WHAT ARE THE DETERMINANTS OF LOSS GIVEN DEFAULT FOR COMMERCIAL REAL ESTATE LOANS?

BY

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In front of you lies my master thesis “the determinants of loss given default for commercial real estate loans”. This thesis extends previous work on loss given default by using a unique confidential loan-level dataset. This thesis was writing during my internship at the Dutch Central Bank (DNB) at the division Financial Stability (department Macroprudential Analysis and Policy) and marks the end of my master Real Estate Studies at the University of Groningen. This thesis combines not only everything that I have learned, but also combines my two main interests; Real Estate and Economics. At the same time, this master thesis marks the beginning of a new period. I am excited to see what the future holds.

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ABSTRACT

Whereas previous research examined defaulted commercial real estate loans and hence the point-in-time loss given default, this paper is the first to examine downturn loss given default for healthy as well as defaulted commercial real estate loans from healthy Dutch banks. Using confidential loan-level data provided by the Dutch Central Bank, this paper shows that borrower and loan characteristics are strong determinants of downturn loss given default. More importantly, the results shows that the downturn loss given default of the collateral type is dependent on the location of the collateral. Thus, heterogeneity should be taken in to account.

Keywords: Loss Given Default, Commercial Real Estate, Bank Loans, Credit Risk

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Disclaimer: Master theses are preliminary materials to stimulate discussion and critical comment. The analysis and conclusions set forth are those of the author and do not indicate concurrence by the supervisor or research staff, nor do they necessarily represent the views of the Dutch Central Bank. More importantly, this master thesis contains confidential data provided by the Dutch Central Bank. Any publication and duplication of this master thesis - even in part – is prohibited.

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1. INTRODUCTION

Since financial institutions incurred substantial losses on commercial real estate (CRE)[1], CRE has received great attention from supervisors at the national and European level (De Nederlandsche Bank, 2012, 2015). In the Netherlands, SNS Property Finance, the real estate subsidiary of SNS Reaal, made tremendous losses on their CRE loans. As a consequence, SNS Reaal was nationalized in 2013. Subsequently regulation and supervision on this specific asset class became stricter. For example, in the Netherlands the Dutch Central Bank (DNB) and the Authority of Financial Markets made recommendations to improve the quality of CRE appraisals. More importantly, DNB closely monitors the CRE loan portfolio of Dutch banks. As a result, Dutch banks are currently less vulnerable to CRE losses since they inter alia reduced the size of their CRE loan portfolio by disposing poor performing CRE loans (De Nederlandsche Bank, 2015). The exposure of Dutch banks on CRE is however still significant. According to DNB (2015) these loans are relatively risky since the underlying collateral is mostly located at B and C locations. To mitigate the risk of the underlying portfolio, banks are forced to hold a minimum amount of capital requirements. Banks have to calculate their own regulatory capital requirements through the Advanced Internal Rating Based (A-IRB) approach based on internal credit risk estimates (Basel Committee on Banking Supervision, 2005). The key parameters that determine credit risk are probability of default (PD), loss given default (LGD) and exposure at default (EAD). PD and LGD are calculated given the EAD. Academics have mainly focused on the PD due to the availability of data but the literature on LGD is growing. Research on LGD is however impeded by a lack of (public) data and as a result there are still large knowledge gaps.

LGD is "a measure of the expected average loss that the bank will experience per unit of exposure should its counterparty default. Unlike PD, where a borrower can have only one borrower rating (and thus one PD), different exposures to that borrower may have very different LGD profiles, given facility-specific features" (Basel Committee on Banking Supervision, 2001: p.18). Under the A-IRB approach, banks are allowed to use internal estimates to calculate LGD, which should reflect economic downturn conditions.[2] Previous research on LGD has mainly focused on loss severity of corporate bonds (Acharya, Bharath & Srinivasan, 2003; Altman, Brady, Resti & Sironi, 2005). However, due to their private nature, less studies have been conducted on bank loans. Studies that have examined the LGD from bank loans, have all focused on defaulted bank loans (Asarnow & Edwards, 1995; Dermine & De Carvalho, 2006; Caselli, Gatti & Querci, 2008; Košak & Poljšak, 2010). Next to corporate bonds and loans, research has been done on the LGD of defaulted residential mortgages (Clauretie & Herzog, 1990; Qi & Yang, 2009; Park & Bang; 2014). Research on CRE loans however has been very limited: Shibut and Singer (2015) examined distressed CRE loans from banks that were resolved by the Federal Deposit Insurance Corporation between 2008 and 2013, whereas Ross and

[1] CRE is defined as incoming-producing real estate (European Systemic Risk Board, 2015).
[2] For more information on inter alia the A-IRB approach, as part of the Basel II framework, see appendix 2.

Shibut (2015) use a subset from the same database. However, Ross and Shibut (2015) acknowledge that their findings should be interpreted with care since they use CRE loans from failed banks, and CRE loans from healthy banks may respond very differently. Furthermore, their dataset is censored and consist of loans that defaulted during a period of sever distress (2008-2014).

This paper looks at the determinants of downturn LGD for CRE loans from healthy Dutch banks.[3] Previous research has solely focused on defaulted bank loans and hence looked at the actual loss of a loan given that the loan is in default (the so called point-in-time LGD). Contrary to previous research, this research will focus on the full CRE portfolio comprising of healthy as well as defaulted CRE loans, thereby examining the so called downturn LGD instead of the point-in-time LGD.[4] Furthermore, whereas previous research mainly focused on the borrower and loan characteristics as determinants of LGD, this paper will look at the impact of collateral characteristics on downturn LGD. By including collateral characteristics, this research will examine inter alia the effect of the location on downturn LGD. Collateral located at B and C locations is generally more risky and vacancy rates are often high in these regions. This study will examine whether the premise that collateral located in B and C locations is riskier (measured by downturn LGD) indeed holds. Next to the location of the collateral, this study will be the first to examine the effect of the amortization schedule, the classification of the counterparty (private borrower or not), the nationality of the borrower (Dutch or non-Dutch), the interest rate type (fixed or variable) and the type of collateral on downturn LGD. More importantly, this paper examines whether the downturn LGD of the collateral type is dependent on the location of the collateral. By looking at both healthy and defaulted CRE loans and including additional variables, this paper extends previous work on LGD by using a unique loan-level dataset from Dutch banks.

The results show that borrower and loan characteristics are strong determinants of downturn LGD. To be specific, this paper finds a negative relationship between downturn LGD and the intensity of the relationship, the age of the loan and the outstanding nominal amount. On the other hand, private borrowers have a higher downturn LGD than non-private borrowers. Interestingly, loans that originated during or after the global financial crisis (GFC) have a lower downturn LGD than loans that originated before the GFC. Furthermore, this paper finds a positive relationship between downturn LGD and PD. CRE loans with a variable interest rate have a higher downturn LGD than loans with a fixed interest rate type. Moreover, bullet loans have a higher downturn LGD than loans with an amortization schedule. Lastly, this paper shows that the downturn LGD of the collateral type is dependent on the location of the collateral. Thus, heterogeneity should be taken in to account.

The rest of the paper is structured as follows. In section 2 the relevant literature will be discussed. Section 3 describes the data and methodology in detail. The results are reported in section 4 and the robustness of the results are examined in section 5. Finally, the conclusions are provided in section 6.

[3] The determinants in this paper are categorized in borrower-, loan- and collateral characteristics.
[4] Appendix 2 provides more information on the difference between the point-in-time and downturn LGD.

2. LITERATURE REVIEW

The literature review is structured as follows. In section 2.1 the borrower characteristics that affect LGD are discussed. In section 2.2 the literature on the loan characteristics as determinants of LGD are reviewed and in section 2.3 the collateral characteristics are discussed.[5]

2.1 Borrower Characteristics

Relatively few studies have included borrower characteristics due to the lack of detailed data. Nevertheless, borrower characteristics are considered to be important determinants of LGD. To begin with, the PD is related to the borrower whereas LGD is related to the loan. Previous research on bonds have found a negative relationship between recovery rates (RR)[6] and default rates (Frye, 2000; Gupton, Hamilton & Berthault, 2001; Altman et al., 2005), where both are related to economic conditions: if there is a recession, defaults rates are higher and RRs are lower since bonds are most likely sold for a lower price than if the economy is stable. Previous studies that examined the point-in-time LGD of bank loans only looked at defaulted bank loans. Consequently, the PD of these loans is 100 percent. Since this study focusses on the downturn LGD of both defaulted and healthy loans, the PD however is not always 100 percent.

Inherent to bank lending is the problem of asymmetric information between the bank and the borrower. According to relationship lending, a strong bank-borrower relationship can overcome the problem of informational asymmetry between the bank and the borrower and hence can reduce credit risk (Belaid, Boussaada & Belguith, 2017). Closes ties between the bank and the borrower are based on the development of a privileged, collaborative and repeated relationship between the bank and borrower, where the bank invests in the collection of soft information (Cotugno, Monferrà & Sampagnaro, 2013). According to Berger and Udell (1995), banks acquire more private information as the bank-borrower relationship intensifies and subsequently use this information. On the other hand, it could be the case that a strong bank-borrower relationship increases the willingness of the borrower to take on risk (Jiménez & Saurina, 2004). Grunert and Weber (2009) examined the effect of the intensity of the bank-borrower relationship on LGD. The intensity of the bank-borrower relationship is measured by several variables, namely (i) a dummy variable that measures whether the borrower had 1 or more contract(s) in the past; (ii) the distance (in kilometers) from the bank headquarters and the domicile of the borrower and (iii) the ratio of the EAD and the total assets of the firm. They found that the RR is higher when the

[5] Besides borrower, loan and collateral characteristics, industry characteristics and macroeconomic variables are found to have an impact on LGD. Since this paper only focusses on commercial real estate, industry characteristics are not relevant. Lastly, this paper does not include macroeconomic variables since the data used in this study is cross-sectional.

[6] The literature does not always focus on the determinants of LGD per se but on the RR. Since LGD is 1 minus the RR, the literature on RR is still relevant and applicable. In the literature review, no explicit distinction is made between RR and LGD and hence the findings on RR and LGD will both be discussed and, if not specifically mentioned, regarded as equal. More importantly, previous studies have focused on the point-in-time LGD and not on the downturn LGD. In the rest of the literature review, LGD is used for both the point-in-time LGD as well as the downturn LGD. When the effect is expected to differ, it is explicitly mentioned.

borrower had 1 or more contract(s) in the past. The other two variables that measure the intensity of the bank-borrower relationship were not significant. They argue that "an intense relationship improves the access to collateral and increases the influence on the business policy and work-out-process of the company" (Grunert & Weber: p. 512). Dermine and De Carvalho (2006) also examined the effect of a strong bank-borrower relationship on LGD, measured by the number of years the borrower was a borrower with the bank. However, they found no significant relationship.

To the author's knowledge, literature has not yet examined the difference in credit risk between private borrowers and non-private borrowers.[7] Under the assumption that private borrowers are more credit constrained than firms, which are less capital constrained, downturn LGD for private borrowers will be higher than for non-private. As a result, non-private borrowers are (more) able to repay the loan than private borrowers, which decreases downturn LGD. Strahan (1999) found that smaller borrowers, borrowers with less cash and borrowers that are harder for outside investors to value are more risky. For outside investors, firms are in general more easy to value since (financial) documentation is publicly available. Private borrowers on the other hand are harder to value and often do not have a track record. Moreover, private borrowers are often smaller borrowers than non-private borrowers.[8]

Lastly, Shibut and Singer (2015) look at the impact of the borrower's location on LGD. They are especially interested in the effect of out-of-territory lending on LGD, where out-of-territory loans are loans to counterparties outside those areas where the failed bank had a branch. They find that LGD is consistently higher for out-of-territory CRE loans. Hence, their results indicate that there is an effect of the location of the borrower on LGD.

2.2. Loan Characteristics

Overall the existing literature has found strong evidence for the influence of loan characteristics on LGD. Research has shown that bank loans (Carty & Lieberman, 1996; Gupton, Gates & Carty, 2000; Araten, Jacobs & Varshney, 2004; Dermine & De Carvalho; 2006; Grunert & Weber, 2009; Khieu, Millineaux & Yi, 2012), bonds (Altman & Kishore, 1996; Altman et al., 2005) and securities (Acharya, Bharath & Srinivasan, 2007) that are securitized by collateral consistently have a lower LGD. If a loan (or bond) is securitized by collateral, the lender would be able to sell the collateral ones the borrower defaults, which would decrease LGD since the RR increases. Given that all CRE loans in this study are securitized by collateral, collateral per se is not relevant for this study. The characteristics of the collateral are however extremely relevant and are therefore discussed separately in subsection 2.3.

Several papers have looked at the effect of the EAD (Grunert & Weber, 2009; Košak & Poljšak, 2010; Shibut & Singer, 2015) or the original loan amount (Dermine & De Carvalho, 2006; Qi & Yang, 2009; Park & Bang, 2014) on LGD. The EAD cannot be used since this paper also includes healthy

[7] A private borrower is borrower than can either be classified as 'private' or 'retail'.
[8] In the dataset private borrowers are indeed smaller borrowers than non-private borrowers (measured by the mean outstanding nominal amount).

CRE loans. Furthermore, if a borrower decides to amortize the loan, the outstanding loan amount will be lower than the original loan amount. For this study, the original loan amount is also less valuable since the dataset contains bullet loans as well as loans with an amortization schedule. Therefore, this paper does not look at the EAD or the original loan amount but at the effect of the outstanding nominal amount on downturn LGD. The question however still remains the same irrespective of the chosen measurement, namely: does loan size have a negative or positive effect on LGD? Scholars have mainly found that a larger EAD results in a higher point-in-time LGD (Hurt & Felsovalysi, 1998; Dermine & De Carvalho, 2006; Park & Bang, 2014). On the contrary, Ross and Shibut (2015) found that larger loans have lower losses. Shibut and Singer (2015) argue that loan size may matter for small CRE loans (smallest quartile) only. Qi and Yang (2009) find similar results for residential mortgages: they find that for residential mortgages less than or equal to 60 or 80 percent of the area median home price at origination LGD is higher.[9] Qi and Yang (2009) and Shibut and Singer (2015) argue that fixed costs related to the sale of a commercial or residential property may explain why LGD is higher for smaller loans than for larger loans, since the costs exceed the expected selling price. Following Qi and Yang (2009), Park and Bang (2014) construct dummy variables that take the value of one if the loan is less than 60 or 80 percent or greater than 110 percent of the area median home price and zero otherwise. Park and Bang (2014) are however not able to replicate the findings of Qi and Yang (2009) since they find that LGD increases with the size of the loan.

Several studies have examined the relationship between LGD and the age of the loan, which is the time between the date of default and the origination date (Lekkas, Quigley & Van Order, 1993; Calem & LaCour-Little, 2004; Qi & Yang; Park & Bang, 2014; Shibut & Singer, 2015). Lekkas, Quigley and Van Order (1993) find a negative relationship between the age of the loan and loss severity, implying that losses are lower for older loans. They argue that the relationship is negative because older loans have a shorter time to maturity. Furthermore, older loans have a lower percentage of the original loan amount outstanding than younger loans, which decreases loss severity.[10] Pennington-Cross (2003), Shibut and Singer (2015) and Ross and Shibut (2015) also found higher LGDs for loans that defaulted shortly after origination. Shibut and Singer (2015) argue that the quality of the loan is lower if the loan quickly defaults after origination. On the other hand, Calem and LaCour-Little (2004) and Qi and Yang (2009) find the opposite, namely that LGD increases if the loan ages, while Park and Bang (2014) found no effect at all.

