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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

The commercial real estate market is pro-cyclical. This feature, together with the relative size of the industry and the large capital inflows, has made this sector relevant for financial stability. Using a novel loan level data set covering the commercial real estate portfolios of Dutch banks we aim to uncover potential drivers of distress in commercial real estate loans. Furthermore, we estimate the relative importance of idiosyncratic and systematic factors and emphasize the importance of bank behavior for distinguishing between good and bad credit growth. We find that loans originated near the peak of the cycle are riskier, confirming the pro-cyclical nature of the market. As opposed to loans originated during busts, the risk of boom loans does not decrease when economic conditions improve. Idiosyncratic factors correlated with higher credit risk are loan-to-value ratios and interest rates, especially when coupled with variable rate contracts. Moreover, we find that collateral type plays a role, as loans for non-residential (office, retail, industrial) real estate with higher vacancy rates are riskier. These results have implications for both macroprudential and microprudential supervision, as they demonstrate the pro-cyclicality of the market and show that indicators like loan-to-value, interest rate structure and vacancy rates must be monitored more carefully in boom times.[1]

Keywords: macroprudential policy; risk monitoring; commercial real estate; procyclicality of credit

[1] Disclaimer and acknowledgements: The views presented below are those of the authors and do not represent official views of De Nederlandsche Bank or the Eurosystem. We thank colleagues and seminar participants at De Nederlandsche Bank, as well as participants at the International Conference on Real Estate Statistics (Luxemburg, February 2019), the International Finance and Banking Society Conference (Angers, June 2019) and the 34th Annual Congress of the European Economic Association (Manchester, August 2019) for useful comments.

1 Introduction

The market for commercial real estate (CRE) has historically shown evidence of strong pro-cyclicality (Davis and Zhu, 2011). Over the last decade, the sector has attracted large inflows of capital while its relative importance in economic activity has risen. Meanwhile, banks have increased their exposure to firms in the sector. These developments make the commercial real estate market prone to systemic risk and thus, relevant for financial stability (European Systemic Risk Board, 2015, 2018). Consequently, there is an increasing need by policy makers to understand the drivers of financial distress in the property market, to be able to design appropriate policies when the economic cycle turns and problems may arise in the sector. As empirical evidence shows that drivers of credit risk and its correlation with the macro-economy differ strongly per industry, we study these aspects for the commercial real estate sector specifically.

The goal of this paper is twofold. First, it aspires to uncover potential drivers of default in the commercial real estate market, and second, it aims to estimate the relative importance of idiosyncratic versus macroeconomic factors as determinants of financial distress in this sector. To do so, we exploit a novel data set on commercial real estate loans extended by the largest Dutch banks. The data set is collected from these banks by the Financial Stability Division of De Nederlandsche Bank and contains over 70 variables on loan, collateral, and borrower characteristics at the individual financing facility level. To uncover the link with systematic factors, we enrich the data with macroeconomic variables at the regional (province) level and with an index of lending standards at the time of loan origination.

We estimate a standard logistic Probability of Default model including a number of control variables and bank fixed effects. We exploit regional variation both current and at the time of loan origination to identify the correlation between credit risk in banks' portfolios and the business cycle. To improve identification, we introduce bank lending standards, which can control for credit supply factors and reduced risk perceptions during the upward part of the business (and real estate) cycle.

We find that interest rates are among the most important drivers of defaults, capturing the illiquidity channel of corporate default. This finding suggests that a fast normalization of monetary policy and tightening of financial conditions could cause tremors in the market. Loan-to-Value ratios are positively correlated with higher credit risk, in line with the theoretical literature on the net-worth covenant channel (Merton, 1974). Further, collateral and loan characteristics, such as the type of interest rates and the type of collateral, are found to have a significant impact on probability of default. Loans collateralized by non-residential (office, retail, industrial) real estate with higher vacancy rates are riskier. Interestingly, the time a borrower has spent in the performing status has a non-linear, hump-shaped effect on probability of default, implying that a negative state dependency effect only appears after a certain amount of time. As regards to the link of credit risk with the business cycle, we find that loans originated during (property) boom years are riskier, *ceteris paribus*, and this effect becomes significant only after controlling for lending standards at loan origination. The latter result highlights that lender behavior during the upturn can be a distinguishing factor between good and bad credit growth. Finally, improvement in the credit risk profile of the commercial real estate portfolios occurs when the economy closes the output gap, while risk remains relatively constant as the economy grows further and the output gap becomes positive.

Our findings suggest that policy makers should be monitoring lending standards closely, as they can be an indicator for subsequent defaults when the business cycle finally turns. This result corroborates the findings of the literature on lending standards and credit booms, and shows that policymakers might want to take this pro-cyclical nature into account when designing policies to cope with systemic risks originating from the property market. The findings on idiosyncratic factors confirm that shorter maturity debt with variable interest rates can potentially create a large strain on borrowers' balance sheets and can be associated with increased credit risk. The type of collateral also plays a role, as loans secured by non-residential real estate collateral are riskier, especially when coupled with high vacancy rates. Our results suggest that supervisors should be monitoring developments in the characteristics of loan portfolios, as well as developments in the performance of collateral.

Our work is closely related to the literature on the determinants of corporate default which examines the importance of various firm, macroeconomic and debt characteristics in predicting corporate bankruptcies. Within this field, we focus on loan defaults in the commercial real estate market. Further, we provide a link between the part of this literature that emphasizes the importance of macroeconomic variables and the literature on lending standards and credit booms. We contribute in a number of ways. First, we provide one of the few sectoral studies for default on commercial real estate bank loans by employing a unique micro data set. Additionally, the analysis enhances understanding of idiosyncratic and systemic factors affecting credit risk in the commercial real estate market, as it explicitly takes into account the effect of the macroeconomic environment. Finally, we emphasize the importance of lender behavior, and specifically lending standards, as an important control for distinguishing between good and bad credit growth.

The rest of the paper is organized as follows. In section 2 we review the related literature. In section 3 we present our novel data set. Section 4 discusses the econometric model and the identification strategy. We provide and interpret a first set of estimation results in section 5. Section 6 presents the model robustness checks and in-sample fit. Section 7 concludes.

2 Related literature

Corporate default, as studied in the academic literature, is generally observed through two main channels, namely the net worth covenant and the flow based covenant channel. Overall, the flow based covenant is linked to default due to illiquidity, whereas the net worth covenant is related to default due to insolvency. According to the first channel, default happens when the net value of the firm, defined as the worth of its assets net of debt, falls below a threshold (Merton, 1974; Black and Cox, 1976). This modelling approach has its root in early option pricing theory (Black and Scholes, 1973). Under certain conditions, the net worth threshold can be zero and firms will default as long as the value of their equity becomes negative. However, the net-worth channel of default could not explain the observed variation in credit spreads, an index of financial distress, and it became apparent that interest rate risk can be an additional channel of default (Jones et al., 1984). The flow based covenant channel aims to capture the interest rate risk of a firms' debt and implies that default will happen when the cash flow generated by the ongoing activity of the firm is not sufficient to cover the necessary debt related payments (Kim et al., 1993; Longstaff and Schwartz, 1995).

Subsequent empirical analysis demonstrated that default does not necessarily happen when the net worth or the cash flow covenants are breached. Apparently, default thresholds are not exogenously determined, but are rather endogenous. Leland and Toft (1996), for instance, argue that the trigger point of asset values for bankruptcy will depend upon the debt maturity structure and show that bankruptcy can happen for positive net worth. Further, default can even occur when the cash flow is sufficient to cover debt payments. A reason for this might be incentives given to firms by the bankruptcy law (White, 1989). Overall, the decision of firm to default and the net worth or cash flow thresholds at which default happens are affected by a number of direct and in-direct costs associated with default. Direct costs relate to the administrative expenses for bankruptcy procedures, such as legal costs, trustees' fees, and liquidation costs. Indirect costs, relate to forgoing income tax shields which can be sizable (Graham and Rogers, 2002), disruption of firm-supplier or firm-customer relationships (Haugen and Senbet, 1978), forgoing investment opportunities as well as sales and profits (White, 1989).

There is a burgeoning empirical literature on explaining and predicting firm bankruptcy. It is observed that additional firm specific factors, such as managerial quality (Daily and Dalton, 1994; Hambrick and D'Aveni, 1992), and a broad range of firm level indicators, as well as operational and regulatory environment variables (Kuipers et al., 2009), add explanatory power and help improve forecasting performance. In more detail, earlier work focused on modelling defaults using only idiosyncratic factors, such as firm-level financial performance indicators (Beaver, 1966; Altman et al., 1977). One of the first studies on corporate default was conducted by Altman (1968) who used profitability, solvency and liquidity indicators as explanatory variables of individual firms performance. In another seminal study, Ohlson (1980) finds that financial information, and specifically measures of size, balance sheet structure, performance and liquidity help explain corporate defaults. The literature advanced quickly towards tackling issues arising from biases in the sample selection process (Begley et al., 1996) and in applying probabilistic models for assessing firm financial distress (West, 1985; Martin, 1977).

However, incorporating exclusively information from financial statements and accounting might miss important fast-moving factors which might influence firm default (Altman and Saunders, 1997). Therefore, several studies add market information regarding firms' performance to improve explanatory power and predictive ability of corporate default models (Altman et al., 1977; Shumway, 2001). All in all, there is consensus that firms with liquid balance sheets, strong equity base and less volatile earnings face lower probability of default. However, only a few studies have focused on corporate bank loan delinquencies and have exploited information on debt and collateral characteristics (Altman and Suggitt, 2000), mainly due to data constraints.

A relatively recent literature has emphasized the role of macroeconomic factors (Nam et al., 2008; Bedendo and Colla, 2015) for predicting and forecasting firm defaults. Macroeconomic factors have a direct impact on defaults beyond their influence through other firm specific explanatory variables, such as the market value of their equity. Bruneau et al. (2012) show that long term interest rates affect negatively the probability of default, while higher GDP growth, measured by the lagged output gap, contributes negatively to the riskiness of firms. Similar results have been obtained by Bonfim (2009). Tinoco and Wilson (2013) stress the role of inflation as an important macroeconomic variable and find that higher inflation is associated with increased financial distress risk.

The strong procyclicality of credit and asset prices has been documented by recent empirical studies (Jordà et al., 2017). The theoretical literature (Kiyotaki and Moore, 1997; Bernanke et al., 1999) focused on information asymmetry as the main driving factor for the pro-cyclical behavior of the financial system. Secured lending induces an increase in asset prices which in turn increases available credit and so on, creating a cycle of increasing credit, asset prices, economic growth and vice versa. However, the recent financial crisis revealed that lenders behavior during the boom phase of the economic cycle can be an important driver of defaults due to overoptimism and excessive risk taking (Borio et al., 2001). During the upward part of the cycle lender's underestimate risk and weaken underwriting standards by lending to less and less creditworthy counterparties and by requiring less collateral or collateral of lower quality. Thus, the subsequent defaults during a downturn are not a direct effect of the crisis, but rather materialization of the risks that were building up during the upturn. Recent empirical evidence shows that collateral usage decreases during upturns and increases in downturns (Jimenez et al., 2006). Further, credit booms appear to be associated with subsequent crisis only when underwriting standards are weak during the boom phase of the cycle (López-Salido et al., 2017; Kirti, 2018). However, the literature on corporate default has not explicitly lender behavior and supply side factors as potential drivers of defaults or control variables for the effect of macroeconomic conditions on default.

