Anchoring in Senior Commercial Mortgage Credit Spreads: an Empirical Analysis

A company research paper for the Master of Real Estate

2022-2024

Amsterdam School of Real Estate

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EXECUTIVE SUMMARY

This company research paper delves into the domain of behavioural economics. A field that has demonstrated since Tversky and Kahneman critical work in 1974, that humans frequently exhibit economically irrational behaviour. This behaviour is manifested through some distinguished cognitive biases, such as the anchoring bias. This study investigates how anchoring bias affects the credit spread in commercial real estate ('CRE') lending. This niche is underexplored, with the only academic precedence being one study that addresses anchoring bias on credit spreads in the corporate loan market in the US.

To explore this issue, I conduct a hedonic pricing analysis on a cross-sectional dataset of senior CRE loans originated by ING Real Estate Finance from 2019 to 2023. The findings reveal a positive effect of anchoring bias on the credit spread level. This effect is apparent across different definitions of the anchor. When defining the anchor as the last realised credit spread on a repeat loan, I observe an average dragging effect of c. 41% towards this anchor is measured for repeat loans with one year or less between them. The measured effect intensifies as the time gap between time between the origination dates of the repeat loan narrows. In the preferred specification the effect diminishes concavely to zero over a period of c. twelve years. When the scope of the anchor is extended to the last realised credit spread on a different borrowing entity belonging to the same sponsor, the effect decreases by c. 75%. Nevertheless, the anchor still has a pull of c. 11%, even though it concerns a different borrowing entity and collateral. The results are robust across multiple additional specifications in the statistical analysis.

The findings imply that anchoring is not only an academic curiosity. It possibly infiltrates everyday commercial loan pricing, disturbing accurate credit risk pricing and influencing loan profitability. Although the factors to be taken into consideration may have (drastically) changed since last origination, the findings imply that involved actors do – at least partially – lean on the last realised level of the credit spread as reference point in determining or agreeing to the price setting.

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1. INTRODUCTION

1.1 Motivation

Banking crises are known to cause severe and prolonged economic downturns and tend to occur cyclically (Reinhart & Rogoff, 2009). These crises often come from a deterioration in bank's financial health, leading to a reduction in credit supply and subsequent slowdown in economic activity. Banking crises are typically not random events. In the last financial crisis of 2008, it was specifically mortgage-related losses and the subsequent fire sale of securitised credit that resulted in a credit crunch (Bernanke, 2018). There is some consensus that an overexposure of (commercial) banks to inadequately valued lending products with real estate as collateral was at least part of the cause.

Credit spreads, which reflect the premium compensating for the risk of an asset, are a critical component of lending as it illustrates the value and associated risk of the underlying loan. In a truly efficient market, devoid of information asymmetry and characterized by perfect rationality among economic actors, risks in lending would consistently be priced appropriately. However, reality has demonstrated the existence of irrational behaviour among economic actors, partly attributable to cognitive biases as first described by Tversky and Kahneman (1974). The influence of cognitive biases in lending is underexplored and limited to Dougal et al. (2015), which this research aims to elaborate upon.

The field of commercial real estate ('CRE') finance has been extensively studied in academic literature. This niche has great studying attributes due to typically having a single property or sector as collateral for a loan, making it very comparable and quantifiable. There have been several studies on the determinants of credit spreads in CRE lending, although these mainly focus on determinants related to the collateral, the borrower, or the relationship between lender and borrower. A subject that remains underexplored is the influence of cognitive biases, specifically anchoring, on the level of credit spreads on CRE loans. Credit spreads in this context refer to the difference between the reference rate, either the Interest Rate Swap ('IRS') or the 3-month EURIBOR ('3M-EUR'), and the rate paid by borrowers, also often referred to as the (gross) margin. This spread is also seen as a risk-premium for lending the desired credit considering the collateral.

1.2 Research problem statement

Without understanding the role of cognitive biases in these spreads, investors, financial institutions, and policymakers may not be accurately assessing the risks associated with CRE lending. This could lead to suboptimal investment decisions and policy interventions. Research is needed to avoid inefficiencies in the pricing of credit risk, as the spreads may currently not fully reflect the borrower's default probability and the expected loss given default. Because as Dougal et al. (2015) states, borrowing histories don't provide insight in the current creditworthiness of a firm. If an anchor, in this context the previous credit spread, still influences the level of credit spreads on loans issued today, it could have implications for the stability and efficiency of lenders and as a result the financial system.

This is why this study aims to provide a comprehensive analysis into the underexplored effect of anchoring on the level of credit spreads in CRE lending. The findings provide further insights in the (subconscious) mechanics of loan pricing. The following central question results from this aim:

How does anchoring influence credit spreads in senior commercial real estate loans?

This question will be answered by addressing a few sub-questions. Together, these form the central theme through this paper, either focusing on the theoretical basis, the empirical research or the implications of the results. The sub-questions are listed below:

- What key factors determine the credit spread in CRE lending?
- How does anchoring bias play a role in CRE and lending?
- What is the impact of anchoring in senior commercial mortgage credit spreads?
- What are the implications of anchoring for CRE lenders?

1.3 Method and key results

To quantitatively identify the presence and degree of anchoring on credit spreads, I make use of econometric modelling. Regression analysis has proven to be suitable in measuring individual determinants of credit spreads in CRE lending (Titman et al., 2005; Ambrose et al., 2018; Eicholtz et al., 2019; Tsolacos & Lux, 2022; and Raffiki et al., 2023). This enables to isolate the effect of the anchor on the level of the credit spread, by controlling for all observable characteristics that have been identified as determinants for credit spreads in (commercial real estate) lending.

I make use of a pooled cross-sectional dataset comprising of individual loans with detailed information on the collateralised property, loan- and relationship characteristics. This dataset concerns senior commercial loans originated in the Netherlands from 2019 up to 2023 by ING

Real Estate Finance. The dependent variable in the model is the credit spread, being the margin above the reference rate, either the IRS or 3m-EUR. To measure the effect of anchoring on the credit spread, I proxy the anchor by using several variables of interest and control for things like changing market conditions and time between the credit spread and the anchor.

The results provide consistent evidence for a positive effect of borrowing histories on credit spreads, strongly indicating the presence of anchoring. Concretely, the preferred specification of the regression modelling shows that on average, the current credit spread is dragged for c. 41% towards the anchoring credit spread. This effect is more influential the more recent the previous origination of a repeat loan, degrading concavely to zero over c. 12-13 years. For the average credit spread of the observed repeat loans in this research, the anchoring effect amounts to a deviation of 4.7bps.

1.4 Company implications

The implications of anchoring to past deal terms can be severe for lenders. Lenders may be influenced by the terms of previous loans when setting the terms for a new one, even if the current market conditions and fundamentals suggest a different rate should be applicable. Anchoring bias leads to possibly inadequate risk pricing, but also to profit losses or excess returns.

The observed average effect of the anchor is relatively minor with only 4.7bps, corresponding to less than 2% of the average credit spread. Nevertheless, this could potentially lead to large deviations in absolute terms, as large sums are typically at play and CRE lending is characterised by relatively high levels of leverage. Moreover, realised credit spreads have been relatively stable for the observations in scope, with on average a change of only 6.8bps between origination times for a repeat loan. If this change would have been larger, then the absolute effect of the anchor would likely have increased (near) proportionally. This would result in larger absolute deviations due to the anchor and monetary implications.

In addition, the results could imply that other cognitive biases may also play a role when setting the terms of a deal. A commercial lender such as ING may use the results to either make its staff more aware of these possible biases. And to imply business rules or pricing models that try to negate the effect of borrowing histories.

1.5 Structure of this Company Research Paper

This remainder of this paper is organised as follows. Section 2 provides a literature review of major relevant academic studies into the area of cognitive biases and its (possible) influence in lending. Chapter 3 continues with a description of the empirical methods applied to perform the hedonic regressions. Chapter 4 elaborates on the source and structure of the dataset, with an overview of the summary statistics. The results of the baseline and alternative models, including robustness testing follows in chapter 5. Chapter 6 concludes with the interpretation and generalisation of the findings, contributing to existing academic literature and the real-life lending practice. In this chapter I also discuss the limitations of this study. Finally, recognizing that some terms may have varying definitions depending on the context, I have included a glossary of the key definitions in Appendix I for clarity.

2. LITERATURE REVIEW

What follows is a brief review about key studies in the fields of heuristics, prospect theory, anchoring bias, and its relevance for (real estate) lending and loan price mechanics. It concludes by illustrating the current academic gap regarding the influence of anchoring as determinant for credit spreads in commercial real estate lending.

2.1 Heuristics, anchoring and its influence in finance and real estate

The academic origin of behavioural finance is based on *heuristics*, originally identified by Simon (1955). Heuristics can loosely be described as mental shortcuts that individuals subconsciously, though very commonly, use to simplify complex problems and make decisions quickly. A downside is, however, that these shortcuts may lead to inaccurate and suboptimal results. Simon (1955) challenged the leading belief and assumption in economic theory that economic actors act fully rational, and argued instead a model of limited, or bounded rationality. This first study led to a plethora of studies into the dynamics of heuristics in decision making.

In their Prospect Theory, Tversky and Kahneman (1974) discuss the concept of the reference point as starting point used by individuals when evaluating potential gains and losses from a decision they need to make. Anchoring refers to the heuristic that people tend to overly rely on this reference point and then adjust from here. These adjustments, however, remain biased toward the initial reference point, commonly known as the "anchor". In other words: individuals are often incapable of sufficiently adjusting their final judgement away from this reference point, leading to inaccurate decisions. The impact of anchoring has been widely studied in a variety of domains, including finance, and been demonstrated to significantly influence human decision-making processes (Furnham & Boo, 2010).

In the context of finance, anchoring can lead investors, lenders or other important actors to making suboptimal choices. For instance, when evaluating the value of a stock, an investor might unconsciously anchor their assessment to a recent high price, a well-publicized valuation, or even the position of earnings vs. the industry median (Cen et al., 2013). Whatever the anchor is, decision makers may be led to overvalue or undervalue the stock, leading to potentially inaccurate investment decisions. Similarly, when negotiating the terms of a deal or setting a price for a product, individuals often anchor their expectations based on existing information, which can impact the outcome (Orr & Guthrie, 2005).

In real estate literature, evidence for the effect of anchoring in the level of bid and transaction prices has also been found. The most influential academic research describing the effect of anchoring on real estate appraisal dates from over three decades, by Northcraft & Neale (1987). They found evidence that manipulated listing prices of real estate would anchor values assigned to the properties, even in an information-rich real-world setting. Or in other words: a potential buyer will often take the listing price into consideration when making a bid for the property, even though the listing price on itself does not per se provide any information on the underlying intrinsic value and may be a fictional fabrication. This finding holds for both experts as well as amateurs engaging in the market. Since then, several studies over the years and in different geographical markets have found evidence for the existence of this effect (Diaz, 1997; Bucchianeri & Minson, 2013; Lambson et al., 2014; Siddiqi, 2016).

Furthermore, studies have found that anchoring plays a role in real estate appraisal. Appraisers or valuers, when conducting repeat appraisals, are anchored to their previous appraisals as they are invariable aware of them (Clayton et al., 2001; Mcalllister et al., 2003). This also contributes to *smoothing* of appraisals, which on its own turn can be partly attributed to the wish of fund managers to decrease volatility in market values. Anchoring may be the result of an active preference for investors for stability in indirect return indices.

Anchoring is one of the most robust and consistent heuristics in behavioural finance. Understanding and recognizing the anchoring bias is crucial for financial professionals, as it can influence pricing, valuation, and negotiation strategies.

2.2 Anchoring in credit spreads

The role of anchoring in credit spreads is underexplored and limited to Dougal et al., (2015). This research had a specific focus on the broad syndicated corporate credit market in the United States, in the period of 1987 to 2008. As this research forms the theoretical backbone into this topic, I elaborate more thoroughly on this paper in this paragraph.

The authors found anchoring as the most plausible explanation for the perceived phenomenon that if market spreads have declined since previous origination, a firm is charged a higher interest rate at a repricing moment than justified by fundamentals, and vice versa. They attribute this to what they argue to be the inclusion of non-informative historical signals by both borrowers and lenders.

