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The effects of the Eurosystem's APP on euro area bank lending: Letting different data speak

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Non-technical summary

Research Question

The Eurosystem's expanded asset purchase programme (APP) aims at stimulating economic growth and thus, inflation by acquisition of securities, especially government bonds, via a number of transmission channels and variables. From a monetary perspective, this effect should be supported by enhanced access of firms to finance, especially bank loans. In order to evaluate the effectiveness of the APP it is thus of great interest to determine whether the impulse provided by the programme actually leads to higher growth rates of bank lending to firms.

Contribution

Using two different measures derived from confidential euro area bank-level data, we identify whether a bank was affected positively by the APP with respect to its lending capacity, and whether this bank in fact subsequently increased its lending to euro area non-financial corporations (NFCs). To that aim, our analysis compares in a novel way the banks' self-assessment to its actual selling behaviour with respect to government bonds.

Results

We find that the APP was effective in stimulating the lending activity with NFCs for a subset of sound banks. This effect is corroborated by both the banks' self-assessment and their government bonds selling behaviour. At the same time, our results show that a non-negligible number of euro area banks whose balance sheets have not recovered yet were not able to transfer the APP's expansive stimulus into higher lending. Instead, such banks appear to have increasingly used the APP stimulus to consolidate their balance sheets, thereby also reducing their lending business with NFCs, which is usually classified as risky. Our evidence is based on the comparison of different subsets of the investigated sample of banks and thus suggests that in monetary policy analyses the heterogeneity among banks has to be taken into account.

Nichttechnische Zusammenfassung

Fragestellung

Das erweiterte Wertpapierankaufprogramm des Eurosystems (APP) soll durch den Erwerb von Schuldtiteln, insbesondere von Staatsanleihen, über eine Vielzahl von Transmissionskanälen und Einflussgrößen stimulierend auf die Wirtschaftsentwicklung und damit auf die Inflationsrate wirken. In monetärer Hinsicht soll diese Wirkung über einen verbesserten Zugang der Unternehmen zu Finanzierungsmitteln, insbesondere Bankkrediten, unterstützt werden. Zur Evaluation der Wirksamkeit des APP ist es daher von großem Interesse, festzustellen, ob die durch das Programm gesetzten Impulse auch zu einer höheren Wachstumsrate von Bankkrediten an Unternehmen geführt haben.

Beitrag

Wir ermitteln anhand zweier verschiedener Maße, die aus vertraulichen Bank-Einzeldaten abgeleitet sind, ob eine Bank durch das APP in ihrer Fähigkeit zur Vergabe von Krediten positiv beeinflusst wurde und ob diese Bank in der Folge auch tatsächlich mehr Kredite an nichtfinanzielle Unternehmen vergeben hat. Unsere Analyse vergleicht zu diesem Zweck in neuartiger Weise Selbsteinschätzungen der Banken mit ihrem tatsächlichen Verkaufsverhalten bei Staatsanleihen.

Ergebnisse

Wir stellen fest, dass das APP für eine Teilmenge solider Banken, die von dem Programm profitiert haben, die monatliche Wachstumsrate der Kredite an nichtfinanzielle Unternehmen erhöht hat. Dieser Effekt wird sowohl von der eigenen Einschätzung der Banken als auch von ihrem Verkaufsverhalten bei Staatsanleihen gestützt. Gleichzeitig zeigen unsere Ergebnisse, dass eine nicht zu vernachlässigende Zahl von Banken im Euroraum, deren Bilanzen noch nicht vollständig gesundet sind, bisher nicht in der Lage war, den expansiven Stimulus des APP in eine höhere Kreditvergabe umzusetzen. Stattdessen nutzten solche Banken den positiven APP-Impuls offenbar verstärkt zur Sanierung ihrer Bilanzen und führten in diesem Zuge auch ihr (üblicherweise als risikoreich geltendes) Kreditgeschäft mit nichtfinanziellen Unternehmen zurück. Diese Erkenntnis basiert auf dem Vergleich verschiedener Abgrenzungen der betrachteten Bankenstichprobe und legt somit nahe, dass bei der Evaluierung von geldpolitischen Effekten die Verschiedenartigkeit der Banken berücksichtigt werden muss.

DEUTSCHE BUNDESBANK DISCUSSION PAPER NO 26/2019

The Effects of the Eurosystem's APP on Euro Area Bank Lending: Letting Different Data Speak[1]

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Abstract

We study the implications of the Eurosystem's expanded Asset Purchase Programme (APP) for the bank lending business of euro area banks with euro area non-financial corporations (NFCs) using microeconometric matching techniques. Based on confidential bank-level data on quantitative balance sheet items and interest rates as well as on qualitative survey responses to the Eurosystem's Bank Lending Survey, we identify the exposure of banks to the APP and corresponding effects on loan growth. We find that the APP was effective in stimulating the lending activity with NFCs for a subset of relatively sound banks. At the same time, our results show that there is a non-negligible number of banks with less healthy balance sheets which could not transfer the APP stimulus into more lending. Instead, such banks appear to have used the APP stimulus for consolidating their balance sheets, thereby also reducing their lending business with NFCs. This confirms the importance of accounting for the large degree of heterogeneity in the euro area banking sector in analyses of the effectiveness of monetary policy measures.

Keywords: Lending to non-financial corporations, bank-level data, bank heterogeneity, unconventional monetary policy, treatment effects, regression-adjusted matching.

JEL-Classification: E52, G21, C21.

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1 Introduction

Since the slowdown of inflation in the aftermath of the sovereign debt crisis, the predominant topic in monetary policy in the euro area was about providing expansionary monetary stimulus to the economy in order to bring inflation back on a sustainable path around the Eurosystem's medium-term inflation aim. Facing the constraint of not being able to lower short-term interest rates much further, the Eurosystem increasingly engaged in unconventional monetary policy (UMP) measures, most notably outright transactions on securities markets.

While these transactions potentially work through several transmission channels, our study investigates empirically one specific aspect, namely the effects of the "expanded asset purchase programme" (APP) on lending to euro area non-financial corporations (NFCs) by euro area monetary financial institutions (MFI). The effects of the APP on bank lending are of great interest, especially to policy makers, as credit growth forms an important part of the monetary transmission mechanism. By referring explicitly to the very favourable financing conditions that are provided by the APP, the Eurosystem expects its measures to stimulate the bank lending business with the non-financial private sector and thus to encourage new investment projects by firms and households. Given the importance of bank-based financing in many euro area countries, enhanced bank lending should play a prominent role in a recovery process.

We contribute to the literature in three ways: First, we use three confidential data sources by combining detailed balance sheet information from the Individual Balance Sheet Items (IBSI) statistics and newly available data on individual replies of banks to the Eurosystem's Bank Lending Survey (IBLS) with bank-specific interest rates from the Individual MFI Interest Rate (IMIR) statistics. The combination of these three non-anonymised data sources is unique in evaluating the connection between bank lending behaviour, bank characteristics, and the APP. Second, our paper evaluates the APP-related effects on bank lending activity by using two different measures for treatment, i.e. affectedness by the programme. On the one hand, we analyse the APP effects on bank lending using subjective self-assessment by banks provided by IBLS information to identify APP-treated banks, i.e. banks impacted most by the APP, like Altavilla, Boucinha, Holton and Ongena (2018). On the other hand, we compare our results with an alternative treatment measure, exploiting individual banks' balance sheet information on actual net government bonds transactions to identify APP-treated banks. In doing so, we examine the sensitivity of our results not only to the two alternative treatment measures, but also with respect to two different sub-samples of banks – a smaller sample of 103 banks regularly surveyed within the BLS versus a larger sample of 254 banks based on IBSI and IMIR data.

The third and most important contribution of our paper is based on the application of a different empirical method. In contrast to Albertazzi, Becker and Boucinha (2018) and Altavilla et al. (2018), which both use the difference-in-difference method to analyse the effects of the APP on euro area bank lending, we refine our analysis by additionally using matching techniques which sharpen the analysis of treatment effects. Although matching methods are commonly used in micro-data based evaluations of policy interventions or experimental studies, especially in the labour market literature and in political sciences,[2] they are still very scarcely employed for evaluating the effects of monetary policy interventions. Our paper fills this gap. The peculiarity of the matching approach lies in the possibility to reweigh units – in our case banks – to improve the covariate balance between the treatment and control group of banks such that the treatment variable becomes as independent as possible of other bank characteristics.

The identification of APP-treated and non-treated banks is an important issue in our analysis. Even if we recognize that nearly all euro area banks may have been affected by the APP – via different transmission channels –, we suppose that some banks could benefit more from this UMP measure than others. Indications for this conjecture can be found in IBLS data. According to the survey results, only in one fifth of the cases, the banks reported a positive impact of the APP on their liquidity position. In the remaining cases, the banks reported "basically no impact" (Table 8). We use these different answers to build two groups of banks – treated and non-treated – which we compare with respect to their lending behaviour during the APP period. In our second identification variant, we use quantitative information from IBSI data to distinguish between treated and non-treated banks. As the quantitative bank-level information regarding APP-induced claims against the Eurosystem is missing in the IBSI dataset for confidentiality reasons, we use bank balance sheet positions related to APP-eligible securities as auxiliary information to identify the APP-treated banks. In particular, we denote those banks as treated which have sold, on balance, APP-eligible securities during the APP period. The intuition behind this approach can be found e.g. in Gennaioli, Martin and Rossi (2014), Ongena, Popov and Van Horen (2016), Andreeva and Vlassopoulos (2016) and Altavilla, Pagano and Simonelli (2017). These studies indicate that during the sovereign stress period, banks located especially in stressed countries had increased their holdings of domestic sovereign debt securities, and that this increase in banks' sovereign exposure tended to result in a stronger reduction of

[2] See e.g. Bryson, Dorsett and Purdon (2002), Marcus (2013).

their lending to the private sector. Corresponding to this finding, we expect a supporting impact of APP-induced sales of government securities on lending activity.

