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

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Inflated credit ratings, regulatory arbitrage and capital requirements: Do investors strategically allocate bond portfolios?[*]

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Abstract

This study investigates whether banks and insurance corporations perform regulatory arbitrage by buying bonds with inflated credit ratings. We argue that flaws in minimum capital requirements incentivize risk-taking behavior by financial institutions, diminishing financial stability. We estimate the probability of a bond having an inflated credit rating using conditional credit default swap spread distributions. We merge this data with a unique bond-level portfolio holdings dataset. The results show that banks and insurance corporations invest more in bonds with inflated credit ratings, while this effect is absent for investors who do not face capital requirements based on credit ratings. Consequently, the regulatory capital buffers of banks and insurance corporations are effectively reduced by respectively 13 and 28 percent.

Key words: Inflated credit ratings, capital requirements, regulatory arbitrage, portfolio choice, securities holdings statistics.

JEL codes: G11, G21, G22, G24, G28.

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1 Introduction

This study investigates whether European banks and insurance corporations perform regulatory arbitrage by buying bonds with inflated credit ratings. To safeguard the financial system European banks and insurance corporations face stringent capital requirements to prevent excessive risk taking behavior (Stanton and Wallace, 2018; Becker et al., 2019). These capital requirements use credit ratings to determine the risk weights and the capital buffers of banks and insurance corporations (EIOPA, 2015b; BCBS, 2010). However, credit ratings do not reflect the true credit risk as they are often inflated (White, 2010; Fulghieri et al., 2013; Sangiorgi and Spatt, 2017). Bonds with inflated credit ratings should have a lower credit rating conditional on their credit risk. Consequently, the regulatory risk weights of these bonds are too low and understate the implied credit risk. In this paper, we hypothesize that European banks and insurance corporations hold more bonds with inflated credit ratings to effectively reduce their capital requirements, increasing the fragility of the financial system.

We contribute empirically to the literature on credit ratings and capital regulation. First, we contribute to the literature by creating a measure of the probability of a bond having an inflated credit rating at the bond level using credit default swaps. Second, we analyze the propensity of different investors to hold bonds with an inflated credit rating using a confidential bond-level holdings from banks, insurance corporations, investment funds and pension funds. The differences in regulatory settings provides us with a quasi-experimental setting to identify regulatory arbitrage of European banks and insurance corporations. We are the first study that distinguishes this propensity for investors with and without capital requirements based on credit ratings. Third, we calibrate the effective reductions of capital buffers of banks and insurance corporations using the probability of a bond having an inflated credit rating and the change in regulatory risk weight when a bond has an inflated credit rating.

European banks and insurance corporations have incentives to perform regulatory arbitrage to effectively reduce their required capital (Admati, 2016). Regulatory capital is costly for banks and insurance corporations. The amount of the capital buffer determines risk-taking abilities. Consequently, the optimal portfolio allocation of banks and insurance corporations is distorted by capital requirements, which lowers expected returns (Becker and Ivashina, 2015). In this study, we define regulatory arbitrage as the deliberate purchases of bonds with inflated credit ratings to effectively reduce required capital. In our definition, financial institutions engage in regulatory arbitrage when they have disproportionately large portfolio weights in bonds with inflated credit ratings to carry more risk.[1,2]

Credit ratings measure credit risk independent of financial cycles and liquidity risk.[3] Especially in corporate bond markets, risk assessments are generally based on credit ratings (Becker and Ivashina, 2015). Credit ratings are standardized, easy to comprehend opinions of credit risk and published across asset classes (Cornaggia et al., 2017). Fitch, Moody's, and S&P, the largest credit rating agencies, mainly rely on accounting information to determine their credit ratings (Acharya et al., 2012).

Credit ratings are often inflated. First, credit rating agencies employ an issuer pay model to generate their income. In this constellation, the issuer of a bond pays the rating agency for rating their bonds. Issuers compel rating agencies to provide opportunistic ratings as they request ratings from multiple rating agencies (Bolton et al., 2012; Kashyap and Kovrijnykh, 2015; Baghai and Becker, 2018). Second, credit rating agencies desire a good reputation to sustain their eligibility for regulatory purposes (Fulghieri et al., 2013; Dimitrov et al., 2015; Frenkel, 2015). By using a "through the cycle" methodology, rating agencies create opacity as they slowly adapt to market conditions (Altman and Rijken, 2006; Sangiorgi and Spatt, 2016). This opacity obscures identifying inflated credit ratings and thus safeguards the reputation of rating agencies when ratings inaccurately reflect credit risk. Third, for corporate bonds rating downgrades occur more frequently than rating upgrades suggesting that credit ratings are inflated (Cornaggia et al., 2017).[4] This paper focuses on non-financial plain vanilla corporate bonds as this asset class is most transparent and easy to rate (Fulghieri et al., 2013; Cornaggia et al., 2017).

This study fills a gap in the literature by estimating which bonds have inflated credit rating.

[1]Prior theoretical models demonstrate that investors facing regulatory requirements based on credit ratings have incentives to engage in regulatory arbitrage and thus realign their portfolio allocations (Jackson and Perraudin, 2000; Milne, 2002; VanHoose, 2007).

[2]There is some anecdotal evidence that investors anticipate which bonds have inflated credit ratings and buy these for their favorable regulatory capital treatment. For example, asset managers provide services to optimize portfolios of insurance corporations to comply with Solvency II requirements (see Aegon Asset Management, 2017).

[3]For a recent review on credit ratings, see Sangiorgi and Spatt (2017).

[4]Inflated credit ratings occur across asset classes and tend to be more severe for more complex asset classes (Skreta and Veldkamp, 2009), see Stanton and Wallace (2018); Vink et al. (2019) on commercial mortgage-backed securities and Kiff et al. (2012) on sovereign bonds. On European corporate bonds, Abidi et al. (2019) show that the corporate sector purchase programme (CSPP) of the Eurosystem raised incentives of credit rating agencies to upwardly adjust credit ratings of bonds eligible under the CSPP.

Prior papers analyze credit risk independently of credit ratings.[5] One stream of research focuses on accounting based methodology to infer credit risk (Acharya et al., 2012; Alp, 2013). Another strand uses credit default swaps (CDS) as a substitute for credit ratings (Flannery et al., 2009; Norden, 2017). These studies do use their credit risk instrument to identify which credit ratings are inflated. In this paper we contribute by using CDS spread distributions to identify the extent to which the credit ratings of individual bonds are inflated. CDS spreads provide a timely market assessment of credit risk independent of inaccuracies in the credit rating methodologies (Becker and Ivashina, 2015).

We estimate the probability of a bond having an inflated credit rating by using a mixed distribution model based on time-dependent CDS spread distributions conditional on credit ratings. This methodology allows us to identify bonds with inflated credit ratings as outliers in the right tails of the distribution of the conditional CDS spreads. These outliers are more likely to belong to the conditional CDS spread distribution of a lower credit rating and thus have inflated credit ratings.[6] Our estimates show that 25 percent of the bonds are more likely to have an inflated credit rating rather than being accurately rated.

Capital regulations constrain investments of banks and insurance corporations, causing adverse incentives to take more risk. Specifically, bank portfolio allocations are distorted in the direction of more risky assets in a way that is often undetected by the regulator (Jokipii and Milne, 2011; Duchin and Sosyura, 2014). In addition, insurance corporations display similar behavior as they search for yield within the limits set by capital requirements (Domanski et al., 2017). Becker and Ivashina (2015) show that US insurers allocate their assets in high-yielding bonds conditional on the credit ratings. In contrast to European banks and insurance corporations, European investment funds and pension funds do not face capital requirements based on credit ratings. Therefore, investment funds and pension funds have few incentives to shape their portfolios satisfying regulatory constraints. These findings are generally consistent with closely related work of Iannotta et al. (2018) and Mink et al. (2020) for banks and Hanley and Nikolova (2018) and Becker et al. (2019) for insurance corporations using different approaches.

[5]There are several other studies that analyze both credit ratings and CDS spreads focusing on the impact of credit rating changes, (See e.g. Hull et al., 2004; Norden and Weber, 2004; Finnerty et al., 2013; Chava et al., 2018).

[6]For example, an A rated bond with a CDS spread of 120 basis points is likely to have an inflated credit rating given a mean CDS spread of respectively 65 and 110 basis points for A and BBB rated bonds with similar volatility.

In this paper we exploit the contrast between different capital regulations to estimate the impact of bonds with inflated credit ratings on portfolio allocations separately for European banks, insurance corporations, investment funds and pension funds. We use an unique dataset containing over half a million bond-level observations during the period of 2013Q4 to 2018Q4. We find that only banks and insurance corporations invest more in bonds with inflated credit ratings. In economic terms, when ratings become inflated the portfolio weights of banks and insurance corporations tend to increase by 21 percent and 52 percent respectively. These results support our hypothesis that banks and insurance corporations perform regulatory arbitrage by allocating their portfolio disproportionately to bonds with inflated credit ratings.

To quantify the consequences for financial stability, we calibrate the effective capital buffer reductions due to inflated credit ratings. To compute these reductions, we adjust risk weights of bonds with the probability of a bond having an inflated credit rating in accordance with the standardized models of Basel III and Solvency II.[7] Specifically, we compute these reductions as the change in risk weights for a single drop in the credit rating of a bond multiplied by the probability of a bond having an inflated credit rating and holding amounts. In aggregate, the effective required capital buffers of European banks are reduced by 13 percent and most pronounced in vulnerable countries. The reductions on a country level are always larger for insurance corporations than for banks and on average 28 percent. Our work suggest that flaws in regulation incentivize risk-taking behavior by financial institutions, diminishing financial stability.

2 Data

This paper uses non-financial plain vanilla corporate bond holdings from the Securities Holdings Statistics (SHS) database of the ECB. This database contains bond-level holdings of European banks, insurance corporations, investment funds and pension funds. We collect quarterly holdings, aggregated to the country level for these investors, covering the period 2013Q4-2018Q4. We have data from all 19 euro area countries, namely Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands,

[7] External credit ratings are used to validate the accuracy of the credit risk assessment of internal rating models (EIOPA, 2015a; BCBS, 2020). Therefore, even banks and insurance corporations who use internal (rating based) models can effectively reduce their required capital by holding bonds with inflated credit ratings.

Portugal, Slovakia, Slovenia and Spain and constrain our sample to investors with a combined holdings of at least 10 million euro in corporate bonds.[8] In our study, we exclude bonds with (i) an amount outstanding of less than 10 million euro, (ii) combined portfolio holdings across investors of less than 1 million euro at a given period, and, (iii) combined portfolio holdings of less than 5% of the amount outstanding. In addition, each bond must have at least five investors on a sector-country level on average over the timespan. The holdings data provides us with 12,604 unique bonds.

