# Quantitative Easing and Credit Rating Agencies

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# Quantitative Easing and Credit Rating Agencies Prepared by Nordine Abidi, Matteo Falagiarda and Ixart Miquel-Flores

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**ABSTRACT:** This paper investigates the behaviour of credit rating agencies using a natural experiment in monetary policy. We exploit the corporate QE of the Eurosystem and its *rating-based* specific design which generates exogenous variation in the probability for a bond of becoming eligible for outright purchases. We show that after the launch of the policy, rating activity was concentrated precisely on the territory where the incentives of market participants are expected to be more sensitive to the policy design. Our findings contribute to better assessing the consequences of the explicit reliance on CRAs ratings by central banks when designing monetary policy. They also support the Covid-19 monetary stimulus, and in particular the waiver of private credit rating eligibility requirements applied to recently downgraded issuers.

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# Quantitative Easing and Credit Rating Agencies

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ABSTRACT

This paper investigates the behaviour of credit rating agencies using a natural experiment in mon-

etary policy. We exploit the corporate QE of the Eurosystem and its rating-based specific design

which generates exogenous variation in the probability for a bond of becoming eligible for outright

purchases. We show that after the launch of the policy, rating activity was concentrated precisely

on the territory where the incentives of market participants are expected to be more sensitive to the

policy design. Our findings contribute to better assessing the consequences of the explicit reliance

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Keywords: Credit Rating Agencies, Monetary Policy, Quantitative Easing.

JEL Classification: E44, E52, E58, G24, G30

"The ratings [...] are and must be construed solely as, statements of opinion and not statements of fact or recommendations to purchase, sell, or hold any securities." (Rating Agency Disclaimer)

## I. Introduction

The statement above has been consistently repeated by credit rating agencies (CRAs) during the global financial crisis of 2008. Nevertheless, a large set of investors continue to rely, directly or indirectly, on the ratings of CRAs to "purchase, sell, or hold securities". Directly, some market participants place restrictions on investing in non investment-grade bonds. Indirectly, most bond benchmarks employed by investors are constructed with underlying CRAs ratings. What is less known is that major central banks around the world (e.g. Federal Reserve, European Central Bank, Bank of England, Bank of Japan) also rely on CRAs for the conduct of their monetary policy operations. As a matter of fact, the assessment of eligible assets to be purchased under their asset purchase programmes – commonly referred to as quantitative easing (QE) – was based, inter alia, on ratings from private agencies.

The recent Covid-19 pandemic has put at the forefront the importance of unconventional monetary policies and the critical role of private credit agencies. Indeed, the spread of the virus throughout the world was accompanied by a rapid deterioration of market conditions and falling prices of risky assets, with bond markets being no exception. Firms deprived of their primary source of cash-flows struggled to meet their financial obligations and faced imminent risk of default, which was often unrelated to the true soundness of their business. In this situation, the economy was at risk of losing valuable productive forces with a long-lasting effect on productivity. These developments prompted an immediate reaction by central banks, especially after the significant credit rating

<sup>&</sup>lt;sup>1</sup>In October 2010, the Financial Stability Board (FSB) issued Principles for Reducing Reliance on CRA Ratings. The goal of the FSB Principles was to end the mechanistic reliance on CRAs ratings by banks, institutional investors and other market participants. Importantly, the FSB Principles recognized that CRAs ratings played an important role and can appropriately be used as an input to agents' own judgment as part of internal credit assessment processes.

downgrades (see Figure 1 for the case of Italian corporate bonds). The inclusion of high-yield bonds within the Federal Reserve's large scale asset purchases (Haddad et al., 2021)<sup>2</sup> or the "frozen" ratings for the collateral easing package of the European Central Bank (ECB)<sup>3</sup> were key examples of the implications of the reliance of private credit rating agencies by central bankers. While these "rating-easing" policies have been successful in boosting debt prices and reducing the adverse effects a potential downward spiral triggered by an avalanche of rating downgrades,<sup>4</sup> understanding the implications of the explicit reliance on CRAs by central banks remains an open question.

In this paper, we empirically investigate the behaviour of credit rating agencies and market participants using a natural experiment in monetary policy. Specifically, we exploit the Corporate Sector Purchase Programme (CSPP) of the European Central Bank (ECB) – commonly known as corporate QE – and its rating-based specific design which generates exogenous variation in the probability for a bond of becoming eligible for outright purchases. We show that an asymmetric change in CRAs rating activity occurred after the launch of the policy. More precisely, we find that rating upgrades were mostly noticeable for bonds initially located below, but close to, the eligibility frontier. In line with the theory, this effect is concentrated exactly on the territory where CRAs' and firms' incentives are expected to be more sensitive to the policy design. Our findings shed light on the consequences of the explicit CRAs reliance by central banks when designing (un)conventional monetary policy.

From an identification perspective, the CSPP offers key advantages compared to other central bank asset purchase programmes. In essence, given the large cross-sectional heterogeneity of corporate bonds in the euro area and the unexpected nature of the announcement, the CSPP constitutes

<sup>&</sup>lt;sup>2</sup>The Fed announced on April 9 that the debt of "fallen angels" (i.e., bonds that have been downgraded from investment-grade to high-yield during the crisis) would remain eligible for purchases under both the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF), as long as issuers had IG rating by March 22, 2020. However, both facilities restrict purchases of HY bonds to those issued by fallen angels that have been downgraded to a rating as low as BB- since the program was first announced on March 23, 2020

https://www.ecb.europa.eu/press/blog/date/2020/html/ecb.blog200422 244d933f86.en.html

 $<sup>^4</sup>$ https://voxeu.org/article/defence-regional-development-banks-covid-19-era

a unique opportunity to overcome major endogeneity obstacles related to time-varying country or industry-specific shocks, time trends, time-varying bond (firm) characteristics or time-constant unobserved heterogeneity between bonds (firms). In other words, focusing on the ECB's corporate QE, we are better able to take a number of steps to mitigate the scope for alternative explanations of our results. Moreover, compared to the ECB's Public Sector Purchase Programme (PSPP) or the Fed's Large-Scale Asset Purchases (LSAPs), the CSPP provides an ideal laboratory experiment to test the transmission channels of non-standard monetary policy since it establishes a direct link between central bank purchases and corporate economic entities.

The theoretical motivation of our analysis follows from the recent literature on the transmission channels of QE and its effects on the economy (Gagnon et al., 2011, Joyce et al., 2011, Christensen and Rudebusch, 2013, Bauer and Rudebusch, 2014, Falagiarda and Reitz, 2015, Borio and Zabai, 2016, Christensen and Gillan, 2018, Dell'Ariccia et al., 2018, Kuttner, 2018). The main mechanism for QE to affect the real economy is through its impact on (long-term) interest rates. In the existing QE literature, various channels of transmission have been already identified and are related to (i) market expectations about future monetary policy (i.e. signaling channel), (ii) the increase in the bargaining power of sellers in the market for the targeted securities (i.e. liquidity channel), and (iii) the decline in risk premiums on debt securities (i.e. portfolio rebalancing channel). Recent analyses suggest that the ECB's corporate QE was successful in reducing euro area firms' financing conditions (Abidi and Miquel-Flores, 2018, ECB, 2017). These studies show that yields on corporate bonds and other securities declined after March 10, 2016 when the ECB announced it would start to hold investment grade corporate bonds. An emerging and burgeoning literature has also started to look at the effects of ECB's corporate QE on the real economy (Bartocci et al., 2017, Montagna and Pegoraro, 2017, Arce et al., 2018, Grosse-Rueschkamp et al., 2018, Ertan et al., 2018). Overall, the CSPP combined with other ECB's non-standard measures appears to have improved the financing conditions of euro area firms and strengthened the pass-through of monetary policy interventions.

While the effectiveness of the CSPP and other unconventional monetary policy measures conducted

by the ECB is well documented in the literature (Hartmann and Smets, 2018, Altavilla et al., 2016, Cahn et al., 2017, De Santis and Holm-Hadulla, 2017, De Santis et al., 2018, ECB, 2017), we argue that the explicit reliance on CRAs by central banks might have had, at the margin, unintended consequences. Indeed, in the context of the Eurosystem, the expanded asset purchase programme (APP),<sup>5</sup> including the corporate QE, is designed upon the Eurosystem Collateral Framework (ESCF) – the set of rules that lays down which assets are acceptable as collateral for monetary policy credit operations. Relying explicitly, but not exclusively, on CRAs, the ESCF also constitutes the basis for determining the eligibility of marketable securities to be purchased under the APP. More specifically, under the CSPP, debt instruments eligible for purchase must: (i) be issued by a non-bank corporation established in the euro area and denominated in euro; (ii) have a minimum remaining maturity of six months and a maximum remaining maturity of 30 years at the time of purchase and, (iii) have a minimum first best credit assessment of at least credit quality step 3 (rating of BBB- on S&P's scale or equivalent) obtained from an external credit assessment institution (i.e. CRAs). Defining a minimum level of credit quality is at the heart of the ESCF (ECB, 2015, Bindseil, 2017). Since October 2008, the minimum requirement is a rating of "BBB-" on S&P's scale. For (un)conventional monetary policies, the ECB recognizes four rating agencies (S&P, Fitch, Moody's, and DBRS) and only the highest rating (first-best rating rule, henceforth) matters.<sup>6</sup> Keeping this as a backdrop, we use the credit rating vector of a bond and the pivotal role of rating agencies (with regards to bond's eligibility) as the most important pieces of information to evaluate CRAs and firms' behaviour.

<sup>&</sup>lt;sup>5</sup>The APP includes all purchase programmes under which private sector securities and public sector securities are purchased.

<sup>&</sup>lt;sup>6</sup>Monetary policy operations often involve the collateralised provision of funds to banks on a temporary basis or the conduct of outright market transactions. These are financial operations entailing risks which need to be managed (ECB, 2015). Central banks are not subject to liquidity risk in the way "normal" market participants are, and can therefore accept less liquid collateral (Bindseil et al., 2017). Since the start of the financial crisis, the Eurosystem had to increase the size and complexity of its monetary policy operations (e.g. large amounts of longer-term credit), which has also led to an increase in potential risks to its balance sheet. All in all, the ESCF has been effective in protecting the Eurosystem from financial losses. Critics to the ESCF (Nyborg, 2016) have proven to reflect misconceptions about the economics of a central bank collateral framework (Bindseil et al., 2017).

From a theoretical perspective, our analysis is built upon a well known critical friction related to CRAs reliance on fees from issuers as a main source of revenue (Bolton et al., 2012). Indeed, a key feature of the rating agencies' business model is that they are compensated by bond issuers and not by investors (White, 2010).<sup>7</sup> This "issuer pays" arrangement, often perceived as a main driver of the 2008 financial crisis (Partnoy, 2010, Coffee, 2011), may create perverse incentives because (i) CRAs have heterogeneous beliefs and issuers can "rating shop" by selectively picking the most favorable ratings for publication (Skreta and Veldkamp, 2009, Faure-Grimaud et al., 2009, Farhi et al., 2013) and (ii) CRAs have an incentive to inflate their ratings in order to increase the probability of being selected to rate the deal (Bolton et al., 2012; Sangiorgi and Spatt, 2017). Reputational concern, a commonly cited counterincentive, is not always considered sufficient for rating agencies to report truthfully (Mathis et al., 2009). Despite the vast existing literature on credit rating agencies (Matthies, 2013, Sangiorgi and Spatt, 2017), no prior theoretical or empirical studies, of which we are aware of, examine the relationship between monetary policy and CRAs behaviour. This paper aims at filling this gap by showing that the design of unconventional monetary interventions may affect directly the incentives of CRAs and debt issuers.

The main obstacle in making a causal claim is the difficulty in isolating changes in CRAs activity which are not due to macroeconomic developments or other confounding factors. Indeed, identifying the effects of central bank asset purchase programmes is particularly challenging given that such policies intentionally respond to current and anticipated aggregate shocks and they also affect the real economy (Di Maggio et al., 2016, Greenlaw et al. 2018). For tractability, a popular approach in the literature employs event studies of high-frequency asset price changes surrounding central bank policy announcements (Krishnamurthy and Vissing-Jorgensen, 2011, Altavilla et al., 2016). We go beyond such before/after comparisons with an identification strategy that exploits the legal restriction that the ECB can only purchase corporate bonds "with at least a BBB-" obtained from at least one of the four recognized CRAs. The methodology can be best understood using the following

<sup>&</sup>lt;sup>7</sup>In practice, CRAs fees involve both a fee at the time of issuance and an annual fee for as long as the issue is outstanding. In addition, CRAs offer related consulting services, such as pre-rating assessments.

example. At the announcement of the corporate QE, bonds that have an "ECB eligibility score", say above the cut-off  $C_{ECB}$  (i.e. bond I with a rating vector  $X_I = [BBB-, BB+, BB+, \#NA]^8$ ), are eligible for the CSPP. We compare the ratings of CSPP non-eligible corporate bonds that barely fail to qualify for eligibility (i.e. bond J with a rating vector  $X_J = [BB+, BB+, BB+, \#NA]$ ) to those of bonds positioned farther away from the frontier of eligibility (i.e. bond K with a rating vector  $X_K = [C, BB, BB-, \#NA]$ ). In other words, the methodology compares the likelihood of becoming CSPP-eligible after March 2016 for corporate bonds with eligibility score of  $C_{ECB} - \delta$  (treatment group) to those with eligibility scores of  $C_{ECB} - \Delta$  (control group), where  $\Delta >> \delta$ , arguing that the announcement of the corporate QE is likely to generate a non-linear increase in the probability of becoming eligible.

We test our hypothesis using a comprehensive monthly dataset of around 1,700 bonds from January 2015 to December 2017 across 16 euro area countries that combines fundamental and credit rating public data on non-financial corporations from Bloomberg, the ECB Statistical Data Warehouse, Consensus Economics and relevant data from other publicly available sources. Our most important result is that, after controlling for macroeconomic developments as well as for bond-level (un)observed characteristics, credit rating activity varied significantly and nonlinearly around the eligibility frontier after the announcement of the ECB's corporate QE. This finding is quite distinct from previous works on credit rating dynamics because the shock we are using is direct and exogenous.

We conduct a large set of exercises and robustness checks to rule out alternative explanations for our results. For example, by analyzing issuer-level characteristics, we provide strong evidence on the key identification assumption that bonds located around the CSPP eligibility frontier (i.e. difference up to a rating) are affected similarly by business cycle fluctuations. Moreover, we show that bonds initially positioned below, but close to, the eligibility frontier had a significantly higher probability

<sup>&</sup>lt;sup>8</sup>#NA is an abbreviation for rating "Not Available". The rating vector has four components, because four rating agencies are used to qualify the eligibility of a bond under the CSPP. Around 1% of our corporate bonds are rated by DBRS.

of experiencing *just one* rating upgrade in the post-CSPP period compared to other rating buckets, confirming the importance of the marginal upgrade for this set of bonds. Finally, by focusing on firms that have issued bonds both in euro and in other currencies, we find that only securities located just below the eligibility frontier and denominated in euro displayed rating upgrades in the post-CSPP period.

In sum, our findings point a way forward in learning about the relationship between (un)conventional monetary policy design and the behaviour of CRAs and market participants. Given the small size of the euro area corporate bond market and the magnitude of the effects established in our paper, we think that the localized rating adjustments induced by the design of the corporate QE are unlikely to have had adverse macroeconomic or financial stability implications. We believe, however, that the consequences of relying explicitly on CRAs must be acknowledged by central banks when designing conventional and unconventional monetary policies.

The remainder of the paper proceeds as follows. Section II presents the CSPP institutional framework and the main predictions. Section III describes the data used in the analysis. The empirical methodology and the results are presented in Section IV. Section V strengthens the identification strategy and presents a large set of robustness checks. Section VI concludes.

# II. The CSPP and the Credit Rating Channel

# A. The institutional framework of the CSPP

To address the risks of a too prolonged period of low inflation and to enhance the functioning of the monetary policy transmission mechanism in the euro area, the Governing Council of the ECB announced in January 2015 the expanded Asset Purchase Programme (APP), which added a purchase programme for public sector securities (PSPP) to the existing private sector asset purchase programmes (third covered bond purchase programme - CBPP3; asset-backed securities purchase

programme - ABSPP). The idea was that large asset purchases would provide additional monetary stimulus to the economy in a context where key ECB interest rates were at historical low levels.

However, given the persistency of weak inflation dynamics, the ECB decided on March 10, 2016 to recalibrate upward its monthly bond purchases by 20 billion per month (EUR 80 billion in total), to launch new four-year long-term refinancing operations to banks (TLTRO II) and to purchase corporate bonds under the corporate sector purchase programme (CSPP), commonly known as corporate QE.

From the viewpoint of market participants, the announcement to purchase investment-grade eurodenominated bonds issued by non-bank corporations established in the euro area was largely unexpected. As the International Capital Market Association (ICMA) pointed out:

"The announcement by the ECB on March 10 to extend its Asset Purchases Programme to include investment grade non-bank corporate bonds caught the market by **complete surprise**. It resulted in an immediate and substantial tightening of credit spreads, not only for corporate bonds potentially eligible for purchase under the programme".