There are several empirical studies that analyse the economic effects of UMP. Most of these studies focus on the transmission of UMP on credit rates and/or on yields and prices of financial assets and provide clear evidence that UMP was effective in lowering lending rates and alleviating financing conditions for firms.[3] Less evidence exists, however, with respect to the further propagation of these "price effects" to banks' lending volumes. Existing studies are mainly conducted for single countries, based on national data sources – in particular credit register information – and provide mixed evidence: For France, the launch of the Eurosystem's very long-term (three-year) refinancing operations (VLTRO) programme is found to have a positive impact on credit supplied to larger firms (Andrade, Cahn, Fraisse and Mesonnier (2015)) as well as high-quality SMEs with a strong single-bank relationship, whereas weak firms with high leverage could not benefit from the programme (Cahn, Duquerroy and Mullins (2017)). In contrast, in Spain the VLTROs increased bank lending to SMEs, but not to large firms (Garcia-Posada and Marchetti (2016)), and the Eurosystem's corporate sector purchase programme (CSPP) even led to a drop in the demand for bank loans by (usually large) bond-issuing firms while at the same time it exhibited a positive effect on the supply of new bank loans to smaller firms which typically do not issue bonds (Arce, Gimeno and Mayordomo (2017)). Studies on Italy (Carpinelli and Crosignani (2017)) and Portugal (Blattner, Farinha and Nogueira (2016)) find overall positive effects of the Eurosystem's UMP, whereas for Germany, there is no evidence of a positive volume effect on bank lending of the VLTROs (Bednarek, Dinger, te Kaat and von Westernhagen (2018)). In contrast, the APP is found to corroborate lending by German banks (Tischer (2018), Paludkiewicz (2018)). Taken together, these findings indicate that in a euro area perspective, the effects of UMP can be expected to entail a large degree of heterogeneity.[4]

So far, there are only two micro-data based studies that analyse APP-related effects on bank lending activity for the euro area as a whole. In contrast to single-country studies, such multi-country analyses enable a more consistent comparison between countries or country groups as they can be investigated within the same modelling framework.[5] Albertazzi et al. (2018) use data on securities holdings for the 25 largest euro area banks

[3] See, e.g., Christensen and Rudebusch (2012), Baumeister and Benati (2013), Altavilla, Carboni and Motto (2015), Falagiarda and Reitz (2015), Altavilla, Canova and Ciccarelli (2016), Albertazzi, Nobili and Signoretti (2016), and Krishnamurthy, Nagel and Vissing-Jorgensen (2018).

[4] Alcaraz et al. (2018) even report a dampening effect of a special UMP event, the "whatever it takes" speech by ECB President Draghi in July 2012, on lending growth.

[5] Also the recent study by Laine (2019) carries out a micro-data based multi-country analysis for euro area banks. However, this study focuses on the effects of targeted longer-term refinancing operations (TLTRO) on bank lending and documents a corroborating effect of TLTRO II on lending to NFCs.

matched with bank-level information on loan amounts and corresponding lending rates for the non-financial private sector. By comparing the composition of bank portfolios between 2014 Q1 and 2015 Q2, the authors find evidence for an APP-related increase in lending volumes which is, however, limited to banks in non-vulnerable countries.[6] Altavilla et al. (2018) employ bank-specific survey responses from the BLS combined with individual balance sheet information for more than 100 euro area banks. Based on the difference-in-difference method, they find positive effects of the APP on the lending behaviour of APP-treated BLS banks. We extend these analyses in three ways: first, by considering complementary indicators for the APP treatment, second, by using a larger sample of heterogeneous banks and third, by applying a different estimation method – the matching approach.

We find that the APP was effective in stimulating the lending activity with euro area NFCs for a subset of the banks. For this group of relatively sound banks, the documented effect is robust to the different identification measures and to the different matching strategies. At the same time, our study shows that there is another group of banks featuring less healthy balance sheets which could not transfer the APP stimulus into more lending to NFCs. Instead, these banks appear to have used the APP stimulus to consolidate their balance sheets, thereby also reducing potentially risky lending business with NFCs. Thus, the APP appears to have encouraged banks with existing deleveraging needs to recapitalize and to restructure their balance sheets accordingly. Our results confirm the importance of accounting for the large degree of heterogeneity in the euro area banking sector in analyses of unconventional monetary policy measures like the APP as such measures might have different effects on different groups of banks.

The remainder of this paper is organised as follows. Section 2 describes the dataset. Section 3 presents our modelling approach, while Section 4 discusses the empirical results and Section 5 concludes.

2 Data

We use a unique dataset by combining three different confidential bank-level data bases compiled by the Eurosystem, i.e. data from the Individual Balance Sheet Items (IBSI) statistics, from the Individual MFI Interest Rate (IMIR) statistics, as well as newly available data on Individual Bank Lending Survey (IBLS) replies.

[6] Altavilla et al. (2017) use the bank-level balance sheet items (IBSI) statistic for a total of 226 euro area banks and analyse the determinants of banks' sovereign exposure and its effects on banks' lending behaviour for the time period from 2008 Q1 to 2014 Q1. In contrast to Albertazzi et al. (2018), however, Altavilla et al. (2017) do not explicitly account for a UMP measure in their loan equation, and therefore do not admit any statement regarding its effectiveness.

The IBSI data contain granular information on the main balance sheet items for approximately 300 euro area banks. The sample of banks was selected to reproduce the structure of the national banking systems of the 19 euro area countries, to reflect the banks' participation in the refinancing operations and to reflect the heterogeneity among the banks depending on their business models relating for example to the bank-funding, risk-taking, or bank-lending behaviour.[7] While the IBSI sample represents a relatively small subset, in terms of numbers, of the total amount of about 8,000 euro area banks, its coverage relating to both, main assets of the euro area banking system and loan provision to the euro area non-financial corporation sector is reasonably large, amounting to approximately 80 percent. The IBSI data are available at a monthly frequency starting in August 2007. The last observation in our analysis corresponds to January 2018. For bank lending activity, we calculate the index of notional stocks of loans to non-financial corporations.[8] The final IBSI sample used in our analysis consists of 254 banks located in 18 euro area countries.

The shrinkage of our sample is caused by the merger with the second data source, the IMIR dataset, as not all banks in the IBSI sample are also included in the IMIR sample. The IMIR data contain bank-level information on lending rates (for both, new business loans and outstanding amounts), on deposit rates, as well as on new business loan volumes. By including individual bank lending rates, we take into account that a bank's lending business, in addition to its balance sheet characteristics, also depends on the interest rates charged, which are determined, inter alia, by bank-specific borrower demand. The lending rates entering our analysis are volume-weighted averages of lending rates applied to newly granted loans by each bank in each month, with weights based on the bank's new business volumes across different maturity windows.

The third dataset used in our analysis is the newly available proprietary individual bank lending survey data IBLS. The IBLS dataset provides qualitative information on banks' past and expected future lending policies by surveying both, the demand for as well as the supply of loans to non-financial corporations and households, from the viewpoint of the bank. The survey questionnaire consists of two blocks: In the regular block, surveyed banks are asked on a quarterly basis, among other things, for the changes in lending standards they apply to the provision of loans, for the factors responsible for these changes, for their perceptions of loan demand, and for the factors responsible for the observed changes in loan demand. Apart from these standard questions asked each quarter, the survey also includes a number of questions asked semi-annually on an ad-

[7] For a detailed overview of the purpose of the IBSI data collection, see Morandi and Bojaruniec (2016).
[8] Notional stocks are adjusted for reclassifications, revaluations (e.g. write-downs) and other breaks in the series, implying that only transaction-based changes are used to compute the chain-linked monthly stock figures.

hoc basis to obtain supplementary information on specific issues, such as on the impact of the Eurosystem's non-standard measures on banks' lending policies. One question asked is how the Eurosystem's expanded asset purchase programme has affected banks' lending behaviour during the past six months. There are five different predefined answer categories ranging from "has contributed considerably to a tightening" to "has contributed considerably to an easing".

Table 7 shows the frequencies of banks' replies on the impact of the APP on credit standards for the three different loan categories included in the BLS, cumulated over seven different survey rounds. According to these numbers, less than 5 percent of the answers refer to banks having adjusted their credit standards for loans to NFCs in response to the APP. As the number of survey replies indicating non-negligible effects of the APP on credit standards is very small, they cannot be used for the analysis of effects on actual loan growth, in particular as banks appear to be traditionally conservative with regard to reporting an easing of their credit standards. For this reason, we look alternatively at the question asking banks to assess the effects of the APP on items indirectly related to their lending policy. In particular, this question deals with the effects of the APP on banks' total assets, on their liquidity position, on market financing conditions, on banks' profitability as well as on their capital ratio. As shown in Table 8, the number of banks indicating non-negligible effects of the APP on these items is substantially larger. For the purpose of our analysis, and in line with Altavilla et al. (2018), we focus on the survey replies referring to the bank's liquidity position as this item can be expected to capture the impact of the APP that is most related to the bank's lending capacity. Overall, using the IBLS information goes along with a further reduction of the number of observations as the IBLS sample comprises fewer banks than the IBSI and IMIR datasets. Thus, our final specification based on IBSI/IMIR/IBLS data contains 110 banks located in 11 countries of the euro area.

As the number of observations shrinks noticeably once the IBLS information is included, we follow two different strategies to analyse the treatment effects: First, we use the IBLS information accepting some loss of observations compared to the larger IBSI/IMIR dataset. Second, we conduct our analysis by accounting solely for the quantitative information based on IBSI and IMIR data. In doing so, we aim at comparing the information content of the IBSI/IMIR/IBLS sample against the IBSI/IMIR dataset.

3 Model

In order to retrieve the effects of the APP on bank lending to NFCs on the basis of individual bank level data, identifying assumptions have to be taken that distinguish banks which were affected by the APP from those who were not. Given the high degree of connectedness of participants in financial markets, this is not a trivial task. In particular, it is not advisable to restrict the group of "treated" banks only to those who actually sold bonds to the Eurosystem – even if such data were available to researchers at all[9] – as the APP had an impact on the overall level of bond prices, triggering much broader reactions. Therefore, we employ two alternative measures which we expect to be suitable proxies for APP affectedness, which represent slightly different aspects of the APP and differ also with respect to data coverage.

On the one hand, we consider each bank's net transactions in government bond securities over the period of the APP (starting in January 2015): if the bank sold government bonds on balance over this period, we classify it as a "treated" bank owing to its net bond selling position. Thereby, we also include banks which sold government bonds to other market participants, potentially due to the favourable pricing of bonds, and we exclude banks which actually bought more bonds than they sold (even if they might have sold them to the Eurosystem), as they were obviously harmed by the higher level of bond prices compared to a world without the APP.[10]

On the other hand, we employ the banks' self-reported affectedness by the APP according to the BLS. We use the answers to the survey question whether a bank's liquidity position was affected by the APP (with higher values denoting more positive effects) and classify a bank as "treated" owing to its BLS response if the average response across several survey rounds is larger than a threshold value. For robustness, this threshold value is computed from different percentiles of the cross-section distribution of the responses. This measure can in principle cover even more indirect effects of the APP, as a bank's liquidity position can also be improved by its customers' sales of bonds if the customer places the revenue with her bank account. On the downside, this measure might entail more data uncertainty due to the qualitative scale of the individual response and the mere fact that it is a subjective self-assessment of the bank. In fact, the two measures are only very weakly correlated across banks (Table 1), suggesting that they are complementary proxies for the treatment status of a bank with respect to the APP. Potentially similar effects on bank lending obtained for these two different measures should therefore strengthen their implications.