We obtain credit ratings and credit watch information of S&P, Moody's and Fitch from Refinitiv, Bloomberg and the Centralised Securities Database (CSDB). Furthermore, we retrieve the yearly issuer CDS spreads interpolated to match the duration of the bond from Refinitiv and Bloomberg. The advantage of using non-financial plain vanilla corporate bonds is that the credit risk of the issuer and the bond are very similar given the duration.[9] We use the CSDB to extract the issuer country and industry as well as the currency of denomination, the yield to maturity, the amount outstanding and the duration of the bond. From Refinitiv we get the bid-ask spreads. The FRED is employed to collect the three month German bund and T-bill rate. When merging all data and retaining bonds with a CDS spread and at least one credit rating, our sample contains 4,079 unique bonds with 540,989 observations.[10]

By the end of 2018, the holdings in our sample cover 610 billion euros representing 46.1% of the total non-financial plain vanilla corporate bond holdings of European banks, insurance corporations, investment funds and pension funds (at market value including accrued interest rate). Aggregated over all investors in the sample, the holding share of European banks, insurance corporations, investment funds and pension funds is on average 32 percent of the amount outstanding of non-financial plain vanilla corporate bonds. Figure 1 shows that the holdings for each investor sector have steadily increased over time. In 2018Q4, investment funds had the largest bond portfolio with approximately 285 billion euros followed by insurance corporations

[8]By removing investors with a combined holdings of less than 10 million form our sample, we remove pension funds from Cyprus, banks and investment funds from Estonia, French pension funds, Lithuanian investment funds and Maltese pension funds.

[9]Whilst bond and issuer credit risks are very similar for non-financial firms, there are large discrepancies for other types of assets, such as bank bonds with different seniority or securitizations with multiple trances (Cornaggia et al., 2017).

[10]For more details on credit ratings, CDS spreads and the other control variables, see respectively Appendix A, B and C.

with almost 250 billion euros. Table 1 further decomposes the holdings by credit rating. Evidently, banks and insurance corporations have the largest combined share of AAA, AA and A rated bonds. In contrast to highly rated bonds, we find that the portfolio shares for speculative grade bonds are substantially higher for investment funds and pension funds.

3 Method

The first part of the methodology focusses on the computation of the probability of a bond having an inflated credit rating using credit default swap (CDS) spreads. The second part present the regression model used to measure the impact of inflated credit ratings on the portfolio weights of European investors separately. This allows us to test whether only banks and insurance corporations hold respectively more bonds with inflated credit ratings, ceteris paribus.

3.1 Estimating inflated credit ratings

CDS spreads are publicly traded derivatives that provide insurance in case of credit events. CDS spreads represent the market price of credit risk (Flannery et al., 2009; Friewald et al., 2014; Norden, 2017). CDS spreads are unrelated to the biases in credit ratings as they represent the market price of the credit risk (Norden and Weber, 2004; Hull et al., 2004; Tang and Yan, 2010; Becker and Ivashina, 2015).[11] Becker and Ivashina (2015) separates the credit risk implied by credit ratings into the actual credit risk of a bond and a potential bias. This bias can be exposed by comparing the credit risk implied by ratings to an accurate estimate of credit risk.

In this paper we contribute to the literature by creating a measure that identifies inflated credit ratings of individual bonds using conditional CDS spread distributions. The credit risk of all bonds with the same credit rating can be expressed as a distribution of CDS spreads conditional on that rating. Suppose credit ratings provide an accurate estimate of credit risk, then the conditional CDS spread distributions should not overlap. In practice, CDS spread distributions overlap extensively across credit ratings. Figure 2 displays the CDS spread distributions for different credit ratings of all bonds within our sample. We observe strong outliers on the right tails of the distributions, indicating that some bonds have a too high CDS spread for their current

[11] See Augustin et al. (2014) for a review on CDS spreads.

credit rating. These outliers allow for the identification of bonds with inflated credit ratings as their CDS spreads indicate that these bonds are more likely to belong to a lower credit rating than to their current rating.[12,13]

The probability of a bond having an inflated credit rating is calculated by employing a mixed distribution model based on conditional CDS spread distributions. Identifying outliers in these distributions gives an indication which bonds are likely to have inflated credit rating. We estimate the mixed distribution model by estimating probability density functions of the CDS spread distributions, conditional on the current- and one lower credit rating of the bond.[14] The probability of a bond having an inflated credit rating is constructed by weighting the relative probabilities of a bond belonging to a conditional CDS spread distribution with the a priori probability of a bond having that credit rating.

The probability of a bond having an inflated credit rating, $\mathbf{P}(\inf)_{i,t}$, is computed with the following formula:[15]

$$P_{(CR=k-1_i, T=t|CDS=x_i)} = \frac{f(x_i, \mu_{k-1,t}, \sigma^2_{k-1,t}) * P_{k-1,t}}{f(x_i, \mu_{k,t}, \sigma^2_{k,t}) * P_{k,t} + f(x_i, \mu_{k-1,t}, \sigma^2_{k-1,t}) * P_{k-1,t}} \tag{1}$$

The first two central moments of the CDS spread distribution conditional on credit rating (CR) k at time period (T) t represent $\mu_{k,t}$ and $\sigma^2_{k,t}$ in equation (1). The log-normal probability density function using a CDS spread distribution with a mean of $\mu_{k,t}$, a variance of $\sigma^2_{k,t}$ and a CDS

[12] CDS spreads are an adequate measure of credit risk even though they represent expected default losses while credit ratings capture the probability of default. The difference between the expected default losses and the probability of default is reflected in the recovery rate of a bond. The advantage of using conditional CDS spread distributions is that only the interdependency of the distributions, and not the level, determines which bond has an inflated credit rating. This interdependency is safeguarded as the recovery rates for different conditional distributions are similar and of low variance. The average recovery rates are relatively stable across conditional CDS spread distributions as recovery rates are largely determined by the industry of a bond, which are appropriately dispersed across the conditional distributions (Jankowitsch et al., 2014). The variance of the recovery rates is relatively low as our sample resides in a period of economic growth (2013Q4 to 2018Q4) (Altman et al., 2005).

[13] We use CDS spreads, a point in time measure, to capture the credit risk of through the cycle credit ratings. CDS spreads are applicable in this setting because they are stable throughout the time-span of this paper (2013Q4-2018Q4). Individual CDS spreads show signs of high autocorrelation as our whole sample resides in a period of economic growth, with little variation in the average CDS spread. To enforce the stable nature of CDS spreads, we smooth CDS spreads by using an average quarterly CDS spread over a rolling interval of a year.

[14] Appendix B gives more details on the estimation of the conditional CDS spread probability density functions and CDS spreads more generally.

[15] In our main analysis we focus on inflated credit ratings in line with the literature. Later, we extend our model by allowing for both inflated and deflated credit ratings.

spread of x is expressed as $f(x, \mu_{k,t}, \sigma^2_{k,t})$. The unconditional a priori probability of a bond having a credit rating k at time t is defined as $P_{k,t}$. The credit rating $k-1$ represents the credit rating below the current credit rating k with both ratings elements of the broad rating categories AAA, AA, A, BBB, BB, B and CCC or lower. Consequently, the probability of a bond having an inflated credit rating, $\mathbf{P}(inf)_{i,t}$, is expressed as the probability of a bond with a CDS spread of x and a credit rating k at time t belonging to the credit rating $k-1$.

Using equation (1) we find an estimated average $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ of 31.33%, with a median of 23.87%. Figure: 3 provides the distribution of our estimated $\widehat{\mathbf{P}(\text{inf})}_{i,t}$. A quarter of the bonds is more likely to have an inflated credit rating than being accurately rated as their $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ is larger than a half numerically.

We argue that the estimated probability of a bond having an inflated credit rating yields plausible properties. First, bonds with credit ratings that experience a downgrade in the next quarter have a higher $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ while bonds that experience future upgrades have a lower $\widehat{\mathbf{P}(\text{inf})}_{i,t}$, conditional on the credit rating of the bond.[16] Second, bonds with a negative credit watch have a higher $\widehat{\mathbf{P}(\text{inf})}_{i,t}$, while bonds with a positive credit watch have a lower $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ conditional on the credit rating of the bond. Finally, $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ is generally lower for bonds with a **+** sub-rating and higher for bonds with a **-** sub-rating, conditional on the credit rating of the bond.[17]

In a bivariate approach, we link the probability of a bond having an inflated credit rating to the portfolio weights of European investors. We split the portfolio weights of banks, insurance corporations, investment funds and pension funds, by above or below the investor median $\widehat{\mathbf{P}(\text{inf})}_{i,t}$. We index the portfolio weights of the bonds with a below median $\widehat{\mathbf{P}(\text{inf})}_{i,t}$ to 100 for each investor. Figure 4 shows that the portfolio weights of banks and insurance corporations are substantially higher for the bonds with an above median $\widehat{\mathbf{P}(\text{inf})}_{i,t}$. However, these weights are relatively lower for investment funds and pension funds. This bivariate observation suggests that only banks and insurance corporations, who have capital requirements based on credit rating, hold more bonds with inflated credit ratings. We test this observation in more detail by applying a regression model in the next section.

[16] This suggests that some of bonds have only temporarily inflated credit ratings. However, rating up- and downgrades are infrequent as they occur only respectively 2.40% and 3.23% of the time in line with (Cornaggia et al., 2017). Therefore, many bonds are also not-temporarily inflated.

[17] Appendix D elaborates on these findings.

3.2 Regression model

In this section we present a regression model to analyze the tendency of different European investors to hold bonds with inflated credit ratings. We separately estimate this tendency for each investor by regressing the probability of a bond having an inflated credit rating on portfolio weights for individual bonds. We hypothesize that only banks and insurance corporations hold more bonds with inflated credit ratings to effectively reduce their required capital. The following model is created to study the impact of the probability of a bond having an inflated credit rating on the portfolio allocation across European investors, whist controlling for other portfolio determinants:

$$
\begin{aligned}
W_{i,s,j,t} = \alpha + \beta_1 \mathbf{P}(\text{inf})_{i,t} + \sum_{s=1}^{3} (\delta_s S_s + \beta_{s+1} \mathbf{P}(\text{inf})_{i,t} S_s) + \sum_{b=1}^{B} \theta_b X_{i,t}^b + \sum_{s=1}^{3} \sum_{b=1}^{B} (\theta_b^{'} X_{i,t}^b S_s) \\
+ \sum_{c=1}^{2} \sum_{s=1}^{3} (\gamma_{c_1} C_{i,t}^c + \gamma_{c_2} S_s C_{i,t}^c + \gamma_{c_3} \mathbf{P}(\text{inf})_{i,t} C_{i,t}^c + \gamma_{c_4} \mathbf{P}(\text{inf})_{i,t} S_s C_{i,t}^c) \\
+ \sum_{d=1}^{D} \zeta_d IC_i + \sum_{m=1}^{M} \xi_m NACE_i + \sum_{j=1}^{J} \sum_{s=1}^{3} (\phi_{j_1} J_j + \phi_{j_2} J_j S_s) \\
+ \sum_{k=1}^{K} (\eta_{k_1} K_{i,t}^k + \eta_{k_2} \mathbf{P}(\text{inf})_{i,t} K_{i,t}^k) + \sum_{c=1}^{2} \sum_{k=1}^{K} (\eta_{k_3} K_{i,t}^k C_{i,t}^c + \eta_{k_4} \mathbf{P}(\text{inf})_{i,t} K_{i,t}^k C_{i,t}^c) \\
+ \sum_{t=1}^{T} \tau_t T_t + \epsilon_{i,s,j,t} \qquad (2)
\end{aligned}
$$

The dependent variable $W_{i,s,j,t}$, defined as $\frac{W_{i,s,j,t}}{\sum_{i=1} W_{i,s,j,t}} * 100\%$, represents the portfolio weight of European investor sectors (S, with $s \in$ banks, insurance corporations, investment funds and pension funds) from country j in an individual bond i at time t. We separately measure the impact of inflated credit ratings on the portfolio weights of banks, insurance corporations, investment funds and pension funds. We do so by using $\mathbf{P}(\text{inf})_{i,t}$ as main explanatory variable with interaction terms of $\mathbf{P}(\text{inf})_{i,t}$ and each investor sector s in line with Boermans and Vermeulen (2019), with investment funds as the reference category. We hypothesize that the estimated coefficients, for banks ($\hat{\beta}_1 + \hat{\beta}_2$) and for insurance corporations ($\hat{\beta}_1 + \hat{\beta}_3$), should both be positive as we argue that European banks and insurance corporations will hold relatively more bonds with inflated credit ratings. The coefficient $\hat{\beta}_1$ for the reference category s investment funds and the coefficients $\hat{\beta}_1 + \hat{\beta}_4$ for pension funds should be insignificant or negative as these investors do not face capital requirements based on credit ratings.