Apart from firm specific characteristics and systematic factors, such as macroeconomic variables and lenders behavior, there has been evidence on significant industry effects on the credit risk of corporate sector (Platt and Platt, 1990; Grice and Dugan, 2001). Sayari and Mugan (2017); Karas and Režňáková (2015) stress the need to build industry specific default models by showing that different set of variables explain financial distress in different industries. Chava and Jarrow (2004) find that industry effects significantly affect both the intercept and the slope coefficients of their bankruptcy forecasting equations. In an applied study for the Netherlands, Simons and Rolwes (2009) estimate the relationship between default rate and macroeconomic variables controlling for sectoral effects, and obtain that the construction and finance sectors show lower sensitivity to GDP growth when compared to other sectors of economic activity.

Overall, the empirical literature on the drivers of default to bank loans granted to the commercial real estate sector is limited. We provide links between the theoretical and empirical literature on corporate default by incorporating the main default channels and including appropriate loan and collateral characteristics. Systematic factors are also taken into account as potential drivers of default, in line with the empirical literature. Further, we investigate whether lender behavior and supply side factors during the upturn play a role for the subsequent evolution of credit risk and we motivate this choice by referring to the macroeconomic literature that emphasizes the role of excessive risk taking and reduced risk perceptions for the build-up of risk during the upward part of the business cycle cycle. The latter question is of particular relevance to policy makers given the importance of the sector for financial stability.

In the next section we present our novel data set and some stylized facts.

3 Data

Our main dataset consists of loan level information on the commercial real estate exposures of the largest Dutch banks. The Dutch Central Bank (DNB), under its Financial Stability mandate, requests the largest domestic banks to report detailed information on their corporate commercial real estate exposures. Banks report snapshots of their loan books at the semi-annual frequency. The reporting covers the period between 2015 and 2018. Because of the short time coverage and data quality issues associated with early reporting, we only use the reporting snapshot for the first half of 2017 (2017H1) for our analysis. Further, we opt to discard observations for loans extended by non-Dutch subsidiaries of banks due to data quality issues. However, external shocks can affect the credit risk in the portfolio of Dutch subsidiaries, through lending to non-domestic counterparties or through lending to counterparties with collateral abroad.

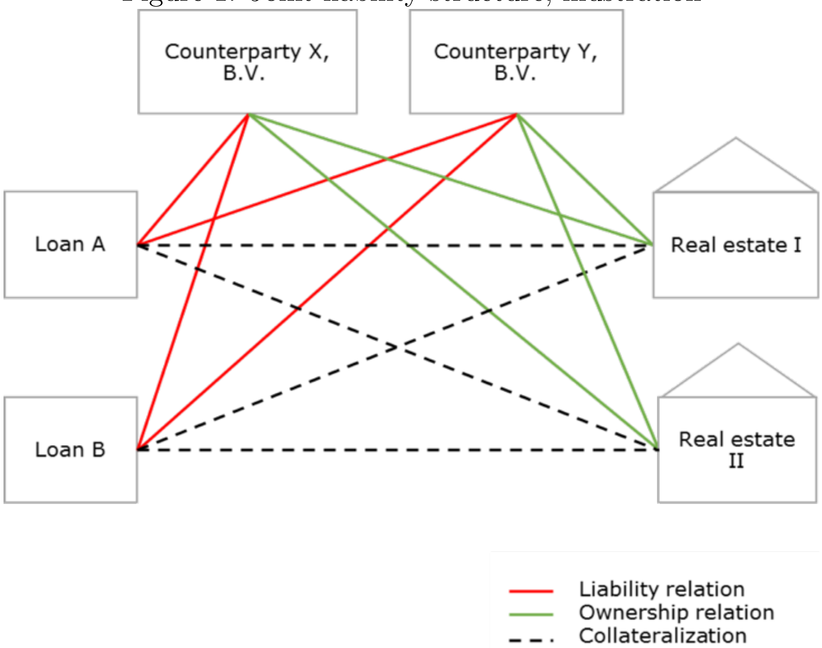
We define as commercial real estate exposures these loans which are secured by income producing real estate. The definition includes various types of real estate collateral which is used for commercial purposes: offices, retail shops, industrial premises but also residential real estate that is rented out or developed. This definition excludes loans secured by owner occupied real estate and individual buy-to-let properties which are properties owned by private individuals.

Each snapshot contains granular information on loan, borrower, and collateral characteristics. In total, our survey contains more than 70 variables, such as the commitment amount per lending facility and per borrower, the maturity schedule of exposures, current interest rates, type of interest rate, amortization schedule, type of real estate collateral (office, retail, residential, industrial), location of real estate collateral (zip code), rental income, and rental contract maturity. Further, we possess information on the structure of the portfolio, such as the individual bank business unit that originally extended the financing facility, which counterparties are liable for each individual facility, and which collateral is pledged for each facility. The information on the portfolio structure allows us to reconstruct the full liability structure and take into account the correlation of credit risk between borrowers.

In commercial real estate lending, it is common that multiple counterparties are liable for an instrument and they all post a common pool of collateral. Due to this joint liability, the default risk of an individual borrower is not independent from the default risk of other borrowers. Thus, joint liability makes the portfolio structure, and therefore probability of default modelling, cumbersome.

Think about a case in which a loan is provided for a commercial real estate project undertaken by two companies. These two companies are both liable for the repayment of the loan, and jointly own and post the same commercial real estate collateral. Assume that the economy enters into a recession and that the commercial real estate collateral posted by the two counterparties records higher vacancy rates. The latter will translate to lower rental income and thus lower Debt Service Ratios for the two counterparties. Assume that company A stops servicing its debt obligations associated with this loan, while company B continues to service its own debt obligations. In this case, B would have to repay back the remaining debt. Therefore, B will have a much lower debt service ratio and thus, a higher probability of default due to the default of A. This illustrates that a recession can trigger the default of some counterparties and the joint liability structure of the lending arrangements can amplify defaults through the spreading of risk between counterparties.

Figure 1: Joint liability structure, illustration



If joint liability is not taken into account, it may lead to underestimation of credit risk. For the purpose of this study, we model probability of default at the joint-liability level by creating portfolios of loans and collateral (see fig. 1 for an example). The joint-liability level refers to a group of borrowers, often called a 'risk pool' by banks. When only one borrower is individually liable for a loan, then the joint-liability level is the same as the borrower level. As a convention we will use joint-liability level, risk pool,and borrower level interchangeably.

After we identify risk-pools in our data set, we transform the loan and collateral level variables into risk-pool level variables. One risk pool might contain one or more lending facilities, collateralized with one or more real estate properties. The lending facilities need not to be of the same type, and collateral need not to be of the same type or located in the same location. The problem of how to aggregate individual loan and collateral characteristics to the risk-pool level arises. We opt to treat loans at the risk-pool level as a portfolio of individual standing facilities, and define collateral posted by the risk pool as a portfolio of individual real estate developments. Then, we derive aggregate measures, such the weighted average interest rate charged for all facilities, the total exposure amount, and the total rental income from the properties. We derive the share of each type of collateral into the total collateral portfolio and we define the portfolio location as the location with the highest frequency among the portfolio.

We perform several other data manipulations. Because some loans, such as overdrafts[2] report zero outstanding amount we use exposures instead of outstanding amounts to capture the risk associated with these instruments. Furthermore, we delete records for which the reported current LTV is 0% or more than 300%. These values are associated with outdated collateral valuations, missing information and unrealistically low collateral values, and thus carry no information value.

3.1 Enriching the data

We enrich the data set with a few external variables. To uncover potential macroeconomic drivers we use regional GDP growth deviations and the growth rate of the national commercial real estate price index. The data on the regional GDP growth, as well as the commercial real estate price index are downloaded from Statistics Netherlands, the Dutch national statistical bureau. Both time series are available at the annual frequency. The regional GDP growth series spans the period from 1995 to 2017, whereas the commercial real estate index is available at the quarterly frequency for the period 1996 -2017. For collateral resided abroad we use Euro Area GDP growth to proxy foreign business conditions. To proxy the business cycle, we transform the GDP series to deviations from their trend using an HP filter.

To control for lender behavior and supply side factors we exploit responses to the ECB Bank Lending Survey, and specifically the index on 'Credit Standards, Total enterprises next quarter, Changes in credit standards for new loans'. The index is available between 2003-2017 at the quarterly frequency. We use the time series in levels and we assign to each borrower the index value at the loan origination.

Below we provide descriptive statistics for the portfolio (table 2). We observe that the total value of pledged collateral is roughly twice the underlying exposure and that the portfolio presents a relatively high share of defaulted exposure, whereas provisions coverage is around 30%.

In table 1 we present descriptive statistics for the main variables used in the empirical analysis. Statistics

[2] An overdraft occurs when money is withdrawn from a bank account and the available balance goes below zero. In this situation the account is said to be "overdrawn".

Table 1: Statistics main variables

	Count	Mean	Min	SD	Max
Outstanding	26111	2.33	0.00	8.98	510.00
Exposure	26111	2.46	0.00	9.76	600.00
Collateral value	26111	4.74	0.00	23.29	1188.81
Current Loan to Value	24090	59.73	0.07	36.17	298.00
Current interest rate	23773	3.16	-0.24	1.23	14.00
Number of loans	26111	17.60	1.00	183.88	24192.00
Time in performing (years)	26058	8.40	0.00	6.20	117.42
GDP growth deviation, inception	25671	0.30	-8.49	2.21	9.66
GDP growth, current	26111	1.86	0.13	0.47	3.28
Lending standards, inception	22431	0.09	-0.47	0.28	0.98
CRE price growth, inception	25671	2.18	-7.78	4.32	9.41
Foreign counterparty	26111	0.02	0.00	0.14	1.00
Real estate firm	26111	0.67	0.00	0.47	1.00
Builder/developer	26111	0.03	0.00	0.16	1.00
Share of bullet loans	26110	11.11	0.00	28.62	100.00
Share of variable rate loans	26110	33.85	0.00	44.39	100.00
Share of residential real estate	23885	27.43	0.00	38.17	100.00
Share office	23885	22.82	0.00	38.36	100.00
Share retail	23885	14.43	0.00	31.17	100.00
Performing	26111	0.87	0.00	0.34	1.00
In arrears	26111	0.02	0.00	0.14	1.00
Special Asset Management	26111	0.06	0.00	0.24	1.00
In default	26111	0.06	0.00	0.23	1.00

are reported at the risk-pool level. The definitions of the variables used in the empirical analysis can be found in appendix A. We observe that current Loan-to-Value ratios are relatively conservative, standing on average at 60% and that interest rates are low and on average 3.2%. Interesting to note that, even though the share of counterparties in default stands at around 5%, the total share of counterparties which are either in arrears, or in special asset management, or in default accounts for 14% of the sample. To classify risk-pools into one of the four categories, performing, arrears, special asset management, and default we take a conservative stance. We assign a risk-pool to performing if none of the involved counterparties is in arrears, special asset management or default. Analogously, we assign a risk pool in default if at least one counterparty associated with the risk-pool is in default. Time spent in performing is reported in months since loan origination. We observe that on average loans have been extended in a less than a year before reporting while the average risk pool is associated with around 18 lending facilities.