Despite the fact that the CSPP took the market by "complete surprise", the main rules underlying the eligibility of a corporate bond for outright purchases were known by investors and firms before the disclosure of the technical details.<sup>9</sup> For transparency reasons, the Governing Council of the ECB announced on April 21, 2016 the details about the CSPP and clarified on additional technical parameters of the programme (e.g. eligibility of insurance corporation). On June 2, 2016, finally, the Governing Council announced that purchases under the CSPP will start on June 8 of the same year

<sup>&</sup>lt;sup>9</sup>For instance, 21 days after the CSPP announcement (i.e. March 31, 2016), Cellnex Telecom, a firm head-quartered in Spain that operates infrastructure for wireless telecommunication declared: "Cellnex Telecom bonds will be eligible for the ECB's high-quality corporate bond purchase programme. [...] The announcement of the inclusion was released yesterday March 30th 2016 and is consistent with Fitch's "investment grade" (BBB-) rating for Cellnex bonds". It is important to notice that, at the same time, S&P has provided a BB+ rating for this firm. Cellnex was therefore CSPP-eligible at the margin, thanks to the rating of Fitch.

and took decisions on the remaining details of the CSPP. The Figure below presents the timeline of the CSPP programme.

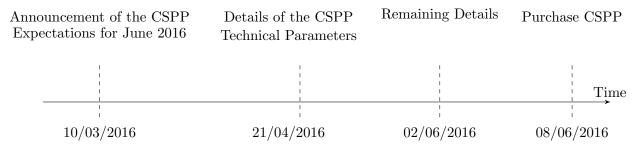


Figure 0. CSPP timeline

Moving to the CSPP technical details, outright purchases of investment-grade euro-denominated bonds issued by non-bank corporations established in the euro area are carried out by six Eurosystem national central banks (NCBs): Banque Nationale de Belgique, Deutsche Bundesbank, Banco de España, Banque de France, Banca d'Italia and Suomen Pankki. Each NCB is responsible for purchases from issuers in a particular part of the euro area. The purchases are conducted in the primary and secondary markets and coordinated by the ECB.

The Eurosystem's collateral framework – the set of rules that lays down which assets are acceptable as collateral for monetary policy credit operations – is the basis for determining the eligibility of corporate sector securities to be purchased under the CSPP. More specifically, debt instruments are eligible for purchase, provided they fulfill the following criteria:

- 1. they are eligible as collateral for Eurosystem credit operations;
- 2. they are denominated in euro;
- 3. they have a minimum first-best credit assessment of at least credit quality step 3 (rating of BBB- on S&P's scale or equivalent) obtained from an external credit assessment institution. The four credit rating agencies recognized by the Eurosystem are Standard & Poor's,

Moody's, FitchRatings and DBRS;

- 4. they have a minimum remaining maturity of six months and a maximum remaining maturity of 30 years at the time of purchase;
- 5. they have a yield to maturity above the deposit facility rate (DFR) at the time of purchase;

### 6. the issuer:

- is a corporation established in the euro area, defined as the location of incorporation of the issuer.<sup>10</sup>
- is not a credit institution,
- does not have any parent undertaking which is a credit institution,
- is not an asset management vehicle or a national asset management and divestment fund established to support financial sector restructuring and/or resolution.

Conditional on being eligible for the CSPP, the Eurosystem also applies these additional restrictions in order to limit its risk exposure:

- 1. An issue share limit of 70% per international securities identification number (ISIN) on the basis of the outstanding amount.
- 2. A limit at issuer group level.

Finally, extensive risk monitoring and due diligence activities are performed on a regular basis by the Eurosystem prior to the purchases to ensure that outright operations are made prudently with the objective of mitigating the risks resulting from its operations. Moreover, to mitigate the credit

<sup>&</sup>lt;sup>10</sup>Corporate debt instruments issued by corporations incorporated in the euro area whose ultimate parent is not based in the euro area are also eligible for purchase under the CSPP, provided they fulfill all the other eligibility criteria.

risk associated with the explicit reliance on CRAs, the Eurosystem Credit Assessment Framework (ECAF), which is the set of standards and procedures that defines the credit quality of collateral used by the Eurosystem in its monetary policy operations, incorporates comprehensive ex-post performance monitoring activities.<sup>11</sup>

By June 2021, the ECB's cumulative CSPP holdings amounted to EUR 282 billion where the vast majority of bonds, around 78%, were purchased in the secondary market (Figure 2A in the Appendix). During the period from June 2016 to December 2017, the ECB purchased more than EUR 130 billion eligible corporate debt from euro area firms, which is a sizable amount with respect to the European corporate bond market. While no exact ex-ante purchase volumes are announced, overall CSPP purchase volumes are published ex-post. The net CSPP purchases accounted for less than 10% of the APP purchases in 2016 and 2017, while they reached larger shares from 2018 onwards, with the reduction of the monthly pace of net purchases of government bonds (Figure 3A in the Appendix).

### B. Theory: The credit rating channel

The theory behind the credit rating channel is intuitive. It is built upon the well known critical friction related to CRAs reliance on fees from issuers as a main source of revenue (White, 2010, Bolton et al., 2012, Efing and Hau, 2015, Baghai and Becker, 2018). This "issuer pays" arrangement may create perverse incentives because (i) CRAs have heterogeneous beliefs and issuers can "rating shop" by selectively picking the most favorable ratings for publication (Skreta and Veldkamp, 2009, Faure-Grimaud et al., 2009, Farhi et al., 2011) and (ii) CRAs have an incentive to inflate their ratings in order to increase the probability of being selected to rate the deal (Bolton et al., 2012, Sangiorgi and Spatt, 2013). Reputational concern, a commonly cited counterincentive, is not always

 $<sup>^{11}</sup>$ For more details, see Coppens et al. (2007), Bindseil et al. (2009), González and Molitor (2009), ECB (2015) and Bindseil et al. (2017).

considered sufficient for rating agencies to report truthfully (Mathis et al., 2009). 12

In our framework, we conjecture that the common knowledge of the ESCF's design (especially with regards to the first-best rating rule) associated with the (institutionalized) oligopolistic competition<sup>13</sup> and conflicts of interest among CRAs may have distorted the typical trade-off faced by CRAs, thereby facilitating rating upgrades for bonds initially located below, but close to, the CSPP eligibility frontier. We define this mechanism as the credit rating channel. In an environment where the eligibility for the CSPP is at the margin contingent on a single rating, the credit rating channel is at work if the "QE eligibility premium" is larger than the reputational costs. Therefore, under the assumption that bonds located around the frontier have the same risk-profile from the viewpoint of investors, and might (conditionally) respond similarly to macroeconomic shocks, we expect reputational costs to be smaller (than the potential gains arising from a marginal rating upgrade) for bonds initially located below, but close to, the eligibility frontier.<sup>14</sup> This prediction is empirically tested in the next sections as well as the key identification assumption.<sup>15</sup>

<sup>&</sup>lt;sup>12</sup>From the viewpoint of market efficiency, distorted ratings are problematic insofar the rating agencies' role is to certify credit risk quality or to reduce asymmetric information. In the former case, inflated certifications could allow market participants such as pension funds to take on greater risks than desired by regulators. In the latter case, if rule-based investors are naive about how ratings are determined, they may underestimate the true risk of their investment strategies (Sean Chu, 2014). Notwithstanding, Goldstein and Huang (2018) show that, under some circumstances, the issuer-pay business model can have positive real effects.

<sup>&</sup>lt;sup>13</sup>In the European Union, the credit rating is a highly concentrated industry, with the "Big Three" credit rating agencies controlling approximately 93% of the ratings business (ESMA, 2017). Moody's and S&P together control 77.5% of the European market, Fitch controls a further 15,65%, and DBRS has less than 2% of the total market share. Figure 1A in the Appendix provides the market shares of CRAs from 2015 to 2017

<sup>&</sup>lt;sup>14</sup>From a theoretical point of view, the basic mechanisms behind the credit rating channel are described in Opp et al. (2013), who analyse the impact of rating-contingent regulation. For empirical studies on the role of regulation, see, for example, Kisgen and Strahan (2010), Bongaerts et al. (2012) and Hanley and Nikolova (2018).

<sup>&</sup>lt;sup>15</sup>As already mentioned, upgrade pressures may arise from both sides - agencies and issuers. In our empirical analysis we show that they were both at work.

# III. Data and Summary Statistics

We collect data on euro area corporate bonds that comply with all the CSPP criteria defined in Section II except the requirement on the "minimum first best credit assessment of at least credit quality step 3". We construct a dataset at monthly frequency (beginning of the month) from January 2015 to December 2017. In what follows, we present our data sources and descriptive statistics.

Our main source of data is Bloomberg, which contains detailed security-level information on all corporate debt issued by euro area corporations. Among the available characteristics at the security level, we collect information on international security identification numbers (ISIN), outstanding amount, currency denomination, security type (e.g. callable, perpetuity, at maturity, etc.), issue date, maturity date, eligibility for Eurosystem credit operations, yield-to-maturity, bid-ask spreads and credit ratings. For the purpose of this study, we clean the data as follows. In the first step, as we use the credit rating vector of a bond and the pivotal roles of rating agencies (with regard to bond's eligibility for the corporate QE), we drop bonds with no rating over the full period. In the second step, we exclude on a monthly basis all bonds that do not comply with the CSPP requirements (remaining maturity, currency, DFR floor, issuer industry, country of incorporation, etc.), except the criterion on the "minimum first best credit assessment of at least credit quality step 3". We finally identify 1750 publicly traded corporate bonds across 16 euro area countries. Descriptive statistics on these bonds are reported in Tables 2A-4A in the Appendix.

Figure 2 shows the distribution of the corporate bonds by first-best credit rating (under S&P scale) at the beginning of March 2016 (i.e. pre-announcement). Bonds on the right of the red dashed-line had at least a BBB- and thus satisfied the first-best rating rule. Out of the 1750 corporate bonds, around 65% were potentially eligible for the corporate QE and 35% were below the "minimum first"

<sup>&</sup>lt;sup>16</sup>Some corporate bonds do not have a rating in March 2016, but exhibit eventually a credit rating afterwards. We focus on these bonds in Section V.

<sup>&</sup>lt;sup>17</sup>We also eliminate bonds with a first-best rating of at least BBB-, over the entire period covered, and not eligible for Eurosystem credit operations. Indeed, the Eurosystem restricts the collateral accepted to simple and transparent debt instruments and does not accept complex coupon structures.

best credit assessment of at least credit quality step 3".18

Our main analysis relies on rating changes of bonds with available credit rating at the date of CSPP announcement. Figure 3 shows that around the CSPP announcement, bonds enter the sample before March 2016 (e.g. newly issued bonds) at the same pace as they leave it afterwards (e.g. because they are getting closer to the maturity). Restricting our attention on this "frozen list" has one important advantage: once bonds are frozen at the month of the CSPP announcement, we can track the credit rating changes before and after the policy shock on the same and well identified sample. Our "frozen list" approach facilitates the identification of rating changes induced by the ECB's first-best rating rule.<sup>19</sup>

Figure 4 plots the share of bonds in the frozen list with at least a BBB-. The share of securities with at least a BBB- was roughly stable – around 63% – from January 2015 to March 2016. After the corporate QE announcement, however, we observe a gradual increase in the share of potentially CSPP-eligible bonds.

By freezing the set of corporate bonds and keeping the ones available in March 2016, Figure 5 depicts the kernel density of the first-best rating distribution for three different months - January 2015 in green, March 2016 in blue and December 2017 in red (see Figure 4A in the Appendix for a three-dimensional representation). In January 2015, the distribution is clearly bimodal and similar to the one observed in March 2016. Formally, a Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level.<sup>20</sup> After the announcement of the corporate QE, a large part of the distribution seems to have "shifted" to the right – to the CSPP-eligibility territory. More specifically, in December 2017, the distribution looks unimodal and "closer" to a normal distribution. This evidence is impressive to the extent that the mode of all distributions has not

<sup>&</sup>lt;sup>18</sup>Note that we say "potentially eligible" because some bonds have a rating of at least BBB- but might be not eligible for Eurosystem credit operations (due to the coupon structure of the bond for example). The opposite is also possible, namely high-yield bonds eligible for the ESCF thanks to the ratings of their guarantor. In Table 5A in the Appendix, we drop these bonds (i.e. 196 securities) and find similar results.

<sup>&</sup>lt;sup>19</sup>In the robustness checks section, we replicate the empirical analysis without freezing the set of bonds.

<sup>&</sup>lt;sup>20</sup>We find similar results for the other months before the CSPP announcement.

moved significantly. This finding suggests that a gradual and monotonic increase of CSPP-eligible securities is likely to have occurred from March 2016 onwards.

As regards the main control variables, we collect monthly data at the euro area and country level such as unemployment rates, industrial production, risk-free short-term rates, GDP and interest rates forecasts, PMI indices, stock market indices, Citigroup economic surprise indices and sovereign long-term interest rates. We also collect the Euro Stoxx 50 Volatility index (VSTOXX), which captures changes in aggregate stock market volatility, which is an important factor in the pricing of credit risk. These variables are collected from the ECB Statistical Data Warehouse, Datastream and Consensus Economics. We also match bond-level data from Bloomberg with issuer-level information such as total assets, leverage ratios, operating revenues, number of employees, and other balance sheet and income statement figures from Orbis Europe and firms' annual reports and financial statements. We finally make also use of the list of bonds that have been actually purchased under the CSPP, which is available on the ECB website on a weekly basis.

# IV. Empirical Strategy and Main Results

We now bring our theoretical prediction on the credit rating channel to the data. In sub-Section IV.A, we look at the aggregate effects of the CSPP by considering all rating buckets. In sub-Section IV.B, we focus on the bonds that are initially located below and around the eligibility frontier. In sub-Section IV.C, we provide a comprehensive set of evidence supporting our main identification assumption, namely that bonds located around the CSPP-eligibility frontier are likely to be affected similarly by macroeconomic shocks.

As mentioned previously, our empirical strategy uses the credit rating vector of a bond and the pivotal roles of some rating agencies (with regard to bond's eligibility) as the most important pieces of information to link the CSPP design with CRAs behavior. By focusing on the bond as a unit of observation, we attempt to learn about the effects of the corporate QE on CRAs ratings through

the dynamic up(down)grades of euro area corporate bonds.<sup>21</sup>

In essence, our identification strategy exploits the legal restriction that the ECB can only purchase corporate bonds "with at least a BBB-" from at least one of the four recognized CRAs. Beyond helping us to conceptually understand the channel through which the ECB outright purchases may affect CRAs responses, the eligibility characteristics of the corporate QE also matter for our econometric identification. Specifically, the eligibility requirements for corporate bonds to be included in the CSPP provide a sharp time-series and cross-sectional prediction on CRAs behaviour (see sub-Section II.B).

The central claim of our paper is that CSPP non-eligible bonds located below, but close to,  $C_{ECB}$  the CSPP eligibility threshold - are more likely to experience rating upgrades via the credit rating channel.<sup>22</sup> The intuition behind the mechanism can be understood using the following example. At the announcement of the corporate QE, bonds that have an "ECB eligibility score", say above  $C_{ECB}$  (i.e. bond I with a rating vector  $X_I = [BBB-, BB+, BB+, \#NA]$ ) are eligible for the CSPP. We compare the rating changes of CSPP non-eligible corporate bonds that barely fail to qualify for eligibility (i.e. bond J with a rating vector  $X_J = [BB+, BB+, BB+, \#NA]$ ) to those of bonds positioned farther away from the eligibility frontier (i.e. bond K with a rating vector  $X_K = [C, BB, BB-, \#NA]$ ). In other words, the methodology compares the likelihood of becoming CSPP-eligible after March 2016 for corporate bonds with eligibility score of  $C_{ECB} - \delta$  (treatment group) to those with eligibility scores of  $C_{ECB} - \Delta$  (control group), where  $\Delta >> \delta$ , arguing that bond J and high-yield securities with similar rating are more likely to jump into the CSPP-eligible side.

<sup>&</sup>lt;sup>21</sup>The baseline analysis is not conducted at the issuer level, as some bonds issued by the same firm in our sample have received different ratings or simply differ in terms of compliance with respect to the ECB eligibility requirements (due to bonds' characteristics). Nevertheless, an analysis performed at the issuer level confirms our baseline results.

<sup>&</sup>lt;sup>22</sup>Notice that even without the CSPP, bonds with a rating of at least BB+ are more likely to obtain a BBB-compared to bonds with a worse rating (controlling for country, maturity, industry etc...). In our framework, we test whether the corporate QE acted as a "rating upgrade accelerator" for bonds located below, but close to, the frontier of eligibility.

Identifying the effects of the CSPP on CRAs behavior remains particularly challenging to the extent that such monetary policy announcement intentionally responds to current and anticipated aggregate shocks. Moreover, the CSPP itself has contributed to the improvement of the macroeconomic conditions by reducing financing costs for firms, stimulating new issuance and strengthening the pass-through of monetary policy interventions (ECB, 2017; Arce et al., 2018; Grosse-Rueschkamp et al., 2018). This makes it difficult to disentangle the CSPP effect on CRAs behavior from the overall macroeconomic conditions. Such (un)observed factors (e.g. endogenous positive macroeconomic outlook) could lead to more rating upgrades than those resulting from a change in CRAs behaviour triggered by the design of the CSPP, and therefore estimates from regression analysis may be biased. Ideally, to identify the credit rating channel, bonds located around the frontier of eligibility should be affected similarly by the macroeconomic shocks. The aim of our empirical analysis is to overcome these obstacles.

