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Abstract
In March 2016 the European Central Bank (ECB) announced the Corporate Sector Purchase Program (CSPP) as part of its expanded asset purchase program. Using hand-collected, weekly lists of bonds purchased and held under the CSPP, we investigate the drivers of the purchase decisions and the impact of the program on the financing decisions of targeted firms. We find that, consistent with the goal of decreasing credit premia while minimizing price distortions, purchases of eligible bonds characterized by both higher credit risk and higher liquidity are more likely and more timely. Bonds issued by firms more likely to face difficulties in tapping the credit market directly are also more likely to be purchased. The CSPP appears effective in alleviating these difficulties. Firms targeted by the program increase their amount of bonds outstanding significantly more than non-targeted eligible issuers; the effect is mostly driven by companies making limited use of market debt before the start of the program. However, no difference is found in the variation of total debt between targeted and non-targeted eligible issuers. Together, these results suggest that the CSPP has favored the substitution of bonds for other forms of debt capital.

Keywords: Corporate Sector Purchase Program, Corporate Bonds, Central Bank Asset Purchases, Quantitative Easing, Corporate Debt

JEL classification: G18, G28, G32

1 Intro

During the last decade, central banks have implemented several Quantitative Easing (QE) programs to provide markets with extra liquidity and foster growth and inflation in low interest rate environments. After expanding its lending operations, the European Central Bank (ECB) announced in 2012 its intention to start buying securities directly. Since then, several Asset Purchase Programs (APPs) have been introduced, allowing the ECB to buy government bonds (PSPP), asset-backed securities (ABSPP), and covered bonds (CBPP3). Whereas this first round of QE has contributed to a significant reduction in market rates (Koijen et al., 2016), non-financial firms' limited access to credit remained a concern in Europe. This could be due to two main reasons. First, initially QE consisted mainly of government bond purchases, which could have had a limited impact on corporate debt yields. According to a "portfolio rebalancing" (e.g., Tobin, 1958, 1969) channel, corporate bonds are imperfect substitutes for e.g. government bonds, especially when they are characterized by (relatively) high credit risk (Greenwood et al., 2016). As such, these operations only had a small impact on credit premia, as shown by Krishnamurthy et al. (2011) for the US case. Second, the liquidity injected in the system did not translate into a proportional increase in lending. The majority of securities purchased by the ECB under the initial APPs were purchased from foreign investors rather than European credit institutions, which implies limited pass-through of liquidity to the banking system (Koijen et al., 2017). Moreover, when banks sold securities to the ECB, they typically used the proceeds to recapitalize (e.g., Joyce and Spaltro, 2014).

Therefore, with the introduction of the Corporate Sector Purchase Program (CSPP) in March 2016, the ECB announced its intention to start buying corporate bonds. CSPP officially started on June 8^{th}, 2016, and is part of the ECB's expanded APP, which initially aimed at buying around 60 billion euros of securities per month until at least the end of 2017.[1] In this study we investigate the European Corporate Sector Purchase Program to address two sets of questions. First, which securities (targets) from the eligible universe does the ECB purchase and which selection criteria determine their targets? Second, how are debt-financing decisions of targeted firms affected?

When selecting which securities to purchase from the eligible universe, the six national central banks in charge of CSPP operations face a series of trade-offs. In particular, we are interested in the trade-offs related to how two key characteristics of fixed income securities—credit risk and liquidity—affect target selections. There are

[1] On October 26th, 2017 the ECB announced its intention to extend the APP until at least September 2018, while at the same time reducing monthly net purchases to 30 billion euros per month.

arguments to support that central banks target bonds with higher credit risk and arguments to support that they focus on bonds with lower credit risk, and likewise for liquidity. Empirically analyzing which effects prevail can therefore shed light on the effective operational strategy behind purchases under CSPP.

Considering credit risk, if the goal is to reduce credit premia, one would expect CSPP to target corporate bonds characterized by high credit risk. However, this also implies that credit risk (Benigno and Nistico, 2015) and interest rate risk (Christensen et al., 2015; Del Negro and Sims, 2015) are transferred from the private sector to the central bank's balance sheet. The ECB mentions the potential deterioration of credit quality and the possibility of defaults as explicit risks linked to the program.[2] These risks are officially contained by limiting the purchasable universe to investment grade (IG) securities. Yet, IG securities can differ substantially in terms of credit quality, and a program systematically targeting the most risky securities in the eligible universe may well go against the explicit goal of keeping credit and default risks associated with the program under control.

As for liquidity, on the one hand the demand shock represented by QE operations can have a disruptive effect on prices (Steeley, 2015), and particularly so for more illiquid bonds (Arrata and Nguyen, 2017). This could be especially relevant for corporate bonds, as they are generally less liquid than government bonds. Market commentators have raised concerns that these distortions have indeed manifested as a result of APPs, as evident for example from misalignments in the pricing of bonds and related derivatives.[3] As such, the ECB may want to limit the price distortion resulting from CSPP purchases by targeting only the most liquid bonds. On the other hand, targeting only the most liquid securities may hamper the liquidity premium channel of transmission (Joyce et al., 2011), i.e., a potential reduction in yields occurring because CBs purchases make it easier for investors to sell assets when needed.

The second set of questions we address relates to the impact of CSPP on the financing decisions of targeted firms. The general assumption behind the program is that it can contribute to lower corporate bonds yields, thereby reducing firms' cost of financing. Indeed, preliminary studies observe a general reduction in yields and credit premia since the announcement of the program.[4] Has this translated into better access to credit markets for companies? More specifically, we are interested in whether there is a direct, differential impact on firms whose bonds are actually purchased, compared to the the

[2] http://www.ecb.europa.eu/mopo/implement/omt/html/cspp-qa.en.html

[3] See for example https://www.bloomberg.com/news/articles/2017-04-06/these-anomalous-spreads-show-the-ecb-distorting-bond-markets

[4] http://www.europarl.europa.eu/RegData/etudes/IDAN/2017/607343/IPOL_IDA(2017)607343_EN.pdf

universe of firms whose bonds are eligible but not targeted. This is particularly relevant because if such a direct effect exists, then the target selection becomes not neutral in terms of which–otherwise similar–companies benefit the most from the program. Finally, we are interested in addressing whether upon being targeted, firms decide to increase their total debt holdings, or alternatively substitute other forms of capital for bonds.

To answer these questions, we build a panel dataset of bonds eligible under the program, and combine it with bond- and issuer-level characteristics retrieved from various sources. To identify securities effectively targeted by CSPP, we hand-collect the weekly updates of CSPP securities available for lending, which the six national central banks in charge of the purchases started publishing on their websites a few weeks after the program started. We therefore have a cross-sectional dataset of eligible bonds covering the first few weeks of the program (referred to in the rest of this paper as the First Wave of the program), as well as a bond-week panel dataset covering the subsequent period (referred to as the Second Wave). These two datasets allow us to investigate the target selection decisions for the first wave of the program and the selection and timing decisions for the second wave. By combining information on eligible and targeted bonds at the issuer level, we can also address the change in financing decisions between targeted and non-targeted firms.

Our data show a substantial increase in the number and amount of eligible bonds outstanding since the advent of the program, consistent with a positive impact of the CSPP on companies' access to market debt. Whereas the number of different securities purchased has steadily increased during the program, by mid-July 2017 less than 55% of the eligible securities have been targeted, and more than 25% of securities issued during the second wave are purchased on the week of issuance (possibly on the primary market). Together, these descriptive statistics suggest a significant heterogeneity in the actractiveness of eligible securities as targets for the program.

