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Liquidity coverage ratios and monetary policy credit in the time of Corona

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Abstract

When a bank receives credit from the central bank, its Liquidity Coverage Ratio (LCR) changes. In most cases, the LCR increases. We investigate how this LCR boost from central bank credit affects banks' behaviour, looking at the euro area during the Corona year 2020. Our theoretical and empirical analyses suggest that banks that get strong LCR boosts from central bank credit tend to take actions that reduce their LCRs. In this sense, banks consume their LCR boosts. In terms of policy conclusions, our analysis suggests that central bank credit operations can provide strong incentives for banks to take actions that reduce their LCRs. Such actions, which could include the provision of additional credit and a shortening of the maturity structure of the liabilities of the banks, plausibly have an impact on the real economy. As such, our analysis reveals what may be called a "LCR channel" of monetary policy transmission.

JEL: E52, E58, G28.

Keywords: Liquidity Coverage Ratio, central bank credit operations, monetary policy transmission, Corona pandemic.

Non-technical summary

Over recent years some central banks have conducted large-scale longer-term credit operations to ease lending conditions. These operations lower banks' funding costs and ease their liquidity management, in particular as they allow banks to improve their Liquidity Coverage Ratios (LCRs). In this paper, we investigate how changes of banks' LCRs resulting from a participation in longer-term central bank credit operations affect the behavior of banks. The analysis focuses on credit operations conducted by the Eurosystem.

We start by defining the immediate impact of central bank credit on a bank's LCR. This impact very much depends on the assets that the bank uses to collateralise the central bank credit. The Eurosystem accepts a wide range of assets as collateral, including high-quality liquid assets (HQLA) and non-HQLA. In most cases banks at least partially use non-HQLA to collateralise Eurosystem credit. This practice increases their LCRs. We therefore call the immediate impact of central bank credit on a bank's LCR the "technical LCR boost". We theoretically and empirically investigate the causal effect that a bank's technical LCR boosts have on the bank's behaviour.

Our empirical analysis focuses on a very special period, the Corona year 2020. The analysis suggests that in 2020, higher technical LCR boosts made banks carry out more activities with a negative impact on the LCR. In this sense, banks consume their technical LCR boosts from central bank credit. Such activities, which could include the provision of additional credit and a shortening of the maturity structure of the liabilities of the banks, plausibly had an impact on the real economy. Therefore, our analysis reveals what may be called a "LCR channel" of monetary policy transmission. These results appear to hold mainly for banks with a relatively low initial LCR. The behaviour of banks with a high initial LCR does not depend in a similar way on the technical LCR boosts that they achieve.

We provide a simple explanation for our results by means of a theoretical model. The model implies that if a bank with a low initial LCR achieves a large technical LCR boost, then it has more space to carry out activities (other than recourse to central bank credit) that have a negative impact on the LCR and it will use this space. A bank with a high initial LCR has space to carry out activities with a negative impact on its LCR anyway, regardless of whether it achieves a large technical LCR boost or not. It therefore has no additional reasons to use such space after a technical LCR boost.

Our model suggests that the central bank can activate the LCR channel of monetary policy transmission by offering attractively priced credit operations in which it accepts a broad range of non-HQLA as collateral. Examples of such credit operations are the Eurosystem's Targeted Longer-Term Refinancing Operations (TLTROs) conducted in 2020.

1. Introduction

Central banks aim to influence the behavior of economic agents into a desired direction. These economic agents are, as a first step in the transmission mechanism, typically commercial banks. It is therefore essential for central banks to understand the impact of central bank measures on banks' behavior. Central bank measures influence banks through various channels. One of the most important channels is the interest rate channel, in which the central bank sets its key policy rates to influence the rates that banks apply on loans and customer deposits. Several other channels have been described in the literature as well and some of them have gained importance with the introduction of non-standard monetary policy measures.[1]

Banking regulation may, under certain circumstances, open very specific transmission channels of monetary policy measures. For example, if central bank measures increase the value of bank capital, regulatory capital ratios improve. This may remove constraints under which banks operated previously and may therefore change banks' behavior. Similarly, some types of central bank operations may allow banks to improve regulatory liquidity ratios. This can create space for banks to engage in activities that they were reluctant to carry out before for regulatory reasons.

In this paper, we study the relevance of the Liquidity Coverage Ratio (LCR) for the way central bank credit can influence banks' behavior. The LCR was proposed by the Basel Committee on Banking Supervision (BCBS) in 2010 as a consequence of the Global Financial Crisis (GFC) in order to enhance banks' resilience to future liquidity shocks. It requires banks to hold a sufficiently high Liquidity Buffer to meet all payment obligations upcoming over a 30-day horizon.[2] It is defined as

$$LCR = \frac{Liquidity\ Buffer}{Net\ Liquidity\ Outflows\ over\ a\ 30\ calendar\ day\ stress\ period}$$

The Liquidity Buffer is composed of unencumbered high-quality liquid assets (HQLA). The Net Liquidity Outflows over a 30-calendar-day stress period is estimated as the sum of (expected) liquidity outflows minus the sum of (expected) liquidity inflows.[3]

[1] See for example Beyer et. al. (2017).

[2] The LCR was approved as part of the Basel III Agreement in January 2013 (see BCBS 2013). It was implemented in all BCBS member countries by 1 January 2015, at that time requiring banks to ensure an LCR of 60% or higher. This minimum requirement was raised in the following years by 10 percentage points annually until reaching 100% on 1 January 2019. In the EU, the minimum requirement of 100% was implemented already as of 1 January 2018. As a reaction to the Corona pandemic, the ECB announced on 12 March 2020 that it will allow banks to operate temporarily below an LCR of 100% (see ECB 2020).

[3] Note that in the calculation of the net liquidity outflow, the sum of (expected) liquidity inflows is capped at 75% of the expected liquidity outflows.

There is a close interaction between LCRs and central bank credit. Additional central bank credit has an immediate impact on a bank's LCR, which is positive in most cases. When a bank receives credit from its domestic central bank, its Net Liquidity Outflow (the denominator of the LCR) does not change, while its Liquidity Buffer (the LCR numerator) increases if the bank collateralizes the central bank credit mainly with assets that are not classified as HQLA (i.e. with non-HQLA) or that are classified as less-liquid assets (e.g., L1B, L2A, L2B). We call the immediate LCR change resulting from central bank credit the "technical LCR boost".

We study empirically and theoretically how technical LCR boosts from central bank credit affects banks' behaviour. We focus on a very specific period of tensions, the "Corona year" 2020. Our empirical analysis is based on a large set of data for all individual banks with access to Eurosystem credit operations. For these banks, we have the LCR as well as most of its components on a quarterly basis for the period from Q4 2019 to Q4 2020. In addition, we have for all these banks data on Eurosystem credit and assets used as collateral for Eurosystem credit throughout 2020. These data allow us to decompose quarterly LCR changes for each bank i and each quarter t into two components: (i) bank i's LCR change in t resulting from net central bank credit - we call this, as mentioned above, the "technical LCR boost"; and (ii) bank i's LCR change in t resulting from all other factors. These other factors may include changes of the market price of HQLAs, changes in the amount or the nominal value of HQLAs and non-HQLAs (excluding reserves received from central bank credit operations) held by the respective bank as well as changes in the maturity structure of the bank's liabilities (which change the denominator of the LCR). Note that the latter two factors depend to a large extent on the bank's behavior, i.e. LCR changes due to factors other than central bank credit are of course not exogenous to the bank. The bank can, for example, reduce its LCR by providing additional loans or by shortening the maturity structure of its liabilities.

A simplified numerical example may give a first idea about how we decompose quarterly LCR changes.[4] Suppose that a bank has an LCR of $LCR_{t-1} = 190\%$ at the end of quarter $t-1$. Suppose that at the end of quarter t, its Liquidity Buffer is $LB_t = 100$ and its Net Liquidity Outflow is $NLO_t = 50$, i.e. its LCR has increased in quarter t to $LCR_t = 200\%$. Suppose that between the end of quarter $t-1$ and the end of quarter t, the bank's outstanding amount of central bank credit has increased by 20 (net central bank credit in quarter t). If the bank had instead received a net central bank credit amount of zero in quarter t, it would need to collateralize at the end of quarter t an amount of 20 less. Suppose that this would unencumber some HQLA which would then account for an amount of 5 in the bank's Liquidity Buffer. (It would also unencumber some non-HQLA, but this is not relevant for the example.) This would mean that with a net central bank

[4] The example illustrates the way we decompose LCR changes only partially and therefore gives only a first idea of our approach. The full approach, which takes into account LCR and Eurosystem haircuts as well as LCR caps, is described in Section 4 and in the Annexes 1 and 2.

credit amount of zero in quarter t, the bank's Liquidity Buffer would be $LB_t^- = 100 - 20 + 5 = 85$. Since the Net Liquidity Outflow would still be $NLO_t = 50$, the LCR would be $LCR_t^- = 170\%$. Hence, the technical LCR boost would be $LCR_t - LCR_t^- = 30\%$ and the LCR change resulting from all other factors would be $LCR_t^- - LCR_{t-1} = -20\%$.

In order to understand how technical LCR boosts from net central bank credit affects banks' behaviour, we investigate the causal effects of technical LCR boosts from net central bank credit on LCR changes due to all other factors, as the latter reflect banks' behavior (other than recourse to central bank credit). We do not analyze the impact of technical LCR boosts on specific types of bank activities, for example the provision of additional loans or the liability maturity management. Such an analysis would be interesting, if it could identify not only which types of activities are affected, but also why (e.g. by showing that different types of banks react differently on technical LCR boosts). This extended analysis goes beyond the scope of the present paper and is left for future research.

Investigating the causal effects of technical LCR boosts on LCR changes due to all other factors is not straightforward as causalities may go into both directions. If a bank achieves a large technical LCR boost, then it has more space to engage in activities (other than recourse to central bank credit) that have a negative impact on the LCR. This suggests that the technical LCR boosts may have a negative impact on LCR changes due to all other factors. At the same time, if the LCR changes due to all other factors are large and positive, the need to achieve large positive technical LCR boosts is reduced. This suggests that LCR changes due to all other factors may have a negative impact on the technical LCR boost. Therefore, a statistical relation between our two central variables may reflect causalities in both directions. However, based on empirical, theoretical and institutional considerations, we will argue that in the euro area during the Corona year 2020, the causal effect from LCR changes due to all other factors on banks' technical LCR boosts was negligible.

Before we start our empirical analysis, we present a simple theoretical model of a bank that maximizes its net benefits. The bank benefits from being compliant with regulatory LCR requirements. More precisely, the benefits of the bank in a specific quarter are increasing in the LCR of that quarter, but marginal benefits are decreasing. During each quarter, the bank can influence its LCR through activities other than recourse to net central bank credit. It can also influence its LCR through a technical LCR boost from net central bank credit at the end of the quarter. However, these two ways of influencing the LCR may imply costs for the bank. In our model, important aspects of the bank's behavior depend on the bank's cost function. We provide theoretical and empirical arguments in favor of a specific absolute value cost function. For this cost function, our model has two important implications:

a) The bank will lower its LCR through factors other than recourse to central bank credit the more, the higher (1) its initial LCR and (2) its technical LCR boosts are.

That means that banks "consume" their LCR boosts from central bank credit. And they do so not only after, but also in anticipation of (i.e. before) upcoming LCR boosts.

b) However, Point a) applies only if the bank has a relatively low initial LCR. If the initial LCR is relatively high, then the bank will choose its LCR change resulting from factors other than recourse to central bank credit independent of its initial LCR and independent of its technical LCR boosts. That means the behaviour of banks with a high initial LCR is not guided by considerations related to the LCR.

In our empirical analysis, we use fixed effect panel regressions to test Points a) and b). We regress quarterly LCR changes resulting from all other factors on (i) the LCR at the end of the previous quarter and (ii) technical LCR boosts at the end of the current quarter. We also include a number of control variables in our regressions. We run our regression on a sample including all banks (except a few outliers), but also on different samples from which we exclude banks with relatively high LCRs.

When using the sample with all banks (except outliers), our regressions shows a highly significant negative relation between our dependent variable and our two main independent variables. Therefore, the lower the technical LCR boost and the previous LCR are, the higher will be the LCR change due to factors other than central bank credit. When we run the regressions with smaller samples, excluding first banks with very high, then banks with high and finally banks with moderate LCR levels, our coefficients of interest go more negative. In addition, the explanatory power of our model strongly increases. This indicates that for banks with high LCRs, the relation between our dependent variable and our two main independent variables gets weaker. We take this as a confirmation of point a) and b) above. We conduct a range of robustness checks which quite consistently confirm the results of our main regressions.

Our analysis suggests concrete policy conclusions. If the central bank designs its credit operations in a way that (i) banks have strong incentives to participate in them (for example due to an attractive pricing of the central bank credit) and (ii) obtain strong technical LCR boosts from participating in them (which requires that the central bank accepts a broad range of non-HQLA as collateral), then banks that have relatively low initial LCRs are likely to take actions that reduce their LCRs. Such actions, which could include the provision of additional credit and a shortening of the maturity structure of the liabilities of the banks, plausibly have an impact on the real economy. As such, our analysis reveals what may be called an "LCR channel" of monetary policy transmission. This LCR channel may be most effective in times of real or expected liquidity tensions when banks may be reluctant to extend new loans to the economy as they fear that regulatory liquidity constraints could kick in.

The paper is organised as follows: Section 2 discusses how our paper relates to the literature. Section 3 describes the data used by us. Section 4 explains in detail how we decompose quarterly LCR changes of individual banks into: (i) the technical LCR boost from net central bank credit of the quarter and (ii) LCR changes due to other factors. Section 5 introduces out theoretical model. The empirical analysis is in Section 6. Section 7 concludes.

2. Literature

There is a number of studies about whether regulatory liquidity ratios are relevant for the demand of banks for central bank reserves. Bech et al. (2017) show in a theoretical model that a bank facing the possibility of an LCR shortfall has a stronger incentive to seek funding that receives favourable regulatory treatment and is more likely to borrow from the central bank. Kedan and Ventula Veghazy (2021) use data on euro area banks to compare their demand for central bank reserves before and after the harmonised LCR regulation was announced in the European Union in 2015. They find that banks with a relatively low LCR and located in euro area countries in which the LCR regulation made the regulatory treatment of central bank reserves more favourable increased their demand for central bank reserves after the announcement. Kroon et. al. (2021) use data on Dutch banks from 2002 to 2005 as the Netherlands introduced a quantitative liquidity regulation similar to the LCR already in 2003 (well before the LCR was introduced). These authors find that the introduction of the Dutch liquidity regulation made banks demand more central bank reserves at higher rates in Eurosystem monetary policy operations. Rezende et. al. (2021) obtain similar results for the US. They show that banks that are subject to the LCR regulation have a higher demand for credit from the Federal Reserve's Term Deposit Facility than very similar banks that are exempt from the LCR regulation.

All these papers suggest that the LCR of a bank has a causal impact on the bank's demand for central bank reserves and credit from the central bank. We, however, argue that in the euro area during 2020 LCR levels had a negligible impact on technical LCR boosts from central bank credit. This shows that we analyse a very special situation. The Corona pandemic made the Eurosystem offer credit at very attractive conditions so that banks took the offer regardless of their LCR levels. The demand for central bank credit in the euro area and the resulting technical LCR boost was presumably hardly caused by LCR related considerations on the side of the banks in 2020.

There is a number of other academic papers that analyse the relation between liquidity regulation and bank behaviour independent of monetary policy so that these papers are only loosely related to our study. Banerjee and Mio (2018) for example look at the introduction of regulatory liquidity guidance for individual banks in the UK in 2010 (which was similar to the LCR introduced later on). They show that, when compared with banks exempt from the guidance, banks subject to the guidance increased the share of HQLA and reduced the share of liabilities that are more likely to trigger liquidity outflows in the short term, but did not reduce the lending to the non-financial sector. Bonner and Eijffinger (2016) look at Dutch banks between 2004 and 2011 and how the Dutch liquidity regulation in place at that time impacted the banks' behaviour in interbank markets. These authors argue that the banks had bank-specific targets above the regulatory requirements and banks below their targets paid more when borrowing and received higher interest rates when lending long-term funding in the interbank market. Other related studies are for example Fuhrer et. al. (2017) and Duijm and Wierths (2016).

There is a large body of literature on how central bank credit influences the behaviour of the borrowing banks. Quite a number of papers look at targeted central bank credit operations like the Eurosystem's TLTROs as they have been designed specifically to provide incentives to the borrowing banks to grant more loans.[5] These papers are related to our study as most credit provided by the Eurosystem in 2020 was provided through TLTROs. However, none of these papers takes liquidity regulation into account. On the methodological side, all these papers have to address reverse causality and other identification issues that we believe not to have due to the attractiveness of the Eurosystem credit operations we include in our study. Benetton and Fantino (2021) analyse the first two TLTROs that the Eurosystem conducted in 2014 and their impact on Italian banks. Using an instrument variable approach to address reverse causalities between the amount borrowed by banks from the Eurosystem and the terms of loans provided to bank customers, they find that banks that received credit from the TLTROs provided more loans and at lower rates than other banks (that provided loans to the same firms). Andreeva and García-Posada (2021) also use an instrument variable approach to analyze the impact of the first two TLTRO operations, but distinguish between direct effects and indirect effects on the conditions of loans granted by a bank. The direct effect comes from the amount borrowed by the bank and the indirect effect comes from the amounts borrowed by other banks located in the same country and works through competition between banks. These authors find that the direct effects lower the interest rates on bank loans while the indirect effects lower the credit standards. Other studies on the Eurosystem TLTROs use difference-in-difference approaches (e.g. De Haan et. al. (2019), Esposito et. al. (2020), Laine (2021)) or specific characteristics of the TLTROs (e.g. Bats and Hudepohl (2019), Da Silva et. al. (2021)) and all underline the effectiveness of the TLTROs.

There are a few studies on the interaction of monetary policy and banking regulation. Budnik and Bochmann (2017) find that for euro area banks between 2007 and 2015, high capital ratios reduce banks' responses to monetary policy shocks, while high liquidity ratios moderately increase banks' responses to such shocks. More specifically, they find that banks with a lower maturity mismatch (between assets and liabilities) increase the provision of loans to non-financial corporations more as a response to a monetary policy easing through unconventional measures (defined as measures that lengthen the central

[5] The Eurosystem conducted three series of TLTROs. In the first series, the "carrot" used to incentivizing banks to provide more loans was the amount that banks were allowed to borrow in the TLTROs and the maturity of the loans, as the rate on the TLTROs was very attractive. In the other two series, the incentives worked through the interest rate to be paid.

bank's balance sheet). Other studies of the impact of capital regulation on the transmission of monetary policy measures include Maddalonia and Peydró (2013) and Imbierowicz et. al. (2019). Hoerova et. al. (2018) argue that liquidity regulation can reduce but cannot completely remove the need for the central bank to act as a Lender of Last Resort.