# A. The aggregate effect of the corporate QE

To begin with, our tests empirically explore the overall effect of the CSPP on the probability of becoming eligible (i.e. including the range of all rating scores in our dataset). We define our main dependent variable,  $QEeligible_{i,j,k,t}$  ("CSPP eligible") as follows:

$$QEeligible_{i,j,k,t} = \begin{cases} 1 & \text{if CSPP rules } \#1 \text{ to } \#6 \text{ are satisfied} \\ 0 & \text{otherwise} \end{cases}$$
 (1)

where the unit of observation is at the (i, j, k, t) level, where i is a bond, j is a country, k is an industry and t is a month. CSPP rules #1 to #6 correspond to the six eligibility requirements presented in Section II.A, where the most important rule we rely on for identification is the rule #3 (i.e. minimum first-best credit assessment of at least credit quality step 3). All requirements being satisfied but rule #3, the CSPP-eligibility follows a known deterministic rule,  $QEeligible_{i,t} = 1\{\max_r\{R_r\} \ge C_{ECB}\}$ , where  $1\{.\}$  is the indicator variable,  $\max_r\{R_r\}$  represents the first best rating,  $R_r$  is rating assigned

by the rating agency r (r=Standard & Poor's, Moody's, Fitch and DBRS) converted in numerical values (Table 1A in the Appendix) and  $C_{ECB}$  is the "BBB-" cut-off.

Figures 4-5 suggest that the share of eligible securities increased after the CSPP announcement. To provide multivariate evidence for this result, we estimate the following panel regression model:

$$QEeligible_{i,j,k,t} = F\left(\alpha + \beta_1 \mathbb{1}\{t > March2016\} + \gamma_1 \Lambda_{i,j,k,t} + FEs\right) + \epsilon_{i,j,k,t}$$
 (2)

where the dependent variable is the probability for bond i to be eligible for the ECB's corporate QE at month t,  $\mathbbm{1}\{t > March2016\}$  is an indicator variable equal to 1 after the announcement of the CSPP and 0 before, and  $\Lambda_{i,j,k,t}$  is a vector of time-varying controls that includes (i) euro area forward-looking macroeconomic and financial variables (e.g. expected GDP growth, expected slope of the yield curve - defined as the difference between the 10-year and 3-year euro area benchmark yields), (ii) global euro area risk indexes (e.g. VIX, Citigroup economic surprise index), (iii) country-level characteristics (e.g. unemployment rate, PMI indices, stock market indices), (iv) industry-level characteristics (e.g. stock market indices), (iv) firm-level characteristics (leverage ratio), and (v) bond-level characteristics (e.g. bid-ask spread, return, amount issued). FEs defines a set of fixed effects (remaining maturity, country, bond type, industry) used to control for unobserved time-invariant characteristics. In our context, controlling for maturity fixed effects is important because non-eligible bonds have, on average, a shorter remaining maturity than the eligible ones. In the baseline specifications, F is a linear function (i.e. linear probability model) and standard errors are

<sup>&</sup>lt;sup>23</sup>Since the rating vectors are taken at the first day of each month, we consider control variables as contemporaneous when they are taken at the end of the previous month. For financial variables (e.g. stock market index), we consider the average of the previous month.

<sup>&</sup>lt;sup>24</sup>For the remaining maturity fixed effects, we fix the date as of March 2016 (i.e. CSPP announcement) and construct six dummy variables based on the following buckets: 0-1 year, 1-3 years, 3-5 years, 5-8 years, 8-10 years, more than 10 years. Our approach closely follows the one employed by Keys et al. (2010). For more details on the four categories used for the fixed effects, see Tables 2A-4A in the Appendix.

<sup>&</sup>lt;sup>25</sup>In Section V, we replicate our empirical exercise by replacing F by the cumulative normal distribution

clustered at the bond level.<sup>26</sup> Moreover, the baseline specification includes only the main forward looking macro and financial controls. The complete set of controls is included in the following sub-sections.

Table 1 reports the estimation results. Our key coefficient of interest is  $\beta_1$ . Column (1) shows that, in the absence of controls, the probability of becoming eligible increased by around 2.9 percentage points after the announcement of the corporate QE.<sup>27</sup> When controlling for the expected euro area macroeconomic outlook and financial volatility (columns (2)-(4)),  $\beta_1$  remained strongly significant, pointing to an increase in the probability of becoming eligible for the corporate QE after March 2016 of around 3.5 percentage points. When we control for time invariant unobserved characteristics (columns (5)-(8)) and perform a double-clustering procedure (column (9)), the coefficient of interest oscillates between 3.0 and 4.5 percentage points, remaining statistically significant at the 1 percent level. These results suggest that non-eligible corporate bonds are more likely to jump into the CSPP-eligible territory after March 2016. As adding controls and fixed effects does not change the magnitude of the key coefficient, our analysis seems to lend further support for a causal interpretation of the credit rating channel.

In Table 1, the estimated effect are pooled across all months before and after March 2016. A potential concern is that the described effect might arise in periods other than March 2016. In order to make sure that we capture the effect of the CSPP instead of something else, we run a placebo test by simulating the application of the treatment in every month from January 2015 to December 2017. Formally, we run the following regression between these two dates, indexing the month by  $\tau$  (omitting the baseline month March 2016):

function (probit model).

<sup>&</sup>lt;sup>26</sup>We also consider two-way clustered standard errors at the bond and month level for some specifications, allowing for a correlation of the error within bonds across months, and across bonds in a given month.

<sup>&</sup>lt;sup>27</sup>Notice that the estimate of the constant suggests that around 59% of the euro area corporate bonds are CSPP-eligible before March 2016. This estimate is slightly different from the ones presented in Figures 4 and 6, as they show the share of *potentially* eligible securities. This small discrepancy is due to the inclusion of bonds rated at least BBB- but not eligible, on a temporary basis, for the Eurosystem collateral framework.

$$QEeligible_{i,j,k,t} = F\left(\alpha + \sum_{\tau \neq \text{March2016}} \beta_{\tau} \mathbb{1}\{t = \tau\} + FEs\right) + \epsilon_{i,j,k,\tau}$$
(3)

where  $\mathbb{1}\{t=\tau\}$  is an indicator variable equal to 1 if  $t=\tau$  and 0 otherwise.<sup>28</sup> Figure 6 presents the probability of becoming CSPP-eligible over time  $(\beta_{\tau})$ . While the coefficient of interest fluctuates around zero before the CSPP announcement, the increase in the probability of being CSPP-eligible becomes gradually visible after March 2016 without fading out. In particular, a strong and statistically significant temporal jump in the probability of becoming CSPP-eligible happened a few months after the announcement of the programme.

### B. Cross-sectional variation in the CRAs response

### B.1. The non-linear effects of the CSPP below the eligibility frontier

While the previous section focuses on the identification of CRAs aggregate response (i.e. increase in the probability of becoming CSPP-eligible across all rating buckets), the credit rating channel outlined in sub-Section II.B predicts a cross-sectional variation in this response. In other words, we expect that bonds located below, but close to, the eligibility frontier in March 2016 are more likely to jump into the CSPP eligibility territory after the announcement of the programme compared to bonds located farther away. To test this hypothesis, we run the following regression for each month between April 2016 and December 2017 and for each first-best rating bucket below the eligibility frontier, indexing the month by  $\tau$  and the rating bucket by  $\omega$ :

<sup>&</sup>lt;sup>28</sup>The placebo regression in Eq.3 only includes maturity fixed effects. Adding the full set of time-varying controls and fixed effect does not alter the results.

$$QEeligible_{i,j,k,\tau} = F\left(\rho_{\omega} \mathbb{1}\{\max_{r}\{R_{r}\}_{\text{March2016}} = \omega\}\right) + \epsilon_{i,j,k,\tau}$$

$$\forall \omega \in \Omega, \quad \forall \tau \in \mathcal{T}$$

$$(4)$$

where  $\Omega$  is the set of first-best rating buckets below the eligibility frontier (i.e. from D to BB+),  $\mathcal{T}$  is the set of months running from April 2016 and December 2017,  $\mathbb{1}\{.\}$  is the indicator variable,  $\max_r \{R_r\}_{\text{March2016}}$  represents the first-best rating of bond i in March 2016 and  $R_r$  is the rating assigned by the rating agency r (r=Standard & Poor's, Moody's, Fitch and DBRS) converted in numerical values. The regression in Eq.4 allows for an easy interpretation of the key coefficient of interest  $\rho_{\omega}$ , as it represents the fraction of bonds that were not eligible in March 2016 but eventually became eligible in a specific month afterwards.

Figure 7 plots the coefficients of interest by rating bucket in the post-CSPP period. In line with the prediction of the credit rating channel, bonds with a first-best rating of BB+ in March 2016 are much more likely to jump into the eligibility side compared to bonds with a worse first-best rating. According to our estimates, around 17% of bonds with an initial first-best rating BB+ were eligible as of December 2017.<sup>29</sup> The increase in this share begins around a few months after the start of the purchases by the Eurosystem. This finding is consistent with the theoretical and empirical literature related to the sluggishness of credit ratings (Altman and Kao, 1992; Lando and Skodeberg, 2002; Altman and Rijken, 2004 and 2006; Cantor, 2004; Löffler, 2004 and 2005; Cheng and Neamtiu, 2009; White, 2010; Alp, 2013). Our results suggest that the CSPP had a significant impact on the eligibility of the corporate bonds initially located slightly below the first-best rating cut-off.

<sup>&</sup>lt;sup>29</sup>This estimate is far larger than the historical short-term transition rates reported by CRAs for the corporate sector (see, for example, S&P (2018)).

### B.2. The non-linear effects of the CSPP around the eligibility frontier

To complement the analysis in the previous sub-section, we now focus on bonds located around the eligibility frontier in March 2016, as we expect more dynamism in rating adjustments for bonds located just below the eligibility threshold (first-best of BB+) compared to those positioned just above (first-best of BBB-). We formally evaluate whether credit rating activity differs for bonds that have similar credit risk profile but are different in terms of CSPP-eligibility by estimating the following equation:

$$\Delta Rating_{i,j,k,t} = \alpha + \beta_1 \mathbb{1}\{t > March2016\} + \gamma_1 \Lambda_{i,j,k,t} + FEs + \epsilon_{i,j,k,t}$$

$$\forall \omega_F \in \Omega_F$$
(5)

where the dependent variable  $\Delta Rating_{i,j,k,t}$  is the change in the first-best credit rating of a bond i from month t to month t-1 (i.e a measure of rating activity), and  $\Omega_F$  includes the bonds located below and above the frontier of eligibility (i.e. from BB to BBB-).<sup>30</sup> The key regressor, the controls and the fixed effects are defined as in Eq.2.

The results, reported in Table 2, show that bonds located below, but close to, the eligibility frontier (BB+) in March 2016 experienced a statistically significant positive rating activity after March 2016 (i.e. more upgrades than downgrades). For bonds rated BB or BBB-, the rating activity seems to have not changed significantly in the post-CSPP period. This evidence suggests that the increase in the probability of becoming eligible observed (on average) in the post-CSPP period mainly reflects the upward rating activity experienced by the bonds located slightly below the eligibility frontier. Overall, the discrete nature of the CSPP-eligibility rating criterion seems to have led to a significant change on the behaviour of CRAs. In line with the theory, the estimated effect for the rating activity is concentrated precisely on the territory where CRAs incentives are expected to be more sensitive to the policy design.

<sup>&</sup>lt;sup>30</sup>We extend the analysis to the entire set of rating buckets and report the results in Table 6A and Table 7A of the Appendix.

When matching our dataset with the data on actual purchases by the Eurosystem, we estimate that 14% of the bonds in our sample with a first-best rating of BB+ in March 2016 (and thus not CSPP-eligible) were purchased as a result of the rating upgrades that occurred in the post-CSPP period. As a benchmark for comparison, we estimate that 45% of the bonds rated at least BBB- in March 2016 in our sample were purchased under the corporate QE.

### C. Incorporating additional controls

The results discussed so far establish a significant relationship between the corporate QE and the rating upward adjustments that occurred after March 2016 on bonds located slightly below the eligibility frontier. However, one possible concern is that we do not sufficiently control for other factors that might affect the probability of becoming CSPP-eligible. To deal with this issue, we first employ an alternative specification that include country and other euro area level time-varying controls (i.e. unemployment rates, stock market indices, the Citigroup economic surprise index). We then augment this model with bond-level information (i.e. the lagged bid-ask spread as a proxy for liquidity, the lagged return and the amount issued as a proxy for bond size). We give to our alternative models the maximum flexibility to capture the explanatory power of the post-CSPP dummy by also incorporating the previous control variables.

Table 3 and Table 8A in the Appendix report the results. The coefficients for the additional control variables display the expected sign and are statistically significant in most of the cases. More importantly, the CSPP time dummy coefficient remains statistically significant across all specifications and oscillates around 3.0 percentage points, consistently with the baseline results. Although comovements with the additional fundamental variables may be important factors for explaining CRAs credit risk assessment, their inclusion has little effect on the post-CSPP coefficient, thereby providing further support to the prediction of the credit rating channel.<sup>31</sup>

<sup>&</sup>lt;sup>31</sup>Unreported analyses incorporating other bond-, issuer-, industry- or country characteristics (i.e. lagged yield-to-maturity, firm leverage ratios, industry stock market indexes, expected default frequencies of non-financial corporations, expected GDP growth for the current year, expected slope of the yield curve for the

### D. Further evidence supporting the identification assumption

Our identification strategy relies on the assumption that in the absence of the CSPP, bonds located slightly below the CSPP eligibility frontier (i.e.  $bond\ J$ ) are affected similarly by business cycle fluctuations to eligible bonds positioned above (i.e.  $bond\ I$ ). Intuitively, controlling for bond type, maturity, industry, country and other pricing-risk characteristics, one can assume that, up to a rating (i.e. first-best rating rule),  $bond\ J$  and  $bond\ I$  have a very similar credit risk profile and, therefore, respond similarly to macroeconomic developments. If this is the case, there should not be any discernible differences in credit rating activity for bonds located around the frontier. We conjecture that any difference in rating adjustments on either side of the cut-off should be due to the impact that the corporate QE has on CRAs rating behavior.<sup>32</sup> In this sub-section, we provide further evidence on the plausibility of this key identification assumption by analyzing the characteristics of firms whose bonds are located around the eligibility frontier.

Figure 5A in the Appendix depicts the kernel density of the logarithm of the total assets in 2016 for two groups of firms: those whose bonds have a first-best rating of BB+ in March 2016 (i.e. 32 firms) and those whose bonds have a first-best rating of BBB- (i.e. 27 firms). The two distributions are very close to each other, suggesting that firms of these two groups have similar size. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Similarly, Figures 6A-12A in the Appendix present the distributions of total assets, the leverage ratio, the number of employees (another proxy for firm size), operating revenues, net income, profit margins and return on equity in 2015 and 2016 for the two groups of firms. Again, we find that the firm characteristics are similar across the two groups in terms of median values and distribution, even for the more volatile profitability indicators. This evidence confirms that our results are not driven by systematic differences in observable firm-level characteristics.

current year) into the set of control variables point to similar findings.

<sup>&</sup>lt;sup>32</sup>More formally, as we approach the ECB rating cut-off from either side, any differences in the characteristics of bonds/issuers are assumed to be random (Abidi and Miquel-Flores, 2018):  $\lim_{\max_{t} \{R_{r}\} \to C_{ECB}^{-}} \mathbb{E}[\epsilon_{i,j,k,t}|Controls] = \lim_{\max_{t} \{R_{r}\} \to C_{ECB}^{+}} \mathbb{E}[\epsilon_{i,j,k,t}|Controls].$ 

### V. Robustness Checks

In this section, we present the findings from additional exercises aimed at sharpening our identification strategy, providing further insights and checking the robustness of our estimates.

### A. Non-euro denominated assets as a control group

We now present a strong check of our identification strategy by relaxing a CSPP-eligibility requirement, namely the currency denomination of the corporate bond (i.e. CSPP rule #2). Specifically, we consider only euro area firms that have issued corporate bonds both in euro and in different currencies. Our new sample consists of 2180 bonds covering 22 currencies where around 50% of the bonds are denominated in euro. We use a difference-in-differences approach with the currency denomination of an asset as the main cross-sectional explanatory variable. The dependent variable is a dummy variable that equals 1 if the bond has a rating above the ECB's rating-based threshold (i.e. at least BBB- from at least one of the four recognized CRAs) and the main regressor is now an interaction term between a euro denomination dummy and a time dummy for the CSPP announcement (which is turned on after March 2016).

Column (1) in Table 4 reports the results of the regression without controls and fixed effects. The coefficient on the post-CSPP dummy is positive and statistically significant suggesting that, regardless of the currency denomination, the probability of jumping into the rating eligibility territory increases – by around 1.3 percentage points – after March 2016. Interestingly, the interaction term in columns (2)-(8) is positive and statistically significant, while the post-CSPP coefficient is no longer different from zero. This implies that the increase in the probability of jumping into the rating eligibility territory, observed in column (1), is driven by securities denominated in euro. The comparison between euro and non-euro denominated assets is illuminating and confirms the importance of the CSPP eligibility rules for the CRAs credit risk assessment.