To explain in simpler terms, suppose that two owners of nearly identical adjacent residential properties have secured the same amount of mortgage, with the only difference being the interest rate due to the timing of the origination. Borrower one originated the mortgage five years ago when average rates were 6% and the other three years ago when rates were 4%. Dougal et al. (2015) find evidence that if both refinance their mortgages today, borrower one would pay a premium compared to borrower two, with the only reason being that the previous loan was originated in a higher interest rate climate.

Although their study does not apply per se to this type of cases, but rather to the corporate lending market. It still describes an irrational phenomenon, which the authors attribute to anchoring bias. Here the negotiation for the credit spread between both borrowers and lenders is (unintentionally) influenced by past terms. They emphasize that they do not think that this is caused by relationship lending, where lenders and firms would implicitly agree to share the ups or downs in market spreads, as they control for the lead arranger of the syndicated facility.

This apparent effect holds in different applied variations, both in models with aggregate market spreads as anchor as well as borrower-specific borrowing histories. Furthermore, the effect is found both when spreads have risen and fallen. This implies that both lenders as well as borrowers are subject to the bias. Furthermore, the impact is most prevalent when the past spread is most apparent such as when the previous loan is recent, when there is no credit rating and when involved individuals in the negotiation are the same.

2.3 Relationship lending and information asymmetry

Studies have found that relationships between bank lenders and borrowers reduces information asymmetries (Berger & Udell, 1995). In other words, a relationship enables banks to gather confidential and non-public data over the time of the relationship about a borrower's competence. When it comes to loan approval decisions, this soft information supports a more thorough risk assessment (Porzio et al., 2020). A reduction of information asymmetry would imply that the credit risk is accurately accounted for thus resulting in more favourable lending terms.

The corporate finance literature on the effect of the reduction of this information asymmetry on credit pricing is ambiguous, however. For instance, Elsas & Krahnen (1998) find that relationship lending leads to more credit liquidity, but no evidence for price differentiation. Others find that relationship duration is positively correlated to credit spread levels, implying that borrowers with longer bank relationships pay higher credit spreads (Degryse & Van Cayseele, 2000; Hernández-Cánovas & Martínez-Solano, 2010). To complete the picture, Bharath et al. (2009) and López-Espinosa et al. (2017) in contrast argue that repeated borrowing from the same lender leads to more favourable pricing for the borrower, especially when the relationship provides more borrower transparency to the bank.

The literature on relationship lending for CRE is limited, however. This is partly attributable to the transaction-based nature of real estate lending: mainly *hard* information is used to assess the credit risk regarding the collateral, such as figures on the value, cashflow or property type. Only a very recent paper from Haffki et al. (2023) connects this *hard* nature with the *soft* nature of relationship leding. They find evidence that the role of the relationship also influences the loan terms for senior CRE lending. Relationship loans for larger sponsors profit from substantially narrower credit spreads, and small to medium sponsors from substantially lower underwriting fees, than those without a prior relationship. As well as for the corporate finance literature, the authors argue that as the prior relationship reduces information asymmetry, lenders can provide more favourable terms.

The interest of relationship lending for this research is that the relationship may severely impact the level of credit spreads, while the available information on the collateral and borrower may provide contradictory information. This should therefore also be considered separately from a cognitive bias, although psychological effects may also play a larger role in relationship lending.

2.4 Typical determinants of credit spreads in CRE lending

There have been several studies in real estate finance literature examining what factors influence credit spreads. Titman et al. (2005) provides empirical evidence with a study on cross-sectional and time-series determinants of commercial mortgages originated to be packaged into commercial mortgage-backed securities ('CMBS') in the U.S. As theory would predict; credit spreads are inversely related to risk. Characteristics related to the loan, borrower and property explain a large part of the variation in credit spreads.

Furthermore, Titman et al. (2005) finds that liquidity in the credit market and the riskiness of the real estate market explain an approximate additional 20% of the observed variation in credit spreads. Additionally, regulatory changes have impacted the variation of spreads in CRE loans (Tsolacos & Lux, 2022). The Basel I though IV regulations introduced new minimum common equity ratio's and significantly changed the calculation of risk-weighted assets ('RWA'). If a lender needs to define a higher portion of its loans as RWA, it also leads to higher return requirements to maintain the same profitability. This then directly translates into a higher required credit spread.

2.5 Academic contribution and hypothesis formulation

Aside from Dougal et al. (2015), there is to my knowledge no other academic study into the effects of anchoring of loan terms. Instead of the corporate loan market in the U.S., this study investigates if the anchoring phenomenon still stands in the context of CRE lending. This is interesting as CRE is capital-intensive thus typically showing substantially higher leverage levels than the corporate lending market. This makes CRE lending more vulnerable to interest volatility and the rate that is paid. The implications of anchoring in credit spreads could therefore be very substantial.

Furthermore, this study is unique as it focuses on a niche lending market with a strong relationship lending character and only considers senior loans. Relationship lending leads to a reduction of information asymmetry, which would then imply that loans are more accurately priced. On the other hand, soft characteristics of the relationship itself may account for a part of the observed variance in the credit spread. Senior loans in this context concerns debt secured by first ranking mortgages, therefore having priority over all claims on a property in the event of a default. This is the least risky tranche in the capital stack. A major benefit of studying senior commercial mortgage spreads is the relative ease to compare and evaluate the collateral, being the properties, versus for example corporate loans (Titman et al. (2005). The data is more accurate due to standardized and regulated valuation and reporting requirements. This would imply a better isolation of the effect of different determinants of the credit spread, such as the presence of anchoring. Finally, I have a chance to use actual administrative loan data from a major lender in the Netherlands to perform the analysis instead of the typical data gathering from secondary sources.

The main goal of this research is to find further evidence for the presence of anchoring bias, specifically in the CRE lending market. The central hypothesis is therefore formulated as:

Hypothesis 1: *Anchoring to historic credit spreads has a positive effect on the current level of credit spreads in commercial real estate lending.*

In the context of Hypothesis 1, "positive" means that there is a direct relationship between the historic credit spread acting as anchor and the current level of a credit spread which moves into the same direction. In other words: if the historic credit spreads increase, the current credit spreads are also expected to increase and vice versa.

3. METHODOLOGY

I make use of hedonic econometric modelling to test the hypothesis that is central to this paper. In this chapter, I elaborate briefly on the concept of hedonic pricing models and their use to identify determinants of credit spreads. This is followed by a description of the baseline specification of the empirical model. The chapter is concluded with a description and operationalisation of the used variables.

3.1 Empirical Model

Rosen’s (1974) study established hedonic price modelling as a formal method for statistical economic analysis. His research laid the groundwork for assessing the marginal value of distinct features of a heterogenous product that are not traded on explicit markets. The assumption is that such a product consists of number of separate features, each with an associated implicit cost. As a result, even if the price of this heterogenous product is known, the valuation of these individual features needs to be done indirectly, as these features on their own are typically not traded on a market and inherently connected to the encompassing product. Hedonic price modelling is often used in property pricing analysis, as the individual attributes of a property each influence the value but are (usually) not traded on a market. A good example are locational (dis-)amenities and their influence on real estate.

Following this line of reasoning, hedonic modelling is also suitable to identify determinants of credit spreads, by valuing the individual aspects of a loan, collateral, and borrower. These individual aspects result in different risk and return requirements, proxied by the credit spread. The complex interplay of these determinants make that they cannot be readily valued independently. Together, these relate to the return requirements of the lender.

There have been several studies covering possible determinants of the credit spreads for CRE lending. Titman et al. (2005) incorporated a variety of characteristics, focusing on risk metrics, mortgage maturity and amortization, and property characteristics. More recently, Ambrose et al. (2018) added the impact of tenant diversification and lease duration on this model. Eicholtz et al. (2019) found that better environmental scores on properties lead to lower credit spreads. Tsolacos & Lux (2022) discussed the impact of liquidity in the market and regulatory changes as determinants. And finally, Haffki et al. (2023) focuses on relationship lending and size of borrowers. All are to some extent relevant for my own research and use a specification like the one below.

Following these prior studies, the baseline specification of the preferred model follows from the equation (1):

$$Credit\ Spread_{it} = \alpha + \beta_1 A_{ip} + \beta_2 Y_i + \beta_3 A_{ip} Y_i + \beta_4 A_{ip} Y_i^2 + \beta_5 Control_{it} + \varepsilon_{it} \quad \textbf{(1)}$$

with the credit spread of a repeat loan *i* at origination time *t* as the dependant variable. α is the intercept, or the value at which the regression line crosses the y-axis. A_{ip} denotes the anchor, specified as the historic credit spread of loan i at the previous origination time p. Y_i concerns the amount of years between origination dates t and p for each respective loan. In addition, coefficients β_3 and β_4 capture the interaction effect between the anchor and the time since origination of the anchor. This is done as the anchor is likely to be more influential if more recent, or *salient* such as Dougal et al. (2015) discuss. The β term concerns a vector of control variables, reflecting regression coefficients for the loan structure, relationship, risk and property characteristics, and additional control variables such as year and branch office dummies that capture for time and specific locational market (and managerial) fixed effects. Finally, error term ε_{it} captures the idiosyncratic error term, robust for heteroscedasticity.

Aside from equation (1), I estimate other specifications to test the robustness of the model. For example, definitions of the anchor with the scope on borrower and sponsor level are used. To further control for possible omitted variables related to client bargaining power I control for sponsor fixed effects in column (1) of Table III. Furthermore, subsamples are created with the intention to test if the coefficients hold in different years, if market interest rates have drastically risen or fallen, and on sponsor size. Lastly, to exclude the possibility of reverse causality or omitted variables, I perform an Instrumental Variable ('IV') regression which addresses the possible issue of endogeneity. The instrumental variable that I use is *years since anchor*, which reflects the number of years between the two origination dates of the repeat loan. This also equals the loan duration in years of the previously originated loan.

3.2 Variable selection and description

In this section I describe the selection of the variables that proxy the determinants found in academic literature. This concerns the dependent variable, the credit spread, as well as the independent variable of interest the *anchor*, and other independent and control variables. This section ends with an overview of the variable definitions in Table I.

To start, the credit spread is defined as the difference between the all-in interest rate and the reference rate. The reference rate can be either the interest rate swap ('IRS') corresponding to the maturity of the loan or the three-month Euro Interbank Offered Rate ('EURIBOR') for respectively fixed or floating rate loans. This definition is the same as used in Haffki et al. (2023) and compares to other related literature where it represents the premium above a risk-free rate that lenders require to compensate for the associated credit risk of providing the loan (Titman et al., 2005; Eicholtz et al., 2019).

To measure the effect of anchoring on the credit spread, I make us of the previous spread on a *repeat loan*. A repeat loan is defined as a loan that is extended at maturity for a new full loan term, acting as the most straight-forward proxy for an anchor. A caveat of this proxy is that this would by nature only include loans that are extended, and never a newly issued loan, substantially reducing the number of observations. Therefore, I model variations where the anchor is defined as the last credit spread on a borrower level and on sponsor level, at origination of the loan. In this research, a sponsor is defined as the lead client or asset manager that is the primary point of contact for the loans. It is thus possible that different borrowing entities belong to the same sponsor, with separate ringfenced credit facilities. These other anchors provide another possible insight to the presence of anchoring even though the characteristics and timing of the loan, collateral and even the borrowing entity may differ.

Regarding the rest of the model built, several variables are added that find their origin in academic literature and are acknowledged by ING as significant determinants of the credit spread. These variables are grouped into five categories: loan, relationship, risk, property, and fixed effects.

The *loan* characteristics are related to structural terms of the loan, being the size, maturity, pricing, and repayment terms, in addition to the type of reference rate and if it concerns a new loan. These determinants are consistently included in previous related research of determinants of credit spreads. In addition, however, I include a variable to proxy the recourse on a borrower's other assets in the case of a default. This is done considering the research by Glancy et al. (2023), who argue that lenders value recourse structure, evidenced by an average discount of 20bps on the credit spread for recourse loans.

For *relationship* characteristics, various proxies are used in empirical studies. In my paper, I focus on the duration of the existing relationship in years and the loan volume outstanding on the sponsor size, both used in Hernández-Cánovas & Martinez-Solano (2010) and Haffki et al. (2023). The sponsor size is proxied by the outstanding loan amount aggregated on sponsor level at origination of the loan *i*.