To our knowledge, our paper is the first that studies the impact of liquidity regulation on how banks' participation in central bank credit operations affects bank behaviour. Also, our paper appears to be the first in which the LCR changes are decomposed into (i) a technical boost from net central bank credit and (ii) LCR changes due to other factors. Grandia (2019), however, note that central bank credit operations can increase the amount of unencumbered HQLA held by banks if the central bank accepts non-HQLA as collateral.

3. Data

As mentioned in the introduction, we use data on LCRs and data on monetary policy credit operations including data on assets used as collateral in these operations. In this section, we provide a detailed description of our data.

3.1. LCR data

To understand the LCR data used for this study and our approach to decompose quarterly changes of LCR levels into two components, it is helpful to describe in detail how LCRs are calculated and reported to regulators in the European Union (EU).[6]

As described in the introduction, a bank's LCR is the Liquidity Buffer of the bank divided by the bank's Net Liquidity Outflows over a 30-calendar day stress period. The Liquidity Buffer is composed of unencumbered HQLA. Four types of HQLA are to be distinguished: Level 1 non-covered bonds, Level 1 covered bonds, Level 2A assets and Level 2B assets. L1 non-covered bonds mainly include claims on or guaranteed by EU, highly-rated non-EU or international public entities (central banks, central and regional governments, public sector credit institutions). In particular excess central bank reserves are HQLA in the form of L1 non-covered bonds.[7] Unencumbered L1 non-covered bonds enter the Liquidity Buffer with 100% of their market value (no LCR haircut). L1 covered bonds are "extremely

[6] The legal basis for this can be found in Regulation (EU) No 575/2013 of the European Parliament and the Council of 10 October 2014 (Capital Requirements Regulation, CRR), the supplementing Delegated Regulation (EU) 2015/61 of 10 October 2014, Implementing Regulation (EU) No 680/2014 of 16 April 2014 and the Delegated Regulation (EU) 2018/1620 which is amending Delegated Regulation (EU) 2015/61.

[7] Note that minimum reserve requirements (MRR) are subtracted from the holdings of central bank reserves, as the regulation defines eligible reserves as those that are withdrawable during times of stress.

high quality covered bonds" (Article 10 of Delegated Regulation (EU) 2015/61). The market value of unencumbered L1 covered bonds is reduced by a 7% (minimum) haircut. L2A assets include claims on or guaranteed by certain public sector entities not classified as L1 assets, highly-rated corporate debt securities, as well as different types of covered bonds not classified as L1 assets. The market value of unencumbered L2A assets enters the Liquidity Buffer with a (minimum) haircut of 15%. L2B assets include different types of asset-backed securities (ABS), certain corporate debt securities not classified as L2A assets, certain covered bonds not classified as L1 or L2A assets and a few other asset categories. The market value of unencumbered L2B assets enters the Liquidity Buffer with haircuts between 25% and 50% as shown in Table 1.

Table 1: LCR haircuts

Asset type	Asset sub-type	LCR haircuts
L1 non-covered bonds	L1 non-covered bonds	0%
L1 covered bonds	L1 covered bonds	7%
L2A	L2A	15%
L2B	L2B RMBS and auto loan ABS	25%
L2B	L2B covered bonds	30%
L2B	L2B commercial and consumer loan ABS	35%
L2B	All other L2B assets	50%

For the calculation of the Liquidity Buffer, an unadjusted and an adjusted asset amount for each of the four types of HQLA must be distinguished. The unadjusted amount is simply the market value after LCR haircuts of unencumbered assets of the respective HQLA type. The adjusted amount is the market value after LCR haircuts of those assets that would be unencumbered, if the bank was to unwind all its collateralised or collateral swap transactions that involve on at least one leg of the transaction liquid assets and that matures within 30 calendar days, including transactions with a central bank. There are caps on the *adjusted* amounts of the respective types of HQLA: the adjusted amount of unencumbered L1 non-covered bonds must account for at least 30% of the Liquidity Buffer, the adjusted amount of unencumbered L1 assets for at least 60% and the adjusted amount of unencumbered L1 plus unencumbered L2A assets for at least 85%. The caps are applied on the adjusted rather than the unadjusted asset amounts to ensure that banks cannot circumvent the caps by for example borrowing HQLA against non-HQLA for a short period around LCR data reporting reference dates.

Let $L1NC$, $L1C$, $L2A$ and $L2B$ denote the unadjusted asset amounts and $L1NC'$, $L1C'$, $L2A'$ and $L2B'$ the corresponding adjusted asset amounts for the four types of HQLA. The Liquidity Buffer is than calculated as:

$$(1)\ \ LB = L1NC + L1C + L2A + L2B - \min\{L1NC + L1C + L2A + L2B; ELAA\}$$

with the Excess Liquid Assets Amount:

$$(2)\ \ ELAA = L1NC' + L1C' + L2A' + L2B' - \min\left\{L1NC' + L1C' + L2A' + L2B'; \frac{100}{30}L1NC'; \frac{100}{60}(L1NC' + L1C'); \frac{100}{85}(L1NC' + L1C' + L2A')\right\}$$

The Excess Liquid Asset Amount equals zero if and only if the caps are not binding. In this case, the Liquidity Buffer is simply the sum of the four unadjusted asset amounts. Note that for the case that the adjusted amounts equal the unadjusted amounts (i.e. $L1NC = L1NC'$ etc.), we get

$$(3)\ \ LB = \min\left\{L1NC + L1C + L2A + L2B; \frac{100}{30}L1NC; \frac{100}{60}(L1NC + L1C); \frac{100}{85}(L1NC + L1C + L2A)\right\}$$

The Net Liquidity Outflows over a 30-calendar day stress period NLO is to be estimated as the sum of (expected) liquidity outflows minus the sum of (expected) liquidity inflows. The outflows and inflows are to be calculated following specific rules. For the purpose of this paper, it is important to note that credit from domestic monetary policy operations that mature within 30 calendar days is not considered a liquidity outflow (see Article 28(3)(a) of the Delegated Regulation (EU) 2015/61). This is so as central bank credit can usually be rolled over at maturity.

For our study, it is important to note that banks can actively manage their LCRs. For example, a bank can increase its LCR through purchases of HQLA that are funded with long-term liabilities, through reducing the share of short-term liabilities and through increasing the share of short-term assets. But also the provision of loans to the economy affects banks' LCRs. Bank loans are not HQLA so that they are not reflected in the Liquidity Buffer. But when a bank grants a new loan, the funds are typically credited to the bank account of the debtor at that bank, i.e. the customer deposits at the bank increase. This typically increases the Net Liquidity Outflow.[8] If the debtor then uses the funds to make purchases, they may be transferred to another bank (where the seller has an account). This transfer is, sooner or later, settled in central bank money. That means that the bank that granted the loan loses central bank reserves and the other banks receives central bank reserves. As excess central bank reserves are L1 non-covered bond HQLA, the Liquidity Buffer of the bank that granted the credit typically declines. A bank's LCR therefore declines when the bank provides additional loans to the economy. At the same time, the LCRs of banks that do not grant additional loans are likely to increase when the aggregate amount of bank loans to the economy increases as customers of these banks will receive payments so that their banks receive additional central bank reserves.

[8] Deposits do not enter the Net Liquidity Outflow fully. Retail deposits, for example, have a run-off factor of between 3% and 10%.

Banks located in the EU have to report LCR data to their regulators on a monthly basis (see Article 15 of Implementing Regulation (EU) No 680/2014). For each month, they have to report data referring to the situation at the respective end of the month (see Article 2(1)(a) of Implementing Regulation (EU) No 680/2014).[9] For our analysis, we have been provided with the data reported to regulators for December 2019 and March, June, September and December 2020, i.e. covering the full Corona year 2020 on a quarterly basis. We do not only have the LCRs of all euro area banks, but also several LCR components for each bank: the Liquidity Buffer, the unadjusted asset amount for each of the four types of HQLA (denoted $L1NC$, $L1C$, $L2A$ and $L2B$ above), the Excess Liquid Asset Amount (denoted $ELAA$ above) as well as the Net Liquidity Outflow. For most banks we have the data on a solo basis and, for banks that are members of a banking groups, also on a consolidated basis. We use data on a consolidated basis only if we don't have data on a solo basis. We do not have the adjusted asset amount for the four types of HQLA so that we have no information to what extent LCR caps are binding or not.

For 1602 bank we have data for all five quarters and we include only these banks in our analysis. That means our full sample comprises of 8010 LCR data points (five times 1602). The average LCR calculated across these data points is, however, 142278%. If we exclude from this full sample all banks that have at least one LCR value in the highest 1% of all LCR values in our full sample, we get a reduced sample with 1573 banks, i.e. 7865 LCR data points. The average LCR calculated across the data points of the reduced sample is 267%. In fact, the average LCR across all banks that have at least once an LCR in the highest 1% is 7845139% (and the average LCR across the banks that have at least once an LCR in the highest 5% is 1602899%). These extreme values refer to banks with a special business model that implies a very low Net Liquidity Outflow (i.e. these banks have almost exclusively long-term liabilities) as compared to the Liquidity Buffer. We will work with the reduced sample as we treat data points excluded as outliers. The highest LCR value in the reduced sample is 3549%.[10]

[9] In the EU, public disclosure requirements are distinct from the regulatory reporting requirements as banks have to quarterly disclose the LCR value as the simple average of month-end observations over the 12 months preceding the end of each quarter, see Annex III Paragraph 20 of European Banking Authority (2017).

[10] 85% of the banks in the full sample have an ELAA of zero. These banks account for about 99% of the aggregate Liquidity Buffer of the full sample, i.e. most of the banks with an ELAA > 0 are relatively small.

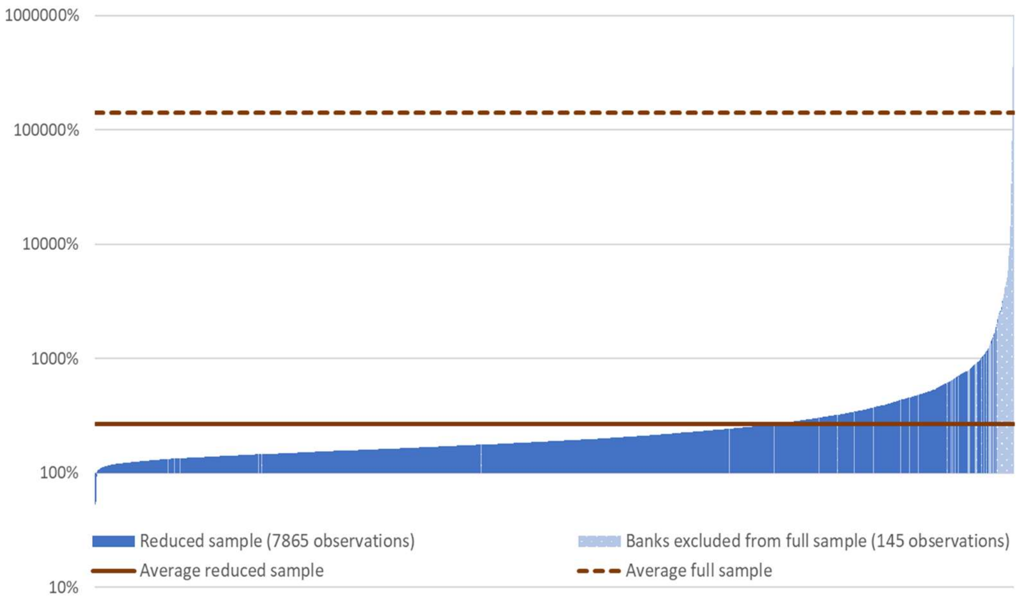
Table 2: Number of banks in sample

	Number of banks	LCR data points	Average LCR	Highest	Liquidity Buffer Share
Full sample	1602	8010	142278%	476370131%	100%
Reduced sample	1573	7865	267%	3549%	99.5%

Note: "Full sample" refers to all banks for which we have LCR data for all five quarters between Q4 2019 and Q4 2020. "Reduced sample" refers to all banks in the full sample that have no LCR in the highest 1% LCR values of the full sample.
Source: ECB.

Chart 1 shows the distribution of LCR values across the full sample as well as across the reduced sample. As can be seen, in contrast to the full sample, the reduced sample does not contain any obvious outliers. Later on in the econometric analysis, we will use the reduced sample, but also three even smaller samples: one excluding all banks with at least one LCR value in the highest 10% of the LCR values of the full sample, one excluding all banks with at least one LCR value in the highest 30% and one excluding all banks with at least one LCR value in the highest 60%. The average LCR is 196% in the 10% reduced sample, 162% in the 30% reduced sample and 139% in the 60% reduced sample. The highest LCR in the 10%-reduced sample is 489%. It is 242% in the 30%-reduced sample and 170% in the 60%-reduced sample.

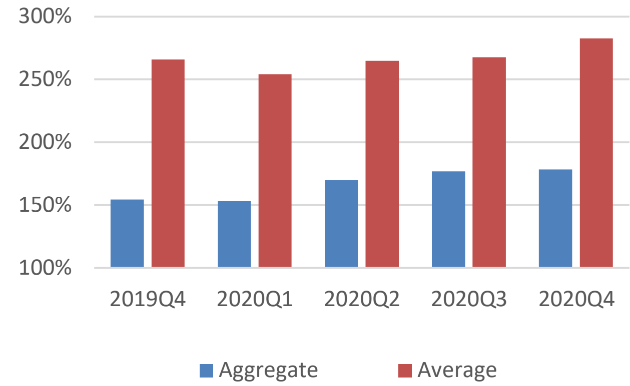
Chart 1: Distribution and average of LCRs



Note: The blue area shows the distribution of the 8010 LCR values in the full sample. The light blue area represents the 1% highest LCR values in the sample. The dark blue area represents the LCRs in the reduced sample. White strips in the dark blue area indicate LCR values that are not in the reduced sample because they belong to banks that had at least once an LCR in the highest 1% of all LCR values and that are therefore not part of the reduced sample. Averages are calculated as simple averages across the full sample (dashed line, at 142278%) and across the reduced sample (solid line, at 267%).
Source: ECB.

Chart 2 shows the average and the aggregate LCR levels across the (1%) reduced sample for each of the five quarters under investigation. As can be seen, average LCRs are higher than aggregate LCRs. This indicates that smaller banks have, on average, a higher LCR as they receive a lower weight in the calculation of the aggregate LCR than in the calculation of the average LCR.

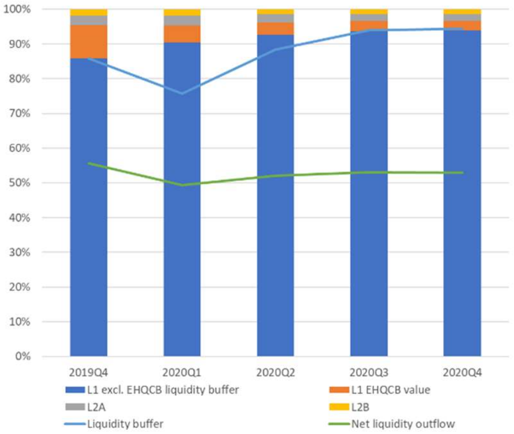
Chart 2: Average and aggregate (weighted average) LCR levels (reduced sample)



Note: Average LCRs are calculated as simple averages across all banks in the reduced sample. Aggregate LCRs are calculated by summing up all Liquidity Buffers across all banks in the reduced sample and dividing the result by the sum off all Net Liquidity Outflows across all banks in the reduced sample.
Source: ECB.

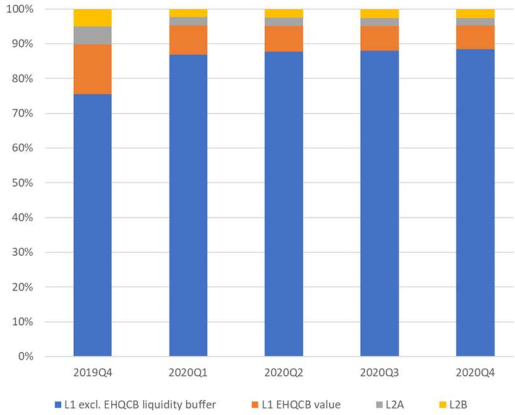
Both the average and the aggregate LCR declined during the first quarter of 2020 (the aggregate LCR much less than the average LCR) and increased for the rest of the year. The decline in the first quarter might be mainly due to a decline in market prices for less liquid types of HQLA when the Corona pandemic hit financial markets around end of February and beginning of March 2020. This is indicated by Charts 3 and 4 which show that the aggregate Liquidity Buffer (Chart 3) as well as the share of (the market value of) less liquid HQLA in the Liquidity Buffer declined in Q1 2020. The Net Liquidity Outflow also went down in that quarter, but less than the Liquidity Buffer. L1 HQLA account for most of the HQLA of euro area banks and suffered, on average, no decline of market prices during the pandemic. This might be the main reason why LCR levels only decreased moderately when the pandemic started to impact financial markets.

Chart 3: Composition of aggregate Liquidity Buffer (reduced sample)



Note: The aggregate Liquidity Buffer is calculated by summing up all Liquidity Buffers across all banks in the reduced sample.
Source: ECB.

Chart 4: Composition of average Liquidity Buffer (reduced sample)



Note: The average Liquidity Buffer is calculated as simple averages across all banks in the reduced sample.
Source: ECB.

The Eurosystem provided large additional amounts of reserves to the banking sector in 2020 which, to a large extent, drove up the LCRs and Liquidity Buffers in the following quarters (see Section 3.2 and EBA (2020)). Additional reserves were provided by the Eurosystem through asset purchases, in particular the Pandemic Asset Purchase Programme (PEPP)[11], and monetary policy credit operations, in particular Targeted Longer-Term Refinancing Operations (TLTROs). Liquidity Buffers increased after the first quarter of 2020 also as market prices of less liquid HQLA recovered after their decline in February and March.