We now focus on the bonds initially located below the eligibility frontier with different currency

denomination. if the credit rating channel is at work, we expect euro denominated bonds having a higher probability of jumping into the rating eligibility territory than non-euro denominated ones. We extend Eq.4 by including a dummy variable  $Euro_{i,j}$  that indicates whether bond i is denominated in euro or in another currency:

$$Rating_{\max_{r} \{R_r\} \geqslant C_{ECB}} = F\left(\rho_{\omega} \mathbb{1}\{\max_{r} \{R_r\}_{\text{March2016}} = \omega\} + \nu_{\omega} Euro_{i,j}\right) + \epsilon_{i,j,k,\tau}$$

$$\forall \omega \in \Omega, \quad \forall \tau \in \mathcal{T}$$
(6)

where  $Rating_{\max_{f} \{R_r\} \geq C_{ECB}}$  is a dummy variable that takes value 1 if the first-best rating of bond i is above the ECB rating threshold and 0 otherwise. It is important to notice that the dependent variable does not refer to the CSPP eligibility as in Eq.2-4 because, by definition, bonds not denominated in euro are not eligible. Figure 8 plots the coefficient  $\nu_{\omega}$  after March 2016 for each rating bucket below the rating cut-off. As regards bonds initially first-best rated BB+, we observe a positive and significant coefficient a few months after the start of the purchases, suggesting that, within this rating bucket, bonds denominated in euro have jumped significantly more into the eligibility side compared to bonds denominated in other currencies. For bonds rated BB, the coefficient  $\nu_{\omega}$  is not statistically significant, and for the remaining rating buckets, it stays at zero.<sup>33</sup> These estimates reveal that the findings in Table 4 are driven by the upward rating adjustments on bonds denominated in euro initially located below, but close to, the eligibility frontier. Overall, the evidence from this treatment-control group experiment further corroborates our main prediction.

# B. Non-recognized CRAs as a control group

Another suitable control group is represented by the bonds in our sample rated by non-recognized CRAs. In this exercise, we restrict our attention to the non-recognized CRAs regulated by ESMA

<sup>&</sup>lt;sup>33</sup>The confidence bands are not reported for the sake of clarity.

for which we can obtain available credit rating data from Bloomberg: Egan Jones, Scope Ratings and AM Best Ratings. Out of our initial sample of 1750 bonds, only 284 are rated at least once by these three CRAs from January 2015 to December 2017. We replicate our baseline regression (Eq.2.) by (i) restricting the set of securities to these 284 bonds and, (ii) taking the first-best rating with respect to our sample of non-recognized CRAs. The main dependent variable is a dummy that is equal to one if the bond is eligible for the corporate QE assuming that that Egan Jones, Scope Ratings and AM Best Ratings are the recognized CRAs. As shown in Table 5, in contrast with our baseline results, we find that the probability of jumping into the eligibility territory is lower after March 2016. The results are robust across all specifications. Put differently, for the set of bonds rated by non-recognized CRAs (i.e not eligible from the viewpoint of the Eurosystem), there are no abnormal credit rating upgrades in the post-CSPP period. Even if sample size for the non-recognized CRAs is relatively small, our findings suggest that the credit rating channel is driven by the four recognized rating agencies and the particular design of the corporate QE (i.e first-best rating rule).

Another possible way to make the control group using non-recognized CRAs a more suitable counterfactual is to restrict the set of bonds to the ones rated in March 2016 (55 out of 284 bonds). We repeat the previous exercise by focusing on the rating dynamics of these 55 bonds and present the results in Table 9A in the Appendix. The results show again that, focusing on non-recognized CRAs, euro area corporate bonds did not observe an upward credit rating adjustment in the post-CSPP period, which lends further support to the credit rating channel.

# C. A two-period difference-in-differences analysis

The analysis in Section IV is performed using the frozen list over the period January 2015-December 2017 (36 months). Therefore, the coefficient of interest might be affected by the fact that the number of bonds displays an inverted V-shape over the sample period (see Figure 3), whereby bonds satisfying the CSPP-criteria (except the first-best rating rule) are included in the sample as

long as they have a rating in March 2016. To address this possible issue, we now consider only two periods, namely pre- and post-CSPP. The eligibility of bonds in the pre-CSPP period is simply defined as of March 2016. As regards the post-CSPP period, we look at the eligibility in December 2017 for the bonds that are still in the sample at that date (around 1200 bonds), while we consider the latest available month for the bonds that are leaving the sample (because they do not satisfy any longer one of the CSPP criteria, except the first-best rating rule, e.g. bonds whose remaining maturity falls below six months).

On this balanced sample, we conduct two difference-in-differences exercises. In the first one, we look at the bonds initially located below the eligibility frontier. The dependent variable is the same as in Eq.4 and the regressors are a post-CSPP dummy, an indicator that equals one if a bond belongs to the rating bucket  $\omega$  and an interaction term of the two. We also include maturity, country, bond-type and industry fixed effects. The regression is estimated for each rating bucket below the eligibility frontier, and the interaction term indicates the probability of moving to the eligibility side for bonds in the rating bucket  $\omega$  (treatment group) after the announcement of the CSPP compared to the other rating buckets (control group). As shown in Figure 9, the coefficients of the interaction term is positive and statistically significant only for the bonds initially located close, but below, the eligibility frontier. In particular, these bonds have a significantly higher probability (around 16%) of jumping into the eligibility side after the CSPP than bonds with a worse rating.

In the second exercise, we change the dependent variable to look at rating upgrades taking place around the eligibility frontier. Instead of having the eligibility dummy, we use a dummy that equals one if the bond experienced *only one* rating upgrade. The coefficient of the interaction term, plotted in Figure 10, shows that only bonds initially first-best rated BB+ had a significantly higher probability of experiencing one rating upgrade in the post-CSPP period versus the other rating buckets. These results are no longer valid when we consider more than one rating upgrades (Figure 11), confirming the importance of the marginal upgrade for bonds located just below the eligibility frontier.

### D. Controlling for CRAs competition

We now analyze whether there is a difference in the CRAs behavior depending on the level of competition among CRAs.<sup>34</sup> We measure CRAs competition at a bond-level by counting the number of publicly available ratings in March 2016. We call this variable  $\sum_r \mathbb{1}_{[R_r \neq \varnothing]}$  where  $\mathbb{1}\{.\}$  is the indicator variable and  $R_r$  is the rating assigned by the rating agency r (r=Standard & Poor's, Moody's, Fitch and DBRS) converted in numerical values. The support of this variable is discrete and runs from 0 to 4. Around 50% of our corporate bonds are rated by two CRAs (Figure 13A in the Appendix). Among the 875 bonds with two CRA ratings, 77% were given by Moody's and S&P. This is consistent with the aggregate overview of the European CRAs industry shown in Figure 1A in the Appendix. It is worth mentioning that DBRS ratings are only available for the bonds with all four publicly available ratings (i.e. 23 bonds).

In the econometric analysis, we distinguish two groups: one including bonds displaying a high CRAs competition as of March 2016 (above or equal the sample median value of 2) and one including bonds having low CRAs competition (below the sample median value of 2). In our first regression, the indicator variable  $Competition_{i,March_{2016}}$  is equal to one (zero) if the number of publicly available credit ratings is above (below) the sample median value. The results, reported in Table 10A in the Appendix, suggest that, on average, being rated by more CRAs seems to be associated with a higher credit rating (i.e. more likely to have a rating above the eligibility cut-off). This finding can be explained by the theory that underlies specific relationship between CRAs and issuers (Alcubilla and Del Pozo, 2012). As revealed by the interaction term, this effect seems to weaken somewhat after the CSPP. In addition to furthering the robustness of our baseline results, this analysis shows that corporate bonds with few ratings have a slightly higher probability of jumping into the CSPP-eligibility side after March 2016.

We aim now to further pin down the effect of CRAs competition with regards to the specificities of rating agencies. We divide the sample of corporate bonds into four subgroups depending on the

<sup>&</sup>lt;sup>34</sup>We also investigate the role of disagreement among rating agencies, without finding any interesting result.

value of  $\sum_{r} \mathbb{1}_{[R_r \neq \varnothing]}$ , as illustrated in Figure 13A in the Appendix. The construction of our groups follows the one by Griffin et al. (2013). Each bond is placed into one of the four mutually exclusive groups. The first group contains all bonds that were rated as of March 2016 by either S&P or Moody's or Fitch or DBRS. The second group contains all bonds that were rated as of March 2016 by either S&P and Moody's or S&P and Fitch or S&P and DBRS or Moody's and Fitch or Moody's and DBRS or Fitch and DBRS. The third group contains all bonds that were rated as of March 2016 by S&P, Moody's and Fitch, while the fourth category includes all bonds that were rated by all CRAs.

Columns (1)-(2) in Table 11A in the Appendix show the results for bonds with only one available rating as of March 2016. Columns (3)-(4) show the results for bonds with only two available ratings in March 2016. Column (5) reports the estimates related to the set of bonds with three ratings from S&P, Moody's and Fitch. Column (6) reports the results for the group of bonds rated by all recognized CRAs in March 2016. The coefficients in the first row suggest that our baseline results seem to be driven by the subset of bonds with two and three ratings as of March 2016. When investigating the origins of the rating upgrades post-CSPP, the results presented are not unequivocal, as no specific CRAs seems to have adjusted credit ratings in a systematic way.

### E. Rating shopping: Extensive versus intensive margin

We further investigate the pivotal role of CRAs by assessing the possibility that issuers "shop" around to find better ratings (Bolton et al., 2012, He et al., 2015). This phenomenon was extensively commented during the global financial crisis of 2008.<sup>35</sup> In our context, we are interested in understanding whether issuers with outstanding bonds located close to the frontier of eligibility

<sup>&</sup>lt;sup>35</sup>As Richard Michalek, a former vice president and senior credit officer at Moody's, testified to the Financial Crisis Inquiry Commission (FCIC): "The threat of losing business to a competitor [...] absolutely tilted the balance away from an independent arbiter of risk [...]". When asked if the investment banks frequently threatened to withdraw their business if they did not get their desired rating, former Moody's team managing director Gary Witt said: "Oh God, are you kidding? All the time. I mean, that's routine. I mean, they would threaten you all of the time [...] It's like, well, next time, we're just going to go with Fitch and S&P".

were more likely to put pressure on CRAs or ask another rating from a competitor in order to obtain a rating of at least BBB-.

We start our analysis by looking at bonds with no changes in the number of publicly available ratings between January 2015 and December 2017. The coefficient of the post-CSPP variable is positive, significant and quantitatively similar to the one found in our baseline model (Table 12A). Focusing on the sample of bonds that have observed at least one change (positive or negative) in the number of available ratings (either new ratings or withdrawals), we find that the post-CSPP coefficient is stronger than in the baseline (Table 6), suggesting that rating shopping might have played a role for the eligibility of bonds after March 2016.

### F. Step-by-step rating migration

Our prediction states that, if distortions on the typical trade-off faced by CRAs emerged, these were likely to materialise on bonds located just below the eligibility frontier, implying only one marginal first-best rating upgrade for these bonds (from BB+ to BBB-). We test this hypothesis by comparing the results from a regression including the bonds that have observed only one change in their first-best rating over the sample period and the estimates from a model which includes bonds that have experienced more than one rating change. The results, reported in Table 7 and Table 13A in the Appendix, clearly show that our main findings are driven by the marginal credit rating changes (in line with the evidence reported in sub-Section V.C).

# G. Cross-country analysis

We now investigate whether our main findings are driven by a subset of countries. To do so, we classify euro area countries into (formerly) vulnerable and less vulnerable countries, following the taxonomy of Altavilla et al., 2016, where the former group includes Ireland, Greece, Spain, Italy, Cyprus, Portugal and Slovenia, and the second the remaining euro area countries. By simply looking at the first-best rating kernel distributions (Figures 14A and 15A in the Appendix), it is

difficult to see whether the baseline results are driven by a particular group of countries, as both distributions display a "shift" of density from the non-eligible territory to the eligible one in the post-CSPP period. To econometrically assess the possibility of a different effect across these two groups, we create a dummy variable called  $Vulnerable_j$ , which takes value 1 if a bond was issued by a firm domiciled in a vulnerable country and 0 otherwise. We also add an interaction term between  $Vulnerable_j$  and the post-CSPP time dummy. The results, presented in Table 14A in the Appendix, points to weak evidence on a different impact across countries, suggesting that the credit rating adjustments that have occurred after March 2016 is a broad-based phenomenon.

### H. Bonds with no rating in March 2016

In our sample, 19 bonds did not have a rating in March 2016, but had a rating during the period covered (Figure 10A in the Appendix). Out of this sample, 12 bonds obtained a rating after March 2016. In this sub-section, we investigate whether the rating they got after the CSPP announcement allowed them to join the group of CSPP-eligible securities. We estimate Eq.4 for the 19 bonds with no publicly available rating in March 2016. The estimates of the key coefficient, plotted in Figure 16A in the Appendix, suggest that the CSPP has spurred the demand for new credit ratings. Moreover, we find that the vast majority of bonds with no ratings in March 2016 obtained eventually one that allowed them to become eligible for the corporate QE. It is worth noting that the upward rating adjustments were more rapid than the one observed in the subsample of corporate bonds initially located below, but close to, the CSPP eligibility frontier.

### I. Probit model

Table 15A in the Appendix reproduces our baseline specification using a probit model ( $F = \Phi$ ). For tractability, we report the marginal effects. The key coefficient is numerically very close to the one in the linear probability, suggesting that the main findings are robust to the selection of the

#### J. Weighting by bond size

In the baseline specification, bonds are treated equally, without considering the fact that some bonds might have a larger size than others. One may therefore wonder whether the main findings of the paper are driven by small-sized bonds. In order to address this concern, we include the bond-size information in the baseline model by weighting the dependent variable by the log of the amount issued for each bond. The results, reported in Table 16A, show that the eligible amount issued increased significantly after the announcement of the CSPP.

#### K. Unfrozen list of bonds

The analysis above is conducted using the "frozen list", which contains only those securities with at least one credit rating as of March 2016. In this sub-section, we ensure that our results are not an artifact of our sample composition. The results for the "unfrozen list", reported in Table 17A in the Appendix, confirm that the probability of becoming CSPP-eligible increased significantly after March 2016. The estimates of this increase range from 3% to 7% and are statistically significant across all of the specifications. The larger impact is likely linked to the increase of bond issuance activity in the post-CSPP period, as documented by Abidi and Miquel-Flores (2018), Arce et al., (2018) and Grosse-Rueschkamp et al., (2018).

Focusing on the new issuances, and hence on securities not in our frozen list, we can see that the share of the bonds issued after the announcement of the CSPP and ending up getting one rating upgrade with respect to the rating of bonds of the same issuer at March 2016 was more pronounced for bonds rated BBB- (Figure 17A in the Appendix). This finding, which is even sharper when considering the amount issued instead of the number of bonds, is fully in line with the prediction of the credit rating channel.

<sup>&</sup>lt;sup>36</sup>The results are also robust to a logit model.

#### VI. Conclusion

Our paper has two readings, a financial and a macro one: the financial view focuses on the credit rating industry and the incentives of market participants, while the macro view concerns the monetary policy measures introduced as a response to the global financial crisis of 2008.

On the financial side, the paper shows that the discrete nature of the eligibility criteria of the corporate QE of the Eurosystem had a significant and asymmetric impact on CRAs rating activity. In particular, we show that, after the launch of the policy, rating upgrades were mostly noticeable for bonds initially located below, but close to, the eligibility frontier. Consistent with the theoretical predictions, this effect is concentrated precisely on the territory where CRAs' and firms' incentives are expected to be more sensitive to the policy design.

On the macro side, given the small size of the euro area corporate bond market and the magnitude of our estimates, the localized rating adjustments induced by the design of the corporate QE are unlikely to have had adverse macroeconomic or financial stability implications. However, evidence suggests that the more recent "credit rating easing" policies (e.g. "frozen ratings" in the ECB's collateral easing package as well as the inclusion of high-yield securities in the Fed's QE programs) provided during Covid-19 has helped lower the cost of borrowing and avoided the downward spiral triggered by an avalanche of downgrades and defaults. As a result, we believe that the consequences of relying explicitly on CRAs must be better acknowledged by central banks when designing monetary policy.

## Figures and Tables

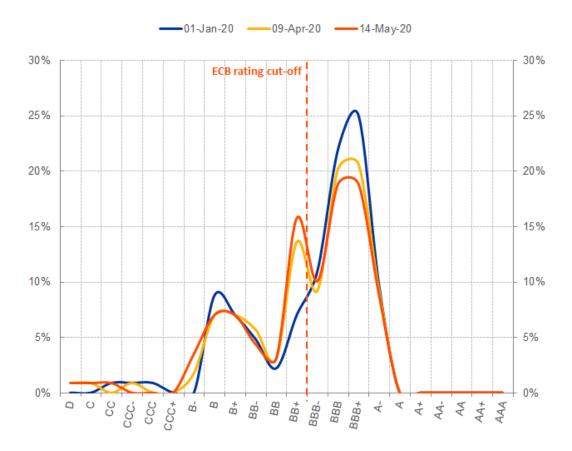


Figure 1. Italy: Dynamic distribution of bonds by first-best rating

The figure depicts the kernel density, in percentages of the Italian corporate bonds by first-best rating for two different dates: 1 January 2020 in blue [pre-Covid] and 9 April 2020 in yellow as well as 14 May 2020 in red [both post-Covid]. The figure shows the distribution of a total of 228 sampled corporate bonds. The red dashed vertical line shows the frontier of first- best rating cut-off of BBB-. A bond is potentially eligible for the CSPP if it has a minimum first-best credit assessment of BBB-.