The *risk* determinants concern easy to interpret metrics of credit risk in real estate lending, such as the loan-to-value ('LTV') and debt-yield ('DY') ratios and the internally used credit rating. The LTV is a universally used measure depicting the loan outstanding versus the market value of the collateral. The DY illustrates the debt service affordability and is captured by dividing the net rental income by the outstanding loan amount. Both are used in the credit assessment of a loan application and corresponding return requirements. An important note for both the LTV and DY is its endogenous nature. As Titman et al. (2005) states, the level of the LTV and DY at origination is the result of negotiations between a borrower and lender. A lender would typically require a lower LTV (and higher DY) for riskier properties, subsequently possibly reversing the positive relationship between risk and spreads. This is deemed acceptable, however, as these variables act as control variable and are not the main variable of interest.

The final risk metric is the internal credit rating. The rating incorporates information on the asset allocation, property marketability, financial performance, and the average remaining lease term. It is vital to include the credit rating, as this is one of the key metrics influencing the risk-weighted-assets ('RWA') and therefore capital requirements of a lender under the Basel regulations (Monfort & Mulder, 2000). The credit rating encompasses also other control variables that I include explicitly in the model, which could result in multicollinearity. I have found very limited evidence for this, however, as can be seen in the pairwise correlation matrix of Appendix II and the assumption testing in Appendix III.

The *property* determinants are related to the assets that act as collateral for the loan. All property variables are computed as the weighted average of all the collateral at time of origination. The cap rate is a measure for the risk and stability of a property. The return requirement for an investor is lower for a prime property, therefore resulting in a higher purchase price and lower cap rate. The impact of tenant diversification and lease duration on credit spreads are evidenced by Ambrose et al. (2018) and proxied with the amount of tenants and the weighted average lease term (WALT). The marketability is determined by an external appraiser and reflects the extent of liquidity of a property. During the origination years in scope of this study, the main appetite for Dutch real estate lenders were residential properties due to their lower (perceived) risk profiles and strong outlook. Therefore, I only include the share of residential assets in the portfolio as variable and consider all other commercial real estate asset types to have an equal risk appeal. The final property variable included is the energy performance, as Eicholtz et al. (2019) found evidence for environmental scores resulting in lower credit spreads. This is proxied by the share of EPC-labels C or better in the portfolio.

To further isolate the possible effect of anchoring, it is vital to control for unobserved quality or trends that determines the credit spread. Year and office branch dummies are therefore included to control for possible fixed effects, capturing macro-economic developments and micro-influences arising from different managerial strategies in a specific branch office.

Most of the control variables are not transformed, as these are already linearly related with the dependent variable. Except for the variables of the loan and sponsor outstanding, for which their natural logarithm is taken due to heavy skewness.

Table I | *Variable definitions*

Variable	Parameter	Description
Credit Spread	%	The difference between the all-in interest rate and the reference rate, on the origination date at time t
Anchor Loan	%	The credit spread on a repeat loan at the previous origination date t - Y_i
Loan Volume	EUR 1,000	The principal amount of the loan at origination date t in thousand
Repeat loan	0 = yes	A dummy variable for a loan that is extended at maturity for a new full loan term
Reference Rate	1 = fixed	A dummy variable indicating if the loan has a fixed or floating interest base rate
Base Rate	%	The maturity-matched reference rate
Funding Costs	%	Additional liquidity costs for providing the loan
Maturity	years	The number of years from loan origination to loan maturity
Repayment rate	%	The amortisation rate of the loan
Recourse	1 = yes	A dummy variable indicating if the loan is recourse
Sponsor Outstanding	EUR 1,000	Defined as the total outstanding loan amount for the sponsor at origination time t
Relationship duration	years	Indicating the prior relationship with the borrower in years
Credit Rating	1 = best, 21 = worst	Indicator variable indicating the internal credit rating issued to the borrower at origination
Loan-to-Value ratio	%	The ratio of the loan amount to the value of the underlying properties at origination
Debt Yield ratio	%	The ratio of the net rental income to the loan amount at origination
Watch List	1 = yes	A dummy variable indicating if a borrower is on watchlist for closer monitoring due to various risk factors
Cap. Rate	%	The net operating income of the properties relative to its appraised value
Nr. of Tenants	#	The number of tenants in the properties
WALT	years	Remaining Weighted Average Lease Term in years
Residential share	%	Share of residential assets relative to the total market value
Marketability	1 = best, 5 = worst	Indicator describing the marketability of the properties as assessed by third-party appraiser
Energy label ≥C	%	Share of energy labels equal or better than C relative to the total market value of the properties
MCD	1 = yes	Dummy variable indicating if a borrower is marked as consumer under the Mortgage Credit Directive

4. DATA

This section provides a detailed insight into the dataset used in this research. It starts with a short note on the originator and generalizability of its data for the rest of the market. The second paragraph elaborates on the main characteristics and structure of the dataset. It concludes with a paragraph on descriptive statistics, including a table with summary statistics for the variables included in the regressions and a graphical exploration into some of these key variables.

4.1 Originator

All loans concern senior commercial tranches originated from 2019 up to 2023 by ING Real Estate Finance. This bank has an originate to hold strategy and there is no offsetting of the credit risk to capital market by securitisation or other types of secondary loan sales. It has a risk averse appetite as lender, therefore only focusing on senior loan tranches. The main reason being its funding structure, mainly driven by deposits and only to a limited extent by bonds or the capital market.

I only make use of data from one bank. When interpreting the results, ING acts as proxy for other Dutch lenders that issue senior commercial real estate. This is deemed acceptable as ING is the leading issuer of this type of CRE, with a market share of over 25% in 2022 (Van Enk, 2023). The market is very competitive with three main players, being the largest Dutch consumer banks, and several other smaller (inter-)national lenders. The three largest Dutch consumer banks have similar risk appetite, operation models and market permeation, therefore suggesting that the results and conclusions can be generalised for the largest share of the market.

On the other hand, confidentiality issues arise from only using the data from one lender. Credit spreads for non-publicly listed companies are sensitive information that directly reflect the profitability of transactions. Others could gain insights into the bank's pricing strategy which could lead to a competitive disadvantage. Furthermore, ING is a listed company for which disclosing sensitive information could influence the stock price. The table with the descriptive statistics and the figure depicting the kernel density line of the credit spread and the anchor are therefore omitted from the published version.

4.2 Sample description

The analysis is performed on a pooled cross-sectional dataset comprising of 10,881 individual loans with detailed information on the collateral, being commercial real estate properties, loan-and relationship characteristics. The property data is indirectly supplied by professional real estate appraisers, administered under the collateral data. The included data is the same as used for the credit assessment that ultimately determined the loan terms, including the level of the credit spread. These represent loans originated in the period from 2019 to 2023.

All loans with a repricing during the observed period are included. This concerns mainly new loans and roll-overs, but also fixed interest repricing without adjusting any of the other terms. As described in section 3., I create several anchors. The main anchor considered is the previous spread on a repeat loan, of which there are 2,055 observations. In addition, anchors on borrower and sponsor levels are included, being the previous spread on the last loan issued on these respective levels.

Loans are structured both with and without (partial) recourse on the sponsor. In this context, non-recourse refers to loan facilities that only have recourse on the financed property, without any further liability from other assets in the borrower or the sponsor. Furthermore, virtually all loan sizes are included, ranging from the small enterprises up to semi-institutional parties. Some of the small loan sizes are explained due to being long-term loans where only a repricing moment during the tenor occurred and not a full renegotiation of loan terms.

The sample includes mainly residential (45%), retail (28%), office (15%) and industrial/logistics (7%) properties, all located in the Netherlands. Due to the business model of ING REF, the collateralised portfolios are mostly mixed-use, however. When issuing new loans to the same borrower, the additional properties also act as collateral for the loans that were originated before this and vice versa. This results in a large share of often granular portfolios with a mix of asset types and several cross-collateralised loans all relying on the same underlying properties.

4.3 Descriptive statistics

In this section, I elaborate on the variables of interest through summary statistics and a brief graphic exploration. To start, Table i in confidential Annex I depicts the summary statistics of the dataset. A few things can be remarked. Most notably, the measures of central tendency of the credit spread and the anchors are very close together, particularly for the anchors on borrower and sponsor level. This is likely attributable to the fact that these specific anchors originated more recently compared to the dependent *credit spread* at time *t* versus the *anchor loan* variable, which concerns the repeat loans at time *p*. The time since origination of the anchor was respectively on average 2.4 years versus 4.3 years. Figure i shown in confidential

Annex I, depicts a kernel density plot of the natural logarithm of both the credit spread and the anchor. This figure illustrates that the observations of these two variables are relatively similarly distributed, although the credit spread exhibits a larger peak with less skewness to the right. The pairwise correlation matrix of appendix II also shows that they are correlated to each other on a 99,9% confidence interval, with a coefficient of 0.661.

Figure I shows the relative change of the credit spread for repeat loans and illustrates how over half of all repeat loans have experienced a credit spread change of less than 5% from the previous value. This pattern is even visible when defining anchors to be the last loan secured by a different borrower though belonging to the same sponsor, thus also excluding repeat loans. Figure II shows that even in this case, approximately a quarter of observations deviate less than 5% from the anchor and c. half less than 10%. This is very surprising as these loans are likely to be secured by different collateral, at different credit ratios etcetera, though still exhibiting relatively similar credit spreads.

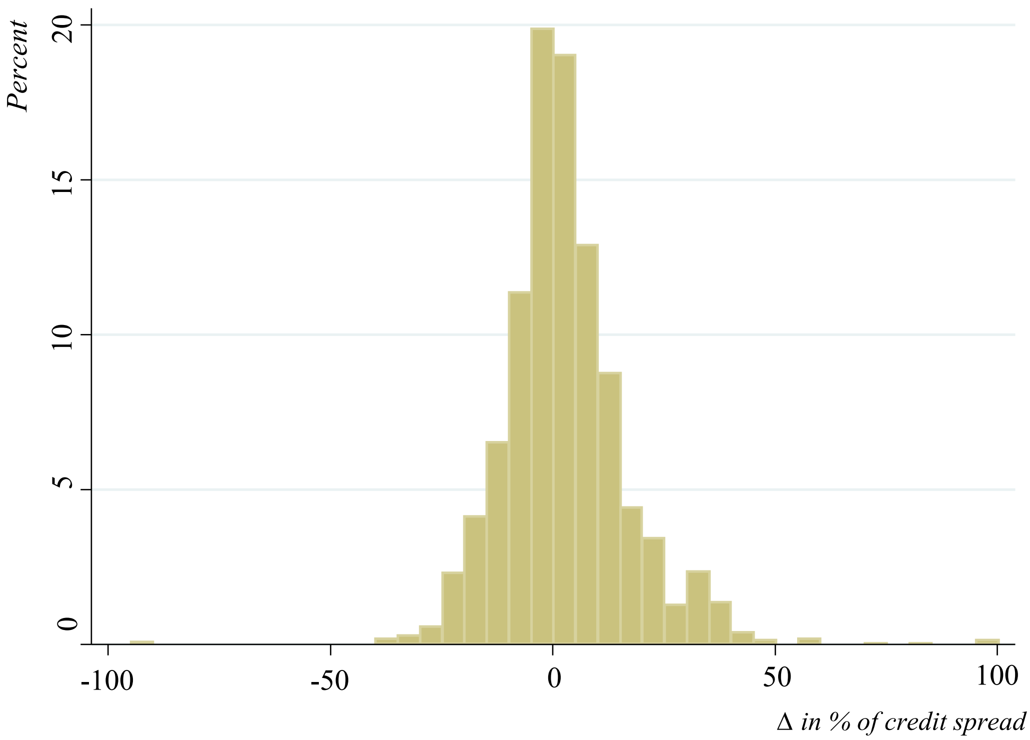


Figure I | *Histogram of the relative change between the credit spread t_0 and the anchor t_{-1}*

