Do loan officers get soft by the month-end? Lending inefficiency and the end-of-month effect: the Portuguese case

Bruno Alves

152417058

Dissertation written under the supervision of
Professor Diana Bonfim

Dissertation submitted in partial fulfilment of requirements for the Master of Science in Finance, at the Universidade Católica Portuguesa

January 2019

Do loan officers get soft by the month-end? Lending inefficiency and the end-of-month effect: the Portuguese case

Bruno Alves

152417058

Abstract:

In this dissertation, we study the monthly distribution of all loans granted to Portuguese non-financial companies, between 2013 and 2016. We find a strong evidence of an end-of-month effect: 38% of all loans were granted in the last three days of the month. We isolate this effect and conclude that it is derived from credit lines, with a default rate 4.5x times higher than similar credit lines granted on the remaining days of the month. We find a reversal pattern on the 15th of each month, which we justify as a possible window dressing strategy from Portuguese banks – they have to report their loans' portfolio by this time of the month. Our results are robust to both the number of operations initiated (extensive margin) and the average loan amount (intensive margin). We perform a back-of-the-envelope computation and compute an increase in potential future credit losses of €3.2 billion as a consequence of the end-of-month relaxation in loan officers' standards. Our dissertation contributes to the field of end-of-month performance misalignments in a banking context, but takes a step forward: prior studies consider this event a consequence of variable compensation based on loan volume. In our context, we are able to split between banks that reward loan officers based on volume-granted and the ones that do not: the end-of-month effect is common to both.

Keywords: end-of-month effect, loan officers, credit lines, risk taking

JEL classification: E51, G21

Os gestores de crédito ficam brandos no fim do mês? Ineficiência na alocação de empréstimos e o efeito de fim de mês: o caso Português

Bruno Alves

152417058

Abstrato:

Nesta dissertação, estudamos a distribuição mensal de todos os empréstimos concedidos a empresas portuguesas não-financeiras, entre 2013 e 2016. Encontramos evidência significativa de um efeito de fim de mês: em média, 38% dos empréstimos foram concedidos nos últimos três dias do mês. Isolamos este efeito e concluímos que é derivado de linhas de crédito com uma taxa de incumprimento 4.5x superior às linhas de crédito concedidas nos restantes dias do mês. No dia 15 de cada mês ocorre um padrão de inversão: os empréstimos concedidos apresentam perspetivas significativamente superiores, o que justificamos como uma possível estratégia de *window dressing* por parte dos bancos portugueses – têm de reportar o seu portfólio de empréstimos nesta altura do mês. Os resultados obtidos são robustos à utilização do número de operações (margem extensiva), bem como ao volume de cada empréstimo (margem intensiva). Efetuamos cálculos de impacto do efeito de fim de mês, e concluímos que aumentaram em €3.2 mil milhões o valor de potenciais futuras perdas. A nossa dissertação contribui para a área que estuda desalinhamentos de performance no fim do período num contexto bancário, mas dá um passo extra: estudos anteriores consideram este evento como uma consequência de compensação variável baseada no volume de empréstimos. No nosso contexto, conseguimos separar entre bancos que recompensam os gestores de crédito com base no volume concedido, e os bancos que não o fazem: o efeito de fim de mês é comum a ambos.

Palavras-chave: efeito de fim de mês, gestores de crédito, linhas de crédito, tomada de risco

Classificação JEL: E51, G21

Acknowledgments

This dissertation represents the end of a journey that started almost five years ago. Its completion would have never been possible without an amazing group of people that supported me since day one.

First, I would like to thank my supervisor, Professor Diana Bonfim, for giving me the chance of being immersed in a research environment at the Bank of Portugal. Your constant support and inspiration has proven to be one of the most valuable resources I ever had. I sincerely hope that the research project where my dissertation is allocated has as much success as I would wish to a project of my own. I thank the Bank of Portugal for providing me access to several databases.

This dissertation was developed in close cooperation with Miguel Cravo Ferreira. A brilliant colleague would have made this dissertation easier, an amazing friend would have made it funnier – you made it both, in a way that I find hard to explain. To be fair, both of us should have our name in the front page of this dissertation. I cannot do that, but from now on the “we” would be used, instead of the “I”. Thank you, Mike!

I am grateful to Professor João Granja, from Chicago Booth, the other half of this project across the Atlantic, for helping us to define a path when we were drowning with multiple findings and possible directions. I also thank Pedro Moreira, from the Bank of Portugal, for helping us to work with complex databases and for being a friendly voice in an environment that was, at the beginning, unfamiliar to us.

To my friends, for dealing with my constant mood swings and for providing me the most amazing time at Católica I could ever ask for. Specially, I thank Miguel Silva, Sofia Gomes, Sara Pereira, Hanna Nikanorova, Jorge Santos, Nuno Plácido, Pedro Venâncio, Frederico Mendes and Maria Martins. I will sincerely miss our nights at the Reuters room, a place that became our second home.

Em último, mas seguramente não menos importante, um agradecimento especial aos meus pais. Sei que nunca vos vou poder agradecer tudo o que me proporcionaram e me ensinaram. Esta tese é o meu agradecimento por serem a maior fonte de inspiração que alguém pode ter. Muito, muito obrigado!

Table of contents

Table of figures

1. Introduction

The role of loan officers in banks' performance is unquestionable (Gao et al., 2017). By being responsible for screening and granting loans, and monitoring its performance, they manage to be at the very core of a commercial bank's business. In the aftermath of the 2007 subprime crisis, a source of market risk was identified in the banking sector: the incentive structure of loan officers. Many studies have, since then, focused both on the banks' executive level and lower-level personnel compensation, as a proxy for risk-taking behaviors. However, there is still little evidence on the time distribution of these behaviors. Is it feasible to assume that the level of risk that loan officers take is always the same? This will be the main research question throughout our dissertation.

Previous studies have revealed biases that stand out by the end of a period. Oyer (1998) showed that firms hold an incentive to shape both prices and the timing of customers' acquisitions, which goes in line with economic agents' paying special attention to performance measures by the end of the fiscal year. In a completely different setting, yet illustrative of this bias, Asch (1990) exposed that navy recruiters manage their effort in an attempt to win awards by having a better output in months prior to becoming eligible to win the award. Larkin (2007) used data from a software vendor and reports that salesman force the closure of the majority of their deals by the last day of the quarter. In a banking context, there is significant literature that proves the existence of behavioral biases that distort the economic efficiency of capital allocation, especially in the end of a period – either a quarter (Ertan, 2017) or a month (Tzioumis and Gee, 2013; Cao et al., 2018).

In this dissertation, we attempt to demystify the risk-taking behavior of Portuguese loan officers, using all loans granted to non-financial corporations from 2013 to 2016. By using proprietary databases of the Bank of Portugal, we manage to isolate the end-of-month effect, *id est*, the universe of loans granted on the last three days of the month. Our first finding, and the main driver of the remaining of our dissertation, is that the end-of-month effect incorporated 38% of all loans granted in the period of analysis. Moreover, this effect has been rising throughout time, reaching 44% in 2016. The increase verified by the end of the month is robust to both an assessment of the number of operations and the loan amount granted. We create six indicators that provide a comprehensive view of a company's credit risk, measured *a priori*: size, age, profitability, liquidity, leverage and tangibility. We conclude that loans granted by the end of the month are conceded to smaller, younger, less profitable and liquid and more levered companies, hence riskier. Even though this evidence of risk-taking may decrease when we acknowledge that the average interest rate increases by the end of the month (from 6.6% to 12.1%), it goes back to its original point when we assess that the average number of collateralized loans decreases from 44% to 27%. As we anticipated, the delinquency rate, measured 1-year after the loan origination, is 2x larger for end-of-month loans.

We further split our sample in term loans and credit lines and conclude that the end-of-month effect is driven by credit lines. Term loans present small, yet, statistically significant, differences between both periods of the month. Credit lines present major differences between both periods, and five out of the six previously defined indicators point out to an increase in risk-taking by the end of the month. The default rate of end-of-month credit lines is 4.5 times higher than credit lines granted during the rest of the month. We analyze whether there is a repetition pattern of credit lines, *id est*, how frequent it is for a bank to grant a credit line to the same company in repeated periods. We assess that 68% of credit lines have a monthly pattern and we justify this fact with a possible utilization of overdraft lines of credit – a tool that companies use when they fall short on liquidity.

The day 15th presents a reversal trend: loans granted by this day have characteristics that reveal a special concern on approving safer loans and, consequently, a lower default rate (3 percentage points lower). We believe that this behavior may be related with the fact that, by this time of the month, commercial banks have to report their loan portfolio status to the Central Credit Register managed by the Bank of Portugal, hence creating an incentive to develop a window dressing strategy (Allen and Saunders, 1992). We also study the monthly evolution of the loans' time to approval, which increases as the end of the month approaches, hence revealing contradictory findings to Tzioumis and Gee (2013) and also to our original intuition – we expected that time to approval by the end of the month would decrease: since loan officers approve riskier loans, it could be the case that they would rush the approval process. However, if we consider that bad prospect loans arrive approximately evenly throughout the month, loan officers may keep those loans in their inventory of prospect loans and only approve them by the end of the month, in case they need to attain a minimum capital allocation quota. This waiting process increases the time to approval, hence justifying with our results.

The field of performance-based compensation has been a subject of interest by several academics that strive to determine the impact it holds, not only in the output *per se*, but also on the long-term consequences of that output. In a banking context, more specifically in the loan concession process, numerous studies (for instance Agarwal and Ben-David, 2018 and Cao et al., 2018) have proven an increase in the end-of-month output as a consequence of volume-based compensation. Our dissertation builds on this foundation, but takes a step forward: we are able to distinguish between banks that hold variable-based compensation and the ones that have a fixed-based compensation, based on the fact that, during the Portuguese Economic Adjustment Program that started in 2011, banks that held negative levels of profitability were not likely to use variable-based compensation systems. A key finding is that the end-of-month effect remains, even though it is more magnified in banks that follow a compensation based on volume, which goes in line with the previously referred authors. In this way, we do acknowledge an impact arising from loan officers' compensation, but we find that this acts as a magnifier, and not as a determinant factor. We also develop a back-of-the-envelope computation on the impact of loan officers' standards relaxation by the end of the month. We forecast that credit overdue might have increased by approximately €3.2 billion during the four years of our study, which represents an increase of 63% compared with the case where loan officers do not change their behavior by the end of the month.

Our study contributes to several streams of ongoing research. The first one relates to the distortionary effects of performance incentives and moral hazard in banks. Existing research in the area of incentive compensation focuses mainly on risk-taking among top-level executives (Bebchuk et al., 2010; Bolton et al., 2015; Fahlenbrach and Stulz, 2012). By concluding that loan officers that are subject to variable-based compensation drive the end-of-month effect to higher levels, our results follow the past literature that mentions that when loan officers' incentives are not aligned with those of their employers (the lender), too many risky loans are approved as a consequence (Inderst, 2008; Heider and Inderst, 2012). By studying the 1-year default rates of loans granted by the end of the month, we add to the current research on banks' risk exposure due to compensation for short-term performance (Bebchuk and Spamann, 2009; Acharya et al., 2013).

Secondly, our dissertation adds to the literature on the end-of-month effect. As we have previously mentioned, banks that do not hold a reward scheme based on performance-based compensation are also driving the end-of-month effect. As such, we extend past research that studied this bias as a "compensation-based" one. The end-of-period effect remains as an open research topic that is transversal to several areas besides banking, ranging from non-financial employees' productivity (Asch, 1990; Larkin, 2007) to financial markets (Lakonishok and Smidt, 1988; Carchano et al., 2011).