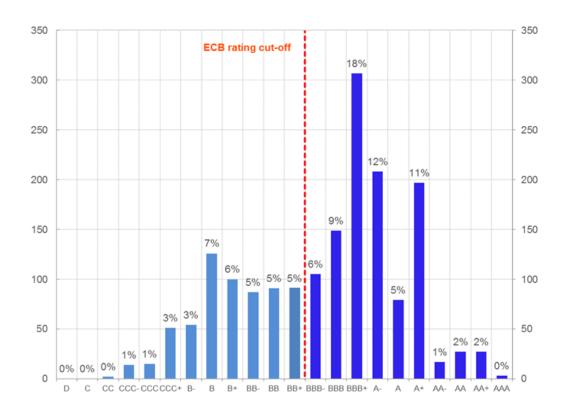


Figure 2. Distribution of bonds by first-best rating

The figure shows the distribution of the 1750 corporate bonds (in number and as percentage of the total) by first-best rating (under S&P scale) with at least one rating from one of the four recognized CRAs in March 2016. A bond is potentially eligible for the CSPP if it has a minimum first-best credit assessment of BBB-.

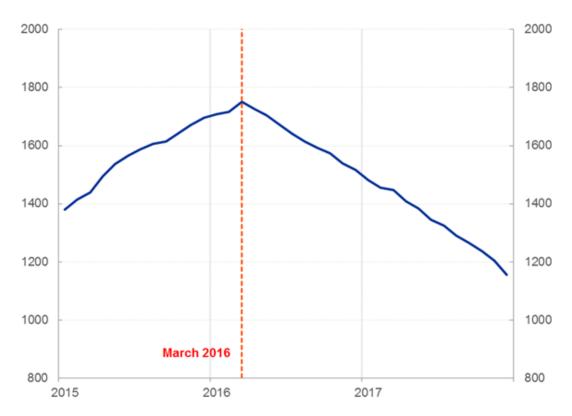


Figure 3. Number of bonds in the frozen list

The figure plots the dynamics of the number of corporate bonds with at least one rating in March 2016. As of March 2016, there are 1750 bonds with at least one rating from one of the four recognized CRAs.

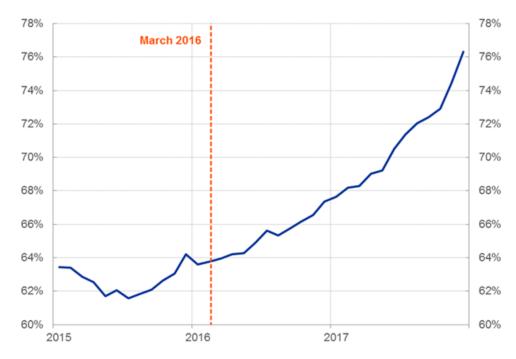


Figure 4. Share of bonds with a first-best rating of at least BBB-

The figure plots the evolution of the share of corporate bonds rated with a first-best rating of at least BBB- (therefore potentially eligible for the CSPP) using the frozen list sample.

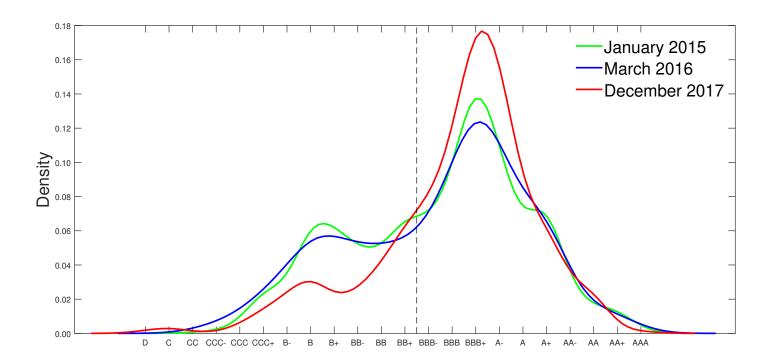


Figure 5. Dynamic distribution of bonds by first-best rating

The figure depicts the kernel density of the bonds in the frozen list by first-best rating for three different months – January 2015 in green, March 2016 in blue and December 2017 in red.

Table 1. The baseline model

Notes: The table presents bond-level regressions using the 1750 bonds in the frozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

$\overline{QEeligible_{i,j,k,t}}$	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)	(6)
$\mathbb{1}\{t > March2016\}$ $\widehat{E}[\text{GDP}]_{t,next\ year}$ $\widehat{E}[\text{Slope}]_{t,next\ year}$ $\Delta VIX_t$ $Constant$	0.029*** (0.007) 0.594*** (0.012)	0.035*** (0.007) 0.035*** (0.007)	0.036*** (0.007) 0.016*** (0.006) 0.039*** (0.005)	0.036*** (0.007) 0.016*** (0.006) 0.040*** (0.005) -0.034 (0.023) 0.530*** (0.019)	0.033*** (0.008) 0.011* (0.006) 0.038*** (0.006) -0.031 (0.024) 0.649*** (0.024)	0.030*** (0.008) 0.013** (0.006) 0.037*** (0.006) -0.041* (0.023) 0.835*** (0.067)	0.045*** (0.007) 0.013*** (0.005) 0.038*** (0.005) -0.043** (0.021) 0.903***	0.036*** (0.007) 0.011** (0.005) 0.032*** (0.005) -0.043** (0.020) 0.832*** (0.065)	0.036*** (0.007) 0.011 (0.007) 0.032*** (0.007) -0.043 (0.089) 0.850*** (0.068)
Maturity FEs	ı			,	>	>	>	>	>
Country FEs	ı	I	ı	ı	ı	>	>	>	>
Bond type FEs	ı	ı	ı	ı	ı	ı	>	>	>
Industry FEs	ı	1	ı	1	ı	ı	ı	>	>
Double-clustered s.e.	1	,	1	1	1	ı	1	1	>
R-squared Observations	0.001 $54,507$	0.001 54,507	0.001 54,507	0.001 $54,507$	0.053 54,507	0.154 54,507	0.424 54,507	0.479 54,507	0.479 54,507

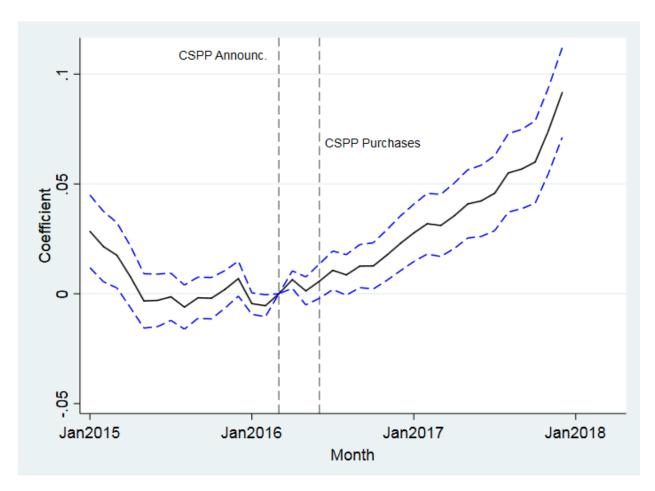


Figure 6. Placebo test

The figure plots the estimated month dummy coefficients from Eq.3 (including only maturity fixed effects) estimated from January 2015 to December 2017 using the 1750 bonds in the frozen list, where the reference month is March 2016 (i.e. CSPP announcement). The dashed lines delimit the 95% confidence interval. Standard errors are clustered at the bond level. The dashed vertical lines indicate the CSPP announcement (i.e. March 2016) and the start of ECB's purchases under the CSPP (i.e. June 2016), respectively.

Source: Authors' calculations.

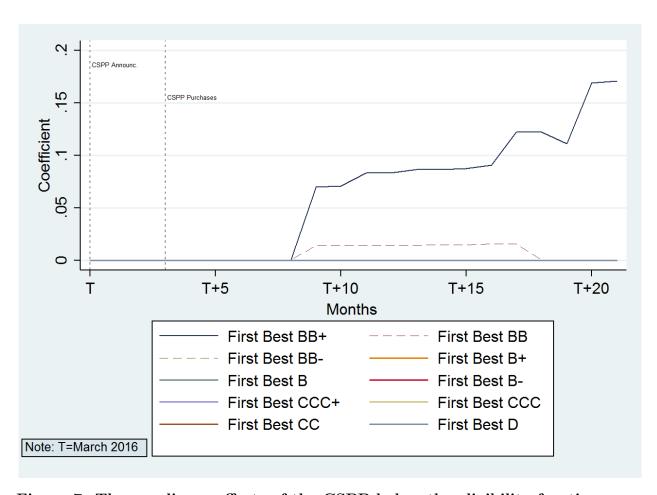


Figure 7. The non-linear effects of the CSPP below the eligibility frontier

The figure shows the estimates for the main coefficient of Eq.4 (Section IV.B) for the bonds in the frozen list located below the eligibility frontier in March 2016. The coefficient is statistically significant at the 5% level for bonds first-best rated BB+, while it is not statistically significant for the other first-best rating buckets.

Source: Authors' calculations.

Table 2. The non-linear effects of the CSPP around the eligibility frontier

Notes: The table presents bond-level regressions by first-best rating bucket using the bonds in the frozen list over the period January 2015 - December 2017 (91 bonds for BB; 91 bonds for BB+; 105 bonds for BBB-). The dependent variable indicates the rating changes observed by a bond at time t. Standard errors are clustered at a bond-level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

$\frac{\text{DEPE}]}{Rating}$	$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ Rating Changes_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
BB	$\mathbb{1}\{t > March2016\}$ R-squared Observations	0.015* (0.008) 0.001 2,726	0.006 (0.007) 0.004 2,726	0.006 (0.007) 0.004 2,726	0.007 (0.007) 0.004 2,726	0.003 (0.007) 0.010 2,726	0.003 (0.007) 0.013 2,726	0.001 (0.007) 0.014 2,726	0.005 (0.007) 0.023 2,726
BB+	$\mathbb{1}\{t > March2016\}$ R-squared Observations	0.015*** (0.005) 0.002 2,977	0.016*** (0.005) 0.002 2,977	0.016*** (0.006) 0.003 2,977	0.016*** (0.006) 0.003 2,977	0.016*** (0.006) 0.006 2,977	0.019*** (0.006) 0.025 2,977	0.017*** (0.006) 0.028 2,977	0.015*** (0.006) 0.050 2,977
BBB-	$1$ { $t > March2016$ } R-squared Observations	0.006 (0.005) 0.000 3,403	0.008 (0.005) 0.001 3,403	0.008 (0.005) 0.001 3,403	0.008 (0.006) 0.001 3,403	0.006 (0.006) 0.006 3,403	0.009 (0.006) 0.010 3,403	0.010* (0.006) 0.017 3,403	0.013** (0.006) 0.025 3,403
	$\widehat{E}[\text{GDP}]_{t,next\ year}$ $\widehat{E}[\text{Slope}]_{t,next\ year}$ $\Delta VIX_t$ Maturity FEs  Country FEs  Bond type FEs  Industry FEs		> 1 1 1 1 1 1	> 1 1 1 1 1	>>>	>>>	>>>>	>>>>	\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \

Table 3. Controlling for additional bond-level factors

- December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are Notes: The table presents bond-level regressions using the 1750 bonds in the frozen list over the period January 2015 clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

DEP. VAR. $QEeligible_{i,j,k,t}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
	-	<del>-</del>	-	-	- - - - -	-	-	-	-
$1 \{t > March 2016\}$	0.020***	0.014*	0.025***	0.025***	0.028	0.031***	0.040***	0.032***	0.032***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
$Liquidity_{i,t-1}$	-0.028***			-0.030***	-0.032***	-0.031***	-0.020***	-0.018***	-0.018***
	(0.005)			(0.000)	(0.007)	(0.006)	(0.005)	(0.004)	(0.004)
$Return_{i,t-1}$		0.000		-0.002**	-0.003***	-0.001	0.001	0.000	0.000
		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
$Size_i$			0.267***	0.208***	0.229***	0.216***	0.118***	0.099***	0.099***
			(0.033)	(0.034)	(0.033)	(0.029)	(0.023)	(0.024)	(0.023)
Constant	0.591***	0.534***	0.378***	0.455***	0.515***	0.720***	0.866***	0.700***	0.870***
	(0.023)	(0.023)	(0.026)	(0.031)	(0.044)	(0.075)	(0.054)	(0.072)	(0.077)
-	\	,	\	\	\		\	\	
Euro area controls	>	>	>	>	>	>	>	>	>
Other macro contr.	>	>	>	>	>	>	>	>	>
Maturity FEs	1		1	1	>	>	>	>	>
Country FEs	ı		1	ı	ı	>	>	>	>
Bond Type FEs	ı	1	1	ı	ı	ı	>	>	>
${\rm Industry\ FEs}$	1	1	ı	ı	I	I	1	>	>
Double-clustered s.e.	ı	ı	ı	ı	I	I	ı	I	>
R-squared	0.030	0.003	0.043	0.061	0.110	0.201	0.397	0.452	0.452
Observations	45,805	42,932	54,444	42,740	42,740	42,740	42,740	42,740	42,740

Table 4. Euro- versus non-euro denominated bonds

other currencies over the period January 2015 - December 2017 (4147 bonds). The dependent variable is a dummy indicating whether a bond has at least a BBB- from at least one of the four recognized CRAs. Standard errors are clustered at a Notes: The table presents bond-level regressions for firms that had bonds outstanding denominated both in euro and bond-level. \*\*\* p < 0.01, \*\* p< 0.05, \* p< 0.1.

DEPENDENT VARIABLE $Rating_{\max_{r} \{R_r\} \geqslant C_{ECB}}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
$\mathbb{1}\{t>March2016\}$	0.013**	-0.007	-0.004	-0.005	-0.018*	0.001	0.002	0.003
$Euro_{i,j}$	(0.006)	(0.011) $0.011$	(0.011) $0.011$	(0.011) $0.034*$	(0.010) $0.018$	$(0.009) \\ 0.026*$	(0.009) $0.007$	$(0.009) \\ 0.007$
$Euro_{i,j}*\mathbb{1}\{t>March2016\}$		(0.020) $0.039***$	(0.020) $0.040***$	(0.020) $0.032**$	(0.019) $0.042***$	(0.015) $0.039***$	(0.015) $0.038***$	(0.015) $0.038***$
$\hat{E}[ ext{GDP}]_{t  next  near}$		(0.013)	(0.013) $0.000$	(0.013) $-0.001$	(0.011) $-0.005$	(0.010) $0.002$	(0.010) $0.003$	(0.010) $0.003$
			(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)
$E[DIOPe]t,next\ year$			(0.004)	(0.006)	(0.020)	(0.005)	(0.005)	(0.005)
$\Delta VIX_t$			-0.028	-0.032	-0.024	-0.040**	-0.033*	-0.033
Constant	0.747***	0.742***	(0.022) $0.710***$	(0.023) $0.644***$	(0.020) $0.287***$	(0.019) $-0.214**$	(0.019) $-0.254***$	(0.096) $-0.219**$
	(0.010)	(0.015)	(0.021)	(0.029)	(0.109)	(0.103)	(0.090)	(0.086)
Maturity FEs				>	>	>	>	\right
Country FEs	ı	ı	ı	ı	>	>	>	>
Bond Type FEs	ı	1	1	1	1	>	>	>
Industry FEs	I	I	ı	I	I	ı	>	>
Double-clustered s.e.	I	I	I		I	I	Ī	>
R-squared	0.000	0.002	0.002	0.037	0.199	0.393	0.449	0.449
Observations	57,509	57,509	57,509	27,509	57,509	57,509	57,509	57,509

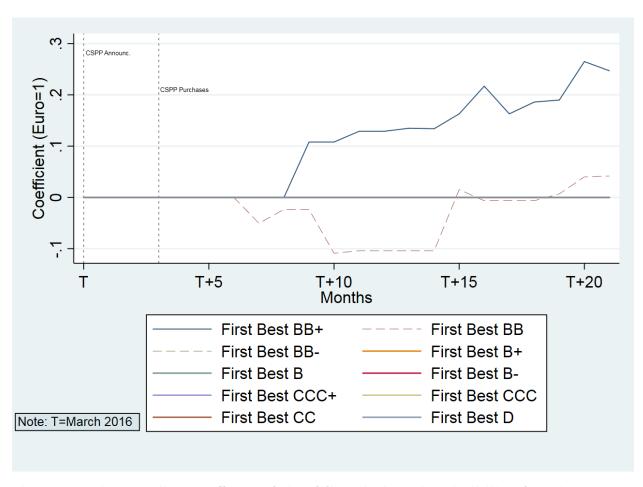


Figure 8. The non-linear effects of the CSPP below the eligibility frontier: Euroversus non-euro denominated bonds

The figure shows the estimates for the main coefficient of Eq.6 (i.e. the dummy of eurodenominated bonds) for the bonds located below the eligibility frontier in March 2016. The coefficient is statistically significant at the 5% level for bonds first-best rated BB+, while it is not statistically significant for the other first-best rating buckets.

Source: Authors' calculations.