Table 2: Portfolio after manipulations

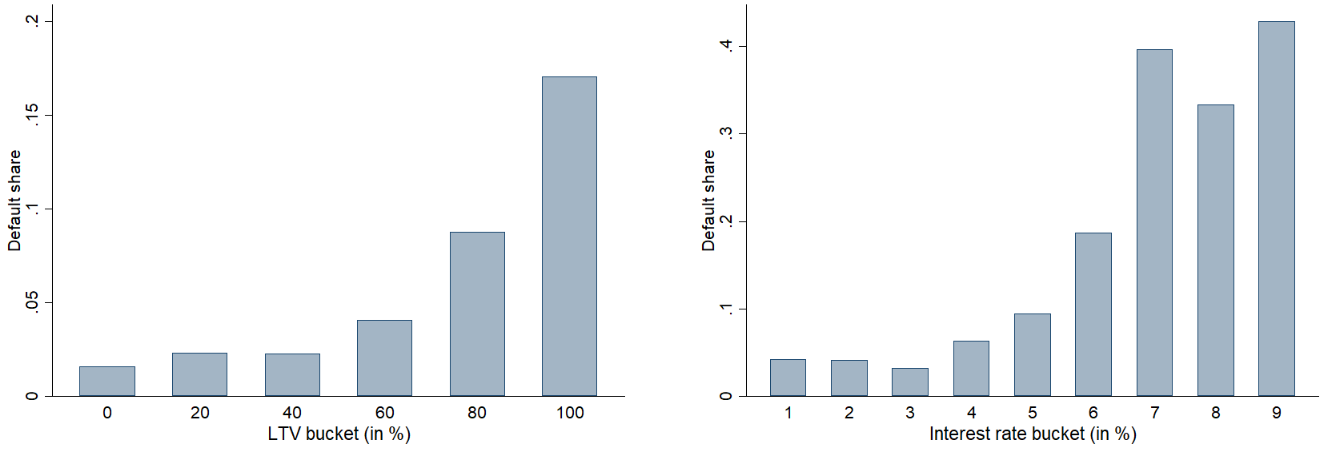
	Sum
Exposure	64.35
Collateral value	123.83
Defaulted exposure	3.78
Provisions	1.22

3.2 Stylized facts

In this subsection, we present some stylized facts and correlations found in the data to motivate our empirical specification and subsequent analysis. First, we focus on idiosyncratic factors and we investigate the presence of the main two channels of default, namely the net-worth channel and the cash-flow channel. Moreover, we present some evidence for state dependency in borrower's behavior. Second, we explore systematic factors of default, and specifically the correlation of default with GDP growth deviations. At last we show that lending standards at loan origination can be a potential useful control variable for disentangling the effect of large positive and large negative GDP growth deviations.

In fig. 2 we present the share of defaulted counterparties per Loan-to-Value bucket and the share of defaulted counterparties per interest rate bucket. With Loan-to-Value we proxy the net-worth channel. A high Loan-to-Value ratio is associated with higher loan leverage and potentially higher incentives for the borrower to default. With the level of current interest rates we aim to proxy the cash flow channel. Borrowers with higher interest rates face relatively lower debt service ratios are potentially more constrained. We observe that both higher Loan-to-Value ratio and higher interest rates are associated with a higher share of defaults. This positive correlation provides evidence in favour of the existence of the two default channels.

Figure 2: Net worth and net cash flow channels

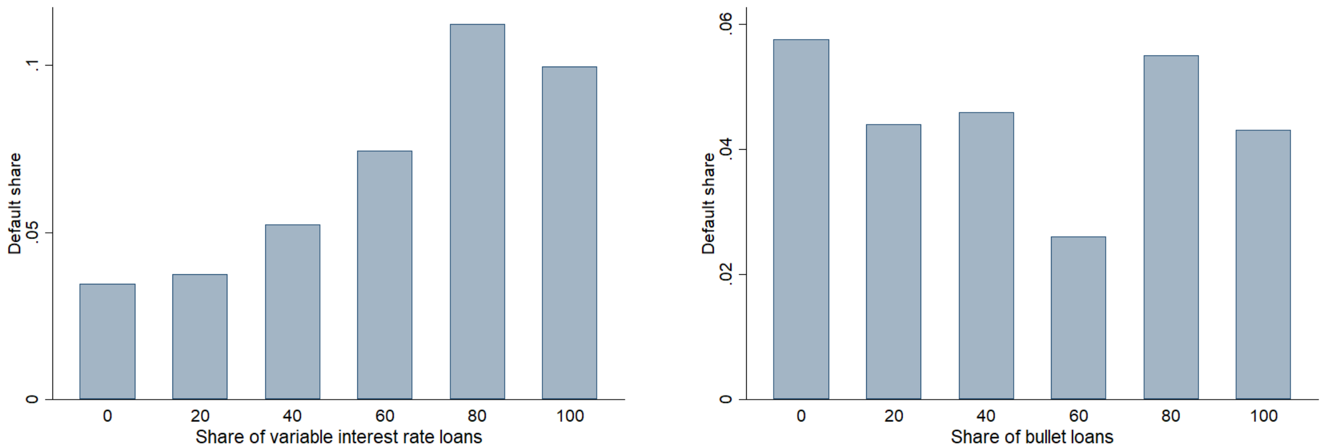


(a) Defaults per LTV bucket

(b) Defaults per interest rate buckets

In fig. 3 we investigate whether loan characteristics, such as variable interest rates and bullet amortization schemes, are positively correlated with defaults and potentially reinforcing the interest rate channel of default. The analysis shows a clear pattern between defaults and the share of variable loans in the lending portfolio of a counterparty as the increase in the share of variable rate loans increases the sensitivity of interest payments, and consequently of debt service ratios to changes in market and policy rates. The pattern between defaults and the share of bullet loans however does not show a clear correlation pattern. The reason could be that since bullet loans are associated with low servicing costs the ability of borrowers to service these loans is less sensitive to income and interest rate shocks, weakening thus the interest rate channel.

Figure 3: Loan characteristics

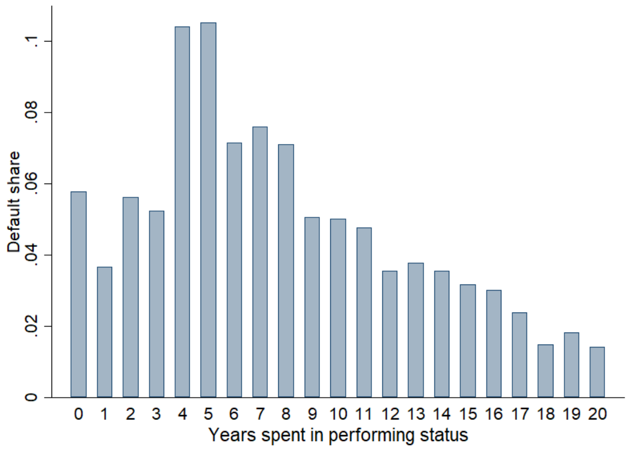


(a) Defaults per share of variable rate loans

(b) Defaults per share of bullet loans

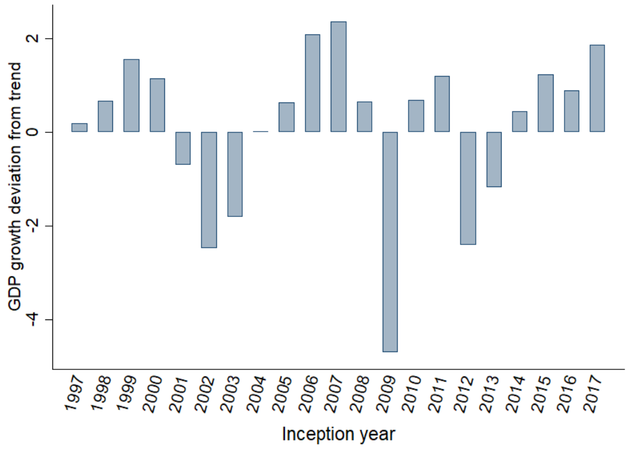
To investigate the existence of state dependency we plot in fig. 4 the share of defaulted counterparties against the years a borrower has spent in performing status since the origination of lending. We observe a hump-shaped relationship between the share of defaulted counterparties and the time that these counterparties spent in the performing status before default. The figure suggests that the risk of default increases during the first years reaching a peak at the 5th year after loan origination and decreasing afterwards. The increase in the share of defaults might reveal weak underwriting standards at loan origination. Further, since borrowers with restructured loans receive a new loan origination date, it might be that the original increase in the share of defaulted counterparties can be attributed to previously delinquent borrowers with restructured loan portfolio.

Figure 4: Share of defaulted counterparties against years spent in performing status

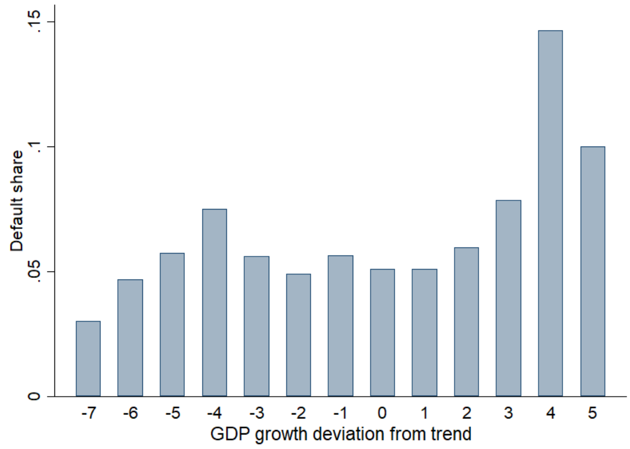


In the rest of the section we explore how defaults are associated with systematic factors, and specifically the business cycle. In fig. 5 we plot the mean regional GDP growth deviation by year and the share of defaulted counterparties against the GDP growth deviation recorded at the time of loan origination. We observe that GDP growth was on average running below trend during the early years of 2000s, after the IT Bubble burst, during the time of Great Financial Crisis, and during 2012-2013 when the Sovereign Debt Crisis was unfolding in Europe. When we look at the pattern of defaults against GDP growth deviations we observe that both negative and positive GDP growth deviations at loan origination are associated with elevated share of defaulted counterparties. Thus, we cannot discern an obvious pattern between defaults and GDP growth deviations in the data.

Figure 5: Macroeconomic environment and defaults



(a) Mean GDP deviation per inception year



(b) Share of defaulted counterparties versus GDP deviation from trend at loan inception

We interpret this lack of a pattern as stemming from two different effects. During the upturn, the increase in collateral values allows for higher debt limits (Bernanke et al., 1999; Kiyotaki and Moore, 1997), while the high growth environment reduces lenders' risk perceptions who become more willing to lend to less credit worthy counterparties (Borio et al., 2001). However, when an economic shock finally hits and the business cycle turns, the elevated risk built up during the upturn materializes and less creditworthy borrowers start to default. Therefore, loans originated during boom years are relatively riskier due to reduced risk perceptions. On the other hand, very negative deviations could also be associated with higher defaults, since a reduction in economic activity can increase the subsequent business risk of borrowers as commercial real estate projects become riskier and economic conditions further worsen. Therefore, the elevated defaults for loans originated during the downward part of the cycle can be attributed to the subsequent further deterioration of the macroeconomic and business environment.