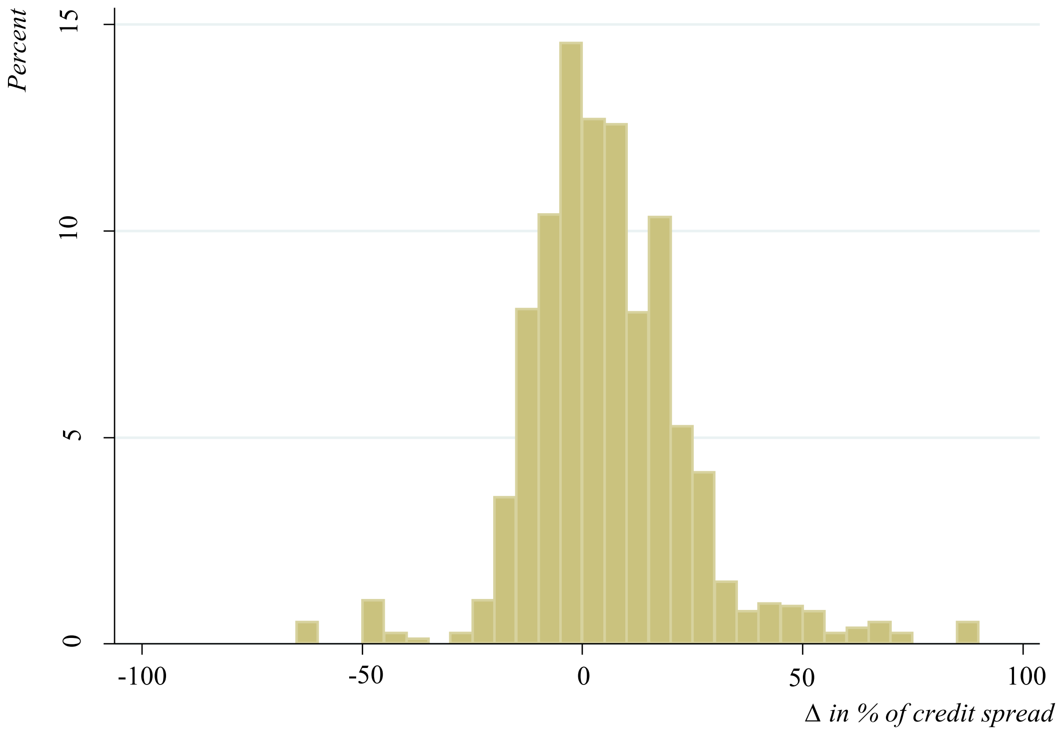


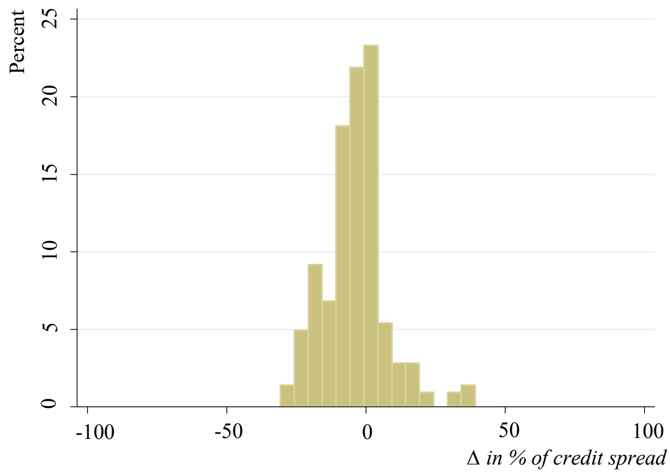
Figure II | *Histogram on the relative change between the credit spread and the anchor on sponsor level, excl. anchors on repeat loans and most recent loans issued to the same borrower.*

Figure III provides a more in-depth view, with graphs of the relative change of the spread sorted for the years between the loans. Panel A through C depict these changes for brackets of two years, with D being the loans with a previous origination date of more than six years since the current observation. These figures imply that the amount of years between the loans also impacts the difference in the credit spread. Panel A shows how that for loans originated within two years of the anchor, most loans have seen a decrease of the credit spread since the last origination. Panel B is skewed the other way around, exhibiting mostly a rise of the credit spread. Panel C en D have relatively the most symmetrical distribution. Surprisingly, the most recent anchors and those that are the furthest in the future exhibit the highest peak around the 0% change.

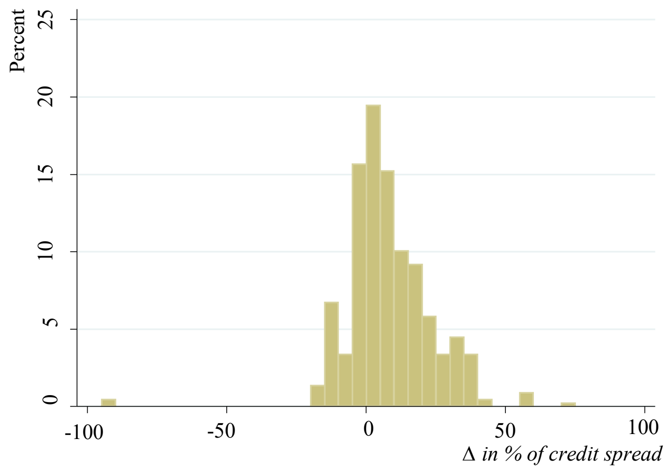
On the other hand, it is interesting to gauge if the loans or the anchors were originated in a high or low interest climate as Neal et al. (2001) found that interest rate rises lead to narrowing credit spreads on the short term. Furthermore, the base rate at origination of the loan proxies for macro-economic conditions, such as policy interventions as quantitative easing or tightening, influencing liquidity. Figure IV illustrates through boxplots in respectively panel A and B the distribution of the base rate of loans i at origination t and p. These show the scope of the repeat loans, including both low and high interest rates as well as a rapidly changing market.

This could separately impact the movement of the credit spread and apparent stickiness to the anchor. Figure V shows that even if the base rate has risen or fallen with over 50% since the previous origination of a repeat loan, the relative change of the credit spread is still clustered around the 0%. These figures are visually appealing and show consistent clustering around the 0% delta between the anchor and current spread, thus strongly indicating a positive influence of the anchor on the current credit spread. Nevertheless, further testing through regression analysis is essential to control for other factors that may have changed over time and paint the full picture. This is done in the next chapter.

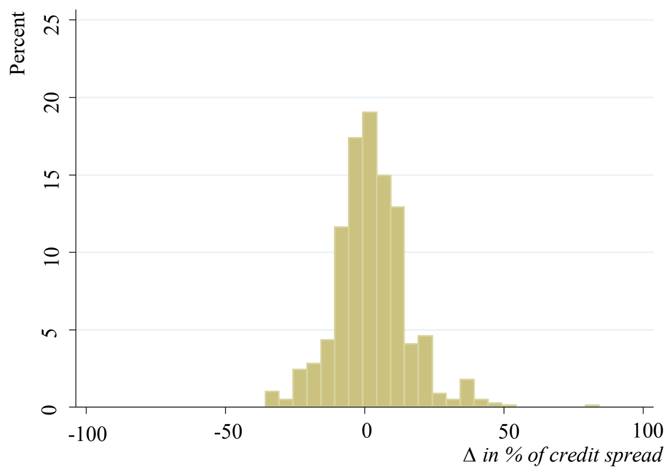
Panel A: <2 years between loans (N=425)



Panel B: 2-4 years between loans (N=459)



Panel C: 4-6 years between loans (N=782)



Panel D: >6 years between loans (N=375)

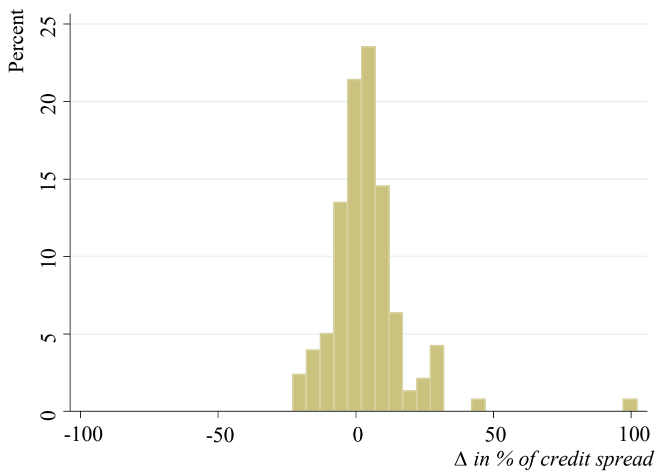
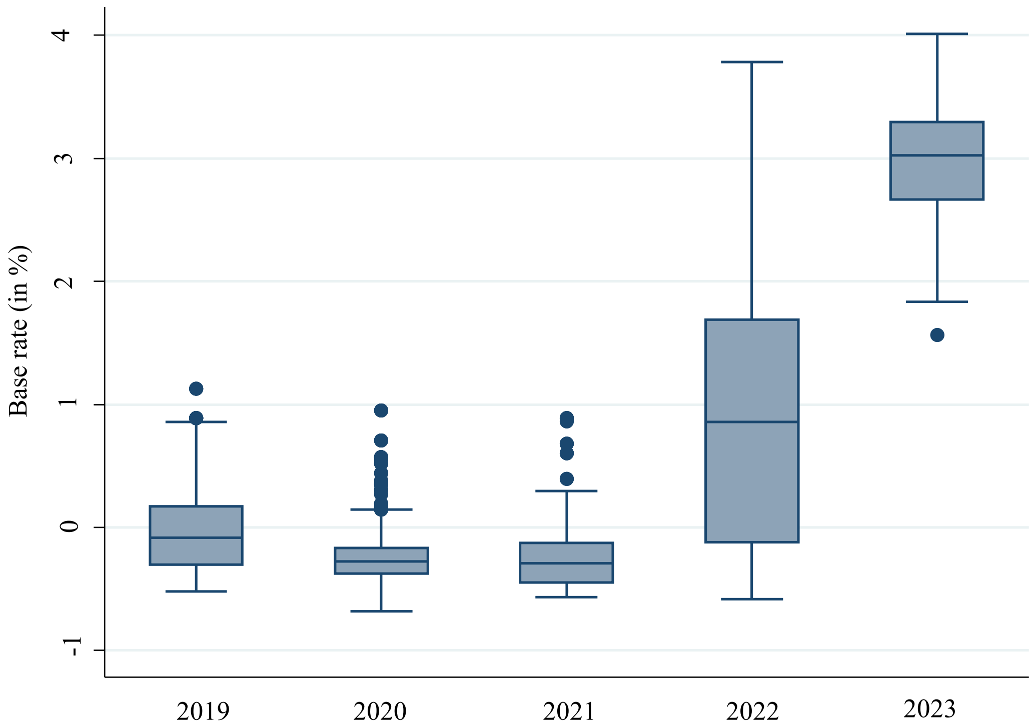


Figure III | *Histograms of the relative change sorted on years between the origination date of the dependent variable and the anchor.*