The origination year of the loan itself may also be a determinant of LGD. Shibut and Singer (2015) found that CRE loans which originated well before the GFC have a lower LGD than loans that originated in the height of the crisis or shortly before the crisis began. Nevertheless, the relationship for commercial and industrial loans is weak and nonexistent for construction and development loans. In the

[9] The author acknowledges that residential and commercial real estate are not completely similar. Unfortunately, less has been written on commercial real estate and therefore findings on residential real estate are often used.
[10] This of course only holds if the loan is amortized.

wake of the crisis, banks were required to inter alia meet stricter capital requirements and restore their balance sheets (Claessens & Van Horen, 2015). Furthermore, liquidity tried up in the interbank market, which caused funding problems. Subsequently, banks reduced lending during the GFC to strengthen their balance sheets. De Haas and Van Horen (2010) found that the reduction in bank lending was partly caused by stricter bank screening and monitoring. Moreover, regulation also strengthened after the GFC (e.g. Basel III).

Extensive research has been done on adjustable rate mortgages (ARM) versus fixed rate mortgages (FRM) for residential mortgages. Surprisingly, to the author's knowledge, no research has been done on adjustable versus fixed interest rate CRE loans. Research on residential mortgages has shown that ARMs are more likely to default than FRMs (Noordewier, Harrison, & Ramagopal, 2001; Smith, 2011; Archer & Smith, 2013). Noordewier, Harisson and Ramagopal (2001) include a dummy variable that takes 1 if the loan is an adjustable rate loan and zero otherwise. As hypothesized, they find that ARMs are more likely to default. Moreover, ARMs are riskier than FRMs due to payment shocks from higher payments. ARMs are also more risky due to borrower characteristics. Posey and Yavas (2001) examined whether "borrowers with different levels of default risk self-select between FRMs and ARMs and whether the mortgage selection can serve the lenders as a signal of borrowers' default risk" (p.55). They showed that under asymmetric information, where the risk appetite of the borrower is unknown by the lender, high-risk borrowers choose ARMs and low-risk borrowers choose FRMs. Thus, the chosen mortgage serves as a signal of default risk. Previous research on LGD has not examined the possible effect of a fixed versus an adjustable rate loan on LGD. To the author's knowledge, this paper will be the first to examine the effect of the chosen interest rate schedule on downturn LGD.

Recall that older loans have a lower percentage of the original loan amount outstanding than younger loans, which is expected to decrease loss severity. Logically, this only holds if the loan is amortized. The loan amortization schedule is therefore expected to have an impact on LGD. If the loan is not amortized, the principal amount is fully repaid in the last installment. Hence, the risk shifts towards the end of the loan which increases credit risk. Credit risk thus reduces significantly when the loan is amortized. Noordewier, Harisson and Ramagopal (2001) include a dummy variable that takes 1 if the loan is a balloon loan and zero otherwise. Balloon loans are loans that do not fully amortize. Furthermore, balloon loans often have a reset option at which the bank and borrower are able to renegotiate the contract. They argue that balloon loans may be more risky because of the large payment due at the expiration date of the loan. As expected, they indeed find that balloon loans are more likely to default. However, the authors acknowledge that they do not know whether this result is from renegotiating the contract (which could inter alia result in an increase in monthly payments due to a higher interest rate) and/or (ii) recontracting delays surrounding the balloon event, or whether the result is an indication of fundamentally differential performance outcomes across loan products. Noordewier, Harisson and Ramagopal (2001) do not specifically test for the amortization schedule of the loan. [11] Although they examined the PD – namely the likelihood of default – of the borrower and not the LGD of the loan, their results do indicate that the amortization schedule of the loan might be an driver of default risk, which would have an effect on LGD. This study will be the first to examine the relationship between the amortization schedule and LGD.

Numerous studies on residential mortgages have found that default risk increases as the initial loan-to-value (LTV) or higher contemporaneous (or current) loan-to-value (CLTV) increases (LaCour-Little, 2004; Elul, Souleles, Chomsisengphet, Glennon & Hunt, 2010; Soyer & Xu, 2010; Ghent & Kudlyak, 2011; Kau, Keenan & Smurov, 2011; Quercia, Pennington-Cross, Tian, 2012; Archer & Smith, 2013). More importantly loan loss severity rates are higher for loans with a higher LTV or CLTV (Quigley & Van Order, 1995; Kau & Keenan, 1999; Pennington-Cross, 2003; Calem & LaCour-Little, 2004; Qi & Yang, 2009; Park & Bang, 2014). Qi and Yang (2009) and Park and Bang (2014) found that CLTV is the single most important determinant of LGD (CLTV had the highest coefficient). Quercia and Stegman (1992) note that CLTV is a better measurement than LTV because the CLTV take into account changes in the borrower's equity position. To test for non-linearity, Qi and Yang (2009) and Park and Bang (2014) include CLTV dummies instead of the continuous variables. However, they both find a positive linear effect between CLTV and LGD, and no evidence of non-linearity.

2.3 Collateral Characteristics

Previous research has indicated that loans which are securitized by collateral have a lower LGD (Altman & Kishore, 1996; Carty & Lieberman, 1996; Gupton, Gates & Carty, 2000; Araten, Jacobs & Varshney, 2004; Altman et al., 2005; Dermine & de Carvalho; 2006; Acharya, Bharath & Srinivasan, 2007; Grunert & Weber, 2009; Khieu, Millineaux & Yi, 2012). Notwithstanding, there are only a few studies that consider the effect of collateral characteristics on LGD, again due to a lack of detailed data. Although not their main focus, Qi and Yang (2009) included some collateral characteristics that may have an impact on LGD for residential mortgages, namely property type (single family, condo and 2-4 units) and whether the property is owner occupied or used as CRE. They found that single-family properties and condos have a lower loss severity than other property types. Furthermore, LGD for owner-occupied properties is lower than for CRE. Park and Bang (2014) specifically look at collateral characteristics for defaulted Korean residential mortgages. They find that during an economic downturn, larger units have a larger LGD than smaller units but during an economic boom the opposite effect is found. They find evidence that "during the housing market downturn collateral characteristics that are overvalued during the boom increase loss severity" (Park & Bang, 2014: p. 209). Moreover, Park and Bang (2014) look at the effect of the location of the collateral by including a dummy variable that takes 1 if the collateral is

[11] Noordewier, Harrisson and Ramagopal (2001) do not specially test for the amortization schedule since the balloon loans included in their study are amortized on a 30-year basis and hence do amortize (although not fully).

located in the region Gangnam.[12] There result indicate that there is indeed a difference in LGD for collateral located in the Gangnam region (or not). Furthermore, Shibut and Singer (2015) also show that the location of the collateral matters for CRE loans. They find that LGD for CRE loans is higher in states that were hit hard by the GFC (Georgia and Florida).

Due to the difference in associated risks and the inherent characteristics of each asset type, each asset type is likely to have a different impact on downturn LGD. In the Netherlands, the vacancy rate for offices is currently around 17% and 10% for retail (PBL Netherlands Environmental Assessment Agency, 2016). According to Hilbers and Nijskens (2016), vacancy rates may be even higher due to 'hidden vacancy', meaning that there are properties that still have a rental contract but these properties are vacant or not completely occupied. Contrary to offices and retail, there is currently a shortage of residential properties especially in the middle segment and therefore vacancy rates are lower. Hence, downturn LGD will likely be higher for offices and retail than for residential properties. Previous research on CRE loans has not yet examined the effect of the collateral type on LGD. Thus, this paper will be the first. The effect of the collateral type on downturn LGD is however most likely dependent on the location of the collateral since there are significant disparities between provinces. In certain provinces the vacancy rate for offices is around 40% while other regions have significantly lower vacancy rates (PBL Netherlands Environmental Assessment Agency, 2016). Moreover, certain regions are shrinking (e.g. Friesland and Groningen), while the population in other regions is increasing significantly (e.g. Utrecht and Noord-Holland). These demographic changes all have an impact on CRE. Lastly, not only are there regional differences, there are also tremendous discrepancies between cities.

To the best of the author's knowledge, this is the first study that examines defaulted as well as healthy CRE loans from healthy Dutch banks. Subsequently, this is the first study that looks at the determinants of downturn LGD instead of point-in-time LGD. Moreover, this is the first study that looks at the effect of PD, the classification of the counterparty (private borrower or not), the nationality of the borrower (Dutch or non-Dutch), the amortization schedule, the interest rate type (fixed versus variable), the type of collateral and the location of the collateral on downturn LGD. In the next section, the data and methodology will be discussed.

[12] Park and Bang (2014) specifically look at the region Gangnam because this region was most affected by housing market speculation (2000-2007) in Korea.

3. DATA AND METHODOLOGY

In section 3.1 the data and descriptive statistics are discussed. The methodology is discussed in section 3.2.

3.1 Data and descriptive statistics

The confidential loan-level data used in this study was provided by DNB. The database was collected in October 2016 and is representative for the overall Dutch banking market. The complete database consists of approximately 68,000 CRE loans that were granted between January 1st 1975 and June 30th 2016. This study employs a subset of the database and only studies loans of which the underlying collateral is located in the Netherlands and loans that are denominated in euros. Loans that are used to finance real estate projects that are not yet completed, are excluded from this study since project finance is not included in the CRE definition used in this study.[13] Moreover, all loans were granted by Dutch bank subsidiaries.[14]

The structure of the full dataset is shown in figure 1A. To begin with, 10% of the loans have more than one counterparty. This can result in, for example, a loan with three counterparties, where one is from the Netherlands and the other two are from Austria. These loans are excluded from this study and hence this study only examines loans with one counterparty. More importantly, 90% of the loans are securitized by more than one property. If a loan is securitized by two (or more) properties, it can be the case that for example one of the properties is a residential property located in Maastricht and the other property an office building located in Groningen. To test for the collateral type and the location of the collateral, these loans cannot be used because LGD is calculated at the loan level. In other words, there would be two entries in the loan-level database for this particular example where the borrower and loan characteristics are similar but the collateral characteristics differ. However, since these loans are not outliers, they cannot simply be dropped. Therefore, if a loan is securitized by two or more properties, the property with the highest collateral value is selected because this property most likely determines the loss severity of the loan. Hence, if in the previous example the residential property in Maastricht is worth 1 million euros and the office building in Groningen 10 million euros, the collateral characteristics of the latter are chosen. The structure of the dataset used in this study is shown in figure 1B, where the dotted arrow represents the selected property for this specific example. Thus, when loans are securitized by more than one property, the collateral characteristics of the property with the highest collateral value

[13] Only 2% of the loan portfolio is used for financing real estate projects.
[14] In the full database, there are also loans granted by foreign bank subsidiaries. However, all loans granted by foreign bank subsidiaries are securitized by collateral located outside the Netherlands and are thus not relevant to this study.

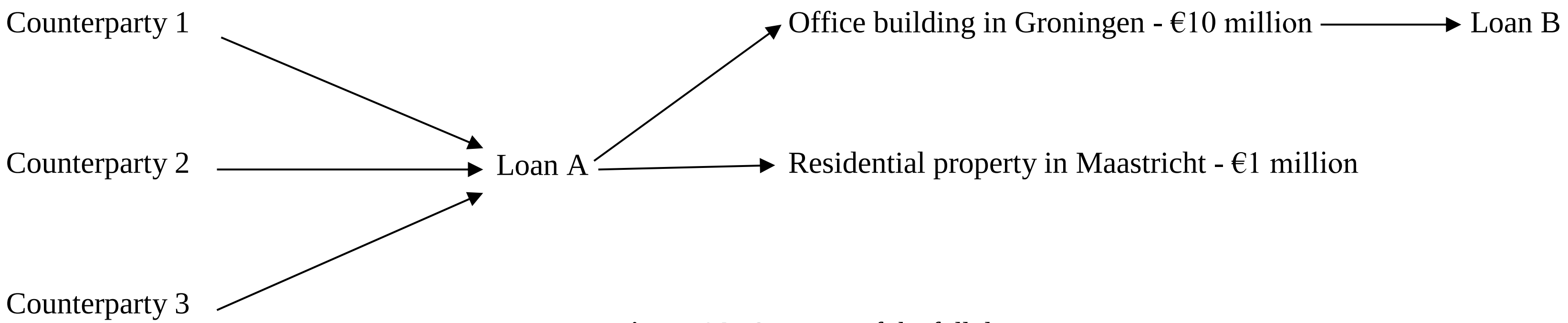

Figure 1A: Structure of the full dataset

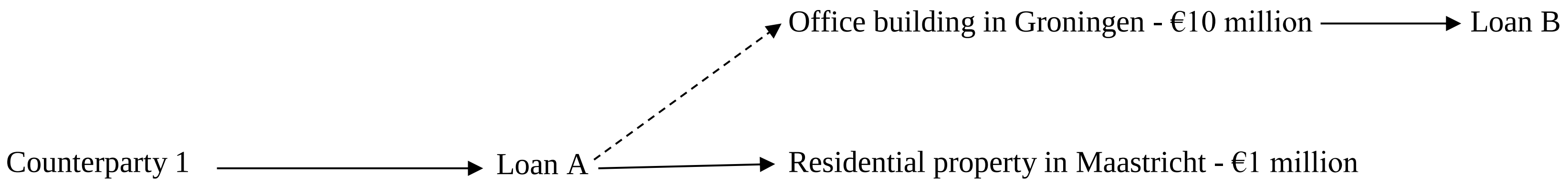

Figure 1B: Structure of the selected dataset

Note: Figure 1A shows the structure of the full dataset. To begin with, 10% of the full loan portfolio compromises of loans that have multiple counterparties. These loans are dropped and as a result the structure of the data looks like figure 1B. From the 45,132 loans, 90% are securitized by more than one collateral. Since these are not outliers, these loans cannot be dropped. Therefore, if a loans is securitized by more than one collateral, the property with the highest values is selected. In the example (figure 1B), this would be the office building in Groningen. Lastly, 90% of the properties have multiple loans. The standards errors are therefore clustered at the level of the collateral.

are chosen. In previous studies, bank loans are securitized by only one residential or commercial property (Qi & Yang, 2009; Park & Bank, 2014; Shibut & Singer, 2015; Ross & Shibut, 2015). Thus, this research uses a novel approach which has not been used before. After cleaning the data, the dataset used consist of 45,132 loans that were granted between December 20th 1979 and June 30th 2016 by Dutch bank subsidiaries.[15]

Appendix 3 shows the variables used in this study. All variables are given except the independent variables 'the intensity of the relationship' and 'age'. As a proxy for the intensity of the relationship, a new variable is created that captures the amount of CRE loans the borrower has with one bank. It is likely that a borrower has multiple loans at multiple banks. Unfortunately, since borrowers have a unique identification code at each bank but not across banks, a borrower cannot be traced across banks. Furthermore, the variable only captures the loans that the borrower currently has with the bank and hence does not capture matured loans. The age for healthy loans is calculated by subtracting the inception date from July 1st 2016. Instead of June 30th 2016, July 1st 2016 is used so that loans which originated on June 30th 2016 are included. For defaulted loans, the age is calculated by subtracting the inception date from the default date. There are however 139 loans that report a default date before their inception date (rollover loans). As a result, these loans have a negative value for the variable age. Moreover, there are 107 loans which are in default but have no default date. For loans with a negative value or loans without a default date, the average age of a defaulted loan is used (2461 days). Lastly, it is important to note that the model does not include a dummy variable for the default status of the loan. Loans that are in default have a PD of 100% and as a result, by including the PD, the model controls for the default status.