To disentangle the effect of high and low growth deviations on default, we introduce the ECB Bank Lending Survey Index Credit Standards, Total enterprises next quarter, Changes in credit standards for new loans. The index is plotted in fig. 6 below. An increase in the index shows an elevated share of lender's restricting access to credit, whereas a decrease in an index shows an increase in the share of lender's willing or expected to reduce hurdles to new credit. The index decreased or remained favourably unchanged during the high growth years on the run to the crisis, and shows the similar behavior before the European Sovereign crisis, as well as during the recovery period starting after 2014. These years are associated with positive GDP growth deviations for the Dutch economy. On the other hand, the index implies an abrupt and strong tightening of lending standards around 2009 and during 2012-2013 when the Dutch non-financial and household sector were showing elevated levels of distress.

Figure 6: ECB Bank Lending Survey Index Credit Standards, Total enterprises next quarter, Changes in credit standards for new loans

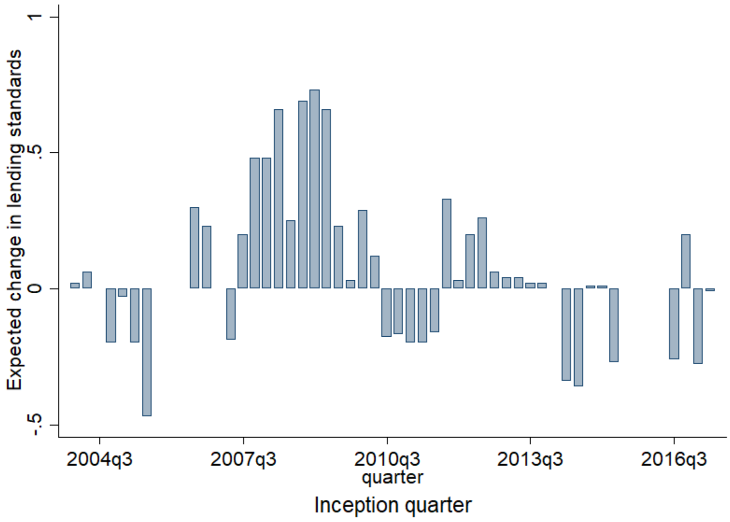
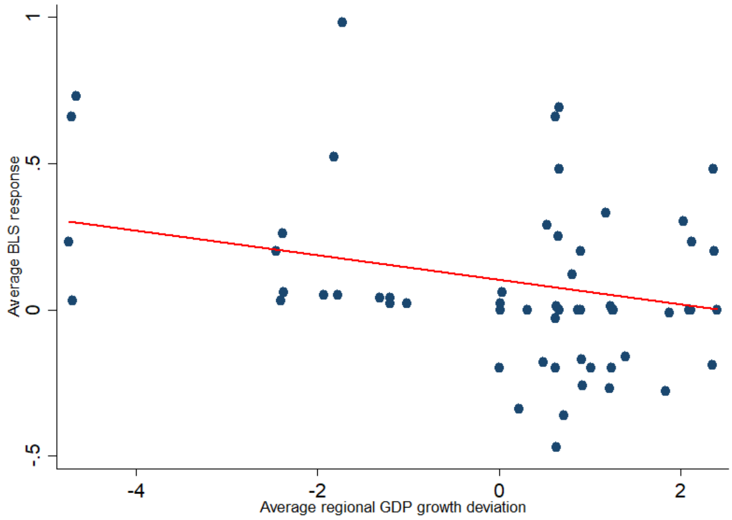


Figure 7: Correlation of bank lending standards and average GDP growth deviations at inception



Plotting the average level of the bank lending survey index against the average regional GDP growth deviation per inception quarter in section 3.2, we observe a negative correlation between the lending standards index and GDP growth deviations. This means that when GDP growth is stronger, lending standards are less tight. In our identification strategy, we will exploit this correlation to control for lender's perceptions during the upturn. This helps to disentangle the effects of the business cycle and lender behaviour on CRE defaults. The correlation between lending standards and CRE price growth at inception is also negative, but less strong than for the GDP growth deviation.

4 Methodology

We estimate a logit model for the probability of default of commercial real estate exposures using the available cross-section of borrowers. The model aims to identify the main drivers of defaults in the commercial real estate portfolio, as well as the impact of the business cycle on credit risk. We predict the probability of default at the counterparty or risk-pool level using characteristics for her loan and collateral portfolios (X), macro variables (Γ), and the time for which the borrower has remained in performing status ($time$) before default takes place. Thus, we include through the cycle and point in time information, but also information on survivorship by using information on the time a borrower has spent in performing status.

Denote with Y_i the observed binary variable that takes the value 1 if the counterparty is in default. Then,

$$\begin{cases} Y_i = 1 \quad if\ Y_i^\star > 0 \\ Y_i = 0 \quad if\ Y_i^\star <= 0. \end{cases} \tag{1}$$

The latent variable $Y_i^\star$ is a linear function of loan, collateral, and macroeconomic characteristics written as:

$$Y_i^\star = X_i'\beta + \Gamma_i'\delta + \gamma time_i + \varepsilon_i\ ,\ for\ i = 1, 2, ..., N\ joint - liability\ pools \tag{2}$$

where $\varepsilon_i \sim Logistic(0, 1)$ and X_i is the vector of loan specific variables, Γ_i is the vector of macroeconomic variables at both current time and time of loan origination, and $time_i$ measures the time a debtor has spent in performing status before default. Moreover, we always control for bank fixed effects and when no regional variable is included as a regressor we also control for province fixed effects. We use robust standard errors and estimate the regressions with no constant in order to ease interpretation of coefficients.

This econometric approach is standard in the literature and forms the starting point for credit risk analysis for financial regulators and institutions alike. It has been extensively used in the empirical literature of corporate default. Martin (1977) conducts one of the first studies of the probability of bank failure using a logit model. The logit model is used by Ohlson (1980) in his influential study on the determinants of firm failure. The logit model has been used extensively in the subsequent empirical literature on firm default (West, 1985; Platt and Platt, 1990; Smith and Lawrence, 1995) as well as for the study of defaults in commercial real estate loans (Chen and Deng, 2013).

5 Empirical results

5.1 Estimates from the logit model

Our main estimation results are presented in table 3. In our initial specification (column 1) we only include loan characteristics, such as the time in performing status, loan to value, current interest rate, the share of bullet loans, the share of variable rate loans and the share of residential real estate in the collateral pool. Since the analysis in section 3 suggests that there might be non-linear effects for time in performing and LTV, we include squared time in performing and squared LTVs. We also add several interaction terms of interest rates and interest rate and loan types, which are not displayed. Finally, we include dummies for client characteristics. These dummies indicate whether is the counterparty is a private client (instead of a company), whether the counterparty is located abroad, and whether it is a specialized real estate company or a builder (based on NACE code). Next to these dummies, we also control for the province in which the client is based.

We find that LTV, and its squared term, are significant. LTV indeed seems to have a non-linear hump-shaped effect on the probability of default (as seen in the stylized facts). Initially, a higher LTV means a higher PD, but this effect levels off at higher levels of LTV. Time in performing and its squared term are both significant, showing a decreasing relationship between time in performing and default risk. We also find that higher interest rates and a higher share of variable rate loans are associated with higher PD. This result is also found for residential real estate mortgages (Archer and Smith, 2013). Moreover, a higher share of residential real estate collateral coincides with a lower default probability; this result is in line with the fact that market for rental housing is more stable than that for e.g. offices or retail due to the full recourse applying to individual borrowers (tenants of the property). Lastly, we see that the client characteristics seem to have no effect. This can mainly be attributed to collinearity among the client variables: adding each variable separately to the regression (not shown) leads to significant dummy coefficients.

To account for interaction between loan characteristics, we have also included interaction terms. Their coefficients are not shown in tabletable 3, but the line at the bottom of the table indicates we use interactions. We interact the share of bullet loans with the share of variable rate loans and the current interest rate, and we add a triple interaction term including all these variables. The interaction terms (which are all significant) show that a higher share of bullet loans, coupled with higher interest rates, can lead to lower default risk. A similar conclusion holds for the share of bullet loans coupled with a higher share of variable rate loans. The triple interaction term has a positive sign, which means that bullet loans with a high variable interest

Table 3: Main estimation results

	(1)	(2)	(3)	(4)	(5)
Time in performing (years)	-3.6965***	0.0762*	0.2278***	0.5089***	0.3951***
	(0.45)	(0.03)	(0.05)	(0.07)	(0.07)
Time in performing, squared	-0.1016***	-0.0056**	-0.0201***	-0.0483***	-0.0352***
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)
Current Loan to Value	0.0304***	0.0340***	0.0365***	0.0384***	0.0357***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Current Loan to Value, squared	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Current interest rate	0.4733***	0.7744***	0.7308***	0.7083***	0.7236***
	(0.08)	(0.06)	(0.06)	(0.07)	(0.06)
Share of bullet loans	-0.0065	0.0192*	0.0225*	0.0277***	0.0231**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of variable rate loans	0.0177***	0.0308***	0.0292***	0.0297***	0.0290***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of residential real estate	-0.0045**	-0.0045***	-0.0045***	-0.0039***	-0.0046***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Private client	-0.5053	-0.1243	-0.1338	0.0673	-0.1126
	(0.38)	(0.31)	(0.32)	(0.28)	(0.32)
Foreign counterparty	0.9951	-1.0893*	-1.1770**	0.7459*	-1.1855**
	(0.63)	(0.43)	(0.44)	(0.36)	(0.44)
Real estate firm	-0.0663	-0.2030*	-0.1986*	-0.1721*	-0.1911*
	(0.14)	(0.09)	(0.10)	(0.09)	(0.10)
Builder/developer	0.1519	-0.2730	-0.1915	-0.1968	-0.1883
	(0.33)	(0.24)	(0.25)	(0.21)	(0.24)
GDP growth deviation, inception		-0.0010	0.0437*		-0.0801**
		(0.02)	(0.02)		(0.03)
GDP growth deviation, default		-1.6277***	-1.6212***		-1.5700***
		(0.10)	(0.11)		(0.11)
CRE price growth, inception				0.1161***	0.1024***
				(0.01)	(0.02)
Lending standards, inception			0.2189	0.0944	-0.0485
			(0.16)	(0.15)	(0.17)
Observations	22798	21428	18702	19897	18702
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	No	No	No	No
Province fixed effects	Yes	No	No	No	No
Client location fixed effects	Yes	Yes	Yes	Yes	Yes
Interaction Terms	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

rate are indeed more risky. However, the exact marginal effect of these variables depends on the value of the other variables. We examine marginal effects in more detail in section 5.2.

In a second step, we add the macroeconomic variables: regional GDP growth deviation from its trend at time of inception of the loan (GDP growth deviation, inception) and the same deviation at the time of loan default (GDP growth deviation, default). The latter variable is the regional GDP growth trend deviation at the time of default in case the loan is defaulted. However, when the loan is not defaulted there is no observation for this variable. Therefore, when the loan is not defaulted, we replace *GDP growth deviation, default* by the most recent regional GDP deviation from trend.