We use the grouping information from each of the two alternative measures to compute the difference in the average growth rate of loans to NFCs over the APP period between

[9] Note that even the use of confidential transactions data would not afford this narrow identification as a large number of transactions between the Eurosystem and bond selling individuals is channelled through intermediaries such that the ultimate seller often remains unknown for the purchasing institution, see e.g. European Central Bank (2017) or Avdjiev, Everett and Shin (2019).

[10] We acknowledge that the APP presumably also improved aggregate demand such that the counterfactual is not simply a world with only higher bond returns. However, for our identification we only have to assume that such demand effects are homogeneous across (groups of) banks.

the treatment group and the non-treatment group of banks. Given that the assumption of statistical independence between these groups is probably violated and therefore, statistical inference on group differences might be biased, we condition the difference in the average loan growth rate on characteristics of the banks that emerged in the pre-APP period, using the method of regression-adjusted matching in the spirit of Heckman, Ichimura and Todd (1997). In particular, we regress the average loan growth rate on the treatment status of each bank and a number of control variables in a weighted least-squares cross-section regression. The weights are obtained from matching algorithms that aim at balancing the pre-APP characteristics of the banks in the different (treated and non-treated) groups.

Table 1: Correlation between different treatment indicators

	Net bond seller	BLS, p50	BLS, p60	BLS, p70
Net bond seller	1			
BLS, p50	0.095	1		
BLS, p60	-0.033	0.654***	1	
BLS, p70	-0.040	0.596***	0.912***	1

Note: Pairwise correlation coefficients of the corresponding dummy variables within the IBLS/IBSI/IMIR cross-section dataset. ***, **, * denote significance at the 1%, 5%, 10% level.

In order to model the conditioning factors that determine both, the bank's propensity to be affected by the APP and its loan growth, we include a number of bank characteristics commonly used in the standard bank lending literature (see e.g. Kashyap and Stein (1995, 2000), Peek and Rosengren (1995), Gambacorta (2005, 2008)) as control variables (Table 6 in the Appendix). For the purpose of our analysis, all control variables are computed as time averages for each bank over the period July 2007 to September 2014.[11]

The amount of securities that the bank held on its balance sheet (as a ratio to its main assets) prior to the APP should be positively related to the propensity to sell these securities under the APP. Banks that held more securities on their balance sheets potentially had limited access to external finance on the capital market and therefore needed a higher stock of securitized assets for liquidity-buffering reasons. Such banks can be considered as less robust to shocks as they refrained from risky lending to the private sector. The APP should have provided incentives to sell government bonds due to the favourable pricing, thus relieving liquidity constraints of such banks and increasing their willingness and ability to engage in lending to NFCs. The degree to which the liability side of the balance sheet is dominated by deposits should be

[11] We use September 2014 as the final period for pre-APP information as an APP-like program might have become increasingly anticipated by market participants thereafter.

inversely related to the bank's ability to finance its assets via capital markets and thus, to the impact the APP has on its refinancing costs. The pre-APP amount of NFC loans (as a ratio to its main assets) is related to the bank's business model and thus, should determine to which degree the bank engages in NFC lending as opposed to alternative investments following a change in its liquidity situation. The degree of capitalization, i.e. the ratio of capital and reserves to main assets, should be related to the financial strength of the bank, i.e. it should be inversely related to the necessity of the bank to participate in the APP to grant new loans. The market share of the bank, measured by the amount of its main assets relative to the sum of main assets across all national competitors, should be related to its market power or size: smaller banks suffer more from informational frictions on financial markets facing a higher cost in raising funds especially in stressed periods. Smaller banks therefore tend to lend less than larger banks in stressed times instead of drawing down cash and securities to avoid to be forced to seek costly external finance in the next period. In addition, smaller banks tend to lend to smaller, more vulnerable firms. For both reasons, in uncertain times they can be expected to sell less of their securities holdings and to engage less in lending compared to larger banks. The lending rate represents the pricing of new loans to NFCs and therefore exhibits both, supply and demand effects on lending volumes. In the context of our regression, given that the other control variables predominantly take account of supply-side influences, we expect the lending rate to capture mainly bank-specific borrower demand effects. In that respect, a higher lending rate before the APP should indicate weaker demand, increasing both the propensity to liquidize government bonds and the potential to foster loan growth by lowering lending rates.[12] Finally, the location of a bank, i.e. whether it resides in a country that was hit severely by the sovereign debt crisis, should affect its willingness to sell (domestic) government bonds and invest freed-up funds into new lending. Again, taking into account these control variables in our regression-adjusted matching approach aims at improving the covariate balance between the treated and non-treated groups of banks such that the estimated treatment effect becomes as independent as possible of other bank characteristics.

We use two different methods for the matching: propensity-score (PS) matching and entropy balancing. Under the former method, we estimate a probit model with the treatment status of the bank as the dependent variable and the bank characteristics as the regressors, and forecast the treatment propensity score, i.e. the probability to receive the treatment conditional on the covariates (Rosenbaum and Rubin (1983), Caliendo and Kopeinig (2008)). Regression weights to be used in the second step to estimate the treatment effects on loan growth are obtained in different ways. The nearest-neighbour PS

[12] Note that we do not aim at identifying loan supply versus loan demand in our model, but rather wish to clean the estimated treatment effects as much as possible from any such factors.

matching selects the non-treated bank with the closest propensity score to each treated bank and calculates weights based on the frequency of selections of each non-treated bank. In contrast, the kernel PS matching attributes for each treated bank a weight to each non-treated bank that decreases with the distance between their propensity scores and sums across matchings (in both cases, a treated bank receives a weight of one).

The alternative matching approach, entropy balancing, focuses on the sample moments of the untreated banks directly instead of using the estimated propensity score (Hainmueller (2012)). Regression weights used in the second step of the regression-adjusted matching approach are retrieved by optimizing over the weights that constitute a weighted average of non-treated banks' observations which comes closest to the average of the treated banks' observation in terms of distance or entropy (with treated banks again receiving a weight of one each).

As the regression-adjusted matching approach entails assigning a weight to each bank according to its time-invariant characteristics in the pre-APP period, and given the question we are interested in (the average benefit of the APP for credit growth), our main analysis will be conducted within a cross-section data setup.[13]

4 Empirical results

4.1 Main findings

Table 2 shows the estimated average treatment effects for our two alternative measures of APP affectedness: the first treatment measure is based on the bank's answer to the BLS question on the APP's impact on its liquidity position ("positive BLS response"), and the second is based on the bank's net selling position with respect to euro area government bonds over the APP period ("net government bond seller").[14] The results for the positive BLS response are based on a sample that is constructed by merging IBSI, IMIR and IBLS data, thus comprising 103 banks (see the first column of Table 3 for the distribution of treated and total banks across countries). The estimates in Table 2 indicate that there is a positive average difference between the loan growth rates of APP-affected and non-affected banks over the APP period. The evidence becomes strongest (in terms of

[13] As a robustness check and for sake of completeness, we also conduct alternative estimations exploiting the panel dimension of our data. The corresponding results are discussed at the end of the following section.

[14] For the full set of results, see Appendix: Tables 9 to 12 present the implications of the matching step, i.e. the sample means of the control variables and how they are affected by propensity score matching and entropy balancing. Both matching variants achieve a fairly high degree of comparability between the groups of treated and non-treated banks across all specifications discussed here. Tables 13 to 16 present the results of the regression step. Since the two steps are considered as complementary approaches to reduce the bias in the comparison of loan growth between treated and non-treated banks, we do not apply any elimination strategy with respect to insignificant coefficient estimates.

magnitude of the estimated coefficient) for the 60^{th} percentile of the cross-section distribution of the average response to the BLS question, suggesting that this threshold is the most likely cut-off between the treatment and the non-treatment group of banks. The difference in loan growth becomes significant (at the 10% level) once the characteristics of treated and non-treated banks in the pre-APP period become more balanced and thus, more comparable, through matching: especially the kernel variant of propensity score matching and the entropy balance matching variant which use the information from all banks in the sample for each match deliver a relatively high degree of estimation precision in the regression step compared to the unweighted and the nearest-neighbour matching variant. According to these estimates, the APP effect amounts to approximately 0.22 percentage points per month on average, i.e. banks that reported a positive impact of the APP on their liquidity position realized an average monthly growth rate of their NFC lending that was 0.22 percentage points higher than the counterfactual average loan growth without this positive APP impact. This result for the monthly growth rate is in line with Altavilla et al. (2018) who estimate, for the same sample of banks, that the average quarterly growth rate of loans to NFCs is approximately 0.6 percentage points higher than the counterfactual.

Table 2: APP effects on NFC loan growth

	Positive BLS response			*Net government bond seller*	
Variants	50th pctl	60th pctl	70th pctl	IBSI / IMIR / IBLS	IBSI / IMIR
Unweighted	0.119	0.214	0.107	0.120	-0.373
	(0.132)	(0.133)	(0.140)	(0.141)	(0.350)
PSW1	-0.027	0.238	0.088	0.229*	-0.182
	(0.112)	(0.177)	(0.113)	(0.123)	(0.311)
PSWK	0.083	0.229*	0.105	0.213*	-0.387
	(0.119)	(0.121)	(0.0978)	(0.114)	(0.280)
EBW	0.021	0.214*	0.096	0.185*	-0.444
	(0.0921)	(0.114)	(0.0961)	(0.108)	(0.276)

Note: Unweighted refers to the estimated coefficient of the treatment indicator in a linear unweighted regression of the average monthly growth rate of NFC loans on the treatment indicator and the control variables; PSW1 / PSWK / EBW denote the corresponding estimated coefficient in the equivalent weighted-least-squares regression using propensity-score weights (nearest-neighbour variant) / propensity-score weights (kernel variant) / entropy-balance weights. Standard errors are given in parentheses below the coefficients; an asterisk denotes significance at the 10 % level.