3.2. Data on monetary policy credit operations and collateral

The Eurosystem conducted 247 monetary policy credit operations in 2020 of which 89 were euro operations and the others were US dollar operations. All operations were conducted as full allotment tenders, meaning that each bank received the amount it requested (subject to collateral availability and, in some operations, maximum amounts – see below).

For our study, operations that settled and mature in the same quarter are not relevant as we are looking only at end-of-quarter situations (in particular changes from one quarter-end to the next). 77 out of the 247 operations in 2020 settle and mature in different quarters (51 USD and 26 EUR operations). 56 of these operations allotted less then EUR 2 bn, 10 operations allotted between EUR 2 bn and EUR 10 bn and three allotted between EUR 10 bn and EUR 20 bn. The remaining eight operations (six euro and two USD

[11] The PEPP started in late March 2020 with a relatively small amount. Large amounts were purchased under the program as of April 2020. The effect of the asset purchases on banks' LCR depends on the extent to which banks have been net sellers of government bonds or other HQLA and how additional reserve holdings are financed.

operations) allotted on average EUR 243 bn. These eight operations all settled within the last ten business days of one of the four quarters in 2020. This fact will be relevant when we decompose quarterly LCR changes. Table 3 provides an overview of the eight operations.

Table 3: 2020 credit operations with allotment above EUR 20 bn and settlement and maturity in different quarters

Currency	Settlement date	Maturity date	Days	Allotment amount (EUR bn)
EUR	18/03/2020	24/06/2020	98	109.1305
USD	19/03/2020	11/06/2020	84	75.82
EUR	25/03/2020	29/03/2023	1099	114.97904
EUR	25/03/2020	24/06/2020	91	79.67379
USD	26/03/2020	18/06/2020	84	27.81
EUR	24/06/2020	28/06/2023	1099	1308.43316
EUR	30/09/2020	27/09/2023	1092	174.46405
EUR	16/12/2020	20/12/2023	1099	50.41356

It should be noted that the four operations in Table 3 with maturities of more than 1000 days are Eurosystem Targeted Longer-Term Refinancing Operations (TLTROs). These credit operations have some very specific features in addition to their long maturities. All four operations had been announced (together with some more operations) already in March and June 2019, but their features were modified in September 2019 and again in March and April 2020. Each modification made the features more attractive. The final interest rate to be paid by a bank for credit from the four TLTROs of 2020 depends on how the bank's lending activities[12] evolve until the end of 2021. As such, the TLTROs provide incentives for banks to provide loans to the economy.[13] Most importantly for our study, all banks will be able to pay an interest rate on credit from the TLTROs in 2020 that equals or is below the interest rate on the Eurosystem deposit facility, i.e. the rate at which banks can deposit excess funds back to the Eurosystem. This is so because for the period from

[12] Lending to non-financial enterprises and households (except loans to households for house purchases) is taken into account here.

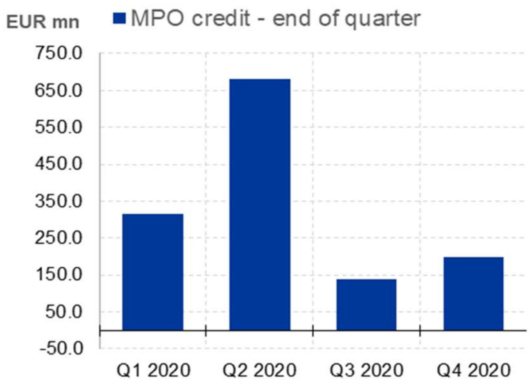
[13] Several studies have found that the TLTROs indeed incentivized banks to provide additional loans to the economy, see for example Benetton and Fantino (2021), Esposito et. al. (2020), Andreeva and Garcia-Posada (2021), Bats and Hudepohl (2019) and Laine (2019), De Haan et. al. (2019), Da Silva et. al. (2021).

24 June 2020 to 23 June 2022, the interest rate on the TLTROs will be between 0 and 50 basis points below the interest rate on the Eurosystem deposit facility (depending on the lending activity of the bank until the end of 2021). And in addition, banks have an early repayment option: as of September 2021, banks can repay on a quarterly basis any amount borrowed from the TLTROs before maturity, provided that at least one year has passed since the settlement of the respective TLTRO. As the TLTROs in 2020 therefore offered an arbitrage opportunity for banks, it is plausible that many (possibly most) banks took as much credit from these TLTROs as possible. For each bank, a maximum amount that can be borrowed in the TLTROs (a "borrowing allowance") has been set, which depends on the size of the loan book of the bank at the end of February 2019.[14]

Also in 2020, some monetary policy credit operations conducted before 2020 matured and banks were allowed to make early repayments from TLTROs conducted before 2020. Taking also maturing operations and early repayments into account, the total outstanding amount of credit provided by the Eurosystem (including all euro and all USD operations) increased from EUR 622 bn at the end of December 2019 to EUR 1796 bn at the end of December 2020.

For our study, the quarterly net Eurosystem credit amounts (i.e. the outstanding amount of Eurosystem credit at the end of a quarter minus that at the end of the previous quarter) during 2020 are of most importance. They are shown in Chart 5 and are mainly driven by the eight operations listed in Table 3 above (but some other operations as well as maturing credit and early repayments influence the figures). The by far largest amount of net credit was provided in the second quarter of 2020, first and foremost by the TLTRO that settled on 24 June of that year.

Chart 5: Quarterly aggregate net Eurosystem credit



Note: The bars show the change between the end of the respective quarter and the end of the previous quarter of the outstanding amount of monetary policy credit provided by the Eurosystem.
Source: ECB.

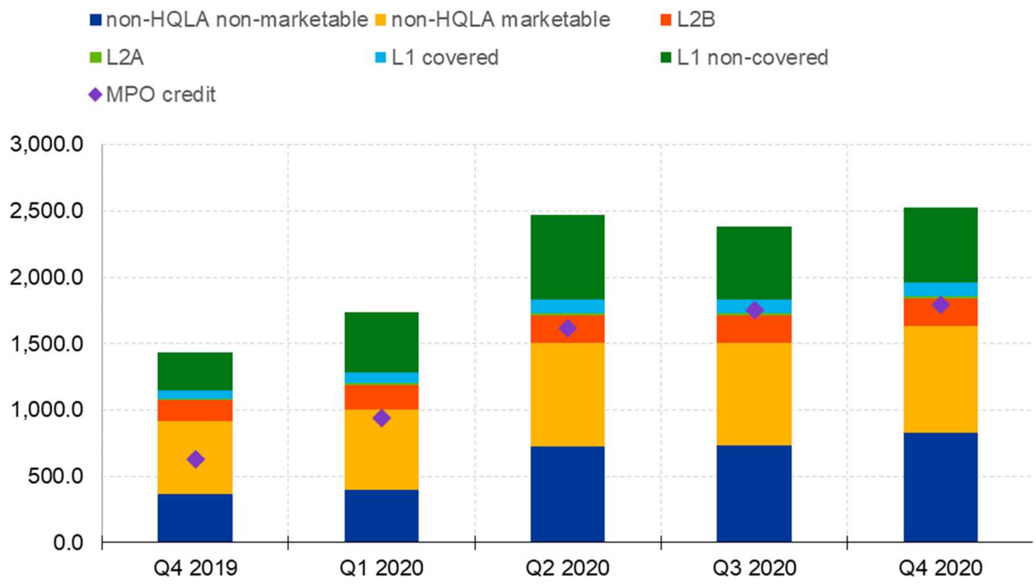
All credit from Eurosystem monetary policy credit operations has to be collateralised. The Eurosystem accepts a broad range of asset types as collateral and applies collateral haircuts that depend on the asset type, the remaining maturity and other characteristics of the assets. The Eurosystem distinguishes between marketable and non-marketable

[14] Not every bank, however, may be able to use its full borrowing allowance as it may not have enough central bank eligible collateral.

collateral assets. Marketable assets are securities, while non-marketable assets are mainly bank loans (or “credit claims”). All non-marketable assets eligible as central bank collateral are non-HQLA. The eligible marketable assets include both HQLA and non-HQLA. The Eurosystem operates a collateral pooling system. That means that individual banks move assets into a pool of assets that they can use as central bank collateral and the overall value after central bank haircuts of the collateral in the pool must at all times be at least as high as the outstanding amount of central bank credit of the respective bank. For most banks, this value is much larger than the outstanding credit to be collateralised, i.e. most banks significantly over-collateralise their central bank credit.

For our analysis, we use detailed data, for all individual banks, on the collateral in the pools shortly after the last relevant central bank credit operation of the respective quarter (Q4 2019 and each quarter of 2020). The data allows us to categorize the collateral assets into nine types: the seven asset types listed in Table 1, marketable non-HQLA and non-marketable non-HQLA. For each of the nine asset types, each bank and each of the five quarters, we have the market value after and before central bank haircuts. Chart 6 shows the evolution of collateral in the pools with the Eurosystem aggregated across all banks with a breakdown into the four main HQLA types and two non-HQLA types. As can be seen, banks added large amounts of eligible assets to their pools during 2020 in line with the increasing amounts of central bank credit.[15]

Chart 6: HQLA classification of mobilised collateral and outstanding Eurosystem credit



Note: The data shows the total value after haircuts of mobilised collateral and outstanding credit at the end of each quarter.

Source: ECB calculations.

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[15] The Eurosystem helped banks here as it took several measures in March and April 2020 to increase the availability of central bank collateral to banks, e.g. made additional types of assets eligible and reduced some of the central bank haircuts.

Most notable here is that the majority of assets in the central bank pools are non-HQLA and that these have been at least on aggregate level sufficient or almost sufficient to collateralize the respective outstanding amounts of Eurosystem credit throughout 2020. An increase of credit (most pronounced between the end of Q1 and the end of Q2) did not encumber, on aggregate level, large additional amounts of HQLA. Note here that banks, for the calculation of their LCR, apply a waterfall approach: the least liquid assets in central bank collateral pools shall be assumed to be encumbered first. Therefore, most HQLA in the pools can be considered unencumbered and count into LCR Liquidity Buffers.

4. Decomposing quarterly LCR changes

When a bank receives credit from the (domestic) central bank, the bank's LCR changes immediately. We call this change the "technical (LCR) boost" from net central bank credit. It is technical as the change is not related to behavioral changes of the bank resulting from the central bank credit. When a bank receives the credit, the credit amount appears on the bank's balance sheet as central bank reserves. These reserves count as L1 non-covered bond HQLA and increase the bank's Liquidity Buffer one to one. The bank has to collateralise the central bank credit with previously unencumbered assets in its monetary policy collateral pool. The amount of encumbered assets on the bank's balance sheet increases accordingly, which reduces the bank's Liquidity Buffer to the extent that the bank uses HQLA as collateral. These are purely technical effects on the Liquidity Buffer. The central bank credit does not have an impact on the bank's Net Liquidity Outflow.[16] As a result, the changes to the bank's LCR are driven by technical effects on the Liquidity Buffer and are therefore themselves technical.

As we want to study the impact of the technical LCR boosts from central bank credit on banks' behavior as reflected in LCR levels, we need to estimate the technical boosts for the individual banks in our sample. In principle, every single credit operation implies a specific technical LCR boost for each bank on the day the operation is settled. And this technical boost could be calculated, if the relevant data is available. This includes data on individual banks' LCRs with its components, central bank credit and central bank collateral close to the settlement date of the credit operation. However, we only have quarter-end LCR data.

Fortunately, the timing and nature of credit operations in 2020 allows us to estimate in a reasonable way one technical LCR boost for each bank and each quarter of 2020. As mentioned in Section 3.2, all large Eurosystem credit operations with settlement date and maturity date in different quarters were settled in the last ten business days of a quarter, i.e. very close to the LCR data reference dates (last day of quarter). We can therefore

[16] As mentioned above, this follows from Article 28(3)(a) of the Delegated Regulation (EU) 2015/61).

reasonably treat the net central bank credit each bank received within one quarter as if this net credit came from one single credit operation at the end of the quarter and use the quarter-end LCR and collateral data to estimate a technical LCR boost from this one (hypothetical) credit operation for the bank.

We proceed as follows for each bank i and quarter t. In a first step, we look at the bank's central bank collateral pool at the end of the quarter. We calculate the difference between (1) the market value (after central bank haircuts) of the assets in the pool that would be unencumbered, if the outstanding amount of credit was the same as at the end of the previous quarter and (2) the market value of the unencumbered assets in the pool given the outstanding amount of central bank credit to be collateralized at that time. In doing so we take into account the required waterfall approach by which the least liquid assets in the pool are encumbered first. We do the calculations separately for each of the seven sub-types of HQLA (see Table 1). In a second step, we look at the bank's unadjusted asset amounts ($L1NC_t$, $L1C_t$, $L2A_t$ and $L2B_t$) for the four HQLA types at the end of the quarter. We calculate the unadjusted asset amounts that the bank would have, if the bank's outstanding amount of central bank credit was the same as at the end of the previous quarter. Call these $L1NC_t^-$ (for L1 non-covered bonds), $L1C_t^-$ (for L1 covered bonds), $L2A_t^-$ (for L2A assets) and $L2B_t^-$ (for L2B assets). To calculate $L1NC_t^-$, we subtract from $L1NC_t$ the net central bank credit of the quarter and then add the difference calculated in the first step for the L1 non-covered bonds. To calculate $L1C_t^-$, we add to $L1C_t$ the difference calculated in the first step for the L1 covered bond, taking into account the 7% LCR haircut (see Table 1). We proceed similarly to get $L2A_t^-$ and $L2B_t^-$.

In a third step, we calculate the Liquidity Buffer that the bank would have if the bank's outstanding amount of central bank credit was the same as at the end of the previous quarter. Call this LB_t^-. We calculate LB_t^- by putting $L1NC_t^-$, $L1C_t^-$, $L2A_t^-$ and $L2B_t^-$ into Equation (3) of Section 3 instead of $L1NC_t$, $L1C_t$, $L2A_t$ and $L2B_t$. This way, we take into account the LCR caps, but assume here that the adjusted asset amounts equal the unadjusted asset amounts. (Remember that we do not have data on adjusted asset amounts.[17]) In a fourth step, we divide LB_t^- by the banks Net Liquidity Outflow NLO_t at the end of the quarter t to get the LCR that the bank would have at the end of t, if the bank's outstanding amount of central bank credit was the same as at the end of the

[17] It is not possible on the basis of our data to directly assess if our assumption that the adjusted asset amounts equal the unadjusted asset amounts is realistic. As shown in Section 3.1, if the assumption is true, then the Liquidity Buffer can be calculated not only according to Equation (1), but also according to Equation (3). Both equations provide the same result in 86% of our observations and almost the same result (less then EUR 1000 deviation) in about 99% of our observations. However, this is not a reliable indication on whether our assumption is realistic as both equations provide the same result also in other cases (in particular if both Equation (1) and Equation (3) imply $LB = L1NC + L1C + L2A + L2B$).

previous quarter. Call this LCR_t^-.[18] In a last step, we calculate the (estimated) technical boost from net central bank credit of quarter t for bank i as the difference $LCR_t - LCR_t^-$. Annex 1 provides all details of our approach and Annex 2 illustrates the approach by means of a simple numerical example.

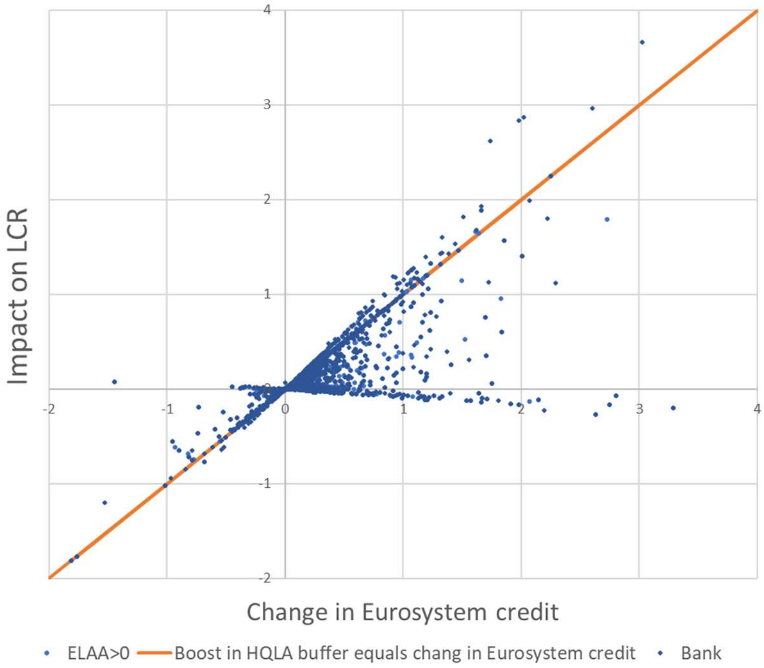
Note that in the second step of our approach, we calculate $L1NC_t^-$ by subtracting from $L1NC_t$ the net central bank credit of the quarter (and then adding L1 non-covered bonds that got encumbered during that quarter). This can lead to a negative value for $L1NC_t^-$, if (and only if) $L1NC_t$ is smaller than the net central bank credit that the bank received in quarter t. A negative $L1NC_t^-$ is somewhat unfortunate as adjusted asset amounts ($L1NC_t$, $L1C_t$, $L2A_t$ and $L2B_t$) cannot be negative. Fortunately, for two reasons we obtain a negative value for $L1NC_t^-$ only in a very few cases. First, if a bank keeps the reserves received from net central bank credit in quarter t on its balance sheet until the end of the quarter, then $L1NC_t$ cannot be smaller than the net central bank credit so that $L1NC_t^-$ will not be negative – and since almost all new credit was provided in the last 10 business days of a quarter in 2020, most reserves received from net central bank credit were kept until the quarter end. Second, banks had plenty of central bank reserves throughout 2020, i.e. they typically started into each quarter already with large (unadjusted) amounts of L1 non-covered bond HQLA. Since we face the problem of negative values for $L1NC_t^-$ only in a very few cases (29 out of 6292 observations)[19], we operate with it.

Chart 7 shows the relation between the quarterly net central bank credit received (horizontal axis) and the technical LCR boost resulting from it (vertical axis) for each quarter and each bank in our (reduced) sample. Dots on the diagonal line are cases where the technical LCR boost equals the related net central bank credit (divided by the Net Liquidity Outflow). Such cases occur when only non-HQLA become encumbered due to the net central bank credit, i.e. the Liquidity Buffer increases exactly by the amount of net central bank credit received (which may be positive or negative).