Thirdly, and an aspect that we have been striving for since the day we initially thought about our research topic: we contribute to the body of research that uses Portugal as a case study, mostly derived from the top-quality data available. More precisely, we add to the literature that studies the Portuguese banking system and its impact on the economy (Crosignani et al., 2015; Blattner et al., 2017; Bonfim and Soares, 2018; Bonfim et al., 2018).

The remainder of our dissertation proceeds as follows. Section 2 presents the most relevant literature regarding the end-of-month effect and the associated incentives for this phenomenon. Section 3 describes the data we used and provides detailed descriptive analysis. Section 4 reports our methodology and empirical findings, whereas Section 5 displays robustness tests. We conclude in Section 6, and present our references, tables and appendices in Sections 7, 8 and 9, respectively.

2. Literature Review

Financial theory has progressed a lot regarding economic agents' assumptions on rationality and market efficiency. We assumed, for a long time, that investors were rational in their decisions and expectations (Muth, 1961; Lucas, 1978) and that the economic system enabled the creation of the widely-known concept of market efficiency (Samuelson, 1965; Fama, 1965; Lo, 2004). Some years before, there was already evidence on the possible irrelevance of capital structure decisions on the value of a firm (Modigliani and Miller, 1958). But similar to all theories, the market efficiency hypothesis started to show some signs of weakness. Behavioral scientists have proven a deviation pattern arising from decision-making under uncertainty, which leads to an unpredictable effect in welfare. This pattern is a combination of several psychological factors, such as overreaction (De Bondt and Thaler, 1987), herding (Welch, 2000; Huberman and Regev, 2001) and hyperbolic discounting (Laibson, 1997).

Moving to an industry context, there is evidence of an end-of-month effect on several activities. Liebman and Mahoney (2017) studied the year-end budget effect on procurement spending by the US Federal Government. The authors report that spending (in a "use-it-or-lose-it" setting) in the last week of the year is substantially higher than the rest of the year's weekly average and that year-end IT projects have lower quality ratings. Oyer (1998) showed that salesperson and executive compensation contracts usually stipulate a nonlinear relationship between revenue and pay, creating an incentive to manipulate prices and the timing of customer purchases. This creates a consistent connection with agents' focusing on performance by the end of the fiscal year. Firms also engage in this "controlled productivity", a practice called "earnings management", which occurs when managers use judgement to assemble a transaction to modify financial reports with the purpose of either misleading other parties or attaining benefits underlying to the reported figures (Healy and Wahlen, 1999). This phenomenon deserves a high level of consideration, given the fact that it twists the allocation of economic funds in the economy (Kedia and Philippon, 2007).

The banking sector is no exception to the previously reported end-of-period variation in multiple business-specific activities. Cao et al. (2018) studied the monthly distribution of loans in two Chinese banks. They find that daily end-of-month lending is 95% higher in the last five days of each month. However, this increase in loan amount comes at the expense of loan quality: end-of-month loans are 2.1 percentage points more likely to be classified as bad loans in the years following issuance. Ertan (2017) performed a similar study using syndicated lending activities, the largest source of external financing for non-financing firms (Sufi, 2007). He finds that, when lead arrangers are falling behind estimated earnings, they tend to increase the amount of loans issued and reduce the long-term price, while increasing short-term proceeds. This will maximize the immediate advantages of lending, but the long-term prospects are worse: the CDS spread on the borrower's outstanding debt increases by approximately 8.5% on the year after the issuance of these loans. Tzioumis and Gee (2013) showed that mortgage officers increase their output by the end of the month when the minimum monthly quota is evaluated, through a mixture of lower processing time and approval of some doubtful applications. They report that mortgages at the last day of the month have a higher rate of delinquency. There is also evidence on strong seasonality in the interest rates' market (Murfin and Peterson, 2016): companies that borrow during the cheaper season (late spring and fall) issue at 19 basis points cheaper than the ones issuing in the winter and summer. Ben-David (2011) presented evidence that mortgage brokers encourage borrowers to artificially inflate transaction prices simply to gain access to larger mortgages, as a way of reducing their monthly payment. Agarwal et al. (2013) exposed that financially constrained borrowers have the incentive to manipulate the appraisal process, with the aim of increasing borrowing or reducing the interest rates. Keys et al. (2009) showed that the securitization process adversely affected the screening incentives of lenders. All the previous studies reveal that misaligned incentives of financial mediators lead to transactions that, in normal conditions, would not occur.

After having acknowledged the existence of variations (either monthly or yearly) in the banking industry, the question that remains concerns its justification. We can take two different perspectives: the company and the bank. Starting by the former, one could argue that companies require bigger amounts of cash by the end of the month. However, given that salaries are paid either by the end or the beginning of the month, we can assume that there is not that much variation in both scenarios. Besides that, the remaining expenses can be assumed to be distributed throughout the month. The only effect that goes in line with this client-driven theory is the existence of budget deviations that would require the companies to ask for loans. Mian and Santos (2018) provided evidence that firm demand-side factors are indeed major drivers of pro-cyclical refinancing patterns over the credit cycle. There is research on household liquidity requirements (Telyukova, 2013), but we were unable to find sustained evidence on firm-driven liquidity constraints by the end of the month.

The other possibility is a bank-driven justification. Agarwal and Ben-David (2018) studied how compensation based on loan-volume affects loan amounts and delinquency rates. Their findings conclude that rewarding-systems based on volume generate more loans and a higher *ex post* default rate on these loans. Cole et al. (2015) reported similar findings for loan officers in a commercial bank in India. The impact of nonlinear contracts in performance is also a typical research object (Asch, 1990; Oyer, 1998). A common pattern of all these studies is that performance spikes at the end of each period. The impact of this type of contracts is currently under debate. Despite being often used in financial institutions, it can sometimes motivate counterproductive behavior (Jensen, 2003). Behr et al. (2017) provided evidence that, using a nonlinear compensation structure that benefits loan volume and punishes poor performance, loan officers that are at risk of losing their bonuses will increase prospecting and monitoring activities, usually by the end of the month. We can therefore conclude that the two effects are not mutually exclusive, since there is evidence on a variation on both demand and supply of credit granting throughout the month.

On a broader setting, several studies examine the effect of nonlinear incentive contracts in organizations. Holström and Milgrom (1991) stated that agents allocate more effort to activities that are directly rewarded, while disregarding uncompensated ones, activities which might be essential for the firm's efficiency. Bénabou and Tirole (2016) investigated this "bonus culture" and found that it takes over the workplace, generating distorted decisions that lead to severe losses of efficiency, especially in the long run.

A different strand of literature assesses the impact of hard and soft information on loan officers' activities. Extensive research has found that the use of soft information (private and qualitative) allows officers to enhance the monitoring and screening of their loan portfolio, thus reducing the likelihood of loan defaults (e.g., Petersen, 2004; Berg et al. 2013). On the other hand, studies from Stein (2002) and Campbell et al. (2017) suggest that agents suffer from cognitive constraints that hinder their capacities of processing and interpreting soft information, hence undermining their loan approval decision process. The authors identified hard information as a potential solution for the internal agency problems within banks.

To sum it all up, we can conclude that the impact of loan officers' behavior on the 2008 financial crises has sparked the interest of the academia. As Liberti and Mian (2009) concluded, banks suffer an intrinsic agency problem: the loan capital is provided by the lender, but it is the loan officer that approves the loan, using information that the bank cannot perceive or authenticate, hence affecting the credit allocation.

3. Data

Our laboratory is Portugal from January 2013 to December 2016. In this section, we first describe the databases we required to perform our analysis. We then proceed by explaining all the data treatment that was required, and we conclude with a description and interpretation of relevant descriptive statistics.

In order to accomplish our study, we had access to several proprietary databases of the Bank of Portugal. The main database we used holds all the new operations (*id est*, loans granted) in Portugal to non-financial corporations. This dataset (hereinafter NewOps) is a comprehensive set of data with 8,825,903 observations and its characteristics include, but are not limited to, anonymized tax identification number (TINA), anonymized bank identification number (BINA), concession date, amount, interest rate and collateral. NewOps effectively comprises all the relevant characteristics regarding the loans that loan officers granted.

We also had access to *Informação Empresarial Simplificada* (hereinafter IES), a Portuguese mandatory company census that includes accounting figures of all Portuguese companies, both from balance sheet, income statement and cash flow statement, for all years of our analysis.

Thirdly, we used *Central de Responsabilidades de Crédito* (hereinafter CRC), a dataset from the Bank of Portugal that contains information of all credit responsibilities assumed by all natural or legal entities, including the type of loan, the debtor, the amount and the status of loans. This status refers to whether credit has become overdue, if it was renegotiated, or if it holds an off-balance sheet exposure, such as a bank guarantee or a credit line that has not been used yet. The objective of the CRC is to allow financial entities to make estimations of the default probability of their prospective borrowers. Banks are required to report the length a loan is overdue at a monthly frequency, for all loans granted above 50 euros. All financial institutions are allowed to consult financial information on their current and perspective clients, with their previous consent, allowing CRC to become a crucial information-sharing mechanism between banks, hence decreasing the level of information asymmetry that arises in the loan granting process.

Lastly, we had access to a dataset that reports the consultation date in which the loan officer consulted the credit status of the prospective client on the CRC database.

We will only consider loans whose operation date is between 1st January 2013 and 31st December 2016. For this reason, we used NewOps as the main dataset, and the remaining three were merged to it. All observations before 2013 and after 2016 were, as previously referred, removed (which reduces our data by more than 18%). Loans that were missing TINA or BINA were excluded. Following Bates et al. (2009), and since we are only interested in active corporations, we exclude companies with a negative value of assets, revenues or employees. Loans conceded to companies established outside Portugal were also removed. In order to avoid double-accounting the same operation, we exclude all credit renegotiations (approximately 17% of the original dataset). The interest rate, maturity, loan amount and all the variables used from IES were winsorized at a 1% and 99% level.

For the period under analysis, we have a total of 2,956,307 new operations, comprising a total of 150,923 different borrowers (TINA) and 47 different lenders (BINA). A thorough analysis on the borrowers' segment allows us to conclude that 94,930 and 108,219 borrowers had a credit line and a term loan, respectively, in our period, whereas 52,226 different companies held both types of credit.

We find it useful to make a preliminary analysis of the financial profile of companies that were granted a loan in our period of analysis, as well as the loan characteristics. Table 1 presents descriptive statistics for the aggregate level (Panel A) and year-level (Panel B). We created six new variables as proxies for size (natural logarithm of assets), age (number of years since the company was founded), tangibility (tangible assets to total assets ratio), profitability (return on assets), leverage (debt to assets ratio) and liquidity (current ratio). We also study the loan amount, collateral (reported as a dummy variable), maturity, interest rate and average processing time, defined as the difference between the consultation date and the operation date. Lastly, we study the one-year default rate, measured at the firm-bank relationship: if the firm fails the payment of one loan to the bank, all the loans that the firm has on that bank are assumed to default during that period.

The mean loan amount for our period of analysis is 59,468€. On average, companies that had access to credit have 21 years of existence, 24.1% of its assets are tangible, a negative ROA of -1.9%, 79.3% of leverage and a current ratio of 1.9. Regarding loan characteristics, on average, 37.0% of loans granted have collateral and hold a maturity of 144 days. The average processing time is 33 days and the average interest rate is 8.7%. The one-year default rate is, on average, 6% across our time period.