The descriptive statistics of the continuous variables are shown in table 1. The mean and median downturn LGD for all loans are 18.98% and 15% respectively. The mean and median downturn LGD for defaulted loans is 31.45% and 20.59% respectively (see table 2), which is significantly lower than Ross and Shibut (2015) who report a mean and median point-in-time LGD of 43.78% and 41.06% for defaulted CRE loans. Previous studies reported a bimodal distribution of the point-in-time LGD for defaulted bank loans (Dermine & De Carvalho, 2006; Shibut & Singer, 2015). As shown in appendix 5A, the downturn LGD for the full loan portfolio is skewed to the right (histogram 1). This also holds for healthy loans (histogram 2). The downturn LGD for defaulted loans is slightly skewed to the right but also not bimodal (histogram 3). Thus, in contrast with previous studious, this study does not find a bimodal distribution. Furthermore, the mean outstanding nominal amount is approximately €868,565. The standard deviation is however large and the maximum outstanding nominal amount is

[15] Loans with missing values were deleted. Furthermore, loans with a CLTV higher than 200 were deleted (this is also the cap that banks use). Loans with an outstanding amount of 0 are also deleted. Furthermore, there were 22 loans that were in default but reported a probability of default below 100. This is a data error and subsequently the probability of default for these loans is set to 100%. Lastly, there were several loans that reported a downturn LGD below 1. These are data errors and are subsequently multiplied by 100.

approximately 357 million. The outstanding nominal amount of the total sample is more than 39 billion euros. The mean and median PD are low, namely 9.03% and 1.27% respectively.

Table 1: Descriptive Statistics of the Continuous Variables

Variables	**Mean**	**Median**	**SD**	**Min**	**Max**
Downturn LGD (%)	18.98	15	15.82	1	100
PD (%)	9.07	1.27	24.61	0.01	100
Intensity of the relationship (amount of loans)	4.17	3	4.15	1	39
Outstanding nominal amount (€)	868564.6	261247	3545410	1	3.57e+08
CLTV (%)	60.20	60	31.07	1	200
Age (days)	2670.25	2625	1625.13	1	13343

Furthermore, the borrower currently has, on average, 4 CRE loans. The mean age of the loan portfolio is 2670 days, which is approximately 7 years and 3 months. Lastly, the mean CLTV is approximately 60%.[16]

The descriptive statistics of the dummy variables for borrower, loan and collateral characteristics can be found in appendix 4A, 4B and 4C. To begin with, more than half of the borrowers is a corporate client. Furthermore, almost all borrowers are Dutch and most of the CRE loans originated before the GFC. Interestingly, the non-Dutch borrowers are mostly private borrowers (65%).[17] Moreover, most of the loans have an amortization schedule and more than 50% of the loans have a fixed interest rate. Measured by the amount of loans, approximately 7% of the total loan portfolio is in default while 15% is placed under special asset management.[18] Furthermore, most of the collateral is located in Noord-Holland, Noord-Brabant and Zuid-Holland and most of the underlying collateral are offices and residential properties. Moreover, the underlying collateral of most of the CRE loans is located in the four big municipalities, to be specific 8% of the total loan portfolio is located in Amsterdam, 5% in Den Haag, 4% in Rotterdam and 3% Utrecht. Hence, more than 20% of the collateral is located in the four big cities (measured by the amount of loans). Measured by the outstanding nominal amount (€)[17], approximately 10% of the total loan portfolio is in default while 18% is placed under special asset management. Lastly, 15% of the total outstanding nominal amount is concentrated in Amsterdam, 6% in Den Haag, 5% in Rotterdam and 3% in Utrecht. Thus, the dataset is concentrated in the Randstad (see appendix 4E).

Appendix 5, table 2 and figure 2 show the downturn LGD for key variables. To begin with, table 2 shows that there is substantial variation in downturn LGD indicated by the high standard deviation and supported by the histograms in appendix 5A. Notably, the downturn LGD for non-Dutch borrowers

[16] Offices and other real estate have the highest CLTV (63% and 65% respectively) whereas industrial real estate has the lowest CLTV, namely 57%. Lastly, the CLTV in Drenthe, Flevoland and Frylân is the highest whereas the CLTV in Zeeland, Limburg and Gelderland is the lowest. The results are not reported

[17] The results are not reported.

[18] An asset is under special asset management when the asset falls into a certain risk category. Hence, these loans are potentially problematic.

is slightly higher than the downturn LGD for Dutch borrowers. On the other hand, the downturn LGD for private borrowers is higher. Shibut and Singer (2015) found that defaulted CRE loans which originated well before the GFC have a lower point-in-time LGD than loans which originated in the height of the GFC or shortly before the GFC began. On the contrary, table 2 shows that loans which originated before the GFC have a higher downturn LGD than loans which originated during or after the crisis. Especially CRE loans that originated in the 1980's and 1990's have a high downturn LGD (see appendix 5B). On average, the downturn LGD of defaulted loans is higher than the downturn LGD of healthy loans. This is not necessarily trivial since the expected loss of a healthy loan can be higher than a loan that is already in default.[19] Interestingly, as shown in appendix 5C, the downturn LGD is significantly higher for loans that defaulted just before the GFC (2007) and during the GFC (2008-2010). Furthermore, the downturn LGD for loans which are placed under special asset management is higher than the downturn LGD for loans which are not placed under special asset management. Lastly, loans with an amortization schedule have, on average, a lower downturn LGD than loans bullet loans.

Table 2: Mean and SD of downturn LGD (%) by key variables

Variables	**Mean**	**SD**
Borrower characteristics		
Nationality of the borrower		
Dutch	18.97	15.82
Non-Dutch	19.83	16.19
Private borrower		
No	15.46	15.24
Yes	23.16	15.48
Loan characteristics		
Inception period		
Before the GFC	20.82	16.94
During the GFC	19.15	14.30
After the GFC	16.87	15.44
Amortization schedule		
Amortization schedule	18.57	15.67
Bullet loans	21.81	17.19
Interest rate type		
Fixed	18.59	15.17
Variable	19.59	16.77
Collateral characteristics		

[19] From the 42,136 healthy loans, 5,615 healthy loans have a higher downturn LGD than the mean downturn LGD of defaulted loans (13%).

Collateral type		
Industrial	19.82	15.89
Mixed use	19.76	14.16
Office	21.64	16.29
Other	17.87	14.94
Residential	16.58	15.73
Retail	18.96	16.28
Province		
Drenthe	21.70	15.33
Flevoland	21.54	15.90
Fryslân	19.43	14.51
Gelderland	19.65	15.34
Groningen	16.88	14.30
Limburg	21.13	16.29
Noord Brabant	19.38	15.48
Noord Holland	18.27	16.58
Overijssel	21.15	15.95
Utrecht	19.34	15.70
Zeeland	19.40	15.61
Zuid Holland	17.52	15.82
Control variables		
Default status		
Not in default	18.10	15.04
Default	31.45	20.59
Special asset management		
No	17.72	14.92
Yes	26.05	18.64

As expected, the downturn LGD for residential real estate is lower than for other collateral types. Moreover, the mean downturn LGD in Groningen and Zuid-Holland is significantly lower than in other provinces. On average, the downturn LGD between the other provinces does not differ tremendously. However, there may be significant differences in downturn LGD within the province per collateral type, indicated by the high standard deviation per province and motivated by the literature. Figure 2 shows the downturn LGD for all CRE per municipality. Nonetheless, figure 2 does not show enormous differences in downturn LGD between municipalities. However, it is highly likely that the downturn LGD differs per collateral type and per municipality. Maps 1 until 6 in appendix 5E clearly indicate that there are substantial differences in downturn LGD per collateral type per municipality. Table 2 indicated that the downturn LGD for offices is higher than for other collateral types. This is again highlighted by map 1. Map 1 shows that the downturn LGD for offices in the provinces Groningen and Drenthe is especially high. For residential real estate, the downturn LGD is high in the provinces Zeeland and

Overijssel (map 2). Furthermore, the downturn LGD for retail is significantly higher in Drenthe than in other provinces (map 3).

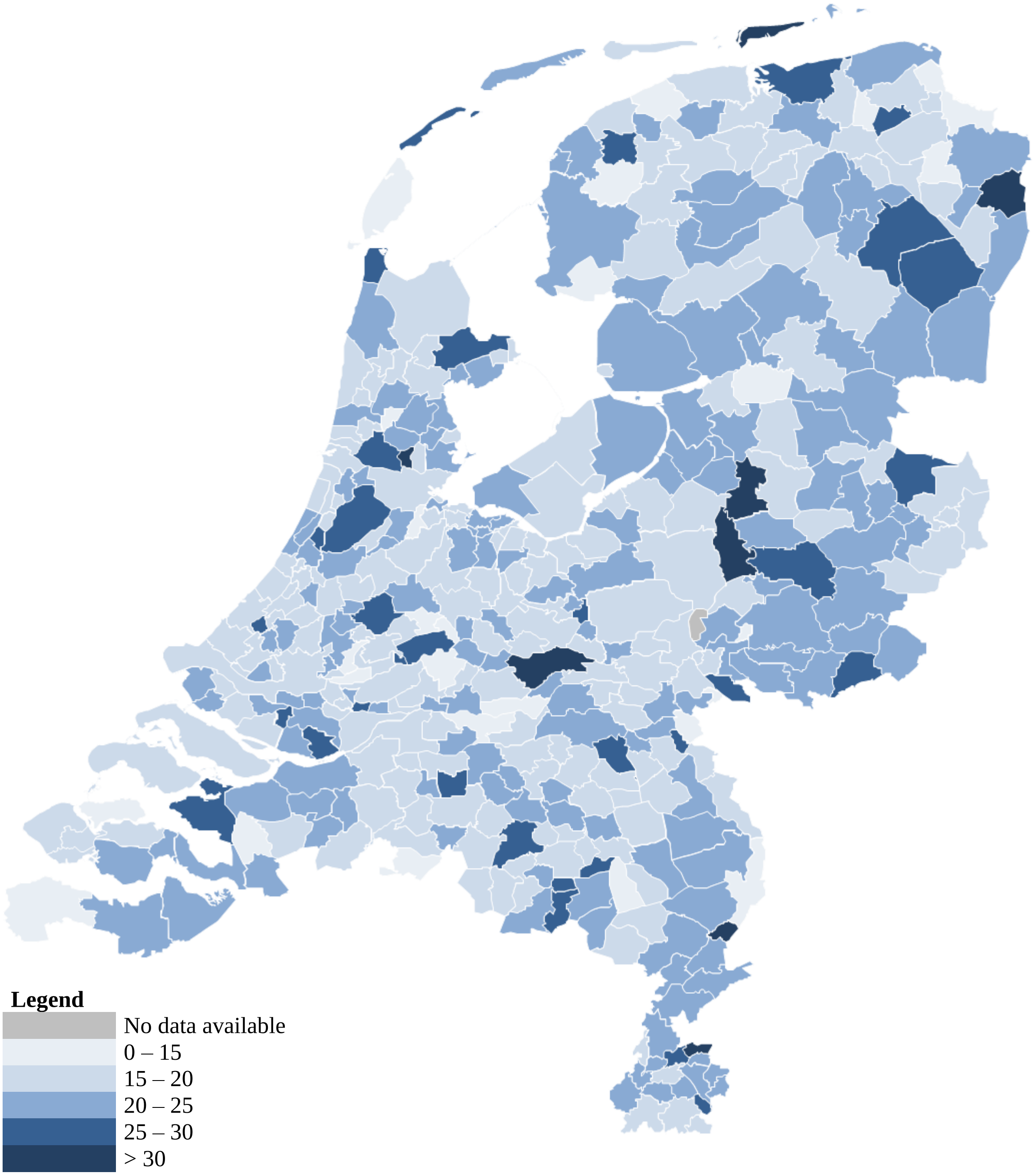

Figure 2: Average downturn LGD for all commercial real estate per municipality (source: DNB and author's own calculations).

For industrial real estate, the downturn LGD is higher in the North-Eastern provinces (map 4). In the municipalities around Meppel and Steenwijk (Friesland and Drenthe), the downturn LGD is clearly higher for mixed use real estate (map 5). Lastly, the average downturn LGD for other real estate properties is high around Zwolle (map 6). All in all, appendix 5E confirm that the downturn LGD for the collateral type might be dependent on the location of the collateral.

3.2 Methodology

The dependent variable is downturn LGD. The independent variables are borrower- and loan-characteristics, the collateral type and the location of the collateral. Finally, control variables are included. The regression model is specified as follows:

$$
\begin{aligned}
downturn\ LGD_i \ = \alpha + \sum_{j=1}^{J} \beta_j\, Borrower_{ij} + \sum_{i=1}^{I} \gamma_i\, Loan_i + \sum_{k=1}^{K} \delta_k\, Collateral_{ik} \\
+ \sum_{k=1}^{K} \pi_k\, Location_{ik} + \sum_{k=1}^{K} \vartheta_k\, (Collateral_{ik} * Location_{ik}) \\
+ \sum_{i=1}^{I} \mu_i\, Control_i + \ \varepsilon_i
\end{aligned}
$$

Where $downturn\ LGD_i$ is the downturn loss given default of the *i*th CRE loan. On the right hand side, $Borrower_{ij}$ is the borrower characteristics of borrower j for the *i*th CRE loan. The borrower characteristics included in this study are PD, the intensity of the relationship, the nationality of the borrower and whether the borrower is a private borrower or not. Similar to studies that have examined the relationship between the RR and default rates of bonds (Frye, 2000; Gupton, Hamilton & Berthault, 2001; Altman et al., 2005), it is expected that the downturn LGD is high when the PD is high since the risk of a loss increases if the borrower is more likely to default. Hence, the expected sign of the coefficient is positive. Moreover, following the theory on relationship lending, this paper hypothesizes that a strong bank-borrower relationship decreases the loss severity of the CRE loan and hence reduces downturn LGD. Therefore, the expected sign of 'the intensity of the relationship' is negative. Lastly, downturn LGD is expected to be higher for private borrowers and non-Dutch borrowers.

$Loan_i$ is the loan characteristics of the *i*th CRE loan. The loan characteristics included in this research are the outstanding nominal amount, the age of the loan, CLTV, the interest rate type (variable versus fixed), the amortization schedule (bullet loans versus loans with an amortization schedule) and the origination year of the loan (whether the loan was granted before, during or after the GFC). As LGD is 1 minus the RR, LGD is low when the lender can recover a high percentage of the loan by selling the collateral. Under the assumption that loan size and collateral value are correlated, a larger loan is securitized by a larger collateral value.[20] Following this line of reasoning, downturn LGD would be low if the loan size is large, since the RR is high because the collateral can be sold for a high price. Following

[20] In the database used, the outstanding nominal amount and the collateral value are positively correlated. Thus, this is a realistic assumption.