Panel A: repeat loans at current origination time t



Panel B: repeat loans at previous origination time p

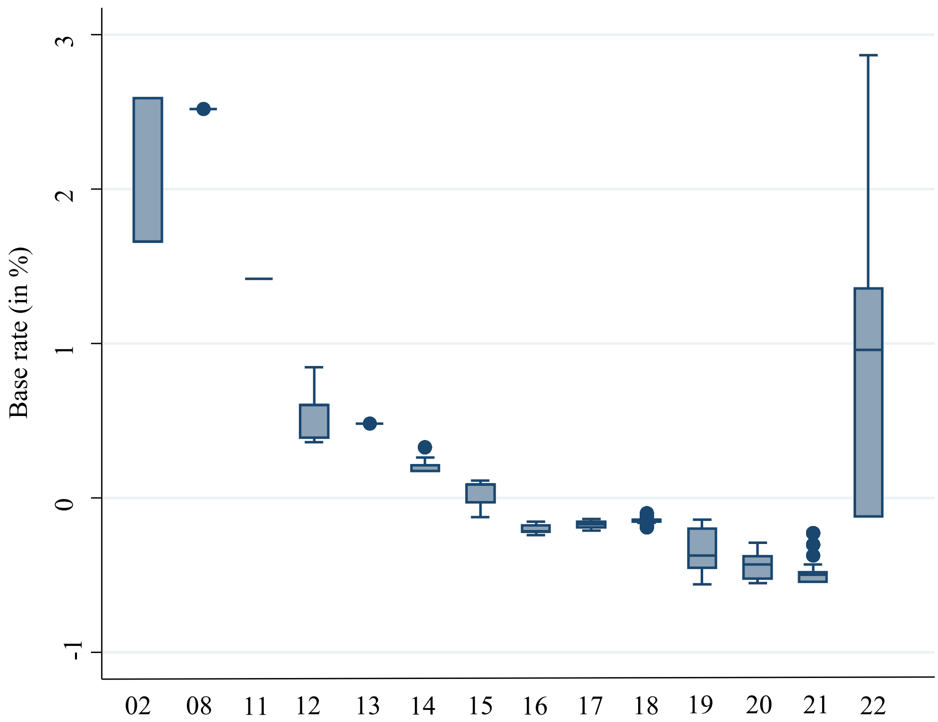
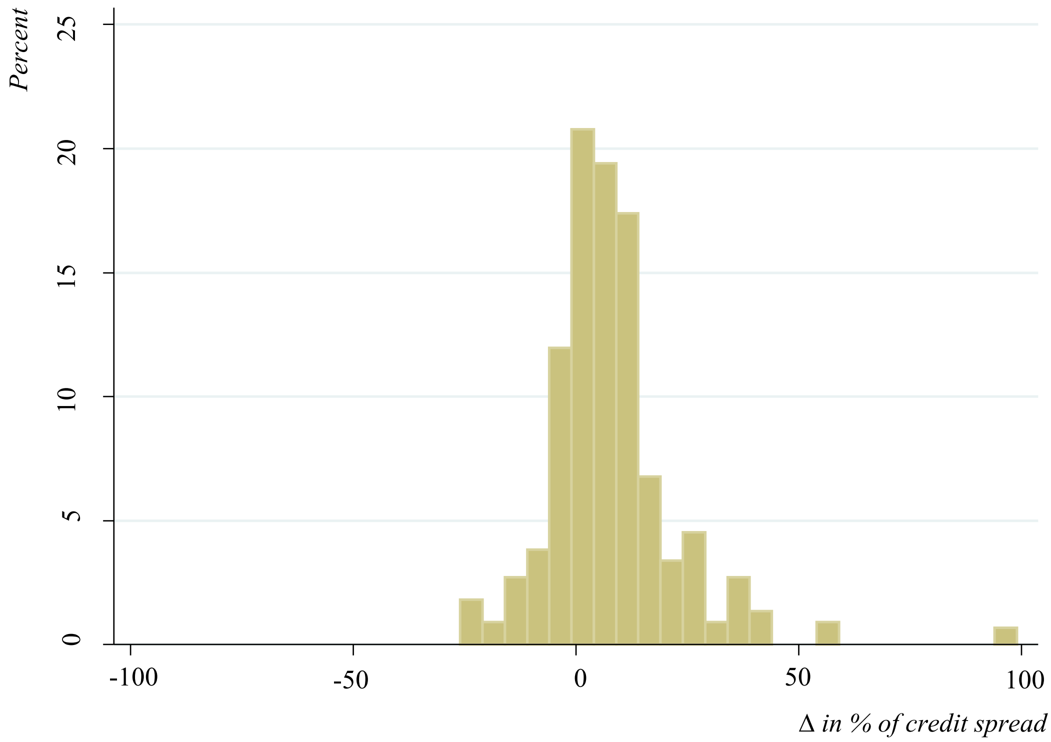


Figure IV | *Boxplots depicting the distribution of the interest base rate (both IRS & 3M-EUR) in the different origination years for repeat loans originated in year* t *(panel A) and* p *(panel B).*

Panel A: rise of >50% in market interest (N = 240)



Panel B: fall of >50% in market interest (N = 1,145)

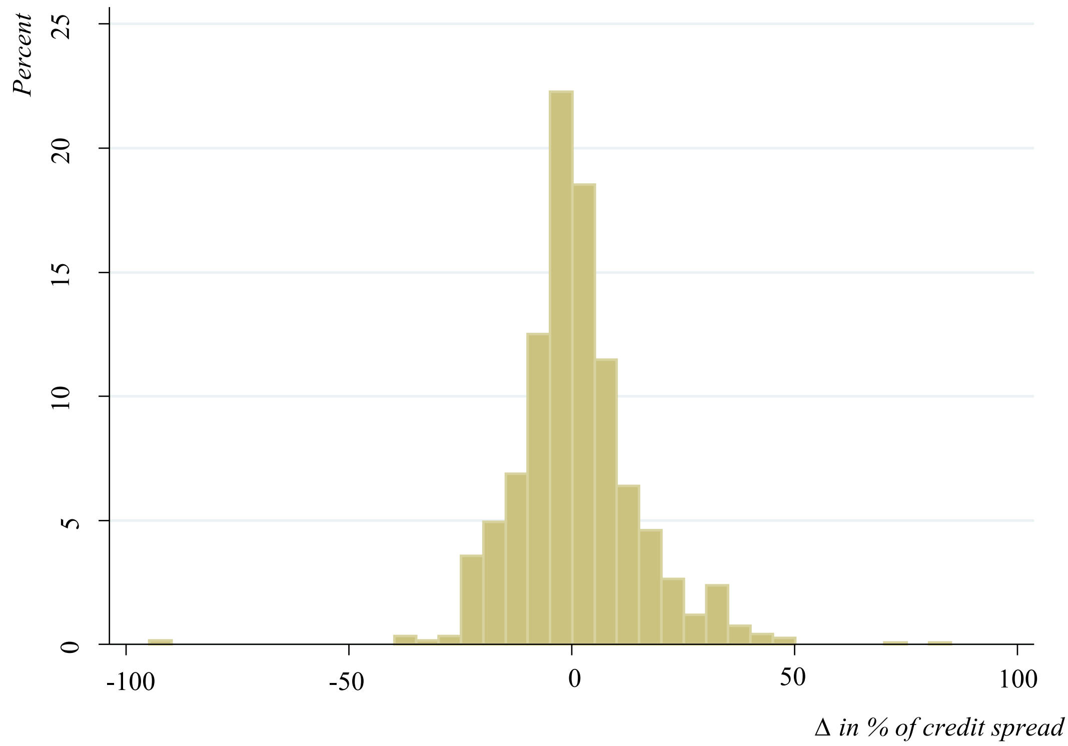


Figure V | *Histograms of the relative change of the credit spread versus the anchor if the market interest has risen or fallen with over 50% since previous origination of the repeat loan.*

5. RESULTS

This chapter presents the regression results for the empirical modelling. It starts with an overview and interpretation of the baseline model's estimation results. The following section provides a short review of the different sensitivity analyses that were performed.

5.1. Baseline specification

Table II provides the model construction of the baseline specification in equation (1), illustrating the effect of gradually adding the control variables on the coefficients, standard errors, and explanatory power. Column (1) displays the results when only including the anchor variables and their interaction. Here the anchor is already a strong predictor when no other determinants are included, partly due to the omitted variables still being captured in the anchor. In every subsequent specification, other control variables are separately included to account for typical determinants of the credit spread and distinguish the marginal influence. Columns (2) through (6) show the results of respectively including variables regarding the *Loan & Structure*, *Relationship, Risk, Property,* and *fixed effects.* The preferred specification reflected in column (7) accounts for all these variables, explaining approximately 76% of the observed variance in the credit spread.

The coefficients are robust, consistently significant and in the same direction under the different model specifications. Furthermore, the assumptions for OLS regression have been assessed. Every model makes use of robust standard errors, appropriate for a pooled cross-sectional model, therefore fulfilling the assumption of homoskedasticity. Through diagnostic testing I have verified that OLS assumptions are true for linearity in parameters, zero mean in errors, and normality and independence of error terms. These are represented in Appendix III.

A full overview of the estimation results of table II can be found in Appendix IV. The control variables with the highest impact on the credit spread are the *Sponsor Outstanding* (-95bps), *Loan Volume* (-64bps), *Credit Rating* (+42bps) and *Cap Rate* (+20bps). This is measured by multiplying the mean of these variables by the coefficients that were found. These variables proxy the size of the client, loan, credit risk and quality or attractiveness of the underlying property. Although insightful, some nuance should be applied as it concerns a quick and dirty comparison of the means of each variable multiplied by the coefficient. If observations of a variable are close together, the relative impact compared to each other will be much smaller.

The coefficient of the variable of interest *Anchor Loan* is positive and significantly different from zero on a 99% confidence interval. The coefficient implies that on average, a repeat loan will exhibit a 4.1bps higher spread for each 10bps that the anchor is higher than for another repeat loan (and 4.1bps lower for each 10bps that the anchor is lower), ceteris paribus. This means that historic borrowing terms appear to have a certain amount of stickiness, where a borrower's current credit spread is dragged about 41% towards the spread at which it last borrowed.

The positive coefficient of *Years since Anchor* illustrates how the further in the past the previous loan originated, the higher the credit spread today. This provides limited information on the anchor itself, however, but would mostly control for fixed effects that credit spreads in general have risen during the loan tenors of the historic loans. The negative coefficients on the interaction variables indicate that the influence of the anchor becomes less present the longer the years between the anchor and the dependent variable. As the coefficient of the squared interaction variable is also negative, this implies that this effect decreases concavely over time and not in a linear fashion.

An example helps to illustrate the measured effect of the anchor and the interaction coefficients. Let us assume a hypothetical situation for a repeat loan with five years between the previous and current origination, with the anchor originated at a level of 220bps and the

Table II | *Estimation results of the baseline specification*

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Anchor Loan	1.008***	0.767***	0.595***	0.870***	0.820***	0.703***	0.408***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years since Anchor	0.181***	0.132***	0.103***	0.155***	0.157***	0.121***	0.0616***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Anchor *Years Since Anchor	-0.0436***	-0.0380***	-0.0260***	-0.0307***	-0.0368***	-0.0344***	-0.0159***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Anchor *Years Since Anchor2	-0.00347***	-0.00221**	-0.00261***	-0.00371***	-0.00299***	-0.00193***	-0.00140***
	(0.002)	(0.011)	(0.002)	(0.000)	(0.001)	(0.01)	(0.006)
Loan & Structure (9)		YES					YES
Relationship (2)			YES				YES
Risk metrics (4)				YES			YES
Property (6)					YES		YES
Year fixed effects (3)						YES	YES
Branch office fixed effects (5)						YES	YES
Constant	-0.129	2.136***	2.557***	-0.565***	-0.0402	0.902***	2.222***
	(0.281)	(0.000)	(0.000)	(0.000)	(0.739)	(0.000)	(0.000)
N	2,055	2,055	2,055	2,055	2,055	2,055	2,055
adjusted R-squared	0.494	0.621	0.613	0.557	0.572	0.626	0.764

Note: ***p<0.01, **p<0.05, *p<0.10. Robust standard errors in parentheses. The credit spread at year t is the dependant variable. An elaborate overview of the coefficients of the control variables for specification (1) through (7) can be found in Appendix IV.

changing market and/or collateral conditions would imply an increase of 30bps today. If we plug in the observed coefficients of column (7), this implies a drag of about 29% towards the anchor, thus resulting in a credit spread of 241bps instead of the expected spread of 250bps. If we only change the previous origination to seven or ten years instead of five, the stickiness decreases to respectively c. 23% and 11%, resulting in current spreads of 243 and 247bps. This shows that anchor has a substantial dragging effect, which decreases concavely over time. The effect nears zero over c. twelve years.

Although the preferred specification (7) includes variables that try to capture general dynamics of a long-standing or sizable relationship, it cannot fully distinguish favourability towards a particular sponsor or the negotiation power and bankability of a client. Column (1) of Table III therefore includes a dummy for each sponsor, capturing sponsor fixed effects. This dramatically increases the R^2 but leads to slightly smaller coefficients on the anchoring variables. Nevertheless, the coefficients of interest are still significant on a 99% confidence interval and consistently pointing in the same direction. This strongly indicates that the perceived effect is due to anchoring bias and not due to relationship lending, in line with the findings of Dougal et al. (2015).

Table III | *Estimation results of specification with borrower and sponsor anchors and fixed effects*

	(1)		**(2)**		**(3)**	
			Borrower Anchor		*Sponsor Anchor*	
Anchor Loan	0.331***	(0.000)				
Anchor Borrower			0.409***	(0.000)		
Anchor Sponsor					0.105***	(0.001)
Years since Anchor	0.0526***	(0.000)	0.0276**	(0.048)	0.0169**	(0.039)
Anchor *Years Since Anchor	-0.148***	(0.000)	-0.00373	(0.504)	-0.00825**	(0.041)
Anchor *Years Since Anchor2	-0.00128***	(0.000)	0.000606	(0.112)	0.000	(0.088)
Loan & Structure (8)	YES		YES		YES	
Relationship (2)	YES		YES		YES	
Risk metrics (4)	YES		YES		YES	
Property (6)	YES		YES		YES	
Year fixed effects (3)	YES		YES		YES	
Branch office fixed effects (5)	YES		YES		YES	
Sponsor fixed effects (371)	YES					
Constant	2.112***	(0.001)	2.249***	(0.000)	3.258***	(0.000)
N	2,053		7,265		1,559	
adjusted R-squared	0.964		0.631		0.423	

Note: ***p<0.01, **p<0.05, *p<0.10. Robust standard errors in parentheses. The credit spread at origination t is the dependant variable.