The vector $X^b_{i,t}$ includes the following bond characteristics (B): amount outstanding, credit spread, duration, bid-ask yield spread and the currency of the bond. In addition, we allow these bond characteristics to vary as determinant of the portfolio weight for each investor sector by introducing the interaction terms $X^b_{i,t}S_s$. $C^c_{i,t}$ is a categorical variable for positive and negative credit watch. A negative credit watch is associated with a higher likelihood of a credit rating downgrade, therefore the CDS spreads, conditional on the credit rating of the bond, tend to be higher (and vice versa for positive credit watch). For investors facing capital requirements, potential credit rating changes are costly as they induce transaction costs due to forced buying and selling of bonds to retained optimal portfolio weights. To control for the impact of credit watch on $\mathbf{P}(\inf)$ and investor preferences, we use three broad interactions $S_sC^c_{i,t}$, $\mathbf{P}(\inf)_{i,t}C^c_{i,t}$ and $\mathbf{P}(\inf)_{i,t}S_sC^c_{i,t}$. The vectors IC_i, $NACE_i$, J_j and J_jS_s covers supply and demand fixed effects similar to Khwaja and Mian (2008). First, IC_i and $NACE_i$ express respectively each issuer country (D) and industry (M) of the bond with dummy variables to capture unobserved idiosyncratic characteristics of the issuer country and industry. These terms take up general bond supply effects. Second, we control for investor country fixed effects (J_j) on a sector level (J_jS_s) to correct for unobserved variation in investor demand. The vector $K^k_{i,t}$ comprises dummies for the granular score of the average credit ratings ranging from 1 to 21, with the average credit rating BBB as a reference category. We demeans $\mathbf{P}(\inf)_{i,t}$ for both average credit ratings and credit watch by introducing the interaction terms $\mathbf{P}(\inf)_{i,t}K^k$, $K^k_{i,t}C^c_{i,t}$ and $\mathbf{P}(\inf)_{i,t}K^k_{i,t}C^c_{i,t}$. These credit rating controls pick up ex ante differences in risk profiles and investment mandates across credit ratings among the different investors.[18] Finally, we include quarterly time fixed effects T_t.[19]

For illustrative purposes we simplify the estimation model by condensing the control variables and fixed effects of equation 2 as follows:

[18]For example, European banks and insurance corporations allocate the largest share of their holdings to highly rated bonds, followed by insurance corporations, investment funds and pension funds (Table 1). Higher rated bonds have a higher $\mathbf{P}(\inf)$ due to lower a priori probabilities and larger overlap in conditional CDS spreads distributions (Figure: 2). Introducing dummies and interactions across credit rating (k) for each investor sector corrects for this differences.

[19]Appendix C provides more details on these control variables.

$$W_{i,s,j,t} = \alpha + \beta_1 \mathbf{P}(\text{inf})_{i,t} + \sum_{s=1}^{3} (\delta_s S_s + \beta_{s+1} \mathbf{P}(\text{inf})_{i,t} S_s) + \theta \mathbf{X}_{i,s,t} + \gamma \mathbf{C}_{i,t} + \kappa \mathbf{I}_i$$
$$+ \phi \mathbf{J}_{s,j} + \eta \mathbf{K}_{i,t} + \tau \mathbf{T}_t + \epsilon_{i,s,j,t} \quad (3)$$

In our first regression model, we measure the impact of inflated credit ratings on the portfolio weights of European investors by controlling for bond characteristics ($\mathbf{X}_{i,t}$) as well as credit watch ($\mathbf{C}_{i,t}$) and time fixed effects ($\mathbf{T}_t$). Furthermore, in a second regression model we exploit the unique structure of our dataset by introducing supply ($\mathbf{I}_i$) and demand ($\mathbf{J}_{s,j}$) fixed effects to control for the distribution of available bonds across industry and country and holder sector-country preferences. Additionally, we introduce credit rating fixed effects ($\mathbf{K}_{i,t}$) to the final regression model to control for investor preferences for different credit ratings and to demean $\mathbf{P}(\text{inf})_{i,t}$.

One of the major benefits of our setup compared to other studies is that we are able to compare the tendency to hold bonds with inflated credit ratings across investor sectors. The interaction terms give rise to a kind of quasi experimental setting, similar to a difference in difference (DiD) estimator where we have one group of investors facing capital requirements based on credit ratings and one ('control') group where these regulatory frameworks do not apply (while in a DiD there is a treatment at a point in time that is mainly relevant for one group and not for the control group).

4 Results

4.1 Baseline estimations

We find that banks and insurance corporations have higher portfolio weights when the probability of a bond having an inflated credit rating $\mathbf{P}(\text{inf})$ is high. Table 2 Column (1) presents the baseline estimation of Equation (3), where we include bank, insurance corporation and pension fund dummies and interaction terms and control for bond characteristics ($\mathbf{X}$), credit watch ($\mathbf{C}$) and time fixed effects ($\mathbf{T}$). We find that the portfolio weights of banks and insurance corporations increase respectively 0.146 and 0.085 percentage points for a 100 percentage point increase in

P(inf).[20] The average portfolio weights of banks and insurance corporations are respectively 0.559% and 0.225%. In economic terms, when the credit rating of a bond becomes inflated, the portfolio weights of banks and insurance corporations increase respectively 26.21% and 37.78%.[21]

While banks and insurance corporations hold more of a bond when **P**(inf) increases, investment funds and pension funds hold less. Table 2 Column (1) shows that investment funds and pension funds reduce portfolio weights by respectively 0.041 and 0.0783 percentage points for a 100 percentage points increase in **P**(inf). The average portfolio weights of investment funds and pension funds are respectively 0.122% and 0.328%. In economic terms, when the credit rating of a bond becomes inflated, the portfolio weights of investment funds and pension funds decrease respectively 23.87% and 33.61%. These results are in line with our hypothesis becayse European banks and insurance corporations, who face capital requirements based on credit ratings, perform regulatory arbitrage by holding more bonds with inflated credit ratings.

When introducing additional controls for supply and demand effects (**I**) and (**J**) as in Equation (3) we also find that banks and insurances corporations hold more bond with inflated credit ratings. In Table 2, Column (2) the explained share of portfolio weight variation (Adj. R^2) increases from 0.035 to 0.309. We find that the portfolio weights of banks and insurance corporations change respectively from 0.146 to 0.094 and from 0.085 to 0.098 percentage points for a 100 percentage point increase in **P**(inf). In economic terms, when the credit rating of a bond becomes inflated and we control for supply and demand effects, the portfolio weights of banks and insurance corporations increase respectively 16.99% and 44.00%. For investment funds and pension funds we show a negative relation between **P**(inf) and portfolio weights. These results are of similar economic magnitude in comparison to Table 2 Column (1).

In addition, Table 2 Column (3) shows that the results are not driven by discrepancies in the portfolio allocations across credit ratings for the different investor sector, nor by differences in the average **P**(inf) across credit ratings. Table 2 Column (3) introduces credit rating controls (**K**)

[20] Due to the interaction terms in Table 2, the coefficients cannot be directly interpreted. By taking a first order derivative of Equation 3 with respect to **P**(inf), the effect for banks is the sum of the coefficients of **P**(inf) and the interaction term of **P**(inf) to the bank dummy. In the case of the first column for banks, the portfolio weight of banks increases by 0.187 - 0.041 = 0.146 for a 100 percentage point increase in **P**(inf).

[21] We define "the credit rating of a bond becoming inflated" as an increase of **P**(inf) from 0% to 100% or a 100 percentage point. This resembles a change in the credit rating of a bond from currently not inflated to inflated.

as in Equation (3). In economic terms, when the credit rating of a bond becomes inflated, the portfolio weights of banks and insurance corporations increase respectively 20.75% and 52.44%. For investment funds we find no relationship between the $\mathbf{P}(\text{inf})$ and the portfolio weight, while for pension funds the portfolio weights decrease when $\mathbf{P}(\text{inf})$ increases.

Our results suggest that European banks and insurance corporations engage in regulatory arbitrage by holding a disproportional amount of bonds with inflated credit ratings to meet their capital requirements.[22] These preferences, evoked by capital requirements imposed by Basel III and Solvency II,persist even after accounting for numerous control variables in our specifications. In contrast, European investment funds and pension funds, who do not face regulatory capital constraints based on credit ratings, have no tendency to hold more bonds with inflated credit ratings.

5 Are there difference across credit rating agencies?

We analyze whether the tendency of European banks and insurance corporations to hold bonds with inflated credit ratings - $\mathbf{P}(\text{inf})$ - is associated with certain credit rating agencies. We verify if our findings are driven by systematic differences in credit ratings of specific credit rating agencies, because discrepancies in individual credit ratings can affect the $\mathbf{P}(\text{inf})$ of the average credit rating and thus the extent of potential for regulatory arbitrage. For example, credit ratings display asymmetries as Bolton et al. (2012) shows that credit rating agencies respond differently to competitive pressure to amend the credit rating of the issuer. Moreover, this affects capital requirements as Bongaerts et al. (2012) find that Fitch acts as a tiebreaker for regulatory purposes when individual credit ratings deviate.

We create three credit rating agency specific $\mathbf{P}(\text{inf})$s based on Equation (1) to re-estimate Equation (3) for individual credit rating agencies. We estimate credit rating agency specific $\mathbf{P}(\text{inf})$ by using the individual credit ratings to compute the a priori probabilities as well as the conditional CDS spread distributions. To make the results comparable to our most strict

[22]The next section presents further tests. In addition, Appendix B, Table B2 show that the main results are not affected by our smoothing assumption of the CDS spreads over a one year period. Appendix C, Table C5 shows that these results are not driven by "small" investor sectors from certain countries. Also, the findings are robust when we remove bonds with an AAA rating and CCC rating (Appendix D, Table D2).

specification as in Table 2 Column (3), we introduce rating agency specific fixed effects for a subset of bonds where we have combined data from S&P, Moody's and Fitch.

The effects of the probability of a bond having an inflated credit rating on the portfolio weights of European banks and insurance corporations for individual credit ratings are similar across credit rating agencies. Table 3 presents separately the analysis for S&P, Moody's and Fitch in the Columns (1) to (3). For S&P we find that the portfolio weights of banks and insurance corporations increase respectively 0.130 and 0.108 for a 100 percentage point increase in the $\mathbf{P}(\text{inf})$ for S&P. For Moody's we find respectively 0.123 and 0.097 and for Fitch 0.089 and 0.090. The portfolio weights of banks and insurance corporations increase respectively between 15.92% to 23.26% and 40.00% to 48.00% when the individual credit rating of a bond becomes inflated. The results are comparable to our main results in Table 2, Column (3), even when we take a subsample of bonds for which we have credit ratings from all three credit rating agencies (Table 3, Column (4)).