The results for the identification approach using the bank's net government bond selling position are depicted in the right part of Table 2. Employing the same sample of 103 BLS banks (although no IBLS information is used for this estimation), we obtain fairly similar APP effects: using the matching information from both the propensity score matching and the entropy balancing, the estimated difference in average monthly growth rates of NFC loans between a bank that sold government bond on balance and its counterfactual bank that did not sell those assets amounts to values around 0.21 percentage points and is statistically significant at the 10% level.[15]

As indicated above, our empirical specification using the information about the actual bond selling behaviour of banks does not rely on IBLS data and therefore does not have to be restricted to the sample that includes IBLS banks only. The second and third columns of Table 3 signify the consequences of relaxing this constraint in terms of numbers of banks: the total number of banks used in the sample increases to 254, while the share of treated banks remains nearly unchanged at about 70%. However, the estimation results for this extended sample (last column in Table 2) differ substantially from those obtained for the smaller sample of 103 BLS banks: the estimated effect is not significant and shows even the reversed sign. This result remains in place even when we account for more balanced bank characteristics between treated and non-treated banks according to the three different variants of matching in the regression.

Table 3: Number of treated and total banks across treatment and samples

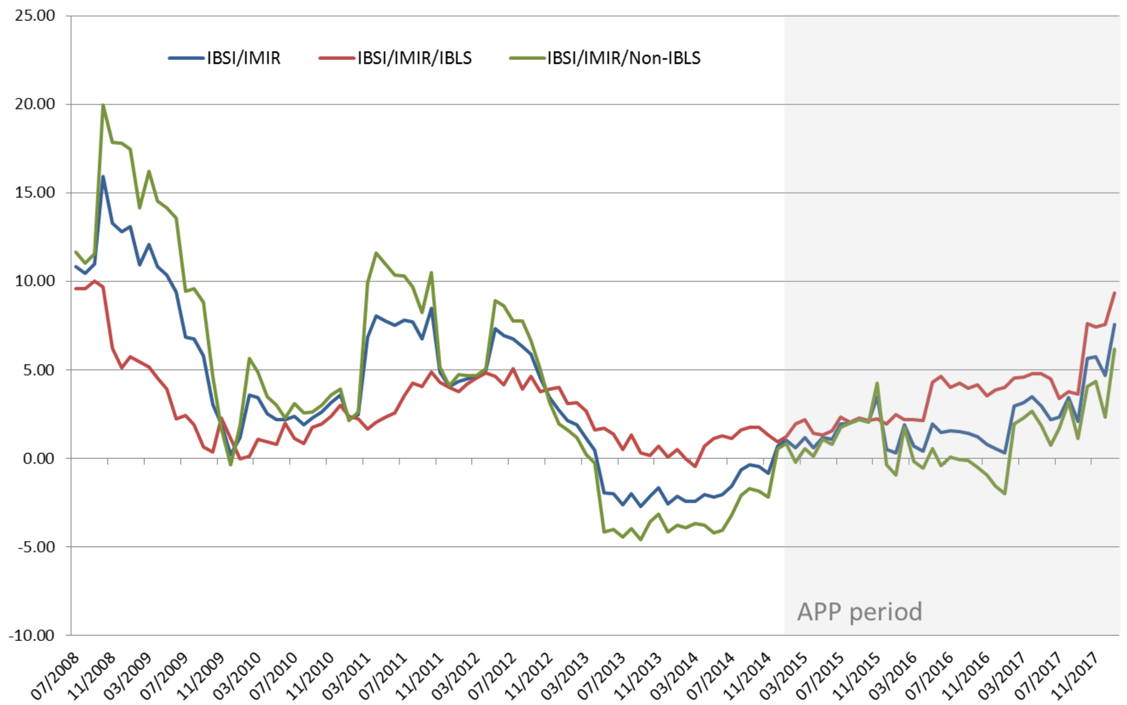
Country	*BLS p60* IBSI / IMIR / IBLS	*Net bond seller* IBSI / IMIR / IBLS	*Net bond seller* IBSI / IMIR
AT	4 / 8	5 / 8	9 / 14
BE	2 / 4	4 / 4	9 / 9
CY			4 / 7
DE	9 / 26	19 / 26	44 / 61
EE	0 / 4	1 / 4	1 / 4
ES	6 / 10	8 / 10	18 / 25
FI			4 / 11
FR	1 / 12	12 / 12	25 / 31
GR			4 / 6
IE	1 / 4	3 / 4	5 / 6
IT	5 / 20	13 / 20	20 / 31
LU	2 / 5	4 / 5	9 / 11
LV			5 / 7
MT			2 / 4
NL			9 / 10
PT	2 / 5	1 / 5	1 / 5
SI			3 / 7
SK	1 / 5	4 / 5	4 / 5
Total	33 / 103	74 / 103	176 / 254

Note: Each entry denotes the number of banks belonging to the corresponding treatment group as well as the total number of banks in the respective country. “BLS p60” abbreviates the treatment selection based on the 60th percentile of the cross-section distribution of banks’ average answers to the BLS question regarding the APP’s impact on their liquidity position.

[15] The estimated effect is robust against stricter definitions of the treatment group including only banks with relatively large net sales of government bonds over the APP period, compared to the size of their balance sheet.

Shedding light on the reasons for these differences in estimation results, Figure 1 demonstrates that the development in credit growth of the 103 banks in the IBLS sample is perceptibly different from those banks that are additionally included in the IBSI/IMIR dataset (the IBSI/IMIR sample consists of 103 IBLS banks and 151 non-IBLS banks, i.e. banks which are not surveyed within the BLS). In fact, the average growth rate of NFC loans for non-IBLS banks displays a considerably larger degree of volatility over the whole sample period, compared to the average growth rate for IBLS banks. This provides first tentative evidence of the reasons for weaker APP effects on the basis of non-IBLS banks' data: their average NFC loan growth even falls during a part of the APP period (especially over the course of the year 2016), before increasing towards the end of the period. This pattern translates into the full IBSI/IMIR sample which displays an almost stagnating growth rate over the first two years of APP while the IBLS banks exhibit a more steady increase in NFC loan growth over the whole APP period.

Figure 1: Average annual growth rate of loans to NFCs in different samples



Note: Cross-sectional averages of annualized monthly growth rates of individual banks' NFC loans (based on notional stocks) in percent for a sample of 254 banks (IBSI/IMIR), of 103 banks (IBSI/IMIR/IBLS) and of 151 banks (IBSI/IMIR/Non-IBLS), respectively.

To further investigate the issue, we set up a probit model for the binary variable *blsbank* (which takes the value of one if the bank is included in the IBLS dataset and zero otherwise). In doing so, we relate the differences in estimation results to the differences between the banks' balance sheet characteristics of IBLS and non-IBLS banks observed in the pre-APP time. Accordingly, the right-hand side variables in this regression comprise the characteristics that we also used for the estimation of the APP treatment effect, plus a measure for the degree of loan growth volatility. For the latter, we employ the standard deviation of each bank's NFC loan growth rate over the pre-APP period. The results of this estimation are shown in Table 4. They suggest that systematic differences between IBLS and non-IBLS banks exist with respect to credit rates, capitalization and loan growth volatility. In particular, non-IBLS banks were on average less capitalized and charged higher credit rates before the APP which could indicate that they had less healthy balance sheets and were less competitive than the banks in the IBLS sample. Moreover, their loan growth exhibited relatively large fluctuations, indicating that their NFC lending business was more vulnerable to shocks.

Table 4: Comparison of sample characteristics

Variables	(1) blsbank
securities	0.00675
	(0.00797)
credit rate	-0.204***
	(0.0750)
deposits	0.00989
	(0.0123)
NFC loans	-0.00724
	(0.00705)
capitalization	0.0564***
	(0.0201)
market share	0.000563
	(0.00934)
stressed country	0.00390
	(0.232)
loan growth volatility	-0.0668**
	(0.0314)
Observations	254

Note: Probit regression of sample affiliation on banks' characteristics provided by pre-APP averages. Standard errors in parentheses; ***, ** , * denote significance at the 1%, 5%, 10% level.

The fact that the APP effect for the full IBSI/IMIR sample is estimated to be negative, but insignificantly different from zero suggests that the (treated) banks in the non-IBLS sample per se could feature a negative APP effect. Table 5 corroborates this conjecture: Estimating the treatment effect of the APP by means of the banks' net government bond selling position for the non-IBLS banks separately (third column) yields a negative and significant difference between the monthly loan growth rate of treated banks and the counterfactual growth rate of more than 0.5 percentage points. Also this effect is estimated very robust across the different matching variants.[16]

Table 5: APP effects on NFC loan growth of IBLS and non-IBLS banks

Variants	*Net government bond seller*	
	IBSI / IMIR / IBLS (103 banks)	IBSI / IMIR / Non-IBLS (150 banks)
Unweighted	0.12	-0.437*
	(0.141)	(0.241)
PSW1	0.229*	-0.403*
	(0.123)	(0.233)
PSWK	0.213*	-0.495***
	(0.114)	(0.186)
EBW	0.185*	-0.616***
	(0.108)	(0.184)

Note: Unweighted refers to the estimated coefficient of the treatment indicator in a linear unweighted regression of the average monthly growth rate of NFC loans on the treatment indicator and the control variables; PSW1 / PSWK / EBW denote the corresponding estimated coefficient in the equivalent weighted-least-squares regression using propensity-score weights (nearest-neighbour variant) / propensity-score weights (kernel variant) / entropy-balance weights. Standard errors are given in parentheses below the coefficients; ***, ** , * denote significance at the 1%, 5%, 10% level. The non-IBLS sample has been adjusted for a negative outlier in the treatment group of banks.

Tracing the development of average loan growth rates over time, the differences between the two sub-samples (IBLS vs. non-IBLS) also become evident in different loan growth dynamics. Starting from a virtually equalized level between treatment group and matched control group in the IBLS sample before the APP, the average growth rate of lending to NFCs in the treatment group increases almost continuously throughout the APP period, while in the control group it remains retained and volatile (Figure 2 in the Appendix). Hence, in this sample of relatively strong banks, the APP has stimulated bank lending by providing additional liquidity. In the non-IBLS sample, the small difference between average growth rates of treatment and matched control group before the APP has been amplified in the treatment period (Figure 3 in the Appendix). At the same time, the dynamic behaviour of the loan growth rate in the APP period in treatment and control group of non-IBLS banks shows a large degree of similarity. Stronger than in the IBLS sample, loan growth in the APP period in this sample appears to be driven by other factors as well: the pattern of increase, decline and renewed increase in loan growth suggests that the Eurosystem’s targeted longer-term refinancing operations (TLTROs) might have had an influence on both treatment and

[16] The estimated effects are also robust against stricter definitions of the treatment group including only banks with relatively large net sales of government bonds over the APP period, compared to the size of their balance sheet.

control group of banks as these operations directly targeted NFC loan growth, with varying degree of conditionality.[17] Hence, the similarity in dynamics suggests that the observed difference in the level of loan growth rates should be attributed predominantly to the APP.