Furthermore, the effects of the anchor continue to be visible when extending the anchoring scope beyond the repeat loan. Column (2) of Table III depicts the stickiness of the credit spread on the last loan issued to the same borrower and collateralised portfolio, including repeat loans. This provides a nearly identical coefficient for the anchor as in (7), although it loses a part of its explanatory power. The results imply that the effect is consistent for all loans to the same borrowing entity.

Column (3) of Table III expands the scope further to the historic credit spread on the last loan issued on sponsor level, though excluding the loans belonging to the same borrowing entity. The level of the coefficient of this anchor is smaller. This is expected, however, as the anchoring credit spread corresponds to a different borrowing entity and collateralised real estate portfolio than that of the credit spread that is affected by it. This finding is even more interesting, as it implies that the level of the credit spread is significantly impacted by the last loan issued to a separate ringfenced entity from the same sponsor. Or in other words, the borrowing history of an affiliated entity, not connected directly to the collateral and the loan, still influences the credit spread at origination.

A few remarks need to be made. First, the explanatory power of the model is substantially lower than in the previous iterations, therefore potentially capturing unobserved qualities in the anchor coefficient. Second, the sponsor may exhibit a specific investment strategy in all related entities that act as separate borrowers. This could for example be a focus on core residential assets in a particular city or region. It would thus be logical that the credit spreads in the loans for these different entities show similar properties and therefore result in a similar level. Nevertheless, this specific investment strategy would likely already be captured in the included determinants of the model specifications. The perceived effect is therefore likely attributable to anchoring bias.

To conclude this paragraph, an important nuance should be made. The perceived anchoring effect seems relatively large with a coefficient of 0.41 in the preferred specification (7) of Table II. However, the average difference between the anchoring and current credit spread for repeat loans is only 6.8bps. This would imply that without the anchoring effect, this difference would be 11.5bps. On average, the effect of the anchor on all repeat loans in scope of this research is thus a mere 4.7bps, corresponding to less than 2% of the average credit spread.

5.2. Sensitivity analyses

In this section I discuss the sensitivity analyses that were performed to assess the robustness of the model and to see if the hypothesis still stands in different specifications. This testing for heterogeneity starts with a quantile regression on the dependant variable and regressions on a few subsamples of smaller and larger loan sizes. I continue with other subsamples regressions that differentiate for the size of the sponsor or the changing market conditions. I conclude this paragraph with an instrumental variable ('IV') regression to mitigate the possible effects of endogeneity.

Table IV depicts a quantile regression for the 25th and 75th percentiles in column (1) and (2). A quantile regression allows for understanding the relationship between the variables outside of the mean of the data (Le Cook & Manning, 2013). In other words, it enables to deviate from the assumption that the independent variables operate the same at the lower or upper tails of the dependant variable distribution as at the mean. This makes the model by nature heteroscedastic. The coefficients show that the effect of the anchor is less influential at the lower end of the credit spread distribution and more at the higher end. This implies that lower credit spreads, which tend to be the larger and more important clients and loan limits, are less influenced by the previous anchor and more by objective other determinants. Nevertheless, the coefficients are relatively similar and in the same direction as in the preferred specification.

Table IV | *Estimation results of the alternative quantile regression specification*

	(1)		**(2)**	
	q25 Credit Spread		q75 Credit Spread	
Anchor Loan	0.232***	(0.000)	0.476***	(0.000)
Years since Anchor	0.014	(0.307)	0.0953***	(0.000)
Anchor *Years Since Anchor	-0.004	(0.407)	-0.0229**	(0.018)
Anchor *Years Since Anchor2	0.000	(0.558)	-0.00262***	(0.008)
Loan & Structure (8)	YES		YES	
Relationship (2)	YES		YES	
Risk metrics (4)	YES		YES	
Property (6)	YES		YES	
Year fixed effects (3)	YES		YES	
Branch office fixed effects (5)	YES		YES	
Constant	2.477***	(0.000)	2.160***	(0.000)
N	2,053		2,053	
Pseudo R-squared	0.4115		0.5402	

Note: ***p<0.01, **p<0.05, *p<0.10. The credit spread at origination t is the dependant variable.
Bootstrapped standard errors in parentheses.

It is equally interesting to discover if subsamples on the control variables exhibit consistent results. Table V provides the results of subsample regressions of equation (1) with subsamples specified on the different quartiles of observations of the variable *Sponsor Outstanding.* Column (1) through (4) depict the results of each respective quartile. Again, these show relatively consistent anchor and interaction coefficients, although not all are equally significant. The differing anchor coefficients illustrate that the perceived anchoring effect is smallest for the smallest sponsor size and highest for mid-range sponsor's loan outstanding at origination.

Remarkable is that it peaks in the second quartile, after which the effect decreases again. There is no readily available explanation for this perceived phenomenon, aside from possible specific pricing strategies for different sponsor sizes. Furthermore, it is interesting to note that the model fit of column (1) is the highest, with an adjusted R-squared of 0.849, while the anchoring effect is the smallest. From these figures it can be deduced that risk is most appropriately captured in the included determinants for the smallest sponsor category, with less omitted variables or irrationality from possible other cognitive biases at play. This is not that remarkable, as smaller clients typically would have less negotiation power and a more standardized and rigid pricing strategy would apply.

Table V | *Estimation results of alternative specifications on sponsor loan outstanding*

	Sponsor Outstanding			
	(1)	**(2)**	**(3)**	**(4)**
	< 2.6m	2.6m - 10.2m	10.2m - 33.0m	>33.0m
Anchor Loan	0.165***	0.539***	0.387***	0.242**
	(0.000)	(0.000)	(0.000)	(0.015)
Years since Anchor	-0.0339***	0.143***	0.0208	0.0356
	(0.000)	(0.000)	(0.048)	(0.439)
Anchor *Years Since Anchor	0.00511	-0.0296***	-0.00999	0.0312
	(0.413)	(0.001)	(0.117)	(0.136)
Anchor *Years Since Anchor2	0.000344	-0.00394***	0.000204	-0.00654***
	(0.470)	(0.000)	(0.830)	(0.000)
Loan & Structure (8)	YES	YES	YES	YES
Relationship (2)	YES	YES	YES	YES
Risk metrics (4)	YES	YES	YES	YES
Property (6)	YES	YES	YES	YES
Year fixed effects (3)	YES	YES	YES	YES
Branch office fixed effects (5)	YES	YES	YES	YES
Constant	4.727***	0.979**	0.708	2.317***
	(0.000)	(0.000)	(0.000)	(0.000)
N	514	513	513	513
adjusted R-squared	0.849	0.695	0.571	0.619

Note: ***p<0.01, **p<0.05, *p<0.10. The credit spread at origination t is the dependant variable. Bootstrapped standard errors in parentheses.

A final subsample regression of equation (1) has been performed with a differentiation between repeat loans that experienced a rise or fall of the market interest (*base rate*) with over 50% since the previous origination date. The results of these two specifications are shown in respectively column (1) and (2) of table VI. The very consistent coefficients and model fit of both specifications lead to conclude that the differences between both specifications are very limited. Mostly very Both when interest rates have sharply risen or deeply fallen, the anchoring spread has a relatively equal effect. The apparent relative rise in credit spreads depicted in Panel A of figure V, must thus likely be explained by other determinants that deteriorate the quality of the loan, possibly because of the rise in interest rates.

The robustness testing is concluded by addressing possible endogeneity issues related to reverse causality, resulting in biased OLS estimates. This would mean that there is a correlation between the main explanatory variable, or the anchor, with the error term. As a result, the statistical correlation between the dependant and independent variables cannot be interpreted. Performing an IV regression analysis can help mitigate the endogeneity problem and strengthen causal claims, such as discussed by Baum (2003).

As Baum (2003) explains, an instrument can be used provided that its changes are associated with changes in the anchor variable *A* but do not lead to changes in the dependant variable or the error term. Here, I exclude the *Years since Anchor* variable from being a regressor in the model and instead use it as an instrument. The reasoning is as follows. While the

Table VI | *Estimation results of alternative specification with subsamples if the market interest has risen or fallen with >50% since origination of anchor*

	(1)		(2)	
	Market Interest Rise		Market Interest Fall	
Anchor Loan	0.360***	(0.000)	0.400***	(0.000)
Years since Anchor	0.0628***	(0.000)	0.0784***	(0.000)
Anchor *Years Since Anchor	-0.0373***	(0.000)	-0.0269***	(0.002)
Anchor *Years Since Anchor2	-0.000894	(0.228)	-0.000475	(0.485)
Loan & Structure (8)	YES		YES	
Relationship (2)	YES		YES	
Risk metrics (4)	YES		YES	
Property (6)	YES		YES	
Year fixed effects (3)	YES		YES	
Branch office fixed effects (5)	YES		YES	
Constant	4.166***	(0.000)	1.684***	(0.000)
N	240		1,145	
adjusted R-squared	0.909		0.721	

Note: ***p<0.01, **p<0.05, *p<0.10. Credit spread at origination is the dependant variable. Robust standard errors in parentheses.

duration of the previous anchoring loan Y_i influences the historic credit spread, on itself it would not have a direct causal relationship with the current credit spread except for its indirect relationship through variable A_{it}. The following diagram shows this association graphically,

$$\begin{tikzcd} Y_i \arrow[r] & A_{it} \arrow[r] & Credit\ Spread_{it} \\ & \varepsilon \arrow[u] \arrow[ur] & \end{tikzcd}$$

where all variables are the same as depicted in equation (1) of 3.1. Two main assumptions need to hold for the instrument to be respectively valid and relevant. The first is that the instrument is not correlated to the error term. Previously I argued that the instrument only influences the credit spread through the anchor and not directly. The second is that the instrument is correlated with the anchor. This has been tested and is the case on a 99% confidence interval. Although the coefficient is not very high, this is still acceptable as many other control variables are included in the model.

Next, a two-stage-least regression can be performed with the instrument as exogenous variable. The results have been summarized in Table VII. These show a substantial decrease of the coefficient of the anchor by c. 55%. Nevertheless, this is still in the same direction and significant on a 99% confidence interval. Furthermore, the explanatory power of the model is still very similar.

Table VII | *Estimation results of IV (2SLS) regression*

	(1)	
Anchor Loan	0.177***	(0.000)
Anchor *Years Since Anchor	0.0048	(0.170)
Anchor *Years Since Anchor2	-0.000903**	(0.013)
Loan & Structure (8)	YES	
Relationship (2)	YES	
Risk metrics (4)	YES	
Property (6)	YES	
Year fixed effects (3)	YES	
Branch office fixed effects (5)	YES	
Constant	3.070***	(0.000)
N	2053	
adjusted R-squared	0.752	

Note: The Anchor Loan variable is instrumented by the years since its origination ***p<0.01, **p<0.05, *p<0.10. Robust standard errors in parentheses.

Overall, the regression analyses and robustness testing show consistent coefficients and explanatory power of the models, providing sufficient evidence to neglect the possibility of heterogeneity and making it widely interpretable. The results show that historic loan terms do positively influence the current level of the credit spread in commercial real estate lending. We can thus confidently accept Hypothesis 1. Further interpretation of the results and translation into main conclusions and management recommendations follow in the next chapter.

6. CONCLUSION

In this chapter I discuss the empirical results that answer the central research question: how does anchoring influence credit spreads in senior commercial real estate loans? Section 6.1 starts with the main conclusions and discussion of the further interpretability and theoretical embedment of the results. Section 6.2 continues with a management recommendation, focusing on the practical contribution and implications, specifically for ING Real Estate Finance. Section 6.3. ends with the limitations and recommendations for future research.