We can also analyze the evolution of credit concession throughout the period of analysis. The number of loans granted by banks grew 29.1%, although we raise the concern that this value may not take into account the entire Portuguese credit market, since at its inception, the NewOps database did not include all banks. Regarding the company characteristics, there is evidence on banks' lending money to smaller, but older companies. Tangibility improved 5.5% during the 4 years. Profitability is raising throughout time, but remains at negative levels, moving from -3% in 2013 to -1% in 2016. The liquidity ratio presents improvements year on year, having improved 13.1% from 2013 to 2016. The leverage ratio remained virtually the same. Loan characteristics also present interesting findings: the collateral and maturity increased 65.3% (from 24% to 43%) and 8.2%, respectively, from 2013 to 2016. The average processing time and the interest rate decreased in our period of analysis, 9.4% and 2.58 percentage points, respectively. The delinquency rate (measured as a 1-year default occurrence) is decreasing, year-on-year, as it goes from 8% in 2013 to 5% in 2016.

There are several conclusions we can extract from our descriptive analysis, for the period of our study. First, the number of loans (and respective amount) grew. The average interest rate decreased, which is in line with the expansionary monetary policy adopted by the ECB in the years that proceeded the 2010 sovereign crisis (Blattner et. al, 2016). Loan quality, measured *a priori* (using companies' financial information) does not present a clear pattern: on one hand, tangibility and liquidity ratios are improving, which decreases the level of credit risk (Bonfim, 2009; Psillaki, 2010) and companies are getting older, thus safer (Thornill and Amit, 2003; Fink et al., 2004); on the other hand, companies are getting smaller, hence riskier (Bunn and Redwood, 2003; Jiménez and Saurina, 2004), and remain with negative levels of profitability. However, the average delinquency rate is decreasing across time. The average processing time decreased, which means that banks are speeding up the approval process (the development of new bank-related technologies may have played a role).

An interesting finding of our analysis is that 38.2% of our sample has zero maturity, meaning it is a credit line. In the next chapter of this dissertation, we will take this effect into account, to assess the impact it holds on the monthly evolution of credit granting. Figure 1 displays the evolution of the Portuguese credit market from 2013 to 2016, regarding the daily number of new operations. The blue dots presented in the graph match the last day of each month in our time period. As one can see, there are spikes in the number of new operations at each of the 48 last days of our period (4 years x 12 months), which provides a preliminary graphical representation of the end-of-month phenomena, which we describe in detail in section 4.1.

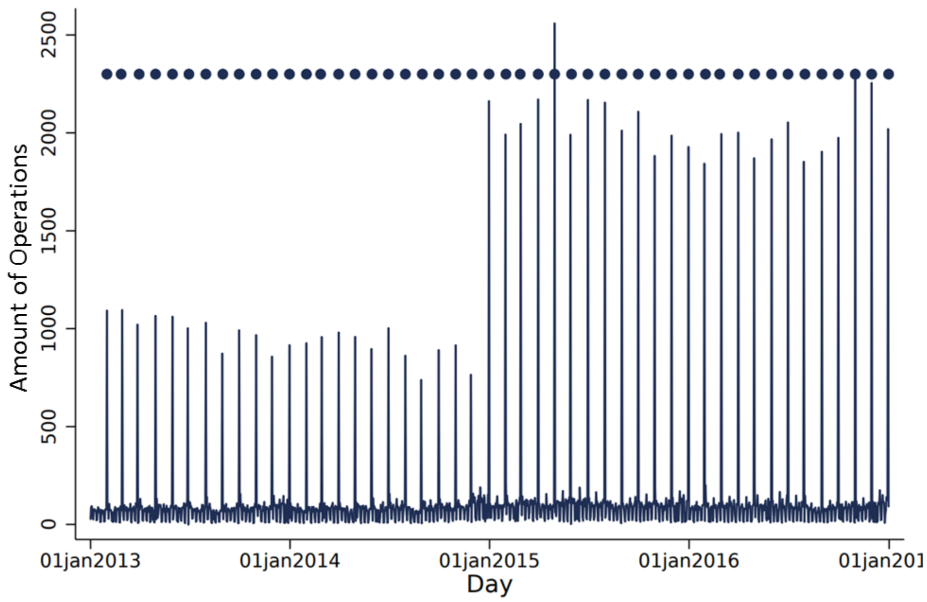

Figure 1: Evolution of new operations

4. Methodology and empirical analysis

In this section, we start by dividing our results in "end-of-month" and "rest of the month" (section 4.1). In order to provide a preliminary robustness test, we also present a comparison between the "end-of-month" and the "beginning of month" (loans granted in the first three days of the month). We continue with a segmentation between term loans and credit lines (section 4.2). The day 15th also presents interesting findings, reported in section 4.3. In section 4.4 we study the variable that represents the time to approval. We conclude with a back-of-the-envelope calculation to gauge the impact of the end-of-month increase in credit concession.

4.1. End of month vs. rest of the month

The core of our research is to study the impact of an eventual end-of-month effect on loan concession. To do so, we start by analyzing the daily distribution of loans granted in our time period. As we can see from Figure 2, there is a major concentration on the number of new operations by the last days of the month. It is important to clarify that we present (in the x-axis) the number of days before the last day of the month, to take into account the fact that not all months have the same number of days. In fact, 37.6% of all loans are approved on the last three days of the month and the last day of the month holds, by itself, 25.9%. Figure 3 presents the evolution of the end-of-month effect across our time-horizon and we can see a growing pattern since 2013. In 2013, 28.3% of all loans granted occurred, on average, on the last three days of the month, whereas in 2016 this effect represented 44.2% of the Portuguese credit market. These results are two folded: on one hand, there is evidence of a decrease in the number of loans granted to companies, year-on-year, since 2013 (Bank of Portugal, 2018), which could lead to a primary intuition of forecasting a decrease in the end-of-month effect. However, one can argue that a decrease in the number of loans conceded to companies may be related to a decrease in the prospects of the same companies. If we consider a minimum monthly-quota setting for loan officers, Tzioumis and Gee (2013) provide evidence that, when this quota is assessed, mortgage officers increase their output by the end of the month by approving marginal applications. Making a parallelism to loan officers and joining both effects, a decrease in the quantity of loans' applications, combined with the reported end-of-month effect, will increase the aggregated end-of-month effect.

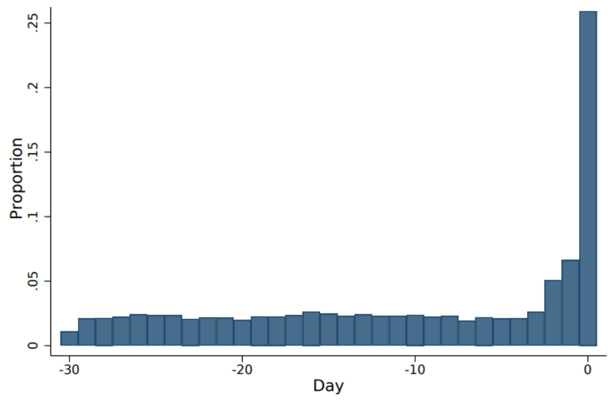

Figure 2: Daily distribution of new operations (new contracts)

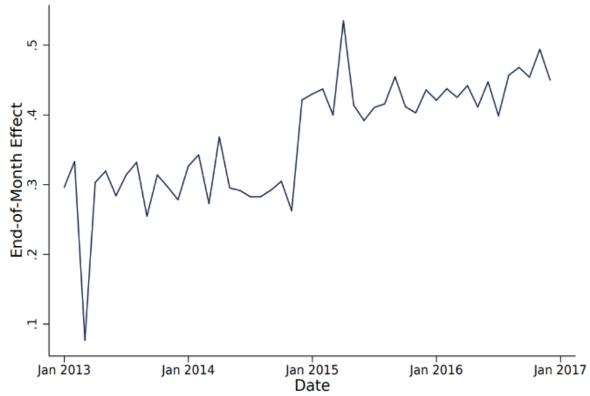

Figure 3: Evolution of the end-of-month effect

Figure 4 reports the average amount of loans granted by each day of the month. The results are parallel to the ones previously reported, as we can assess an increase in the average volume by the end of the month. We can therefore conclude the existence of both an extensive (number of operations) and intensive (average volume granted) margin at the end-of-month effect.

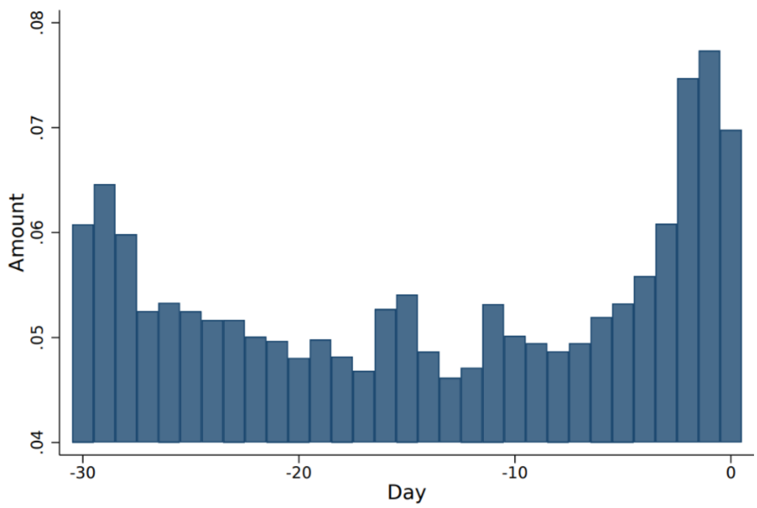

Figure 4: Daily distribution of average loan amount

In order to confirm our findings, we run regression (1), where the variables of interest, $I(d(t) = d)$ are a set of dummy variables, designating that date t is on day-of-the-month d. The other variables include fixed effects for the day-of-the-week (dow_t) and month x year (ym_t). Our dependent variable, $NewOperations_t$, is number of loans granted at day t. Figure 5 plots the regression coefficients $\{\beta_{-1}, \ldots, \beta_{-30}\}$, where β_{-t} represents the impact of the day of the month $30 - t$. The results are virtually the same as the ones presented in Figure 2.

$$NewOperations_t = \sum_{d=0}^{30} \beta_d \; I(d(t) = d) + dow_t + ym_t + \; \varepsilon_t \tag{1}$$

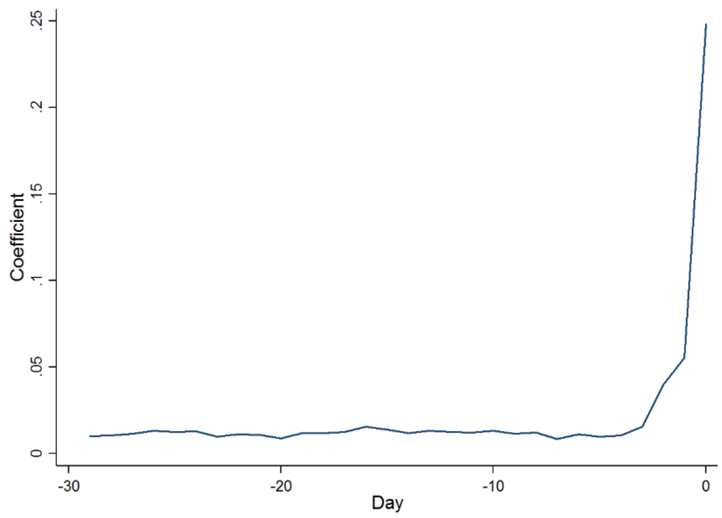

Figure 5: Coefficient plot for regression (1)

Following Cao et al. (2018) we create a new specification of our model: we will also study the differences between the end-of-month and the beginning-of-month effect. For this, we start by running regression (2) that uses that same fixed effects as regression (1), but now considers the cluster of loans granted by the first three days of the month, against the end-of-month cluster. The results are reported on Table 2. We find a strong impact on the number of operations for loans granted by the end of the month: the number of operations increases by 10.2%, compared with the average of the rest of the month. The impact of the first three days is also statistically significant, but economically meaningless.

$$NewOperations_t = \; Last3days_t + First3days_t dow_t + ym_t + \; \varepsilon_t \tag{2}$$

The question that remains concerns the intrinsic characteristics of the loans originated by the end of the month. In order to make a pre-study on the quality of these loans we split the loans originated into two categories concerning its approval date: loans granted on the last three days of the month and loans conceded on the remaining days. Table 3 presents our results.