Using logit models for the first wave and Cox proportional hazard models for the second wave, we find that both credit risk and liquidity have a positive impact on the likelihood and timing of purchases. This is consistent with the idea that central banks factor in their target selection both concerns about the effective impact of the program on credit premia and concerns about the potential impact of the program on pricing efficiency and markets liquidity. The result is robust to the use of different models specifications and different proxies for credit risk and liquidity. Bonds issued by firms more likely to face difficulties when tapping credit markets directly, as proxied by their size and share of market over total debt, are also more likely to be targeted.

CSPP operations appear to be effective in improving access to market debt capital specifically for targeted firms: all else equal, issuers targeted during the first wave have increased their amount of bonds outstanding during 2016 by an additional 22.4 percentage points compared to non-targeted but otherwise eligible firms. This effect is mostly driven by issuers making limited use of market debt before the start of the program. Targeted firms also exhibit a significantly larger increase in the proportion of market over total debt, but we find no difference between targeted and non-targeted firms in the variation of total debt capital since the advent of the program. Together, these results suggest that firms targeted by the CSPP have not raised additional debt; instead they increased their use of market debt at the expense of other forms of debt capital.

This paper contributes to the literature on the assets purchase programs operated since the advent of the 2008 financial crisis (e.g. Eser and Schwaab, 2016; Fratzscher et al., 2016; Joyce et al., 2011). In particular, several recent concurrent papers (Abidi et al., 2017; Arce et al., 2017; Grosse-Rueschkamp et al., 2017) have addressed the European CSPP specifically. Our study augments this emerging literature on two salient dimensions. First, to the best of our knowledge this is the first study addressing the target selection and timing of first-purchase decisions. We show that not all eligible bonds are purchased, and that targeted and non-targeted eligible bonds significantly differ on several relevant characteristics, most notably credit risk and liquidity. Second, we investigate the impact of CSPP on corporate financing decisions by comparing effectively targeted issuers vis-à-vis non-targeted but otherwise eligible firms, whereas other studies consider all firms with eligible bonds as treated by the program, and use non-eligible firms as the control group. That is, whereas other studies investigate the effect of eligibility, we study the direct effect of being targeted by the program.

The rest of this paper proceeds as follow. In Section 2 we provide institutional details over the Corporate Sector Purchase Program. Section 3 reviews the relevant literature. The dataset is described in Section 4. Section 5 presents our empirical results. Finally, Section 6 concludes.

2 The Corporate Sector Purchase Program

In response to the global financial crisis and the European sovereign debt crisis, the ECB initiated a series of unconventional monetary policy instruments, including Long-Term Refinancing Operations (LTRO) and Asset Purchase Programs (APP). In January 2016 the ECB announced an “expanded asset purchase programme”, encompassing the existing programs for covered bonds and asset-backed securities. Under this expanded programme, the combined monthly purchases of public and private securities were planned to amount to 60 billion Euros.

On 10 March 2016, the ECB decided to further expand the APP from 60 to 80 billion Euros, with an intention to continue the program to at least March 2017. In addition, the ECB introduced the Corporate Sector Purchase Program (CSPP) aimed at the purchase of investment-grade, euro-denominated bonds issued by non-bank corporations. On 21 April 2016, the ECB announced further details on the program. Bonds purchases started on June 8, 2016. Between June 2016 and July 2017, net purchases have averaged 7.22 billion euro per months according to official ECB statistics. By the end of July 2017, the book value of holdings under the CSPP at amortized costs was 102.23 billion euro.

The six national Central Banks (CBs) of Belgium, Finland, France, Germany, Italy, and Spain are in charge of purchases on the primary and secondary markets under the CSPP. Each individual CB is responsible for the purchase of corporate bonds from a specific set of countries. Since July 18, 2016 holdings under the CSPP have been made available for lending by the six CBs.[5]

Several detailed eligibility criteria have been set within the program.[6] First, purchased securities must be euro-denominated and eligible as collateral for Eurosystem credit operations according to the guideline ECB/2014/60 and its subsequent amendements. Second, the issuer is incorporated in a member state whose currency is the euro. The country of origin of the ultimate parent of the issuer is not taken into account. Third, the issuer (or its ultimate parent) cannot be a credit institution, or more generally an entity which is subject to banking supervision inside or outside the euro area. Fourth, the debt instrument has a minimum remaining maturity of 6 months and a maximum maturity less than 31 years at the time of purchase. Fifth, an issue needs to have a minimum credit rating of investment grade (i.e. BBB-/Baa3/BBBL) from at least one rating agency. Finally, purchases of assets with a (negative) yield to maturity below the deposit facility rate are permitted only to the extent neccessary.[7]

The ECB tries to take into account potential adverse impacts of its purchase program on market liquidity. Whereas there is no minimum issuance volume for corporate bonds to be eligible, a maximum share limit of 70% per individual security applies. In addition, there is a predefined (but unspecified) limit per issuer group. Securities can be purchased in both primary and secondary markets. In the primary market, the ECB tries to balance on the one hand the objective of the program with the need to ensure that the market keeps on functioning properly. Also when purchasing in the secondary

[5] `https://www.ecb.europa.eu/mopo/implement/omt/lending/html/index.en.html`

[6] See `https://www.ecb.europa.eu/mopo/implement/omt/html/cspp-qa.en.html`, question 2.8

[7] `https://www.ecb.europa.eu/ecb/legal/pdf/celex_32017d0004_en_txt.pdf`

market it considers the scarcity of debt instruments and general market conditions like having the flexibility to take seasonal differences into account.

The ECB does not publish any purchase volumes *ex ante*, but does publish data on actual holdings *ex post*. It provides aggregate statistics on the total Euro amounts purchased, and more detailed statistics on which bonds it purchases (without indicating the amount). The ECB applies a maximum issue share limit of 70% per ISIN on the basis of outstanding amounts, in addition to a predefined (but unspecified) limit per issuer group. This allows for sufficient leeway to build up the portfolio, while ensuring a diversified allocation of purchases across issuers. In addition to the aforementioned minimum credit quality requirements, such a diversified allocation of purchases also reduces the ECB's portfolio credit risk.

3 Literature review

This paper is part of an extensive literature that studies the impact of central bank asset purchase programs. Initially, macroeconomic literature did not predict any effect of central bank asset purchase programs (Wallace, 1981; Eggertsson and Woodford, 2003), regardless of whether these are private assets or government securities. In frictionless financial markets, assets held by the central bank are perfect substitutes for privately held assets and the monetary policy stance can be entirely be described by the current and expected policy interest rate. Any expansion of the central bank balance sheet has zero impact on asset prices. In such a world, any impact of asset purchases could only be produced indirectly, for instance through a *signaling channel* (Eggertsson and Woodford, 2003; Krishnamurthy et al., 2011) in which asset purchases act as forward guidance.