6.1 Conclusion & Discussion

There is no academic precedence estimating the influence of anchoring bias on the level credit spreads for CRE loans through hedonic analysis. But solely being the first of its kind does not automatically equate to academic or societal relevance. The relevance arises from the expectation that anchoring bias can lead to inaccuracies in loan pricing as borrowing histories do not make good forecasts. A result of this fallacy would be an inappropriate risk pricing reflected in the credit spread. This research thus provides insights into the subconscious mechanics of loan pricing by quantifying the impact of the historic credit spread level on the price of newly issued CRE loans.

Through the empirical research performed in this paper, I find the existence of a positive effect of anchoring bias on the level of credit spreads. This effect is apparent across different definitions of the anchor. For the preferred specification in column (7) of Table II, when defining the anchor as the last realised credit spread on a repeat loan, an average dragging effect of c. 41% towards this anchor is measured for repeat loans with one year or less between them. This coefficient is in line with Dougal et al. (2015), who found an effect of 33% for deals within the same time frame. This is interesting as they applied a different statistical method with the scope on the wider corporate loan market in the US.

Furthermore, the measured effect is stronger if there is less time between the two origination dates of the repeat loan. In my preferred specification the effect degrades concavely to zero over a period of c. twelve years. Dougal et al. (2015) found a monotonical degradation of the effect, however. This is likely due to that study using categorical subsamples for the number of years between the different origination dates, instead of the continuous variable for the time between origination dates that I use.

As mentioned, these findings hold for different specifications of the anchor and in different subsamples. When the scope of the anchor is extended to the last realised credit spread on a different borrowing entity belonging to the same sponsor, the effect decreases by c. 75%. Nevertheless, the anchor still has a pull of c. 11%, even though it concerns a different borrowing entity and collateral. Furthermore, the different subsample specifications show consistently significant anchor coefficients in the same order as the preferred model.

Considering the relationship banking character, bargaining power of- or favourability towards specific sponsors could have potentially been captured in the anchor coefficient. Nevertheless, the robustness testing with the fixed effects on sponsor level still yield consistent and relatively similar coefficients. Combined with the included proxy variables for relationship determinants, I can firmly state that this is not the case.

In contrast, the relationship-based character could possibly result in an inter-temporal interest rate smoothing, such as described in Boot & Schmeits (2006). This concretely means that lenders and borrowers have an implicit agreement to partially share the profits and the losses if the interest rate has risen or fallen substantially since the last origination of a loan. The effect that I measure could thus not (fully) be attributable to anchoring bias. This notion is strengthened by the subsample analysis on these different market interest changes since origination, reflected in Table VI. These results show nearly equal coefficients, which could then imply that although market interest rates have risen or fallen, the anchor still has a nearly equally dragging effect.

Furthermore, benchmarking the anchor coefficient against the coefficients of the control variables provides insights into the magnitude of their impact. Beforehand, it is important to note that nearly all the coefficients for the control variables, being all other determinants drawn from existing literature, align with expectations drawn from these studies (Titman et al., 2005; Ambrose et al., 2018; Eicholtz et al., 2019; Tsolacos & Lux, 2022; and Raffiki et al., 2023). The credit spread is significantly impacted by nearly all included control variables, capturing the effects by the loan-, relationship, risk, property characteristics and fixed effects. This underpins the belief that nearly all possible determinants are identified and included in the model, capturing all the variance that is unrelated to the ones that proxy for anchoring bias. When benchmarking the coefficients of the different variables, it becomes clear that the anchor coefficient of the preferred specification (7) has on average the most influence on the credit spread. This is followed by variables that proxy sponsor and loan size and the most important variables that proxy credit risk and the quality an attractiveness of the underlying property.

But merely describing the coefficients does not paint the full picture of how and why anchoring would occur in the setting of a bank-borrower relationship. To start by stating the obvious; the actors involved in the final determination of the credit spread are human, who since Tversky and Kahneman (1974) on many occasions have proven to be susceptible to economically irrational behaviour. Although the factors to be taken into consideration may have (drastically) changed since last origination, the findings imply that actors do – at least partially – lean on the last realised level of the credit spread as reference point in determining or agreeing to the price setting.

There is a final nuance to be made, however. The measured coefficients are consistent under different assumptions, but in practice the bias affects the credit spread to a relatively limited extent. The estimations yield that on average, the effect of the anchor only contributes to 4.3bps on the credit spread. This corresponds to less than 2% of the credit spread even less on the all-in interest rate, except for times when the base rate is negative. Nevertheless, as loan volumes can amount to several hundreds of millions, it is not negligible in absolute terms and could therefore be rationally included for in a lender's pricing strategy.

6.2 Practical implication and management recommendation

This company research paper dives into the domain of behavioural economics, exploring how anchoring bias affects the credit spread in CRE lending. The findings show in accordance with Dougal et al. (2016) that anchoring is not only an academic curiosity. It possibly infiltrates everyday commercial loan pricing, disturbing accurate credit risk pricing. The implications are also widespread, likely impacting banks across the globe. In this section I shortly touch on these implications. Followed suit by a recommendation of a few management actions for a commercial real estate bank lender to counter these. Both the implications as well as the recommendations have been empirically embedded through an expert panel discussion with commercial and risk leads active in CRE lending. A report of the process and results of this panel discussion can be found in Annex II.

The most critical implications are related to credit risk. Anchoring bias may lead to pricing of CRE loans that does not accurately reflect the current market risk. When a bank lender fixates on historical credit spreads as reference point, they may under- or overestimate the true risk associated with a loan. If a bank then consistently underprices loans due to this bias, borrowers could take on more debt than they can handle. This could subsequently result in higher default rates during economic downturns. The implications could thus become very substantial. The expert panel also suggests that this implication is prevalent: in practice risk repricing for a repeat loan is neglected and anchoring to a previously realised credit spread is favoured if certain return hurdles are met. Nevertheless, the nuance should be made that the observed effect in this paper is still relatively limited, therefore not likely resulting in disastrous credit impairments.

On the other hand, the most significant implications are related to profitability. If anchoring affects both lenders and borrowers equally, it would theoretically result in a net zero balance. However, it is more likely that either the lender or a borrower profit from the bias when a final price of a new loan is determined. For instance, in a market characterised by persistently rising credit spreads, a lender may forfeit interest income on a structural basis and thus not be fully compensated for the current credit market conditions it's exposing itself to. Nevertheless, findings from the expert panel indicate that in practice a return floor is often established. The return floor represents the minimum acceptable return for the lender. If the final price exceeds this floor, it is considered acceptable, even if it is influenced by anchoring bias. This suggests that the impact of anchoring bias is significantly influenced by internal policies and guidelines.

The following management actions can be undertaken by a CRE bank lender to mitigate anchoring bias. This is based on insights from the empirical research. This advice is twofold, focusing either on *soft* managerial, strategic and education related interventions and secondly on *hard* measures to be taken relating to risk modelling and stress testing.

It is first and foremost advisable to seek feedback from bank actors responsible for closing CRE loans to gauge the awareness of anchoring bias as determinant for the credit spread. These would likely be the local sales departments and their managers. This is vital as leaning on the historic credit spread may be a conscious and perhaps intended part of the individual's or local branch's pricing strategies. Nevertheless, anchoring can result in deviations from fully rational benchmark spreads after changing market conditions.

After acknowledgment, lending teams and credit analysts could be educated into the impact of anchoring bias. This may help ensure that they understand how it may impact loan pricing, but also other widespread implications on credit risk and profitability. A concrete measure can be to provide training on recognizing the presence of possible biases during loan origination and pricing processes. Furthermore, dynamic pricing strategies may be implemented which adapt to changing market conditions. Particularly in the case of receding or increasing market liquidity. This could help avoid overly adhering to the historical spread.

As a *hard* measure, the existing pricing models may be evaluated to identify any inherent biases related to historical credit spreads. A consideration could be to incorporate these adjustments to account for the possibility of anchoring. From this evaluation, new models may be developed that explicitly address the last realised credit spread on repeat loans or within a borrowing entity as a reference point.

Additionally, new pricing policies could be implemented by introducing multiple margin floors tailored to different risk buckets. This approach ensures that each loan is priced according to its specific risk profile, providing a more nuanced and accurate reflection of the associated credit risk. To further enhance this strategy, pricing models should place a greater emphasis on accurate repricing based on changing market conditions.

Lastly, it could potentially help to be transparent with borrowers about the loan pricing process and anchoring bias is influencing the thought process of both lender and borrower. This would particularly be helpful if credit spreads have substantially risen since the last origination. During the negotiation, the lender could explain that the historical spread does not accurately reflect the current credit risk when originating a new loan. Vice versa, the credit spread should also be lowered to show fairness to borrowers.

6.3 Limitations and Future Research

While this study contributes to the understanding of credit spread determinations, there are some limitations that justify some discussion. First, there may be some representability issues related to using the data from only one bank lender in the Netherlands. Although ING is a market leader, the perceived anchoring bias could perhaps not be applicable for all other banks as these may have different pricing strategies or operating models negating this effect. Nevertheless, this is deemed acceptable as I focus on senior loans and the three main banks in the Netherlands are very similar. On the other hand, the Dutch market is underbanked with only three large lenders. If one (temporarily) withdraws, liquidity quickly recedes. As Boot & Schmeits (2000) argue, the effect of relationship lending differentiates based on the bank competition. This may also skew the results and make it less replicable to other markets outside of the Netherlands.

Moreover, the results provide consistent evidence of the presence of anchoring to historic loan terms when determining a new credit spread. The results do not show, however, if the anchoring is deliberate or part of subconscious behaviour of the involved actors. The expert panel provides some insights into the influence of pricing policy on (mitigating) anchoring bias. Nevertheless, it could be that both lenders and/or borrowers deliberately clench to this reference point or even specifically target it.

These limitations present interesting features for future research. First, expanding this research to include data from multiple lenders within the Netherlands would strengthen the robustness of the conclusions. A broader sample could validate or refine these findings.

Additionally, conducting a similar study in a country with higher banking competition could shed light on whether credit spreads are more effectively priced when competition is higher. Finally, a deeper exploration of the psychology behind the perceived anchoring could provide valuable insights into loan pricing mechanisms.

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APPENDIX I – GLOSSARY

Term	Definition
3-Month Euribor	The Euro Interbank Offered Rate for a three-month term, which is a benchmark interest rate at which banks lend to one another in euros
Bankability	The likelihood that a project or borrower will qualify for financing from a bank
Borrower	The individual or entity that receives funds from a lender with the obligation to repay the loan
Capital Stack	The hierarchy of all financial sources used to fund a real estate project, including debt and equity
Client	The entity or individual responsible for backing the commercial real estate project which engages the services of a commercial real estate lender. Often synonymous with Sponsor.
Collateral	Real estate assets pledged by a borrower to secure a loan, which can be seized by the lender if the borrower defaults
Credit spread	the difference between the reference rate, either the Interest Rate Swap or the 3-month EURIBOR and the rate paid by borrowers, also often referred to as the (gross) margin.
Cross-collateralisation	The practice of using multiple properties as collateral for a single loan or multiple loans
Debt Service	Total amount required to cover the loan obligation; the repayment of interest and amortisation
Default	The failure of a borrower to meet the legal obligations or conditions of a loan
First Ranking Mortgage	Mortgage that has priority over all other claims on a property in the event of a default
Interest Rate Swap	Global benchmark for the rate at which two parties exchange cash flows based on a linked maturity term
Liquidity	The ease at which credit can be attracted to fund the purchase of assets or refinance existing debt
Origination	The process of creating a new loan, including application, underwriting and funding
Recourse	The lender’s legal right to claim the borrower’s assets beyond the collateral if the loan defaults
Risk Weighted Assets	Metric to determine a bank’s capital requirements under regulatory guidelines
Secured Debt	Debt that is backed by collateral, such as real estate or other assets
Senior Loan Tranche	A loan that has priority over other debt in terms of claims on assets
Sponsor	The entity or individual responsible for backing the commercial real estate project which engages the services of a commercial real estate lender. Multiple borrowing entities can be related to one specific sponsor.