[18] The variable $LCR_{i,t}^-$ can also be interpreted as the LCR level that the bank would end up with, if it had to unexpectedly repay its net Eurosystem credit received during quarter t at the end of that quarter without being able to do anything else before the quarter ends.

[19] In 16 of these cases, we even get a negative value for LB_t^-.

Chart 7: Net Eurosystem credit and technical LCR boosts (reduced sample)



Note: Each blue dot represents a bank at quarter-end for one of the four quarters in 2020. The x-axis shows the net Eurosystem credit amount (divided by the net liquidity outflow) received by the bank during the quarter and the y-axis shows the Technical LCR boost from this net Eurosystem credit amount for the bank. Source: ECB.

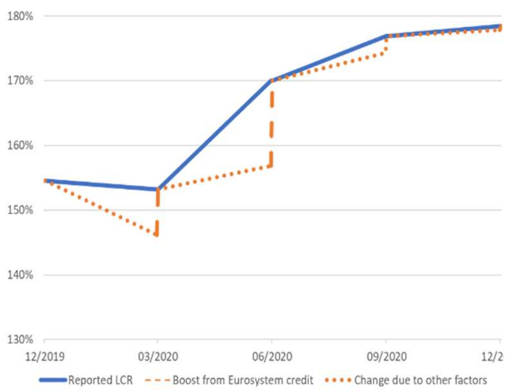
Most dots (71% of observations) are between the diagonal and the x-axis. These concern cases in which the net central bank credit and the technical LCR boost are positively related, but the technical boost falls short of the net central bank credit amount (divided by the Net Liquidity Outflow). The net credit amount (if positive) increases the Liquidity Buffer and the additional amount of encumbered assets (used as collateral for the credit amount) reduces it. But the increase is stronger than the reduction, if some of the assets that get additionally encumbered are non-HQLA. Cases like this are the most common because most assets used as collateral in Eurosystem credit operations are non-HQLA (see Section 3.2).

Less common (17% of observations) are observations below the x-axis (or for negative net central bank credit amounts: values above the axis). For these cases a net increase in the Eurosystem credit has a negative impact on the bank's LCR. This can happen if the collateral that gets encumbered because of the net central bank credit is mainly L1 non-covered bonds. The reason is that such assets are subject to central bank haircuts, but not subject to LCR haircuts. If a bank receives for example EUR 100 ml credit and the credit is collateralized with government bonds that are subject to a 2% central bank haircut, the bank's Liquidity Buffer first increases by EUR 100 ml (new central bank reserves) and then decreases by about EUR 102.04 ml as this is the amount of government bonds that become encumbered.

Observations above the diagonal (12% of observations) are least common. For these cases the increase of the Liquidity Buffer is higher than the amount of central banks credits received. These cases can be explained by the caps which are applied in the calculation of the LCR. When a bank receives central bank reserves, its amount of L1 increases and previously binding caps on L2A and L2B assets may become non-binding, allowing for a boost to the Liquidity Buffer that is larger than the received amount of central bank reserves.[20]

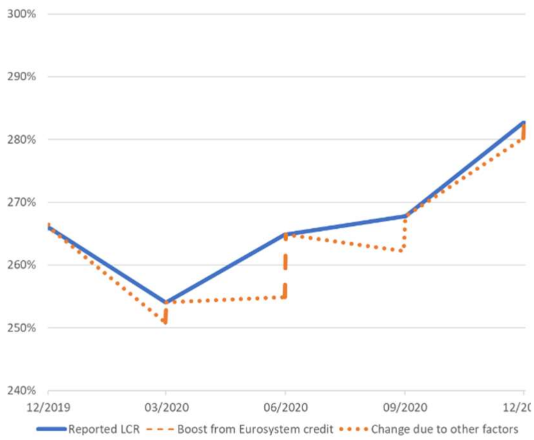
After calculating technical LCR boosts, we can decompose quarterly LCR changes $LCR_t - LCR_{t-1}$ into two components: (i) the LCR boosts $LCR_t - LCR_t^-$ and (2) LCR changes due to other factors $LCR_t^- - LCR_{t-1}$. We can do this decomposition for individual banks, but also on an aggregate and on an average basis. The results of the decomposition on an aggregate and on an average basis are shown in Charts 8 and 9. The dotted lines show how the (aggregate or average) LCR would have changed from one quarter to the next without the technical LCR boost from central bank credit, and the dashed lines show the technical LCR boosts.

Chart 8: Evolution of aggregate LCR, reported and hypothetical case (reduced sample)



Note: Aggregate reported LCR (blue) is calculated as the sum of liquidity buffers across all banks divided by the sum of net liquidity outflows across all banks. The "Boost from Eurosystem credit" shows how much lower the aggregate reported LCR would have been, if the banks had received a net credit amount of zero from the Eurosystem in the respective quarter (hypothetical case).
Source: ECB.

Chart 9: Evolution of average LCR, reported and hypothetical case (reduced sample)



Note: Average reported LCR (blue) is calculated as the simple average of the liquidity buffers across all banks divided by the simple average of the net liquidity outflows across all banks. The "Boost from Eurosystem credit" shows how much lower the average reported LCR would have been, if the banks had received a net credit amount of zero from the Eurosystem in the respective quarter (hypothetical case)
Source: ECB.

[20] Relatively few observations are left of the vertical axes. In these cases, the net central bank credit is negative (i.e. the bank has reduced its outstanding amount of central bank credit during the quarter), typically implying a negative technical LCR boost. In some of these cases, the assets in the bank's collateral pool at the end of the quarter would not suffice to collateralize the bank's central bank credit, if the bank had not received a net central bank credit (or better: had received a net central bank credit of zero). This means the bank's central bank credit would be undercollateralized. Such cases are, however, very rare as banks typically strongly overcollateralize their central bank credit (see Chart 7).

5. Theoretical analysis

We want to study the causal relation between technical LCR boosts from net central bank credit and LCR changes resulting from all other factors. In this section, we present a simple theoretical one-period model of a bank to shed some first light on this relation. Before the start of period t, the bank has an LCR of LCR_{t-1}. During period t until shortly before the end of this period, the bank decides on activities (other than recourses to central bank credit) with an impact x_t on its LCR. At the end of period t, the bank decides on an LCR boost y_t through a net recourse to central bank credit. Boosting up the LCR is beneficial for the bank in particular if the bank's LCR would otherwise be close to 100. The bank's benefits of achieving an LCR level of LCR_t at the end of period t are given by

$$B_t = d \cdot \ln(LCR_t - 100)$$

with

$$LCR_t = LCR_{t-1} + x_t + y_t$$

Due to the logarithmic function for the benefits, boosting up the LCR creates benefits, but marginal benefits are decreasing.[21] The costs that the bank incurs from choosing specific levels x_t and y_t in t are given by a cost function $C_t(x_t, y_t)$ so that the net benefit function of the bank is given by

$$(4)\quad NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) - C_t(x_t, y_t)$$

Note that this setting relates closely to our notation in the previous section as $x_t = LCR_t^- - LCR_{t-1}$ and $y_t = LCR_t - LCR_t^-$. The bank chooses x_t and y_t to maximise NB_t. The initial LCR, LCR_{t-1} is exogenous and assumed to be greater than 100.

How could the cost function $C_t(x_t, y_t)$ look like? One possibility is that the cost function is additive separable in x_t and y_t and that costs and marginal costs are increasing in both variables. Such a cost function would for example be

$$(5)\quad C_t(x_t, y_t) = K - \tilde{a} \cdot \ln[\tilde{A} - x_t] - \tilde{b} \cdot \ln[\tilde{B} - y_t]$$

[21] We assume here that the benefits of an LCR below 100% are infinitely negative as banks are normally required to have an LCR of at least 100%. However, on 12 March 2020, the ECB allowed banks to temporarily operate with an LCR below 100% (see European Central Bank (2020)). It could therefore be argued that a lower LCR value at which the benefit function becomes infinitely negative should be assumed. This would, however, not change any of our results in a substantial way.

The parameters d, K, $\tilde{a}$, $\tilde{A}$, $\tilde{b}$ and $\tilde{B}$ are all assumed to be positive.[22] As the logarithmic function is not defined for negative values, the parameters $\tilde{A}$ and $\tilde{B}$ set maximum values for x_t and y_t. Maximizing the net benefit function NB_t with this cost function gives:

$$(6)\quad x_t = \frac{d}{d+\tilde{a}} \cdot \tilde{A} - \frac{\tilde{a}}{d+\tilde{a}} \cdot [LCR_{t-1} + y_t - 100]$$

and

$$(7)\quad y_t = \frac{d}{d+\tilde{b}} \cdot \tilde{B} - \frac{\tilde{b}}{d+\tilde{b}} \cdot [LCR_{t-1} + x_t - 100]$$

From an econometric perspective, this result suggests estimating a simultaneous equation model of the form

$$(8)\quad x_t = \alpha_x + \beta_x \cdot LCR_{t-1} + \gamma_x \cdot y_t + \varepsilon_x$$
$$(9)\quad y_t = \alpha_y + \beta_y \cdot LCR_{t-1} + \gamma_y \cdot x_t + \varepsilon_y$$

We would have to assume a causal relation from the technical LCR boost y_t to the LCR change due to factors other than recourse to central bank credit x_t and also from x_t to y_t. However, the above net benefit function may not be realistic. It assumes that the bank benefits only from high LCR levels and everything else is not relevant. So for $d = 0$, the bank would minimize its costs without constraints, i.e. x_t and y_t would be infinitely negative.

To make the cost function more realistic, we assume that costs arise from deviations of x_t from some level A and deviations of y_t from some level B. For simplicity, we assume that these costs are linear in the amount of deviation:

$$(10)\ C_t(x_t, y_t) = a \cdot |x_t - A| + b \cdot |y_t - B|$$

The parameters a and b are assumed to be non-negative, while A and B may be positive or negative or zero. If $d = 0$, then it would be optimal to choose $x_t = A$ and $y_t = B$. Or to put it differently: if there was no LCR regulation, then the bank would choose $x_t = A$ and $y_t = B$. If we instead have $d > 0$, i.e. if there is an LCR regulation, it may not be optimal anymore for the bank to choose $x_t = A$ and $y_t = B$. Instead, the bank may choose $x_t > A$ or $y_t > B$ to obtain a sufficiently high LCR level (see below). The net

[22] We omit time indices to these parameters but note that they can of course change from quarter to quarter.

benefit function (4) with the cost function (10) therefore describes the impact of the LCR regulation on the behavior of banks in an intuitive way.

In Annex 3, we prove:

RESULT 1:

a) If $a < b$, then

(11) $y_t = B$

and

$$(12)\ x_t = \begin{cases} \frac{d}{a} - [LCR_{t-1} + B - 100], & if\ LCR_{t-1} \leq \frac{d}{a} - (A + B - 100) \\ A, & otherwise \end{cases}$$

b) If $a > b$, then

(13) $x_t = A$

and

$$(14)\ y_t = \begin{cases} \frac{d}{b} - [LCR_{t-1} + A - 100], & if\ LCR_{t-1} \leq \frac{d}{b} - (A + B - 100) \\ B, & otherwise \end{cases}$$

Now y_t does not depend anymore on x_t, if $a < b$, but x_t depends on y_t (since x_t depends on B and $y_t = B$). That means the causalities work into one direction, we do not have reverse causality anymore.

What is the intuition for Result 1? The bank has two tools to steer its LCR in quarter t: x_t and y_t. If deviations of x_t from A are less costly than deviation of y_t from B, then the bank does not use y_t to steer the LCR because it is not efficient to do so. Instead, the bank will set $y_t = B$. It will use only x_t for steering its LCR. But even x_t will not be used by the bank to steer the LCR, if LCR_{t-1} is large (and $A + B$ not very negative). This is so because in this case (due to the logarithmic benefit function), deviations of x_t from A do not change the LCR much. That means not only y_t, but also x_t is not an efficient tool to steer the LCR. The bank will therefore set $x_t = A$, i.e. x_t may not depend on LCR_{t-1}, if LCR_{t-1} is large. If, however, LCR_{t-1} is small (and $A + B$ not very large), steering the LCR through x_t becomes efficient. The bank will set x_t the higher, the lower LCR_{t-1} is and also the lower $y_t = B$ is.

The latter point may be made clearer by means of a stylized example. Consider two banks that have the same parameters d, a, b with $a < b$, $A = -10$ and $B = 10$. But bank 1 started with a previous LCR of $LCR_{1,t-1} = 100$, while bank 2 has $LCR_{2,t-1} = 1000$. Both banks $i = 1,2$ choose $y_{i,t} = B = 10$ (because $a < b$). If bank 1 chooses $x_{1,t} = A = -10$, it would end up with a very low LCR of $LCR_{1,t} = 100$. It appears plausible to expect the bank to therefore choose a higher value for $x_{1,t}$. Bank 2, however, appears more likely to choose $x_{2,t} = A = -10$, as the bank would then again achieve an LCR level of $LCR_{1,t} = 1000$, which is a very comfortable level.

The above intuitions refer to the first case considered in Result 1, i.e. the case of $a < b$. The intuition for $a > b$ is of course analogous. In the next section, we will argue empirically that for the euro area during the year Corona 2020, the first case considered in Result 1 has been prevailing. Starting from this insight, we run some panel regressions (see Section 6) which confirm in our view that our model above might be a good description of the relation between technical LCR boosts from central bank credit and banks' activities with an impact on LCRs.

Our model has interesting policy implications. The central bank can influence the parameters b and B. For example, it could make the central bank credit it offers very attractive (e.g. through the pricing) and easily accessible (e.g. through accepting a broad range of assets as collateral). This would increase b and B. As a result, y_t would increase and x_t would decrease. In other words: very attractively priced and easily accessible central bank credit operations provide incentives to banks to take actions that reduce x_t. Such actions, which could include the provision of additional credit and a shortening of the maturity structure of the liabilities of the banks, plausibly have an impact on the real economy. All this, however, holds in our model only if $d > 0$, i.e. only if the regulatory LCR requirement is in place. As such, our theoretical model suggests a "LCR channel" of monetary policy transmission. In Section 6 below, we will provide an empirical analysis that supports our theoretical model and therefore makes us conclude that this LCR channel of monetary policy transmission really exists.

Note also that our model suggests that the LCR regulation has no impact on x_t, if $a > b$ (as we would have $x_t = A$, regardless of whether $d = 0$ or $d > 0$). In this case, the LCR regulation would only make banks change y_t. One may conclude that the LCR regulation may therefore not achieve its aim, if $a > b$. However, this result is due to the simplicity of our model and may not be very realistic. For example, if we were using a quadratic cost function, a different result would be obtained (see Footnote 27 below).

The benefit function in our model is of course ad hoc as it is not derived from basic assumptions (e.g. about how precisely the bank benefits from a larger LCR and what may motivate the bank beyond LCR-related considerations to demand central bank credit). Providing a detailed foundation, which should show that the benefit function can be interpreted as a profit function of the bank, goes beyond the scope of this paper and is left for future research.

Our model is based on a number of strong assumptions which could be relaxed. First, there is no uncertainty in the model. To relax this assumption, we could assume that $LCR_t = LCR_{t-1} + z_t + y_t + \varepsilon_t$, where the bank chooses z_t and y_t, the LCR change due to factors other than central bank credit would be $x_t = z_t + \varepsilon_t$ and ε_t would be a random variable the value of which the bank would know only after it has chosen z_t. This approach would also reflect the fact that the variable x_t does not only depend on actions of the bank, but also on factors that are exogenous to the bank, in particular (changes to) the market value of HQLA. Second, we assume that the costs from deviations of x_t and y_t from A and B are linear in the amount of deviations, i.e. marginal costs are constant. We could instead assume that marginal costs are increasing, like for example with a quadratic cost function $C_t(x_t, y_t) = a \cdot |x_t - A|^2 + b \cdot |y_t - B|^2$. Third, we assume that the parameters A and B are exogenous. But in reality A may depend on y_t and B may depend on x_t (i.e. the optimal level of one choice variable may depend on the level of the other). To relax this assumption in an adequate way may require a proper micro foundation of the net benefit function. Fourth, we assume that the bank reports its LCR only once during period t (and that the reporting period is t). However, in the next section we will understand our period t as a quarter of the year 2020. And European banks have to report their LCRs monthly. To relax the assumption, we could for example assume that the bank has to report more than once during period t.

We don't expect to get major new insights from relaxing the first assumption mentioned here. Relaxing the second assumption would likely change one important aspect of Result 1: even when $a < b$, there could be a causal impact not only from y_t on x_t but also the other way around. This is so because the marginal costs of deviations between x_t and A get high very fast, if such costs are quadratic, while the marginal costs of deviations between y_t and B are low as long as the deviation is small.[23] In the next section, we will provide empirical evidence indicating that there was no casual impact from LCR levels on technical LCR boosts in 2020. This suggests that at least for the euro area in 2020, our linear cost function might be more realistic than a quadratic one.

We will briefly discuss a model with two LCR reporting periods in Annex 3a. The main result from that model resembles very much our Result 1 as (for the case of $a < b$) y_t is still independent of LCR_{t-1} and x_t and x_t is still decreasing in LCR_{t-1} and in B for relatively small values of LCR_{t-1} and independent of LCR_{t-1} and B for relatively large values of LCR_{t-1}. However, in the model with two LCR reporting periods, x_t is not a linear function of B. So relaxing the assumption that the bank reports its LCR only once during period t creates non-linear relations.

6. Empirical analysis

In this section, we study empirically the relation between technical LCR boosts from net central bank credit and LCR changes due to all other factors. The analysis is guided by the theoretical considerations of the previous section, in particular Result 1.

[23] A quadratic cost function $C_t(x_t, y_t) = a \cdot |x_t - A|^2 + b \cdot |y_t - B|^2$ would mean that for $d = 0$, we would still have $x_t = A$ and $y_t = B$. But for $d > 0$, we would get $x_t > A$ and $y_t > B$, regardless of whether we have $a < b$ or $a > b$. Hence, the LCR regulation would now have an impact on x_t under all parameter constellations.