However, central bank asset purchases could have an impact on asset prices also via a "portfolio rebalancing channel" (Tobin, 1958, 1969; Gertler and Karadi, 2011, 2013), due to the existence of preferred habitat investors combined with limits to arbitrage Vayanos and Vila (2009); Greenwood and Vayanos (2014). These theories would predict that asset purchases by a central bank would have an impact on related assets, as investors selling these bonds use the proceeds to purchase substitute assets. Due to market segmentation, the "portfolio rebalancing channel" is predicted to be stronger on assets that can be seen as closer equivalents of those purchased by the central bank. Consequently, the choice of securities purchased under quantitative easing operations should take into account which market segment (in terms of e.g. duration and credit risk) the program wants to target.

A large existing literature analyzes central bank assets purchase programs. One strand of literature empirically analyzes the price impact of these programs. Eser and Schwaab (2016) analyze the effect of the European Securities Market Program and find both large announcement effects and purchase effects. Ghysels et al. (2016) use high-frequency data on purchases of the ECB and sovereign bond quotes and show that SMP interventions have been effective in reducing the yields of government bonds for the countries in the program. Joyce et al. (2011) analyze the impact of QE in the UK and find both announcement and purchase effects on the order of 100 basis points. Kettemann and Krogstrup (2014) also find evidence for an announcement effect of Swiss National Bank's covered bond purchase program, even though they do not find evidence for a purchase effect. Several studies focus explicitly on ECB's APP: Georgiadis and Gräb (2016) investigate the impact of announcing the complete Eurosystem APP program on the euro exchange rate, global equity prices and bond yields. Abidi et al. (2017) use an event study to investigate the *ex ante* effect of the announcement of the CSSP program in March 2016. They distinguish the differential announcement effect on bonds that are eligible versus those that are not eligible, and find evidence of significant announcement effects.

A second strand of empirical literature studies the effect of central bank purchases programs on firms' financing decisions. Rodnyansky and Darmouni (2017) show that quantitative easing (QE1 and QE3) increased bank lending in the US. Likewise, Joyce and Spaltro (2014) and Bowman et al. (2015) find a positive affect of quantitative easing on bank lending in the UK and in Japan, respectively. Foley-Fisher et al. (2016) analyze the US maturity exentension program (MEP) and find that firms more dependent on long-term debt also issue more long-term debt during the MEP. Lo Duca et al. (2016) find that purchases and holdings of MBS and Treasuries by the Fed strongly affect gross corporate bond issuance in advanced and emerging economies. Several studies explicitly focus on the (announcement) effect of ECB's APP and CSPP in particular. Albertazzi et al. (2016) use security holdings data to study the announcement of APP and find that portfolio rebalancing seems to have been an active channel for APP mostly for economies more affected by the financial crisis. Arce et al. (2017) analyze the effect of CSPP in Spain. They combine information on which corporate bonds were acquired by the ECB with credit registry and bond issuance data. They find that firms whose bonds are eligible reduce their demand for bank loans, which seems to free up credit allocated to small firms not issuing bonds. Likewise, Grosse-Rueschkamp et al. (2017) find that eligible firms shift the composition of credit from loan to bond financing based on the total universe of CSPP data in combination with Dealscan and Amadeus data. The latter two papers provide evidence that CSPP has a positive spillover effect on the supply of bank loans to firms without access to bond markets.[8] Our paper contributes to this literature by analyzing the effect of actual CSPP purchases—instead of the effect of eligibility—on firms' financing decisions.

4 Data

4.1 Eligible bonds

To identify a universe of bonds eligible under the CSPP we start from the lists of marketable bonds accepted as collateral for Eurosystem credit operations that are published daily by the ECB.[9] For each week, we consider the latest list–a Friday in all but one case. All weekly data included in this study are accordingly measured as of Friday. The ECB lists include some key characteristics of the bonds such as the ISIN code, the type of instrument and issuer, the issuance and maturity date, and the haircut applied when the bond is used as collateral. Consistent with CSPP eligibility criteria, we retain from this initial dataset only euro-denominated securities: a) labelled as bonds (type AT01) or medium-term notes (AT02), and; b) issued by corporations (issuer group IG3) and financial corporations other than credit institutions (IG9) residing in one of the EU-19 countries. The final dataset includes 2,227 bonds considered as eligible for at least one week since week 22 of 2016 (just before the start of the program) and until week 27 of 2017 (the latest date included in this study). All bonds purchased under the CSPP (discussed below) are part of this eligible universe. Figure 1 presents the number and total Amount Outstanding (AOS; source: Datastream) of eligible bonds over time.

[Insert Figure 1 about here]

It is interesting to observe how the number and amount of eligible bonds outstanding are essentially stable over the first few weeks of 2016, and suddenly increase during the 3 months between the announcement and the start of the program. The number of eligible bonds increases by 1.3%, from 1,752 to 1,774; the average outstanding amount per bond by 1.1%, from 510 to 516 million euros. The number and amount of bonds remain then substantially stable during the first few weeks of the program. This pattern suggests that some scheduled bond issuances have been anticipated and increased in

[8] Note that in addition to CSSP, there is a developing literature on the PSPP program. For instance, Arrata and Nguyen (2017) analyze the Public Sector Purchase Program (PSPP) for the French bond market.

[9] Data available at `https://www.ecb.europa.eu/paym/coll/assets/html/list-MID.en.html`

size in an attempt to fully benefit from the program since its start. Over the first year of the CSPP, the number of eligible bonds outstanding has further increased by 4.2%; and the average amount per bond by 6.2%. By mid-July 2017, the total amount of eligible bonds outstanding has reached euro 992.5 billions.

For each bond, we collect from Thompson EIKON the Organization ID, the RIC code, and the SIC code for both the immediate issuer of the bond and for its parent company. Assigning each bond to a unique corporation is non-trivial, as several bonds are technically issued by financial vehicles. Whereas we use the Organization ID as our main company identifier (as it is always available),[10] to identify the ultimate corporation issuing the bond we rely on the RIC and SIC code. If: a) the RIC code is available for the parent company of the issuer but not for the issuer itself, and; b) the immediate issuer is classified as a financial company (based on its SIC code), we then treat the immediate issuer as a vehicle and consider the parent company as the ultimate issuer of the bond. In all other cases, the immediate issuer is considered to be also the ultimate issuer of the bonds. Under this approach, the 2,227 bonds in the eligible universe are categorized as issued by 324 unique corporations.

4.2 CSPP bonds

A few weeks into the program, the six national Central Banks (CBs) in charge of market operations under the CSPP started publishing weekly updates of the lists of bonds purchased and available for lending. Since October 10th, 2016 we hand-collect every week the updated list of CSPP bonds from each CB. Lists updates are typically published on Mondays; bonds included in a list are considered as being held by the CB until the end of the previous week. We therefore have a cross-sectional dataset of eligible bonds bought upto and including week 41 of 2016 (2016w41), and a weekly panel dataset covering the subsequent period from 2016w42 to 2017w27. We refer henceforth to the initial weeks of the CSPP (upto and including 2016w41) as the First Wave of the program, and to the subsequent period as the Second Wave. For bonds targeted for the first time during the second wave, the weekly panel dataset allows us to identify the exact week of the first purchase.

Table 1 presents the distribution of bonds purchased during the CSPP so far, subdivided by CB and period. Until 2017w27, 998 different bonds from 226 unique issuers have been purchased under the CSPP, 641 of which are purchased already during the first wave. The CB of France is the most represented, purchasing almost 28% of all

[10] Company-level data, discussed below, are retrieved based on the selected RIC code. The selected Organization ID is used to identify unique issuers for descriptive statistics and performed analyses.

the bonds targeted.