Qi and Yang (2009) and Ross and Shibut (2015), this paper therefore hypothesizes that downturn LGD is lower for larger loans. Furthermore, similar to Lekkas, Quigley and Van Order (1993), Pennington-Cross (2003), Shibut and Singer (2015) and Ross and Shibut (2015), this paper hypothesizes that there is a negative relationship between the age of the loan and downturn LGD. Moreover, following the results of residential mortgages (Lekkas, Crawford & Rosenblatt, 1995; Quigley & Van Order, 1995; Kau & Keenan, 1999; Pennington-Cross, 2003; Calem & LaCour-Little, 2004; Qi & Yang, 2009; Park & Bang, 2014), this paper hypothesizes that loans with a higher CLTV have a higher downturn LGD. Furthermore, following previous research of residential mortgages (Noordewier, Harrison, & Ramagopal, 2001; Smith, 2011; Archer & Smith, 2013), this paper hypothesizes that adjustable rate CRE loans have a higher downturn LGD than fixed rate CRE loans. Next, downturn LGD is expected to be higher for bullet loans. Considering that bank screening and monitoring increased during the GFC (De Haas & Van Horen, 2010), loans which originated during and after the GFC are expected to have a lower downturn LGD than loans which originated before the GFC since ex-ante risk is reduced. $Collateral_{ik}$ is the collateral type of collateral k of the ith CRE loan. In this study, CRE is categorized in offices, residential, retail, industrial, mixed use and other CRE. It is expected that downturn LGD is higher for loans that are securitized by offices, retail, industrial, mixed use and other CRE than loans which are securitized by residential properties. $Location_{ik}$ is the location of collateral k of the ith CRE loan, where location either refers to (i) the province or (ii) whether the collateral is located in Amsterdam, Den Haag, Rotterdam or Utrecht (or not). In this paper, it is hypothesized that the downturn LGD is lower when the collateral of the CRE loan is located in (i) the province Noord-Holland or (ii) the municipality Amsterdam, Den Haag, Rotterdam or Utrecht. $Collateral_{ik} * Location_{ik}$ is the interaction term between the type and the location of collateral k of the ith CRE loan. Following the literature study, the base category of the interaction term is residential properties located in (i) the province Noord-Holland or (ii) the municipality Amsterdam, Den Haag, Rotterdam or Utrecht. Thus, the coefficient of the interaction term is expected to be positive. $Control_i$ is the control variables of the ith CRE loan. To be specific, the control variables are a dummy variable that takes 1 if the asset is under special asset management and a bank specific dummy to account for heterogeneity among the banks.

All continuous variables - the dependent variable as well as the independent variables - are log transformed since the variables are not normally distributed. Lastly, 90% of the properties have multiple loans. Meaning that in our example the office building in Groningen has two loans, namely loan A and B (see figure 1B). It is likely that these loans are not independent. Therefore, the observations are clustered at the level of the collateral. Thus, this paper uses an OLS regression with robust clustered standard errors.

4. RESULTS

Table 3 shows the correlation matrix for the continuous variables. Surprisingly, downturn LGD and PD are negatively correlated, although moderately. As expected, the downturn LGD and the age of the loan are positively correlated. Furthermore, the downturn LGD and the intensity of the relationship are negative correlated while the downturn LGD and the CLTV are positively correlated. Lastly, the correlation matrix does not indicate multicollinearity among the variables.

Table 3: Correlation Matrix

	LGD	**PD**	**Intensity**	**ONA**	**CLTV**	**Age**
LGD	1,0000					
PD	-0.2197*	1,0000				
Intensity	-0.1373*	0.0297*	1,0000			
ONA	0.0028	0.0319*	-0.0188*	1,0000		
CLTV	0.2116*	0.2604*	0.0375*	0.0595*	1,0000	
Age	0.0905*	-0.0101*	0.0074	-0.1040*	-0.1029*	1,0000

* p <0.05

The results of the log-log estimates of downturn LGD for borrower- and loan characteristics are partially reported in table 4 (see appendix 6A for all regression results). As expected, model 1 shows that the LGD is lower for larger loans and the LGD is higher for loans with a higher CLTV. However, there might be a non-linear relationship between the outstanding nominal amount and LGD and CLTV and LGD. Following Qi and Yang (2009), model 2 therefore includes dummy variables for the outstanding nominal amount and CLTV. For the CLTV, a dummy variable is constructed that captures the increase in CLTV where the base category is CLTV less than 50%. For the outstanding nominal amount the base category is an outstanding amount between 0 and 25 percentile. Contrary to Qi and Yang (2009) and Park and Bang (2014), this study finds a non-linear relationship between CLTV and LGD (model 2). The LGD for loans with a CLTV between 50-60%, 60-70% and 70-80% is lower than the base category (CLTV less than 50%). However, the LGD for loans with a CLTV higher than 80% is higher than the base category. Moreover, all CLTV dummy variables are highly significant. On the

Table 4: Log-log estimates of downturn LGD for borrower and loan characteristics

Variables	**Model 1**	**Model 2**	**Model 3**
ONA	-0.0254***		-0.0196***
	(0.00421)		(0.00392)
CLTV	0.172***		
	(0.0108)		
CLTV 50-60%		-0.0588***	-0.0604***
		(0.0186)	(0.0186)
CLTV 60-70%		-0.127***	-0.127***
		(0.0186)	(0.0186)
CLTV 70-80%		-0.0869***	-0.0871***
		(0.0206)	(0.0206)
CLTV 80-90%		0.279***	0.277***

		(0.0254)	(0.0254)
CLTV 90-100%		0.521***	0.520***
		(0.0341)	(0.0341)
CLTV 100-110%		0.539***	0.538***
		(0.0377)	(0.0377)
CLTV 110-120%		0.686***	0.685***
		(0.0446)	(0.0447)
CLTV >120%		0.722***	0.722***
		(0.0329)	(0.0330)
ONA 25-50 percentile		-0.0543***	
		(0.0101)	
ONA 50-75 percentile		-0.0967***	
		(0.0119)	
ONA > 75 percentile		-0.0680***	
		(0.0160)	
Bank control variables	Yes	Yes	Yes
Observations	45,132	45,132	45,132
R-squared	0.249	0.301	0.301
Adjusted R-squared	0.249	0.301	0.301

Note: Significance at ***1%, **5% and *10% levels respectively. The robust clustered standard errors are reported in parentheses. Table 4 reports the regressions results for some variables, see appendix 6A for all regression results.

other hand, this paper does not find a non-linear relationship between the outstanding nominal amount and LGD. Subsequently, model 3 includes dummy variables for CLTV and the log of the outstanding amount.[21] Next, the type of collateral, the location and the interaction term are added to regression model 3.

The results of the log-log estimates of downturn LGD for the full model (including borrower-, loan- and collateral characteristics) are partially reported in table 5 (see appendix 6B for all regressions results). Model 4 includes the type and the location (province) of the collateral but not the interaction term, whereas model 5 does. Model 6 includes the type of the collateral and a dummy variable that takes 1 if the collateral is not located in Amsterdam, Den Haag, Rotterdam or Utrecht but not the interaction term, whereas model 7 does. This paper is mainly interested in the (potential) interaction effect between the type and the location of the collateral. If not specifically mentioned, the results therefore refer to regression model 5.

To begin with, there is a positive and statistically significant relationship between downturn LGD and PD: if PD increases from 10% to 10.1%, downturn LGD increases from 10% to 10.091%, holding all other variables constant. This finding is in line with previous studies that examined the relationship between LGD and PD for bonds (Frye, 2000; Gupton, Hamilton & Berthault, 2001; Altman, Brady, Resti & Sironi, 2005) as is as expected. Similar to Grunert and Weber (2009), this paper finds a negative relationship between downturn LGD and the intensity of the relationship, meaning that downturn LGD is lower if the borrower has more CRE loans with the bank. If the borrower is a private borrower, the downturn LGD is significantly higher than when the borrower is not a private borrower. To be specific, private borrowers, on average, have a downturn LGD 88% higher than non-private

[21] See appendix 4D for descriptive statistics of the CLTV dummies.

borrowers holding all other variables constant. The nationality of the borrower, on the other hand is significant, note however that the sign is negative and not, as expected, positive. A possible explanation for the insignificant result is that only 1.5% of the borrowers are non-Dutch and hence the sample is rather small.

Table 5: Log-log estimates of downturn LGD for borrower, loan and collateral characteristics

Variables	**Model 4**	**Model 5**	**Model 6**	**Model 7**
PD	0.0917***	0.0911***	0.0906***	0.0909***
	(0.00480)	(0.00479)	(0.00480)	(0.00479)
Intensity of the relationship	-0.104***	-0.104***	-0.103***	-0.102***
	(0.0100)	(0.00992)	(0.0101)	(0.0101)
Private borrower (Yes)	0.634***	0.630***	0.627***	0.624***
	(0.0128)	(0.0129)	(0.0130)	(0.0131)
Nationality of the borrower (Non-Dutch)	-0.0247	-0.0232	-0.0152	-0.0121
	(0.0486)	(0.0486)	(0.0472)	(0.0472)
Outstanding nominal amount	-0.0361***	-0.0359***	-0.0383***	-0.0381***
	(0.00616)	(0.00616)	(0.00617)	(0.00618)
Age	-0.0294***	-0.0297***	-0.0286***	-0.0294***
	(0.00378)	(0.00376)	(0.00380)	(0.00378)
Inception year (between 2008-2010)	-0.0390***	-0.0391***	-0.0379***	-0.0378***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Inception year (after 2010)	-0.163***	-0.159***	-0.160***	-0.160***
	(0.0153)	(0.0153)	(0.0153)	(0.0154)
Bullet loans	0.0630***	0.0647***	0.0677***	0.0686***
	(0.0139)	(0.0139)	(0.0139)	(0.0139)
Interest rate type (Variable)	0.0166*	0.0163*	0.0149	0.0144
	(0.00991)	(0.00990)	(0.00995)	(0.00996)
CLTV 50-60%	-0.0546***	-0.0528***	-0.0520***	-0.0507***
	(0.0183)	(0.0182)	(0.0183)	(0.0183)
CLTV 60-70%	-0.121***	-0.119***	-0.119***	-0.117***
	(0.0184)	(0.0183)	(0.0183)	(0.0183)
CLTV 70-80%	-0.0639***	-0.0603***	-0.0613***	-0.0585***
	(0.0203)	(0.0202)	(0.0203)	(0.0203)
CLTV 80-90%	0.293***	0.293***	0.290***	0.293***
	(0.0254)	(0.0255)	(0.0257)	(0.0258)
CLTV 90-100%	0.532***	0.531***	0.527***	0.530***
	(0.0340)	(0.0339)	(0.0343)	(0.0344)
CLTV 100-110%	0.552***	0.553***	0.548***	0.550***
	(0.0381)	(0.0380)	(0.0380)	(0.0379)
CLTV 110-120%	0.694***	0.696***	0.694***	0.693***
	(0.0452)	(0.0451)	(0.0454)	(0.0456)
CLTV >120%	0.734***	0.734***	0.733***	0.733***
	(0.0331)	(0.0333)	(0.0335)	(0.0335)
Industrial*Gelderland		-0.152**		
		(0.0693)		
Mixed use*Limburg		-0.504***		
		(0.103)		
Office*Gelderland		-0.119*		
		(0.0654)		
Other*Overijssel		-0.150*		
		(0.0878)		
Retail*Flevoland		-0.347**		
		(0.161)		
Outside top 4			0.129***	0.224***
			(0.0165)	(0.0276)
Industrial*Outside top 4				-0.142**

				(0.0560)
Bank control variables	Yes	Yes	Yes	Yes
Observations	45,132	45,132	45,132	45,132
R-squared	0.316	0.318	0.317	0.318
Adjusted R-squared	0.315	0.317	0.317	0.318

Note: Significance at ***1%, **5% and *10% levels respectively. The robust clustered standard errors are reported in parentheses. Table 5 reports the regressions results for some variables, see appendix 6B for all regression results.

All regression models find strong support for the effect of loan characteristics on downturn LGD. First of all, in contrast to previous studies that found a positive effect between EAD and the point-in-time LGD (Hurt & Felsovalysi, 1998; Dermine & de Carvalho, 2006; Park & Bang, 2014), this study finds that larger loans have a lower downturn LGD than smaller loans. A possible explanation for this findings it that the point-in-time LGD measures the actual loss on the loan, while the downturn LGD measures the expected loss on the loan during an economic downturn. If banks ex ante put substantially more effort in reducing the loss of larger loans, the expected loss ex post on a larger loan is lower and hence downturn LGD will be lower. Similar to previous findings on CRE loans (Shibut & Singer, 2015; Ross & Shibut, 2015), this paper finds that younger loans have a higher downturn LGD: if the age of the loan increases with 1%, downturn LGD decreases by approximately 0.03%. Hence, losses are lower for older CRE loans. The origination year of the loan is also highly significant: loans that originated during and after the GFC have a lower downturn LGD than loans that originated before the GFC. On average, loans that originated during the GFC have a downturn LGD of approximately 4% lower than loans that originated before 2008, holding all other variables constant. Loans that originated after the GFC have, on average, a downturn LGD of approximately 15% lower than loans that originated before the GFC, holding all other variables constant. To examine whether the downturn LGD for loans which originated after the GFC is lower than the downturn LGD for loans which originated during the GFC, the base category is changed to loans that originated during the GFC.[22] The results show that indeed the downturn LGD for loans that originated after the GFC is lower than for loans that originated during the GFC. To be precise, loans that originated after the GFC have a downturn LGD of approximately 11% lower than loans that originated during the GFC. Thus, this paper finds support for hypothesis 7.

The downturn LGD for CRE loans bullet loans is roughly 7% higher than the downturn LGD for loans with an amortization schedule, holding all other variables constant. Furthermore, the dummy variable which takes 1 if the loan has a variable interest rate is significant at the 10% level for models 4 and 5. However, the variable is not significant in regression models 6 and 7. Model 5 shows that the expected loss for variable interest rate loans is only 2% higher than fixed interest rate loans, ceteris paribus. Hence, the downturn LGD for variable interest rate loans is only marginally higher than for fixed interest rate loans. Although research on residential mortgages has shown that adjustable rate loans

[22] The base category in model 1-7 is loans with an origination year before the GFC. To test if there is a significant difference between loans that originated during and after the GFC, the base category is loans with an origination year during the GFC. The results are not reported.

are more likely to default than fixed rate loans (Noordewier, Harrison, & Ramagopal, 2001; Smith, 2011; Archer & Smith, 2013), this paper does not find a strong and robust result for the interest rate dummy, implying that during an economic downturn loss severity of variable and fixed interest rate CRE loans are more or less the same (holding all other variables constant).

