash holdings and lines of credit. *Journal of Financial Economics*, **98**(1), 160–176.

Loukoianova, E., Neftci, S., and Sharma, S. (2006). Pricing and Hedging of Contingent Credit Lines. *IMF Working Paper*, (06/13).

Marker, J. (1997). Studies of Revolver Usage: Step inside Citibank, NA, New York, to hear the results of a study on revolving credit usage conducted by the bank's Portfolio Strategies Group. *Journal of Lending and Credit Risk Management*, **79**, 86–93.

Mileva, E. (2007). Using Arellano-Bond Dynamic Panel GMM Estimators in Stata. Fordham University, Economic Department.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, **49**(6), 1417–1426.

Norden, L. and Weber, M. (2010). Credit Line Usage, Checking Account Activity, and Default Risk of Bank Borrowers. *Review of Financial Studies*, **23**(10), 3665–3699.

Peltoniemi, J. (2007). Collateral Requirements and Relationship Banking: Empirical Evidence from Unique Finnish Credit-files. *LTA*, **4**, 393–414.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, **9**(1), 86–136.

Roodman, D. (2009b). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics*, **71**(1), 135–158.

Schertler, A., Pfingsten, A., and Hubensack, C. (2010). Bank Lines of Credit in Liquidity Management - The Impact of Recall Risk for German SMEs. Conference Paper, Jahrestagung des Vereins für Socialpolitik 2010 (Kiel): Ökonomie der Familie.

Shockley, R. L. and Thakor, A. V. (1997). Bank Loan Commitment Contracts: Data, Theory, and Tests. *Journal of Money, Credit and Banking*, **29**(4), 517–34.

Stiglitz, J. E. and Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *American Economic Review*, **71**(3), 393–410.

Sufi, A. (2009). Bank Lines of Credit in Corporate Finance: An Empirical Analysis. *Review of Financial Studies*, **22**(3), 1057–1088.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, **126**(1), 25–51.

Yun, H. (2009). The Choice of Corporate Liquidity and Corporate Governance. *Review of Financial Studies*, **22**(4), 1447–1475.