[Inser Table 1 about here]

As illustrated by Figure 2, the number of bonds held under the CSPP has steadily increased over time, both in absolute terms and as a share of the eligible bonds available. From 2016w41 to 2017w27 the number of bonds purchased under the CSPP and available for lending has increased from 641 to 948, corresponding respectively to 36% and 53% of all eligible bonds outstanding at the time.

[Insert Figure 2 about here]

Of the 357 bonds purchased for the first time during the second wave, 181 were already outstanding on 2016w41, whereas the remaining 176 have been issued subsequently. Figure 3 presents the Kaplan-Mayer survival curves during the second wave separately for the two groups of bonds, i.e., those already outstanding at the beginning of the second wave but not targeted during the first wave (continuous line) and those issued after 2016w41 (dashed line). The analysis time is measured starting at the beginning of the second wave for the first group and at issuance for the second group.

[Insert Figure 3 about here]

The estimated survival probability is generally higher for bonds already outstanding at the beginning of the second wave; for eligible bonds issued subsequently, the estimated probability of survival drops dramatically already during the first week of a bond's life; after 2-3 weeks, the estimated survival probability decays slowly and in a similar fashion for the two group of bonds. Taken together, the two survival curves suggest that central banks tend to purchase bonds of interest as soon as they become eligible; if a bond is not target immediately, its cumulative probability of being purchased is only slightly increasing over time. This in turns is highly indicative of a significant heterogeneity in the attractiveness of different eligible bonds as targets for the CSPP. Investigating the drivers of this selection is the goal of the analysis presented in Section 5.1.

4.3 Bond characteristics

The two main bond-level characteristics of interest in this study are credit risk and liquidity. To measure the credit risk of a bond we use two alternative (time-varying) proxies. The first one ($Haircut$) is the haircut applied to the security when used as collateral in Eurosystem credit operations (source: ECB). It is expressed as a percentage over the face value. The second one ($Rating$) is the bond long-term domestic rating expressed in a numerical scale (source: Thompson EIKON). The scale for Investment Grade securities ranges from 17 (Baa3/BBB-) to 27 (AAA/Aaa); when multiple ratings are available, consistently with CSPP policies over eligibility we consider the highest rating among those assigned by Moody's, S&P, and/or Fitch.[11]

Our main measure for liquidity is the bid–ask spread, which is also the most commonly used proxy in the literature (Chen et al., 2007). The variable $Bid - Ask$ is defined as the difference between the Thompson's composite ask price ($CMPA$; source: Datastream) and the composite bid price ($CMPB$), expressed as a percentage of the mid–price. As a robustness check, we also consider as an alternative proxy the spread (in basis points) between the bond's yield and the swap rate for the same maturity ($SWSP$; source: Datastream). Liquidity is generally considered as the main factor behind the variance in yields that is not explained by credit risk (e.g., Duffee, 1999; Longstaff et al., 2005); when controlling for credit risk $SWSP$ should therefore mostly capture the effect of liquidity.[12] With both proxies, higher spreads indicate a relatively illiquid bond. To control for the size and maturity of the bond we use respectively the natural logarithm of one plus: i) the Amount Outstanding in thousands of euros (AOS; source: Datastream), and; ii) the time to maturity (TTM; source: ECB) expressed in days.

Table 2 reports summary statistics. To facilitate the comparison between bonds purchased and not purchased, only bonds already outstanding and eligible at the beginning of the program are included in this Table. Bonds characteristics are measured on 2016w22, i.e., just before the start of the CSPP. We present descriptive statistics separately for three mutually exclusive group of bonds: those not yet purchased as of 2017w27 (non-targeted; Panel A), those already purchased during the first wave (Panel B); those purchased for the first time during the second wave (Panel C).). We also present in Panel D the difference in the sample mean of each variable between non-targeted bonds and targeted (either during the first or the second wave) bonds.

[11] A good illustrative example is Telecom Italia; during our sampling period, the company's bonds are rated speculative grade by Moody's and S&P but investment grade by Fitch; by mid-July 2017, 11 of the 14 eligible bonds issued by Telecom Italia have been purchased under the CSPP.

[12] Huang and Huang (2012) argue that, for IG corporate bonds, non-credit risk factors such as liquidity may even be the primary drivers of spreads.

[Insert Table 2 about here]

Panel D shows that the average haircuts just before the start of the program is 2.24 percentage points higher for targeted bonds, and the average rating is almost one notch lower; both differences are statistically significant at the 1% confidence level. The average amount outstanding is around 272 million euros larger for targeted bonds, and the average bid-ask spread is 35 basis points lower; the two differences are significant respectively at the 1% and at the 5% confidence level. Taken together these simple univariate analyses suggest that, as expected, targeted bonds are characterized on average by higher credit risk and liquidity. It is interesting to notice how, with the exception of *Rating*, mean values for bonds targeted during the second wave tend to be somewhere in between the mean values for non-targeted bonds and for bonds targeted during the first wave. Bonds with higher credit risk and more liquid bonds appear to be not only more likely to be targeted, but also more likely to be targeted sooner in the program. Finally, there does not seem to be a significant difference between targeted and non-targeted bonds in terms of average residual maturity.

4.4 Issuer characteristics

Table 2 also reports descriptive statistics for the issuer-level variables considered in this study. All accounting variables are obtained from the Worldscope database, retrieved via Datastream, and measured at the end of 2015. To proxy for the size of the issuer, we use the natural logaritm of total assets in thousands of euros ($LNTA$). To account for growth opportunities we use Tobin's Q, defined as the sum of the market value of equity and the book value of total assets, minus the book value of equity and deferred taxes, all divided by total assets. Finally, two variables are considered to account for the capital structure of the issuer. The first one is the ratio between the book value of debt and the market value of equity (D/E). The second variable, *Bond ratio*, is used to proxy for the ability of the issuer to resort to long-term bonds as a source of debt financing. Previous studies (e.g., Cantillo and Wright, 2000; Denis and Mihov, 2003) show that companies that are less likely to face difficulties in raising debt capital are also more likely to tap credit markets directly. *Bond ratio* can therefore be seen as a proxy for the ability of the issuer to collect market debt capital. The variable is computed for each issuer as the ratio of the total amount of outstanding bonds and medium-term notes in the ECB database ($\overline{AOS}$; measured on the first week of 2016), to the book value of debt.[13]

[13]There are two issuers for which $\overline{AOS} > D$; in those cases, we set *Bond ratio* equal to 1.

5 Empirical Results

In this Section we present our empirical results. Analyses of the determinants of target selection and timing of CSPP purchases are discussed in Section 5.1. Section 5.2 focuses on the impact of the program on the debt financing decisions of the eligible issuers.

5.1 CSPP bonds selection

We use two different classes of econometric models to investigate the drivers of bond selection and timing of purchases under the CSPP. For the first wave of the program (i.e., up to and including week 41 of 2016) we use Logit models. These models include all bonds outstanding and eligible as of week 22 of 2016 (i.e., just before the start of the program). Panel A, B and C of Table 2 provide summary statistics of this sample. The dependent variable is an indicator equal to one if the bond has been purchased under the CSPP up to and including week 2016w41 (563 bonds) and zero otherwise (539 eligible bonds are not targeted during the entire program and 148 only during the second wave). Bond-level explanatory variables are measured on 2016w22, whereas issuer-level variables based on accounting data are computed using 2015 values.