As indicated previously, this paper finds a non-linear relationship between downturn LGD and CLTV. The results show that loans with a CLTV higher than 80% have a higher downturn LGD than loans with a CLTV below 50% (base category). Specifically, the downturn LGD for loans with a CLTV between 70% and 80% is 34% higher than loans with a CLTV below 50%. For loans with a CLTV above 120% the LGD is even 108% higher. On the other hand, loans with a CLTV between 50% and 80% have a lower downturn LGD than loans with a CLTV below 50%. These results however have to be interpreted with care since a higher CLTV may not necessarily imply that the expected loss is higher. It may be the case that the quality of the underlying collateral of these loans is low, resulting in a lower asset value and hence a higher CLTV. This is supported by the negative correlation between the CLTV and the collateral value.[23]

According to models 4 and 6, the downturn LGD for all collateral types is higher than for residential real estate except for the collateral type 'other'. Moreover, according to model 4, the downturn LGD for loans of which the underlying collateral is located in Drenthe, Gelderland, Limburg, Overijssel and Zeeland is significantly higher than in Noord-Holland. According to model 6, the downturn LGD for properties located outside the top 4 cities is significantly higher than the downturn LGD of properties located Amsterdam, Den Haag, Rotterdam or Utrecht. However, this paper is mostly interested in the interaction between the type and the location of the collateral (models 5 and 7). Surprisingly, all the interaction terms that are significant are negative and not positive, which was expected. This means that the downturn LGD for these loans is lower than the downturn LGD for loans of which the underlying collateral is residential real estate located in Noord-Holland. To begin with, loans of which the underlying collateral is industrial real estate located in Gelderland, Limburg and Noord-Brabant have a lower downturn LGD than the base category. Notably, the LGD of industrial real estate located in Limburg, on average, is 49% lower than the base category, ceteris paribus. Furthermore, loans of which the underlying collateral is mixed use located in Flevoland, Limburg and Noord-Brabant have a lower downturn LGD than the base category. The results however for mixed use in Flevoland are biased since there are only 2 observations and there is no variation in downturn LGD. The downturn LGD for loans of which the underlying collateral is mixed use real estate located in Limburg and Flevoland is, on average and holding all other variables constant, 46% and 40% lower than loans of which the underlying collateral is residential real estate located in Noord-Holland. Furthermore, the downturn LGD of offices located in Limburg, Noord-Brabant and Gelderland is lower than the base category. Moreover, the downturn LGD of other commercial real estate located in Flevoland,

[23] The correlation between CLTV and the collateral value is not reported.

Gelderland, Limburg and Noord-Brabant is lower than residential real estate in Noord-Holland. Lastly, the downturn LGD of retail properties located in Limburg, Noord-Brabant, Flevoland and Zeeland is lower than the base category. Whereas model 6 indicates that the downturn LGD for loans of which the underlying collateral is not located in Amsterdam, Den Haag, Rotterdam and Utrecht is higher than the base category, the interaction terms in model 7 show the opposite: namely for all collateral types the downturn LGD is lower outside the top 4 municipalities.

Thus, all the interaction terms in model 5 and 7, which are significant, are negative. This is contrary to what was expected. This might be due to the loss of observations. The subset consists of 45,132 loans and hence 45,132 properties. However, in total there are actually 332,872 properties securitized by these 45,132 loans (on average a loan is securitized by 7 properties). This means that, despite the best efforts of the author to keep as many observations as possible, a significant amount of information on the collateral characteristics is still lost. Just as the results for CLTV, the results for the collateral characteristics have to be interpreted with care since data on e.g. the occupancy rate, the quality of the collateral and the size of the property is missing. Hence, the results may be driven by omitted variables. Moreover, it may be the case that banks cherry pick loans of which the underlying collateral is located outside in peripheral areas, which would reduce risk ex ante and subsequently the expected loss severity.

5. ROBUSTNESS

As indicated in appendix 5A, the majority of the CRE loans is small: 95% of the loans have a nominal outstanding amount equal to or below €3 million while the maximum outstanding nominal amount is €357 million. It may be the case that the results are driven by these outliers. Therefore, the largest loans, loans with an outstanding nominal amount above €3 million, are dropped. The results however do not change significantly. More importantly, the results are still robust if loans with an outstanding nominal amount above €680,000 are dropped (25% of the dataset is above €680,000). On the contrary, the results might be driven by small loans, since the outstanding nominal amount is skewed to the right. The results however are still robust if loans with an outstanding nominal amount below €110,000 are dropped (25% of the dataset is below €110,000). Thus, dropping loans in the right or left tail of the distribution does not alter the results. More importantly, the results remain robust if only the healthy loans are included and the loans which are in default are excluded.

All regressions models show that loans which originated during or after the GFC have a lower downturn LGD than loans which originated before the GFC. These results might be driven by loans that originated before 2000 since the downturn LGD for these loans is especially high (see appendix 5B). To examine whether these loans drive the results (or not), these loans were dropped. The results however remain robust and the coefficients even increase. Thus, the results are not driven by loans which originated before 2000. Lastly, to examine the effect of loan size on LGD, the outstand nominal amount was chosen. Another measurement which can be used as a proxy for loan size is the exposure value. The regression results are almost identical when using the exposure value. This was expected since the outstanding nominal amount and the exposure value are strongly correlated.

This paper uses an OLS regression with standard errors clustered at the collateral level. It may however be the case that the observations are correlated within banks/provinces, but independent between banks/provinces. If this is indeed the case, the residuals are not independent which would problematic since OLS assumes independent residuals. To examine this potential bias, the standard errors are clustered by bank and by province. The coefficients and standard errors however do not change significantly indicating that the residuals are not clustered by bank or province.

Lastly, this paper uses CRE loans from all banks and corrects for bank specifics. However, the results might be different per bank. To examine whether this, regression model 5 is estimated for each bank. The results show that the results indeed differ somewhat per bank. Notably, this paper found a non-linear relationship between downturn LGD and CLTV. However, when regression model 5 is estimated per bank, the results indicate a positive (and significant) relationship between downturn LGD and CLTV for most banks. For others, downturn LGD is lower when the borrower has more CRE loans, while the opposite was found for the pooled dataset. Lastly, the results on the interaction terms remain rather similar: only some interaction terms are positive and statistically significant (at the 10% level). The nationality of the borrower remains insignificant.

6. DISCUSSION & CONCLUSION

This paper looks at the determinants of downturn LGD for CRE loans and extends previous work on LGD by using a unique confidential loan-level dataset from Dutch banks provided by DNB, which is representative for the overall Dutch banking market. The data contains 45,132 loans which were granted between December 20th 1979 and June 30th 2016. Contrary to previous research this study includes defaulted as well as healthy CRE loans from healthy Dutch banks. Therefore, this paper does not examine the point-in-time LGD but the downturn LGD. In this study, the determinants of downturn LGD for CRE loans are categorized in borrower-, loan- and collateral characteristics. The findings are the following: similar to findings on bonds (Frye, 2000; Gupton, Hamilton & Berthault, 2001; Altman, Brady, Resti & Sironi, 2005), this paper finds a positive relationship between downturn LGD and PD. Furthermore, this study is the first to examine whether downturn LGD differs for corporate clients versus private borrowers. The results indicate that downturn LGD for CRE loans is lower when the borrower is a corporate client. Furthermore, in line with theory on relationship lending, this paper finds that downturn LGD is lower when the borrower has more CRE loans with the bank. This paper however does not find a significant relationship between downturn LGD and the nationality of the borrower.

Contrary to studies that have found a positive relationship between EAD and point-in-time LGD (Hurt & Felsovalysi, 1998; Dermine & De Carvalho, 2006; Park & Bang, 2014), this paper finds that larger loans have a lower downturn LGD than smaller loans. Furthermore, loss severity is lower when the loan is older. Interestingly, this paper finds that loans which originated during or after the GFC have a lower downturn LGD than loans which originated before the GFC. These results are robust and not driven by loans which originated well before the GFC (loans which originated during the 80's and 90's). Loans which originated after the GFC also have lower downturn LGD than loans which originated during the GFC. Moreover, CRE loans with a variable interest rate have a higher downturn LGD than CRE loans with a fixed interest rate. The dummy variable is however only significant at the 10% level and is not even significant in all regression models. Hence, the effect is only marginal. Furthermore, CRE loans with an amortization schedule have a lower downturn LGD than bullet loans. Contrary to Qi and Yang (2009) and Park and Bang (2014), this study indeed finds a non-linear relationship between downturn LGD and CLTV. CRE loans with a CLTV higher than 80% have a higher downturn LGD than loans with a CLTV below 50%. On the other hand, loans with a CLTV between 50% and 80% have a lower downturn LGD than loans with a CLTV lower than 50%. As already indicated, these results however have to be interpreted with care since a higher CLTV may not necessarily mean that the expected loss is higher. It may be the case that the quality of the underlying collateral of these loans is low, resulting in a lower asset value and hence a higher CLTV.

This paper was mainly interested in the (potential) interaction effect between the type of collateral and the location of the collateral. Contrary to what was expected, the results for the interaction term between the location and the type of collateral indicate, when significant, a negative effect.

Meaning that mixed use real estate in Flevoland or Limburg has a lower downturn LGD than residential real estate in Noord-Holland. Just as the results for CLTV, the results for the collateral characteristics have to be interpreted with care since data on e.g. the occupancy rate and the quality of the collateral is missing. Hence, this paper may suffer from omitted variable bias. Moreover, it may be the case that banks cherry pick loans of which the underlying collateral is located outside in peripheral areas, which would reduce risk ex ante and hence reduced the expected loss severity.

There are however some limitations to this study, mainly related to the data. As already mentioned, this paper is not able to control for the quality of the collateral and the occupancy rate since data is missing or incorrect. Subsequently, the results for the CLTV and the collateral characteristics have to be interpreted with care. Furthermore, the size of the collateral is likely to have an impact on downturn LGD. Park and Bang (2014) find that larger houses have a larger point-in-time LGD. Moreover, they find include an interaction term between the floor area and the location of the collateral which is significant. Hence, there may be a relationship between the size and the location of the collateral. Unfortunately, this paper is not able to include the size of the collateral since data is missing. Furthermore, the data is cross-sectional and it is therefore unknown if the reported characteristics are the 'original' characteristics. The reported characteristics of the loan could be different from the original characteristics of the loan, if the terms and conditions of the loan are renegotiated, which is not uncommon for bank loans. This is especially relevant for the loan characteristics. As been mentioned before, it is likely that a borrower has multiple loans at multiple banks. The variable 'intensity of the relationship' however only measures the amount of CRE loans the borrower currently has with one bank. Posey and Yavas (2001) showed that under asymmetric information, where the risk appetite of the borrower is unknown by the lender, high-risk borrowers choose ARMs and low-risk borrowers choose FRMs. Subsequently, the chosen mortgage serves as a signal of default risk. Unfortunately, it is not possible to correct for the possible self-selection effect of the borrower with the available data. Lastly, the subset consists of 45,132 loans and hence 45,132 properties, since the property with the highest value is selected for loans which are securitized by two (or more) properties. However, in total there are actually 332,872 properties securitized by these 45,132 loans (on average a loan is securitized by 7 properties). This means that, despite the best efforts of the author to keep as many observations as possible, a significant amount of information on the collateral characteristics is still lost. Unfortunately, this is inevitable due to the structure of the data. Although information is lost on the characteristics of the collateral, this study is the first to examine the effect of collateral characteristics on downturn LGD for CRE loans

The implications of this study on the determinants of downturn LGD for the full CRE loan portfolio are the following: borrower and loan characteristics are strong determinants of downturn LGD. On the other hand, the downturn LGD of the collateral type is dependent on the location of the collateral. Hence, heterogeneity should be taken in to account. The results also indicate that there are differences between this study and previous studies which have solely focused on defaulted bank loans. To begin with, previous research on defaulted bank loans found a strong bimodal distribution for the point-in-time LGD. On the other hand, the downturn LGD in this study is skewed to the right and not bimodal, this holds for the full portfolio as well as for defaulted and healthy loans. Furthermore, there is a positive relationship between the EAD and the point-in-time LGD while there is a negative relationship between the outstanding nominal amount and the downturn LGD. Furthermore, this paper found a non-linear relationship between CLTV and downturn LGD whereas previous studies found a linear (and positive) relationship between CLTV and the point-in-time LGD.

Since the database is a first attempt to gather more loan level data on CRE, data is missing or incorrect for certain variables. This is especially true for the collateral characteristics. As previously stated, this research may therefore suffer from omitted variable bias. For future research, it is interesting to include more collateral characteristics, like the size of the property, the quality of the building and the occupancy rate. Furthermore, many hypotheses were derived from research on residential mortgages. The reason is that less research has been done on CRE loans in general. To the author's knowledge, this study is the first to even examine the effect of the amortization schedule, the interest rate type and the CLTV for CRE. The author therefore suggests that more research should be done on CRE loans to, amongst other things, verify the findings in this paper.

For future research it would be interesting to compare the downturn LGD and the point-in-time LGD for defaulted (CRE) loans to examine the differences and similarities. Moreover, examining the point-in-time LGD and the downturn LGD would be valuable for assessing the correctness of the A-IRB models. Banks that use their own A-IRB model have an incentive to underestimate downturn LGD since this may reduce capital requirements. For society it is important that (i) downturn LGD is higher than the point-in-time LGD, implying that the estimated loss is higher than the actual loss, and as a result banks have enough capital to absorb the loss or; (ii) downturn LGD and the point-in-time LGD are more or less the same so that the loss can be absorbed. If the point-in-time LGD is significantly higher than the downturn LGD, the actual loss is higher than the estimated loss. This would mean that the bank did not build up enough capital to absorb the loss. Thus, if downturn LGD is systematically lower than the point-in-time LGD, this can result in bank instability because of insufficient buffers.

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8. APPENDICES

Appendix 1: List of Abbreviations

A-IRB	Advanced Internal Rating Based
ARM	Adjustable Rate Mortgage
CRE	Commercial Real Estate
DNB	De Nederlandsche Bank (Dutch Central Bank)
EAD	Exposure at Default
FRM	Fixed Rate Mortgage
GFC	Global Financial Crisis
IRB	Internal Ratings Based
LGD	Loss Given Default
ONA	Outstanding Nominal Amount
PD	Probability of Default
RR	Recovery Rate

Appendix 2: Basel II Framework

In June 1999, the Basel committee proposed a new capital adequacy framework to replace the Basel I accord, which dated back to 1988. In June 2006, the Basel committee issued the Revised Framework on International Convergence of Capital Measurement and Capital Standards, better known as the Basel II accord. The fundamental objective of the Basel Committee was "to develop a framework that would further strengthen the soundness and stability of the international banking system while maintaining sufficient consistency that capital adequacy regulation will not be a significant source of competitive inequality among internationally active banks. The Committee believes that the revised Framework will promote the adoption of stronger risk management practices by the banking industry, and views this as one of its major benefits" (Basel Committee on Banking Supervision, 2006: p. 14).

The Basel II accord is based on three pillars. The first pillar (minimum capital requirements) provides banks with guidelines on how to calculate their minimum capital requirements that captures the credit; market and operational risks the bank is exposed to. The regulatory framework for the first pillar is specified in the second pillar (the supervisory review process). The second pillar is designed to ensure adequate risk management techniques, which banks and supervisors can use to evaluate and monitor risks. The purpose of the last pillar, market discipline, is to complement pillar 1 and 2 by developing a set of disclosure requirements.

The first pillar stipulates that banks are allowed to calculate their credit risk capital requirements according to the standardized approach or the internal ratings based (IRB) approach. Under the standardized approach banks use credit risk measurements, which are determined by the Basel II accord. Furthermore, banks use external credit ratings to determine the appropriate risk weights (Basel Committee of Banking Supervision, 2015). Under the IRB approach banks are allowed to use internal credit risk ratings provided that the bank meets certain minimum conditions and disclosure requirements (Basel Committee of Banking Supervision, 2006). More importantly, banks need approval from the supervisor in question. The four parameters used to estimate credit risk in the IRB approach are:

i. The borrower's PD over a one-year horizon, which is the probability that a borrower does not meets its obligations before it is fully repaid and hence defaults on the loan;
ii. EAD, which is the amount to which the bank is exposed to at the time of default (Basel Committee of Banking Supervision, 2006: p. 3);
iii. The maturity of the exposure;
iv. LGD, which is the outstanding amount of the loan at default (1 minus the recovery rate (RR)).