APPENDIX II - PAIRWISE CORRELATION MATRIX

	Credit Spread	Anchor Loan	Log Loan Volume	New Loan	Ref. Rate	Base Rate	Fund. costs	Maturity	Rep. rate	Recourse	Sponsor Out. (log)	Rel. dur.	Rating	LTV	DY	Watch List	Cap. Rate	Nr. of Tenants	WALT	Resi share	Market.	Energy label ≥C	MCD
Credit Spread	1																						
Anchor Loan	**0.6613***	1																					
Loan Volume (log)	**-0.5031***	-0.4862*	1																				
New Loan	-0.3225*	-0.0590*	0.3189*	1																			
Reference Rate	0.0733*	0.1270*	0.0026	0.1421*	1																		
Base Rate	-0.1151*	-0.0501	0.0783*	0.0627*	0.0068	1																	
Funding Costs	-0.0360*	0.0569*	-0.0333*	0.0742*	0.0993*	-0.4448*	1																
Maturity	-0.1139*	0.0355	0.0159	0.2038*	0.3467*	-0.1525*	0.3114*	1															
Repayment rate	0.2482*	0.1403*	-0.3896*	-0.2039*	0.0122	-0.0761*	0.0328*	-0.0865*	1														
Recourse	0.0599*	0.0377	-0.1158*	-0.1174*	0.0072	0.0188	-0.0096	0.0533*	0.0750*	1													
Sponsor Outstanding (log)	**-0.5626***	**-0.5769***	**0.6052***	0.2018*	-0.1176*	0.0045	-0.0211	-0.0284*	-0.2262*	-0.2241*	1												
Relationship duration	0.1528*	0.0679*	-0.1455*	-0.3930*	-0.1234*	0.0253*	-0.0721*	-0.1177*	0.1603*	0.1129*	0.1510*	1											
Credit Rating	0.2080*	0.2000*	-0.0885*	-0.1445*	-0.0792*	0.0225	-0.0256*	-0.0706*	0.1386*	0.2000*	-0.1490*	0.1310*	1										
Loan-to-Value ratio	-0.1005*	-0.0593*	0.2700*	0.1746*	0.0360*	-0.1287*	0.0600*	0.0254*	-0.1579*	-0.1347*	0.2540*	-0.1527*	0.1168*	1									
Debt Yield ratio	0.0891*	0.2003*	-0.1233*	-0.0630*	0.0113	-0.0072	0.013	-0.0217	0.1503*	0.0399*	-0.1500*	0.0868*	0.0417*	-0.2267*	1								
Watch List	0.1069*	0.1216*	-0.0460*	-0.0574*	-0.0247*	-0.004	0.0125	-0.0430*	0.0444*	-0.0156	-0.0696*	0.0211	0.1239*	0.0219	-0.0115	1							
Cap. Rate	0.3142*	0.2777*	-0.2055*	-0.2454*	0.0032	-0.1068*	0.0524*	-0.0719*	0.2455*	0.0924*	-0.2429*	0.2151*	0.3400*	0.0499*	0.1309*	0.0516*	1						
Nr. of Tenants	-0.3166*	-0.3426*	0.3212*	0.0853*	-0.0686*	-0.0066	0.0036	0.0447*	-0.0489*	-0.0526*	0.3778*	0.1237*	-0.2206*	-0.0238	-0.0387*	-0.0331*	-0.1420*	1					
WALT	-0.1456*	-0.1516*	0.1063*	0.0936*	0.0319*	0.0394*	0.0138	0.0471*	-0.0915*	-0.0926*	0.1776*	-0.0565*	-0.2900*	0.0532*	-0.0485*	-0.0477*	-0.1817*	0.0758*	1				
Residential share	-0.0869*	-0.0534	-0.0477*	0.1951*	0.0141	0	0.0223	0.1231*	-0.1869*	-0.1055*	-0.0243	-0.2037*	**-0.5141***	-0.0931*	-0.0910*	-0.0599*	-0.4981*	0.2011*	0.2166*	1			
Marketability	0.2456*	0.2107*	-0.1974*	-0.2383*	-0.0509*	-0.0181	-0.0184	-0.0790*	0.2074*	0.0559*	-0.1871*	0.1959*	0.3359*	-0.0495*	0.0829*	0.0619*	**0.5184***	-0.0781*	-0.1228*	-0.2841*	1		
Energy label ≥C	-0.1907*	-0.2292*	0.1956*	0.1204*	-0.0539*	0.1836*	-0.1972*	-0.0647*	-0.0752*	-0.0617*	0.1519*	-0.0472*	0.0188	0.0429*	0.0194	-0.0253*	-0.0727*	0.0295*	0.0141	-0.0756*	-0.0769*	1	
MCD	0.3901*	0.3031*	-0.2986*	-0.1634*	0.0445*	-0.0275*	0.0336*	0.1055*	0.1127*	0.0443*	-0.3109*	0.1405*	0.0824*	-0.0924*	0.0930*	0.0768*	0.1395*	-0.0537*	-0.0574*	0.0132	0.1228*	-0.1006*	1

Note: * $p<0.01$

APPENDIX III – FURTHER ASSUMPTION TESTING

Normal distribution of residuals

To conduct valid hypothesis testing, we need a normal distribution of the residuals (Brooks & Tsolacos, 2010). The quantile plot below does not follow the quantiles of a normal distribution perfect However, the deviation seems minor and acceptable, considering the sample size and market share reflected by the sample. As we accept that the residuals are close to a normal distribution, the hypothesis testing can be deemed valid.

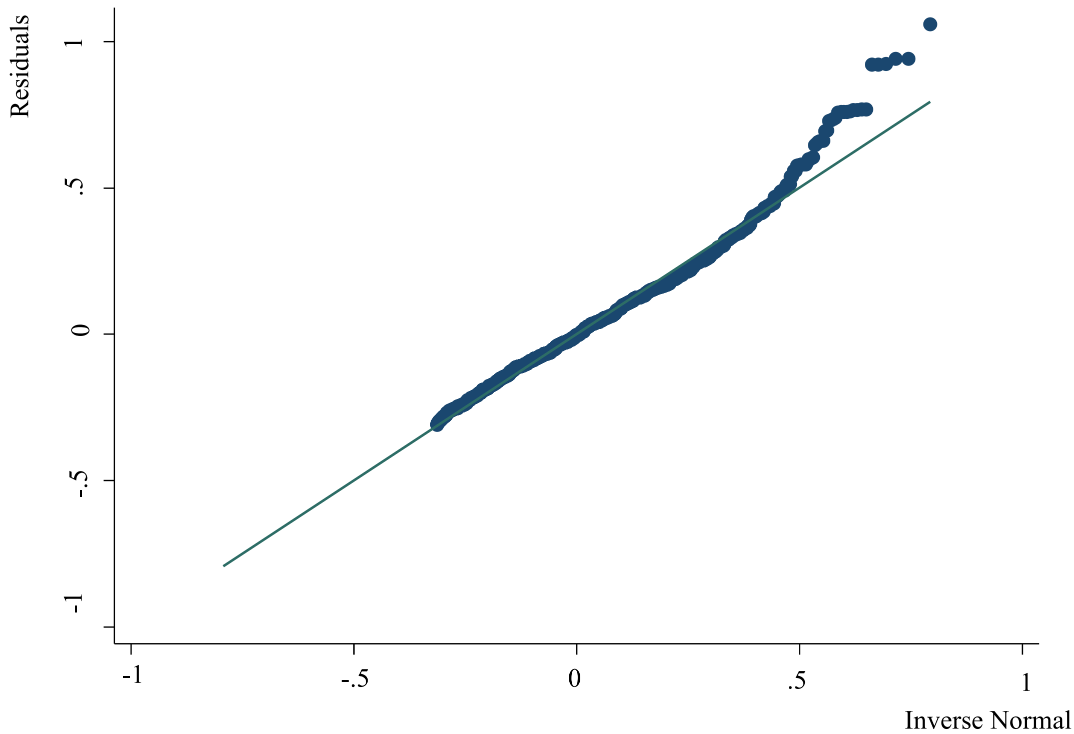

Figure xx | *Quantile distribution of residuals, plotted against a normal distribution*

Multicollinearity

Although strictly not assumption of a linear regression, multicollinearity can cause problems in estimating the regression coefficients. By using the variable inflaction factor (VIF), I test for possible multicollinearity between the independent variables for model specification (7), excluding the factor variables. All VIF values are relatively low considering the rule of thumb that levels above 4 merit further investigation and those exceeding 10 imply serious multicollinearity (Zuur et al., 2010). This is in line with the pairwise correlation matrix, where only a few independent variables exhibit relatively high correlation coefficients (in bold).

Variable	VIF	1/VIF
Sponsor Outstanding (log)	2.74	0.36562
Residential share	2.40	0.41737
Cap. Rate	2.25	0.44512
Loan Volume (log)	2.20	0.45428
Credit Rating	2.19	0.45720
Loan-to-Value ratio	1.89	0.52775
Anchor Loan	1.76	0.56928
Relationship duration	1.53	0.65260
Maturity	1.48	0.67644
Debt Yield ratio	1.45	0.68975
Marketability	1.44	0.69401
MCD	1.41	0.70956
Reference Rate	1.41	0.71038
Nr. of Tenants	1.35	0.73898
WALT	1.33	0.74928
Energy label ≥C	1.27	0.78586
Repayment rate	1.24	0.80898
Base Rate	1.22	0.81953
Funding Costs	1.19	0.84264
Watch List	1.11	0.89934
Recourse	1.11	0.90374
New Loan	1.04	0.96192
Mean	1.59	

APPENDIX IV – FULL ESTIMATION RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Anchor Loan	1.008***	0.767***	0.595***	0.870***	0.820***	0.703***	0.408***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years since Anchor	0.181***	0.132***	0.103***	0.155***	0.157***	0.121***	0.0616***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Anchor *Years Since Anchor	-0.0436***	-0.0380***	-0.0260***	-0.0307***	-0.0368***	-0.0344***	-0.0159***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Anchor *Years Since Anchor2	-0.00347***	-0.00221**	-0.00261***	-0.00371***	-0.00299***	-0.00193***	-0.00140***
	(0.002)	(0.011)	(0.002)	(0.000)	(0.001)	(0.01)	(0.006)
Log(loan volume)		-0.117***					-0.0423***
		(0.000)					0.000
Reference rate		0.006					-0.0333**
		(0.720)					-0.029
Base rate		-0.0378***					-0.0371***
		(0.000)					0.000
Funding costs		-0.883***					-0.869***
		(0.000)					0.000
Maturity (years)		0.0221***					0.0207***
		(0.000)					0.000
Repayment rate		0.00548***					0.00428***
		(0.000)					0.000
Recourse		0.000					-0.0843***
		(0.988)					-0.002
MCD							0.731***
							(0.000)
Log(sponsor outstanding)			-0.111***				-0.0538***
			0.000				0.000
Relationship duration			0.0132***				0.00503***
			0.000				0.000
Credit rating				0.0649***			0.0388***
				0.000			0.000
LTV				-0.001			0.00143***
				-0.250			-0.007
DY				0.00397***			0.00149**
				0.000			-0.043
Watchlist				0.223***			0.125*
				0.000			-0.058
Cap. Rate					5.629***		3.612***
					0.000		0.000
# Tenants					-0.000282***		-0.000239***
					0.000		0.000
WALT					-0.0237***		-0.003
					-0.001		-0.499
Share residential					0.000996***		0.00106***
					0.000		0.000
Marketability					0.0654***		0.006
					0.000		-0.671
Share energylabel ≥C					-0.127***		-0.018
					0.000		-0.244
Origination year 2021						0.000	0.000
						(.)	(.)
Origination year 2022						-0.105***	-0.0691***
						(0.000)	0.000
Origination year 2023						-0.0923***	0.007
						(0.000)	-0.826
Branch NE						-0.301***	-0.147***
						(0.000)	-0.001
Branch NW						-0.248***	-0.0367*
						(0.000)	-0.073
Branch MKB						0.000	0.000
						(.)	(.)
Branch SE						-0.246***	-0.0816***
						(0.000)	0.000
Branch SW						-0.287***	-0.0886***
						(0.000)	0.000
Constant	-0.129	2.136***	2.557***	-0.565***	-0.0402	0.902***	2.222***
	(0.281)	(0.000)	(0.000)	(0.000)	(0.739)	(0.000)	0
N	2053	2053	2053	2053	2053	2053	2053
adjusted R-squared	0.494	0.621	0.613	0.557	0.572	0.626	0.764

Note: ***p<0.01, **p<0.05, *p<0.10. Robust standard errors in parentheses. Dependent variable is the credit spread