Starting our analysis with the six company characteristics we selected, operations started on the end of the month are granted, on average, to younger (Δ=-3 years) companies, that have lower profitability (Δ=-5 p.p.) and liquidity (Δ=-0.09) and a higher leverage ratio (Δ=17 p.p.). The level of tangibility remains the same, but the difference between the end-of-month and the rest of the month is not statistically significant. Since size is defined as the natural logarithm of assets, we have to perform a logarithmic transformation, defined as e^{assets}. We conclude that loans granted by the end of the month are provided to smaller companies (653 thousands vs 1,983 thousands of euros in assets). Concerning the average loan contract, loans granted in the end-of-month period have, on average, a higher loan amount (Δ≈20,000€) and a smaller percentage of it is collateralized (Δ=17 p.p.). Maturity is significantly lower (Δ=-178 days) and the interest rate is higher (Δ=5.6 p.p.). Loans granted at the end of the month have a higher processing time (Δ=8 days), a finding exploited in section 4.4, and the default rate, measured as a 1-year delinquency rate, is higher. (Δ=4 p.p.). Besides the variable defined to measure tangibility, all the remaining differences between loans granted by the end of the month and the rest of the month are statistically significant at a 1% level.

From a risk perspective, these results provide an initial background on banks' risk-taking behavior: operations initiated on the last three days of the month are granted, on average, to riskier companies, *id est*, smaller, younger, less profitable and liquid and more levered. The loan contract itself holds a higher amount and a small percentage of them are collateralized. The higher interest rate verified may be an attempt by the loan officer to offset the higher risk of the contract. The default rates observed verify our initial intuition that these loans are indeed riskier: it doubles (from 4% to 8%), when comparing loans granted at the end of the month with loans compared on the remainder of the month.

We run regression (2), but we use as dependent variable a vector of firm characteristics and loan contracts' details. The results are presented in Table 2 and confirm our earlier assessment on banks' risk-taking by the end of the month. All variables show a decline in the companies' prospects towards the month-end, except the level of tangibility that remains virtually the same. The details of the contract also confirm three findings that are worth reporting, since they drive a major part of our henceforth analysis. The first one is that the coefficient associated with the default rate of loans granted on the last three days is positive (0.04), whereas the same coefficient for the first three days is 0.00. The second finding is a major decrease in the maturity of end-month loans, compared with the average of the remaining of the month (-181.1). Lastly, the time to approval for the last three days shows a positive coefficient of 7.1, against 0.1 for the first three days. All previously reported coefficients are statistically significant at a 1% significance level. The last two conclusions are developed in sections 4.2 and 4.4, respectively.

4.2. Term loans vs. credit lines

As pointed out in chapter 3., 38.2% of our sample is composed of credit lines. For that reason, we feel the need to establish a division between term loans (loans with a reported maturity higher than zero days) and credit lines (loans reported with a maturity of zero days). A firm that gets a credit line (also called a revolving credit facility) will take a nominal amount of debt capacity against which the firm withdraws funds. The used amount of the credit line is a debt obligation, whereas the unused portion remains off the balance sheet. The pricing of a credit line does not match the one of a typical term loan: companies will pay a commitment fee on the unused portion and a pre-established funding rate on the used share.

In Table 4, we present a comparison between term loans and credit lines. Credit lines present a higher risk-profile, derived from the fact they are granted, on average, to smaller, younger, less profitable and more levered companies. Both the amount of the operation and the interest rate is higher for credit lines, whereas only 33% of credit lines are collateralized (against 40% of term loans). The default rate is 2x higher for credit lines (8%). All the differences are statistically significant at a 1% level.

Following this initial analysis, we then assess if the end-of-month exists on both credit lines and term loans. Figures 5 and 6 present our findings, applying the same methodology as the one reported for Figure 2. We can see that credit lines drove the end-of-month effect – term loans do not present any variation regarding the amount of new operations.

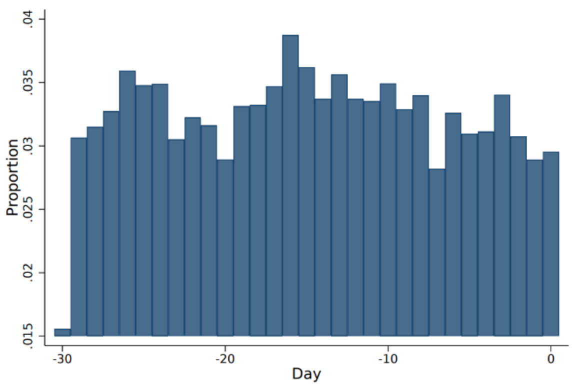

Figure 6: Daily distribution of new operations (new contracts) for term loans

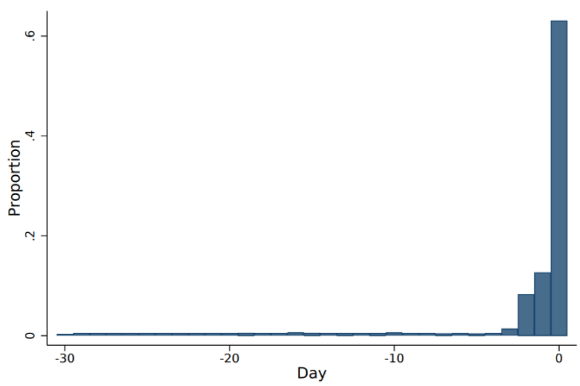

Figure 7: Daily distribution of new operations (new contracts) for credit lines

In Table 5 we present a summary of the differences between credit lines and term loans, as well as operations initiated at the end of the month against the ones started during the rest of the month.

Term loans present small, nevertheless statistically significant differences (at a 1% significance level) between both periods of the month. Term loans granted by the end of the month are conceded to larger (Δ=313 thousand of euros in assets), slightly older (Δ=0.2 years), less liquid (Δ=-0.06) and more levered (Δ=1 p.p.) companies, even though we did not find statistical significance on the last variable. Profitability is, on average, the same throughout the month. At the last three days of the month, loans hold, on average, a higher amount (Δ≈10,000€), lower maturity (Δ=-13 days) and a lower interest rate (Δ=-1 p.p.). The processing time decreases by 4 days and the percentage of collateralized loans decreases from 40% to 36%. The default rate remains the same across the month, which provides evidence on a non-risk-taking behavior regarding term loans.

Credit lines present a significantly higher variation between both periods. Compared with the rest of the month, credit lines granted by the end of the month are conceded to companies that are smaller (Δ=-83 thousand of euros in assets), older (Δ=1.1 years), less tangible (Δ=-2 p.p.), less profitable (Δ=-4 p.p.), more levered (Δ=15 p.p.) and less liquid (Δ=-0.08). Making a comparison between the contracts' characteristics also presents interesting findings. End-of-month credit lines have, on average, a lower amount (Δ≈-20,000), a higher interest rate (Δ=4.8 p.p.) and processing time (Δ=21 days). Major differences also arise when we acknowledge that only 25% are collateralized (compared with 74% on the rest of the month) and they are 4.5x more likely to default (9% against 2% from the rest of the month).

We re-run regression (2), where γ_t is a vector of the previously used company and loan contract's specificities, but this time we split our sample into term loans and credit lines. We present our results in Table 6. For term loans, there are no major variations between the beginning and the end of the month, compared with the remaining of the month: tangibility, profitability, leverage and liquidity remain constant, even though this last coefficient is hardly significant. The size and age factors present an improvement as the month goes by. Regarding the term loan contract, both the amount and the default rate increase at the beginning and at the end of the month, when compared with the average of the remainder of the month. The collateral decreases as the month goes by and so does the interest rate. Hence, regression (3) proves the conclusions we have initially forecasted with the descriptive analysis made earlier on this section: the major variations from both periods of the month arise from credit lines. Moving now to the regression analysis of credit lines (using the model outlined in regression (4)) the differences between both periods are magnified. As initially predicted, credit lines granted on the last three days present significant (statistically and economically) evidence on a decrease in the borrowers' quality: lower size, tangibility, profitability and liquidity, and higher leverage. As outlined earlier, the only improvement in a risk perspective is an increase on the average age of companies.

$$\gamma_t |\, Term\ Loan = Last3days_t + First3days_t + dow_t + ym_t + \varepsilon_t \quad (3)$$

$$\gamma_t |\, Credit\ Line = Last3days_t + First3days_t + dow_t + ym_t + \varepsilon_t \quad (4)$$

We have also studied the evolution of the proportion of term loans and credit lines in the Portuguese credit market. The proportion of term loans (credit lines) is decreasing (increasing) throughout time, moving from 74.0% (26.0%) in 2013 to 52.8% (47.2%) in 2016. In Appendix 1 we present the detailed yearly evolution of term loans and credit lines in the Portuguese market.

After acknowledging the increasing weight of credit lines in the Portuguese credit market, we considered its justification. To do so, we analyzed the repetition pattern of credit lines granted to the same company by the same bank or, in other words, a common BINA-TINA credit relationship. We conclude that there is a 68%, 6%, 3% and 1% monthly, bi-monthly, trimester and semester repetition pattern, respectively. Focusing on the monthly results, our findings conclude that 68% of the entire universe of credit lines granted in Portugal are granted at least in two consecutive months, by the same bank to the same company. Our reasoning for it has as an underlying a product commonly issued by banks: overdrafts lines of credit, a tool used by companies to cover bank overdrafts. These instruments are typically issued at the end of the month, which goes in line with the reported end-of-month effect.

4.3. Day 15th

The end of the month is not the only period when there is a variation on the variables studied. During our study, we have assessed that the 15th of each month holds certain specificities that are worth reporting, both on the companies' indicators and contracts 'details. The results are presented in Table 7, and we believe that this variation is due to the fact that banks have to report, by this time of the month, the status of their loan portfolio to the CRC managed by the Bank of Portugal, including the credit overdue for more than 90 days. It is our intuition, before any empirical analysis, that this may create a bias towards an attempt to concede loans on the 15th to entities that, *ex ante*, present better financial prospects – in other words, a window dressing strategy. In a similar fashion, Allen and Saunders (1992) find a systematic upward window dressing adjustment made by US banks in order to improve the quality and amount of assets, prior to the reporting date to the Federal regulators.

Table 7 presents our results concerning the differences between the 15th and the rest of the month. Starting with Panel A (aggregate level), five out of six company indicators forecast firms with better prospects: older, bigger, more profitable, less levered and more liquid. Only the tangibility proxy shows a decrease in the companies' prospects. These indicators go in line with a lower default rate of 3% (against 6% on the rest of the month). 55% of loans granted at the 15th are collateralized, whereas only 37% hold this status on the remainder of the month. The average maturity almost triples, from 136 days to 402 days, which provides evidence that all these effects are driven by an increase on the proportion of term loans granted at this day. Given a reduction in the risk of these loans by the 15th, the fact that the average interest rate from 8.7% to 6% was expected, as well as the previously referred decrease in the delinquency rate (from 6% to 3%).