To fully exploit the panel nature of the data, for the period from 2016w42 to 2017w27 we estimate Cox proportional hazard models. The sample in this case includes all of the eligible bonds outstanding as of 2016w41 and not targeted already during the first wave, as well as eligible bonds issued subsequently. Bonds are considered at risk of being purchased during the second wave since 2016w42–or when they enter the eligible universe after that week. Securities exit the duration analysis when they are purchased under the CSPP for the first time, when they stop being eligible (for example because their residual maturity is less than 6 months), or at the end of our sampling period (whichever occurs first). One-week lags of proxies for credit risk, liquidity, and size at the bond level are considered as the main explanatory variables. To account for the time-invariant characteristics of the issuer, as it is customary (e.g., Lugo et al., 2015) we estimate a shared frailty model with a gamma-distributed latent effect at the issuer level. Coefficients estimates for both groups of models are reported in Table 3.

[Insert Table 3 about here]

The first four columns present coefficient estimates for the Logit models. Models (1) and (2) are the most parsimonious, including only bond-level proxies for credit risk, liquidity, and size. $Haircut$ and $Bid - Ask$ are used as proxies in Model (1), whereas $Rating$ and $SWSP$ are used in Model (2). Both models include $ln(1 + AOS)$. Models

(3) and (4) augment Models (1) and (2) respectively by adding issuer-level variables, including sector (at the 1-digit SIC code level) indicators, and $ln(1+TTM)$ to proxy for the bond's maturity. Models (5) and (6) refer to the duration analysis for the second wave.

Regardless of the model and proxy considered, credit risk appears to have a significant (at least at the 10% confidence level) positive impact on the likelihood of a purchase during the first wave. The effect is also economically relevant; given the coefficient estimates for Models (2) and (4), a one-notch better rating is associated to a decrease in the odds of being targeted by 16-20%. The result is similar when addressing the second wave of the program; according to Model (6) estimates, a 1-notch higher rating is associated with a decrease in the purchase hazard by 13%.

Liquidity also appear to have a significant positive impact on the likelihood of being purchased under the CSPP. A one percentage point increase in the bid-ask spread (as a share of the mid-price) corresponds to 19-33% decrease in the odds of being targeted during the first wave, and to a 22% decrease in the purchase hazard during the second wave. Estimates for $SWSP$ render consistent results. Moreover larger bonds, which are generally regarded as more liquid, are *ceteris paribus* significantly (at the 1% confidence level) more likely to be targeted.

Looking at coefficient estimates for issuer-level characteristics, it appears that targeted firms tend to be significantly smaller and to make a more limited use of bonds for debt financing. Taken together, these two pieces of empirical evidence seem to point toward central banks favoring bonds issued by firms more likely to face difficulties when trying to raise market debt capital, which is fully consistent with the aim of the CSPP. Finally, bonds issued by relatively less levered firms are, all else equal, also more likely to be purchased –albeit the coefficient for D/E is statistically significant at the 10% level only for Model (3). Recalling that Models (3) and (4) include controls for credit risk, a relatively low leverage could be seen as indicative of a firm facing debt funding constraints (Leary, 2009). The estimated negative coefficient for D/E is therefore also consistent with the idea that firms more likely to experience difficulties in raising debt are also more likely to be targeted under the CSPP.

5.2 Issuers reaction to CSPP

To address the relationship between CSPP purchases and corporate debt financing decisions, we estimate a set of models for the determinants of the variation (at the issuer level) in the amount and composition of debt outstanding during 2016. Our main explanatory variable of interest is $Target$, an indicator equal to 1 for issuers with at least one bond purchased during the first wave of the program and equal to 0 for those issuers that, despite having eligible bonds outstanding during the first wave, are not yet targeted by the program by the end of 2016. Firms with no eligible bonds outstanding during the first wave and firms targeted for the first time in 2016 but during the second wave are thus excluded from these analyses.

We consider three dependent variables. The first one, $\Delta\ln(\overline{AOS})$, is the change in the natural logarithm of $\overline{AOS}$ between the first and last week of 2016, where $\overline{AOS}$ is the total amount of bonds outstanding from the same issuer. The second variable, $\Delta Bond\,ratio$, aims at capturing the change in the relevance of bonds as an instrument for debt financing; it is computed as the change in $Bond\,ratio$ between the end of 2015 and the end of 2016.[14] Finally, $\Delta\ln(D)$ is the change in the logarithm of the issuer's total debt between 2015 and 2016.

5.2.1 CSPP and bonds financing decisions

Table 4 reports coefficient estimates for models where $\Delta\ln(\overline{AOS})$ is the dependent variable.

[Insert Table 4 about here]

Model (1) estimates show that, on average, both targeted and non-targeted eligible issuers significantly increase the amount of bonds outstanding during 2016; however, the increase is significantly (at the 1% confidence level) larger for targeted firms. Non-targeted firms with eligible bonds increase on average their amount of bonds outstanding by 11.2% during 2016, whereas the average increase for targeted issuers is 24.6% (i.e., 0.112 + 0.134).

As revealed by the analyses presented in Section 5.1, CSPP target selection decisions are not random, and issuer-level characteristics play a significant role. Therefore, it may be argued that the observed difference in $\Delta\ln(\overline{AOS})$ between targeted and non-targeted firms is driven by the difference in the characteristics of the firms.

To partially mitigate this concern we perform two robustness checks. First, Model (2) augments Model (1) by including also the issuer-level control variables presented in Section 4.4 and the sector (at 1-digit SIC code level) indicators. Even controlling for observable characteristics, targeted firms exhibit a significantly (at the 1% confidence

[14]As illustrated in Section 4.4, $Bond\,ratio$ at the beginning of 2016 is computed as $\overline{AOS}/D$, where $\overline{AOS}$ is measured on the first week of 2016 and D is the 2015 total debt. Accordingly, $Bond\,ratio$ at the end of 2016 is computed using the value of $\overline{AOS}$ measured on the first week of 2017 and the 2016 value for D.

level) greater increase in the amount of bonds outstanding. Second, we check whether targeted and non-targeted firms already exhibit a significantly different trend in $\overline{AOS}$ before the program starts. To do so, we re-estimate Models (1) and (2) using as the dependent variable the log-change in $\overline{AOS}$ between week 1 and week 22 (i.e., just before the start of the program) of 2016. The results are presented as Models (4) and (5). For both models, the estimated coefficient for $Target$ is not statistically (at customary confidence levels) different from zero. We cannot therefore reject the null hypothesis of a pre–event common trend between targeted and non-targeted firms, which in turns supports a causal interpretation of the positive relationship between $Target$ and $\Delta \ln(\overline{AOS})$.

Model (3) augments Model (2) by including the cross-product of $Target$ and *Bondratio*. We expect the CSPP program to favor the use of bonds as a source of debt financing especially for those firms that appear to face more difficulties in directly tapping the market for credit, as proxied by a lower *Bond ratio* before the start of the program. We find that this is indeed the case. The estimated coefficient for the interaction term is negative and significant (at the 1% confidence level), suggesting a smaller positive impact of $Target$ on firms with a higher value for *Bond ratio*. Compared to a non-targeted but otherwise similar firm, a targeted issuer with a *Bond ratio* of 5% is estimated to increase on average its bonds outstanding by an extra 32 percentage points; for *Bond ratio* values of 0.33 or above, there does not appear to be a significantly (at customary confidence level) larger increase in bonds outstanding for targeted versus non-targeted firms, all else being equal. The difference between targeted and non-targeted firms is thus primarily driven by those issuers who made a limited use of long-term market debt before the start of the program.