6 Deflated bonds

Even though credit ratings tend to be frequently inflated in some cases credit ratings can also be deflated (see White, 2010; Fulghieri et al., 2013). In our sample we find a significant share of bonds that are likely to have a deflated credit rating, because they have a low $\widehat{\mathbf{P}(\text{inf})}$. In our computation of $\mathbf{P}(\text{inf})$ in Equation 1, we assume that bonds can only have either a correct credit rating or an inflated credit rating. Consequently, all bonds with a deflated credit rating obtain a $\widehat{\mathbf{P}(\text{inf})}$ close to zero. In the previous analysis we considered deflated bonds indirectly. In this section we explicitly introduce deflated bonds to enhance the level of variation of $\mathbf{P}(\text{inf})$ for bonds with deflated credit ratings by removing the truncation at zero.

To allow for more variation of $\mathbf{P}(\text{inf})$ for bonds with deflated credit ratings, $\mathbf{P}(\text{inf})$ is extended to a net probability of a bond having an inflated credit rating. The probability of a bond having a deflated credit rating is calculated using a similar methodology as for bonds with inflated credit ratings. For bonds with deflated credit ratings, the relative likelihood of a bond belonging to a higher, instead of a lower, credit rating is computed. The net probability of a bond having an inflated credit rating, $\mathbf{P}(\text{net})$, is constructed by subtracting the probability of a bond having a deflated credit rating from the probability of a bond having an inflated credit rating. The net probability ranges from -1 to 1, where a bond with a net probability of -1 has a deflated credit rating and a bond with a net probability of 1 an inflated credit rating. In our main specification, an increase of a 100 percentage points in $\widehat{\mathbf{P}(\text{inf})}$ represents a bond becoming inflated as $\mathbf{P}(\text{inf})$ ranges from 0 to 1. In this section, the net probability ranges from -1 to 1, causing a 200 percentage points increase in the net probability to resemble the similar effect in economic terms.

Table 4 shows that explicitly introducing deflated bonds by considering $\mathbf{P}(\text{net})$ confirms our main results from Table 2, Column (3). When allowing for deflated bonds, we find that the portfolio weights of banks and insurance corporations increase respectively 47.22% and 60.62% when the credit rating of a bond becomes inflated. Compared to our main results, the relationship between $\mathbf{P}(\text{net})$ and the portfolio weights of banks and insurance corporations is stronger than with $\mathbf{P}(\text{inf})$ (respectively 20.75% and 52.44%). This may indicate that especially banks, but also to a lesser extent insurance corporations tend to avoid holding bonds with deflated credit ratings, while we do not find this for investment funds and pension funds. Thus, even when allowing for deflated credit ratings, the findings suggest that European banks and insurance corporations perform regulatory arbitrage by acquiring bonds with inflated credit ratings and eschew bond with deflated credit ratings.

7 Calibrations of regulatory capital buffers

European banks and insurance corporations face stringent capital requirements based on credit ratings to ensure that they maintain sufficient capital to sustain financial losses. Specifically, Basel III and Solvency II, the capital regulations of European banks and insurances corporations, use the credit ratings of individual bonds to determine the risk weights used to compute regulatory capital buffers. We argue that bonds frequently have inflated credit ratings and that therefore these bonds are held disproportionately by European banks and insurance corporations. Our unique bond-level holdings dataset allows us to quantify the economic impact of inflated credit ratings on required capital.

We employ our probability of a bond having an inflated credit rating, $\mathbf{P}(\text{inf})$, to assess the effective change in regulatory risk weights. In our calibration, a larger $\widehat{\mathbf{P}(\text{inf})}$ is associated with a higher risk weight and therefore higher required capital. In aggregate, the effective required capital reductions on an investor sector-country level are captured by the following formula:

$$\text{REDUCT}_{s,j} = \frac{\sum_{i=1} HOLD_{i,s,j} * \mathbf{P}(\text{inf})_i * (r_{s,k-1,d} - r_{s,k,d})}{\sum_{i=1} HOLD_{i,s,j} * r_{s,k,d}} \tag{4}$$

Equation 4 computes the effective reduction in regulatory capital, $REDUCT$, for each investor sector s by country j using information of individual bonds i with credit rating k and duration d for the single period 2018Q4. The required capital for an individual bond as applied by regulation is computed by multiplying the holding amount of that bond, $HOLD_{i,s,j}$, with the respective risk weight $r_{s,k,d}$. We estimate an adjusted risk weight by weighting the regulatory risk weight of the current credit rating and the credit rating below $(k-1)$ with 1-$\mathbf{P}$(inf) and $\mathbf{P}$(inf). We compute the effective reduction in regulatory capital by subtracting the risk weight of the current credit rating from the adjusted risk weight, multiplied by the holding amount. $REDUCT$ is expressed as the fraction of the aggregated effective reduction in regulatory capital over the aggregated current regulatory capital.[23]

The expected reductions in regulatory capital buffers of European banks and insurance corporations are sizable and heterogeneous across country. Table 5 shows the effective reductions in regulatory capital buffers for European banks and insurance corporations by country in respectively Column (1) and Column (2). The arithmetic average reductions in effective regulatory capital buffers for European banks and insurance corporations are respectively 13.09% and 27.93% (holding-weighted these reductions are 13.82% and 30.00%). In economic terms, the required capital of European banks and insurance corporations must increase by a factor of respectively 1.15 and 1.39 to obtain the same level of required capital in the presence of inflated credit ratings. For banks, the effective reductions in required capital are more severe in vulnerable European countries (e.g. Slovakia, Portugal and Italy) (see Greenwood et al., 2015). For insurances corporations we find that the impact of inflated credit ratings on regulatory capital requirements is strongest in non-vulnerable countries (e.g. Germany, Austria and France with the exception of Slovakia), however, for each individual country the effective reductions are larger for insurance corporations than for banks.[24]

In our paper, we observe that banks from vulnerable countries more actively perform regu-

[23]Our approach is conservative because we only allow bonds to have inflated credit ratings by at most one single credit rating $(k-1)$.

[24]When explicitly considering inflated as well as deflated credit ratings, we still find that inflated credit ratings cause significant reductions in regulatory capital. We find average effective capital reductions for banks and insurance corporations of respectively 4.91% and 17.32%.

latory arbitrage by holding bonds with inflated credit ratings. We find that banks in vulnerable euro area countries tend to face very substantial reductions in regulatory capital with inflated credit ratings: e.g. Slovakia (25%), Portugal (23%), Italy (22%). One interpretation is that in countries that are more vulnerable, the banking system "gambles" for resurrection by taking more risk with less capital (Laeven and Levine, 2009; Plosser and Santos, 2018) (Ben-David et al., 2019, for a contrasting view). For example, Iannotta et al. (2018) calibrate that the regulatory capital of banks must be raised by about 13.7% to 16.0% when taking into account that US banks exploit credit ratings. These estimates are reminiscent to our estimated 1.15 factor increase in required capital for banks, but we find larger effects in more vulnerable countries. One explanation is that banks in vulnerable countries have greater incentives to perform regulatory arbitrage because their capital buffers are closer to the required minimum (in line with Mink et al., 2020, for a different asset class (sovereign bonds)). Our work suggest that flaws in regulation incentivizes risk-taking behavior by banks in vulnerable countries, diminishing financial stability.

For insurance corporations, the impact of inflated credit ratings on capital buffers is substantial in all euro area countries. In related work Hanley and Nikolova (2018) (p.14) shows that due to problems with risk assessments in asset-backed securities, US insurance corporations save up to 5.5% of required capital due to regulatory shifts related to credit standards. In our study, the impact of inflated credit ratings for European insurance corporations is much higher, with a 27.9% reduction of the capital buffer. These findings are similar to Becker et al. (2019), although they do not present calibrations for regulatory capital.

The difference between the effective reduction of regulatory capital for banks and insurance corporations is attributed mechanically to higher marginal risk weight changes for investment grade bonds in Solvency II compared to Basel III. Holding bonds with inflated credit ratings has a larger impact on required capital when marginal changes in risk weights are larger. Both European banks and insurance corporations keep the majority of their portfolio in AAA, AA and A rated bonds (see Table 1). For banks we find relatively small marginal risk weight increases as the risk weights for corporate bonds, indexed at 1 for AAA rated bonds, are respectively 1 for AA rated bonds, 1.14 for A rated bonds and 1.43 for BBB rated bonds (BCBS, 2010).[25]

[25] For banks, AAA and AA rated bonds face the same capital requirements, thus AA also has an indexed risk weight of 1.

However, for insurance corporations we find much larger marginal risk weights as the indexed risk weights are respectively 1.22 for AA rated bonds, 1.52 for A rated bonds and 2.83 for BBB rated bonds (given an average duration of 7.71 years) (EIOPA, 2015b). Consequently, insurance corporations experience relatively more effective required capital reductions when holding bonds with inflated credit ratings compared to banks (as in line with Table 2 Column (3)).[26, 27]

We provide policy recommendations to reduce the effective reductions in capital requirements of European banks and insurance corporations due to inflated credit ratings. We recommend supervisors to use market-based CDS spread data in addition to credit ratings to compute the capital buffers of financial institutions. This market based estimate allows the risk weights of individual bonds to be adjusted for inflated credit ratings. Moreover, market based estimates of credit risk update information faster than credit ratings do, allowing the risk weights to be more timely. Regulators may focus on individual banks or insurance corporations with regulatory capital close to their required minimum as these investors have more incentives to perform regulatory arbitrage by buying bonds with inflated credit ratings. Our research suggest to be more careful in future treatments of credit ratings as the "holy grail" for credit risk assessments. Moreover, policy makers might reduce the opportunity to perform regulatory arbitrage to effectively reduce regulatory capital requirements by combining multiple credit risk measures.

8 Conclusion

This paper investigates how European banks and insurance corporations engage in regulatory arbitrage by buying bonds with inflated credit ratings to reduce their effective required capital.

[26] We provide a theoretical example to signal the magnitude of the impact of inflated credit ratings on the required capital of banks and insurance corporation. We compute the change in effective required capital for banks by assuming that only corporate bonds have inflated credit ratings and that they contribute to 20% of the required capital of banks. The average reduction in effective capital of European banks is 13.09%, effectively reducing the total required capital by 20%*13.09% or 2.62%. This indicates that solely due to the impact of inflated credit ratings on corporate bonds, banks should not have 10.5% regulatory capital, but 10.5%*1.0262 = 10.8%. When we consider that other asset classes also have inflated credit ratings, the increase in total regulatory capital is of a larger magnitude ((Cornaggia et al., 2017)). If we assume that all other asset classes are similarly effected as corporate bonds, the total required capital should be 11.87%, instead of 10.5%.

[27] Insurance corporations keep many high rated high duration bonds as the maximum duration of bonds is constraint by their credit rating. The duration is more constraining for lower rated bonds, causing demand for high rated high duration bonds. (see EIOPA, 2015b, articles 164, 175 and 176 for the exact computation of the required capital for European insurance companies).