The results show that the coefficient estimate of GDP growth deviation at inception is small, negative and insignificant. The trend deviation at default has a negative and significant coefficient estimates, which we interpret as indicating that boom times are associated with lower share of loan defaults; a standard economic finding. Additionally, the time spent in performing status now has a significant non-linear relationship to the probability of default, as both the linear and the squared term are significant when we include the GDP deviation variables. They are positive and negative, respectively. We will explore this result further in section 5.2. All other loan-specific variables remain significant.

In section 3 we identified a U-shaped relationship between regional GDP growth deviation at inception and defaults. This means that both high and low GDP growth deviations at inception are associated with higher defaults in the data set. In other words, loans originated in booms and busts both have high default probabilities. Our assumption is that the positive GDP deviations are associated with reduced risk perceptions and thus riskier lending, while negative deviations are associated with better lending decisions but initially elevated subsequent defaults due to worsening of macro-economic conditions. This U-shaped relationship should result in insignificant estimates for the coefficient of regional GDP growth deviation at inception, which is indeed what we see in table table 3. Therefore, we need a control variable to disentangle the two effects.

To this end, we introduce bank lending standards at loan inception. As described in section 3, we employ the ECB Bank Lending Survey, and use the index *Credit Standards, Total enterprises next quarter, Changes in credit standards for new loans.* This variable aims to capture expectations about tightening/loosening of lending standards at loan inception; a positive change indicates an expected tightening of lending standards and vice versa.[3] In section 3 we observed that when GDP is above trend, lending standards are expected to be relaxed. Therefore, we expect that after controlling for lending standards at the time of inception of the

[3]Note that these lending standards are not specific to commercial real estate, but hold for corporate credit generally. However, it is reasonable to assume that corporate and commercial real estate credit standards are highly correlated.

loan, we will be able to disentangle good and bad credit growth by capturing the change in risk perceptions.

Indeed, the coefficient of GDP growth misalignment at inception becomes significantly positive after we control for the tightening of lending standards at inception. Moreover, we see that the Bank Lending Survey Credit standards index coefficient is positive. This result is intuitive as the expectation of a tightening in lending standards is correlated positively with higher defaults. However, we do not argue that this represents a causal relationship. Further, note that the coefficient on lending standards is insignificant.

We consider the national commercial real estate price index as an alternative macroeconomic variable. We use the growth rate of CRE prices at the national level. We expect price growth at inception to be positively correlated with the probability of default, as high price growth would indicate a real estate boom. Loans extended during real estate booms generally see higher default rates compared to loans originated in calmer times.

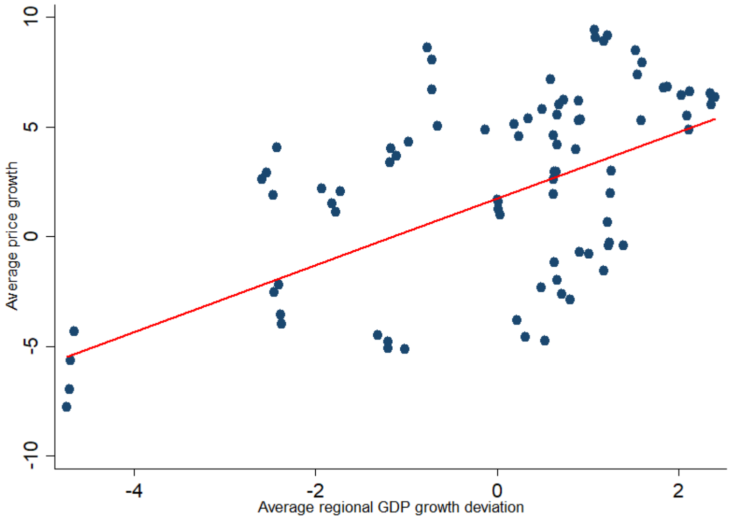
Column 4 in table 3 shows that the coefficient is significantly positive. As expected (strong) price growth also indicates boom times, just like GDP, it confirms the notion that loans made in boom times are more risky. Note that the result holds despite the fact that CRE prices are only available quarterly at the national level, and not at the regional level. Apparently, the time series variation is sufficient to identify the pro-cyclical effect.

In column 5, we include both GDP variables and CRE price growth as regressors. The results show that most loan characteristics remain significant and their coefficients are qualitatively similar to previous models. However, we see that the GDP deviation and price growth at inception now have opposite signs. The most straightforward interpretation for this result is that both variables are collinear. Indeed, the simple correlation of the two variables is 65%. Figure section 5.1 also shows this relationship visually.

We conclude that loans originated at the peak of both the business cycle (measured by GDP growth deviations from trend) and the property cycle (measured by CRE price growth) are riskier, when controlling for lending standards. This suggests that the link between business cycle and credit risk works via lender behaviour. Property price growth has a similar effect as GDP growth deviations, reflecting that the (commercial) property price cycle co-moves with the business cycle in our sample period; this also follows from the data.

In the next section, we examine the economic significance of the estimates. We use the cyclical relationship that runs via the business cycle since the regional variation in the GDP data allows for better identification of trend deviations.

Figure 8: Correlation of average CRE price growth and average GDP growth deviations at inception



5.2 Economic significance of the results

In the previous section we have shown that the estimated coefficients effects are statistically significant. In this section, we investigate whether the marginal effects also have economic significance. To this end, we plot the predicted PDs for different values of the key variables, while the other variables are set to their mean value. The predictions are based on specification (5) in table 3. Along with the PD we also plot the 95% confidence intervals, shaded in grey.

We can see in fig. 9 that the time in performing status has a hump-shaped effect on PD, which means that this variable especially matters for the PD of younger loans. The first 5 years spent in performing status see an increase in PD, whereas after this period the PD drops strongly and the loan has a higher survival probability.

Moreover, the effect of LTV is slightly nonlinear. At higher levels of LTV, an increase in LTV leads to a proportionally higher increase in PD. Especially when approaches negative equity territory, i.e. when LTV> 100% (or 1), the PD increases increases at a higher rate. This result supports the existence of the negative equity channel. When LTV rises to above 100, the owner of the real estate is in negative equity and thus more likely to default. Adding a negative equity dummy to our preferred specification confirms this assumption (not shown). Being in negative equity increases PD by approximately 2.5%.

The interest rate also has an increasing marginal effect. Figure 11 shows that at interest rates above 4%, the effect of interest rates on PD increases markedly. On the other hand, the uncertainty surrounding marginal effects above this level of interest rates is also greater due to the smaller amount of observations.

Figure 9: Effect of time spent in performing status

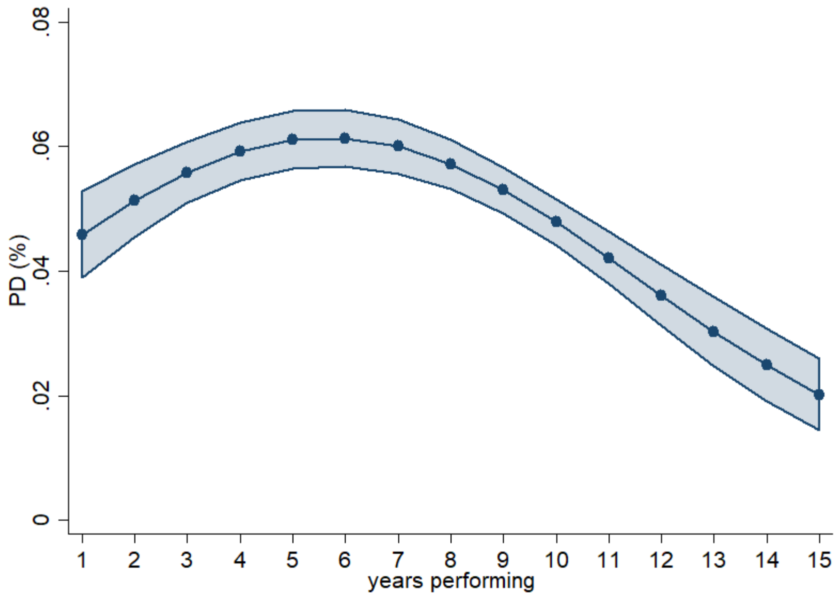
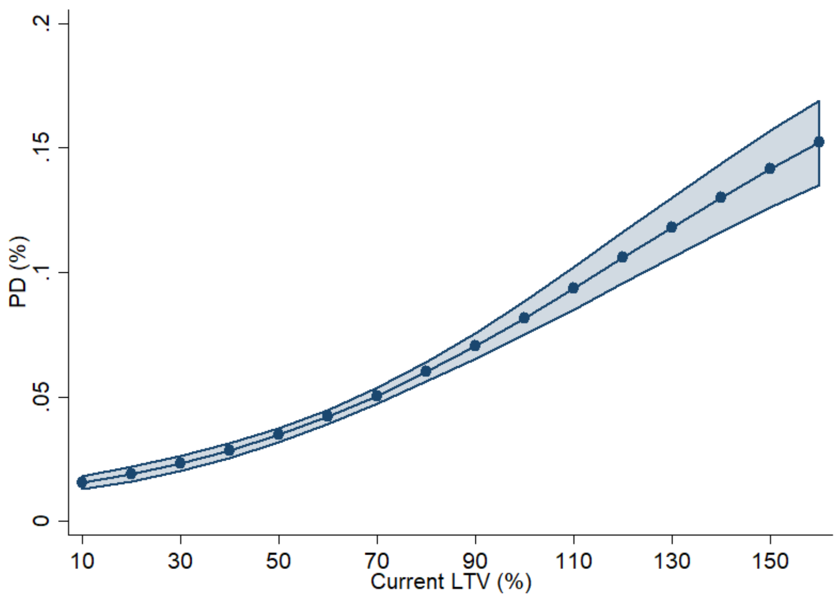
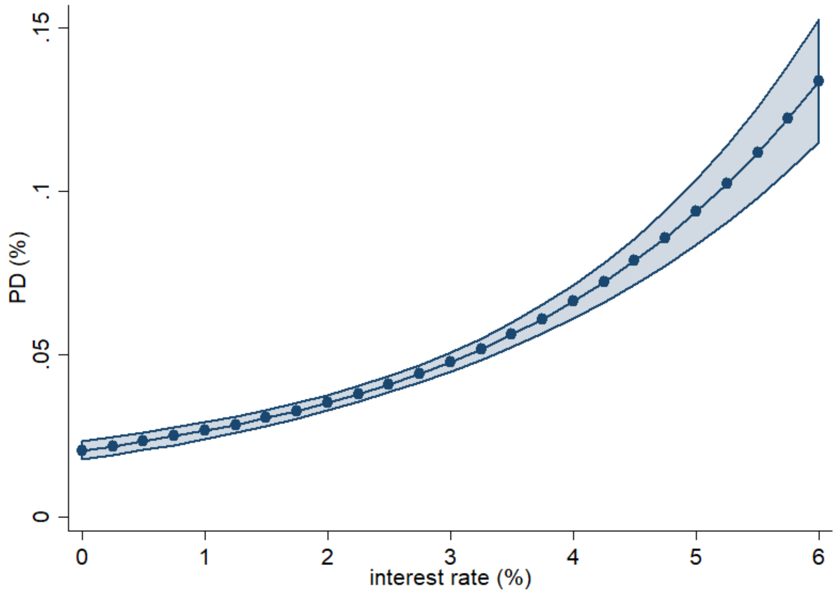


Figure 10: Effect of LTV on predicted PD



These results suggest that an increase in interest rates, e.g. due to monetary policy tightening, might impact the credit quality of CRE portfolios. Current interest rates appear to be significant driver of defaults, after we control for macroeconomic conditions, as well as loan and collateral characteristics.