Banks can choose between two alternatives under the IRB approach, namely the foundation approach or the A-IRB approach. The main difference between these two approaches is in how the parameters can be measured and whether or not they can be determined internally (Schuermann, 2004). Banks have to determine the four key parameters under the A-IBR approach while under the foundation approach only the PD has to be determined internally. The PD is borrower specific and grounded on historical experience. The LGD and EAD on the other hand are specific to the exposure. Under the A-IRB approach, LGD must be measured as a percentage of the EAD (Basel Committee of Banking Supervision, 2004).

As been explained before, LGD is the amount that the bank loses (as a percentage of EAD) when a borrower is not able to meets its obligations and hence defaults on the loan. Under the Basel II accord, "a default occurs when one (or more) of the following events has taken place:

i. It is determined that the obligor is unlikely to pay its debt obligations (principal, interest, or fees) in full;
ii. A credit loss event associated with any obligation of the obligor, such as a charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
iii. The obligor is past due more than 90 days on any credit obligation; or
iv. The obligor has filed for bankruptcy or similar protection from creditors" (Basel Committee of Banking Supervision, 2005: p. 30).

Once a borrower defaults on the loan, the LGD is the total loss that consists of the loss of principal, the carrying costs of non-performing loans and the workout expenses. For CRE loans, this would be the difference between the EAD and the selling price of the collateral plus additional workout expenses. This is the so-called "point-in-time LGD" (the actual loss). Under Basel II banks are also required to estimate the "downturn LGD" (estimated loss), which is an estimation of the amount that could be lost during an economic downturn due to a default. Hence, the downturn LGD captures the relevant risks related to the loan, whether the loan is in default or not.

Appendix 3: Variable Definitions

Variables		Variable definitions
Dependent variable	Downturn LGD	The loss given default ratio of the amount that could be lost on the exposure during economic downturns due to a default over a one-year period to the amount that would be outstanding at default, in accordance with Article 181 of Regulation (EU) No 575/2013 (%)
Independent variables		
Borrower characteristics	PD	The counterparty's point-in-tine probability of default over one year determined in accordance with Articles 160, 163, 179 and 180 of Regulation (EU) No 575/2013 (%)
	Intensity of the relationship	The amount of CRE loans the borrower has with the bank
	Private borrower dummy	Yes is 1; 0, otherwise
	Nationality of the borrower dummy	Non-Dutch is 1; 0, otherwise
Loan characteristics	Outstanding nominal amount (ONA)	The outstanding nominal amount including unpaid past due interest but excluding accrued interest in euros.
	Age	Non-defaulted loans: July 1st 2016 minus the inception date (in days) Defaulted loans: default date mins the inception date (in days)
	Inception period dummy	1 if the loan was incepted after 2010 (after the GFC); 0, otherwise. 1 if the loan was incepted between 2008 and 2010 (during the GFC); 0, otherwise.
	Amortization schedule dummy	1 if bullet loan; 0 if amortization schedule.
	Interest rate type	1 if variable; 0 if fixed.
	CLTV	Outstanding nominal amount / (approximated) market value
Collateral characteristics	Collateral type dummy	1 if retail; 0, otherwise 1 if other; 0, otherwise 1 if office; 0, otherwise 1 if mixed use; 0, otherwise 1 if industrial; 0, otherwise *Base category: residential real estate*
	Province dummy	1 if Zuid-Holland; 0, otherwise 1 if Zeeland; 0, otherwise 1 if Utrecht; 0, otherwise 1; Overijssel; 0, otherwise 1 if Noord-Brabant; 0, otherwise 1 if Limburg; 0, otherwise 1 if Groningen; 0, otherwise 1 if Gelderland; 0, otherwise 1 if Fryslân; 0, otherwise 1 if Flevoland; 0, otherwise 1 if Drenthe; 0, otherwise *Base category: Noord-Holland*
	Top 4 municipality dummy	1 if the collateral is not located in Amsterdam, Utrecht, Den Haag or Rotterdam; 0 if the collateral is located in Amsterdam, Utrecht, Den Haag or Rotterdam.
Control variables	Special asset management dummy	1 if the asset is under special asset management; 0 if the asset is not under special asset management
	Bank dummy	Dummy variable to control for bank specific variation

Appendix 4: Descriptive statistics

Appendix 4A: Borrower Characteristics

Private Borrower	**Frequency**
No	24,477
Yes	20,655

Nationality of the borrower	**Frequency**
Dutch	44,519
Non-Dutch	613

Appendix 4B: Loan characteristics

Inception year	**Frequency**
Before the GFC (1979-2007)	17,072
During the GFC (2008-2010)	12,267
After the GFC (2011- June 30th 2016)	15,793

Amortization Type	**Frequency**
Amortization schedule	39,327
Bullet loans	5,805

Interest rate type	**Frequency**
Fixed	27,427
Variable	17,705

Special asset management	**Frequency**
No	38,278
Yes	6,854

Default	**Frequency**
Not in default	42,136
Default	2,996

Appendix 4C: Collateral characteristics

Province	**Frequency**
Drenthe	1,008
Flevoland	689
Fryslân	1,742
Gelderland	4,940
Groningen	1,703
Limburg	2,515
Noord Brabant	7,326
Noord Holland	8,978
Overijssel	2,466
Utrecht	3,486
Zeeland	799
Zuid Holland	9,480

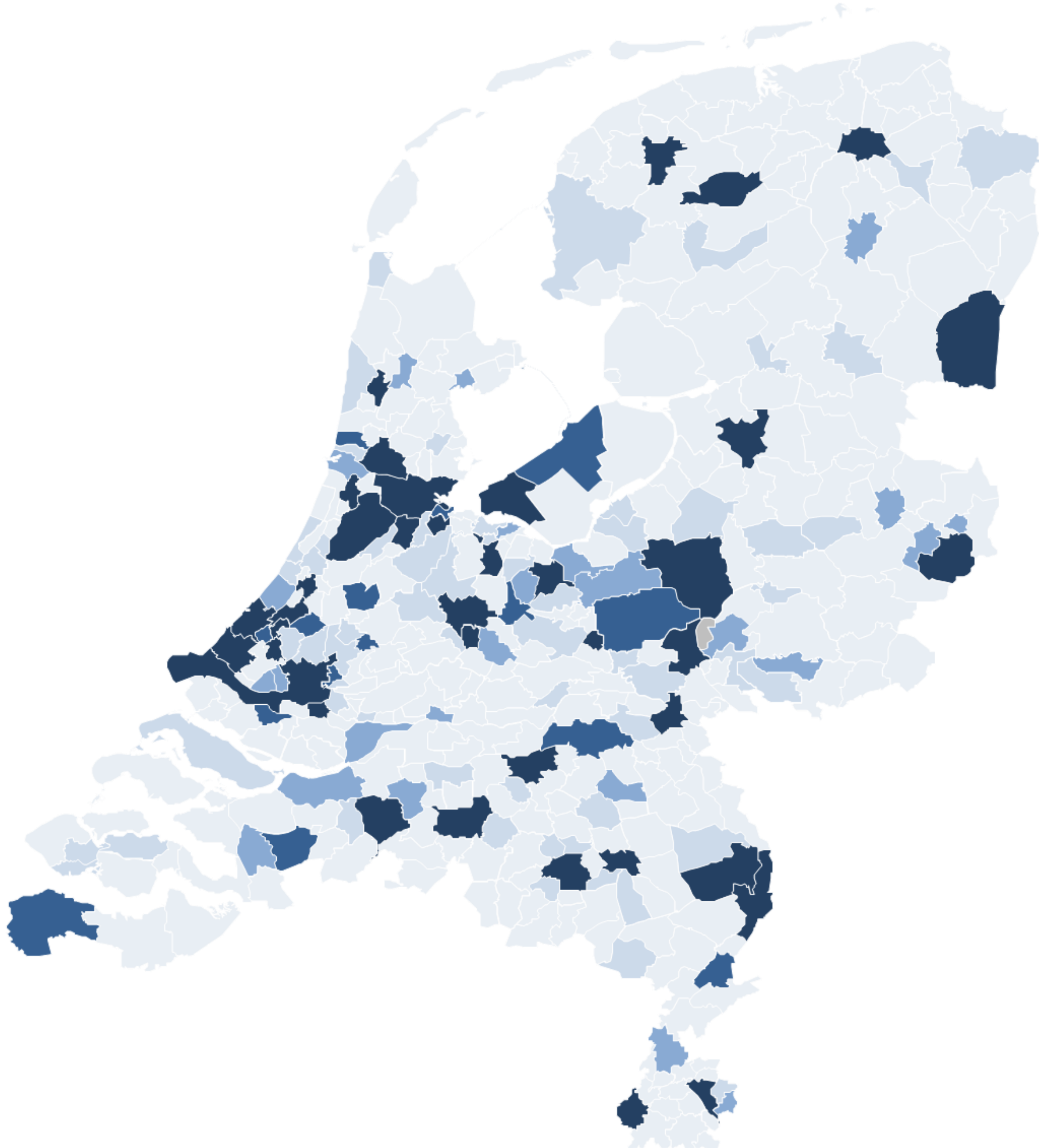
Top 4 municipalities	**Frequency**
Loans with collateral in the top 4 municipalities	9,324
Loans with collateral outside the top 4 municipalities	35,808

Type of Real Estate	**Frequency**
Industrial	6,529
Mixed use	2,379
Office	10,746
Other	9,401
Residential	10,495
Retail	5,582

Appendix 4D: CLTV

CLTV	**Frequency**
CLTV<50%	15,956
CLTV 50-60%	6,520
CLTV 60-70%	7,598
CLTV 70-80%	5,904
CLTV 80%-90%	3,338
CLTV 90-100%	2,023
CLTV 100-110%	1,125
CLTV 110-120%	829
CLTV >120%	1,729

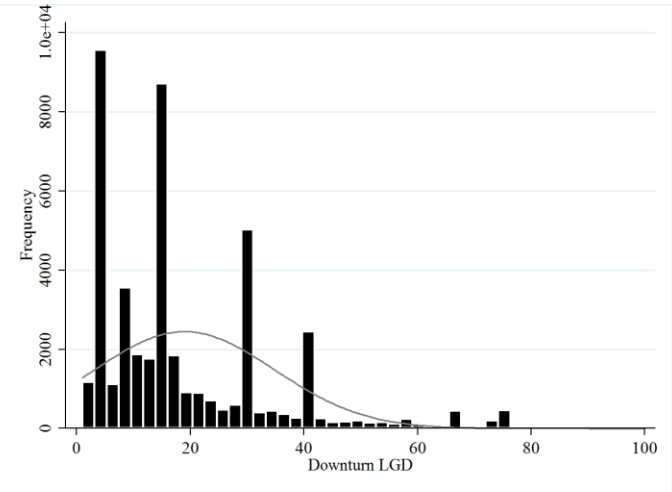
Appendix 4E: Total outstanding nominal amount per municipality (€)



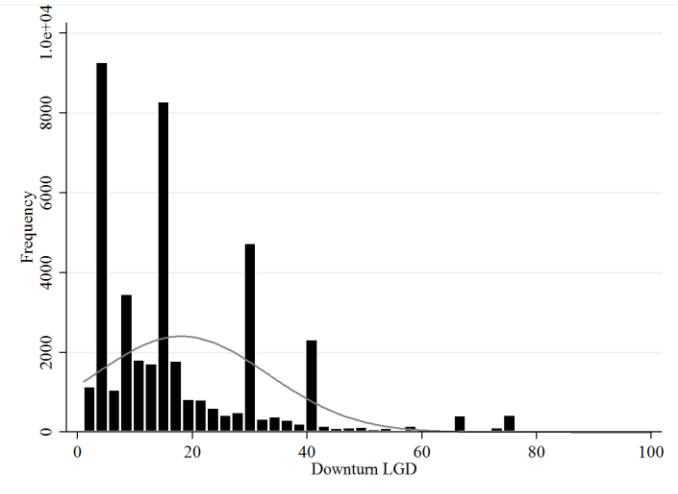
Source: DNB and author’s own calculations.

Appendix 5: Downturn LGD for key Variables

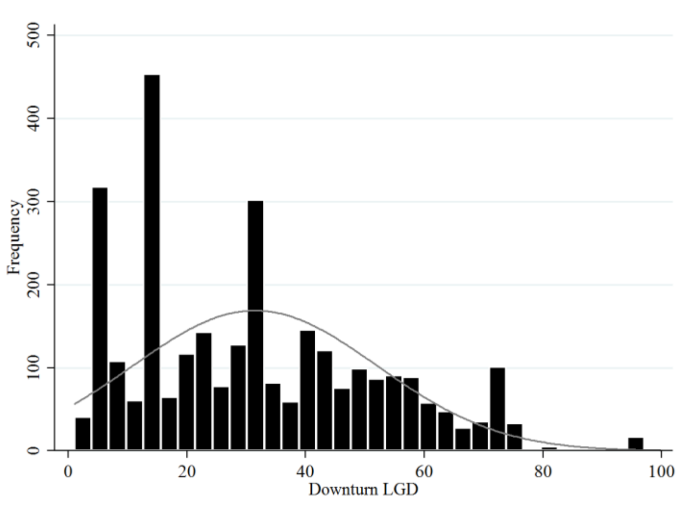
Appendix 5A: Histograms of Default Status