European banks and insurance corporations have incentives to reduce their required capital in order to take on more risk and thus expected return. We contribute to literature by empirically computing the probability of an individual non-financial corporate plain vanilla bond having an inflated credit rating, using a market based measure of credit risk, namely CDS spreads. We compute this probability by comparing the relative likelihood of a bond belonging to the CDS spread distribution conditional on the current credit rating of the bond with likelihood of a bond belonging to the CDS spread distribution of a one lower rating. This approach allows us to expose mismatches between market based estimate of credit risk and credit risk implied by credit ratings.

We test for regulatory arbitrage of European banks and insurance firms by measuring the impact of the probability of a bond having an inflated credit rating on the portfolio weights of European banks, insurance corporations, pension funds and investment funds on a bond-level using the unique SHS database of the ECB. We are the first study to test how portfolio allocations towards bonds with inflated credit ratings differ across investors, allowing us to create a quasi-natural experiment. We find that the bond holdings of European banks and insurance corporations, who face capital requirements based on credit ratings, are positively related to the probability of a bond having an inflated credit rating. Under our most strict set of controls, we find that when a bond which is certainly not inflated becomes certainly inflated, the portfolio weights of European banks and insurance corporations increase respectively 21% and 52%. European investment funds and pension funds do not display a preference to hold more bonds with inflated credit ratings, often the opposite. The results confirm our hypothesis that banks and insurance corporations perform regulatory arbitrage to reduce their capital requirements.

We recommend that policy makers consider additional credit risk measures, like CDS spreads, in their assessment of the risk weights used for regulatory purposes to prevent the impact of inflated credit ratings. With the use of our probability of a bond having an inflated credit rating, we recalibrate the capital requirements of European banks and insurance corporations when considering the impact of inflated credit ratings. European banks and insurance corporations have effective reductions in their required capital of respectively 13% and 28% when considering the impact of inflated credit ratings on the risk weights. The reductions are most pronounced for banks from vulnerable countries. A possible explanation is that banks have greater incentives to perform regulatory arbitrage if their required capital approaches the required minimum. The effective reductions in capital requirements are likely to be of larger magnitude for asset classes less transparent than non-financial plain vanilla corporate bonds, as these bonds are relatively easy to rate and their ratings less opaque (Cornaggia et al., 2017), an avenue for future research.

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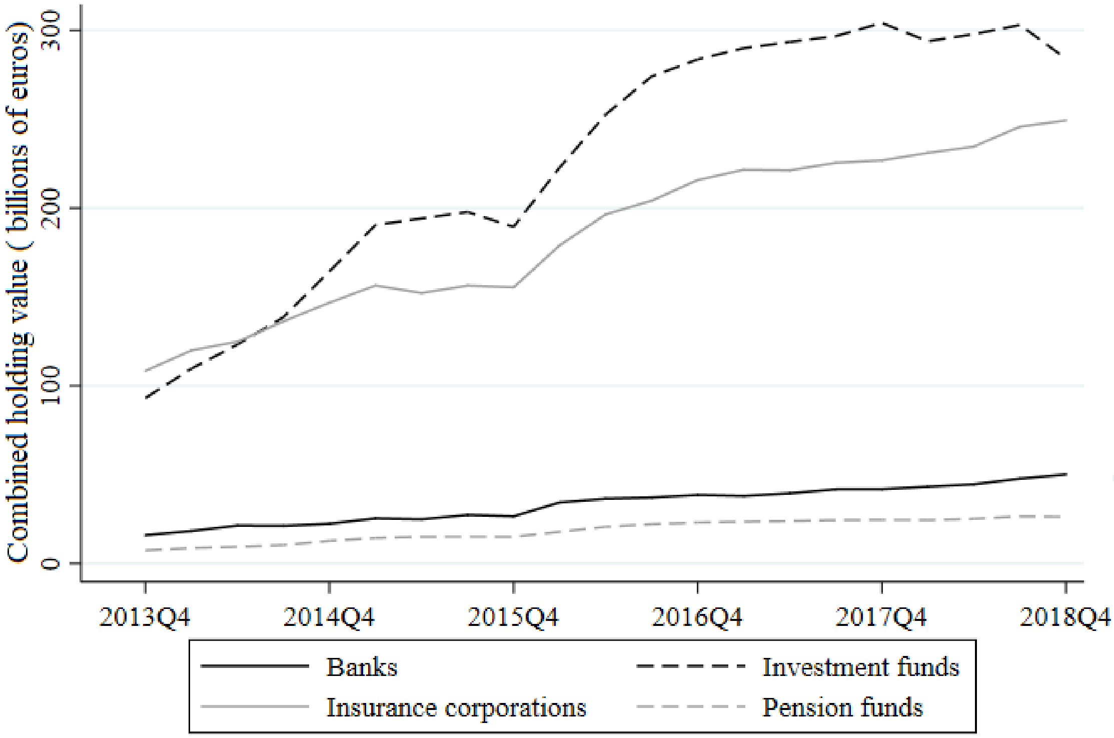
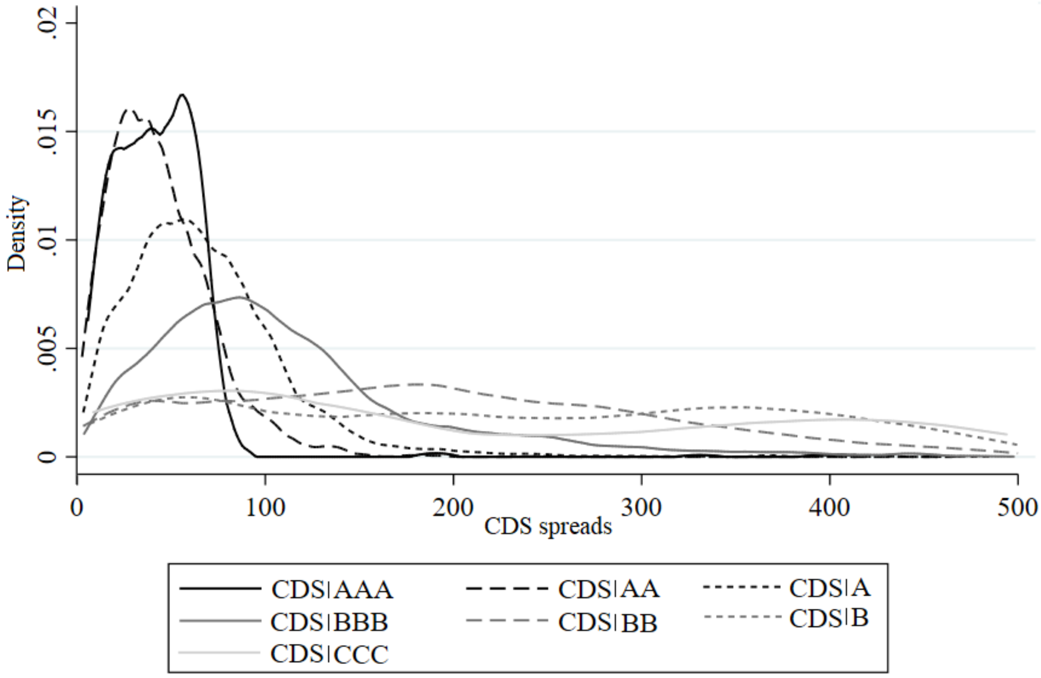
Tables and Figures

Figure 1: Portfolio holdings of non-financial plain vanilla corporate bonds by investor sector (in billions of euros)



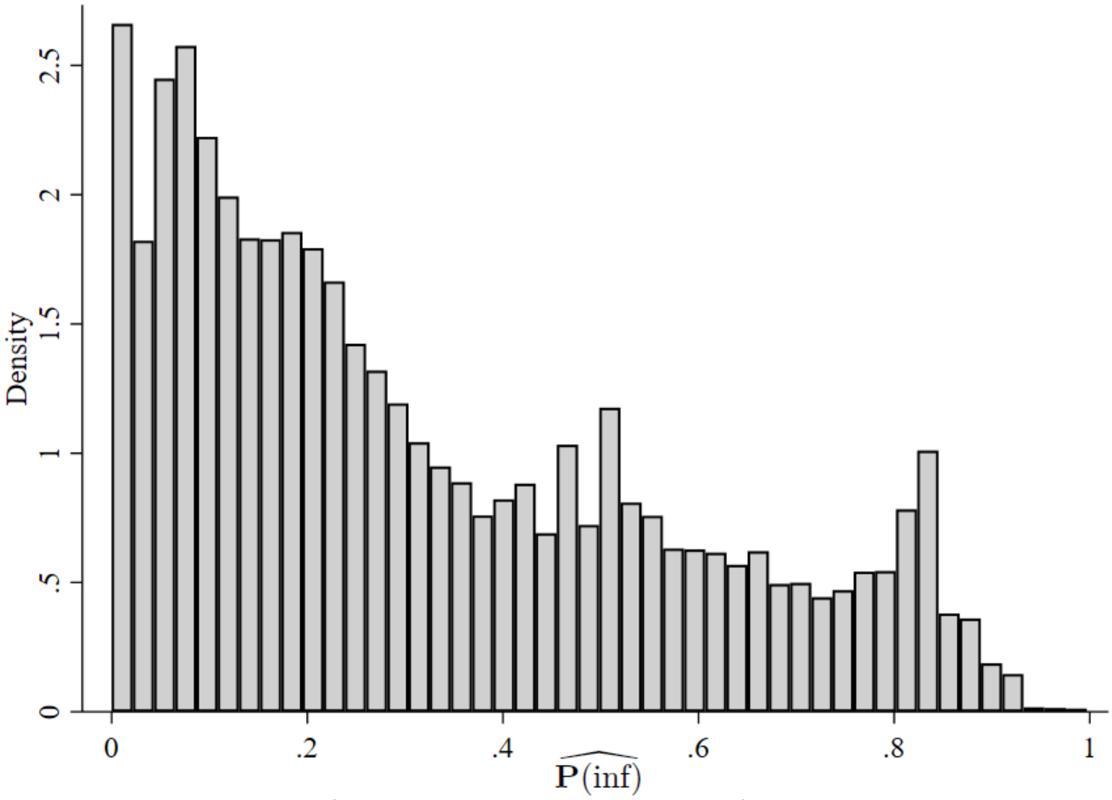
Notes: This figure presents the non-financial plain vanilla corporate bond holdings of European banks, insurance corporations, investment funds and pension funds in the final sample. The holdings are aggregated to a sector level and expressed in billions of euros on a quarterly basis.