Taken together, our analyses provide evidence on heterogeneous effects of the APP on lending activity of euro area banks. On the one hand, we identify banks characterised by overall stronger balance sheets which have been able to pass on the positive APP stimulus to non-financial corporations through higher lending. On the other hand, we identify banks with overall weaker balance sheets which have reduced their lending activity in response to the APP. These banks apparently made greater use of the positive APP impulse for “cleaning up” their balance sheets. In fact, different from what we observe for the IBLS sample, treated banks in the non-IBLS sample feature lower growth of wholesale funding liabilities as well as of main assets than non-treated banks.[18] This suggests that in relative terms, these banks invest more of the capital gains from the APP into paying back their debt than into extending new loans. Higher lending growth by weak banks who nevertheless did not sell their holdings of safe government bonds (control group), arguably due to a strong precautionary motive, thus cannot necessarily be seen as sustainable or preferable from a monetary policy perspective. Instead, given that the APP was not tailored to be a “credit support policy”, in contrast to other measures of UMP like the TLTROs, it is not implausible to register versatile effects on banks in different financing situations.

In order to put the relative magnitudes of the effects into perspective – given the potential differences in average bank size between our two sub-samples –, we compute the amounts of additional net lending to NFCs by the treated banks in our sample that can be attributed to the APP. On the one hand, the positive APP effect found for net bond sellers in the IBLS sample per se increased the total net lending by all treated banks in this sample by about € 1.3 billion on average per treated bank over the three-year horizon 2015 to 2017 (using the pre-APP amount of outstanding NFC loans as a basis). On the other hand, the negative APP effect found for net bond sellers in the Non-IBLS sample per se decreased the total net lending by all treated banks in this sample by about € 1.8 billion on average per treated bank over the same three-year horizon.[19]

[17] TLTRO I was launched in June 2014, TLTRO II was launched in March 2016. For details of these operations see e.g. Deutsche Bundesbank (2016).

[18] Wholesale funding comprises inter-bank liabilities, debt securities issued and external liabilities. Results are available on request.

[19] The relative magnitude of effects remains nearly unchanged if we reweight the estimated APP effects for the IBLS and the Non-IBLS sample with the respective shares of treated banks. In particular, the positive APP effect found for net bond sellers in the IBLS sample increases the total lending by € 0.9 billion on average per bank in this sample, whereas the weighted negative APP effect amounts to € 1.2 billion on average per bank in the Non-IBLS sample.

Hence, although the banks in the IBLS sample have a larger lending volume on average than the banks in the Non-IBLS sample, the negative effect found for the latter part of the IBSI dataset is not less important than the former in quantitative terms.[20]

4.2 Further results

Given the different sizes and characteristics of national credit markets in the euro area, the question arises whether our results are driven by country-specific effects. We evaluate this aspect by repeating the estimations for which we obtained clear-cut results, imposing the restriction that banks from one of the four largest countries in the euro area (Germany, France, Italy, and Spain) are excluded from the estimation sample.

Table 17 presents the estimated APP effects for both, the BLS-based and the transactions-based identification using the IBSI/IMIR/IBLS sample, as well as for the latter identification using the IBSI/IMIR/non-IBLS sample. For the IBLS-based identification, the results corroborate a strong role for German banks: excluding those banks from the sample renders all estimated coefficients weaker and statistically insignificant from zero, while no such effect is found if any other country is excluded from the sample.[21] In contrast, there is no single country – including Germany – that has a comparable impact on the transaction-based identification results. In order to rationalize this result, note that there is only a relatively small number of banks that reported a positive impact of the APP on their liquidity position in the first place, compared to the number of banks that actually sold government bonds. This suggests that the BLS response behaviour can be considered as relatively "conservative", only rarely reporting strong positive or negative assessments. Sufficient confidence in an effective stimulus provided by the APP appears to prevail rather for German banks than for others. In turn, the actual conduct of granting new loans out of the liquidity received through the sale of APP-eligible assets does not appear to be limited to a specific country of residence of banks, although there are some indications that the lending business of banks especially located in Italy might have been less affected by the APP stimulus.

Performing the same exercise for the non-IBLS sample (bottom of Table 17) shows that there is no single country whose exclusion significantly weakens the negative result.

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[20] We obtain very similar results when differentiating not between IBLS and Non-IBLS banks, but between "sound" and "weak" banks instead. In doing so, we use the predictions of the probit equation describing the sample characteristics (Table 4), and attribute the estimated positive APP effect to all treated "sound" banks (i.e. banks exhibiting a predicted probability larger than 0.5) in the full IBSI sample while attributing the estimated negative APP effect to all treated "weak" banks (i.e. banks exhibiting a predicted probability up to 0.5) in the full IBSI sample.

[21] This is not simply due to the larger number of banks that are left out if Germany is excluded. The result is also valid if compared to the exclusion of the same number of treated and non-treated banks from other countries.

This suggests that the estimated negative APP effect in the non-IBLS sample is likely to be a broad-based phenomenon across countries.

As a further robustness check of our results, we estimate a model that exploits the panel dimension of our data. To that aim, we set up a difference-in-difference (DID) model for the monthly growth rate of each bank's NFC loans. In accordance with our identification approach, we use the binary variable D_i^{APP} as an indicator whether a bank is treated owing to its BLS response ($D_i^{APP,IBLS} = 1$) or to its net government bond selling position ($D_i^{APP,IBSI} = 1$). The coefficient of the binary variable D_t^{APP}, a time dummy equal to one with the beginning of the APP period and zero before, covers the overall difference in lending growth between APP and pre-APP period. The causal APP effect is estimated as the coefficient of the interaction of D_i^{APP} with D_t^{APP}. Furthermore, the specification takes the endogenous dynamics of credit growth and the characteristics of the banks into account. The former effects are included via lagged NFC growth rates up to a lag order of twelve; the latter are considered via the regression weights obtained from our cross-section matching analysis. In particular, we do not include the corresponding balance sheet characteristics of the banks as linear regressors into the model as they are subject to endogeneity with respect to the APP given that they would also be specified for the APP period. Instead, the matching weights, which are based on pre-APP information only, are designed to take account of these characteristics in a way that does not conflict with the treatment. To ensure that the estimated treatment effect can be attributed to the APP, we further control for potential demand-side factors. First, using bank fixed effects we aim at capturing the unobserved time-invariant bank-specific variation in credit demand. Second, time-varying influences that arise due to the macroeconomic environment, in particular business-cycle dynamics are taken into account via country-time effects, capturing aggregate demand conditions that affect the lending business of banks within each country homogeneously.

The results of this panel estimation are presented in Tables 18 to 21. They confirm the picture gained from the cross-sectional analysis showing that the estimated positive effect of the APP on loan growth in the IBLS sample lies in the same range as for the cross-section data analysis. In particular, the point estimates for this effect lie in a range between 0.19 and 0.31 for the BLS-based identification (Table 18) and between 0.17 and 0.35 for the transaction-based identification in the IBLS sample (Table 19), respectively. Again, using the larger IBSI/IMIR sample for the transaction-based identification, the range of estimated APP effects extends into negative territory, lying between -0.26 and 0.64 (Table 20). Consistent with our findings based on cross-sectional data, the negative APP effect in the non-IBLS sample (Table 21) is substantiated in the panel estimation: the point estimates for this effect lie in a range between -0.15 and -0.94.

However, the larger degree of estimation uncertainty owing to the time variation over the APP and the pre-APP periods prevents most of the estimated coefficients from becoming significant at conventional levels. We attribute this fact to the lacking ability of the panel data model to explain the very volatile monthly credit growth over the period 2007 to 2017.

5 Conclusion

Facing the difficulty of lowering short-term interest rates much further, the Eurosystem increasingly engaged in unconventional monetary policy measures in order to achieve a more expansionary monetary policy stance. Among these measures, the expanded Asset Purchase Programme (APP) plays an important role as it is designed to alleviate financing conditions for banks and non-banks, thereby stimulating investment in order to foster output growth and inflation. By employing matching techniques, we study the implications of the APP for bank lending as an important part of external financing for non-financial corporations (NFCs). Based on confidential bank-level data on both quantitative balance sheet and interest rate information and on qualitative survey responses to the Eurosystem’s Bank Lending Survey (BLS), we identify the exposure of banks to the APP and the corresponding effects on the growth rate of loans to NFCs. Our analysis provides two important findings. First, our results suggest that the APP was effective in stimulating the lending activity with euro area NFCs for a subset of the banks. For this group of relatively sound banks dominating the BLS sample, the documented effect is robust to the different identification measures and to the different matching strategies that we use. Second, our findings show that there is a non-negligible number of banks with less healthy balance sheets which could not transfer the APP stimulus into more lending. Instead, such banks appear to have used the APP stimulus to consolidate their balance sheets by paying back their debt. Thus, the APP appears to have encouraged banks with existing deleveraging needs to recapitalize and to sanitize their balance sheets accordingly. In this respect, the APP has affected also such less solid banks. In terms of effectiveness, however, for total lending to NFCs by euro area banks, the negative effect found for this group of banks is at least as relevant as the positive effect found for the group of relatively sound banks. Altogether, our results document the large diversity of effects of unconventional monetary policy measures like the APP on banks, and they confirm the importance of accounting for the large degree of heterogeneity in the euro area banking sector in analyses of such measures.