1. Histogram downturn LGD for defaulted and healthy loans

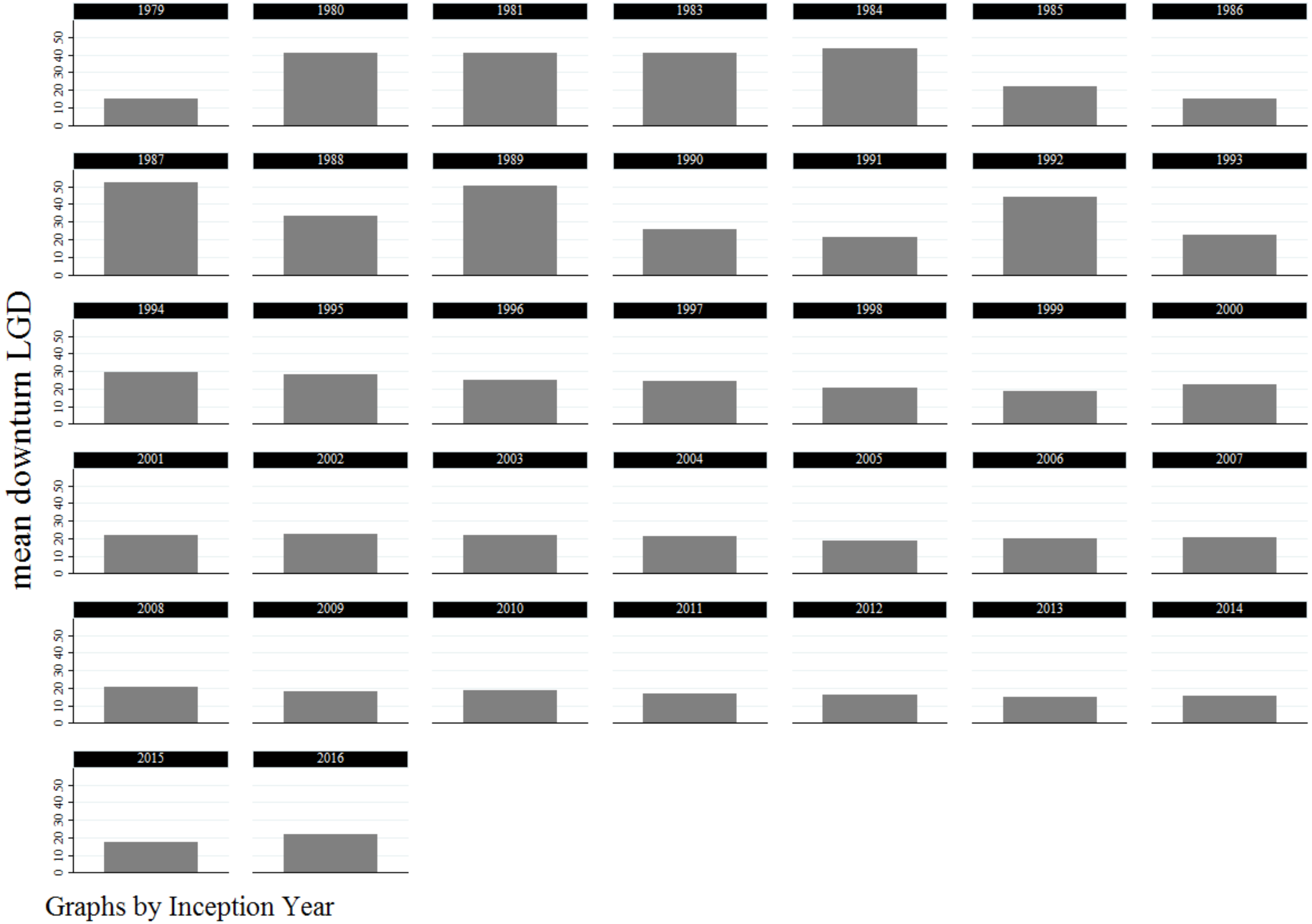


2. Histogram downturn LGD for healthy loans

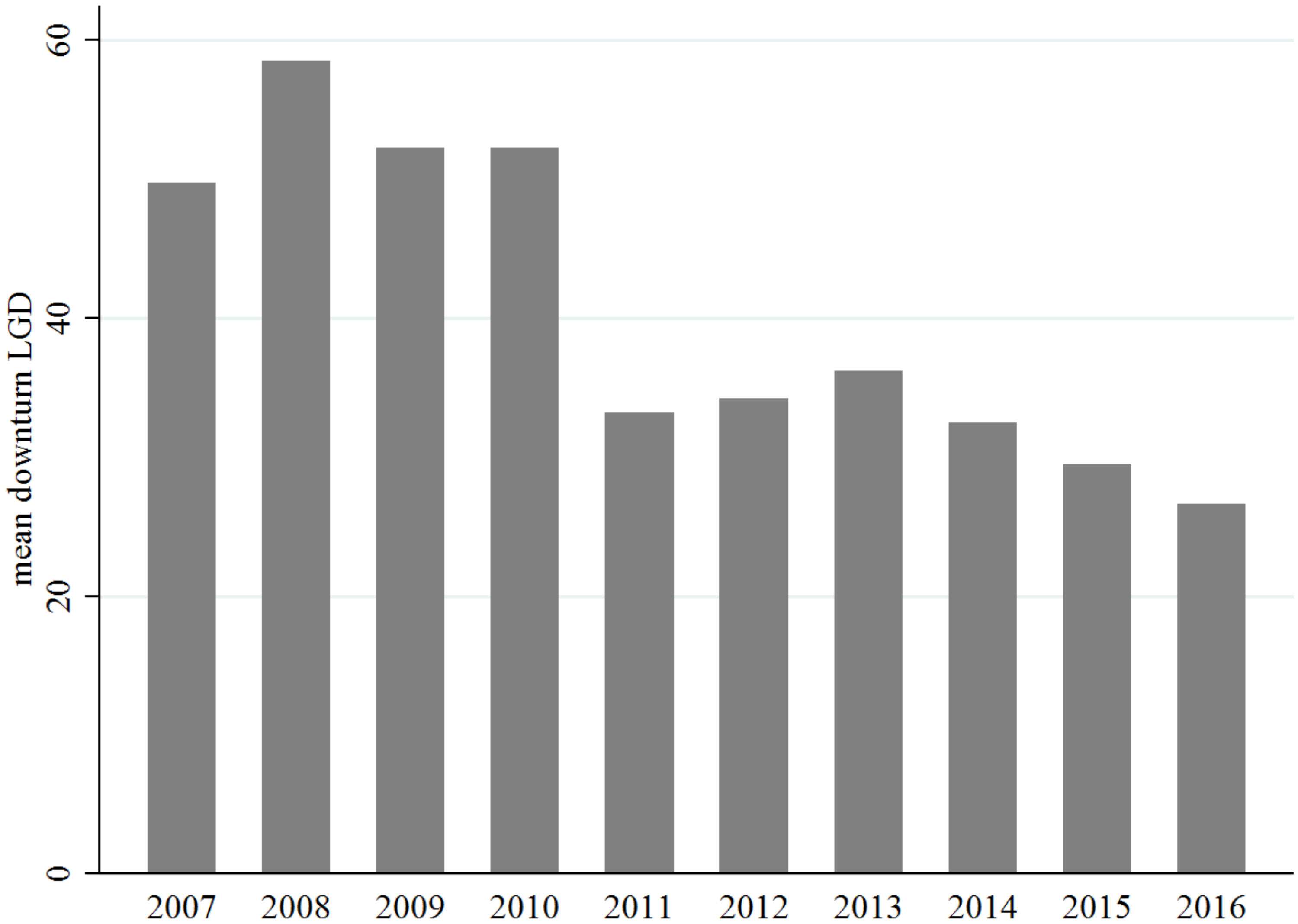


3. Histogram downturn LGD for defaulted loans

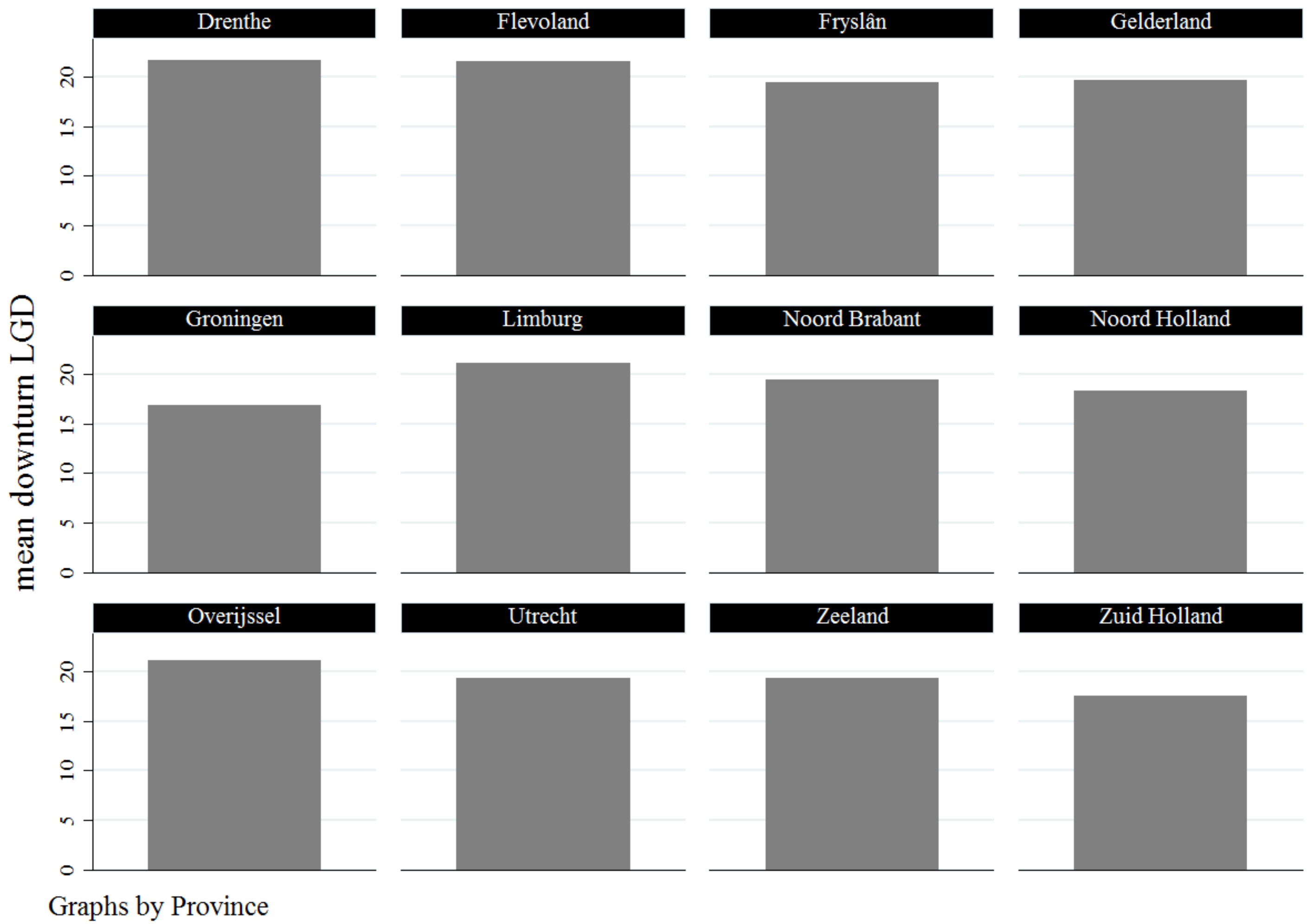
Appendix 5B: Downturn LGD by Inception Year



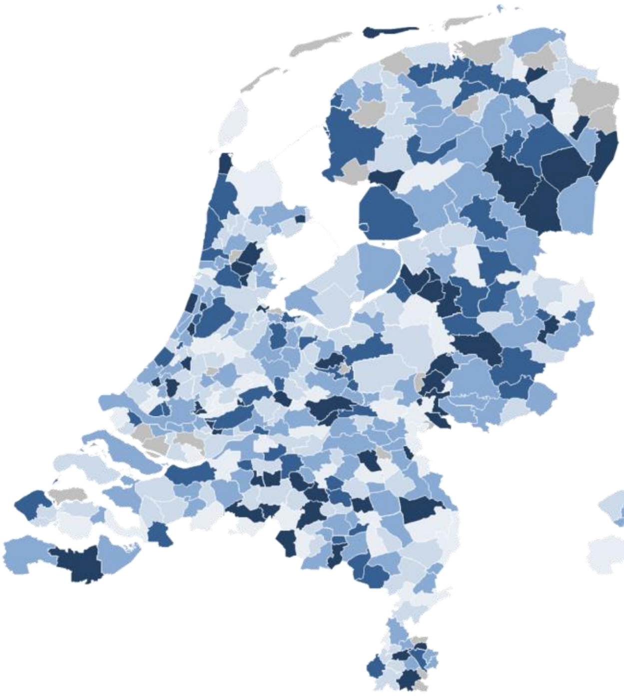
Appendix 5C: Downturn LGD by Default Year



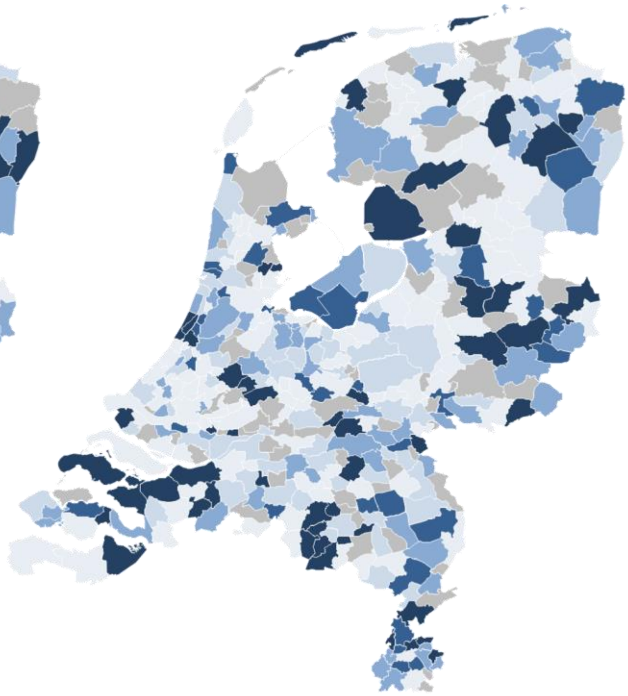
Appendix 5D: Downturn LGD by Province



Appendix 5E: Downturn LGD per Municipality



1. Average downturn LGD for offices per municipality

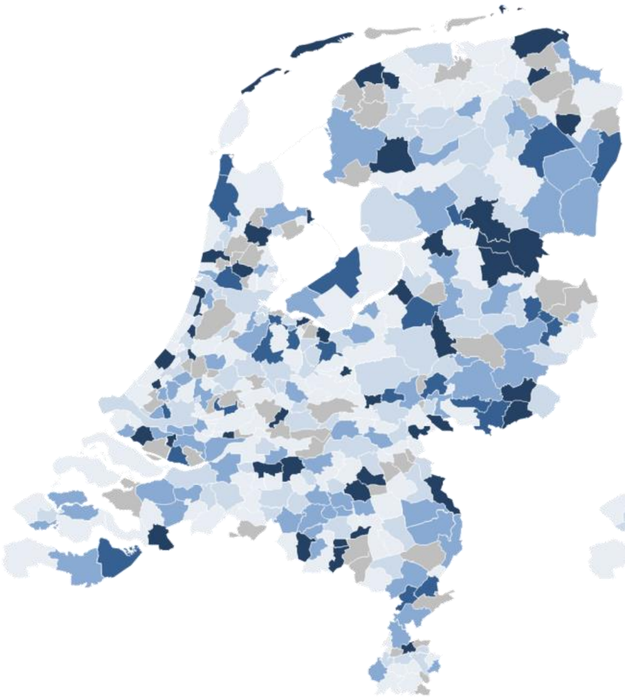


2.. Average downturn LGD for residential real estate per municipality

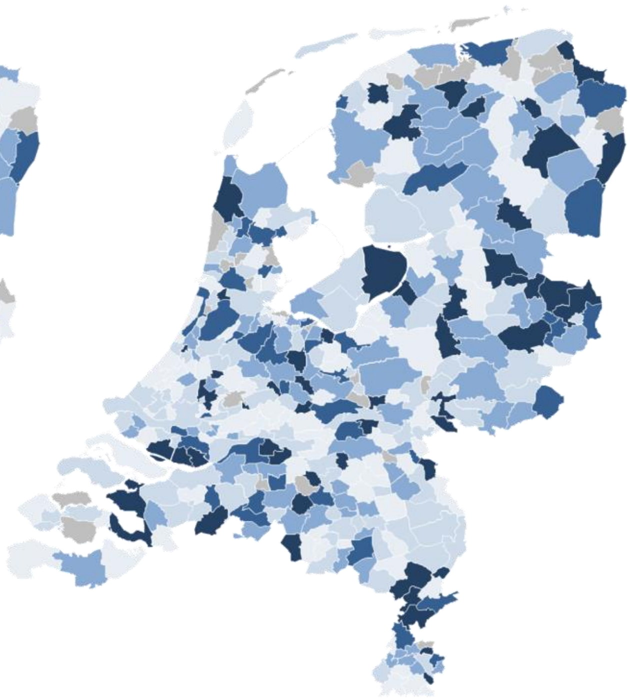
Legend

No data available
0 – 15
15 – 20
20 – 25
25 – 30
> 30

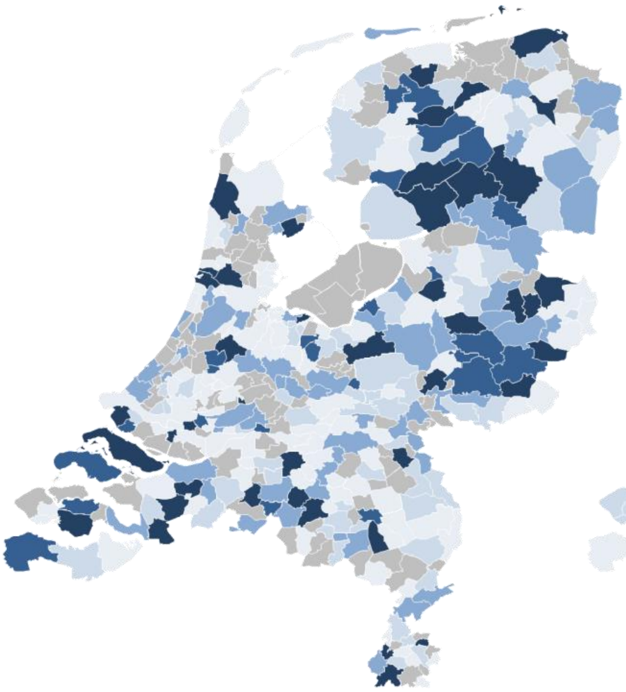
Source: DNB and author’s own calculations.