Figure 2: CDS spread distributions conditional on credit ratings



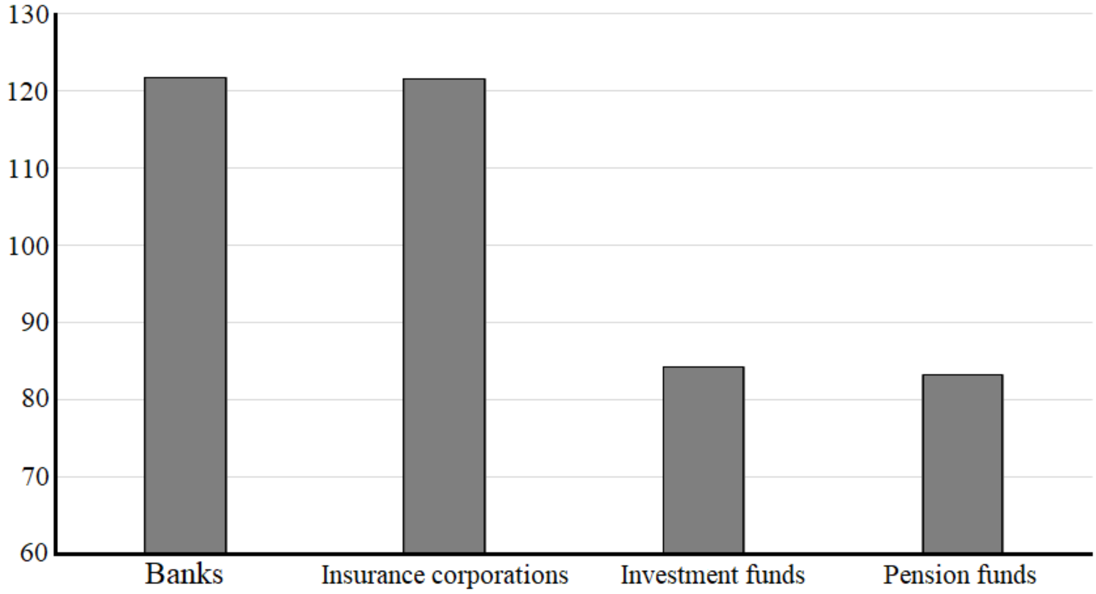
Note: The conditional CDS spread kernel density functions are computed using CDS spreads on a quarterly basis using the Epanechnikov method. The CDS spread density functions show a similar pattern for individual points in time and for the whole sample.

Figure 3: The probability of a bond having an inflated credit rating



Note: The kernel density of $\widehat{\mathbf{P}(\text{inf})}$ is computed by considering the $\widehat{\mathbf{P}(\text{inf})}$ of all bonds once every quarter, using Equation 1.

Figure 4: The portfolio weights of bonds with an above median probability of having an inflated credit rating, separated by investor



Note: The average portfolio weights for non-financial plain vanilla corporate bond portfolios of European banks, insurance corporations, investment funds and pension funds are computed separately by investor and $\widehat{\mathbf{P}(\text{inf})}$. For each investor, the median $\widehat{\mathbf{P}(\text{inf})}$ is computed unconditional on the portfolio weights. Next, the median $\widehat{\mathbf{P}(\text{inf})}$ is used to compute the average portfolio weight by separating the bond portfolios for bonds with a below or above median $\widehat{\mathbf{P}(\text{inf})}$ for each investor. The portfolios are split on an equal number of bonds as they are separated by the investor specific median $\widehat{\mathbf{P}(\text{inf})}$, instead of the mean $\widehat{\mathbf{P}(\text{inf})}$ (we find similar effects when using a mean $\widehat{\mathbf{P}(\text{inf})}$). Figure 4 shows the average portfolio weights for bonds with a $\widehat{\mathbf{P}(\text{inf})}$ higher than the investor specific median $\widehat{\mathbf{P}(\text{inf})}$, indexed at 100 when equal to the average portfolio weights for bonds with a below median $\widehat{\mathbf{P}(\text{inf})}$ for each investor.

Table 1: Portfolio holdings by investor sector by credit rating

Credit rating	Banks		Insurance corporations		Investment funds		Pension funds	
	Euro	(%)	Euro	(%)	Euro	(%)	Euro	(%)
AAA	0.53	1.60	3.33	1.79	3.48	1.52	0.38	2.03
AA	7.43	22.41	26.67	14.33	19.19	8.40	2.28	12.23
A	12.52	37.77	84.29	45.49	60.48	26.48	6.14	32.94
BBB	10.81	32.61	66.67	35.82	94.76	41.48	7.52	40.34
BB	1.64	4.95	4.91	2.64	34.19	14.97	1.73	9.28
B	0.21	0.63	0.25	0.13	14.43	6.32	0.53	2.84
CCC	0.01	0.03	0.02	0.01	1.98	0.87	0.06	0.32
Total	33.15	100%	186.14	100%	228.42	100%	18.64	100%

Notes: The holdings are expressed in billions of euros or as a percentage of the total non-financial corporate bond holdings of each investor. The combined average non-financial corporate bond holdings of European banks, insurance corporations, pension funds and investment funds are 466 billion euro, with 650 billion euro or a third of the total amount outstanding in 2018Q4 (see also Figure 1).

Table 2: The impact of inflated credit ratings on portfolio weights

	(1) Portfolio weight (%)	(2) Portfolio weight (%)	(3) Portfolio weight (%)
$\mathbf{P}(\text{inf})_{i,t}$	-0.041***	-0.021***	0.001
	(0.004)	(0.004)	(0.021)
$\mathbf{P}(\text{inf})_{i,t}$ * Banks	0.187***	0.115***	0.116***
	(0.038)	(0.026)	(0.026)
$\mathbf{P}(\text{inf})_{i,t}$ * Insurance corp.	0.126***	0.119***	0.118***
	(0.007)	(0.006)	(0.006)
$\mathbf{P}(\text{inf})_{i,t}$ * Pension funds	-0.037*	-0.039**	-0.040**
	(0.021)	(0.016)	(0.016)
Bond controls	YES	YES	YES
Credit watch FE	YES	YES	YES
Time FE	YES	YES	YES
Supply and demand FE	NO	YES	YES
Credit rating FE	NO	NO	YES
Observations	540,989	540,989	540,989
Adjusted R^2	0.035	0.309	0.309

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. The regression model is based on Equations (2) and (3) for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$ from Equation (3).

Table 3: The impact of inflated credit ratings on portfolio weights across credit rating agencies

	(1) Portfolio weight S&P	(2) Portfolio weight Moody's	(3) Portfolio weight Fitch	(4) Portfolio weight All bonds
$\mathbf{P}(\text{inf})_{i,t}$	0.018	0.061	0.014	-0.024
	(0.016)	(0.045)	(0.029)	(0.020)
$\mathbf{P}(\text{inf})_{i,t}$ * Banks	0.130***	0.123***	0.089**	0.098***
	(0.033)	(0.036)	(0.035)	(0.030)
$\mathbf{P}(\text{inf})_{i,t}$ * Insurance corp.	0.108***	0.097***	0.090***	0.101***
	(0.009)	(0.009)	(0.010)	(0.009)
$\mathbf{P}(\text{inf})_{i,t}$ * Pension funds	0.017	0.015	-0.007	-0.005
	(0.015)	(0.018)	(0.015)	(0.015)
Bond controls	YES	YES	YES	YES
Credit watch FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Supply and demand FE	YES	YES	YES	YES
Credit rating FE	YES	YES	YES	YES
Observations	221,713	221,713	221,713	221,713
Adjusted R-squared	0.355	0.355	0.355	0.355

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. The portfolio weights are expressed in percentage points. The $\mathbf{P}(\text{inf})$ used in this table represent the $\mathbf{P}(\text{inf})$ computed by using only the individual credit ratings of the credit rating agency presented in the upper row of the table. The regression model is based on Equations (2) and (3) for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$ from Equation (3).

Table 4: The impact of inflated as well as deflated credit ratings on portfolio weight

	(1) Portfolio weight (%)	(2) Portfolio weight (%)	(3) Portfolio weight (%)
$\mathbf{P}(\text{net})_{i,t}$	-0.029***	-0.015***	0.010
	(0.002)	(0.002)	(0.007)
$\mathbf{P}(\text{net})_{i,t}$ * Banks	0.201***	0.136***	0.132***
	(0.021)	(0.014)	(0.014)
$\mathbf{P}(\text{net})_{i,t}$ * Insurance corp.	0.078***	0.071***	0.068***
	(0.004)	(0.004)	(0.004)
$\mathbf{P}(\text{net})_{i,t}$ * Pension funds	-0.022	-0.016	-0.017*
	(0.013)	(0.010)	(0.010)
Bond controls	YES	YES	YES
Credit watch FE	YES	YES	YES
Time FE	YES	YES	YES
Supply and demand FE	NO	YES	YES
Credit rating FE	NO	NO	YES
Observations	538,230	538,230	538,230
Adjusted R-squared	0.036	0.309	0.310

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. The $\mathbf{P}(\text{net})_{i,t}$ represent the difference between $\mathbf{P}(\text{inf})_{i,t}$ and $\mathbf{P}(\text{def})_{i,t}$, explicitly introducing deflated bonds to the model. The regression model is based on Equations (2) and (3) for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$ from Equation (3).

Table 5: Calibrations of required capital and credit spread risk for European banks and insurance corporations

Countries	(1) **Banks**	(2) **Insurance corporations**	(3) **Banks**	(4) **Insurance corporations**
Austria	11.53	31.81	6.69	25.16
Belgium	11.56	28.71	4.72	19.12
Finland	10.91	21.73	0	7.34
France	13.39	30.67	0.43	21.69
Germany	13.55	33.80	5.85	27.06
Greece	14.10	26.38	4.19	14.33
Ireland	8.27	27.11	2.93	17.06
Italy	21.97	28.58	10.61	18.08
Lithuania	16.51	-	10.32	-
Luxembourg	11.87	25.70	4.60	12.40
Malta	-	25.59	-	13.46
the Netherlands	3.57	24.72	1.09	13.29
Portugal	22.83	23.54	15.08	9.89
Slovenia	9.29	24.84	2.63	12.95
Slovakia	24.82	36.88	16.69	29.38
Spain	15.84	28.85	2.88	18.59
Total	13.09 (13.82)	27.93 (30.00)	4.91 (4.08)	17.32 (20.81)

Notes: We calibrate the effective reductions in required capital and credit spread risk in percentages for European banks and insurances corporations on an investor country basis for the period 2018Q4. The total reductions represent the arithmetic and in parenthesis portfolio weighted means of the effective capital reductions across countries. The effective reductions are computed using Equation 4 and the risk weights given by the standardized models of Basel III and Solvency II for transparency and comparability. The internal rating based models also use external credit ratings as an input for the risk weights. Columns (3,4) contain the effective capital reductions for respectively banks and insurance corporations when considering inflated as well as deflated credit ratings. Only investors with at least a 100 million euro in non-financial corporate bonds are considered to ensure a relevant economic impact.

A Appendix A: Details on bond ratings

We collect credit rating data from Refinitiv, Bloomberg and the CSDB. For 96.63% of the bonds we have credit ratings from S&P, 80.44% from Moody's and 51.48% from Fitch. These credit ratings have positive and negative credit watch statuses respectively 1.82% and 4.94% of the time. For analytical purposes we use the average rating based scoring shown in Table A1, a common approach in the literature (e.g. Bongaerts et al. (2012)). Table A2 elaborates on the credit rating decomposition of the average credit rating and individual credit ratings by rating categories. The majority of the bonds have investment grade credit ratings (80.39%), for which 43.46% has a BBB rating and 26.39% an A rating.

The correlation of each individual credit rating agency to the average rating is even higher than its correlation to any other credit rating agency (see Table A3). This high correlations partially justifies our approach to take the average across credit rating agencies. Moreover, Basel III and Solvency II use the second highest rating for regulatory purposes. While we do not observe credit ratings from all approved external credit rating agencies, the average rating is a good proxy to the regulatory standard as it closely mimics the second highest rating (especially in a case with small or no disagreement) (BCBS, 2010; EIOPA, 2015b). For completeness, Table **??** separately disentangles the number of credit ratings obtained by data source and credit rating agency.