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Appendix

Figure 2: Average annual growth rate of loans to NFCs in the IBLS sample (Treatment: net bond seller)

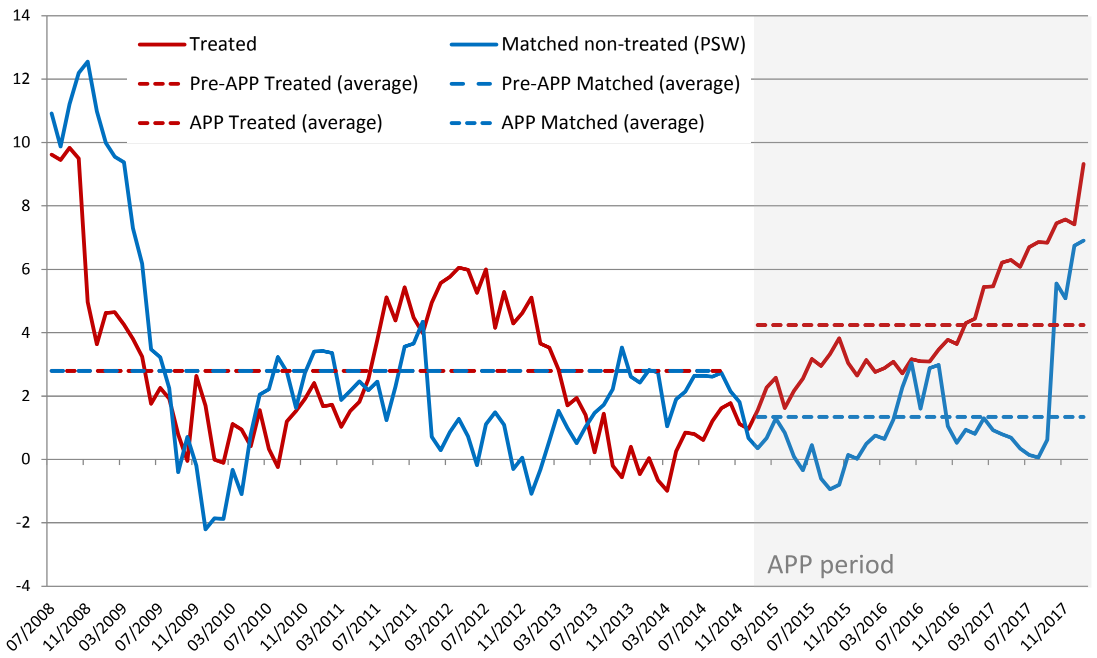

Figure 3: Average annual growth rate of loans to NFCs in the non-IBLS sample (Treatment: net bond seller)

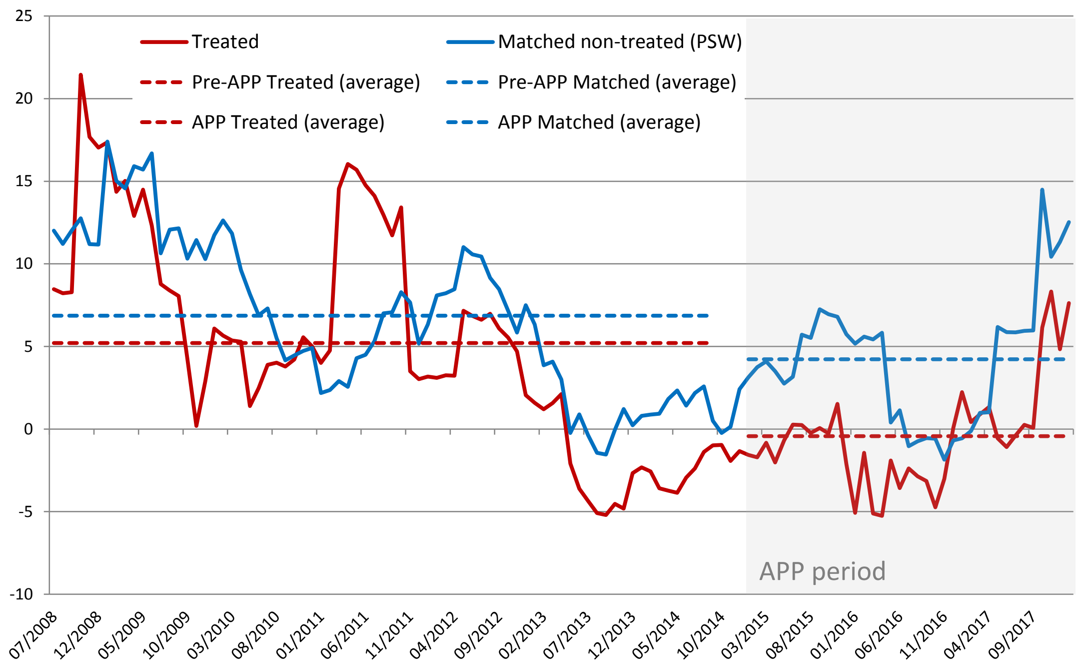

Table 6: Bank characteristics used for the matching

Variable	Definition
securities	Securities issued by domestic or other euro area government, by euro area MFIs, or by the euro area private non-MFI sector (incl. equity) as a ratio to main assets
credit rate	Interest rate charged on new loans to NFCs
deposits	Deposits held by all sectors relative to other liabilities (incl. capital and reserves)
NFC loans	Loans to NFCs (outstanding amount) as a ratio to main assets
capitalization	Capital and reserves as a ratio to main assets
market share	Main assets (total assets minus remaining assets) as a ratio of the sum of main assets across all included banks of the respective country
stressed country	Dummy variable equal to one for a bank residing in CY, ES, GR, IE, IT, MT, PT, or SI, and equal to zero for a bank residing in AT, BE, DE, EE, FI, FR, LT, LU, LV, NL, or SK.

Table 7: Answering behaviour of IBLS sample regarding APP impact on bank lending policies (frequencies of answers*)

	Impact of EAPP during past 6 months on credit standards for …			Impact of EAPP during next 6 months on credit standards for …		
	loans to enterprises	loans to households for house purchase	consumer credit	loans to enterprises	loans to households for house purchase	consumer credit
contributed considerably to tightening	1	1	1	1	1	1
contributed somewhat to tightening	4	2	2	2	0	0
basically no impact	578	566	576	577	567	577
contributed somewhat to easing	20	10	6	22	9	6
contributed considerably to easing	0	0	0	0	0	0

* for BLS survey rounds 2015Q1, 2015Q3, 2016Q1, 2016Q3, 2017Q1, 2017Q3, 2018Q1

Table 8: Answering behaviour of IBLS sample regarding APP impact on different bank items (frequencies of answers*)

Impact of APP during past six months on bank's ...	... total assets	... liquidity position	... market financing conditions	... profitability	... capital ratio
contributed considerably to a decrease or deterioration	0	0	0	11	0
contributed somewhat to a decrease or deterioration	32	2	5	171	11
basically no impact or not applicable	612	565	524	456	655
contributed somewhat to an increase or improvement	62	132	172	67	39
contributed considerably to an increase or improvement	0	7	5	1	1
Impact of APP during next six months on bank's ...	**... total assets**	**... liquidity position**	**... market financing conditions**	**... profitability**	**... capital ratio**
contributed considerably to a decrease or deterioration	0	0	0	21	0
contributed somewhat to a decrease or deterioration	32	2	5	161	17
basically no impact or not applicable	615	609	571	471	659
contributed somewhat to an increase or improvement	59	93	123	53	28
contributed considerably to an increase or improvement	0	2	7	0	2

* for BLS survey rounds 2015Q1, 2015Q3, 2016Q1, 2016Q3, 2017Q1, 2017Q3, 2018Q1

Table 9: Covariate balance before and after matching
Treatment: positive BLS response (60th percentile)

Variable and weighting method		Sample means: Treated	Sample means: Non-treated	Bias
securities	Unweighted	21.77	18.827	27.8
	PSWK	21.77	21.826	0.5
	EBW	21.77	21.766	0
credit rate	Unweighted	3.429	3.034	40.8
	PSWK	3.429	3.333	9.9
	EBW	3.429	3.429	0.1
deposits	Unweighted	4.488	4.124	8.2
	PSWK	4.488	4.449	0.9
	EBW	4.488	4.487	0
NFC loans	Unweighted	21.854	21.611	1.8
	PSWK	21.854	20.652	8.9
	EBW	21.854	21.852	0
capitalization	Unweighted	9.734	10.417	11.8
	PSWK	9.734	9.059	11.7
	EBW	9.734	9.736	0.1
market share	Unweighted	6.861	7.837	11.3
	PSWK	6.861	7.043	2.1
	EBW	6.861	6.864	0
stressed country	Unweighted	0.424	0.357	13.6
	PSWK	0.424	0.360	13.1
	EBW	0.424	0.424	0

Note: Sample means of variables before ("unweighted") and after matching, where PSWK denotes propensity score weighting (kernel variant) and EBW denotes entropy balance weighting. Bias is the absolute difference of the sample means in the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups. Good covariate balance at bias values < 5 %; poor covariate balance at bias values > 20 %.

Table 10: Covariate balance before and after matching
Treatment: net government bond seller (IBSI/IMIR/IBLS)

Variable and weighting method		Sample means		Bias
		Treated	Non-treated	
securities	Unweighted	19.877	19.496	3.3
	PSWK	20.046	18.409	14.3
	EBW	20.046	19.873	1.5
credit rate	Unweighted	3.080	3.365	31.7
	PSWK	3.108	3.132	2.7
	EBW	3.108	3.080	3
deposits	Unweighted	4.047	4.734	15.1
	PSWK	4.078	4.092	0.3
	EBW	4.078	4.048	0.7
NFC loans	Unweighted	19.743	26.654	50.8
	PSWK	19.931	21.400	10.8
	EBW	19.931	19.748	1.3
capitalization	Unweighted	9.997	10.710	12.3
	PSWK	10.056	9.828	3.9
	EBW	10.056	9.997	1
market share	Unweighted	7.188	8.382	13.3
	PSWK	7.204	7.362	1.8
	EBW	7.204	7.189	0.2
stressed country	Unweighted	0.338	0.483	29.4
	PSWK	0.342	0.310	6.6
	EBW	0.342	0.338	1

Note: Sample means of variables before ("unweighted") and after matching, where PSWK denotes propensity score weighting (kernel variant) and EBW denotes entropy balance weighting. Bias is the absolute difference of the sample means in the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups. Good covariate balance at bias values < 5 %; poor covariate balance at bias values > 20 %.