Figure 11: Effect of interest rates on predicted PD

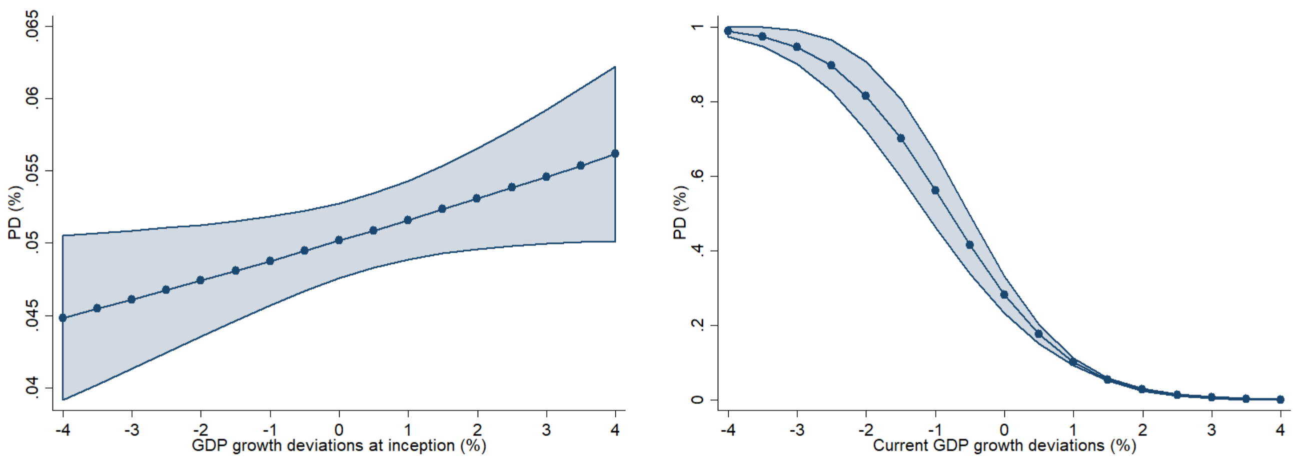


Loans extended in times of high growth and loose lending standards have a higher proportion of defaults, often accompanied by a more prolonged de-leveraging cycle. Such "boom" loans, originated during years with significant above-trend GDP growth (the peak of the cycle) have a higher PD; see fig. 12, left panel. Note that this effect is linear. Recent research (Kirti, 2018) supports the conclusion that a larger share of high yield bond issuance, a proxy for lending standards, during a credit boom goes hand in hand with lower GDP growth in the future. On the other hand, loans that have been originated during slump years are less risky, mainly due to a tightening of lending standards during these years, resulting in more conservative lending decisions. The Bank Lending Survey lending standards index at origination is instrumental in discriminating between good and bad economic growth, even though its coefficient is insignificant.

As opposed to loans originated during busts, the risk of "boom" loans does not decrease when economic conditions improve. The effect of current macroeconomic conditions on PDs is stronger in the recovery phase, which is when the economy moves from negative GDP growth deviations towards its long-run trend (fig. 12, right panel). On the contrary, when GDP growth deviations become even more positive (such as when the economy is close to trend, but growth accelerates) the marginal effect of GDP growth on credit risk becomes negligible and PD does not improve when the economy grows.

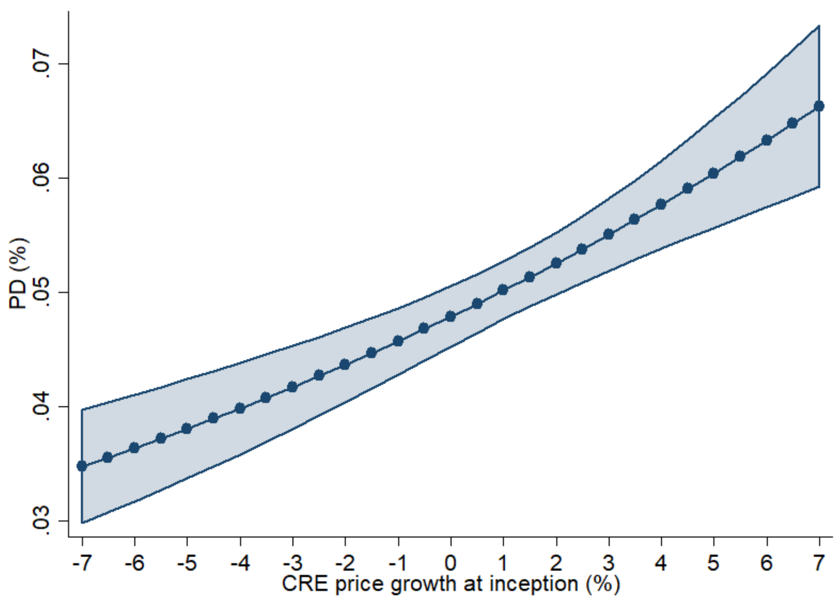
To complement the results for GDP growth deviation, we also look at the economic significance of

Figure 12: Effect of GDP deviations on predicted PD



price growth at inception. Figure 13 shows the strong positive relationship between CRE price growth at inception and PD: the default probability is nearly twice as high between the peak and the trough of the property cycle. Indeed, this result confirms that loans made at the peak of a property boom are riskier.

Figure 13: Effect of price growth at inception on predicted PD



Finally, readers familiar with the CRE market may have missed an important aspect relevant for credit risk: the occupancy rate of the real estate collateral. CRE investors' main source for servicing their debt is the rental income they derive from their collateral. A sufficient stream of rental payments requires that the real estate is largely, if not fully, occupied. Thus, a low occupancy rate (high vacancy rate) can signal an impending inability to make debt payments and thus higher credit risk. Unfortunately, the reported data are quite scarce on occupancy rate information; when we use the occupancy rate the number of observations drops by 70%. Moreover, the missing observations do not drop out randomly. To alleviate concerns regarding possible omitted variables bias, we present estimation results including occupancy rates in section 6.

6 Post-estimation and robustness tests

In this section we provide some post estimation and robustness tests. Specifically, we provide statistics and performance measures for the in-sample predictive ability of our baseline model specification. Then, we test for the presence of possible survivorship bias in our coefficient estimates and for the presence of heteroscedasticity, and we do a few robustness checks on omitted or confounding variables.

6.1 Predictive power

We investigate the in-sample performance of specification (5) of table 3, and specifically, the ability of the model to correctly classify defaults and non-defaults while minimizing false classification.

First, we examine the ROC curve which is depicted in fig. 14. This plot illustrates the diagnostic ability of the selected model, that is, to correctly classify a defaulted observation as default. It plots the True Positive rate (Sensitivity) against the False Positive Rate (1- Specificity).[4] An important statistic is the Area Under the Curve. A statistic number equal to 1 means that the model has perfect discrimination power giving no false positives, whereas if this statistic is 0.5, it means the model is no better than a random classification. In our case, the selected model has an area under the curve of 0.8799 which is quite satisfactory and implies good in-sample performance.

To further examine the performance of the model, we produce classification tables. However, our estimation sample is highly unbalanced with around 95.5% of counterparties performing and only around 4.5% of counterparties in default. This sample feature, called class imbalance, needs to be taken into account in the classification tables.

The model will classify a counterparty as defaulted when the predicted probability is above a certain cut-off point. For low cut-off points the model gives a high rate of true positives, but also a low rate of true negatives. In this case, we classify everything as defaulted. Therefore, we capture all defaults, but we also classify many non-defaulted exposures as defaulted. For higher cut-off points, we are more reluctant to

[4]True positive rate is the percentage of defaults classified correctly as defaults by the model; false Positive rate is the percentage of non-defaults classified incorrectly as defaults by the model; true Negative rate is the percentage of non-defaults classified correctly as non-defaults by the model.

Figure 14: ROC curve for selected specification

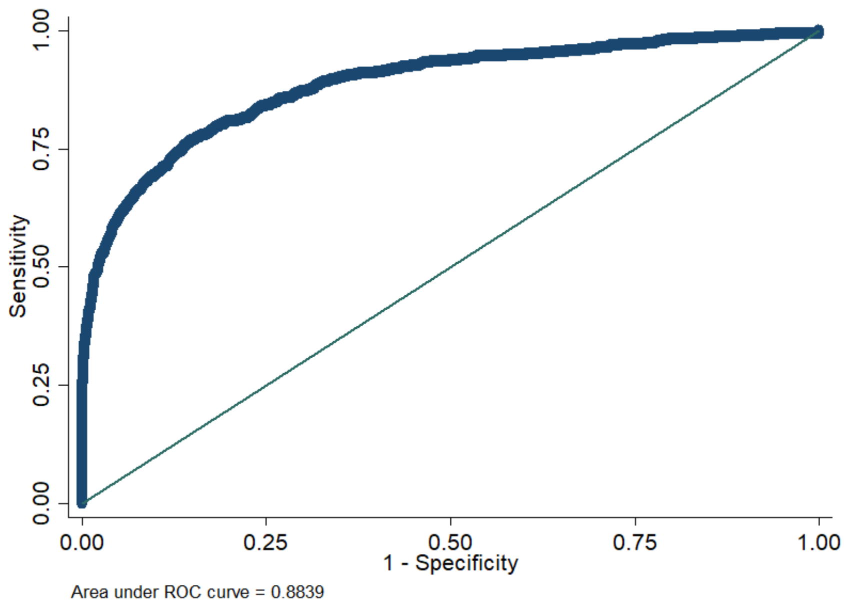


Table 4: Classification of observations for selected specification

	True		
Classified	Default	Performing	Total
Default	763	3450	4213
Performing	184	14305	14489
Total	947	17755	18702

classify an observation as defaulted. Therefore, we get only few true positives and too many true negatives, since everything is seen as non-defaulted. By varying the probability cut-off we obtain different combinations of true positive and true negative rates.

We chose the probability cut-off such that the correctly classified proportions of defaulted and performing counterparties are equal. To find this cut-off we examine the Sensitivity-Specificity plot in fig. 15. The intersection of these two curves will give the optimal true positive and true negatives rates. In our case this is achieved for a probability cut-off of around 4%.

For the chosen probability cut-off, we provide the classification table (table 4) and classification statistics (table 5). We observe that the chosen specification can correctly classify around 80% of defaulted and performing counterparties. Further, our model improves the false positive rates for classified defaults and the false negative rates for classified performing counterparties relative to a strict classification that sets all observations to default or all observations to non-default.