6.1. Causalities

As a first step of the empirical analysis, we study the causalities between initial LCR levels ($LCR_{i,t-1}$), technical LCR boosts ($y_{i,t}$) and LCR changes due to all other factors ($x_{i,t}$). Consider Charts A1 to A6 in Annex 4. Charts A1 to A3 are scatter plots with the LCR of the previous quarter ($LCR_{i,t-1}$) on the horizontal axes and the LCR change in the current quarter due to factors other than net central bank credit ($x_{i,t}$) on the vertical axes. Chart A1 is based on our reduced sample (i.e. all banks are removed that have an LCR level at least in one of the quarters that is among the highest 1% LCRs) while Charts A2 and A3 are based on even smaller sample (Chart A2: all banks are removed that have an LCR level at least in one of the quarters that is among the highest 10% LCRs; Chart A3: all banks are removed that have an LCR level at least in one of the quarters that is among the highest 60% LCRs). All three charts clearly indicate a negative statistical relation between $LCR_{i,t-1}$ and $x_{i,t}$.

Charts A4 to A6 are scatter plots with the LCR of the previous quarter ($LCR_{i,t-1}$) on the horizontal axes and the technical LCR boost in the current quarter ($y_{i,t}$) on the vertical axes. Chart A4 is based on the (1%-) reduced sample and Charts A5 and A6 are based on the 10%-reduced and the 60%-reduced samples. All three charts indicate that there was no statistical relation between $LCR_{i,t-1}$ and $y_{i,t}$.

Our model of Section 5 suggests that if there is a negative statistical relation between $LCR_{i,t-1}$ and $x_{i,t}$, but no statistical relation between $LCR_{i,t-1}$ and $y_{i,t}$, then Case a) of Result 1 (i.e. $a < b$) prevails. This case implies, according to our model, that there is no causal effect from $x_{i,t}$ to $y_{i,t}$ (but one from $y_{i,t}$ to $x_{i,t}$). We therefore conclude that in 2020, LCR changes due to factors other than recourse to Eurosystem credit had negligible causal effects on technical LCR boosts from net Eurosystem credit.

How can this be explained? The by far most important Eurosystem credit operations in 2020 were Eurosystem Targeted Longer-Term Refinancing Operations (TLTROs). These operations have had a very attractive pricing. Banks can make sure that the interest rate that they have to pay on credit from these TLTROs will not exceed the interest rate that they receive when they deposit funds back to the Eurosystem. For many banks, the TLTRO interest rate will come out even lower, implying an arbitrage opportunity for them. In addition, the Eurosystem relaxed some of its collateral requirements in 2020 so that also the cost of collateral used in Eurosystem credit operations was lowed. Therefore, for most banks, the optimal strategy was to (i) borrow in the 2020 TLTROs close to the maximum amount possible (where this maximum amount may for example be set by the TLTRO borrowing allowance of the bank or the bank's stock of central bank eligible collateral), regardless of the LCR of the bank and (ii) choose activities other than recourse to Eurosystem credit to change the LCR if desired whereby taking into account the previous LCR level and the technical LCR boost from upcoming Eurosystem credit operations (including the TLTROs). This would mean that a bank's LCR changes due to factors other than recourse to Eurosystem credit would depend on the bank's previous LCR level and its LCR boosts, but LCR boosts would not depend on the banks previous LCR level or its LCR changes due to factors other than recourse to Eurosystem credit.

Referring to the model of the previous section, the considerations of the bank could be summarized as follows: the bank first decides what it would do, if there was no LCR regulation. Given the attractive pricing of the TLTROs, it would "tentatively" choose a borrowing amount from the TLTROs that is close to the maximum amount possible. It would also choose "tentatively" all other activities. The bank would then consider the resulting LCR. If this LCR is sufficiently high, the bank would stick to its tentative decisions. If it considers the LCR too low, it would think about how to deviate from the tentative decisions to obtain a higher LCR. If a higher TLTRO borrowing amount would increase its LCR, then the bank would realize that it cannot borrow even more from the TLTROs as its tentative borrowing amount is already close to the maximum. If a lower TLTRO borrowing amount would increase its LCR (which is possible, if most of the assets used by the bank as central bank collateral is HQLA), then the bank would realize that it would be very costly to reduce the TLTRO borrowing amount given the attractive TLTRO pricing. So in both cases, the bank would end up adjusting other activities to increase its LCR.

As all this suggests that Case a) of Result 1 of our theoretical model has been prevailing in the euro area in 2020, the further steps in the empirical analysis of the present section will be guided by Equations (11) and (12) of Section 5.

6.2. Main regressions

In line with the notation in Section 5, let $x_{i,t} = LCR_{i,t}^{-} - LCR_{i,t-1}$ and $y_{i,t} = LCR_{i,t} - LCR_{i,t}^{-}$. On the basis of the upper arm of Equation (12) (taking into account Equation (11)), we estimate the following time fixed effects panel regression model:

$$(15)\ \mathrm{x_{i,t}} = \alpha \cdot \mathrm{LCR_{i,t-1}} + \beta \cdot \mathrm{y_{i,t}} + \gamma \cdot \log\left(\mathrm{size_{i,4}}\right) + \delta \cdot \left(\frac{\mathrm{TLTRO_{i,t-1}}}{\mathrm{size_{i,4}}}\right) + \theta \cdot \mathrm{LR_{i,t-1}} + \mathrm{v_t} + \mathrm{u_{i,c,t}}$$

Here, t (for $t = 1, \ldots, 4$) refers to the tth quarter of 2020 and $t = 0$ to the last quarter of 2019 (i.e. $LCR_{i,0}$ is the LCR of bank i at the end of December 2019). In line with the theoretical analysis of Section 5, we expect that a bank with a relatively low LCR at the end of quarter $t-1$ tries to increase its LCR at the end of quarter t through activities other than recourses to central bank credit. The coefficient α should therefore be negative. Similarly, we expect also the coefficient β to be negative as banks that envisage a large technical LCR boost from a recourse to central bank credit in or at the end of quarter t may engage in activities other than recourses to central bank credit that have a negative impact on the LCR.

The variable $size_{i,4}$ is the market value of the total assets of bank i at the end of Q4 2020. Chart 2 as well as Charts 8 and 9 suggest that large banks have on average much lower LCRs and may also behave differently in other ways. We therefore correct for possible effects coming from the size of the banks.[24] $TLTRO_{i,t-1}$ is the outstanding amount of TLTRO credit of bank i at the end of quarter $t-1$. As explained in Section 3.2, the Eurosystem TLTROs are designed to provide specific incentives to banks to increase their lending to the economy. As explained in Section 3.2, if a bank increases its lending to the economy, its Net Liquidity Outflow is likely to increase and its Liquidity Buffer is likely to decline. We would therefore expect the parameter δ to be negative. The variable $LR_{i,t-1}$ is bank i's regulatory Leverage Ratio at the end of quarter $t-1$.[25] If a bank has a very low Leverage Ratio, it might need to sell assets at short notice and use the proceeds to repay liabilities in order to increases the Leverage Ratio. As the assets that can be sold easiest at short notice are HQLA, this may reduce the bank's Liquidity Buffer and therefore its LCR. We therefore expect that the coefficient θ may be positive. We add the variables $\log(size_{i,4})$, $\frac{TLTRO_{i,t-1}}{size_{i,4}}$ and $LR_{i,t-1}$ to correct for effects not considered in the model of Section 5, but run regressions also without them.[26]

The time fixed effect is v_t. It may appear plausible to add as another independent variable the quarterly HQLA price changes as they should be positively related to our dependent variable. But since we run panel regression with time fixed effects, quarterly HQLA changes due to asset price changes are already reflected in the time fixed effect variables v_t.

Table 4 shows the summary statistics for our variables.

Table 4: Summary Statistics regression variables

			Percentile		
Statistic	Mean	SD	75th	50th	25th
LCRt$^-$ - LCRt-1 (pps)	-1.11	160.27	22.55	-1.21	-25.02
Previous LCR (%)	263.14	264.55	260.94	184.55	151.50
Technical boost (pps)	5.31	53.49	0.00	0.00	0.00
Previous TLTRO (EUR mn)	666.82	4,310.63	70.00	0.00	0.00
Size (EUR bn)	16.29	98.03	4.74	1.88	0.71
Previous leverage ratio (%)	9.17	6.73	9.65	8.24	6.86

[24] As we have only annual data on the size of the banks, the size variable does not change from quarter to quarter.

[25] The regulatory Leverage Ratio is the ratio of Tier 1 Capital over the sum of all on and off balance sheet assets and backs are expected under Basel III to have a Leverage Ration above 3%.

[26] We also ran regressions with capital ratios as additional control variables, but the coefficients for capital ratios turned out to be insignificant whenever leverage ratios were also included as control variables.

Note the percentiles of the technical boosts in Table 4. As they are all zero, we have only relatively few observations of technical boosts unequal zero. This does not mean that only very few banks achieved a technical boost in 2020 as the table refers to quarterly observations. But many banks achieved a technical boost in only one or two quarters of 2020, but not in the other quarters of that year.

We run regression on different samples, starting with our reduced sample (i.e. all and only banks are removed that had at least once an LCR in the highest 1% LCR values), followed by a 10%-reduced sample from which all (and only) banks that had at least once an LCR in the highest 10% LCR values are removed. In addition, we run regressions on a 30%-reduced sample and on a 60%-reduced sample. The highest LCR in the 1%-reduced sample is 3549%. The highest LCR in the 10%-reduced sample is 489%. In the 30%-reduced sample the highest LCR is 242%. Finally, the highest LCR in the 60%-reduced sample is 170%.

Table 5 summarizes our main results for Equation (15). All results based on Equation (15) are shown in Table A1 of Annex 4.

Table 5: Main results

Panel regressions - Equation 15 - Time FEs, cluster-robust SEs

	Dependent variable:			
	$LCR_t^- - LCR_{t-1}$			
	1%-reduced sample	10%-reduced sample	30%-reduced sample	60%-reduced sample
	(1)	(2)	(3)	(4)
Previous LCR	-0.158***	-0.241***	-0.403***	-0.419***
	(0.027)	(0.026)	(0.037)	(0.020)
Technical boost	-0.681***	-0.831***	-0.786***	-0.928***
	(0.117)	(0.046)	(0.020)	(0.015)
previousTLTRO/Size	11.617	51.065	9.664	5.177
	(30.747)	(36.170)	(11.077)	(22.879)
log(Size)	-1.903	-0.306	0.264	0.109
	(2.764)	(1.242)	(0.854)	(0.908)
Previous leverage ratio	2.525***	0.110	0.134	0.128
	(0.980)	(0.129)	(0.174)	(0.173)
Time FE	Yes	Yes	Yes	Yes
Observations	6,228	5,280	3,360	1,052
R^2	0.117	0.257	0.380	0.618
Adjusted R^2	0.116	0.256	0.378	0.615
F Statistic	164.659***	365.176***	410.174***	337.996***

Note: The table shows the results of a fixed effects estimation using time fixed effects. The separate columns report the results of the regressions for the different subsamples depending on the percentile (1th, 10th, 30th or 60th percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

In all regressions that we run on Equation (15), the coefficients α (Previous LCR) and β (Technical boost) are highly significant and negative as expected. As can be seen from Table A1 in Annex 4, they are very much the same as long as we use the same sample, regardless of whether we correct for other effects. The other coefficients (γ, δ and θ) are mostly insignificant, but have signs in line with what we expected if they are significant.

What is striking is that the coefficients α and β almost always get more negative and the R^2 increases when we reduce the sample size. In the 1%-reduced sample, α is around -0.16, β is around -0.68 and R^2 below 12%. And in the 60%-reduced sample, α is around -0.42, β is around -0.93 and R^2 is 62%. So our results depend heavily on whether the sample includes only banks with relatively low LCRs or also banks with higher LCR.

These results are in line with our theoretical analysis of Section 5 as summarized in Result 1 Case a: while banks with a low (previous) LCR increase their LCR through activities excluding recourse to central bank credit when the (previous) LCR or the technical LCR boost gets lower (higher), banks with a high (previous) LCR show more or less of such activities independently of the (previous) LCR and the technical LCR boost. Therefore, the more banks of the latter type we include in our linear panel regression, the lower will be the explanatory power of the regression and the closer to zero will be the coefficients.

For the banks in the 60%-reduced sample, we find that an increase of the previous LCR by one percentage point leads on average to activities excluding recourse to central bank credit that lower the LCR by 0.42 percentage points (while for the banks in the 1%-reduced sample this figure is 0.16 percentage points). And a technical LCR boost from central bank credit by one percentage point leads on average to activities excluding recourse to central bank credit that lower the LCR by 0.93 percentage points (while for the banks in the 1%-reduced sample this figure is 0.68 percentage points). That means that these banks on average almost fully consume their LCR boosts from net central bank credit.

Since $LCR_{t-1} = LCR^{-}_{t-1} + y_{t-1}$, we get from Equations (11) and (12) of Section 5:

$$x_t = \begin{cases} \dfrac{d}{a+\tilde{a}} - [LCR^{-}_{t-1} + y_{t-1} + y_t - 100], & if\ LCR_{t-1} \leq \dfrac{d}{a+\tilde{a}} - (\tilde{A} + y_t - 100) \\ \tilde{A} & , otherwise \end{cases}$$

This suggest that in addition to Equation (15), it makes sense to estimate the following time fixed effects panel regression model:

$$(16)\ x_{i,t} = \alpha \cdot LCR^{-}_{i,t-1} + \tilde{\alpha} \cdot y_{i,t-1} + \beta \cdot y_{i,t} + \gamma \cdot \log(size_{i,4}) + \delta \cdot \left(\frac{TLTRO_{i,t-1}}{size_{i,4}}\right) + \theta \cdot LR_{i,t-1} + v_t + u_{i,t}$$

Compared with the regressions based on Equation (15), the independent variables have changed. We do not use $LCR_{i,t-1}$ anymore, but instead $LCR^{-}_{i,t-1}$ and $y_{i,t-1}$. The variable $LCR^{-}_{i,t-1}$ is the LCR that bank i would have had at the end of quarter $t-1$, if its net central bank credit had been zero in that quarter. The variable $y_{i,t-1}$ is the technical LCR boost achieved at the end of quarter $t-1$.

Table A2 in Annex 4 shows the results of the panel regression based on Equation (16) for the four sample sizes. The results are similar to those of the regressions based on Equation (15): as expected on the basis of the theoretical analysis, the coefficients α, $\tilde{\alpha}$ and β are all negative, highly significant and broadly the same regardless of whether we correct for other effects. The sum of the coefficients α and $\tilde{\alpha}$ as well as the coefficient β get more negative and the R^2 increases when we reduce the sample size.[27]

These results indicate that banks' activities (excluding recourse to central bank credit) with an impact on LCRs are influenced by technical LCR boosts that took already place as well as those that are upcoming. To put it differently: banks typically consume a technical LCR boost before that boosts (i.e. in anticipation of it) as well as after it.

6.3. Robustness

Although all banks in our sample are subject to the unified regulation of the European Union, banking regulation is often implemented by national authorities of the country in which the respective bank is located. In addition, many banks are active mainly in their home country. To reflect country-specific aspects, we now include country fixed effects in our regressions. Let $x_{i,c,t} = LCR^{-}_{i,c,t} - LCR_{i,c,t-1}$ and $y_{i,c,t} = LCR_{i,c,t} - LCR^{-}_{i,c,t}$, where c is bank i's country of location. On the basis of the upper arm of Equation (12) of Section 5 (taking into account Equation (11)), we estimate the following time fixed effects country fixed effects panel regression model:

$$(17)\ x_{i,c,t} = \alpha \cdot LCR_{i,c,t-1} + \beta \cdot y_{i,c,t} + \gamma \cdot \log\left(size_{i,c,4}\right) + \delta \cdot \left(\frac{TLTRO_{i,c,t-1}}{size_{i,c,4}}\right) + \theta \cdot LR_{i,c,t-1} + v_t + w_c + v_t \cdot w_c + u_{i,c,t}$$

The variable w_c is a country fixed effect where we distinguish six "countries": France, Germany, Italy, Spain, the Netherlands and the rest of the euro area. Equation (17) includes a term $v_t \cdot w_c$ to capture possible interaction between time and country fixed effects. The results obtained for equation (17) are shown in Table 3 of Annex 4. Comparing Tables A1 and A3 of Annex 4 shows that including country fixed effects has hardly any impact on our main coefficients α and β. Including country fixed effects does have a bit

[27] The other coefficients (γ, δ and θ) are still mostly insignificant. But note that the coefficient δ is now in some cases significant and positive, which is not in line with what we had expected.

more impact on the coefficients of our control variables, but as for the regression on Equation (15), they have signs in line with what we expected if they are significant.

Next, we add also country fixed effects to Equation (16) above to get the model:

$$(18)\ x_{i,c,t} = \alpha \cdot LCR^{-}_{i,c,t-1} + \tilde{\alpha} \cdot y_{i,c,t-1} + \beta \cdot y_{i,c,t} + \gamma \cdot \log{(size_{i,c,4})} + \delta \cdot \left(\frac{TLTRO_{i,c,t-1}}{size_{i,c,4}}\right) + \theta \cdot LR_{i,c,t-1} + v_t + w_c + v_t \cdot w_c + u_{i,c,t}$$

The results for Equation (18) are shown in Table A4 of Annex 4. Comparing Tables A2 and A4 of Annex 4 shows that including country fixed effects has hardly any impact on our coefficients α, $\tilde{\alpha}$ and β.

554 of the banks in our 1%-reduced sample have a technical LCR boost of zero in all four quarters of 2020. We run the regression for Equation (17) and (18) also without these banks. The results are displayed in Table A5 of Annex 4. They are very similar to those obtained with these banks.

To check the robustness of our results further, we also run panel regressions with bank fixed effects instead of country fixed effects. Instead of Equation (15) or (17), we now have

$$(19)\ x_{i,t} = \alpha \cdot LCR_{i,t-1} + \beta \cdot y_{i,t} + \delta \cdot \left(\frac{TLTRO_{i,t-1}}{size_{i,4}}\right) + \theta \cdot LR_{i,t-1} + v_t + w_i + u_{i,t}$$

As the bank fixed effects (w_i) capture the size of the respective bank, the bank size variable is now dropped from the regression equation. The results for Equation (19) are shown in Table A6 of Annex 4. As before, the coefficients α and β continue to be negative and highly significant. As before, both coefficients tend to get more negative and R^2 increases when we exclude banks with high LCRs from the sample. Introducing bank fixed effects therefore still leads to a confirmation of our theoretical results. The parameter β does not change much compared to the regressions without bank fixed effects, while the parameter α is much more negative now. The parameters δ and θ of our control variables are significant now only in the regressions with the 30%- and the 60%-reduced samples. And here, they have signs that are not in line with what we had expected.