Table 11: Covariate balance before and after matching
Treatment: net government bond seller (IBSI/IMIR)

Variable and weighting method		Sample means		Bias
		Treated	Non-treated	
securities	Unweighted	18.931	17.661	10.8
	PSWK	18.542	17.349	10.1
	EBW	18.542	18.928	3.3
credit rate	Unweighted	3.321	3.411	7.1
	PSWK	3.286	3.297	0.8
	EBW	3.286	3.321	2.7
deposits	Unweighted	4.591	4.474	1.8
	PSWK	4.553	4.737	2.8
	EBW	4.553	4.590	0.6
NFC loans	Unweighted	21.026	23.146	50.8
	PSWK	21.146	21.982	10.8
	EBW	21.146	21.032	0.8
capitalization	Unweighted	8.738	9.626	16.1
	PSWK	8.769	9.031	4.8
	EBW	8.769	8.741	0.5
market share	Unweighted	6.701	6.888	2.1
	PSWK	6.732	6.067	7.4
	EBW	6.732	6.701	0.3
stressed country	Unweighted	0.324	0.436	23.1
	PSWK	0.326	0.324	0.3
	EBW	0.326	0.324	0.3

Note: Sample means of variables before ("unweighted") and after matching, where PSWK denotes propensity score weighting (kernel variant) and EBW denotes entropy balance weighting. Bias is the absolute difference of the sample means in the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups. Good covariate balance at bias values < 5 %; poor covariate balance at bias values > 20 %.

Table 12: Covariate balance before and after matching
Treatment: net government bond seller (IBSI/IMIR/Non-IBLS)

Variable and weighting method		Sample means Treated	Sample means Non-treated	Bias
securities	Unweighted	18.415	16.575	15.2
	PSWK	18.091	16.986	14.3
	EBW	18.091	18.412	2.7
credit rate	Unweighted	3.516	3.439	5.3
	PSWK	3.484	3.380	7.1
	EBW	3.484	3.516	2.2
deposits	Unweighted	5.022	4.320	9.0
	PSWK	5.043	4.203	10.8
	EBW	5.043	5.020	0.3
NFC loans	Unweighted	22.033	21.069	6.6
	PSWK	22.063	23.691	11.1
	EBW	22.063	22.031	0.2
capitalization	Unweighted	7.891	8.984	21.1
	PSWK	7.745	7.946	3.9
	EBW	7.745	7.894	2.9
market share	Unweighted	6.402	6.004	4.4
	PSWK	6.564	6.241	3.6
	EBW	6.564	6.402	1.8
stressed country	Unweighted	0.317	0.408	18.9
	PSWK	0.306	0.300	1.2
	EBW	0.306	0.317	2.2

Note: Sample means of variables before ("unweighted") and after matching, where PSWK denotes propensity score weighting (kernel variant) and EBW denotes entropy balance weighting. Bias is the absolute difference of the sample means in the treated and non-treated sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups. Good covariate balance at bias values < 5 %; poor covariate balance at bias values > 20 %.

Table 13: Matching regression results with controls
Dependent variable: NFC loan growth
Treatment: Positive BLS response, 60th percentile

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW
APP treatment	0.214	0.238	0.229*	0.214*
	(0.133)	(0.177)	(0.121)	(0.114)
securities	0.00572	0.0139	0.00788	0.00643
	(0.00680)	(0.0100)	(0.00696)	(0.00639)
credit rate	-0.0978	-0.123	-0.0651	-0.0631
	(0.0727)	(0.103)	(0.0727)	(0.0670)
deposits	0.0412**	0.0349*	0.0420***	0.0451***
	(0.0166)	(0.0186)	(0.0156)	(0.0150)
NFC loans	-0.00500	-0.0101	-0.00413	-0.00508
	(0.00571)	(0.00879)	(0.00591)	(0.00552)
capitalization	-0.00460	0.00635	-0.00396	-0.000280
	(0.0132)	(0.0238)	(0.0168)	(0.0145)
market share	0.00227	-0.0101	0.000665	-0.00100
	(0.00743)	(0.0115)	(0.00843)	(0.00808)
stressed country	-0.377**	-0.361	-0.438**	-0.387**
	(0.184)	(0.270)	(0.182)	(0.173)
constant	0.573*	0.571	0.408	0.408
	(0.305)	(0.511)	(0.346)	(0.320)
Observations	103	58	103	103
R-squared	0.293	0.352	0.313	0.338

Note: Regression of average monthly growth rate of loans to NFCs over the APP period (January 2015 to January 2018) on average pre-APP variables. Unweighted refers to linear least-squares regression, PSW1/PSWK/EBW refer to weighted least-squares regressions using propensity score weights (PSW1: nearest-neighbour variant; PWSK: kernel variant) and entropy balance weights, respectively. Standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 14: Matching regression results with controls
Dependent variable: NFC loan growth
Treatment: Net government bond seller (IBSI/IMIR/IBLS)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW
APP treatment	0.120	0.229*	0.213*	0.185*
	(0.141)	(0.123)	(0.114)	(0.108)
securities	0.00708	0.00708	0.00696	0.00639
	(0.00683)	(0.00741)	(0.00694)	(0.00670)
credit rate	-0.0731	-0.0325	-0.0480	-0.0543
	(0.0725)	(0.0808)	(0.0746)	(0.0690)
deposits	0.0423**	0.0418**	0.0448***	0.0545***
	(0.0168)	(0.0177)	(0.0167)	(0.0175)
NFC loans	-0.00355	0.00279	-0.000431	0.00108
	(0.00587)	(0.00648)	(0.00597)	(0.00602)
capitalization	-0.00643	-0.00921	-0.00941	-0.0135
	(0.0133)	(0.0153)	(0.0140)	(0.0136)
market share	0.00241	0.00621	0.00562	0.00963
	(0.00754)	(0.00852)	(0.00780)	(0.00788)
stressed country	-0.377**	-0.356*	-0.314*	-0.312*
	(0.186)	(0.200)	(0.181)	(0.171)
Constant	0.433	0.0680	0.182	0.179
	(0.346)	(0.342)	(0.330)	(0.308)
Observations	103	99	102	103
R-squared	0.279	0.213	0.243	0.276

Note: Regression of average monthly growth rate of loans to NFCs over the APP period (January 2015 to January 2018) on average pre-APP variables. Unweighted refers to linear least-squares regression, PSW1/PSWK/EBW refer to weighted least-squares regressions using propensity score weights (PSW1: nearest-neighbour variant; PWSK: kernel variant) and entropy balance weights, respectively. Standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 15: Matching regression results with controls
Dependent variable: NFC loan growth
Treatment: Net government bond seller (IBSI/IMIR)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW
APP treatment	-0.373	-0.182	-0.387	-0.444
	(0.350)	(0.311)	(0.280)	(0.276)
securities	0.0255*	0.0360**	0.0360**	0.0214*
	(0.0145)	(0.0148)	(0.0139)	(0.0130)
credit rate	0.0271	0.167	0.132	0.0125
	(0.130)	(0.135)	(0.128)	(0.119)
deposits	0.0479**	0.0410*	0.0537**	0.0514**
	(0.0234)	(0.0237)	(0.0222)	(0.0219)
NFC loans	0.0168	0.0355***	0.0186*	0.0128
	(0.0129)	(0.0130)	(0.0112)	(0.0113)
capitalization	0.0416	-0.0751**	0.0241	0.0480
	(0.0360)	(0.0312)	(0.0324)	(0.0337)
market share	0.0154	0.0292	0.0120	0.00724
	(0.0182)	(0.0183)	(0.0170)	(0.0167)
stressed country	-0.755*	-0.813*	-1.017***	-0.754**
	(0.434)	(0.433)	(0.389)	(0.378)
constant	-1.162*	-1.430**	-1.462**	-0.899
	(0.685)	(0.704)	(0.625)	(0.589)
Observations	254	234	253	254
R-squared	0.041	0.133	0.069	0.051

Note: Regression of average monthly growth rate of loans to NFCs over the APP period (January 2015 to January 2018) on average pre-APP variables. Unweighted refers to linear least-squares regression, PSW1/PSWK/EBW refer to weighted least-squares regressions using propensity score weights (PSW1: nearest-neighbour variant; PWSK: kernel variant) and entropy balance weights, respectively. Standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 16: Matching regression results with controls
Dependent variable: NFC loan growth
Treatment: Net government bond seller (IBSI/IMIR/Non-IBLS)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW
APP treatment	-0.437*	-0.403*	-0.495***	-0.616***
	(0.241)	(0.233)	(0.186)	(0.184)
securities	0.00363	0.00952	0.0114	-0.00449
	(0.00935)	(0.0101)	(0.00930)	(0.00844)
credit rate	-0.0770	-0.0130	-0.0400	-0.113
	(0.0808)	(0.0909)	(0.0809)	(0.0729)
deposits	0.0298**	0.0499***	0.0442***	0.0412***
	(0.0137)	(0.0154)	(0.0126)	(0.0126)
NFC loans	0.0161*	0.0151*	0.00937	0.00521
	(0.00834)	(0.00801)	(0.00670)	(0.00686)
capitalization	-1.71e-05	0.0225	0.0715***	0.0579**
	(0.0269)	(0.0293)	(0.0273)	(0.0264)
market share	0.0137	0.00705	-0.00291	-0.00485
	(0.0124)	(0.0139)	(0.0109)	(0.0106)
stressed country	-0.388	-0.795**	-0.821***	-0.459*
	(0.301)	(0.304)	(0.261)	(0.259)
Constant	-0.0498	-0.504	-0.473	0.274
	(0.423)	(0.448)	(0.389)	(0.385)
Observations	150	130	146	150
R-squared	0.090	0.152	0.184	0.174

Note: Regression of average monthly growth rate of loans to NFCs over the APP period (January 2015 to January 2018) on average pre-APP variables. Unweighted refers to linear least-squares regression, PSW1/PSWK/EBW refer to weighted least-squares regressions using propensity score weights (PSW1: nearest-neighbour variant; PWSK: kernel variant) and entropy balance weights, respectively. Standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 17: APP effects on NFC loan growth under country exclusion restrictions