Figure 15: Sensitivity-Specificity graph for selected specification

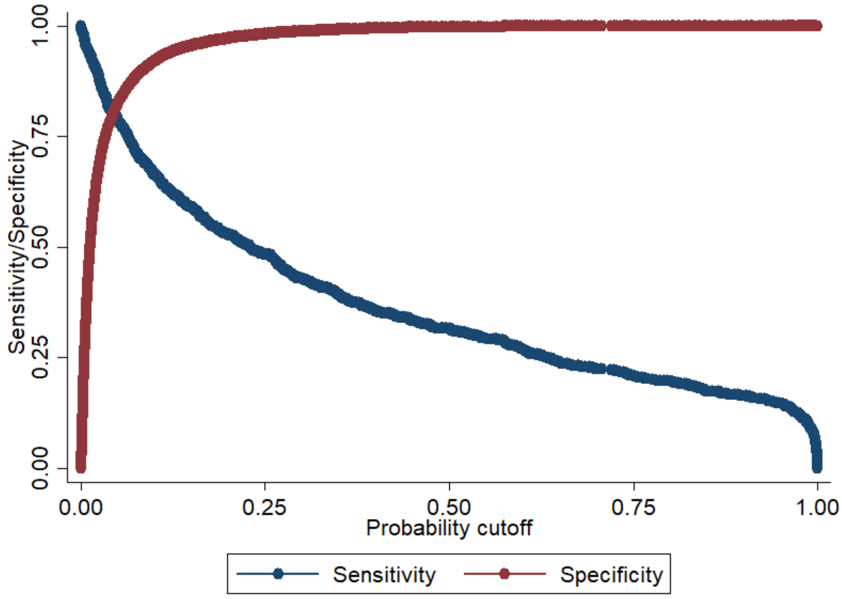


Table 5: Classification statistics for selected specification

Sensitivity	80.57%
Specificity	80.57%
Positive predictive value	18.11%
Negative predictive value	98.73%
False-positive rate given true negative	19.43%
False-negative rate given true positive	19.43%
False-positive rate given classified positive	81.89%
False-negative rate given classified negative	1.27%
Correctly classified	80.57%

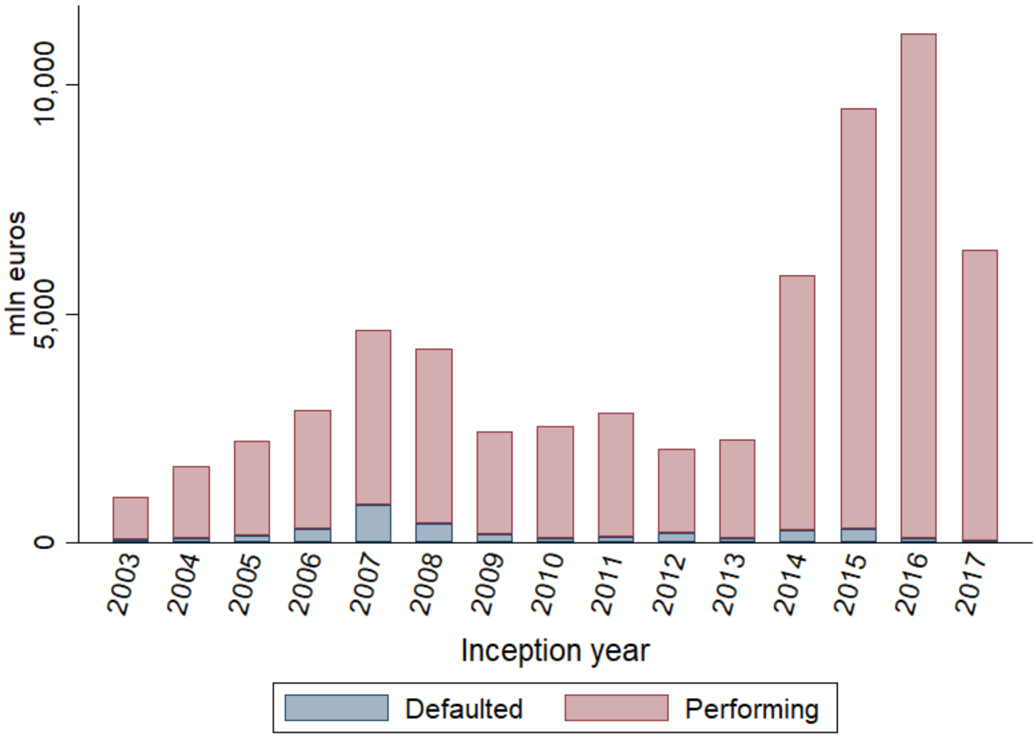
Probability cut-off has been set to 4.5%.

6.2 Survivorship bias

A possible caveat of using a snapshot of loan portfolios is the existence of possible survivor effects. Our data set contains only loans which are still performing at the time of reporting and loans which have been defaulted and have not been written-off at the time at the reporting date. The data set does not contain defaulted loans which have been removed from the loan book. This creates a potential survivorship bias which might impact our estimations.

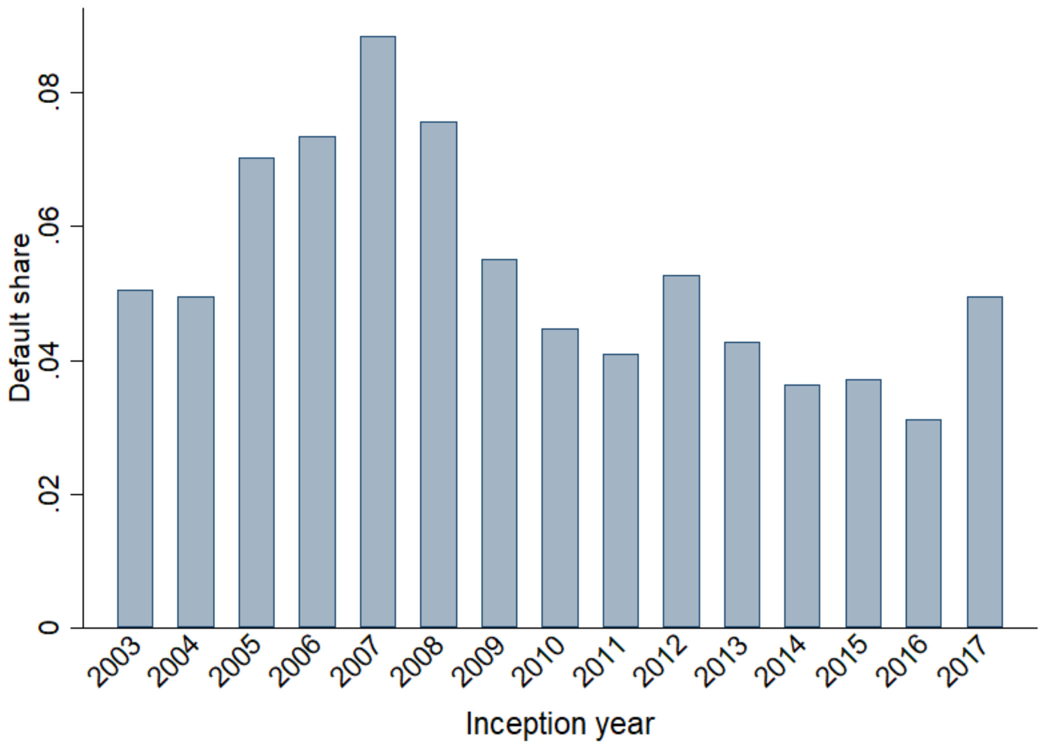
To illustrate the possible existence of the survivorship bias problem, first we plot in fig. 16 the total exposure per origination year. We observe that the bulk of the exposure in the portfolio is originated between 2014 and 2017. Consequently, exposures originated in older years are under-represented. This might happen due to portfolio structure, such as in the case the portfolio has relatively more short maturity loans which are frequently rolled-over and less longer maturity loans which remain for longer. Further, less exposures could appear to be originated in older years, either because loans have been defaulted and written-off or because loans have been amortized. The result in the latter cases will be that older origination years will present a deteriorating risk profile, since the good exposures are removed.

Figure 16: Total performing and default exposure per inception year



To investigate the risk profile of exposures with older origination years we plot the share of defaulted counterparties per inception year in fig. 17. We observe that indeed, older origination years are associated with more defaults. However, the result does not need to be only due to possible survivorship bias, but it can occur due to the fact that exposures originated in the run up and during the crises were simply riskier.

Figure 17: Share of defaulted counterparties per inception year



To test how the selection of the sample affects our estimates, we split the sample into loans originated before 2010 and loans originated after 2010 and we replicate our baseline logit specification. The estimation results are presented in table 6 below. Coefficients for the main loan and collateral characteristics remain relatively stable and significant. Coefficients of interaction terms turn insignificant when we split the sample. The coefficients of GDP and price deviations at inception turn insignificant at the second half of the sample. Moreover, one can note that the time a borrower spends in performing status has opposing effects on the probability of defaults in the two sub-samples. In the first half of the sample the time spent in performing has a negative coefficient, whereas in the full sample and the second half of the sample this coefficient estimate has a positive sign. The result can be attributed to the fact that exposures originated in the first half of the sample have been on average performing for longer time than exposures originated during the second half of the sample, implying a potential downward bias for the estimate of this coefficient in the first half of the sample. Further, the coefficient of GDP growth deviations at inception remains positive only for the first half of the sample and not the second, implying that the effect of the business cycle at origination on PD is mostly driven by the events that occurred around the Financial Crisis.

Table 6: Main estimation results, splitting the estimation sample

	(1) full sample	(2) before 2010	(3) after 2010
In default			
Time in performing (years)	0.2278***	-6.9125***	0.1573
	(0.05)	(0.47)	(0.15)
Time in performing, squared	-0.0201***	0.3016***	-0.0484*
	(0.00)	(0.02)	(0.02)
Current Loan to Value	0.0365***	0.0261***	0.0464***
	(0.00)	(0.00)	(0.01)
Current Loan to Value, squared	-0.0001***	-0.0001***	-0.0001***
	(0.00)	(0.00)	(0.00)
Current interest rate	0.7308***	0.6782***	0.7924***
	(0.06)	(0.08)	(0.13)
Share of bullet loans	0.0225*	0.0225*	0.0221
	(0.01)	(0.01)	(0.02)
Share of variable rate loans	0.0292***	0.0260***	0.0298***
	(0.00)	(0.00)	(0.01)
Share of residential real estate	-0.0045***	-0.0035*	-0.0066**
	(0.00)	(0.00)	(0.00)
Private client	-0.1338	0.3201	-0.5262
	(0.32)	(0.51)	(0.54)
Foreign counterparty	-1.1770**	0.5575	-2.1253***
	(0.44)	(0.70)	(0.64)
Real estate firm	-0.1986*	-0.1690	-0.1588
	(0.10)	(0.14)	(0.18)
Builder/developer	-0.1915	0.0335	-0.2624
	(0.25)	(0.38)	(0.42)
GDP growth deviation, inception	0.0437*	0.4060***	-0.1489*
	(0.02)	(0.03)	(0.06)
GDP growth deviation, default	-1.6212***	-1.6167***	-1.7122***
	(0.11)	(0.18)	(0.19)
Lending standards, inception	0.2189	-2.1580***	0.9346*
	(0.16)	(0.23)	(0.45)
Observations	18702	9461	9157
Bank fixed effects	Yes	Yes	Yes
Time fixed effects	No	No	No
Province fixed effects	No	No	No
Client location fixed effects	Yes	Yes	Yes
Interaction Terms	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, it is difficult to judge to what extent possible survivorship effects might bias our estimates. When we divide our sample into old and new exposures, it becomes apparent that possible negative bias might be present in the estimates of the coefficient for the time a borrower has spent in performing status and potential positive bias in the coefficient of GDP growth deviations at inception. The rest of the coefficients, however, seem to be robust to this sample split.