Table 5: Non-recognized CRAs

by the Eurosystem. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1. Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 284 bonds in the frozen list also rated by non-recognized CRAs at least once over the sample period. The dependent variable is a dummy indicating the hypothetical eligibility for the corporate QE, assuming that non-recognized CRAs were the ones recognized

$\widehat{QEeligible}_{i,j,k,t}^{\mathrm{AR.}}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$\mathbb{1}\{t>March2016\}$ $\widehat{E}[\mathrm{GDP}]_{t,next\ year}$ $\widehat{E}[\mathrm{Slope}]_{t,next\ year}$ $\Delta VIX_t$ $Constant$	-0.213*** (0.025) 0.937*** (0.014)	-0.209*** (0.025) 0.027* (0.015) 0.892***	-0.208*** (0.026) 0.017 (0.012) 0.021** (0.010)	-0.212*** (0.026) 0.016 (0.012) 0.032*** (0.010) -0.643*** (0.080) 0.883*** (0.029)	-0.206*** (0.028) 0.017 (0.013) 0.035*** (0.012) -0.643*** (0.080) 0.833*** (0.071)	-0.209*** (0.028) 0.014 (0.012) 0.032*** (0.012) -0.635*** (0.079) 0.942*** (0.123)	-0.217*** (0.029) 0.010 (0.013) 0.028** (0.012) -0.631*** (0.078) 0.976*** (0.128)	-0.215*** (0.028) 0.012 (0.012) 0.032*** (0.011) -0.646*** (0.080) 1.021*** (0.141)	-0.215*** (0.030) 0.012 (0.019) 0.032** (0.016) -0.646 (0.714) 1.018*** (0.122)
Maturity FEs Country FEs	1 1	1 1	1 1	1 1	> -	>>	>>	>>	>>
Bond type FEs Industry FEs	1 1	1 1		1 1	1 1	1 1	> 1	>>	>>
Double-clust. s.e. R-squared Observations	- 0.076 9,126	- 0.076 9,126	- 0.076 9,126	- 0.077 9,126	- 0.078 9,126	0.110 9,126	0.117 9,126	- 0.200 9,126	0.200 9,126

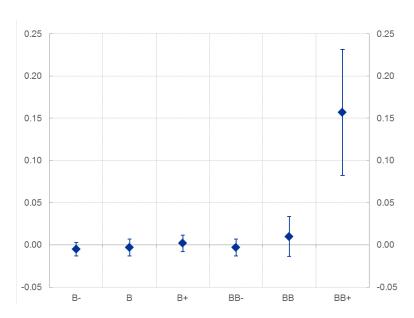


Figure 9. Coefficient of the interaction term (post-CSPP dummy and  $\omega$ ) by rating bucket (5% confidence interval) - Eligibility

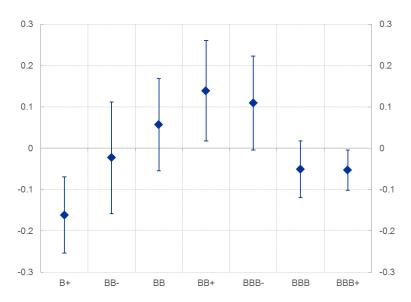


Figure 10. Coefficient of the interaction term (post-CSPP dummy and  $\omega$ ) by rating bucket (5% confidence interval) - Only one upgrade

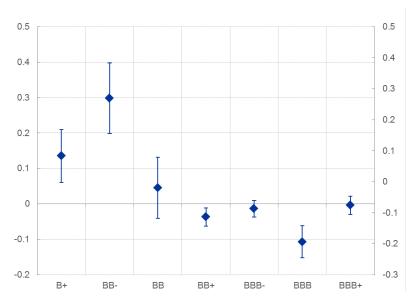


Figure 11. Coefficient of the interaction term (post-CSPP dummy and  $\omega$ ) by rating bucket (5% confidence interval) - More than one upgrade

Table 6. CRAs pivotal role: at least one change in the number of CRAs

Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 345 bonds variable is a dummy indicating the hypothetical eligibility for the corporate QE, assuming that non-recognized CRAs were the ones recognized by the Eurosystem. Standard errors are clustered at a bond-level, except in column (9) where standard in the frozen list that have observed at least one change in the number of CRAs over the sample period. The dependent errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

DEPENDENT VAR. QEeligible <sub>i,j,k,t</sub>	(1)	(2)	(3)	(4)	(5)	(9)	(7)	(8)	(6)
$\mathbb{1}\{t>March2016\}$ $\widehat{E}[\mathrm{GDP}]_{t,next\ year}$ $\widehat{E}[\mathrm{Slope}]_{t,next\ year}$ $\Delta VIX_t$ $Constant$	0.056*** (0.014) 0.391*** (0.027)	0.060*** (0.015) 0.027 (0.018)	0.062*** (0.015) -0.017 (0.015) 0.074*** (0.014)	0.062*** (0.015) -0.017 (0.015) 0.074*** (0.014) 0.022 (0.052) 0.349*** (0.043)	0.056*** (0.019) -0.032** (0.016) 0.071*** (0.016) 0.052 (0.055) 0.501***	0.076*** (0.019) -0.007 (0.015) 0.073*** (0.016) 0.029 (0.055) 0.028 (0.010)	0.107*** (0.017) 0.005 (0.013) 0.082*** (0.015) 0.027 (0.051) 0.282*** (0.105)	0.092*** (0.016) -0.001 (0.012) 0.073*** (0.014) 0.025 (0.048) 0.280*** (0.098)	0.092*** (0.017) -0.001 (0.031) 0.073*** (0.018) 0.025 (0.127) 0.525*** (0.090)
Maturity FEs	i	ı	1	1	>	> `	> `	\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \	>
Country FES Bond type FES	1 1	1 1	1 1	1 1	1 1	> '	<b>&gt;</b> >	<b>&gt;</b> >	<b>&gt;</b> >
Industry FEs	ı	ı	ı	ı	1	ı	ı	>	>
Double-clustered s.e.	1	ı			1	ı	ı		>
R-squared Observations	0.003	0.003	0.004	0.004	0.017 $10,730$	0.158	0.395 $10,730$	0.470 $10,730$	0.470

Table 7. CRAs pivotal role: only one single rating bucket change

a dummy indicating the hypothetical eligibility for the corporate QE, assuming that non-recognized CRAs were the ones Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 576 bonds in the frozen list that have observed only one single rating bucket change over the sample period. The dependent variable is recognized by the Eurosystem. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

DEPENDENT VAR. $QEeligible_{i,j,k,t}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$\mathbb{1}\{t>March2016\}$ $\widehat{E}[\mathrm{GDP}]_{t,next\ year}$ $\widehat{E}[\mathrm{Slope}]_{t,next\ year}$ $\Delta VIX_t$ $Constant$	0.031*** (0.011) 0.534*** (0.021)	0.036*** (0.012) 0.031** (0.013)	0.037*** (0.012) 0.017 (0.010) 0.029*** (0.009)	0.037*** (0.013) 0.017 (0.010) 0.029*** (0.009) -0.018 (0.037) 0.478***	0.027* $(0.016)$ $0.006$ $(0.011)$ $0.026**$ $(0.011)$ $-0.020$ $(0.038)$ $0.644***$ $(0.065)$	0.032** (0.015) 0.010 (0.010) 0.032*** (0.010) -0.064* (0.036) 0.864*** (0.113)	0.054*** (0.014) 0.019** (0.009) 0.036*** (0.009) -0.088** (0.034) 0.696*** (0.110)	0.040*** (0.014) 0.017* (0.009) 0.028*** (0.009) -0.086*** (0.031) 0.792*** (0.148)	0.040*** (0.013) 0.017 (0.015) 0.028* (0.016) -0.086 (0.132) 0.919*** (0.146)
Maturity FEs Country FEs Bond Type FEs Industry FEs Double-clustered s.e. R-squared Observations	- - - 0.001 18,431	- - - 0.001 18,431	- - - 0.001 18,431	- - - 0.001 18,431	0.060 18,431	- 0.200 18,431	, , ,	0.472 18,431	\ \ \ \ \ \ \ \ \ \ 18,431

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## Appendix for

# "Quantitative Easing and Credit Rating Agencies"

Nordine Abidi\* Matteo Falagiarda<sup>†</sup> Ixart Miquel-Flores<sup>‡§</sup>

This Appendix serves as a companion to the paper "Quantitative Easing and Credit Rating Agencies". It contains additional findings and robustness checks not included in the main text. We present the results in the order they appear in the main text.

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The views expressed are those of the authors and do not necessarily reflect those of the European Central Bank, the Eurosystem or the International Monetary Fund.

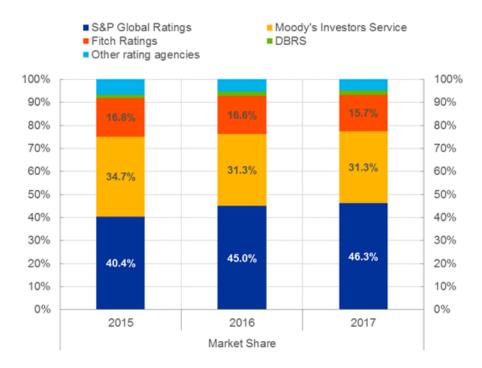


Figure 1A. CRAs market share in the European Union

This figure shows the evolution of the market share of CRAs in the European Union (2015-2017). In the European Union, the credit rating is a highly concentrated industry, with the "Big Three" credit rating agencies controlling approximately 93% of the ratings business. In 2017, Moody's and S&P together controlled 77.5% of the European market, Fitch 15,7%, and DBRS less than 2%.

Source: ESMA, authors' calculations.

### Table 1A. Harmonized rating scale

**Notes:** This table maps the ratings of S&P, Moody's, Fitch and DBRS into 22 numerical values, with 10 corresponding to the highest rating (AAA/Prime High Grade) and -11 to the lowest (D/in default). The horizontal dashed-line separate assets from "High Yield" to "Investment Grade".

DBRS	Moody's	S&P	Fitch	Rating description	Ranking
AAAu	Aaa	AAA	AAA	Prime	10
AAH	Aa1	AA+	AA+	High grade	9
AA	Aa2	AA	AA		8
AAL	Aa3	AA-	AA-		7
AH	A1	A+	A+	Upper medium grade	6
A	A2	A	A		5
AL	A3	A-	A-		4
BBBH	Baa1	BBB+	BBB+	Lower medium grade	3
BBB	Baa2	BBB	BBB	_	2
BBBL	Baa3	BBB-	BBB-		1
BBH	Ba1	BB+	B	Non-investment grade	
BB	Ba2	BB	BB	$_{ m speculative}$	-1
BBL	Ba3	BB-	BB-		-2
BH	B1	B+	B+	Highly speculative	-3
В	B2	В	В		-4
$\operatorname{BL}$	В3	B-	B-		-5
CCCH	Caa1	CCC+	CCC+	Substantial risks	-6
CCC	Caa2	CCC	CCC		-7
CCCL	Caa3	CCC-	CCC-		-8
CC	Ca	CC	CC	Extremely speculative	-9
C		$\mathbf{C}$	$\mathbf{C}$	Default imminent	-10
D	С	D	D	In default	-11

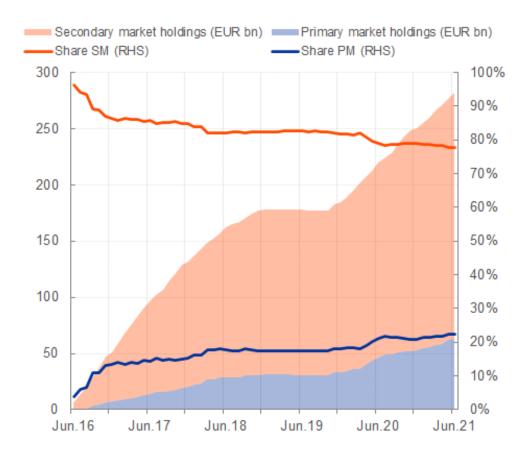


Figure 2A. Overview of the CSPP purchases

The figure shows the Eurosystem corporate bond purchases under the CSPP as well as the breakdown of primary and secondary market purchases (monthly data). By the June 2021, the ECB's cumulative CSPP holdings amounted to EUR 282 billion where the majority of bonds, around 78%, were purchased in the secondary market. The Eurosystem started to buy corporate sector bonds under the CSPP on 8 June 2016.

Source: https://www.ecb.europa.eu/mopo/implement/omt/html/index.en.html

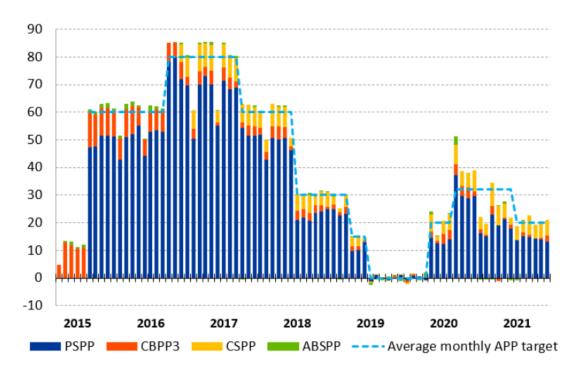


Figure 3A. Net purchases of the ECB's QE programmes

The figure presents the Eurosystem's monthly net purchases by asset purchase programme in EUR billion. The expanded asset purchase programme (APP) includes all purchase programmes under which private sector and public sector securities are purchased. It consists of the: (I) third covered bond purchase programme (CBPP3), (II) asset-backed securities purchase programme (ABSPP), (III) public sector purchase programme (PSPP) and (IV) corporate sector purchase programme (CSPP).

Source: https://www.ecb.europa.eu/mopo/implement/omt/html/index.en.html

Table 2A. Bonds by remaining maturity in months - March 2016

	Mean	Median	Std. dev.	Min	Max	Obs.
First-best rating < BBB-	57.433	52	33.690	6	342	631
First-best rating $\geq$ BBB-	69.461	59	53.414	6	360	1119
All bonds (frozen list)	65.124	56	47.602	6	360	1750

Table 3A. Bonds by country of domicile

	<i>U</i>	
	Observations	Percent
Austria	33	1.89
Belgium	68	3.89
Cyprus	1	0.06
Estonia	4	0.23
Finland	28	1.60
France	500	28.57
Germany	210	12.00
Ireland	29	1.66
Italy	153	8.74
Latvia	1	0.06
Luxemburg	204	11.66
The Netherlands	406	23.20
Portugal	13	0.74
Slovakia	4	0.23
Slovenia	2	0.11
Spain	94	5.37
All bonds (frozen list)	1750	100

Table 4A. Bonds by industry

Table III. Bollas sy II.	i a a s o i j	
	Observations	Percent
Basic materials	126	7.20
Communications	213	12.17
Consumer, cyclical	287	16.40
Consumer, non-cyclical	283	16.17
Diversified	17	0.97
Energy	79	4.51
Financial	108	6.17
Industrial	309	17.66
Technology	23	1.31
Utilities	305	17.43
All bonds (frozen list)	1750	100

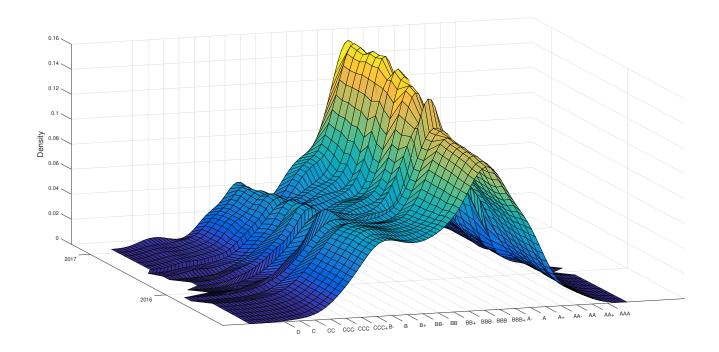


Figure 4A. Dynamic 3D distribution of bonds by first-best rating

The figure depicts the set of kernel densities of the 1750 bonds in the frozen list by first-best rating over the period March 2015-March 2017 (1-year window around the announcement).