5.2.2 CSPP and debt composition decisions

Does the (extra) increase in bonds outstanding for targeted firms lead to an increase in their use of debt capital? Or is it the result of a substitution between bonds and other forms of debt financing? Models presented in Table 5 tackle these questions by addressing the relationship between $Target$, on the one hand, and the yearly change in *Bond ratio* and total debt on the other hand.

[Insert Table 5 about here]

Our results support the substitution argument: CSPP targets do not appear to increase their total debt more than non-targeted issuers; the coefficient estimates for $Target$ in Models (1) and (2) are small and not statistically significant. As total debt does not increase more on average for targeted firms, the extra increase in the amount of bonds outstanding translates into a greater proportion of debt being represented by (eligible) bonds, as the coefficient estimates for Models (3) and (4) demonstrate. Ceteris paribus, targeted firms increase on average their *Bond ratio* by 5 percentage points more than non-targeted firms; the coefficient estimate for *Target* is statistically significant at the 1% and at the 10% confidence level for Models (4) and (5) respectively.

In summary, the CSPP appears to have favored an increase in the use of bonds by targeted issuers–especially for firms making a rather limited use of this source of financing–but not an increase in the use of debt capital.

6 Conclusions

This paper studies the actual central bank bond purchases made under the European Corporate Sector Purchase Program to address two sets of questions. First, which securities (targets) from the eligible universe does the ECB purchase? We find that within the eligible universe, CSPP systematically targets securities characterized by higher credit risk. This could be understood by considering a portfolio rebalancing channel. Corporate bonds characterized by higher credit risk are less close substitutes for government bonds. Because CSPP is executed on top of a government bond purchase program (PSPP), targeting more risky bonds is likely to increase the effectiveness of the program. Similarly, targeting less liquid bonds could also be more effective, because this would increase the effectiveness of transmission via a liquidity premium channel. However, we find evidence of the opposite: Conditional on credit risk, liquidity has a positive impact on the likelihood of a bond to be purchased under the CSPP. We interpret this as an attempt by central banks to limit the price distortions created by CSPP.

Second, how are debt-financing decisions of targeted firms affected? Concurrent papers on CSPP find that eligible firms have shifted their debt compositions from banks loans to bonds compared to non-eligible firms. We contribute to this set of empirical evidence by showing that, within the eligible universe, the CSPP has a significantly stronger impact on the financing decisions of firms whose bonds are actually purchased. Targeted firms increase their bonds outstanding and their proportion of bonds over total debt significantly more than non-targeted firms. The difference is mostly driven by firms making a limited use of market debt before the start of the program, suggesting a direct, positive impact of the program on the ability of firms to tap in credit markets directly. Finally, we do not find a significantly larger increase in total debt for targeted firms, which indicates a pure substitution effect occurring between bonds and other forms of debt capital.

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Figure 1: Eligible bonds outstanding

The figure presents the total number (right-axis) and amount (in billions of euros; left-axis) of eligible bonds outstanding over time. The two dashed lines represent respectively the week when the CSPP was firstly announced (2016w10) and when the program started (2016w22).

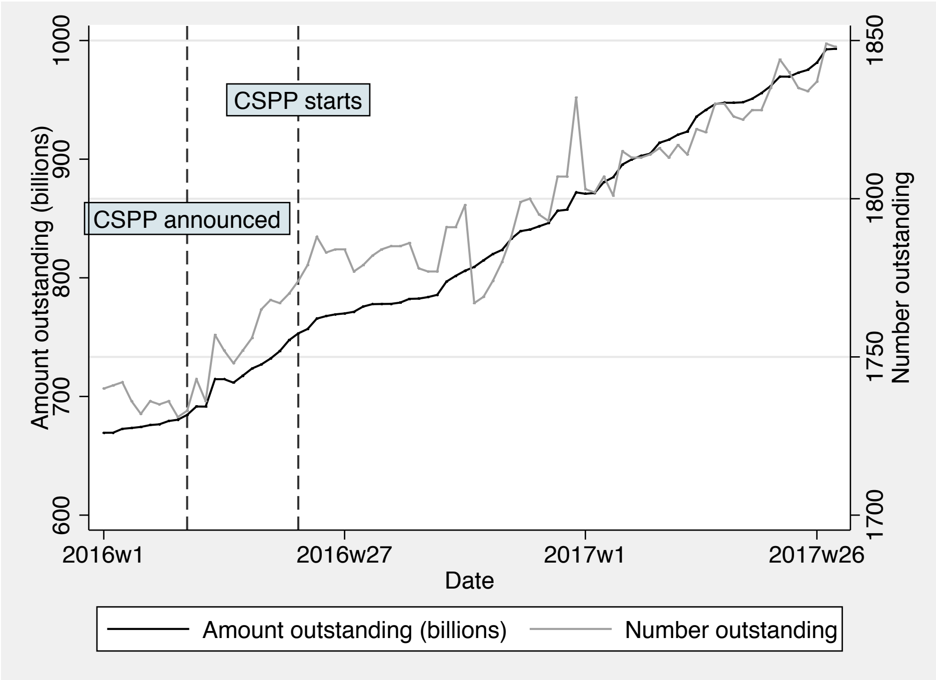

Figure 2: Bonds held under CSPP

This figure presents the number of CSPP bonds over time. The continuous line (left axis) represents for each week the total number of bonds bought under CSPP and still held by national central banks on that week; the dashed line (right axis) presents the share of CSPP bonds over the total number of eligible bonds available on that week.

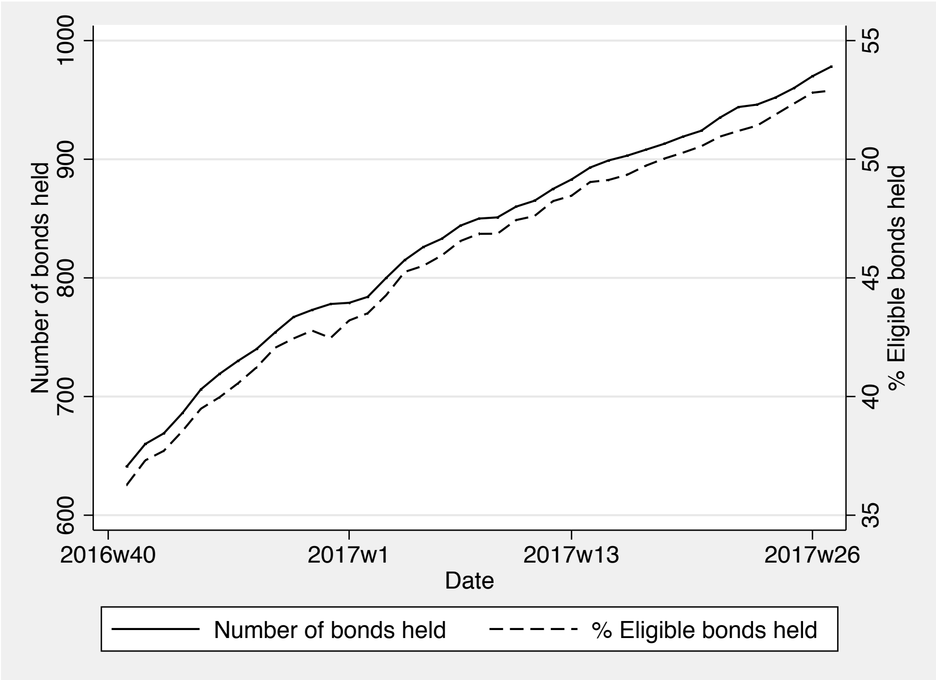

Figure 3: Kaplan-Meier survival curves, second wave

This figure presents Kaplan-Meier survival probabilities estimates for bonds eligible during the second wave of the CSPP program (i.e., after 2016w41) for two group of bonds: those already outstanding at the beginning of the second wave but not yet targeted ($after = 0$; continuous line), and those issued subsequently ($after = 1$; dashed line). Analysis time is measured in weeks. Securities are at risk of being purchased since 2016w42, or since issuance for bonds issued subsequently.