We run regressions with bank fixed effects instead of country fixed effects also on an equation that is analogous to Equations (16) and (18):

$$(20)\ x_{i,t} = \alpha \cdot LCR^{-}_{i,t-1} + \tilde{\alpha} \cdot y_{i,t-1} + \beta \cdot y_{i,t} + \delta \cdot \left(\frac{TLTRO_{i,t-1}}{size_{i,4}}\right) + \theta \cdot LR_{i,t-1} + v_t + w_i + u_{i,t}$$

The results are in Table A7 of Annex 4. As before, the coefficients α, $\tilde{\alpha}$ and β continue to be negative and highly significant. The parameters δ and θ of our control variables are now insignificant in all regressions.

Our panel model with bank fixed effects has a dynamic structure as the right hand side of Equation (19) implicitly includes the lagged dependent variable $x_{i,t-1}$ (as $LCR_{i,t-1} = LCR_{i,t-2} + x_{i,t-1} + y_{i,t-1}$). Using a static panel data estimator for the coefficients of the bank fixed effects model could thus produce biased results in such dynamic panel models. The lagged dependent variable ($x_{i,t-1}$) cannot be treated as exogenous as it is correlated with the mean of the error term (Nickell, 1981). To account for this, we will use as a robustness check of our results the difference generalised methods of moments (GMM) estimator developed by Arellano-Bond (1991) which uses lagged levels as instruments for endogenous variables.[28]

The Arellano–Bond (1991) estimation starts by transforming all regressors by differencing to remove the unobserved individual bank-specific effects (w_i). The issue of endogeneity is addressed by using the lagged dependent variables as valid instruments for the first-differences. Hence, we estimate Equation (19) in first-differences using e.g. x_{t-2} and further lags to instrument for Δx_{t-1}.

$$(21)\ \Delta x_{i,t} = \alpha_1 \cdot \Delta LCR_{i,t-2} + \alpha_2 \cdot \Delta x_{i,t-1} + \alpha_2 \cdot \Delta y_{i,t-1} + \beta \cdot \Delta y_{i,t} + \delta \cdot \Delta\left(\frac{TLTRO_{i,t-1}}{size_{i,4}}\right) + \theta \cdot \Delta LR_{i,t-1} + \Delta v_t + \Delta u_{i,t}$$

As standard in the literature, we use three specification tests to assess our results. An important assumption for the validity of GMM is that the instruments are exogenous, which is tested by the Hansen test for the joint validity of instruments. The GMM validity also depends on the assumption that the model is not subject to second-order serial correlation in $u_{i,t}$ which we test with the Arellano-Bond test for autocorrelation. Finally, we use the Wald test for joint significance of the coefficient which sheds light on the overall significance of our results.

It is important to note that until now we have been using only four periods for our estimations. We have focused on the four quarters as our identification strategy relies on the hypothesis that the year 2020 was special due to the Corona crisis and during the year the causality ran only in one direction - from technical boost to the change in LCR due to other factors. However, to be able to estimate the test for second-order autocorrelation we need to have at least 5 periods. Thus, we include the first quarter of 2021 to our panel

[28] The Arellano-Bond method is designed for samples where the ratio of T to N goes to 0. Our panel data set has a short time dimension (T=5) relative to the number of banks (N between 1573 and 263 for the different subsamples), i.e. the Arellano-Bond method is appropriate here also from this perspective.

data set. To a large extend adding an additional period to our sample, does not change the results of our main regression (equation 15).

The dynamic panel bias analysis of Nickell (1981) also warns that the number of instruments used in the regression must be less than or equal to the number of banks. This should not be a problem in our case as for all samples the number of instruments is always less than the number of banks. Thus, estimated coefficients are said to be unbiased and consistent.

The results of the Arellano–Bond estimation are shown in Table A8 of Annex 4. We receive conclusive results for our smallest sample. For this sample, the coefficient of the technical boost now changes slightly, decreasing from -0.892 to -0.906 in comparison to the results of the fixed effects estimator, and remains highly significant. The slight increase of the standard errors reflects the less efficient estimation. The low p-value of the Wald test statistic shows that the overall significance of the coefficients is highly acceptable. The AR(1) tests rejects expectedly the null hypothesis of no first order autocorrelation while the AR(2) test confidently confirms the lack of second order autocorrelation, which is important for the validity of the results. The Hansen statistic shows that the overidentifications restrictions that we have imposed are valid which indicates that the instruments are exogenous. While the results for the other samples are also in line with those from our fixed effects estimator, in terms of sign and magnitude, the results of the tests indicate that we cannot concluded that the assumptions for applying the instruments are not violated.

Finally, it could be argued that banks that received a higher demand for loans provided more loans. These additional loans reduced their LCRs (i.e. lowered their variable x_t) and, if they are eligible as collateral for Eurosystem credit, increased the amount these banks could borrow from the Eurosystem. As banks borrowed close to as much as they could from the Eurosystem in 2020 and the amount borrowed had a mostly positive impact on the technical LCR boosts, we may have an omitted variable bias in our regressions: an increased demand for loans had a negative impact on x_t and a positive impact on y_t, so omitting the loan demand at individual banks as an independent variable in our regression implies a bias.

However, the Eurosystem increased the availability of collateral significantly in early 2020 to ensure that collateral constraints were not binding. What constrained banks in borrowing from the TLTROs of the Eurosystem was the maximum borrowing amounts set by the Eurosystem (see Section 3.2). And these depended on the size of the loan book of the bank at the end of February 2019. The additional demand for bank loans therefore had most likely no strong impact on the amount that banks could borrow from the Eurosystem in 2020 so that a strong omitted variable bias appears not very probable.

7. Conclusions

In this study, we have estimated for every bank and quarter of the Corona year 2020 the technical LCR boost from net central bank credit. The technical LCR boost is typically positive if the net central bank credit amount is positive. However, if the bank uses mainly HQLA as collateral for the net central bank credit, the technical LCR boost can be negative.

We have analyzed the relation between (initial) LCR levels, technical LCR boosts from net central bank credit and LCR changes resulting from all other factors, the latter variable reflecting the behavior of banks excluding recourse to central bank credit. We have argued that the technical LCR boost was hardly influenced by the (initial) LCR level during 2020, suggesting that it was also hardly influenced by the LCR changes resulting from all other factors. We have therefore treated the technical LCR boost as an independent variable in our panel regressions. The LCR changes resulting from other factors than recourse to net central bank credit is therefore the only dependent variable.

We have found that banks that received a larger LCR boost experienced a stronger LCR decline resulting from all other factors. This suggests that these banks showed a tendency to take actions that reduced their LCRs. In this sense, banks consumed their LCR boosts from central bank credit. Banks typically did so not only after, but also before (in anticipation of upcoming) LCR boosts. For banks with a high initial LCR, however, the relation between LCR boosts from central bank credit and actions with a negative impact on the LCR was much weaker. We have explained these empirical results with a simple theoretical model of a bank that maximises its net benefits.

An interesting question is to what extent our results, which have been based on data for the very special year 2020, are indicative for the behaviour of banks in other times. Here, one could argue as follows: Our empirical analysis suggests that the theoretical model of Section 5 combined with specific assumptions on the parameters of the model ($a < b$ and B relatively large) seems to describe relatively well the behaviour of many banks in 2020. This suggests that the same model, but possibly with other parameter constellations, would also describe banks' behaviour well in other times.[29] Therefore, our empirical results of Section 6 will not be applicable to all other times, but our theoretical model of Section 5 may well describe the behaviour of individual banks more generally (although the model is of course very simplistic, see the discussion at the end of Section 5).

In terms of policy conclusions, our analysis suggests that central bank credit operations can create incentives to banks with relatively low LCR levels to take actions that reduce their LCRs.[30] Such actions, which could include the provision of additional credit and a shortening of the maturity structure of the liabilities of the banks, plausibly have an impact on the real economy. As such, our analysis reveals what may be called an "LCR channel" of monetary policy transmission. However, two preconditions must be fulfilled for this channel to be effective: (1) the central bank credit must be attractively priced to

[29] This claim is also supported by the literature mentioned in Section 2 that empirically finds a negative causal effect from individual banks' LCR levels to their demand for central bank credit – this is in line with our model with $a > b$.

[30] To refer to our theoretical model, such incentives would be created, if the central bank sets B quite large and b higher than a for many banks.

ensure that banks demand the credit and (2) the technical LCR boost from (a positive amount of) central bank credit must be positive and sufficiently high. Precondition (2) is fulfilled, if the central bank accepts a broad range of non-HQLA as collateral. If both preconditions are fulfilled, then the "LCR channel" works as follows: banks take recourse to central bank credit as the credit is attractively priced; the central bank credit boosts up the LCRs of the banks; this boost allows banks with a low (initial) LCR to take actions that have a negative impact on their LCRs, which may include the provision of additional loans to the economy or a shortening of the maturity structure of the liabilities of the banks.

The LCR channel illustrates that central banks are able to ease banks' regulatory liquidity constrains and banks are willing to consume the provided boost. The observed anticipation effect might also imply that banks take into account the interaction between lending operations and their LCR in a forward-looking way. Therefore, banks might also be able to anticipate the withdrawal of these instruments – easing concerns about cliff effects when instruments are withdrawn and banks need to rely once again on their own capabilities to comply to the LCR requirement. Nevertheless, regulators and central banks should be aware of the prudential consequences. Activating the LCR channel can imply that many banks may end up with a higher LCR, but large parts of the LCR may be solely due to central bank credit. Moreover, heavy use of the LCR channel may decrease banks' ability to make recourse of the central bank in times of liquidity stress.

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Annex 1: Calculating quarterly technical LCR boosts

Step 1

As a first step, we calculate the market value before central bank and LCR haircuts of the *unencumbered* asset in a bank's central bank collateral pool. Let $CL1NC_t$, $CL1C_t$, $CL2A_t$, $CL2B25_t$, $CL2B30_t$, $CL2B35_t$ and $CL2B50_t$ be the market value before central bank (and LCR) haircuts of all (encumbered and unencumbered) assets in the pool at the end of quarter t for the different types and sub-types of HQLA assets. That means for example that $CL1NC_t$ refers to HQLA assets of sub-type L1 non-covered bonds of types L1 assets and so on (see Table 1). Furthermore, let CRM_t and $CRNM_t$ denote the market value before haircuts of all (encumbered and unencumbered) non-HQLA marketable and non-HQLA non-marketable assets in the bank's pool at the end of quarter t. Let $CL1NC'_t$, $CL1C'_t$, $CL2A'_t$, $CL2B25'_t$, $CL2B30'_t$, $CL2B35'_t$, $CL2B50'_t$, CRM'_t and $CRNM'_t$ denote the corresponding market values after central bank haircuts. The average central bank haircut $h_{L1NC,t}$ on L1 non-covered bonds in the pool is then given by

$$1 - h_{L1NC,t} = \frac{CL1NC'_t}{CL1NC_t}$$

For the other eight asset types in the pool, the haircuts are to be calculated analogously. Let CC_t be the outstanding amount of central bank credit of the bank at the end of quarter t. The market value before central bank and LCR haircuts of unencumbered assets in the pool can now be calculated for each of the nine asset types:

$$UCRNM_t(CC_t) = \max\{CRNM_t - CC_t \cdot \frac{1}{1-h_{RNM,t}}; 0\}$$

$$UCRM_t(CC_t) = \max\{\min\{CRM_t; CRM_t - (CC_t - CRNM'_t) \cdot \frac{1}{1-h_{RM,t}}\}; 0\}$$

$$UCL2B50_t(CC_t) = \max\{\min\{CL2B50_t;\ CL2B50_t - (CC_t - CRNM'_t - CRM'_t) \cdot \frac{1}{1-h_{L2B50,t}}\}; 0\}$$

$$\dots$$

$$UCL1NC_t(CC_t) = \max\{\min\{CL1NC_t;\ CL1NC_t - (CC_t - CRNM'_t - CRM'_t - \dots - CL1C'_t) \cdot \frac{1}{1-h_{L1NC,t}}\}; 0\}$$

For the hypothetical case that the bank had not received additional credit in quarter t, the market values before central bank and LCR haircuts of unencumbered assets in the pool would instead be $UCRNM_t(CC_{t-1})$, $UCRM_t(CC_{t-1})$ and so on. Here, we assume that even without the additional credit, the bank had the same assets in its pool at the end of quarter t.

Step 2

The unadjusted asset amounts for our hypothetical case can now be defined as

$$L1NC_t^- = L1NC_t - (CC_t - CC_{t-1}) + [UCL1NC_t(CC_{t-1}) - UCL1NC_t(CC_t)]$$

$$L1C_t^- = L1C_t + (1 - 0.07) \cdot [UCL1C_t(CC_{t-1}) - UCL1C_t(CC_t)]$$

$$L2A_t^- = L2A_t + (1 - 0.15) \cdot [UCL2A_t(CC_{t-1}) - UCL2A_t(CC_t)]$$

$$L2B_t^- = L2B_t + (1 - 0.25) \cdot [UCL2B25_t(CC_{t-1}) - UCL2B25_t(CC_t)] + (1 - 0.30) \cdot [UCL2B30_t(CC_{t-1}) - UCL2B30_t(CC_t)] + (1 - 0.35) \cdot [UCL2B35_t(CC_{t-1}) - UCL2B35_t(CC_t)] + (1 - 0.50) \cdot [UCL2B50_t(CC_{t-1}) - UCL2B50_t(CC_t)]$$

Step 3:

For the hypothetical case that the bank had not received additional credit in quarter t, the Liquidity Buffer is calculated on the basis of Equation (3) of Section 3.1, i.e. we assume here (as discussed in Section 4) that in the hypothetical case the adjusted asset amounts equal the unadjusted asset amounts:

$$LB_t^- = \min\left\{L1NC_t^- + L1C_t^- + L2A_t^- + L2B_t^-; \frac{100}{30} L1NC_t^-; \frac{100}{60}(L1NC_t^- + L1C_t^-); \frac{100}{85}(L1NC_t^- + L1C_t^- + L2A_t^-)\right\}$$

Step 4:

Let NLO_t denote a bank's Net Liquidity Outflows at the end of quarter t. The LCR at the end of quarter t without additional net central bank credit during this quarter would then simply be

$$LCR_t^- = \frac{LB_t^-}{NLO_t}$$

Step 5:

Let LB_t denote a bank's Liquidity Buffer at the end of quarter t. The bank's LCR at the end of the quarter t would then be

$$LCR_t = \frac{LB_t}{NLO_t}$$

The technical LCR boost from net central bank credit in quarter t can now be calculated as the difference $LCR_t - LCR_t^-$.

Annex 2: Numerical example on calculating technical LCR boosts

To illustrate our approach for estimating technical LCR boosts from central bank credit, consider the simple numerical example of a bank shown in Table A0. The bank has a Liquidity Buffer of 100 at the end of quarter t , consisting only of L1 non-covered bonds and L2A assets (with ELAA = 0), and Net Liquidity Outflows of 50 expected over a 30-day stress period starting at the end of quarter t. It increases its outstanding amount of central bank credit from 10 to 30 during quarter t. At the end of quarter t, the bank has only two types of assets in its central bank collateral pool, L2A assets and marketable non-HQLA assets. The values before and after central bank haircuts of these assets are given in Table A0.

Table A0: Numerical example for estimating technical LCR boosts

Liquidity Buffer at the end of t	100
Unadjusted L1 non-covered bond asset amount at the end of t	60
Unadjusted L2A asset amount at the end of t	40
Net Liquidity Outflows as of end of t	50
Central bank credit at the end of t-1	10
Central bank credit at the end of t	30
Value before central bank haircuts of L2A assets in pool with central bank at end of t	36
Value after central bank haircuts of L2A assets in pool with central bank at end of t	30
Value before central bank haircuts of marketable non-HQLA in pool with central bank at end of t	40
Value after central bank haircuts of marketable non-HQLA in pool with central bank at end of t	20

Step 1: There are only L2A and non-HQLA in the pool. The average central bank haircut on L2A is 1-(30/36) = 16.6%. The unencumbered market value before haircuts of L2A assets in the pool is $UCL2A_t(CC_t = 30) = \max\left\{\min\left\{36; 36 - \frac{30-20}{1-0.16}\right\}, 0\right\} = 24$ for a central bank credit amount of 30. As an amount of 20 is collateralized by non-HQLA, L2A has to cover the remaining 10, i.e. two-third of L2A remains unencumbered, which is 24. For a central bank credit amount of 10, we trivially get $UCL2A_t(CC_{t-1} = 10) = 36)$, because all credit is now collateralized by non-HQLA.

Step 2: For the unadjusted asset amounts for the hypothetical case that the bank had not received any net central bank credit in the quarter, we get

$$L1NC_t^- = L1NC_t - (CC_t - CC_{t-1}) + [UCL1NC_t(CC_{t-1}) - UCL1NC_t(CC_t)] = 60 - (30 - 10) + (0 - 0) = 40$$

$$L2A_t^- = L2A_t + (1 - 0.15) \cdot [UCL2A_t(CC_{t-1}) - UCL2A_t(CC_t)] = 40 + (1 - 0.15) \cdot (36 - 24) = 50.2$$

So the unadjusted L1 non-covered bond asset amount would be lowered by 20 without net central bank credit in quarter t as the bank would have less central bank reserves. The unadjusted L2A asset amount would increase as more L2A in the collateral pool would become unencumbered.

Steps 3: The Liquidity Buffer without net central bank credit in quarter t would be

$$LB_t^- = \min\left\{40 + 50.2;\ \frac{100}{30}40; \frac{100}{60}40; \frac{100}{85}90.2\right\} = 66.6$$

Note that the cap of 40% on non-L1 assets is now binding.

Steps 4 and 5: The LCR at the end of quarter t without additional net central bank credit during this quarter would be $LCR_t^- = \frac{66.6}{50} = 133.3\%$. The technical LCR boost is then $LCR_t - LCR_t^- = 200\% - 133.3\% = 66.6\%$.

Annex 3: Proof of Result 1

The net benefit function is

(A1) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) - a \cdot |x_t - A| - b \cdot |y_t - B|$

The bank chooses x_t and y_t so that NB_t is maximized.

For $x_t < A$, we get from (A1)

(A2) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) + a \cdot x_t - a \cdot A - b \cdot |y_t - B|$

Obviously, NB_t is increasing in x_t as long as $x_t < A$. That means that $x_t \geq A$. For analogous reasons, we have $y_t \geq B$. That means that the bank chooses x_t and y_t to maximize

(A3) $NB_t(x_t \geq A, y_t \geq A) = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) - a \cdot x_t + a \cdot A - b \cdot y_t + b \cdot B$

(which we get from (A1) for $x_t \geq A$ and $y_t \geq B$) subject to $x_t \geq A$ and $y_t \geq B$.