Table 5A. Excluding investment grade bonds not in the ESCF and vice-versa

rating rule, (ii) CSPP eligible from the viewpoint of the firs-best rating rule but not from the ECSF. The dependent variable is Notes: The table presents bond-level regressions using the bonds in the frozen list over the period January 2015 - December 2017, a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level, except in column (9) where excluding 196 bonds that are either (at some point): (i) CSPP eligible from the perspective of the ESCF but not from the first-best standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

DEPENDENT VARIABLE $QEeligible_{i,j,k,t}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$\mathbb{1}\{t>March2016\}$	0.039***	0.045***	0.047***	0.047***	0.043***	0.038***	0.050***	0.041***	0.041***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.000)	(0.000)
$\widehat{E}[ ext{GDP}]_{t,next\ year}$		0.041***	0.021***	0.021***	0.016**	0.017***	0.015***	0.015***	0.015**
		(0.008)	(0.000)	(900.0)	(0.007)	(0.006)	(0.004)	(0.004)	(0.000)
$\widehat{E}[\mathrm{Slope}]_{t,next\ year}$			0.040***	0.040***	0.037***	0.034***	0.031***	0.026***	0.026***
			(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)
$\Delta VIX_t$				0.012	0.016	0.004	0.003	0.002	0.002
				(0.021)	(0.022)	(0.020)	(0.015)	(0.014)	(0.072)
Constant	0.617***	0.549***	0.544***	0.544***	0.702***	0.879***	0.760***	0.687***	0.775***
	(0.013)	(0.019)	(0.020)	(0.020)	(0.035)	(0.068)	(0.056)	(0.065)	(0.063)
Maturity FEs			ı	ı	>	>	>	>	>
Country FEs	ı	ı	ı	ı	1	>	>	>	>
Bond type FEs	ı	ı	1	ı	1	ı	>	>	>
Industry FEs	ı	ı	1	ı	ı	ı	ı	>	>
Double-clustered s.e.	Ī	I	I	I	I	I	I	Ī	<i>&gt;</i>
$ m R ext{-}squared$	0.002	0.002	0.002	0.002	0.061	0.189	0.532	0.583	0.583
Observations	48,573	48,573	48,573	48,573	48,573	48,573	48,573	48,573	48,573

Table 6A. The non-linear effects of the CSPP far below the eligibility frontier

2015 - December 2017 (187 bonds for BB- and B+; 180 bonds for B and B-; 66 bonds for CCC+ and CCC; 16 bonds for CCC-, CC, C Notes: The table presents bond-level regressions by first-best rating bucket using the bonds in the frozen list over the period January and D). The dependent variable indicates the rating changes observed by a bond at time t. Standard errors are clustered at a bond-level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Rating	$RatingChanges_{i,j,k,t}$		(4)	(c)	(4)	(c)	(9)	(4)	<u>®</u>
BB-	$\mathbb{1}\{t>March2016\}$	0.025***	0.011	0.009	0.004	0.009	0.005	0.005	0.013
B+		(0.008)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.011)	(0.010)
	${ m R ext{-}squared}$	0.001	0.003	0.004	0.005	0.007	0.012	0.027	0.033
	Observations	5,364	5,364	5,364	5,364	5,364	5,364	5,364	5,364
В	$1 \{t > March 2016\}$	0.002	0.003	0.004	0.003	0.004	0.003	0.003	0.006
B-		(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(900.0)
	R-squared	0.000	0.000	0.000	0.001	0.002	0.006	0.006	0.011
	Observations	5,120	5,120	5,120	5,120	5,120	5,120	5,120	5,120
+DDD	$\mathbb{1}\{t>March2016\}$	0.014	0.013	0.010	0.010	0.014	0.009	0.011	0.014
CCC		(0.010)	(0.012)	(0.013)	(0.012)	(0.016)	(0.018)	(0.018)	(0.019)
	R-squared	0.000	0.001	0.001	0.001	0.004	0.027	0.031	0.046
	Observations	1,898	1,898	1,898	1,898	1,898	1,898	1,898	1,898
-222	$1 \{t > March 2016\}$	0.207***	0.201***	0.172***	0.196***	0.100	0.158***	0.160***	0.160***
CC		(0.023)	(0.041)	(0.033)	(0.039)	(0.069)	(0.052)	(0.053)	(0.053)
C	R-squared	0.026	0.026	0.041	0.053	0.070	0.103	0.103	0.103
О	Observations	477	477	477	477	477	477	477	477
	$\widehat{E}[ ext{GDP}]_{t,next\ year}$		>	>	>	>	>	>	>
	$\hat{E}[\mathrm{Slope}]_{t,next\ year}$	ı	ı	>	>	>	>	>	>
	$\Delta VIX_t$	ı	ı	1	>	>	>	>	>
	Maturity FEs	ı	1	1	1	>	>	>	>
	Country FEs	I	ı	ı	ı	ı	>	>	>
	Bond type FEs	ı	ı	1	ı	I	1	>	>
									`

Table 7A. The non-linear effects of the CSPP far above the eligibility frontier

Notes: The table presents bond-level regressions by first-best rating bucket using the bonds in the frozen list over the period January 2015 - December 2017 (456 bonds for BBB and BBB+; 484 bonds for A-, A and A+; 74 bonds for AA-, AA, AA+ and AAA). The dependent variable indicates the rating changes observed by a bond at time t. Standard errors are clustered at a bond-level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

DEPE. Rating	$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ RatingChanges_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
BBB BBB+	$\mathbb{1}\{t > March2016\}$ R-squared Observations	-0.008*** (0.002) 0.001 14,712	-0.006*** (0.002) 0.001 14,712	-0.006*** (0.002) 0.001 14,712	-0.006*** (0.002) 0.001 14,712	-0.007*** (0.002) 0.002 14,712	-0.007*** (0.002) 0.007 14,712	-0.007*** (0.002) 0.007 14,712	-0.007*** (0.002) 0.012 14,712
A + +	$\mathbb{1}\{t > March2016\}$ R-squared Observations	-0.011*** (0.002) 0.001 15,110	-0.012*** (0.002) 0.001 15,110	-0.011*** (0.002) 0.002 15,110	-0.009*** (0.002) 0.002 15,110	-0.011*** (0.002) 0.004 15,110	-0.010*** (0.002) 0.011 15,110	-0.010*** (0.002) 0.011 15,110	-0.010*** (0.002) 0.017 15,110
AA- AA AA+ AAA	$\mathbb{1}\{t > March2016\}$ R-squared Observations	-0.035*** (0.005) 0.011 2,378	-0.036*** (0.005) 0.011 2,378	-0.034*** (0.005) 0.013 2,378	-0.033*** (0.005) 0.013 2,378	-0.035*** (0.006) 0.015 2,378	-0.034*** (0.006) 0.019 2,378	-0.036*** (0.006) 0.022 2,378	-0.034*** (0.006) 0.033 2,378
	$\hat{E}[\text{GDP}]_{t,next\ year}$ $\hat{E}[\text{Slope}]_{t,next\ year}$ $\Delta VIX_t$ Maturity FEs  Country FEs  Bond type FEs  Industry FEs		> 1 1 1 1 1 1	>	>>>	>>>	>>>>		

Table 8A. Controlling for additional macro factors

Notes: The table presents bond-level regressions using the 1750 bonds in the frozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

$\frac{\text{DEP. VARIABLE}}{QEeligible_{i,j,k,t}}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$1 \} \{t > March2016\}$	0.031***	0.030***	0.036***	0.025***	0.023***	0.026***	0.042***	0.033***	0.033***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.000)
$Citigroup \ ESI_t$	0.371***			0.334***	0.318***	0.324***	0.216***	0.171***	0.171***
	(0.051)			(0.052)	(0.053)	(0.050)	(0.041)	(0.041)	(0.048)
$\Delta Unemployment_{j,t}$		-0.179***		-0.178***	-0.167***	-0.007	-0.011	-0.008	-0.008
		(0.040)		(0.040)	(0.039)	(0.008)	(0.007)	(0.007)	(0.008)
$\Delta StockMarket_{j,t}$			***986.0	1.328***	1.289***	0.610***	0.090	0.112	0.112
			(0.341)	(0.373)	(0.367)	(0.173)	(0.160)	(0.153)	(0.798)
Constant	0.533***	0.525***	0.521***	0.517***	0.637***	0.833***	0.904***	0.833***	0.851***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)	(0.067)	(0.051)	(0.065)	(0.069)
Euro area controls	>	>	>	>	>	>	>	>	>
Maturity FEs	1	1	1	1	>	>	>	>	>
Country FEs	1	1	1	1	ı	>	>	>	>
Bond Type FEs	ı	ı	ı	ı	ı	I	>	>	>
${\rm Industry~FEs}$	ı	ı	ı	ı	ı	ı	ı	>	>
Double-clustered s.e.	I	I	I	I	ı	ı	I	I	>
${ m R-squared}$	0.002	0.003	0.001	0.003	0.054	0.154	0.424	0.479	0.479
Observations	54,507	54,507	54,507	54,507	54,507	54,507	54,507	54,507	54,507

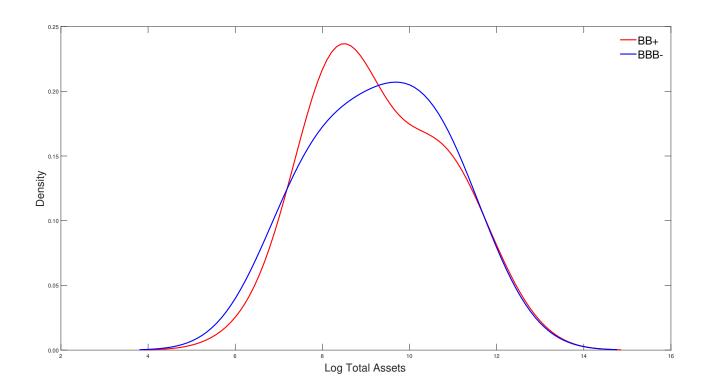


Figure 5A. Distribution of total assets (kernel density)

This figure depicts the kernel density of the logarithm of total assets for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2016 are reported. The null hypothesis for equality of distribution functions (Kolmogorov-Smirnov test) cannot be rejected at the 1% level.

Source: Orbis Europe, Bloomberg, annual reports and financial statements, authors' calculations.



Figure 6A. Distribution of total assets

The figure depicts the median and the 25-75 percentiles of total assets for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2015 and 2016 are reported.



Figure 7A. Distribution of leverage ratio

The figure depicts the median and the 25-75 percentiles of leverage (defined as the ratio of total liabilities to total assets) for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2015 and 2016 are reported.

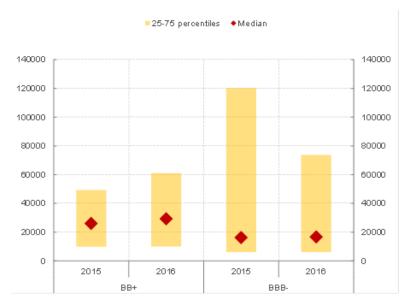


Figure 8A. Distribution of number of employees

The figure depicts the median and the 25-75 percentiles of the number of employees for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BB-in March 2016. Data for 2015 and 2016 are reported.



Figure 9A. Distribution of operating revenues

The figure depicts the median and the 25-75 percentiles of operating revenues for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BB-in March 2016. Data for 2015 and 2016 are reported.

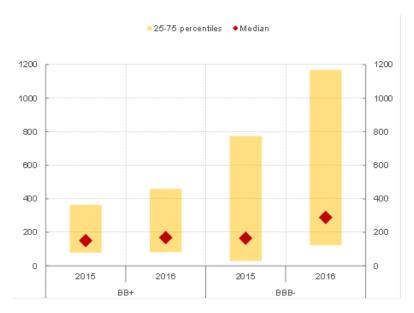


Figure 10A. Distribution of net income

The figure depicts the median and the 25-75 percentiles of the net income for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2015 and 2016 are reported.

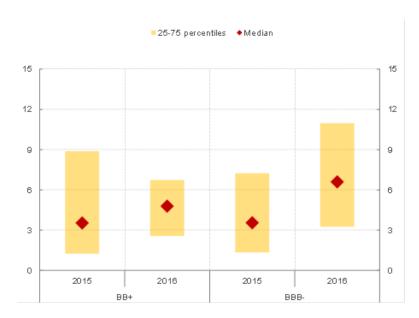


Figure 11A. Distribution of profit margins

The figure depicts the median and the 25-75 percentiles of profit margins for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2015 and 2016 are reported.



Figure 12A. Distribution of return on equity (ROE)

The figure depicts the median and the 25-75 percentiles of the return on equity (ROE) for two groups of firms - those whose bonds are rated BB+ and those whose bonds are rated BBB- in March 2016. Data for 2015 and 2016 are reported.

Table 9A. Non-recognized CRAs (restricted)

also rated by non-recognized CRAs as of March 2016. The dependent variable is a dummy indicating the hypothetical eligibility for the Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 55 bonds in the frozen list level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p <0.05, \* p <0.1. corporate QE, assuming that non-recognized CRAs were the ones recognized by the Eurosystem. Standard errors are clustered at a bond-

$QEeligible_{i,j,k,t}$								6	6
$\mathbb{1}\{t>March2016\}$	-0.092*	-0.094**	-0.094*	-0.094*	-0.096**	-0.094*	-0.074	-0.075	-0.075*
$\widehat{E}[ ext{GDP}]_{t,next\ year}$	(0.041)	(0.041) $-0.018$	(0.047) $-0.016$	(0.048) $-0.016$	(0.048) $-0.014$	(0.048) $-0.007$	(0.040) $-0.003$	(0.040) $-0.008$	(0.043) $-0.008$
		(0.021)	(0.021)	(0.021)	(0.023)	(0.019)	(0.017)	(0.017)	(0.026)
$\widehat{E}[\mathrm{Slope}]_{t,next\ year}$			-0.005	-0.005	-0.004	-0.007	0.007	0.005	0.005
			(0.014)	(0.014)	(0.017)	(0.016)	(0.016)	(0.015)	(0.025)
$\Delta VIX_t$				-0.005	-0.011	-0.024	-0.043	-0.045	-0.045
				(0.070)	(0.071)	(0.062)	(0.064)	(0.064)	(0.316)
Constant	***096.0	0.991***	0.992***	0.992***	0.646**	0.159	0.484***	0.384***	0.384***
	(0.024)	(0.033)	(0.034)	(0.035)	(0.305)	(0.315)	(0.121)	(0.055)	(0.113)
Maturity FEs	ı	1	1	ı	>	>	>	>	>
Country FEs	ı	ı	ı	ı	ı	>	>	>	>
Bond type FEs	ı	ı	ı	ı	ı	ı	>	>	>
Industry FEs	ı	1		ı	,	1	ı	>	>
Double-clustered s.e.	ı	ı	ı	ı	ı	ı	ı	ı	>
R-squared	0.026	0.026	0.026	0.026	0.110	0.216	0.444	0.490	0.490
Observations	1 716	1 716	1 716	1 716	1 716	1 716	1 716	1 716	1 716

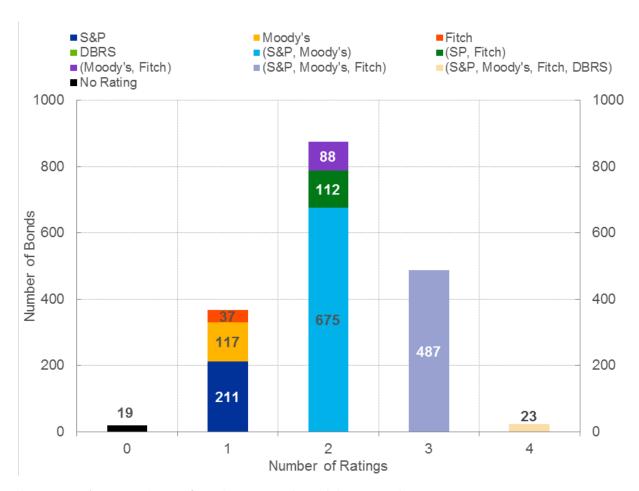


Figure 13A. Number of ratings per bond in March 2016

The figure plots the number of ratings by the four recognized CRAs at a bond level in March 2016  $(\sum_r \mathbb{1}_{[R_r \neq \varnothing]})$ . 19 bonds are rated during the sample period, but not in March 2016.

Source: Bloomberg, authors' calculations.

Table 10A. CRAs competition

Notes: The table presents bond-level regressions using the bonds in the 1750 frozen list over the period January 2015 - December 2017 The demondant variable is a dummy indicating the alicibility for the compared OE. Standard errors are clustered at a hond-level

$\begin{array}{c} \overline{\text{DEPENDENT VARIABLE}} \\ QEeligible_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)
$1 \{t > March2016\}$	0.037***	0.034***	0.035***	0.035***	0.049***	0.038***	0.038***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
$Competition_{i.March2016}$	0.169***	0.167***	0.171***	0.198***	0.056***	0.037*	0.037*
	(0.025)	(0.025)	(0.024)	(0.023)	(0.021)	(0.021)	(0.021)
Competition <sub>i,March2016</sub> * $\mathbb{1}{t > March2016}$	-0.023*	-0.022*	-0.028**	-0.020*	-0.020*	-0.016	-0.016**
	(0.012)	(0.012)	(0.013)	(0.012)	(0.010)	(0.010)	(0.008)
Constant	0.542***	0.468***	0.587***	0.819***	0.734***	0.709***	0.851***
	(0.014)	(0.021)	(0.035)	(0.072)	(0.057)	(0.068)	(0.070)

	1	>	>	>	>	>	>
Additional macro controls	ı	>	>	>	>	>	>
Maturity FEs	ı	ı	>	>	>	>	>
Country FEs	ı	ı	ı	>	>	>	>
Bond Type FEs	I	ı	ı	ı	>	>	>
Industry FEs	I	ı	1	ı	ı	>	>
Double-clustered s.e.	ı	ı	ı		ı	1	>
R-squared	0.023	0.025	0.076	0.183	0.425	0.479	0.479
Observations	54,507	54,507	54,507	54,507	54,507	54,507	54,507

## Table 11A. CRAs pivotal role: identifying pivotal CRAs

Notes: The table presents bond-level regressions by number of ratings as of March 2016 using the bonds in the frozen list over the (6): 4 ratings). The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a period January 2015 - December 2017 (columns (1) and (2): 1 rating; columns (3) and (4): 2 ratings; column (5): 3 ratings; column bond-level. \*\*\* p < 0.01, \*\* p< 0.05, \* p< 0.1.