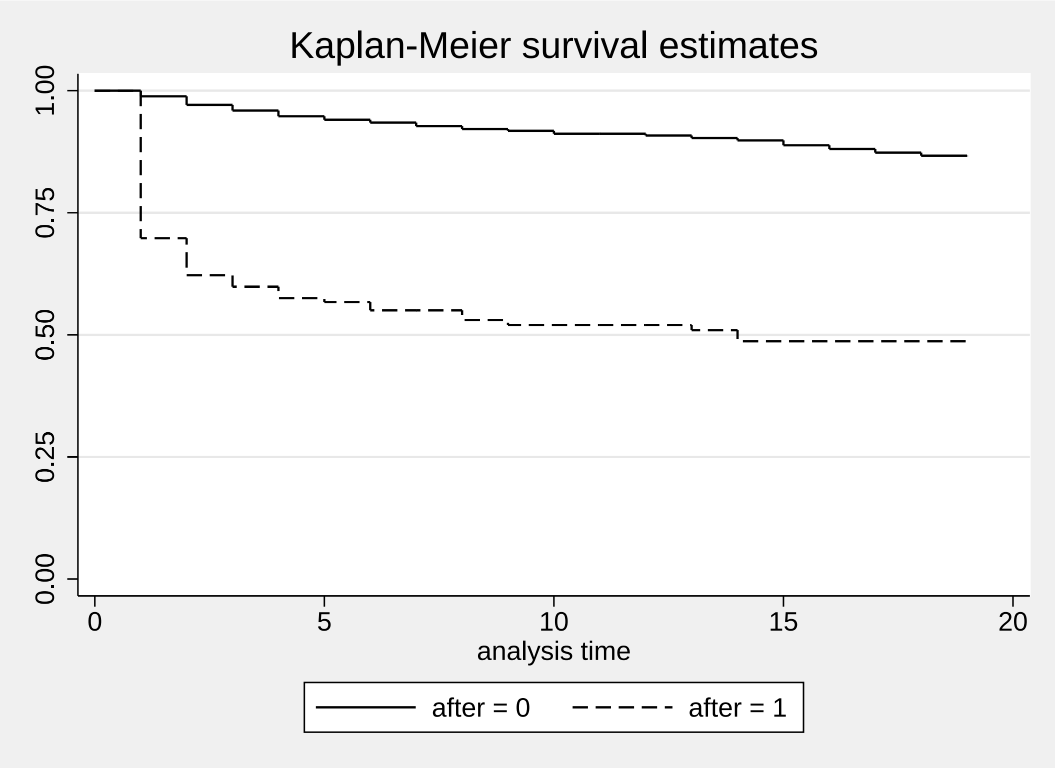

Table 1: Distribution of bonds bought under the Corporate Sector Purchase Program

This table presents the distribution of bonds targeted under the European Corporate Sector Purchase Program (CSPP) by Central Bank (CB) purchasing the bond and by period of the first purchase. First wave bonds are purchased for the first time between week 23 and week 41 of 2016 (included). Second wave bonds are purchased for the first time between week 42 of 2016 and week 27 of 2017. Share (%) represent the fraction of bonds purchased by each CB for each period.

	Whole period		First wave		Second wave	
	N	share (%)	N	share (%)	N	share (%)
Belgium	222	22.24	146	22.78	76	21.29
Finland	65	6.51	41	6.4	24	6.72
France	279	27.96	164	25.59	115	32.21
Germany	226	22.65	161	25.12	65	18.21
Italy	111	11.12	72	11.23	39	10.92
Spain	95	9.52	57	8.89	38	10.64
Total	998	100	641	100	357	100

Table 2: Descriptive statistics, bonds eligible at the start of the program

This table presents descriptive statistics for bond-level and issuer-level variables, including only securities outstanding and eligible as of 2016w22. Bond-level variables are as measured on 2016w22, whereas issuer-level variables are measured at the end of 2015. Statistics are presented for three mutually exclusive group of bonds: those not yet purchased under the CSPP as of 2017w27 (Non-targeted, Panel A); those purchased before 2017w42 (First wave targets, Panel B); and those purchased between 2017w42 and 2017w27 included (Second wave targets, Panel C). Panel D reports for each variable the difference in mean between targeted (both first and second wave) and non-targeted bonds, as well as the t-statistic for a test on the equality of the mean between the two groups. All variables are as defined in Section 4.

	Haircut	Rating	Bid-Ask	SWSP	Ln(1+AOS)	Ln(1+TTM)	LNTA	D/E	Q	Bond ratio
Panel A: Non-targeted										
N	539	470	539	506	539	539	329	327	326	329
Mean	14.02	20.86	0.88	86.58	12.29	7.61	17.91	1.34	1.24	0.36
SD	10.66	3.33	3.96	86.39	1.31	0.87	1.65	1.72	0.41	0.31
P5	1.00	17.00	0.08	-2.20	10.09	6.21	15.06	0.10	0.79	0.02
P50	9.00	20.00	0.43	66.05	12.43	7.65	17.77	0.79	1.13	0.30
P95	36.00	27.00	2.53	255.20	14.08	8.89	21.00	6.09	1.83	1.00
Panel B: First wave targets										
N	563	561	563	559	563	563	456	453	453	456
Mean	16.49	20.07	0.53	63.80	13.36	7.55	17.62	0.78	1.35	0.46
SD	11.28	2.04	0.38	45.75	0.48	0.57	1.23	0.67	0.49	0.25
P5	2.00	17.00	0.10	17.60	12.61	6.49	15.68	0.10	0.93	0.10
P50	14.00	20.00	0.42	54.20	13.30	7.63	17.53	0.73	1.16	0.43
P95	37.00	24.00	1.12	148.80	14.22	8.37	19.44	1.58	2.36	0.98
Panel C: Second wave targets										
N	148	147	148	148	148	148	127	127	127	127
Mean	15.34	20.05	0.55	67.78	13.30	7.63	17.69	0.80	1.35	0.47
SD	11.14	1.83	0.37	48.43	0.46	0.55	1.18	0.59	0.48	0.25
P5	2.00	17.00	0.14	21.00	12.61	6.61	15.75	0.14	0.93	0.11
P50	12.50	20.00	0.45	55.00	13.30	7.70	17.88	0.73	1.19	0.44
P95	36.00	24.00	1.22	152.00	14.00	8.47	19.44	2.29	2.10	1.00
Panel D: difference in mean, targeted vs. non-targeted										
Diff	2.24	-0.79	-0.35	-21.95	1.05	-0.04	-0.28	-0.56	0.10	0.10
t-stat	3.56***	5.11***	2.35**	5.71***	19.764***	1.00	2.90***	7.01***	3.26***	5.47***