Splitting the results between term loans and credit lines (Panels B and C), the improvements in company characteristics are common to both types of credit. Contracts' features appear to be more pronounced in credit lines, where the major effects occur in the average number of credit lines that are collateralized (Δ=45 p.p.), leading to large-scale reduction in the interest rate (Δ=-5.3 p.p.). The default rate decreases, on average, from 6% to 3% – credit lines drive this effect, with a reduction from 8% to 2%.

We perform a regression analysis on our three variables of interest: beginning of the month, end of the month and, now, we also consider the day 15th. Specifically, we run regression (5), including the same time-fixed effects considered before. Our results are presented in Table 8.

$$\gamma_t = Day15_t + Last3days_t + First3days_t + dow_t + ym_t + \varepsilon_t \tag{5}$$

Our conclusions for the aggregate effect are that all the six characteristics studied for companies present significant improvements compared with the rest of the month. The level of collateral also shows a positive increase (0.1) and, as expected, the default rate is negatively (it decreases) affected by the day 15th (-0.01). Table 8 also allows to compare the end-of-month with the day 15h, and the differences between both periods are clear: the first presents a clear relaxation in standards, whereas the second one shows a major concern on approving safer loans.

4.4. Time to approval

The time to approval is defined as the difference between the consultation date (when the loan officer consulted the credit status of the prospective client on the CRC database) and the operation date (effective loan's concession date). The average time to approval in our period is 33 days. Figure 8 plots the monthly evolution of time to approval and we can see a major increase by the end of the month: it starts rising three days before the end of the month and achieves 42 days by the last day of the month. Dividing our sample in loans granted at the end of the month and the rest of the month, the average time to approval is 39 and 31 days, respectively. However, this increase by the end of the month is driven by credit lines (24 to 45 days) – loan officers decrease the processing time of term loans as the month approaches its end, from 32 to 28 days, which goes in line with Tzioumis and Gee, 2013.

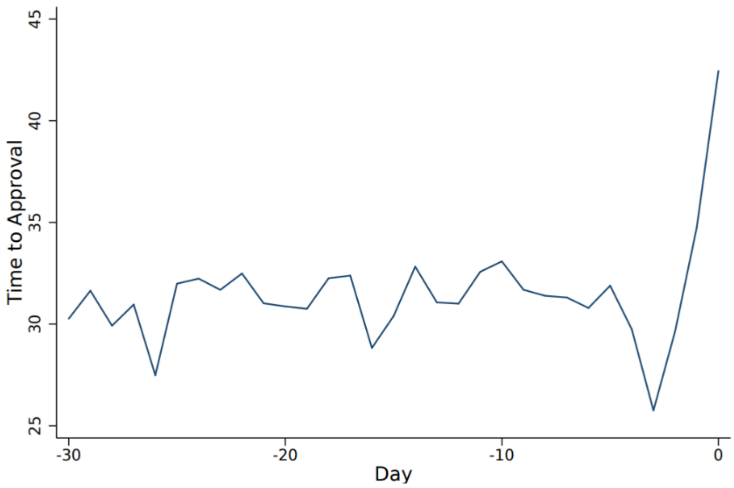

Figure 8: Daily evolution of loans' time to approval

An increase in the processing time by the end of the month went against our initial intuition. Since we have already provided evidence on a risk-taking behavior for loans granted on the last days, we were expecting that loan officers would decrease their screening efforts, hence the processing time. However, we found an alternative justification that proves to be robust to the assumption that loans' requests are approximately uniformly distributed throughout the month. One could argue that loan officers approve loans with positive prospects during the month (which can be justified by a default rate 4 percentage points lower, opposed to loans granted at the end of the month) and shift an eventual approval of loans with lower quality to the end of the month – these loans will only be approved if loan officers need to attain a certain monthly quota of capital allocation. By employing a "hold and grant if needed" strategy, the time to approval of these loans rises, as they remain in the loan officers' inventory during the remaining days until the end of the month.

In order to further explore the impact of time to approval, we divide this variable into "fast time to approval" for loans whose time to approval is below the 25th percentile (11 days) and "slow time to approval" for the ones above the 75th percentile (61 days). After that, we run regression (6) to study the differences between companies and contracts according to how fast the processing time of their loan was. The results, presented in Table 9, are aligned with our forecast that supports the "hold and grant if needed" strategy: loans that take more time to be approved present worse prospects. A curious fact is that loans that are approved fast also contribute (yet in a smaller scale) negatively for the prospects of the loan. Taking "age" as an example, one can see that the coefficient for a fast time to approval is -0.78 and for the slow time to approval is -0.91. In other terms, even though that a slow time to approval is more harmful for the loan prospects, a fast time to approval also affects it negatively – the same occurs with tangibility, leverage, liquidity and collateral. However, the default rate is not impacted by a fast time to approval, but it is by a slow time to approval, as previously forecasted (0.01). Loans that take more time to be approved are very likely to be credit lines, given the coefficient obtained by studying the variable "maturity" (-159.34).

$$\gamma_t = FastTimeToApproval_t + SlowTimeToApproval_t + dow_t + ym_t + \varepsilon_t \tag{6}$$

4.5. Impact of the end-of-month effect

In the previous sections, we have identified and studied the end-of-month impact for term loans and credit lines. In this section we perform a set of simple back-of-the-envelope calculations to measure the impact of this phenomenon in terms of credit overdue

Our approach is as follows. Using the CRC database, we get data from the total amount of credit granted to Portuguese non-financial corporations from 2013 to 2016, divided between credit lines and term loans. Our previous computations also allow us to divide the amount granted in each month into end-of-month and the rest of the month, and the default rates for each period. Hence, we can gauge the effect of the end-of-month "boost" as

$$End\ of\ month\ impact_t = Credit\_Overdue_t^{with\ end\ of\ month\ effect} - Credit\_Overdue_t^{no\ end\ of\ month\ effect}$$

The credit overdue with no end of month effect assumes that the default rate throughout the month is always the same, and can be computed as follows.

$$\sum_{t=2013}^{2016}[(Term\ loans_t\ \times\ Default\ rate_t) + (Credit\ lines_t \times\ Default\ rate_t)]$$

The credit overdue estimated with end of month effect splits the default rate into two possibilities, to take into account the previously reported increase by the end of the month. We also manage to isolate the percentage of term loans and credit lines, divided by end-of-month and the rest of the month. We compute it as follows.

$$\sum_{t=2013}^{2016} Credit\_Overdue_t^{credit\ lines} + Credit\_Overdue_t^{term\ loans}, where:$$

$$Credit\_Overdue_t^{credit\ lines} = [(EOM_t^{CL}) \times \left(Default\ rate_{EOM}^{CL}\right) + (ROM_t^{CL}) \times \left(Default\ rate_{ROM}^{CL}\right)]\ and$$

$$Credit\_Overdue_t^{term\ loans} = [(EOM_t^{TL}) \times (Default\ rate_{EOM}^{TL}) + (ROM_t^{TL}) \times (Default\ rate_{ROM}^{TL})]$$

$$where\ EOM = end\ of\ month;\ ROM = rest\ of\ month;\ CL = credit\ line;\ TL = term\ loan$$

We provide our detailed computations in Appendix 2. We assess a total amount of potential credit overdue, in Portugal, for the period comprised between 2013 and 2016 of €8.28 billion, of which 38.7% (€3.2 billion) are a consequence of the end-of-month effect, and the associated relaxation on loan officers' standards.

5. Robustness

In this section, we provide two insights that act as robustness checks. First, we want to check whether the end-of-month effect is not just a consequence of variable-based compensation as a function of the amount granted by each loan officer. For this, we use the economic and financial crisis that led to the Economic Adjustment Program for Portugal in 2011 as our ground basis. During this period, many banks were making sizable losses and thus there were no profits to be distributed. Variable remuneration was thus either inexistent or substantially reduced for these banks during this period. To study this effect, and following the stream of research of several authors (for instance Agarwal and Ben-David, 2014 and Cao et al., 2018), we split our sample between loans granted by profitable and non-profitable banks. We then assess the end-of-month effect in the two samples. Figures 9 and 10 present the evolution of the end-of-month effect for the two groups, and we can see that, even though profitable banks have a higher end-of-month effect, non-profitable banks present a significant trend of this effect (almost 25%). For this reason, we extend the previous authors' analysis, in a sense that we verify an end-of-month effect that occurs in banks that hold a reward system based on loan amount, but also in the ones that do not.

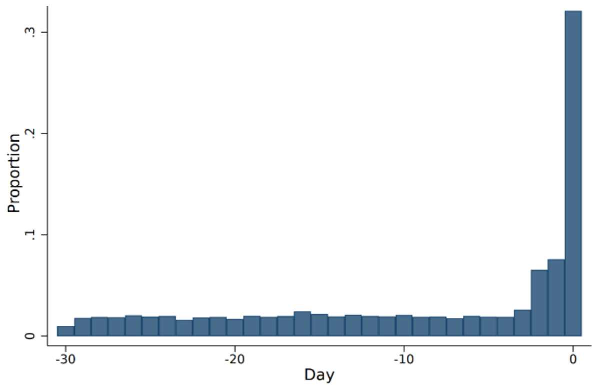

Figure 9: Daily distribution of new operations (new contracts) for profitable banks

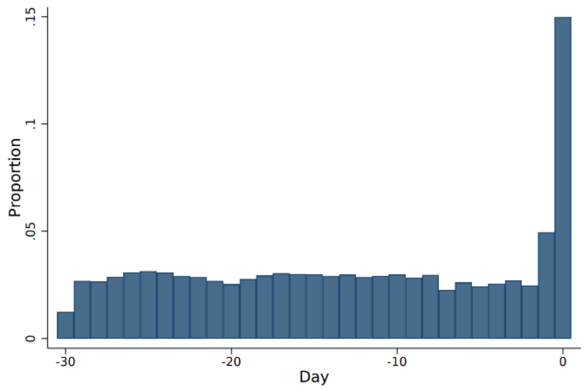

Figure 10: Daily distribution of new operations (new contracts) for non-profitable banks

It is also important to mention that we are using perturbed data, a method used by the Bank of Portugal to preserve the anonymity of the databases. This technique holds the drawback of reducing the magnitude off all the statistical inference performed on it. For this reason, our results can potentially become more impactful if they are replicated in the original (non-perturbed) databases.

6. Conclusions

In this dissertation, we document a strong monthly cycle in the Portuguese credit market: credit quantity sharply increases towards the end of the month, while quality follows the opposite pattern. We isolate this effect and conclude that it is a consequence of credit lines granted at the end of the month, to companies that show *ex ante* worse prospects (compared with companies that get credit during the rest of the month). The default rate, measured as a 1-year failure in payment is 4.5x larger, when we establish a comparison with credit lines conceded during the remaining days of the month. The repetition pattern of the end-of-month effect points towards the use of overdraft lines of credit. Its impact, measured as the increase in credit overdue, is €3.2 billion throughout our period of analysis.

We finish our dissertation by presenting shortcomings of our analysis, and possible extensions for future research. Firstly, the field of end-of-month performance misalignments is still in a freshman stage and, for that reason, we cannot compare our results for Portugal with the ones for different countries. Cao et al. (2018) is, to the best of our knowledge, the closest study to ours, but only considers two banks in the Chinese market, which raises concerns regarding the representativeness of the sample used. Secondly, banking activity in Portugal is, to some extent, less sophisticated than in other markets. This fact prevents us to deepen our analysis to the field of syndicated lending and study whether the pattern remains. Thirdly, we lack data on CDS spreads for the majority Portuguese banks, which does not allow us to evaluate if the market is aware of such risk-taking towards the end of the month.