Variant	full sample	without DE	without FR	without IT	without ES
	Positive response to BLS question (60th percentile)				
Unweighted	0.214	0.081	0.269**	0.318**	0.187
	(0.133)	-0.159	(0.127)	(0.158)	(0.147)
PSW1	0.238	0.082	0.391*	0.217	-0.0648
	(0.177)	-0.226	(0.196)	(0.190)	(0.221)
PSWK	0.229*	0.179	0.278**	0.310**	0.277**
	(0.121)	-0.142	(0.124)	(0.142)	(0.124)
EBW	0.214*	0.118	0.260**	0.313**	0.184
	(0.114)	-0.117	(0.119)	(0.135)	(0.125)
	Net government bond seller (IBSI/IMIR/IBLS)				
Variant	full sample	without DE	without FR	without IT	without ES
Unweighted	0.12	0.075	0.102	0.106	0.0916
	(0.141)	-0.158	(0.134)	(0.178)	(0.156)
PSW1	0.229*	0.171	0.176	0.305**	0.154
	(0.123)	-0.126	(0.122)	(0.137)	(0.121)
PSWK	0.213*	0.165	0.142	0.159	0.194
	(0.114)	-0.126	(0.114)	(0.134)	(0.125)
EBW	0.185*	0.141	0.113	0.214*	0.210*
	(0.108)	-0.114	(0.110)	(0.128)	(0.117)
No. of banks	103	77	91	83	93
	Net government bond seller (IBSI/IMIR/Non-IBLS)				
Variant	full sample	without DE	without FR	without IT	without ES
Unweighted	-0.437*	-0.101	-0.526*	-0.436*	-0.550**
	(0.241)	(0.238)	(0.267)	(0.259)	(0.244)
PSW1	-0.403*	-0.287	-0.545**	-0.418*	-0.415*
	(0.233)	(0.246)	(0.224)	(0.219)	(0.222)
PSWK	-0.495***	-0.0737	-0.542***	-0.459**	-0.541***
	(0.186)	(0.214)	(0.194)	(0.194)	(0.203)
EBW	-0.616***	-0.570***	-0.657***	-0.548***	-0.633***
	(0.184)	(0.173)	(0.201)	(0.195)	(0.201)
No. of banks	150	115	131	139	135

Note: Unweighted refers to the estimated coefficient of the treatment indicator in a linear unweighted regression of the average monthly growth rate of NFC loans on the treatment indicator and the control variables subject to the exclusion of banks from the specified country; PSW1 / PSWK / EBW denote the corresponding estimated coefficient in the equivalent weighted-least-squares regression using propensity-score weights (nearest-neighbour variant) / propensity-score weights (kernel variant) / entropy-balance weights. Standard errors are given in parentheses below the coefficients; ***, **, * denotes significance at the 1%, 5%, 10 % level.

Table 18: Panel regression of NFC loan growth (treatment: positive BLS response, 60th percentile)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW	(5) Unweighted	(6) PSW1	(7) PSWK	(8) EBW
$\Delta \text{loans}_{t-1}$	-0.0171	-0.161*	-0.0803	-0.0824	-0.0159	-0.157*	-0.0760	-0.0778
	(0.0827)	(0.0847)	(0.0776)	(0.0777)	(0.0818)	(0.0904)	(0.0840)	(0.0835)
$\Delta \text{loans}_{t-3}$	0.0745**	0.0963***	0.0923***	0.0902***	0.0715**	0.0926***	0.0918***	0.0903***
	(0.0318)	(0.0272)	(0.0282)	(0.0285)	(0.0326)	(0.0287)	(0.0284)	(0.0289)
$\Delta \text{loans}_{t-12}$	0.00114	-0.0396	-0.0519	-0.0541	-0.00677	-0.0484	-0.0633	-0.0654
	(0.0664)	(0.0648)	(0.0846)	(0.0852)	(0.0691)	(0.0712)	(0.0845)	(0.0845)
D_t^{APP}	0.195	0.270	0.184	0.159				
	(0.134)	(0.256)	(0.170)	(0.159)				
$D_t^{APP} \cdot D_i^{APP,IBLS}$	0.213	0.193	0.254	0.281	0.219	0.197	0.273	0.307
	(0.192)	(0.296)	(0.227)	(0.221)	(0.196)	(0.313)	(0.228)	(0.229)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	7,098	4,407	7,013	7,013	7,098	4,407	7,013	7,013
R-squared	0.006	0.041	0.021	0.021	0.078	0.140	0.110	0.107
Number of MFIs	107	58	103	103	107	58	103	103

Note: The monthly growth rate of NFC loans is approximated by the log difference of the index of notional stocks, Δloans_t. D_t^{APP} denotes a binary variable that takes the value of one over the APP period (January 2015 to January 2018), and zero before; $D_i^{APP,IBLS}$ denotes a binary variable that takes the values of one for each bank whose average response to the BLS question regarding the APP's impact on its liquidity position exceeds the 60th percentile of the cross-section distribution, and zero else. Robust standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 19: Panel regression of NFC loan growth (treatment: net government bond seller, IBSI/IMIR/IBLS)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW	(5) Unweighted	(6) PSW1	(7) PSWK	(8) EBW
$\Delta \text{loans}_{t-1}$	-0.0171	-0.115*	-0.108*	-0.105*	-0.0158	-0.0975	-0.0937	-0.0957
	(0.0828)	(0.0619)	(0.0631)	(0.0632)	(0.0819)	(0.0699)	(0.0706)	(0.0704)
$\Delta \text{loans}_{t-3}$	0.0746**	0.0791***	0.0815***	0.0897***	0.0717**	0.0871***	0.0826***	0.0884***
	(0.0317)	(0.0269)	(0.0256)	(0.0248)	(0.0326)	(0.0237)	(0.0240)	(0.0236)
$\Delta \text{loans}_{t-12}$	0.00132	0.0121	0.00294	0.00262	-0.00653	-0.0220	-0.0252	-0.0223
	(0.0664)	(0.0623)	(0.0637)	(0.0646)	(0.0690)	(0.0661)	(0.0659)	(0.0665)
D_t^{APP}	0.119	0.0816	0.0168	0.0157				
	(0.133)	(0.223)	(0.158)	(0.149)				
$D_t^{APP} \cdot D_i^{APP,IBSI}$	0.227	0.291	0.354	0.352*	0.165	0.220	0.272	0.281
	(0.185)	(0.270)	(0.215)	(0.206)	(0.209)	(0.237)	(0.229)	(0.237)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	7,098	6,826	6,984	7,013	7,098	6,826	6,984	7,013
R-squared	0.006	0.021	0.020	0.021	0.077	0.211	0.161	0.145
Number of MFIs	107	99	102	103	107	99	102	103

Note: The monthly growth rate of NFC loans is approximated by the log difference of the index of notional stocks, Δloans_t. D_t^{APP} denotes a binary variable that takes the value of one over the APP period (January 2015 to January 2018), and zero before; $D_i^{APP,IBLS}$ denotes a binary variable that takes the values of one for each bank which sold euro area government bond securities on balance over the APP period, and zero else. Robust standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 20: Panel regression of NFC loan growth (treatment: net government bond seller, IBSI/IMIR)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW	(5) Unweighted	(6) PSW1	(7) PSWK	(8) EBW
$\Delta loans_{t-1}$	-0.129	0.0186	0.00388	-0.00278	-0.135	0.0139	0.00158	-0.00444
	(0.111)	(0.0586)	(0.0651)	(0.0703)	(0.109)	(0.0596)	(0.0618)	(0.0668)
$\Delta loans_{t-3}$	-0.00930	0.0570	0.0973***	0.113***	-0.0137	0.0691	0.0994***	0.113***
	(0.0797)	(0.0522)	(0.0362)	(0.0353)	(0.0801)	(0.0423)	(0.0346)	(0.0340)
$\Delta loans_{t-12}$	0.0279	0.0692	0.0384	0.0389	0.0266	0.0562	0.0318	0.0307
	(0.0724)	(0.0565)	(0.0487)	(0.0517)	(0.0734)	(0.0532)	(0.0461)	(0.0485)
D_t^{APP}	-0.249	-0.811	-0.135	0.0565				
	(0.335)	(1.105)	(0.280)	(0.152)				
$D_t^{APP} \cdot D_i^{APP,IBSI}$	0.0645	0.632	-0.0528	-0.243	0.0265	0.639	-0.0160	-0.263
	(0.399)	(1.128)	(0.338)	(0.247)	(0.466)	(0.960)	(0.449)	(0.309)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	18,633	15,917	17,140	17,165	18,633	15,917	17,140	17,165
R-squared	0.016	0.006	0.006	0.008	0.065	0.154	0.080	0.065
Number of MFIs	288	234	253	254	288	234	253	254

Note: The monthly growth rate of NFC loans is approximated by the log difference of the index of notional stocks, $\Delta loans_t$. D_t^{APP} denotes a binary variable that takes the value of one over the APP period (January 2015 to January 2018), and zero before; $D_i^{APP,IBLS}$ denotes a binary variable that takes the values of one for each bank which sold euro area government bond securities on balance over the APP period, and zero else. Robust standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.

Table 21: Panel regression of NFC loan growth (treatment: net government bond seller, IBSI/IMIR/Non-IBLS)

Variables	(1) Unweighted	(2) PSW1	(3) PSWK	(4) EBW	(5) Unweighted	(6) PSW1	(7) PSWK	(8) EBW
$\Delta \text{loans}_{t-1}$	-0.211*	-0.0555*	-0.0811**	-0.0883**	-0.214*	-0.0571*	-0.0822**	-0.0885**
	(0.109)	(0.0313)	(0.0321)	(0.0357)	(0.112)	(0.0338)	(0.0342)	(0.0378)
$\Delta \text{loans}_{t-3}$	-0.0345	0.0801**	0.0994**	0.116***	-0.0387	0.0838**	0.103***	0.117***
	(0.0878)	(0.0365)	(0.0417)	(0.0419)	(0.0892)	(0.0365)	(0.0387)	(0.0400)
$\Delta \text{loans}_{t-12}$	0.0235	-0.00940	0.000731	0.00328	0.0245	-0.0111	-0.00301	-0.00180
	(0.0722)	(0.0220)	(0.0276)	(0.0304)	(0.0741)	(0.0224)	(0.0284)	(0.0303)
D_t^{APP}	-0.472	-0.520	0.0441	0.228				
	(0.544)	(0.428)	(0.224)	(0.177)				
$D_t^{APP} \cdot D_i^{APP,IBSI}$	-0.180	-0.152	-0.715*	-0.894**	-0.178	-0.337	-0.759*	-0.947**
	(0.658)	(0.533)	(0.392)	(0.372)	(0.752)	(0.606)	(0.449)	(0.437)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time effects	No	No	No	No	Yes	Yes	Yes	Yes
Observations	11,515	8,799	9,938	10,132	11,515	8,799	9,938	10,132
R-squared	0.043	0.008	0.013	0.016	0.094	0.148	0.094	0.075
Number of MFIs	180	130	146	150	180	130	146	150

Note: The monthly growth rate of NFC loans is approximated by the log difference of the index of notional stocks, Δloans_t. D_t^{APP} denotes a binary variable that takes the value of one over the APP period (January 2015 to January 2018), and zero before; $D_i^{APP,IBLS}$ denotes a binary variable that takes the values of one for each bank which sold euro area government bond securities on balance over the APP period, and zero else. Robust standard errors in parentheses; ***, **, * denote significance at the 1%, 5%, 10% level.