Table A1: Codelist: Average rating and credit rating per rating agency

Average rating	S&P	Fitch	Moody's
1	AAA	AAA	Aaa
2	AA+	AA+	Aa1
3	AA	AA	Aa2
4	AA-	AA-	Aa3
5	A+	A+	A1
6	A	A	A2
7	A-	A-	A3
8	BBB+	BBB+	Baa1
9	BBB	BBB	Baa2
10	BBB-	BBB-	Baa3
11	BB+	BB+	Ba1
12	BB	BB	Ba2
13	BB-	BB-	Ba3
14	B+	B+	B1
15	B	B	B2
16	B-	B-	B3
17	CCC+	CCC+	Caa1
18	CCC	CCC	Caa2
19	CCC-	CCC-	Caa3
20	CC	CC	C
21	C	C	C

Note: This table shows the conversion of individual credit ratings form different credit rating agencies to a numeric average rating.

Table A2: Credit ratings by credit rating agency

Credit rating agency	Average rating	S&P	Moody's	Fitch
AAA	639	639	638	123
AA	3,625	3,666	2,686	1,384
A	10,663	10,689	8,165	6,306
BBB	17,563	16,373	13,712	9,513
BB	5,360	5,195	4,526	2,643
B	2,184	2,103	2,209	764
CCC	379	386	572	70
Final sample	40,413	39,051	32,508	20,803

Note: This table separates credit ratings by credit rating agency and broader credit rating categories. The average rating is computed by taking the mean of all available credit ratings from either S&P, Moody's and Fitch as shown in Table A1. The number of bonds with an individual credit rating can be higher than number of bonds with an average credit rating for individual credit ratings when there is high coverage and disagreement across credit rating agencies.

Table A3: Correlations across credit rating agencies

Ratings	Moody's	Fitch	S&P	Average rating
Moody's	1			
Fitch	0.954	1		
S&P	0.949	0.943	1	
Average rating	0.983	0.976	0.978	1

Note: This table presents the pairwise Pearson correlation coefficients across individual credit ratings as well as the constructed average credit rating.

Table A4: Data coverage of credit rating information

Data source	S&P	Moody's	Fitch
Refinitiv	38,998	2,169	208
CSDB	127	2,314	959
Bloomberg	43	28,145	20,325
Whole sample	39,168	32,628	21,492

Note: This table shows the databases used to collect credit rating information by credit rating agency. The CSDB stands for the Centralised Securities Database of the ECB. Each row presents the number of credit ratings extracted from an individual credit rating agency by source.

B Appendix B: Details on the CDS spread distributions

Appendix B provides information on the conditional credit default swap (CDS) distributions used in Equation 1 for the computation of $\widehat{\mathbf{P}(\text{inf})}_{i,t}$.

When estimating CDS spread distributions conditional on credit ratings, we only consider the broader rating categories AAA, AA, A, BBB, BB, B and CCC or lower.[28] Sub-ratings (like B+ or B-) are aggregated to the broader rating categories for three reasons. Firstly, sub-ratings are not considered in Basel III and Solvency II (BCBS, 2010; EIOPA, 2015b). Secondly, the probability of a bond having an inflated credit rating is more conservative when using the broader categories, as these conditional CDS spread distributions show less overlap than when using sub-ratings. Finally, we can estimate the CDS spread distributions with higher accuracy as the number of observations per rating is on average three times larger.

Table B1 presents summary statistics on the estimated conditional CDS spread distributions. Both the mean and standard deviation of the conditional CDS spread distributions are increasing with deteriorating credit ratings, indicating that both CDS spreads and the credit ratings seem to capture credit risk. However, the 5^{th} and 95^{th} percentiles of the conditional CDS spread distributions show extensive overlap. This overlap allows us to capture the $\mathbf{P}(\text{inf})_{i,t}$ of a bond.

The estimation of the probability of a bond having an inflated credit rating requires assumptions on the probability density functions of conditional CDS spread distributions. We assume that these conditional CDS spread distributions are log normally distributed as they are constrained at the lower bound. Moreover, we observe a distribution similar to a normal distribution when we plot the kernel density function of the natural logarithm of CDS spreads (Figure B1).

We estimate the CDS spread distributions conditional on time as well as credit ratings. Using time dependent conditional CDS spread distributions vastly reduces the impact of fluctuations in the average CDS spread credit rating relationship due to macroeconomic conditions. Moreover, we remove the impact of outliers by winterising the estimated time dependant conditional CDS spread distributions at the 95% level over the last year.[29]

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[28] We merge the ratings CCC, CC and C as they occur infrequently and have no steady distribution. We assign a probability of a bond having an inflated credit rating of 0 to bonds which are rated CCC or lower, as defaults are observable. We find similar results for the main analysis when omitting AAA and CCC rated bonds (which have a small number of observations, see table A2).

[29] We find similar results in Table 2 when using either time varying or the time in-varying CDS spread distributions. However, we prefer the time varying CDS spread distributions as they allow more flexility

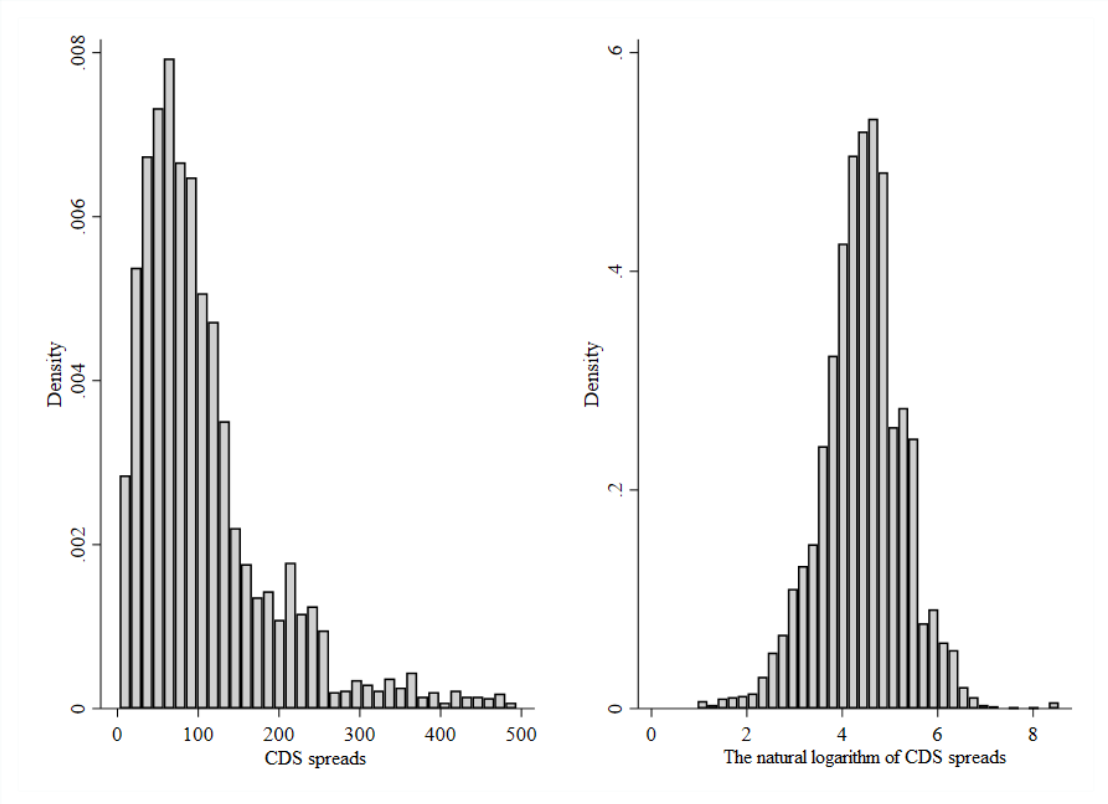
Table B1: CDS spreads per credit rating

Credit Rating	observations	mean	sd	p5	median	p95
AAA	639	40.90	19.23	11.03	40.90	70.50
AA	3,625	42.88	24.56	8.26	40.00	92.90
A	10,663	65.77	34.60	14.12	62.10	131.40
BBB	17,563	107.93	63.34	22.50	95.90	251.48
BB	5,360	208.94	136.99	18.99	189.71	471.175
B	2,184	343.58	240.89	36.17	315.25	817
CCC	379	978.47	1,378.97	13.90	534.85	4,730.41
Total:	40,413	124.21	194.02	16.29	83.49	353.10

Note: The mean, median, standard deviation and percentiles are expressed in basis points.

in macroeconomic conditions.

Figure B1: CDS spread distributions for unadjusted CDS spreads and the natural logarithm of CDS spreads



Note: The CDS spread distribution on the left represents the unadjusted CDS spreads, while the distribution on the right shows the natural logarithm of CDS spreads. The natural logarithm of CDS spreads loosely resembles a normal distribution, arguing in favour of estimating the conditional CDS spread density functions by assuming a log normal distribution.

Table B2: The impact of inflated credit ratings on portfolio weights using non-smoothed CDS spreads

	(1) Portfolio weight (%)	(2) Portfolio weight (%)	(3) Portfolio weight (%)
$\mathbf{P}(\text{inf})_{i,t}$	-0.072***	-0.042***	-0.026**
	(0.004)	(0.004)	(0.013)
$\mathbf{P}(\text{inf})_{i,t}$ * Banks	0.375***	0.285***	0.284***
	(0.042)	(0.030)	(0.030)
$\mathbf{P}(\text{inf})_{i,t}$ * Insurance corp	0.171***	0.164***	0.162***
	(0.009)	(0.008)	(0.008)
$\mathbf{P}(\text{inf})_{i,t}$ * Pension funds	-0.099***	-0.067***	-0.069***
	(0.022)	(0.016)	(0.016)
Bond controls	YES	YES	YES
Credit watch FE	YES	YES	YES
Time FE	YES	YES	YES
Supply and demand FE	NO	YES	YES
Credit rating FE	NO	NO	YES
Observations	540,989	540,989	540,989
Adjusted R^2	0.036	0.309	0.310

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. In this regression, we consider only investors that have a combined non-financial corporate bond holdings of at least 100 million on a sector-country basis. The regression model is based on Equations (2) and (3) for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$ from Equation (3). The $\mathbf{P}(\text{inf})_{i,t}$ used in this formula are computed by using non-smoothed CDS spreads.

C Appendix C: Sample description

This appendix provides summary statistics on the control variables of Equation 2 (Table C1). The bonds in our sample have an average amount outstanding of 767 million euro. Their yield to maturity range between 0 percent to 7 percent, with an average of 3.22 percent, with an average duration of almost eight years. The average bid-ask spread amounts to 8.55 basis points. Most of the bonds are denominated in either USD (62.22%), EUR (31.67%) or GBP (4.76%). We control for differences in macroeconomic conditions by considering the credit spread instead of the yield to maturity. We define the credit spread as difference between the yield to maturity and the risk free rate. We use the 3-month German bund rate as a proxy for the risk free rate when bonds have European issuers and the 3-month T-bill rate for all other issuers. We have a well diversified sample in terms of issuer industry (Table C2), issuer country (Table C3) and non-financial corporate bond holdings (Table C4). We find similar results when we consider only investors with at least 100 million euro in non-financial corporate bond holdings (Table C4 and

Table C5).