Future streams of research in this field could include an incorporation of hard and soft information in the end-of-month effect. Specifically, we find it curious whether "lending relationships" play a role on the relaxation of loan officers' standards by the end of the month. There is already research on the impact of lending relationships on the loan contract (Berger and Udell, 1995), but its monthly evolution is still an open topic. Besides it, forthcoming research could study whether specific banks tend to engage in this activity towards the end of the month - in fact, we may be in the presence of a risk-shifting mechanism. Lastly, our dissertation presents evidence on a decrease in borrowers' quality by the end of the month. The question that remains is what would be the impact to those borrowers if banks did not engage in this activity. Companies that constantly use overdraft lines of credit may lead us to believe that they would default if they could not use this product. In other words, can we be in the presence of zombie lending (Caballero et al., 2008) in the Portuguese credit market?

7. References

Acharya, V., Litov, L. V., & Sepe, S. M. (2013). *Non-Executive Incentives and Bank Risk-Taking*. Working Paper.

Agarwal, S., & Ben-David, I. (2018). Loan prospecting and the loss of soft information. *Journal of Financial Economics*.

Allen, L., & Saunders, A. (1992). Bank window dressing: Theory and evidence. *Journal of banking & finance*, *16*(3), 585-623.

Asch, B. J. (1990). Do incentives matter? The case of navy recruiters. *ILR Review*, *43*(3), 89-S.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to?. *The journal of finance*, *64*(5), 1985-2021.

Bebchuk, L. A., & Spamann, H. (2009). Regulating bankers' pay. *geo. Lj*, *98*, 247.

Bebchuk, L. A., Cohen, A., & Spamann, H. (2010). The wages of failure: Executive compensation at Bear Stearns and Lehman 2000-2008. *Yale J. on Reg.*, *27*, 257.

Behr, P., Drexler, A., Gropp, R., & Guettler, A. (2017). Financial incentives and loan officer behavior: Multitasking and allocation of effort under an incomplete contract.

Ben-David, I. (2011). Financial constraints and inflated home prices during the real estate boom. *American Economic Journal: Applied Economics*, *3*(3), 55-87.

Bénabou, R., & Tirole, J. (2016). Bonus culture: Competitive pay, screening, and multitasking. *Journal of Political Economy*, *124*(2), 305-370.

Berg, T., Puri, M., & Rocholl, J. (2013). *Loan officer incentives and the limits of hard information* (No. w19051). National Bureau of Economic Research.

Berger, A. N., & Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of business*, 351-381.

Blattner, L., Alcoforado Farinha, M., & Nogueira, G. (2016). The effect of quantitative easing on lending conditions.

Blattner, L., Farinha, L., & Rebelo, F. (2017). *When Losses Turn Into Loans: The Cost of Undercapitalized Banks* (No. pbl215). Job Market Papers.

Bolton, P., Mehran, H., & Shapiro, J. (2015). Executive compensation and risk taking. *Review of Finance*, *19*(6), 2139-2181.

Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking & Finance*, *33*(2), 281-299.

Bonfim, D., Dai, Q., & Franco, F. (2018). The number of bank relationships and borrowing costs: The role of information asymmetries. *Journal of Empirical Finance*, *46*, 191-209.

Bonfim, D., & Soares, C. (2018). The Risk-Taking Channel of Monetary Policy: Exploring All Avenues. *Journal of Money, Credit and Banking*, *50*(7), 1507-1541.

Bunn, P., & Redwood, V. (2003). Company accounts-based modelling of business failures and the implications for financial stability.

Caballero, R. J., Hoshi, T., & Kashyap, A. K. (2008). Zombie lending and depressed restructuring in Japan. *American Economic Review*, *98*(5), 1943-77.

Campbell, D., Loumioti, M., & Wittenberg Moerman, R. (2017). Making Sense of Soft Information: Interpretation Bias and Ex-post Lending Outcomes.

Cao, Y., Fisman, R., Lin, H., & Wang, Y. (2018). *Target setting and Allocative Inefficiency in Lending: Evidence from Two Chinese Banks* (No. w24961). National Bureau of Economic Research.

Carchano, O., & Pardo Tornero, Á. (2011). Calendar Anomalies in Stock Index Futures.

Cole, S., Kanz, M., & Klapper, L. (2015). Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers. *The Journal of Finance*, *70*(2), 537-575.

Crosignani, M., Faria-e-Castro, M., & Fonseca, L. (2015). The Portuguese banking system during the sovereign debt crisis.

De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, *42*(3), 557-581.

Ertan, A. (2017). Real Earnings Management through Syndicated Lending.

Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance*, *67*(6), 2139-2185.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, *38*(1), 34-105.

Fink, J., Grullon, G., Fink, K., & Weston, J. (2004). Firm age and fluctuations in idiosyncratic risk.

Gao, J., Martin, X., & Pacelli, J. (2017). Do loan officers impact lending decisions? Evidence from the corporate loan market.

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. *Accounting horizons*, *13*(4), 365-383.

Heider, F., & Inderst, R. (2012). Loan prospecting. *The Review of Financial Studies*, *25*(8), 2381-2415.

Holmstrom, B., & Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *JL Econ. & Org.*, *7*, 24.

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *The Journal of Finance*, *56*(1), 387-396.

Inderst, R., & Mueller, H. M. (2008). Bank capital structure and credit decisions. *Journal of Financial Intermediation*, *17*(3), 295-314.

Jensen, M. C. (2003). Paying people to lie: The truth about the budgeting process. *European Financial Management*, *9*(3), 379-406.

Jiménez, G., & Saurina, J. (2004). Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of banking & Finance*, *28*(9), 2191-2212.

Kedia, S., & Philippon, T. (2007). The economics of fraudulent accounting. *The Review of Financial Studies*, *22*(6), 2169-2199.

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2009). Financial regulation and securitization: Evidence from subprime loans. *Journal of Monetary Economics*, *56*(5), 700-720.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443-478.

Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *The review of financial studies*, *1*(4), 403-425.

Larkin, I. (2007). The cost of high-powered incentives: Employee gaming in enterprise software sales. *Unpublished manuscript*.

Liberti, J. M., & Mian, A. R. (2008). Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, *22*(10), 4057-4090.

Liebman, J. B., & Mahoney, N. (2017). Do expiring budgets lead to wasteful year-end spending? Evidence from federal procurement. *American Economic Review*, *107*(11), 3510-49.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective.

Lucas Jr, R. E. (1978). Asset prices in an exchange economy. *Econometrica: Journal of the Econometric Society*, 1429-1445.

Mian, A., & Santos, J. A. (2018). Liquidity risk and maturity management over the credit cycle. *Journal of Financial Economics*, *127*(2), 264-284.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review*, *48*(3), 261-297.

Murfin, J., & Petersen, M. (2016). Loans on sale: Credit market seasonality, borrower need, and lender rents. *Journal of Financial Economics*, *121*(2), 300-326.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, 315-335.

Oyer, P. (1998). Fiscal year ends and nonlinear incentive contracts: The effect on business seasonality. *The Quarterly Journal of Economics*, *113*(1), 149-185.

Petersen, M. A. (2004). Information: Hard and soft.

Psillaki, M., Tsolas, I. E., & Margaritis, D. (2010). Evaluation of credit risk based on firm performance. *European Journal of Operational Research*, *201*(3), 873-881.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial management review*, *6*(2).

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The journal of finance*, *57*(5), 1891-1921.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance*, *62*(2), 629-668.

Telyukova, I. A. (2013). Household need for liquidity and the credit card debt puzzle. *Review of Economic Studies*, *80*(3), 1148-1177.

Thornhill, S., & Amit, R. (2003). Learning about failure: Bankruptcy, firm age, and the resource-based view. *Organization science*, *14*(5), 497-509.

Tzioumis, K., & Gee, M. (2013). Nonlinear incentives and mortgage officers' decisions. *Journal of Financial Economics*, *107*(2), 436-453.

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, *58*(3), 369-396.

8. Tables

8.1. Descriptive statistics on credit evolution

Table 1
Descriptive Statistics on Credit Evolution, from 2013 to 2016.

Table 1 reports the descriptive statistics on the evolution of credit, from 2013 to 2016. Panel A and Panel B presents the aggregate and the year-level summary statistics, respectively. We measure size, age, tangibility, profitability, leverage and liquidity as firm-specific characteristics (section 3 describes these variables). Concerning the loan contract, we assess the amount (in millions of Euros), collateral (reported as a dummy variable), maturity (in years), interest rate (in percentage points), processing time (in days) and default occurrence (as the percentage, from 0 to 1, of loans granted in that year that defaulted one year after). Column (1) presents the variable studied, columns (2) to (6) report statistical measures, namely, mean, standard deviation, percentile 25, percentile 50, percentile 90, and column (7) displays the number of observations for each variable.

Panel A - Aggregate level

Variable	Mean	Standard Deviation	Percentile 25	Percentile 50	Percentile 90	Number of observations
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	14.08	2.01	12.66	14.02	18.68	2,954,167
Age	21.29	14.43	10	19	40	2,887,234
Tangibility	0.24	0.22	0.06	0.18	9.57	2,954,374
Profitability	-0.02	0.20	0.00	0.01	0.09	2,954,374
Leverage	0.79	0.56	0.57	0.72	1.02	2,954,374
Liquidity	1.90	2.09	1.03	1.37	3.26	2,952,627
Amount	0.06	0.14	0.00	0.01	0.14	2,956,307
Collateral	0.37	0.48	0	0	1	2,956,307
Maturity	143.51	372.40	0	43	182	2,956,307
Interest rate	8.66	7.23	3.96	6.04	21.97	2,956,307
Processing time	32.57	25.61	11	26	73	216,522
Default	0.06	-	-	-	-	-

Panel B - Year level (2013)

Variable	Mean	Standard Deviation	Percentile 25	Percentile 50	Percentile 90	Number of observations
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	14.26	1.95	12.89	14.23	16.77	633,843
Age	21.13	14.33	11	19	39	633,843
Tangibility	0.23	0.21	0.06	0.17	0.54	633,843
Profitability	-0.03	0.19	-0.01	0.01	0.06	633,843
Leverage	0.79	0.21	0.06	0.17	0.54	633,843
Liquidity	1.76	1.85	2.00	1.32	2.87	633,188
Amount	0.06	0.14	0.00	0.01	0.12	633,843
Collateral	0.26	0.44	0	0	1	633,843
Maturity	135.85	330.12	0	59	180	633,843
Interest rate	10.00	7.09	5.27	7.16	22.67	633,843
Processing time	35.13	26.16	12	30	76	37,913
Default	0.08	-	-	-	-	-

Panel B - Year level (2014)

Variable (1)	Mean (2)	Standard Deviation (3)	Percentile 25 (4)	Percentile 50 (5)	Percentile 90 (6)	Number of observations (7)
Size	14.15	1.99	12.75	14.09	16.81	636,436
Age	21.00	14.51	10	19	40	636,436
Tangibility	0.24	0.22	0.06	0.18	0.56	636,436
Profitability	-0.02	0.20	0.00	0.01	0.09	636,436
Leverage	0.79	0.53	0.58	0.73	1.02	636,436
Liquidity	1.86	2.01	1.03	1.36	3.11	635,825
Amount	0.06	0.14	0.00	0.01	0.13	636,436
Collateral	0.34	0.47	0.0	0.0	1.00	636,436
Maturity	149.7	371.4	0.0	58.0	183.0	636,436
Interest rate	9.28	7.12	4.69	6.54	22.66	636,436
Processing time	32.8	25.9	10	27	73	45,422
Default	0.06	-	-	-	-	-