6.3 Heteroscedasticity tests

Parametric binary choice models such as probit and logit impose restrictive assumptions on the error term distribution. Specifically, these models assume, among others, that errors are homoscedastic. In practice, this assumption is rarely satisfied, and a usual problem that arises is biased coefficient estimates.

To test for the presence of this form of heteroscedasticity, we estimate an heteroscedastic probit which relaxes the assumption of constant variance and allows it to depend on a number of observable characteristics. We opt to model the variance of the error term as a function of time spent in performing, current LTV and our loan and client characteristics. We test for the presence of heteroscedasticity by testing whether the coefficients of the variables included in the variance specification are jointly significant. The F-test suggests that we reject the null hypothesis at the 1% confidence level and that heteroscedasticity might be present in the data. An alternative reason for the presence of heteroscedasticity might be that we have misspecified the baseline logit functional form. However, a misspecification of the heteroscedasticity functional form will lead to different sources of bias in the estimates. In any case, we do not attempt to further solve the heteroscedasticity problem since possible solutions are also prone to misspecification errors.

6.4 Testing for several omitted variables

Table 7 displays several robustness checks. As a benchmark, column 1 shows our preferred specification.

A first check is to see whether the price effect that we find in our main results section is due to its interplay with LTV. Prices can affect probability of default through current LTVs: when prices decline, LTVs will increase and the risk of default will go up through the negative equity channel. This means that the price effect is already partly captured, indirectly, by LTVs. Column 2 shows what happens when we leave out LTV; as we have seen that GDP is strongly correlated with prices, leading to confounding, we also leave out the two GDP variables. We see that the effect on PD of price growth at inception is now even larger than in our main results (column 4 of table 3). This indeed suggests that part of the price effect at inception is captured by LTV: peak prices at inception are likely to be followed by price drops at time of default, and thus a high LTV at default. As this price effect is partly captured by LTV, we see a drop in the price coefficient when LTV is also included (in the main regression).

In column 3 we add another variable important to commercial real estate, namely the occupancy rate of the real estate collateral (as explained at the end of section 5). Unfortunately, this variable is only available for 30% of the observations in our main specification. The lack of data points seriously impedes estimation power, which is exemplified in column 3 of table 7. In this specification the number of observations drops drastically, and the standard errors of our observations increase markedly, to the extent that the coefficient estimate of GDP deviation at inception is no longer significant (it remains positive, but slightly smaller). On the other hand, the sign and significance of most other coefficients remains the same, although their magnitude changes slightly. Leaving out occupancy rate thus has some effect, but it is not major.

A final check, shown in column 4, is for the effect of non-CRE collateral. When extending commercial real estate mortgage loans, bank often ask for more credit risk protection than just a claim on the the real estate: they can demand guarantees, pledged securities or even cash collateral. This is especially helpful for more risky loans or loans with real estate of questionable quality underlying them, as the non-real estate collateral provides an extra cushion against credit risk. To test this hypothesis, we create a dummy that indicates whether a loan has one or more non-CRE collateral items pledged. One would expect the relationship between this dummy and default risk to be positive. Indeed, the coefficient confirms this, but it is insignificant. A possible reason for this insignificance is that only 94 defaulted loans (out of 947 in the estimation sample) have non-CRE collateral; there are just too few degrees of freedom.

Table 7: Checking for confounding and omitted variables

	(1)	(2)	(3)	(4)
In default				
GDP growth deviation, inception	0.0437*		0.0380	0.0437*
	(0.02)		(0.04)	(0.02)
GDP growth deviation, default	-1.6212***		-1.7288***	-1.6233***
	(0.11)		(0.17)	(0.11)
Lending standards, inception	0.2189	0.3331*	0.1142	0.2177
	(0.16)	(0.15)	(0.30)	(0.16)
Time in performing (years)	0.2278***	0.6219***	0.3309**	0.2290***
	(0.05)	(0.08)	(0.11)	(0.05)
Time in performing, squared	-0.0201***	-0.0583***	-0.0285***	-0.0202***
	(0.00)	(0.01)	(0.01)	(0.00)
Current Loan to Value	0.0365***		0.0607***	0.0364***
	(0.00)		(0.01)	(0.00)
Current Loan to Value, squared	-0.0001***		-0.0001***	-0.0001***
	(0.00)		(0.00)	(0.00)
Current interest rate	0.7308***	0.7459***	0.6244***	0.7303***
	(0.06)	(0.07)	(0.13)	(0.06)
Share of bullet loans	0.0225*	0.0307***	0.0193	0.0226*
	(0.01)	(0.01)	(0.02)	(0.01)
Share of variable rate loans	0.0292***	0.0327***	0.0269***	0.0292***
	(0.00)	(0.00)	(0.01)	(0.00)
Share of residential real estate	-0.0045***	-0.0047***	-0.0039	-0.0045***
	(0.00)	(0.00)	(0.00)	(0.00)
CRE price growth, inception		0.1467***		
		(0.02)		
Occupancy rate			-0.0105***	
			(0.00)	
Non-CRE collateral posted				0.1154
				(0.17)
Observations	18702	18634	6483	18702
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	No	No	No	No
Province fixed effects	No	No	No	No
Client location fixed effects	Yes	Yes	Yes	Yes
Interaction Terms	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Conclusions

Buoyant activity in the commercial real estate (CRE) sector over the last years has attracted the attention of investors and regulators alike. The CRE market has demonstrated strong pro-cyclicality in the past and has proven to be quite volatile. It is thus a sector closely monitored for financial stability purposes. With this paper we aim to shed light to the main drivers of default in the CRE market, as well as to provide insights on the relationship between the business cycle and credit risk in the CRE market. To do so, we exploit a unique granular data set for the CRE exposures of the largest Dutch banks. To improve identification of macroeconomic factors we introduce regional macroeconomic variation, both current and at the time of loan origination, by making use of the real estate location. To disentangle the effect of the business cycle on defaults we control for lending standards at origination.

Our main findings suggest that borrowers with loans originated at the peak of the cycle are riskier, as these borrowers have a higher Probability of Default (PD). This effect holds for the business cycle as well as the property cycle: we find higher PDs at the peak of both cycles. Indeed, in our estimation both cycles largely coincide. Moreover, these borrowers remain risky, despite further improvement of macroeconomic conditions. We interpret these findings as evidence of the cyclical nature of commercial real estate finance. The worst performing loans are originated at the peak of the cycle, while during a bust lenders are conservative. Note that we find this effect above and beyond the effect of banks' self-reported lending standards: even when controlling for these, the effect remains.

We also find that interest rates are strongly positively correlated with default risk, and in line with the literature, we find that variable rate loans are riskier. This means that an increase in interest rates, for instance due to a tightening of monetary policy, can be accompanied with more defaults on commercial real estate loans. On top of that, when risk premia for CRE loans rise we may also see more defaults.

Loans with a higher LTV have a higher default probability as well, which supports the negative equity channel that is already well-documented for residential mortgages and corporate loans in general. We show it also holds for CRE loans: above an LTV of 100% (negative equity territory), PD increases even steeper with LTV. Loans with a higher share of non-residential real estate (offices, retail shops, industrial buildings) as collateral are also more risky, which indicates that volatility in the these market segments can negatively affect debt service ratios and trigger defaults.

Interestingly, time has a non-linear, hump-shaped effect on PDs. In the first few years, borrowers become riskier, but after five years time works in favour of their survival. This result can also be interpreted as a survivor effect, which is partly supported by our robustness checks.

Our results have implications for both microprudential and macroprudential supervisors. Policy makers should be monitoring lending standards closely, especially towards the peak of the cycle, since they can serve as an indicator for subsequent defaults when the business cycle finally turns. Moreover, the relationship of credit risk with the business cycle suggests that a dynamic provisioning scheme (Jiménez et al., 2017) could discourage lenders to take excessive risks during the upturn and make them less reluctant to lend during the downturn. Such provisioning scheme would not allow banks to reduce loan loss provision coverage for new loans as the economy further improves. Similarly, to stimulate lending during the recovery phase of the business cycle, policy makers could allow banks to reduce loan loss provision coverage of new loans in line with the decrease in the underlying credit risk. As regards to microprudential supervision, our results suggest that supervisors should be monitoring developments in the characteristics of the portfolios as well those of the collateral. Supervisors can use the uncovered relationships between loan characteristics, cyclical developments and default risk to target those loans that are more likely to cause problems for banks.

Naturally, our analysis comes with caveats, mainly due to the lack of comprehensive panel data and remaining data quality issues in our data set. Nevertheless, we think this analysis increases our collective understanding of the link between credit risk in the CRE market, lender behavior and the macro-economy, and therefore contributes to the on-going policy debate. Future work could focus on how lending standards and lenders' behaviour changes over the business cycle and also how price and non-price terms of lending are affecting by changes in risk perceptions driven by the business cycle. As time progresses, we will be able to create a panel data set, which can help in analysing the evolution of lender behaviour.

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A Definitions of variables

Table 8: Variables definitions

variable	definition	transformation
Counterparty level variables		
Outstanding	sum of current outstanding balances for all instruments related to the counterparty	log and levels
Exposure	sum of current exposure for all instruments related to the counterparty	log and levels
Allocated value	sum of current collateral value for all collateral posted by the counterparty	log and levels
Current loan to value, reported	reported current LTV at the risk pool level	percentage
Current interest rate	exposure weighted average of current insterest rate on all instruments of the counterparty	percentage
Number of loans	number of instruments linked to the counterparty	levels or logs
Time in performing	years since the inception date of the oldest instrument of the counterparty	levels or logs
Foreign counterparty	indicator for foreign counterparties	dummy
Real estate firm	indicator if NACE2 activity code is 68	dummy
Builder/developer	indicator if NACE2 activity code is 41 or 42	dummy
Share bullet loans	exposure share of bullet loans for the counterparty	percentage
Share variable loans	exposure share of variable interest rate loans for the counterparty	percentage
Share residential	collateral value share in residential RE for the counterparty	percentage
Share office	collateral value share in offices RE for the counterparty	percentage
Share retail	collateral value share in retail RE for the counterparty	percentage
Performing	indicator if borrower is performing	dummy
Arrears	indicator if borrower is in arrears	dummy
Special Asset Management	indicator if borrower is in a SAM facility	dummy
Default	indicator if borrower is defaulted	dummy
Bank	dummy for each bank	percentage
Macro-economic variables		
GDP deviation at inception	Deviation of regional yearly GDP growth rate from its 1996-2016 trend* at the time of inception of the first loan	percentage
Current GDP deviation	Current deviation of regional yearly GDP growth rate from its 1996-2016 trend*	percentage
Lending standards at inception	Bank Lending Survey Credit Standards index, Total enterprises next quarter at the time loan inception	level
CRE price growth at inception	Quarterly growth rate of CRE price index for all properties at inception	percentage

* The trends are estimated at the region level with an HP filter.

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