$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ QEeligible_{i,j,k,\tau} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)
$1\hspace{-0.1cm}1\{t>March2016\}$	0.032*	0.009	0.040***	0.037***	0.022**	0.055
(Moodys == 1)	(0.017) $0.012$	$(0.021) \\ 0.003 \\ 0.003$	(0.009)	(0.007)	(0.010)	(0.056)
(Fitch == 1)	(0.047) $-0.042$	(0.049) $-0.041$				
$1 \{t > March2016\}^* (Moodys == 1)$	(0.00)	(0.072) $0.023$				
$1 \{t > March2016\}^* (Fitch == 1)$		0.029 $0.026$				
(Moodys == 1 & Fitch == 1)		(0.041)	0.003	0.005		
(S&P == 1 & Fitch == 1)			(0.037)	(0.045) $0.052$		
$1 \{t > March2016\}^* (S\&P == 1 \& Fitch == 1)$			(0.044)	(0.045) $-0.115***$		
$\mathbb{1}\{t > March2016\}^*(Moodys == 1 \& Fitch == 1)$				(0.031) $0.042$		
				(0.032)		
Firm control						

Euro area controls	>	>	>	>	>	\_\>
Additional macro controls	>	>	>	>	>	>
Maturity FEs	>	>	>	>	>	>
Country FEs	>	>	>	>	>	>
Bond Type FEs	>	>	>	>	>	>
Industry FEs	>	>	>	>	>	>
R-squared	0.381	0.372	0.567	0.542	0.439	0.389
Observations	11,363	11,363	26,800	26,800	15,641	703
# Bonds	365	365	875	875	487	23

Table 12A. CRAs pivotal role: no change in the number of CRAs

Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 1405 bonds in the frozen list that have observed no change in the number of CRAs over the sample period. The dependent variable is a dummy indicating the hypothetical eligibility for the corporate QE, assuming that non-recognized CRAs were the ones recognized by the Eurosystem. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

DEPENDENT VARIABLE $QEeligible_{i,j,k,t}$	(1)	(2)	(3)	(4)	(2)	(9)	(2)	(8)	(6)
$1\hspace{-0.1cm}1\{t>March2016\}$	0.031***	0.037***	0.039***	0.039***	0.039***	0.031***	0.038***	0.029***	0.029***
•	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.00)	(0.008)	(0.007)	(0.008)
$\widehat{E}[ ext{GDP}]_{t,next\ year}$		0.044***	0.027***	0.027***	0.028***	0.024***	0.019***	0.016***	0.016**
,		(0.008)	(0.000)	(0.006)	(0.007)	(0.000)	(0.005)	(0.005)	(0.007)
$\widehat{E}[\mathrm{Slope}]_{t,next\ year}$			0.035***	0.036***	0.037***		0.031***	0.026***	0.026***
			(0.000)	(0.006)	(0.000)	(0.006)	(0.005)	(0.005)	(0.008)
$\Delta VIX_t$				-0.054**	-0.068***		-0.072***	-0.064***	-0.064
				(0.025)	(0.026)		(0.021)	(0.021)	(0.084)
Constant	0.639***	0.564***	0.560***	0.559***	0.663***	0.863***	0.763***	0.715***	0.852***
	(0.013)	(0.020)	(0.021)	(0.021)	(0.036)	(0.069)	(0.059)	(0.075)	(0.075)
Maturity FEs	1	1	1	1	>	>	>	>	>
Country FEs	ı	ı	ı	I	1	>	>	>	>
Bond Type FEs	I	ı	ı	ı	ı	1	>	>	>
Industry FEs	1	1	ı	1	1	ı	ı	>	>
Double-clustered s.e.	ı	ı	ı	I	ı	I	I	ı	<i>&gt;</i>
$ m R ext{-}squared$	0.001	0.001	0.001	0.001	0.076	0.195	0.445	0.495	0.495
Observations	43,777	43,777	43,777	43,777	43,777	43,777	43,777	43,777	43,777

Table 13A. CRAs pivotal role: more than one single rating bucket change

Notes: The table presents bond-level regressions over the period January 2015 - December 2017 using the 220 bonds in the frozen list that have observed more than one rating bucket change over the sample period. The dependent variable is a dummy indicating the hypothetical eligibility for the corporate QE, assuming that non-recognized CRAs were the ones recognized by the Eurosystem. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ QEeligible_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$1\hspace{-0.1cm}1\{t>March2016\}$	0.016	0.016	0.017	0.018	0.003	0.006	0.013	0.009	0.009
•	(0.012)	(0.014)	(0.015)	(0.015)	(0.021)	(0.021)	(0.017)	(0.012)	(0.011)
$\hat{E}[ ext{GDP}]_{t,next\ year}$		-0.000	-0.011	-0.011	-0.023	-0.014	-0.006	-0.007	-0.007
		(0.020)	(0.016)	(0.016)	(0.017)	(0.016)	(0.010)	(0.007)	(0.013)
$\widehat{E}[\mathrm{Slope}]_{t,next\ year}$			0.022	0.020	0.004	0.002	-0.005	-0.003	-0.003
			(0.016)	(0.016)	(0.019)	(0.018)	(0.017)	(0.012)	(0.016)
$\Delta VIX_t$				0.113**	0.159***	0.130**	0.075*	0.028	0.028
				(0.054)	(0.061)	(0.052)	(0.041)	(0.035)	(0.166)
Constant	0.359***	0.360***	0.358***	0.359***	0.527***	0.124	0.632***	0.552***	0.536***
	(0.033)	(0.048)	(0.049)	(0.049)	(0.104)	(0.132)	(0.106)	(0.074)	(0.069)
Maturity FEs	1	1	1	1	>	>	>	>	>
Country FEs	1	1	1	I	1	>	>	>	>
Bond Type FEs	ı	ı	ı	ı	ı	ı	>	>	>
Industry FEs	1	ı	ı	I	1	1	1	>	>
Double-clustered s.e.	ı	I	I	I	ı	ı	I	I	>
R-squared	0.000	0.000	0.000	0.000	0.050	0.113	0.514	0.790	0.790
Observations	6,836	6,836	6,836	6,836	6,836	6,836	6,836	6,836	6,836

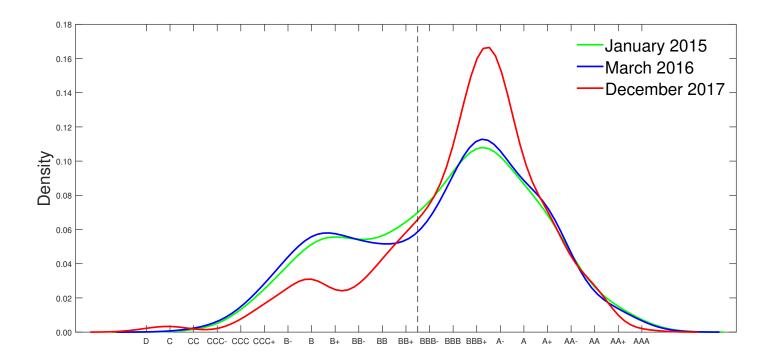


Figure 14A. Dynamic distribution of bonds by first-best rating - Less vulnerable countries

The figure depicts the kernel density of the bonds in the frozen list (less vulnerable countries) by first-best rating for three different months – January 2015 in green, March 2016 in blue and December 2017 in red.

Source: Bloomberg, authors' calculations.

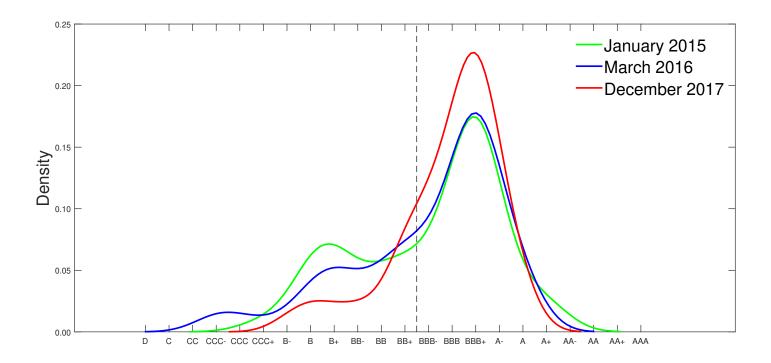


Figure 15A. Dynamic distribution of bonds by first-best rating - Formerly vulnerable countries

The figure depicts the kernel density of the bonds in the frozen list (formerly vulnerable countries) by first-best rating for three different months – January 2015 in green, March 2016 in blue and December 2017 in red.

Source: Bloomberg, authors' calculations.

Table 14A. Vulnerable versus less vulnerable countries

Notes: The table presents bond-level regressions using the 1750 bonds in the frozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

	(1)	(2)			6	6	
$1\!\!1 \{t > March2016\}$	0.024***	0.017**	0.017**	0.020**	0.040***	0.029***	0.029***
$Vulnerable_j$	0.000 $0.016$ $0.016$	(0.001) -0.004 (0.039)	0.003 $0.007$ $0.031$	(0.003)	(00.0)	(100.0)	(0.001)
$Vulnerable_j*\mathbb{1}\{t>March2016\}$	0.035*	0.049***	0.040**	0.032*	0.013	0.022	0.022*
Constant	$(0.018) \\ 0.591***$	$(0.019) \\ 0.518***$	$(0.019) \\ 0.648***$	$(0.018) \\ 0.843***$	$(0.014) \\ 0.740***$	$(0.014) \\ 0.713***$	$(0.012) \\ 0.853***$
	(0.013)	(0.020)	(0.035)	(0.072)	(0.057)	(0.068)	(0.069)
Euro area controls	ı	>	>	>	>	>	>
Additional macro controls	ı	>	>	>	>	>	>
Maturity FEs	1	1	>	>	>	>	>
Country FEs	ı	ı	ı	>	>	>	>
Bond type FEs	1	ı	1	ı	>	>	>
Industry FEs	ı	ı	I	ı	ı	>	>
Double-clustered s.e.	ı	ı	ı	ı	ı	ı	>
R-squared	0.002	0.004	0.055	0.154	0.424	0.479	0.479
Observations	54,507	54,507	54,507	54,507	54,507	54,507	54,507

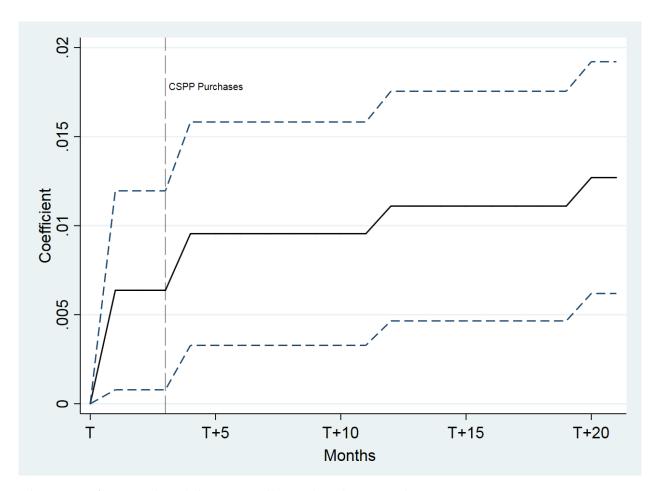


Figure 16A. Bonds with no credit rating in March 2016

The figure shows the main coefficient of Eq.4 considering the 19 bonds with no publicly available ratings in March 2016, but with at least one rating during the sample period (and therefore excluded from the frozen list).

Source: Authors' calculations.

Table 15A. Probit model

Notes: The table presents bond-level Probit regressions using the 1750 bonds in the frozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level,

$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ QEeligible_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(2)	(9)	(2)	(8)	(6)
$1\!\!1\{t>March2016\}$	0.029***	0.035***	0.036***	0.036***	0.032***	0.030***	0.046***	0.034***	0.034***
$\widehat{\widehat{E}}[ ext{GDP}]_{t,next\ year}$		>	\right\>	>	>	>	>	>	>
$\widehat{E}[ ext{Slope}]_{t,next\ year}$	ı	ı	>	>	>	>	>	>	>
$\Delta VIX_t$	ı	ı	ı	>	>	>	>	>	>
Maturity FEs	1	1	1	1	>	>	>	>	>
Country FEs	ı	ı	1	1	1	>	>	>	>
Bond type FEs	ı	ı	1	1	1	ı	>	>	>
Industry FEs	ı	ı	ı	I	I	ı	ı	>	>
Double-clustered s.e.	1	1	1	1	1	1	1	1	>
Pseudo R-squared	0.001	0.001	0.001	0.001	0.041	0.121	0.357	0.435	0.435
Observations	54 507	54.507	77 707	77 707	77 207	54.507	77 ZO7	77 707	77 707

Table 16A. Weighting by bond size

Notes: The table presents bond-level regressions using the 1750 bonds in the frozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE weighted by the log of the amount issued. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

DEFENDENT VARIABLE $QEeligible_{i,j,k,t}$	(1)	(2)	(3)	(4)	(2)	(9)	(7)	(8)	(6)
$\mathbb{1}\{t>March2016\}$	0.570***	0.674***	***202.0	0.703***	0.621***	0.572***	0.871***	0.680***	***089.0
$\widehat{E}[ ext{GDP}]_{t,next\ year}$	(0.130)	$(0.139) \ 0.708***$	$(0.142) \\ 0.323***$	(0.143) $0.322***$	$(0.167) \\ 0.232*$	$(0.159) \\ 0.271**$	$(0.139) \ 0.285***$	(0.136) $0.238**$	(0.140) $0.238*$
$\widehat{E}[ ext{Slope}]_{t,next\ year}$		(0.147)	(0.120) $0.773***$	(0.120) $0.785***$	(0.127) 0.745***	(0.120) $0.725***$	(0.096) $0.734***$	(0.092) $0.628***$	(0.143) 0.628***
$\Delta V I X_t$			(0.107)	(0.109) $-0.681$	(0.119) $-0.662$	(0.114) $-0.874*$	(0.101) $-0.912**$	(0.097) $-0.904**$	(0.151) $-0.904$
Constant	11.828**	10.634**	10.554**	(0.465)	(0.478)	(0.449)	(0.405)	(0.391)	(1.694)
	(0.238)	(0.366)	(0.373)	(0.374)	(0.478)	(1.313)	(1.003)	(1.273)	(1.341)
Maturity FEs	1	1	1	1	>	>	>	>	>
Country FEs	ı	ı	ı	ı	ı	>	>	>	>
Bond type FEs	ı	ı	ı	ı	ı	ı	>	>	>
Industry FEs	I	1	1	I	I	ı	1	>	>
Double-clustered s.e.	ı	ı	ı	ı	ı	1	ı	ı	>
R-squared	0.001	0.001	0.001	0.001	0.046	0.147	0.415	0.471	0.471
Observations	54.507	54.507	54.507	54 507	54 507	54 507	54 507	54 507	54.507

Table 17A. Unfrozen list

Notes: The table presents bond-level regressions using the 2909 bonds in the unfrozen list over the period January 2015 - December 2017. The dependent variable is a dummy indicating the eligibility for the corporate QE. Standard errors are clustered at a bond-level, except in column (9) where standard errors are two-way clustered at the bond and month level. \*\*\* p <0.01, \*\* p<0.05, \* p<0.1.

$\begin{array}{c} \text{DEPENDENT VARIABLE} \\ QEeligible_{i,j,k,t} \end{array}$	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
$1 \{t > March2016\}$ $\hat{E}[\text{GDP}]_{t,next\ year}$ $\hat{E}[\text{Slope}]_{t,next\ year}$ $\Delta VIX_t$ $Constant$	0.031*** $(0.008)$ $0.592***$ $(0.011)$	0.037*** (0.008) 0.043*** (0.008) 0.519***	0.038*** (0.008) 0.022*** (0.007) 0.040*** (0.006)	0.038*** (0.008) 0.022*** (0.006) 0.041*** (0.006) -0.040 (0.027) 0.516*** (0.021)	0.029*** (0.008) 0.014** (0.006) 0.041*** (0.006) -0.050* (0.027) 0.705***	0.024*** (0.007) 0.015** (0.006) 0.039*** (0.006) -0.059** (0.026) 0.879*** (0.063)	0.067*** (0.006) 0.032*** (0.005) 0.057*** (0.005) -0.059** (0.024) 0.716***	0.060*** (0.006) 0.030*** (0.005) 0.053*** (0.005) -0.054** (0.024) 0.691***	0.060*** (0.008) 0.030** (0.012) 0.053*** (0.008) -0.054 (0.173) 0.827***
Maturity FEs Country FEs Bond type FEs Industry FEs Double-clustered s.e. R-squared Observations	- - - 0.001 65,435	- - - 0.001 65,435	- - - 0.001 65,435	- - - 0.001 65,435	- - - 0.067 65,435	- - 0.162 65,435	, , , 0.402 65,435	, , , , 0.453 65,435	\ \ \ \ \ \ 0.453 65,435

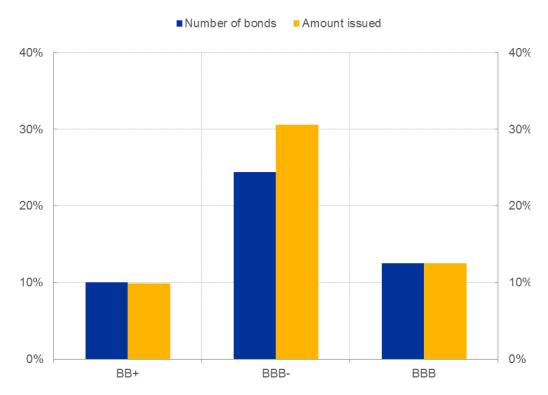


Figure 17A. Share of bonds issued after March 2016 ending up getting one upgrade with respect to the rating of bonds of the same issuer in March 2016.

Source: Authors' calculations.