Panel B - Year level (2015)

Variable (1)	Mean (2)	Standard Deviation (3)	Percentile 25 (4)	Percentile 50 (5)	Percentile 90 (6)	Number of observations (7)
Size	14.02	2.04	12.58	13.94	16.79	867,782
Age	21.29	14.44	10	19	40	867,782
Tangibility	0.24	0.23	0.06	0.18	0.58	867,782
Profitability	-0.02	0.20	0.00	0.01	0.10	867,782
Leverage	0.80	0.59	0.56	0.72	1.03	867,782
Liquidity	1.96	2.17	1.04	1.39	3.45	866,549
Amount	0.06	0.14	0.00	0.02	0.16	867,782
Collateral	0.43	0.50	0	0	1	867,782
Maturity	141.27	378.97	0	30	182	867,782
Interest rate	8.40	7.38	3.46	5.70	22.01	867782
Processing time	31.7	25.4	11	24	73	73,825
Default	0.05	-	-	-	-	-

Panel B - Year level (2016)

Variable (1)	Mean (2)	Standard Deviation (3)	Percentile 25 (4)	Percentile 50 (5)	Percentile 90 (6)	Number of observations (7)
Size	13.96	2.04	12.53	13.87	16.70	818,246
Age	21.67	14.43	11	19	40	818,246
Tangibility	0.25	0.23	0.06	0.18	0.59	818,246
Profitability	-0.01	0.20	0.00	0.02	0.10	818,246
Leverage	0.79	0.59	0.56	0.72	1.01	818,246
Liquidity	1.99	2.21	1.04	1.41	3.51	817,065
Amount	0.06	0.14	0.00	0.02	0.15	818,246
Collateral	0.43	0.49	0	0	1	818,246
Maturity	147	396.13	0	27	182	818,246
Interest rate	7.42	7.04	2.78	4.90	19.91	818,246
Processing time	31.8	25.2	10	25	72	59,362
Default	0.05	-	-	-	-	-

8.2. Regression output, using the last three days and the first three days

Table 2
Regression output on Credit Evolution, using the end-of-month and the beginning-of-month effect, from 2013 to 2016.

Table 2 reports the regression output from regression 2, for the aggregate level. The variables presented in column (1) are the same as the ones described in Table 1. Column (2) and (3) present the coefficient obtained by regressing each variable of column (1) on the end-of-month and beginning-of-month effect. Column (4) presents the R-squared and column (5) the Prob>F. Robust standard errors are presented below each coefficient in parenthesis. ***, ** and * denotes statistical significance at a 1%, 5% and 10% level, respectively.

Variable (1)	Last 3 days (2)	First 3 days (3)	R^2 (4)	Prob > F (5)
New Operations	0.10***	0.00***	0.51	0.00
	(0.01)	(0.00)		
Size	-1.10***	-0.05***	0.08	0.00
	(0.00)	(0.00)		
Age	-3.10***	-0.13***	0.01	0.00
	(0.02)	(0.04)		
Tangibility	0.00***	0.00***	0.00	0.00
	(0.00)	(0.00)		
Profitability	-0.05***	0.00***	0.02	0.00
	(0.00)	(0.00)		
Leverage	0.17***	0.00**	0.02	0.00
	(0.00)	(0.00)		
Liquidity	3.00**	0.08	0.00	0.14
	(1.53)	(0.95)		
Amount	0.02***	0.01***	0.01	0.00
	(0.00)	(0.00)		
Collateral	-0.20***	0.04***	0.07	0.00
	(0.00)	(0.00)		
Maturity	-181.09***	35.45***	0.06	0.00
	(0.41)	(1.14)		
Interest rate	5.93***	0.10***	0.19	0.00
	(0.00)	(0.01)		
Processing time	7.94***	0.14	0.03	0.00
	(0.14)	(0.21)		
Default	0.04***	0.00***	0.01	0.00
	(0.00)	(0.00)		

8.3. Company and loans’ differences between the end of the month and the rest of the month

Table 3

Loans and companies' comparison between the end of the month and the rest of the month, from 2013 to 2016.

Table 3 reports the comparison regarding the average company and the average loan contract, from 2013 to 2016, divided into end of month (2) and the rest of the month (3). The variables presented in column (1) are the same as the ones described in Table 1. Column (4) outlines the p-value for the difference in means between column (2) and column (3).

Variable (1)	End of month (2)	Rest of month (3)	p-value (4)
Size	13.39	14.50	0.00
Age	19.40	22.43	0.00
Tangibility	0.24	0.24	0.19
Profitability	-0.05	0.00	0.00
Leverage	0.90	0.73	0.00
Liquidity	1.87	1.96	0.00
Amount	0.72	0.52	0.00
Collateral	0.27	0.44	0.00
Maturity	32.59	210.63	0.00
Interest rate	12.12	6.57	0.00
Processing time	38.77	30.81	0.00
Default	0.08	0.04	0.00

8.4. Company and loans' differences between term loans and credit lines

Table 4

Term loans and credit lines comparison, from 2013 to 2016.

Table 4 reports the comparison regarding the average term loan and credit line from 2013 to 2016. The variables presented in column (1) are the same as the ones described in Table 1. The mean of each variable studied is presented in column (2) for term loans and in column (3) for credit lines. Column (4) outlines the p-value for the difference in means between column (2) and column (3).

Variable	Term Loans	Credit Lines	p-value
(1)	(2)	(3)	(4)
Size	14.64	13.17	0.00
Age	22.93	18.28	0.00
Tangibility	0.24	0.24	0.00
Profitability	0.00	-0.05	0.00
Leverage	0.72	0.90	0.00
Liquidity	1.85	2.00	0.00
Amount	0.05	0.08	0.00
Collateral	0.40	0.33	0.00
Maturity	232.12	-	0.00
Interest rate	6.38	12.36	0.00
Processing time	31.52	35.60	0.00
Default	0.04	0.08	0.00

8.5. Company and loans' differences between term loans and credit lines, the end and the rest of the month

Table 5

Loans and companies' comparison between the end of the month and the rest of the month, from 2013 to 2016, divided into term loans (Panel A) and credit lines (Panel B).
Table 5 reports the comparison regarding the average company and the average loan contract, from 2013 to 2016, divided into end of month (2) and the rest of the month (3), both for term loans (Panel A) and credit lines (Panel B). The variables presented in column (1) are the same as the ones described in Table 1. Column 4 outlines the p-value for the difference in means between column (2) and column (3).

Panel A - Term Loans

Variable (1)	End of month (2)	Rest of month (3)	p-value (4)
Size	14.76	14.63	0.00
Age	23.13	22.91	0.00
Tangibility	0.24	0.24	0.00
Profitability	0.00	0.00	0.00
Leverage	0.73	0.72	0.20
Liquidity	1.79	1.85	0.00
Amount	0.06	0.05	0.00
Collateral	0.36	0.40	0.00
Maturity	220.63	233.26	0.00
Interest rate	6.29	6.39	0.00
Processing time	27.90	31.95	0.00
Default	0.04	0.04	0.13

Panel B - Credit Lines

Variable (1)	End of month (2)	Rest of month (3)	p-value (4)
Size	13.15	13.30	0.00
Age	18.74	17.65	0.00
Tangibility	0.24	0.26	0.00
Profitability	-0.06	-0.02	0.00
Leverage	0.93	0.78	0.00
Liquidity	1.99	2.07	0.00
Amount	0.07	0.09	0.00
Collateral	0.25	0.74	0.00
Maturity	-	-	-
Interest rate	13.13	8.30	0.00
Processing time	44.74	24.19	0.00
Default	0.09	0.02	0.00

8.6. Regression output, using the last three days and the first three days, divided into term loans and credit lines

Table 6

Regression output on Credit Evolution, using the end-of-month and the beginning-of-month effect, divided into term loans (Panel A) and credit lines (Panel B), from 2013 to 2016.

Table 6 reports the regression outputs from regressions 3 and 4, for term loans (Panel A) and credit lines (Panel B). The variables presented in column (1) are the same as the ones described in Table 1 Column (2) and (3) present the coefficient obtained by regressing each variable of column (1) on the end-of-month and beginning-of-month effect. Column (4) presents the R-squared and column (5) the Prob>F. Robust standard errors are presented below each coefficient in parenthesis. ***, ** and * denotes statistical significance at a 1%, 5% and 10% level, respectively.

Panel A - Term Loans

Variable (1)	Last 3 days (2)	First 3 days (3)	R^2 (4)	Prob > F (5)
New Operations	0.00***	0.00***	0.26	0.00
	(0.00)	(0.00)		
Size	0.11***	-0.05***	0.00	0.00
	(0.00)	(0.00)		
Age	0.18***	-0.22***	0.00	0.00
	(0.04)	(0.04)		
Tangibility	0.00***	0.00***	0.01	0.00
	(0.00)	(0.00)		
Profitability	0.00***	0.00***	0.01	0.00
	(0.00)	(0.00)		
Leverage	0.00***	0.00***	0.00	0.00
	(0.00)	(0.00)		
Liquidity	-0.22	-0.22	0.00	0.74
	(0.29)	(0.41)		
Amount	0.01***	0.01***	0.01	0.00
	(0.00)	(0.00)		
Collateral	-0.03***	0.04***	0.03	0.00
	(0.00)	(0.00)		
Maturity	-4.36***	38.87***	0.02	0.00
	(1.16)	(1.24)		
Interest rate	-0.05***	0.15***	0.11	0.00
	(0.01)	(0.01)		
Processing time	-3.45***	0.20	0.02	0.00
	(0.20)	(0.23)		
Default	0.00***	0.00***	0.00	0.00
	(0.00)	(0.00)		

Panel B - Credit Lines

Variable (1)	Last 3 days (2)	First 3 days (3)	R^2 (4)	Prob > F (5)
New Operations	0.28***	0.00	0.53	0.00
	(0.02)	(0.00)		
Size	-0.20***	0.03**	0.01	0.00
	(0.00)	(0.01)		
Age	1.06***	0.56***	0.01	0.00
	(0.04)	(0.11)		
Tangibility	-0.01***	0.00	0.00	0.00
	(0.00)	(0.00)		
Profitability	-0.04***	0.00	0.01	0.00
	(0.00)	(0.00)		
Leverage	0.17***	-0.02***	0.01	0.00
	(0.00)	(0.00)		
Liquidity	-0.47	2.55	0.00	0.93
	(3.09)	(8.68)		
Amount	-0.02***	0.01***	0.00	0.00
	(0.00)	(0.00)		
Collateral	-0.49***	0.00	0.27	0.00
	(0.00)	(0.00)		
Maturity	-	-	-	-
	-	-		
Interest rate	5.63***	-0.05	0.10	0.00
	(0.02)	(0.05)		
Processing time	19.51***	-0.62	0.16	0.00
	(0.22)	(0.45)		
Default	0.06***	0.00	0.02	0.00
	(0.00)	(0.00)		

8.7. Company and loans' differences between term loans and credit lines, the day 15th and the rest of the month

Table 7

Loans and companies' comparison between the day 15th and the rest of the month, from 2013 to 2016, divided into an aggregate level (Panel A), term loans (Panel B) and credit lines (Panel C).