Table 3: CSPP target selection

This table presents coefficients estimates for Logit and Cox proportional hazard models for the selection and timing of purchases under the CSPP. The first four columns refer to Logit models estimated on a cross-sectional sample including all bonds outstanding and eligible as of 2016w22 (just before the start of the program); the dependent variable is an indicator equal to one if the bond has been purchased under the CSPP by 2016w41 (included) and zero otherwise. Bond-level variables are measured on 2016w22, whereas issuer-level variables based on accounting variables (i.e., those included only in Models 2 and 4) are measured at the end of 2015. Sector indicators are based on 1-digit SIC codes. Robust standard errors clustered by issuer are reported in round brackets. Columns 5 and 6 refer to duration models estimated on a bond-week panel sample including eligible bonds not yet targeted as of 2016w41, as well as eligible bonds issued subsequently. Securities are considered at risk of being targeted since 2016w42, or since their issuance for bonds created subsequently; they exit the analysis when they are first purchased, when they become no longer eligible, or at the end of the sampling period (2017w27). Unobserved issuer-level effects are modelled as the result of a gamma-distributed latent variable (shared frailty models). N bonds (N targeted) is the number of distinct (purchased) bonds in the sample; N issuers is the number of distinct bonds issuers. All independent variables are as defined in Section 4. *, **, and *** identify statistically significant coefficients respectively at the 10%, 5%, and 1% confidence level.

	First wave–Logit model				Second wave--Duration model	
	(1)	(2)	(3)	(4)	(5)	(6)
Haircut	0.026***		0.018*		0.033***	
	(0.009)		(0.010)		(0.012)	
Bid-Ask	-0.213*		-0.396*		-0.252**	
	(0.127)		(0.202)		(0.112)	
Rating		-0.175**		-0.229**		-0.138**
		(0.082)		(0.103)		(0.063)
SWSP		-0.005***		-0.011***		-0.007***
		(0.002)		(0.003)		(0.002)
Ln (1+AOS)	1.115***	1.067***	2.001***	1.960***	1.306***	1.193***
	(0.143)	(0.145)	(0.166)	(0.178)	(0.139)	(0.148)
Ln(1+TTM)			0.179	0.542***		
			(0.129)	(0.180)		
LNTA			-0.531***	-0.514***		
			(0.128)	(0.145)		
D/E			-0.284*	-0.228		
			(0.167)	(0.191)		
Q			0.070	-0.126		
			(0.278)	(0.275)		
Bond ratio			-1.230*	-1.525***		
			(0.688)	(0.590)		
Frailty variance					2.107***	1.716***
					(0.426)	(0.386)
Sector indicators	No	No	Yes	Yes	No	No
N observations	1250	1167	889	831	20414	17712
N bonds	1250	1167	889	831	749	659
N targeted	563	557	444	441	181	189
N issuers	247	237	177	173	196	184
Pseudo R^2	0.15	0.14	0.27	0.25		

Table 4: Targeted issuers and bonds outstanding

This table presents OLS coefficient estimates for a model of the change in outstanding bonds during 2016. Each observation in the sample represent a firm with at least one bond eligible under the CSPP during the first wave of the program. The dependent variable is $\Delta \ln(\overline{AOS})$, defined as the log-change in the total amount of outstanding bonds and medium-term notes from the same issuer. For Models (1) to (3), $\Delta \ln(\overline{AOS})$ is computed using $\ln(\overline{AOS})$ values on the first and last week of 2016. For Models (4) and (5), the change in $\ln(\overline{AOS})$ between week 1 and week 22 (i.e., just before the start of the CSPP) of 2016 is considered. $Target$ is an indicator equal to one if the issuer has at least one bond purchased under the CSPP during the first wave (i.e., before 2016w42) and zero if no bond from that issuer has been purchsed yet by the end of 2016. Firms targeted for the first time during the last 10 weeks of 2016 are thus excluded. Sector indicators are based on 1-digit SIC codes. All other variables are as defined in Section 4.4. Robust standard errors are reported in round brackets. *, **, and *** identify statistically significant coefficients respectively at the 10%, 5%, and 1% confidence level.

$\Delta \ln(\overline{AOS})$	Up to 2016w52			Up to 2016w22	
	(1)	(2)	(3)	(4)	(5)
$Target$	0.134***	0.224***	0.355***	0.041	0.064
	(0.045)	(0.085)	(0.106)	(0.025)	(0.043)
$Target \times Bond\,ratio$			-0.703***		
			(0.244)		
$LNTA$		-0.021	-0.010		-0.002
		(0.029)	(0.028)		(0.015)
D/E		-0.015	-0.006		-0.016
		(0.028)	(0.029)		(0.010)
Q		-0.024	-0.017		-0.011
		(0.087)	(0.086)		(0.041)
$Bond\,ratio$		-0.425	0.236		-0.129
		(0.265)	(0.258)		(0.098)
$Constant$	0.112***			0.046**	
	(0.033)			(0.021)	
Sector indicators	No	Yes	Yes		
N observations	245	164	164	245	164
N $target = 1$	176	137	137	176	137
R^2	0.02	0.10	0.11	0.01	0.11

Table 5: Targeted issuers and debt financing

This table presents OLS coefficient estimates for models of the change in total debt and debt composition during 2016. Each observation in the sample represent a firm with at least one bond eligible under the CSPP during the first wave of the program. Two dependent variables are considered, both focusing on the variation in outstanding debt between the beginning and the end of 2016. $\Delta Bondratio$ is the change in $Bondratio$; the ratio at the end (beginning) of 2016 is computed using the 2016 (2015) balance sheet value for total debt (D) as the denominator, and the total amount of outstanding bonds and medium-term notes from the same issuer measured on the first week of 2017 (2016) as the numerator. $\Delta ln(D)$ is the log-change in D between 2015 and 2016. $Target$ is an indicator equal to one if the issuer has at least one bond purchased under the CSPP during the first wave (i.e., before 2016w42) and zero if no bond from that issuer has been purchsed yet by the end of 2016. Firms targeted for the first time during the last 10 weeks of 2016 are thus excluded. Sector indicators are based on 1-digit SIC codes. All other variables are as defined in Section 4.4. Robust standard errors are reported in round brackets. *, **, and *** identify statistically significant coefficients respectively at the 10%, 5%, and 1% confidence level.

	Δ ln(D)		$\Delta Bond\,ratio$	
	(1)	(2)	(3)	(4)
$Target$	0.031	-0.016	0.050***	0.052*
	(0.050)	(0.062)	(0.019)	(0.027)
$LNTA$		0.012		-0.013
		(0.019)		(0.009)
D/E		-0.028**		-0.003
		(0.012)		(0.005)
Q		0.048		-0.011
		(0.048)		(0.017)
$Bond\,ratio$		0.194		-0.076
		(0.135)		(0.079)
$Constant$	0.028		0.014	
	(0.046)		(0.015)	
Sector indicators	No	Yes	No	Yes
N observations	170	164	170	164
N $target = 1$	140	136	140	136
R^2	0.00	0.13	0.03	0.08