Obviously, if $a < b$, $x_t > A$ and $y_t > B$, the bank can increase its net benefit by increasing x_t and decreasing y_t by the same amount as this would not change the benefits, but would reduce the costs. It follows that for $a < b$, we have $y_t = B$. Analogously, we have $x_t = A$ for $a > b$.

We consider the case of $a < b$, i.e. $y_t = B$. From (A3), we get

(A4) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + B - 100) - a \cdot x_t + a \cdot A - b \cdot B$

This is to be maximized subject to $x_t \geq A$. Disregarding the constraint for a moment, the first order condition is

$$\frac{d}{LCR_{t-1} + x_t + B - 100} = a$$

Rearranging gives

$$x_t = \frac{d}{a} - B - (LCR_{t-1} - 100)$$

If the right-hand side is greater than A, then x_t equals the right-hand side. Otherwise, we have $x_t = A$.

For the case of $a > b$, i.e. $x_t = A$ we get the analogous result.

Annex 3a: A model with two LCR reporting periods

In this annex, we study a model that is similar to the one of Section 5. But the period t is divided into two sub-periods 1 and 2. In sub-period 1, the bank chooses x_t and reports an LCR that is given by $LCR_{t,1} = LCR_{t-1} + x_t$. In sub-period 2, the bank chooses y_t and reports an LCR that is given by $LCR_{t,2} = LCR_{t-1} + x_t + y_t$. The bank's benefits now depend on the two reported LCRs:

$$B_t = d \cdot \ln\big(LCR_{t,1} - 100\big) + d \cdot \ln\big(LCR_{t,2} - 100\big)$$

The cost function is unchanged. Below, we proof the following:

RESULT 2:

If $a < b$, then $y_t = B$ and

$$x_t = \begin{cases} \frac{d}{a} - \left[LCR_{t-1} + \frac{1}{2}B - 100\right] + \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}, & if\ LCR_{t-1} \leq \frac{d}{a} - (A + \frac{1}{2}B - 100) + \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2} \\ A & , otherwise \end{cases}$$

Note that for the upper arm of the equation for x_t, we have, $\frac{\partial x_t}{\partial \boldsymbol{B}} = -\frac{1}{2} + \frac{B}{4\sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}}$. $\frac{\partial x_t}{\partial \boldsymbol{B}} > 0$ would imply $\frac{1}{2}B > \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}$. But this is impossible. Therefore, x_t is decreasing in B (and of course also in LCR_{t-1}) for relatively small values of LCR_{t-1}. In addition, x_t is independent of LCR_{t-1} and B for relatively large values of LCR_{t-1}.

Also note that in the model with one LCR reporting period (and $a < b$), it can be optimal for the bank to have a negative x_t, if LCR_{t-1} is close to 100 (i.e. very low) and B is large. This is not so in the model with two LCR reporting periods, because it would imply that $LCR_{t,1} < 100$. This explains the specific functional relation between x_t and B (for relatively small values of LCR_{t-1}) in the model with two LCR reporting periods? It means that banks with a (very) low LCR in quarter $t-1$ and a very high technical LCR boost in quarter t may choose activities other than recourse to net central bank credit that have a negative impact on LCR_t, if there is only one LCR reporting period in quarter t. But they would not do this, if there are two such reporting periods.

PROOF OF RESULT 2:

The net benefit function is now

(A5) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t - 100) + \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) - a \cdot |x_t - A| - b \cdot |y_t - B|$

The bank chooses x_t and y_t so that NB_t is maximized.

For $x_t < A$, we get from (A5)

(A6) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t - 100) + \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) + a \cdot x_t - a \cdot A - b \cdot |y_t - B|$

Obviously, NB_t is increasing in x_t as long as $x_t < A$. That means that $x_t \geq A$. For analogous reasons, we have $y_t \geq B$. That means that the bank chooses x_t and y_t to maximize

(A7) $NB_t(x_t \geq A, y_t \geq A) = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t - 100) + \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + y_t - 100) - a \cdot x_t + a \cdot A - b \cdot y_t + b \cdot B$

(which we get from (A5) for $x_t \geq A$ and $y_t \geq B$) subject to $x_t \geq A$ and $y_t \geq B$.

Obviously, if $a < b$, $x_t > A$ and $y_t > B$, the bank can increase its net benefit by increasing x_t and decreasing y_t by the same amount as this would increase the benefits and reduce the costs. It follows that for $a < b$, we have $y_t = B$. We consider the case of $a < b$, i.e. $y_t = B$. From (A7), we get

(A8) $NB_t = \mathrm{d} \cdot \ln(LCR_{t-1} + x_t - 100) + \mathrm{d} \cdot \ln(LCR_{t-1} + x_t + B - 100) - a \cdot x_t + a \cdot A - b \cdot B$

This is to be maximized subject to $x_t \geq A$. Disregarding the constraint for a moment, the first order condition is

$$\frac{d}{LCR_{t-1} + x_t - 100} + \frac{d}{LCR_{t-1} + x_t + B - 100} = a$$

Rearranging gives

$$x_t = \frac{d}{a} - \frac{1}{2}B - (LCR_{t-1} - 100) +/- \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}$$

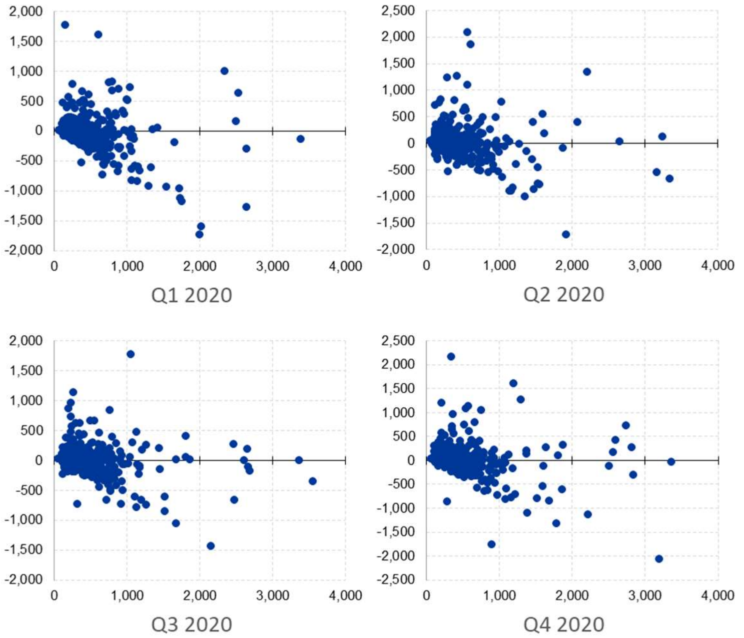
Since the arguments in the logarithmic function parts of the net benefit function must not be negative, we need to ensure that $x_t > -(LCR_{t-1} - 100)$ and $x_t > -(LCR_{t-1} - 100) - B$. That means if there was a minus sign in front of the square root, then we would need (i) $\frac{d}{a} - \frac{1}{2}B > \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}$ and (ii) $\frac{d}{a} + \frac{1}{2}B > \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}$. Condition (i) cannot be fulfilled, if $\frac{d}{a} - \frac{1}{2}B \leq 0$. If instead we have $\frac{d}{a} - \frac{1}{2}B > 0$, then Condition (i) implies $B < 0$ (simply take both sides of Condition (i) to the square and rearrange). But Condition (ii) requires $B > 0$ (simply take both sides of Condition (ii) to the square and rearrange). Thus, there is a plus sign in front of the square root:

$$x_t = \frac{d}{a} - \frac{1}{2}B - (LCR_{t-1} - 100) + \sqrt{(\frac{1}{2}B)^2 + (\frac{d}{a})^2}$$

If the right-hand side is greater than A, then x_t equals the right-hand side. Otherwise, we have $x_t = A$.

Annex 4: Charts and tables

Chart A1: Relation between previous LCR ($LCR_{i,t-1}$) and quarterly LCR change due to factors other than central bank credit ($x_{i,t}$), reduced sample

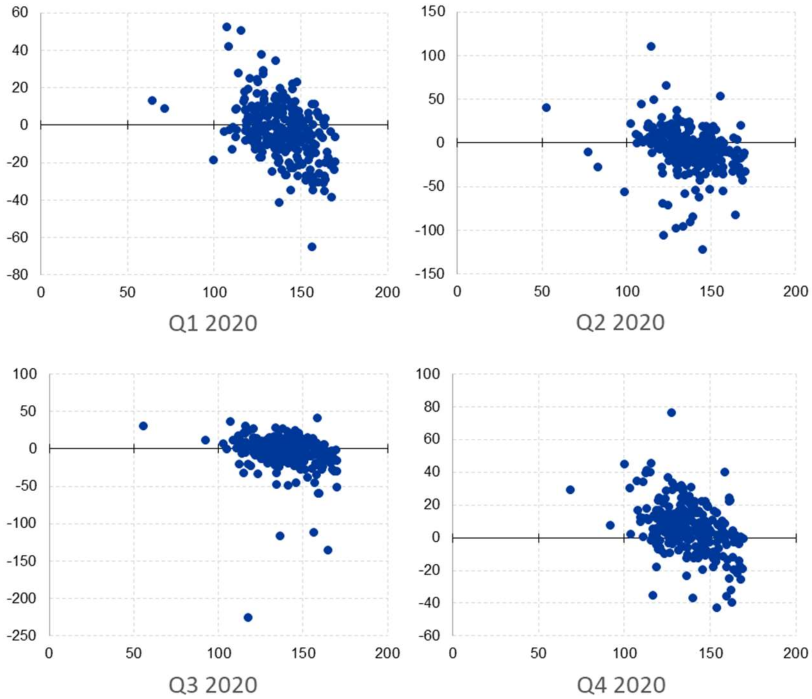


Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly LCR change due to factors other than central bank credit, in percentage points.
Source: ECB calculations.

Chart A2: Relation between previous LCR ($LCR_{i,t-1}$) and quarterly LCR change due to factors other than central bank credit ($x_{i,t}$), the 10% highest LCR banks removed

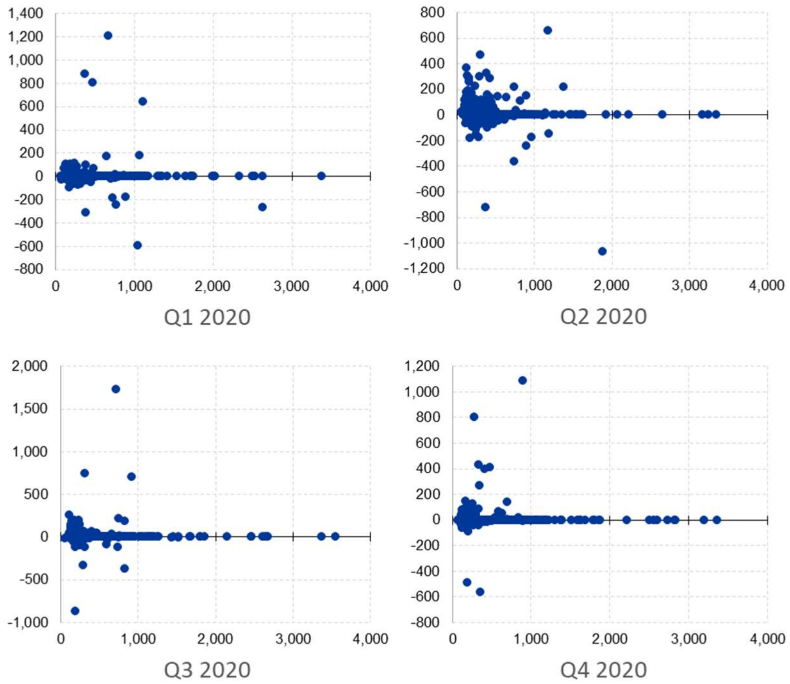
Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly LCR change due factors other than central bank credit, in percentage points.
Source: ECB calculations.

Chart A3: Relation between previous LCR ($LCR_{i,t-1}$) and quarterly LCR change due to factors other than central bank credit ($x_{i,t}$), the 60% highest LCR banks removed



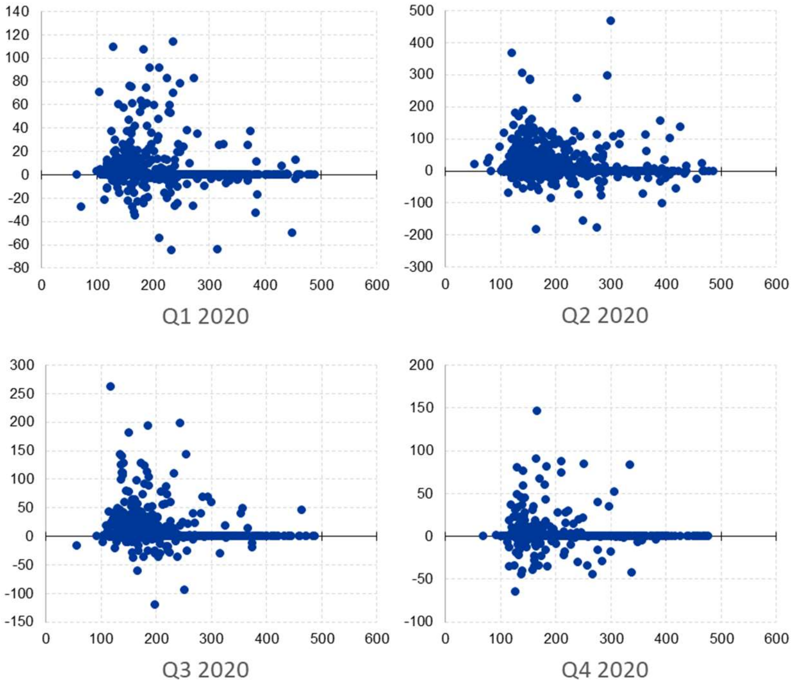
Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly LCR change due to factors other than central bank credit, in percentage points.
Source: ECB calculations.

Chart A4: Relation between previous LCR ($LCR_{i,t-1}$) and technical LCR boost ($y_{i,t}$), reduced sample



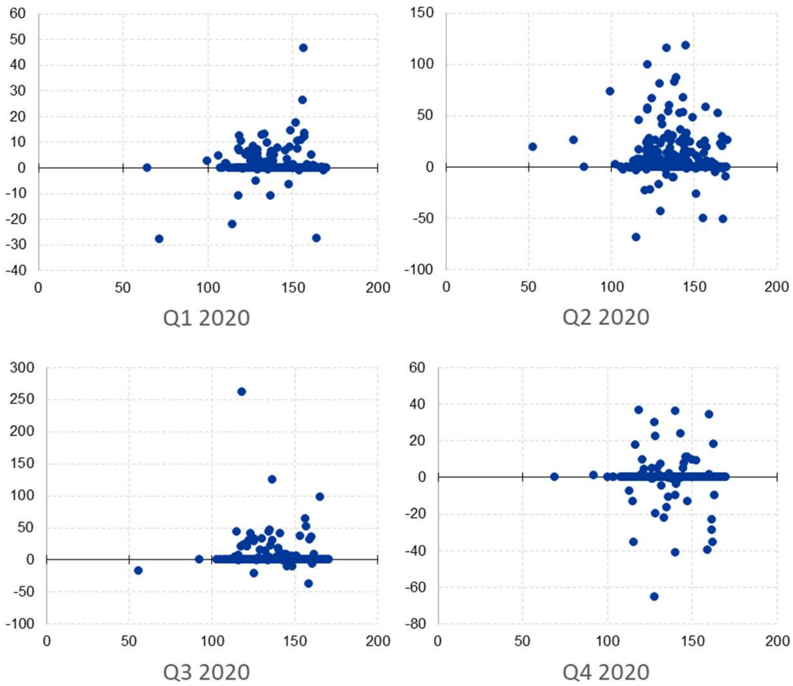
Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly technical LCR boost, in percentage points.
Source: ECB calculations.

Chart A5: Relation between previous LCR ($LCR_{i,t-1}$) and technical LCR boost ($y_{i,t}$), the 10% highest LCR banks removed



Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly technical LCR boost, in percentage points.
Source: ECB calculations.

Chart A6: Relation between previous LCR ($LCR_{i,t-1}$) and technical LCR boost ($y_{i,t}$), the 60% highest LCR banks removed



Note: horizontal axes: previous LCR, in percent. Vertical axes: quarterly technical LCR boost, in percentage points.
Source: ECB calculations.