Table 7 reports the comparison regarding the average company and the average loan contract, from 2013 to 2016, divided into the day 15th (2) and the rest of the month (3), both for the aggregate level (Panel A), term loans (Panel B) and credit lines (Panel B). The variables presented in column (1) are the same as the ones described in Table 1. Column 4 outlines the

Panel A - Aggregate level

Variable (1)	Day 15 (2)	Rest of month (3)	p-value (4)
Size	14.86	14.05	0.00
Age	23.98	21.21	0.00
Tangibility	0.29	0.24	0.00
Profitability	0.01	-0.02	0.00
Leverage	0.72	0.80	0.00
Liquidity	1.82	1.91	0.00
Amount	0.06	0.06	0.00
Collateral	0.55	0.37	0.00
Maturity	402.18	135.58	0.00
Interest rate	6.02	8.74	0.00
Processing time	28.60	32.80	0.00
Default	0.03	0.06	0.00

Panel B - Term Loans

Variable (1)	Day 15 (2)	Rest of month (3)	p-value (4)
Size	14.96	14.63	0.00
Age	24.18	22.87	0.00
Tangibility	0.29	0.24	0.00
Profitability	0.01	0.00	0.00
Leverage	0.72	0.72	0.40
Liquidity	1.80	1.85	0.00
Amount	0.05	0.05	0.00
Collateral	0.52	0.40	0.00
Maturity	443.28	222.48	0.00
Interest rate	5.91	6.40	0.00
Processing time	29.03	31.70	0.00
Default	0.03	0.04	0.00

Panel C - Credit Lines

Variable (1)	Day 15 (2)	Rest of month (3)	p-value (4)
Size	13.83	13.17	0.00
Age	21.92	18.56	0.00
Tangibility	0.28	0.24	0.00
Profitability	-0.01	-0.05	0.00
Leverage	0.71	0.91	0.00
Liquidity	2.00	2.00	0.87
Amount	0.10	0.08	0.00
Collateral	0.82	0.37	0.00
Maturity	-	-	-
Interest rate	7.10	12.40	0.00
Processing time	24.65	35.84	0.00
Default	0.02	0.08	0.00

8.8. Regression output, using day 15th, the last three days and the first three days

Table 8

Regression output on Credit Evolution, using the day 15th, the end-of-month and the beginning-of-month effect, from 2013 to 2016.

Table 8 reports the regression output from regression 5, for the aggregate level. The variables presented in column (1) are the same as the ones described in Table 1 Column (2), (3) and (4) present the coefficient obtained by regressing each variable of column (1) on the day 15th, end-of-month and beginning-of-month effect. Column (5) presents the R-squared and column (6) the Prob>F. Robust standard errors are presented below each coefficient in parenthesis. ***, ** and * denotes statistical significance at a 1%, 5% and 10% level, respectively.

Variable (1)	Day 15th (2)	Last 3 days (3)	First 3 days (4)	R^2 (5)	Prob > F (6)
Size	0.39***	-1.08***	-0.02***	0.08	0.00
	(0.01)	(0.00)	(0.00)		
Age	1.57***	-3.00***	-0.05	0.01	0.00
	(0.05)	(0.02)	(0.04)		
Tangibility	0.05***	0.00***	0.01***	0.00	0.00
	(0.00)	(0.00)	(0.00)		
Profitability	0.01***	-0.05***	0.00***	0.02	0.00
	(0.00)	(0.00)	(0.00)		
Leverage	-0.01***	0.17***	0.00	0.02	0.00
	(0.00)	(0.00)	(0.00)		
Liquidity	1.18***	-5.63***	-0.79***	0	0.00
	(0.24)	(0.09)	(0.16)		
Amount	0.00***	0.02***	0.01***	0.01	0.00
	(0.00)	(0.00)	(0.00)		
Collateral	0.10***	-0.19***	0.05***	0.07	0.00
	(0.00)	(0.00)	(0.00)		
Maturity	201.67***	-169.65***	46.90***	0.07	0.00
	(2.05)	(0.41)	(1.14)		
Interest rate	0.51***	5.91***	0.07***	0.19	0.00
	(0.02)	(0.01)	(0.01)		
Processing time	-1.63***	7.80***	0.00	0.03	0.00
	(0.21)	(0.14)	(0.21)		
Default	-0.01***	0.04***	0.00***	0.01	0.00
	(0.00)	(0.00)	(0.00)		

8.9. Regression output, using slow and fast time to approval

Table 9
Regression output on Credit Evolution, using slow and fast time to approval, from 2013 to 2016.

Table 9 reports the regression output from regression 6, for the aggregate level. The variables presented in column (1) are the same as the ones described in Table 1 Column (2), (3) and (4) present the coefficient obtained by regressing each variable of column (1) on the day 15th, end-of-month and beginning-of-month effect. Column (5) presents the R-squared and column (6) the Prob>F. Robust standard errors are presented below each coefficient in parenthesis. ***, ** and * denotes statistical significance at a 1%, 5% and 10% level, respectively.

Variable (1)	Fast time to approval (2)	Slow time to approval (3)	R^2 (4)	Prob > F (5)
Size	-0.34***	-0.07***	0.04	0.00
	(0.01)	(0.01)		
Age	-0.78***	-0.91***	0.03	0.00
	(0.08)	(0.08)		
Tangibility	-0.01***	-0.02***	0.02	0.00
	(0.00)	(0.00)		
Profitability	-0.01***	-0.01***	0.01	0.00
	(0.00)	(0.00)		
Leverage	0.02***	0.03***	0.01	0.00
	(0.00)	(0.00)		
Liquidity	-0.54	-1.60***	0.01	0.00
	(0.48)	(0.46)		
Amount	-0.01***	0.00***	0.01	0.00
	(0.00)	(0.00)		
Collateral	-0.01***	-0.13***	0.05	0.00
	(0.00)	(0.00)		
Maturity	-19.38***	-159.34***	0.04	0.00
	(3.25)	-2.90		
Interest rate	1.02***	0.26***	0.06	0.00
	(0.04)	(0.04)		
Processing time	-23.14***	42.02***	0.85	0.00
	(0.04)	(0.06)		
Default	0.00***	0.01***	0.01	0.00
	(0.00)	(0.00)		

9. Appendices

9.1. Evolution of term loans and credit lines, from 2013 and 2016

In this Appendix, we present the yearly evolution of term loans and credit lines in the Portuguese credit market, from 2013 to 2016 (we used data from the Ministry of Economy regarding the total credit amount). The results are as follows.

Year	Term loans (million €)	Term loans (%)	Credit lines (million €)	Credit lines (%)	Total (million €)
2013	36,340	74.0%	12,768	26.0%	49,108
2014	28,904	70.1%	12,328	29.9%	41,232
2015	18,766	55.5%	15,046	44.5%	33,812
2016	15,753	52.8%	14,083	47.2%	29,836

As we have previously reported, the weight of term loans (credit lines) is decreasing (increasing) as time goes by. Term loans represented 74% of the total market at 2013 and decreased 21.2 percentage points to 2016, whereas credit lines followed the opposite evolution.

The total amount of credit granted to Portuguese non-financial companies is, according to the table, decreasing as time goes by. This fact is against our findings that report an increase in the loan amount. This is due to the fact that the data from the Ministry of Economy only includes capital that has effectively been used (ignoring unused portions of committed credit lines, which are a significant share of our data).

9.2. Back-of-the-envelope computation on the end-of-month impact in credit overdue

In this Appendix, we develop our method to compute the effect in credit overdue arising from the previously studied end-of-month effect. We also present all the intermediate computations that allowed us to attain the amount displayed in section 4.5. All the computations are presented in billions of euros, unless specified otherwise.

Using the CRC database, we are able to extract data regarding the amount of term loans and credit lines granted, for each year of our analysis. The results for this yearly division are presented in the following table.

Year	Term loans (million €)	Term loans (%)	Credit lines (million €)	Credit lines (%)	Total (million €)
2013	36,340	74.0%	12,768	26.0%	49,108
2014	28,904	70.1%	12,328	29.9%	41,232
2015	18,766	55.5%	15,046	44.5%	33,812
2016	15,753	52.8%	14,083	47.2%	29,836

We then proceed to the calculation of the end-of-month effect for each type of credit (term loan and credit line), for each year under analysis. The results are as follows.

Year	Term loans (EOM)	Term loans (ROM)	Credit lines (EOM)	Credit lines (ROM)	Total (million €)
2013	2,907	33,433	10,981	1,788	49,108
2014	2,601	26,302	10,479	1,848	41,232
2015	1,877	16,887	12,488	2,558	33,812
2016	1,418	14,336	11,829	2,253	29,836

Using the default rates computed in Section 4, we are able to determine the amount that defaulted in each period of the month, applying formula (1). The results are presented in the following table.

$$\sum_{t=2013}^{2016} [(Term\ loans_t \times Default\ rate_t) + (Credit\ lines_t \times Default\ rate_t)] \qquad (1)$$

Year	DR Term loans (EOM)	DR Term loans (ROM)	DR Credit lines (EOM)	DR Credit lines (ROM)	Total DR (million €)
2013	116	1,137	988	36	2,277
2014	104	1,052	943	37	2,136
2015	75	676	1,124	51	1,926
2016	57	573	1,065	45	1,740

We have to consider two scenarios. The first one assumes that the end-of-month effect does not exist: the default rate is the same throughout the month. The second one assumes the existence of the end-of-month effect, hence we have two different default rates (one for the end of the month and a different one for the rest of the month). Specifically, we use formula (2) to compute the end-of-month impact.

$$End\ of\ month\ impact_t = Credit\_Overdue_t^{with\ end\ of\ month\ effect} - Credit\_Overdue_t^{no\ end\ of\ month\ effect} \quad (2)$$

The second segment of formula (2) matches the first scenario we previously described. Under this scenario, it is feasible to assume that the default rate is the same across the month. For this reason, we compute it as:

$$Credit\_Overdue_t^{no\ end\ of\ month\ effect} = \sum_{t=2013}^{2016} [(Term\ loans_t \times Default\ rate_t) + (Credit\ lines_t \times Default\ rate_t)] \quad (3)$$

To compute the first segment, one must take into account the end-of-month effect, and the associated difference between default rates in the two periods of the month. We compute it as follows.

$$Credit\_Overdue_t^{end\ of\ month\ effect} = Credit\_Overdue_t^{credit\ lines} + Credit\_Overdue_t^{term\ loans}, \text{where:}$$

$$Credit\_Overdue_t^{credit\ lines} = \left[(EOM_t^{CL}) \times \left(Default\ rate_{EOM}^{CL}\right) + (ROM_t^{CL}) \times \left(Default\ rate_{ROM}^{CL}\right)\right]\ and\ (4)$$

$$Credit\_Overdue_t^{term\ loans} = [(EOM_t^{TL}) \times (Default\ rate_{EOM}^{TL}) + (ROM_t^{TL}) \times (Default\ rate_{ROM}^{TL})] \quad (5)$$

The following tables present the results of our computations for credit overdue, assuming non end-of-month effect on the first table, and its existence on the second one.

Year	Overdue Term loans	Overdue Credit lines	Total Overdue
2013	1,454	255	1,709
2014	1,156	247	1,403
2015	751	301	1,052
2016	630	282	912
			5,076

Year	Overdue Term loans	Overdue Credit lines	Total Overdue
2013	1,454	1,024	2,478
2014	1,156	980	2,136
2015	751	1,175	1,926
2016	630	1,110	1,740
			8,280

The difference between the two outputs (8,280 and 5,076) is a direct match with formula (2). Hence, the impact from the end-of-month relaxation in loan officers' standards is approximately 3.2 billion euros on credit overdue, a 63% increase from the base scenario.