Table C1: Summary statistics of bond characteristics

Control variable	N	mean	sd	p.5	median	p.95
Amount outstanding	40,413	767	546	254	631	1,750
Credit spread	40,413	2.71	2.29	-0.16	2.33	6.40
Duration	40,413	7.71	4.80	2.42	6.55	16.51
Bid-ask spread	40,413	8.55	9.80	2.02	5.04	27.80

Notes: This table provides details on the bond characteristics $\mathbf{X}_{i,t}$ in Equation 3. Bond size is captured by the nominal amount outstanding in million euros. The credit spread represents the difference between the yield to maturity and the risk free rate in percentage points. The duration is given in years and computed from the yield to maturity, the coupon frequency and the price of the bond. As a liquidity measure, we use the bid-ask yield spread expressed in basis points. This liquidity proxy is preferred over the bid-ask yield spread divided by the mid-yield as the mid-yield often approximates zero, creating large outliers in bonds with a low bid-ask spread.

Table C2: Issuer 2-digit NACE code

NACE	Bonds
Mining and Quarrying	2,362
Manufacturing	8,098
Manufacturing Petroleum and Chemicals	2,391
Manufacturing Pharmaceutical	1,359
Electricity, Gas, Steam and Air Conditioning Supply	4,424
Construction	747
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	1,955
Transportation and Storage	2,832
Accommodation and Food Service Activities	814
Information and Communication	5,464
Real Estate Activities	1,230
Professional, Scientific and Technical Activities	4,381
Other	4,356
Total	42,499

Notes: The manufacturing industry is split into general manufacturing, the manufacturing of petroleum and chemicals and the manufacturing of pharmaceutical products to further segregate the industry. We do so only for the manufacturing industry as they dominate other industries in number of observations and display large internal diversity. We assign the industry other when an industry has only a very limited number of observations or the industry is missing.

Table C3: Issuer country

Country	Bonds	Country	Bonds	Country	Bonds
Argentina	25	Hong Kong	29	Panama	64
Australia	359	India	122	Peru	23
Austria	200	Indonesia	229	Portugal	42
Bermuda	128	Ireland	43	Qatar	10
Belgium	344	Isle of Man	36	Republic of Korea	142
Brazil	79	Israel	44	Singapore	44
Bulgaria	3	Italy	1,012	Slovakia	17
Canada	917	Japan	108	Spain	148
Cayman Islands	249	Jersey	5	Sweden	485
Chile	407	Kazakhstan	14	Switzerland	1
Colombia	45	Latvia	7	Thailand	55
Costa Rica	1	Liberia	38	Trinidad and Tobago	25
Croatia	13	Lithuania	6	Turkey	27
Czech Republic	41	Luxembourg	233	United Arab Emirates	102
Denmark	151	Malaysia	84	United Kingdom	1,679
Estonia	38	Morocco	49	United States	23,178
Finland	298	Mexico	995	Venezuela	6
France	5,044	the Netherlands	1,241	Zambia	84
Germany	1,151	New Zealand	30	**Total**	**40,413**
Greece	2	Norway	461		

Notes: This table presents number of bonds originating from each country in our sample. The majority of the bonds originate from the United States (57.35%), followed by France (12.48%) and the United Kingdom (4.15%).

Table C4: Holdings on a investor-sector investor-country level in 2018Q4

Countries	Banks	Insurance corporations	Pension funds	Investment funds
Austria	1,858	3,474	-	6,366
Belgium	1,397	12,033	176	1,807
Estonia	-	47	91	-
Finland	331	1,704	20	2,309
France	17,254	143,446	-	23,557
Germany	21,907	23,560	3,531	94,070
Greece	112	518	54	56
Ireland	382	6,918	124	39,496
Italy	2,687	31,854	2,693	5,729
Latvia	98	14	117	12
Lithuania	100	18	20	-
Luxembourg	967	4,228	37	94,910
Malta	53	182	-	98
the Netherlands	377	10,351	15,668	11,251
Portugal	326	1,763	228	277
Slovenia	115	427	108	76
Slovakia	135	192	676	32
Spain	1,924	8,554	2,638	4,027
Total	50,033	249,303	26,181	284,073

Notes: This table presents the non-financial corporate bond holdings by investor sector in 2018Q4. Only the holdings for investors with at least 10 million are displayed.

Table C5: The impact of inflated credit ratings on portfolio weights for large investors

	(1) Portfolio weight (%)	(2) Portfolio weight (%)	(3) Portfolio weight (%)
$\mathbf{P}(\text{inf})_{i,t}$	-0.040***	-0.022***	0.005
	(0.002)	(0.003)	(0.017)
$\mathbf{P}(\text{inf})_{i,t}$ * Banks	0.131***	0.089***	0.091***
	(0.035)	(0.025)	(0.025)
$\mathbf{P}(\text{inf})_{i,t}$ * Insurance corp	0.137***	0.126***	0.125***
	(0.006)	(0.005)	(0.005)
$\mathbf{P}(\text{inf})_{i,t}$ * Pension funds	-0.011	-0.024*	-0.025*
	(0.016)	(0.013)	(0.013)
Bond controls	YES	YES	YES
Credit watch FE	YES	YES	YES
Time FE	YES	YES	YES
Supply and demand FE	NO	YES	YES
Credit rating FE	NO	NO	YES
Observations	531,423	531,423	531,423
Adjusted R^2	0.042	0.273	0.274

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. In this regression, we consider only investors that have a combined non-financial corporate bond holdings of at least 100 million on a sector-country basis. The regression model is based on Equations (2) and (3) for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$ from Equation (3).

D Appendix D: Details on the probability of a bond having an inflated credit rating

We control for discrepancies in the probability of a bond having an inflated credit rating across different credit ratings. The estimated probability of a bond having an inflated credit rating differs across credit ratings (Table D1). There are two reasons why the probability of a bond having an inflated credit rating is largest for the higher rated bonds. Firstly, the a priori probability of a bond having a certain credit rating (independent of the CDS spread) is ascending for all investment grade bonds. The difference in the CDS spread distributions conditional on the current and the one lower credit rating are less distinctive for A or higher rated bonds as their conditional CDS spread distributions experience larger overlap. We control for discrepancies in the average probability of a bond having an inflated credit rating across credit ratings by introducing dummies for each average credit rating (1 to 21, with BBB+ as reference category) and interaction terms of these dummies to the probability of a bond having an inflated credit rating ($\mathbf{K}_{i,t}$ in Equation 2 and Equation 3).

We argue that the estimated probability of a bond having an inflated credit rating yields plausible properties. Table D1 shows that $\widehat{\mathbf{P}(\text{inf})}$, conditional on the credit rating of the bond, is lower for bonds with a + sub-rating and higher for bonds with a - sub-rating. Bonds with a - sub-rating have, on average, a higher credit risk than bonds with a + sub-rating and thus should be more likely have an inflated credit rating. A similar argument holds for bonds with positive and negative credit watch. Bonds with negative credit watch are more likely to experience rating downgrades in the future and are thus more likely to have inflated credit ratings (vice versa for bonds with positive credit watch). We find that bonds with negative credit watch have a higher $\widehat{\mathbf{P}(\text{inf})}$ and that bonds with a positive credit watch have a lower $\widehat{\mathbf{P}(\text{inf})}$. Finally, bonds that experience downgrades in the next quarter are likely to have inflated credit ratings now as the credit risk of individual bonds shows signs of autocorrelation. We find that bonds which experience credit rating downgrades in the next quarter have a higher $\widehat{\mathbf{P}(\text{inf})}$ now and that bonds that experience credit rating upgrades experience a lower $\widehat{\mathbf{P}(\text{inf})}$ now (Table D1).

We find similar results when we estimate our model without bonds with a credit rating of either AAA or CCC (Table D2). We also present robust findings when we drop the smoothing over time assumption of the CDS spread data. Table D3 shows our main findings when we apply the current CDS spreads directly to Equation 1 instead of the one-year smoothed average CDS spread.

Table D1: Conditional $\widehat{\mathbf{P}(\text{inf})}$ by credit rating: sub-ratings

Credit rating		AAA	AA	A	BBB	BB	B	CCC
All bonds	N	639	3,625	10,663	17,563	5,360	2,184	379
All bonds	mean (%)	84.43	62.78	49.36	18.47	23.63	12.13	-
Future downgrade	N	8	147	396	326	230	154	23
Future downgrade	mean (%)	85.45	68.99	57.38	29.93	34.58	20.78	-
Future upgrade	N	-	21	142	316	288	140	48
Future upgrade	mean (%)	-	64.27	41.65	15.44	19.64	8.22	-
Positive credit watch	N	-	-	51	457	148	77	2
Positive credit watch	mean (%)	-	-	45.33	13.03	17.36	8.45	-
Negative credit watch	N	69	105	545	967	258	46	6
Negative credit watch	mean (%)	84.44	77.72	58.11	19.03	32.30	13.48	-
Sub-rating +	N	-	768	2,638	6,975	2,276	943	237
Sub-rating +	mean (%)	-	55.79	44.44	13.89	22.62	10.35	-
Sub-rating -	N	-	2,090	4,379	4,405	1,186	577	40
Sub-rating -	mean (%)	-	63.64	52.46	25.03	25.16	14.43	-

Notes: This table separates $\widehat{\mathbf{P}(\text{inf})}$ by the average credit rating over multiple characteristics.

Table D2: The impact of inflated credit ratings on portfolio weights without AAA,CCC

	(1) Portfolio weight (%)	(2) Portfolio weight (%)	(3) Portfolio weight (%)
$\mathbf{P}(\text{inf})_{i,t}$	-0.046***	-0.022***	-0.000
	(0.004)	(0.004)	(0.021)
$\mathbf{P}(\text{inf})_{i,t}$ * Banks	0.195***	0.138***	0.138***
	(0.039)	(0.027)	(0.027)
$\mathbf{P}(\text{inf})_{i,t}$ * Insurance corp.	0.131***	0.124***	0.123***
	(0.008)	(0.007)	(0.007)
$\mathbf{P}(\text{inf})_{i,t}$ * Pension funds	-0.047**	-0.043**	-0.044**
	(0.022)	(0.017)	(0.017)
Bond controls	YES	YES	YES
Credit watch FE	YES	YES	YES
Time FE	YES	YES	YES
Supply and demand FE	NO	YES	YES
Credit rating FE	NO	NO	YES
Observations	530,081	530,081	530,081
Adjusted R^2	0.035	0.308	0.308

Notes: Robust standard errors in parenthesis. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively. The regression model is based on Equation 2 and Equation 3 for which bond controls represent $\mathbf{X}_{i,t}$, credit watch fixed effects represent $\mathbf{C}_{i,t}$, the time fixed effects represent $\mathbf{T}_t$, supply and demand fixed effects respectively represent $\mathbf{I}_i$ and $\mathbf{J}_s$ and credit rating fixed effects represent $\mathbf{K}_{i,t}$. Bonds with a credit rating of AAA or CCC are removed form this analysis as they respectively have a high average $\widehat{\mathbf{P}(\text{inf})}$ or a $\widehat{\mathbf{P}(\text{inf})}$ set to zero.

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