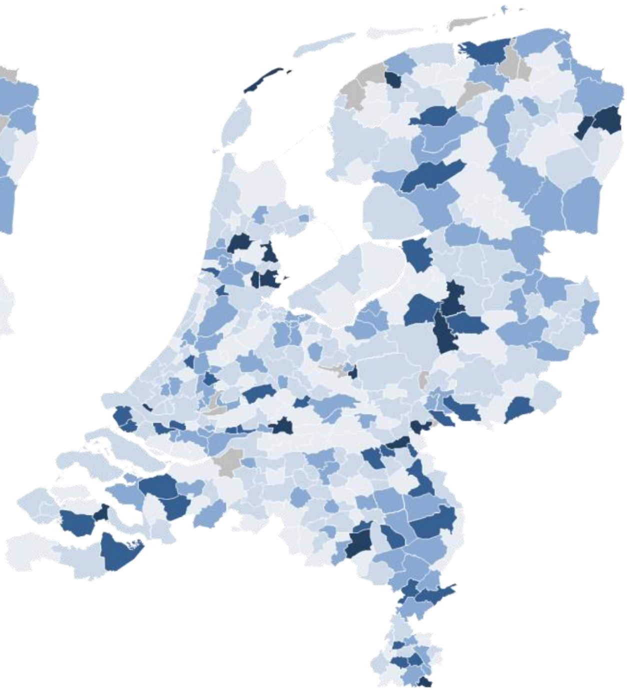
3. Average downturn LGD for retail per municipality



4. Average downturn LGD for industrial real estate per municipality



5. Average downturn LGD for mixed use real estate per municipality



6. Average downturn LGD for other real estate per municipality

Appendix 6: Regression Results

Appendix 6A: Regressions Results for Borrower and Loan Characteristics

Log-log estimates of downturn LGD for borrower and loan characteristics

Variables	Model 1	Model 2	Model 3
PD	0.115***	0.101***	0.101***
	(0.00514)	(0.00476)	(0.00478)
Intensity of the relationship	-0.131***	-0.111***	-0.111***
	(0.0114)	(0.0102)	(0.0102)
Private borrower (Yes)	0.685***	0.652***	0.647***
	(0.0130)	(0.0129)	(0.0127)
Nationality of the borrower (Non-Dutch)	-0.0350	-0.0267	-0.0229
	(0.0512)	(0.0497)	(0.0495)
Age	-0.0351***	-0.0417***	-0.0405***
	(0.00652)	(0.00628)	(0.00623)
Inception year (between 2008-2010)	-0.0507***	-0.0527***	-0.0519***
	(0.0117)	(0.0111)	(0.0111)
Inception year (after 2010)	-0.214***	-0.191***	-0.187***
	(0.0164)	(0.0153)	(0.0153)
Bullet loans	0.0723***	0.0502***	0.0504***
	(0.0150)	(0.0141)	(0.0141)
Interest rate type (Variable)	0.0412***	0.0284***	0.0280***
	(0.0107)	(0.0101)	(0.0101)
ONA	-0.0254***		-0.0196***
	(0.00421)		(0.00392)
CLTV	0.172***		
	(0.0108)		
CLTV 50-60%		-0.0588***	-0.0604***
		(0.0186)	(0.0186)
CLTV 60-70%		-0.127***	-0.127***
		(0.0186)	(0.0186)
CLTV 70-80%		-0.0869***	-0.0871***
		(0.0206)	(0.0206)
CLTV 80-90%		0.279***	0.277***
		(0.0254)	(0.0254)
CLTV 90-100%		0.521***	0.520***
		(0.0341)	(0.0341)
CLTV 100-110%		0.539***	0.538***
		(0.0377)	(0.0377)
CLTV 110-120%		0.686***	0.685***
		(0.0446)	(0.0447)
CLTV >120%		0.722***	0.722***
		(0.0329)	(0.0330)
ONA 25-50 percentile		-0.0543***	
		(0.0101)	
ONA 50-75 percentile		-0.0967***	
		(0.0119)	
ONA > 75 percentile		-0.0680***	
		(0.0160)	
Special asset management (Yes)	0.144***	0.0439**	0.0452**
	(0.0239)	(0.0216)	(0.0217)
Constant	2.507***	2.800***	2.982***
	(0.0873)	(0.0578)	(0.0777)
Bank control variables	Yes	Yes	Yes
Observations	45,132	45,132	45,132
R-squared	0.249	0.301	0.301
Adjusted R-squared	0.249	0.301	0.301

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 6B: Regressions Results for Borrower, Loan and Collateral Characteristics

Log-log estimates of downturn LGD for borrower, loan and collateral characteristics

Variables	Model 4	Model 5	Model 6	Model 7
PD	0.0917***	0.0911***	0.0906***	0.0909***
	(0.00480)	(0.00479)	(0.00480)	(0.00479)
Intensity of the relationship	-0.104***	-0.104***	-0.103***	-0.102***
	(0.0100)	(0.00992)	(0.0101)	(0.0101)
Private borrower (Yes)	0.634***	0.630***	0.627***	0.624***
	(0.0128)	(0.0129)	(0.0130)	(0.0131)
Nationality of the borrower (Non-Dutch)	-0.0247	-0.0232	-0.0152	-0.0121
	(0.0486)	(0.0486)	(0.0472)	(0.0472)
Outstanding nominal amount	-0.0361***	-0.0359***	-0.0383***	-0.0381***
	(0.00616)	(0.00616)	(0.00617)	(0.00618)
Age	-0.0294***	-0.0297***	-0.0286***	-0.0294***
	(0.00378)	(0.00376)	(0.00380)	(0.00378)
Inception year (between 2008-2010)	-0.0390***	-0.0391***	-0.0379***	-0.0378***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Inception year (after 2010)	-0.163***	-0.159***	-0.160***	-0.160***
	(0.0153)	(0.0153)	(0.0153)	(0.0154)
Bullet loans	0.0630***	0.0647***	0.0677***	0.0686***
	(0.0139)	(0.0139)	(0.0139)	(0.0139)
Interest rate type (Variable)	0.0166*	0.0163*	0.0149	0.0144
	(0.00991)	(0.00990)	(0.00995)	(0.00996)
CLTV 50-60%	-0.0546***	-0.0528***	-0.0520***	-0.0507***
	(0.0183)	(0.0182)	(0.0183)	(0.0183)
CLTV 60-70%	-0.121***	-0.119***	-0.119***	-0.117***
	(0.0184)	(0.0183)	(0.0183)	(0.0183)
CLTV 70-80%	-0.0639***	-0.0603***	-0.0613***	-0.0585***
	(0.0203)	(0.0202)	(0.0203)	(0.0203)
CLTV 80-90%	0.293***	0.293***	0.290***	0.293***
	(0.0254)	(0.0255)	(0.0257)	(0.0258)
CLTV 90-100%	0.532***	0.531***	0.527***	0.530***
	(0.0340)	(0.0339)	(0.0343)	(0.0344)
CLTV 100-110%	0.552***	0.553***	0.548***	0.550***
	(0.0381)	(0.0380)	(0.0380)	(0.0379)
CLTV 110-120%	0.694***	0.696***	0.694***	0.693***
	(0.0452)	(0.0451)	(0.0454)	(0.0456)
CLTV >120%	0.734***	0.734***	0.733***	0.733***
	(0.0331)	(0.0333)	(0.0335)	(0.0335)
Collateral type (Industrial)	0.127***	0.223***	0.104***	0.203***
	(0.0194)	(0.0443)	(0.0196)	(0.0520)
Collateral type (Mixed use)	0.0895***	0.195***	0.0730***	0.163***
	(0.0236)	(0.0600)	(0.0236)	(0.0611)
Collateral type (Office)	0.197***	0.245***	0.178***	0.285***
	(0.0179)	(0.0384)	(0.0182)	(0.0452)
Collateral type (Other)	-0.120***	-0.0376	-0.138***	-0.0262
	(0.0218)	(0.0399)	(0.0218)	(0.0407)
Collateral type (Retail)	0.0875***	0.174***	0.0712***	0.177***
	(0.0214)	(0.0487)	(0.0215)	(0.0502)
Drenthe	0.0971**	0.148		
	(0.0390)	(0.0925)		
Flevoland	0.0720	0.263**		
	(0.0448)	(0.112)		
Fryslân	0.0414	0.0912		

	(0.0282)	(0.0701)
Gelderland	0.0574***	0.163***
	(0.0208)	(0.0479)
Groningen	0.00602	0.0404
	(0.0319)	(0.0538)
Limburg	0.0980***	0.340***
	(0.0247)	(0.0537)
Noord-Brabant	0.0243	0.165***
	(0.0187)	(0.0399)
Overijssel	0.112***	0.203***
	(0.0248)	(0.0739)
Utrecht	0.0368	0.0548
	(0.0257)	(0.0515)
Zeeland	0.0987**	0.291**
	(0.0420)	(0.148)
Zuid-Holland	-0.0107	0.0162
	(0.0190)	(0.0370)
Industrial*Drenthe		-0.0920
		(0.145)
Industrial*Flevoland		-0.161
		(0.142)
Industrial*Fryslân		-0.0165
		(0.0979)
Industrial*Gelderland		-0.152**
		(0.0693)
Industrial*Groningen		-0.155
		(0.117)
Industrial*Limburg		-0.399***
		(0.0781)
Industrial*Noord-Brabant		-0.194***
		(0.0633)
Industrial*Overijssel		-0.110
		(0.0957)
Industrial*Utrecht		-0.00996
		(0.0823)
Industrial*Zeeland		-0.296
		(0.192)
Industrial*Zuid-Holland		-0.0813
		(0.0616)
Mixed use*Drenthe		-0.0738
		(0.129)
Mixed use*Flevoland		-0.620***
		(0.128)
Mixed use*Fryslân		-0.0240
		(0.102)
Mixed use*Gelderland		-0.132
		(0.0874)
Mixed use*Groningen		-0.0498
		(0.109)
Mixed use*Limburg		-0.504***
		(0.103)
Mixed use*Noord-Brabant		-0.196**
		(0.0779)
Mixed use*Overijssel		-0.177
		(0.119)
Mixed use*Utrecht		-0.119
		(0.106)
Mixed use*Zeeland		-0.190
		(0.181)
Mixed use*Zuid-Holland		-0.0480

	(0.0808)
Office*Drenthe	-0.0470
	(0.109)
Office*Flevoland	-0.164
	(0.138)
Office*Fryslân	-0.0774
	(0.0905)
Office*Gelderland	-0.119*
	(0.0654)
Office*Groningen	0.107
	(0.0909)
Office*Limburg	-0.262***
	(0.0725)
Office *Noord-Brabant	-0.163***
	(0.0550)
Office*Overijssel	-0.0608
	(0.0893)
Office*Utrecht	0.00187
	(0.0755)
Office*Zeeland	-0.235
	(0.169)
Office*Zuid-Holland	0.0304
	(0.0547)
Other*Drenthe	-0.0700
	(0.137)
Other*Flevoland	-0.318**
	(0.158)
Other*Fryslân	-0.0809
	(0.0899)
Other*Gelderland	-0.174***
	(0.0651)
Other*Groningen	-0.0884
	(0.0846)
Other*Limburg	-0.254***
	(0.0729)
Other*Noord-Brabant	-0.176***
	(0.0576)
Other*Overijssel	-0.150*
	(0.0878)
Other*Utrecht	-0.0421
	(0.0726)
Other*Zeeland	-0.194
	(0.163)
Other*Zuid-Holland	-0.0310
	(0.0540)
Retail*Drenthe	-0.0816
	(0.126)
Retail*Flevoland	-0.347**
	(0.161)
Retail*Fryslân	-0.114
	(0.108)
Retail*Gelderland	-0.0886
	(0.0776)
Retail*Groningen	-0.0705
	(0.112)
Retail*Limburg	-0.284***
	(0.100)
Retail*Noord-Brabant	-0.176**
	(0.0689)
Retail*Overijssel	-0.142

	(1)	(2)	(3)	(4)
		(0.103)		
Retail*Utrecht		-0.0122		
		(0.0915)		
Retail*Zeeland		-0.328*		
		(0.181)		
Retail*Zuid-Holland		-0.0901		
		(0.0704)		
Outside top 4			0.129***	0.224***
			(0.0165)	(0.0276)
Industrial*Outside top 4				-0.142**
				(0.0560)
Mixed use*Outside top 4				-0.133**
				(0.0657)
Office*Outside top 4				-0.154***
				(0.0488)
Other*Outside top 4				-0.160***
				(0.0434)
Retail*Outside top 4				-0.157***
				(0.0555)
Special asset management (Yes)	0.0453**	0.0456**	0.0461**	0.0466**
	(0.0215)	(0.0215)	(0.0215)	(0.0216)
Constant	2.966***	2.910***	2.914***	2.865***
	(0.0777)	(0.0802)	(0.0778)	(0.0789)
Bank control variables	Yes	Yes	Yes	Yes
Observations	45,132	45,132	45,132	45,132
R-squared	0.316	0.318	0.317	0.318
Adjusted R-squared	0.315	0.317	0.317	0.318

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1