Table A1: Results of panel regression based on Equation (15) - time FEs

	Dependent variable:															
	$LCR_t - LCR_{t-1}$															
	1%-reduced sample				10% sample				30% sample				60% sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Previous LCR	-0.137***	-0.144***	-0.148***	-0.158***	-0.236***	-0.240***	-0.241***	-0.241***	-0.404***	-0.404***	-0.404***	-0.403***	-0.417***	-0.418***	-0.418***	-0.419***
	(0.023)	(0.026)	(0.028)	(0.027)	(0.024)	(0.028)	(0.026)	(0.026)	(0.037)	(0.039)	(0.037)	(0.037)	(0.023)	(0.023)	(0.019)	(0.020)
Technical boost	-0.685***	-0.684***	-0.681***	-0.681***	-0.835***	-0.832***	-0.831***	-0.831***	-0.786***	-0.786***	-0.786***	-0.786***	-0.928***	-0.928***	-0.928***	-0.928***
	(0.117)	(0.116)	(0.116)	(0.117)	(0.045)	(0.048)	(0.046)	(0.046)	(0.018)	(0.019)	(0.020)	(0.020)	(0.013)	(0.013)	(0.015)	(0.015)
previousTLTRO/Size		-46.290*	-15.170	11.617		46.675	50.195	51.065		11.109	8.690	9.664		4.572	4.514	5.177
		(27.113)	(27.154)	(30.747)		(47.697)	(36.492)	(36.170)		(14.554)	(10.380)	(11.077)		(15.675)	(23.136)	(22.879)
log(Size)			-3.936*	-1.903			-0.379	-0.306			0.182	0.264			0.005	0.109
			(2.115)	(2.764)			(1.250)	(1.242)			(0.840)	(0.854)			(0.799)	(0.908)
Previous leverage ratio				2.525***				0.110				0.134				0.128
				(0.980)				(0.129)				(0.174)				(0.173)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,292	6,228	6,228	6,228	5,316	5,280	5,280	5,280	3,372	3,360	3,360	3,360	1,052	1,052	1,052	1,052
R^2	0.103	0.108	0.109	0.117	0.254	0.257	0.257	0.257	0.378	0.379	0.379	0.380	0.618	0.618	0.618	0.618
Adjusted R^2	0.102	0.107	0.108	0.116	0.253	0.256	0.256	0.256	0.377	0.378	0.378	0.378	0.616	0.616	0.615	0.615
F Statistic	359.18***	249.78***	190.35***	164.66***	902.67***	608.20***	456.38***	365.18***	1,024.11***	683.19***	512.45***	410.17***	845.57***	563.28***	422.05***	338.00***

Note: The table shows the results of a fixed effects estimation using time fixed effects. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1^{th}, 10^{th}, 30^{th} or 60^{th} percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A2: Results of panel regression based on Equation (16) - time FEs

	Dependent variable:															
	$LCR_t^- - LCR_{t-1}$															
	1% sample				10% sample				30% sample				60% sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Previous LCR^-	-0.111***	-0.116***	-0.118***	-0.128***	-0.222***	-0.226***	-0.227***	-0.227***	-0.378***	-0.378***	-0.376***	-0.377***	-0.427***	-0.427***	-0.425***	-0.428***
	(0.006)	(0.011)	(0.012)	(0.011)	(0.030)	(0.037)	(0.034)	(0.034)	(0.048)	(0.049)	(0.046)	(0.046)	(0.028)	(0.028)	(0.019)	(0.022)
Previous technical boost	-0.522***	-0.526***	-0.528***	-0.532***	-0.350***	-0.370***	-0.371***	-0.371***	-0.452***	-0.461***	-0.458***	-0.458***	-0.472***	-0.474***	-0.468***	-0.470***
	(0.113)	(0.111)	(0.113)	(0.115)	(0.024)	(0.049)	(0.043)	(0.043)	(0.029)	(0.029)	(0.027)	(0.027)	(0.042)	(0.034)	(0.030)	(0.030)
Technical boost	-0.743***	-0.742***	-0.740***	-0.737***	-0.843***	-0.839***	-0.839***	-0.839***	-0.789***	-0.788***	-0.789***	-0.788***	-0.936***	-0.936***	-0.936***	-0.935***
	(0.075)	(0.075)	(0.074)	(0.080)	(0.048)	(0.052)	(0.051)	(0.051)	(0.016)	(0.017)	(0.018)	(0.018)	(0.009)	(0.009)	(0.010)	(0.010)
previousTLTRO/Size		9.438	30.432	54.463***		49.166	54.115	55.254		19.283	11.709***	11.840**		3.367	-5.068	-4.363
		(24.613)	(19.780)	(18.035)		(61.419)	(44.301)	(44.301)		(18.050)	(4.321)	(5.649)		(13.777)	(20.328)	(19.660)
log(Size)			-2.617	-0.768			-0.534	-0.435			0.551	0.563			0.618	0.753
			(2.625)	(3.828)			(1.870)	(1.865)			(1.117)	(1.184)			(0.724)	(0.917)
Previous leverage ratio				2.330				0.148				0.020				0.163
				(1.455)				(0.159)				(0.200)				(0.245)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,719	4,671	4,671	4,671	3,987	3,960	3,960	3,960	2,529	2,520	2,520	2,520	789	789	789	789
R^2	0.121	0.126	0.127	0.134	0.285	0.289	0.289	0.289	0.398	0.399	0.400	0.400	0.675	0.675	0.677	0.678
Adjusted R^2	0.121	0.125	0.126	0.132	0.284	0.288	0.288	0.288	0.396	0.397	0.398	0.398	0.673	0.673	0.674	0.675
F Statistic	217.26***	168.34***	135.49***	119.86***	529.07***	401.73***	321.70***	268.18***	555.19***	416.70***	334.37***	278.54***	543.19***	406.92***	327.96***	273.79***

Note: The table shows the results of a fixed effects estimation using time fixed effects. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1^{th}, 10^{th}, 30^{th} or 60^{th} percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A3: Results of panel regression based on Equation (17) - time and country FEs

	Dependent variable:															
	$LCR_t^{-} - LCR_{t-1}$															
	1%-reduced sample				10%-reduced sample				30%-reduced sample				60%-reduced sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Previous LCR	-0.146***	-0.153***	-0.162***	-0.170***	-0.253***	-0.253***	-0.256***	-0.256***	-0.405***	-0.405***	-0.404***	-0.404***	-0.425***	-0.425***	-0.424***	-0.426***
	(0.024)	(0.026)	(0.029)	(0.029)	(0.031)	(0.033)	(0.031)	(0.031)	(0.038)	(0.040)	(0.039)	(0.039)	(0.014)	(0.014)	(0.011)	(0.013)
Technical boost	-0.677***	-0.678***	-0.673***	-0.674***	-0.825***	-0.824***	-0.821***	-0.822***	-0.784***	-0.784***	-0.784***	-0.784***	-0.926***	-0.926***	-0.926***	-0.926***
	(0.117)	(0.115)	(0.115)	(0.116)	(0.048)	(0.048)	(0.047)	(0.047)	(0.018)	(0.018)	(0.019)	(0.019)	(0.010)	(0.010)	(0.014)	(0.014)
Previous TLTRO/Size		-124.158***	-79.765**	-59.289*		-12.865	-5.575	-5.081		1.504	-1.169	-0.170		3.859	3.193	3.981
		(31.914)	(37.648)	(33.963)		(18.500)	(11.272)	(10.657)		(10.400)	(12.031)	(11.510)		(14.020)	(22.137)	(21.836)
log(Size)			-6.464***	-4.335*			-1.003	-0.946			0.235	0.346			0.058	0.167
			(2.008)	(2.573)			(1.044)	(1.035)			(0.707)	(0.699)			(0.866)	(0.965)
Previous leverage ratio				2.384**				0.077				0.167				0.138
				(0.927)				(0.156)				(0.169)				(0.167)
Country x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,292	6,228	6,228	6,228	5,316	5,280	5,280	5,280	3,372	3,360	3,360	3,360	1,052	1,052	1,052	1,052
R^2	0.114	0.118	0.122	0.129	0.267	0.270	0.271	0.271	0.389	0.389	0.389	0.390	0.627	0.627	0.627	0.628
Adjusted R^2	0.111	0.114	0.118	0.125	0.264	0.266	0.267	0.267	0.384	0.384	0.384	0.385	0.618	0.618	0.617	0.617
F Statistic	36.752***	36.040***	35.813***	36.577***	87.679***	84.366***	81.170***	77.922***	96.713***	92.352***	88.527***	85.067***	78.407***	74.934***	71.746***	68.971***

Note: The table shows the results of a fixed effects estimation using country and time fixed effects, as well as an interaction term. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1th, 10th, 30th or 60th percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A4: Results of panel regression based on Equation (18) - time and country FEs

	Dependent variable: $LCR_t^- - LCR_{t-1}$															
	1%-reduced sample				10%-reduced sample				30%-reduced sample				60%-reduced sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Previous LCR^-	-0.118***	-0.122***	-0.128***	-0.137***	-0.236***	-0.236***	-0.238***	-0.238***	-0.376***	-0.375***	-0.374***	-0.374***	-0.426***	-0.426***	-0.425***	-0.428***
	(0.007)	(0.012)	(0.013)	(0.014)	(0.042)	(0.045)	(0.041)	(0.041)	(0.047)	(0.048)	(0.045)	(0.045)	(0.020)	(0.019)	(0.012)	(0.016)
Previous technical boost	-0.521***	-0.521***	-0.525***	-0.529***	-0.356***	-0.359***	-0.361***	-0.361***	-0.459***	-0.467***	-0.464***	-0.464***	-0.478***	-0.481***	-0.478***	-0.481***
	(0.108)	(0.110)	(0.113)	(0.114)	(0.031)	(0.042)	(0.038)	(0.038)	(0.033)	(0.037)	(0.038)	(0.038)	(0.039)	(0.032)	(0.031)	(0.030)
Technical boost	-0.732***	-0.732***	-0.728***	-0.727***	-0.832***	-0.831***	-0.830***	-0.830***	-0.784***	-0.784***	-0.785***	-0.785***	-0.933***	-0.933***	-0.935***	-0.935***
	(0.079)	(0.079)	(0.078)	(0.083)	(0.052)	(0.053)	(0.051)	(0.051)	(0.017)	(0.017)	(0.018)	(0.018)	(0.005)	(0.005)	(0.007)	(0.007)
PreviousTLTRO/Size		-26.366	8.465	26.456		8.233	15.818	16.569		19.313**	11.192	11.485		5.552	-3.208	-2.399
		(54.183)	(61.250)	(54.374)		(29.309)	(16.999)	(16.963)		(8.064)	(11.882)	(11.068)		(12.786)	(20.562)	(19.773)
log(Size)			-4.823**	-2.877			-0.985	-0.890			0.678	0.718			0.721	0.858
			(2.103)	(3.315)			(1.565)	(1.551)			(0.805)	(0.862)			(0.792)	(0.965)
Previous leverage ratio				2.215				0.129				0.060				0.170
				(1.379)				(0.192)				(0.201)				(0.236)
Country x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,719	4,671	4,671	4,671	3,987	3,960	3,960	3,960	2,529	2,520	2,520	2,520	789	789	789	789
R^2	0.134	0.137	0.139	0.145	0.297	0.300	0.301	0.301	0.410	0.411	0.412	0.412	0.683	0.683	0.685	0.686
Adjusted R^2	0.130	0.133	0.135	0.141	0.294	0.296	0.297	0.297	0.406	0.406	0.407	0.407	0.675	0.674	0.676	0.676
F Statistic	40.396***	38.720***	37.453***	37.455***	93.191***	88.895***	84.734***	80.716***	97.008***	91.684***	87.438***	83.253***	91.868***	86.941***	83.265***	79.465***

Note: The table shows the results of a fixed effects estimation using country and time fixed effects, as well as an interaction term. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1^{th}, 10^{th}, 30^{th} or 60^{th} percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A5: Results of panel regression based on Equations (17) and (18) - time and country FEs, excluding all banks with zero tech boost in all quarters

	Dependent variable:							
	$LCR_t^- - LCR_{t-1}$							
	1% sample	10% sample	30% sample	60% sample	1% sample	10% sample	30% sample	60% sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Previous LCR	-0.169***	-0.246***	-0.405***	-0.423***				
	(0.049)	(0.038)	(0.021)	(0.019)				
Previous LCR^-					-0.127	-0.241***	-0.384***	-0.433***
					(0.084)	(0.056)	(0.026)	(0.025)
Previous technical boost					-0.524***	-0.350***	-0.466***	-0.478***
					(0.083)	(0.045)	(0.034)	(0.027)
Technical boost	-0.666***	-0.815***	-0.785***	-0.930***	-0.719***	-0.824***	-0.787***	-0.939***
	(0.119)	(0.053)	(0.021)	(0.018)	(0.091)	(0.058)	(0.019)	(0.011)
Previous TLTRO/Size	-68.155*	-12.443	-11.238	-9.896	34.283	8.178	-3.745	-23.842
	(35.555)	(15.453)	(13.529)	(30.699)	(43.577)	(26.714)	(15.727)	(27.465)
log(Size)	-3.728***	-1.137	0.608	0.406	-2.916**	-1.250	1.083	1.020
	(0.811)	(0.760)	(0.846)	(1.135)	(1.437)	(1.188)	(1.016)	(1.363)
Previous leverage ratio	0.022	0.106	0.242	0.170	0.579	0.018	0.122	0.205
	(1.021)	(0.592)	(0.180)	(0.214)	(1.139)	(0.798)	(0.198)	(0.292)
Country x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,060	3,636	2,452	732	3,045	2,727	1,839	549
R^2	0.199	0.325	0.436	0.689	0.247	0.377	0.464	0.743
Adjusted R^2	0.194	0.320	0.429	0.677	0.241	0.371	0.457	0.732
F Statistic	40.165***	69.571***	74.873***	62.332***	47.154***	77.730***	74.867***	72.190***

Note: The table shows the results of a fixed effects estimation using country and time fixed effects, as well as an interaction term. The separate columns report the results of the regressions for the different subsamples depending on the percentile (1th, 10th, 30th or 60th percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels

Table A6: Results of panel regression based on Equation (19) - time and bank FEs

	Dependent variable:											
	$LCR_t^- - LCR_{t-1}$											
	1%-reduced sample			10%-reduced sample			30%-reduced sample			60%-reduced sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Previous LCR	-0.951***	-0.949***	-0.947***	-0.964***	-0.970***	-0.969***	-1.036***	-1.050***	-1.049***	-1.009***	-1.033***	-1.029***
	(0.066)	(0.067)	(0.066)	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.039)	(0.037)	(0.038)
Technical boost	-0.651***	-0.652***	-0.653***	-0.866***	-0.850***	-0.850***	-0.850***	-0.816***	-0.815***	-0.923***	-0.894***	-0.892***
	(0.091)	(0.093)	(0.093)	(0.049)	(0.055)	(0.055)	(0.030)	(0.033)	(0.032)	(0.035)	(0.034)	(0.034)
Previous TLTRO/Size		-27.104	4.989		72.427	62.583		114.171***	103.360***		100.242**	90.662**
		(178.729)	(180.827)		(53.412)	(54.571)		(33.120)	(33.553)		(44.786)	(45.291)
Previous leverage ratio			3.335			-0.994			-1.517*			-1.549**
			(3.588)			(1.210)			(0.831)			(0.774)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,292	6,228	6,228	5,316	5,280	5,280	3,372	3,360	3,360	1,052	1,052	1,052
R^2	0.478	0.479	0.479	0.542	0.544	0.544	0.614	0.618	0.619	0.741	0.745	0.746
Adjusted R^2	0.303	0.304	0.305	0.388	0.391	0.391	0.485	0.490	0.491	0.653	0.658	0.659
F Statistic	2,156.568***	1,428.499***	1,073.457***	2,353.281***	1,571.457***	1,179.992***	2,011.323***	1,357.471***	1,020.045***	1,121.505***	761.983***	575.446***

Note: The table shows the results of a fixed effects estimation using individual bank and time fixed effects. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1th, 10th, 30th or 60th percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A7: Results of panel regression based on Equation (20) - time and bank FEs

	Dependent variable:											
	$LCR_t^- - LCR_{t-1}$											
	1%-reduced sample			10%-reduced sample			30%-reduced sample			60%-reduced sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Previous LCR^-	-1.083***	-1.074***	-1.074***	-1.078***	-1.076***	-1.075***	-1.214***	-1.221***	-1.220***	-1.147***	-1.158***	-1.158***
	(0.077)	(0.078)	(0.078)	(0.028)	(0.028)	(0.028)	(0.023)	(0.023)	(0.023)	(0.040)	(0.041)	(0.041)
Previous technical boost	-1.187***	-1.176***	-1.178***	-1.062***	-1.059***	-1.057***	-1.189***	-1.199***	-1.199***	-1.145***	-1.165***	-1.165***
	(0.135)	(0.137)	(0.136)	(0.043)	(0.045)	(0.045)	(0.031)	(0.031)	(0.031)	(0.045)	(0.050)	(0.051)
Technical boost	-0.822***	-0.819***	-0.821***	-0.864***	-0.865***	-0.865***	-0.878***	-0.863***	-0.862***	-0.939***	-0.922***	-0.921***
	(0.073)	(0.075)	(0.075)	(0.043)	(0.045)	(0.045)	(0.034)	(0.038)	(0.038)	(0.042)	(0.042)	(0.042)
Previous TLTRO/Size		-40.269	-18.827		-13.373	-24.830		43.288	39.413		56.112	55.183
		(192.814)	(189.130)		(56.662)	(57.037)		(37.673)	(38.624)		(52.450)	(53.497)
Previous leverage ratio			2.141			-1.157			-0.594			-0.239
			(3.285)			(0.791)			(0.986)			(1.120)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,719	4,671	4,671	3,987	3,960	3,960	2,529	2,520	2,520	789	789	789
R^2	0.541	0.535	0.535	0.611	0.614	0.615	0.698	0.701	0.701	0.814	0.815	0.815
Adjusted R^2	0.311	0.301	0.301	0.415	0.420	0.420	0.546	0.550	0.550	0.719	0.719	0.719
F Statistic	1,233.905***	893.028***	714.820***	1,387.101***	1,047.593***	839.505***	1,297.774***	980.042***	783.796***	759.621***	571.665***	456.539***

Note: The table shows the results of a fixed effects estimation using individual bank and time fixed effects. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1^{th}, 10^{th}, 30^{th} or 60^{th} percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Table A8: Results of Arellano-Bond difference GMM estimation of Equation (19)

	Dependent variable:			
	LCR^{-}_{t} - LCR_{t-1}			
	1%-reduced sample	10%-reduced sample	30%-reduced sample	60%-reduced sample
	(1)	(2)	(3)	(4)
LCR_{t-2}	0.041	-0.358	-1.487***	-1.009***
	(0.810)	(0.218)	(0.325)	(0.306)
LCR^{-}_{t-1} - LCR_{t-2}	-0.115	-0.492***	-1.334***	-0.969***
	(0.637)	(0.160)	(0.233)	(0.212)
Technical boost$_{t-1}$	-0.554	-0.539***	-1.350***	-0.978***
	(0.514)	(0.161)	(0.219)	(0.197)
Technical boost	-0.854***	-0.885***	-0.866***	-0.906***
	(0.086)	(0.064)	(0.034)	(0.047)
previousTLTRO/Size	274.360	-129.785*	93.526	28.696
	(220.678)	(70.173)	(69.302)	(65.254)
Previous leverage ratio	-1.151	-1.800	1.336	0.307
	(5.830)	(1.113)	(2.675)	(0.740)
Hansen test (p-value)	0.953	0.091	0.000	0.708
AR(1) test (p-value)	0.046	0.000	0.495	0.055
AR(2) test (p-value)	0.825	0.157	0.187	0.511
Wald test (p-value)	0.000	0.000	0.000	0.000
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	7,865	6,645	4,215	1,315
Observations used	4,671	3,960	2,520	789

Note: The table shows the results of an Arellano-Bond difference GMM estimator estimation. The separate panels report the results of the regressions for the different subsamples depending on the percentile (1th, 10th, 30th or 60th percentile, respectively) of banks with highest LCR that have been removed. Robust standard errors (clustered at the bank level) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

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