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# Mercati, infrastrutture, sistemi di pagamento

(Markets, Infrastructures, Payment Systems)

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## Approfondimenti
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# Banks' liquidity transformation rate: determinants and impact on lending

by Raffaele Lenzi,* Stefano Nobili,* Filippo Perazzoli* and Rosario Romeo*


## Abstract

This paper examines the interaction between the liquidity coverage ratio (LCR), the composition of the collateral pool, banks' characteristics, and lending activity. Our contribution is twofold. Firstly, we analyse how banks' characteristics correlate with their liquidity transformation rate. The main finding is that variables relating to banks' liquidity and efficiency have an impact on their liquidity transformation rate, though we did not find any link with financial soundness indicators. This supports the view that central banks can provide liquidity and relax the collateral framework without taking on excessive risks on their balance sheets. Secondly, we investigate how banks' liquidity transformation rate correlates to credit supply. Our findings show that the banks that pledged more illiquid assets against central bank reserves are those that increased their lending to the economy the most, suggesting that the broad range of eligible collateral in the euro area may have supported the provision of credit to the real economy in recent years and, in particular, during the pandemic.



**JEL Classification:** E50, E58, G21, G28.

**Keywords:** Liquidity transformation rate; Liquidity Coverage Ratio; central bank credit operations; collateral assets; Covid-19 pandemic; loans.



## Sintesi

Il lavoro esamina l'interazione tra il liquidity coverage ratio (LCR), la composizione del collateral pool, le caratteristiche delle banche e l'attività di prestito. Il contributo è duplice. In primo luogo, si analizza come le caratteristiche delle banche siano correlate al loro tasso di trasformazione della liquidità. Il risultato principale è che le variabili relative alla liquidità e all'efficienza delle banche hanno un impatto sul loro tasso di trasformazione della liquidità, mentre non risulta alcun legame con gli indicatori di solidità patrimoniale. L'analisi conferma, pertanto, l'idea che le banche centrali possano fornire liquidità e ampliare la gamma di garanzie idonee, senza assumere rischi eccessivi nei loro bilanci. In secondo luogo, si esamina la correlazione tra il tasso di trasformazione della liquidità delle banche e l'offerta di credito. Dall'indagine emerge che le banche che impegnano più attività illiquide in cambio di riserve di banca centrale sono quelle che hanno aumentato maggiormente i loro prestiti all'economia, suggerendo che l'ampia gamma di garanzie idonee nell'area dell'euro avrebbe supportato l'erogazione di credito all'economia reale negli ultimi anni e, in particolare, durante la pandemia.


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## 1. Introduction[1]

The global financial crisis (GFC) highlighted how important it is for banks to hold an adequate liquidity buffer in order to withstand severe short-term liquidity shocks. On 1st October 2015 the liquidity coverage ratio (LCR) was introduced as the first quantitative liquidity requirement for financial institutions at the European Union level. Under the LCR regulation, banks are required to hold an adequate stock of unencumbered high-quality liquid assets (HQLA) to meet their expected net cash outflows over a 30-day stress scenario.

Over recent years, central banks have conducted longer-term credit operations to ease funding conditions for banks. Between 2014 and 2019, the Eurosystem launched three series of targeted longer-term refinancing operations (TLTROs), after the introduction of two rounds of very long-term refinancing operations (VLTROs) in December 2011. By offering banks long-term funding at attractive conditions, these operations lowered banks' funding costs and facilitated liquidity management. They strengthened the transmission of monetary policy by incentivizing bank lending to the real economy.

The outbreak of the COVID-19 pandemic posed great challenges to the real economy worldwide. There was concern of a large wave of non-financial firms' defaults, possibly generating a credit crunch. The major fear was that banks' inability or unwillingness to supply credit would have exacerbated the effects of the pandemic. Against this background, since March 2020 the Eurosystem has taken a range of measures to ensure the transmission of the monetary policy to bank lending rates and, ultimately, to preserve the flow of credit to households and firms in all sectors and countries.

The Eurosystem eased the conditions of the TLTRO-III programme and introduced new LTROs. The TLTRO-III programme has been a powerful tool to counteract credit contraction, since it directly addressed the elevated credit requests from many firms, especially the small and medium-sized enterprises (SMEs) which lacked access to capital markets. The in-built incentive scheme made it attractive for banks to call on TLTRO-III funding in order to extend credit to firms and households (see Lane, 2020).

According to the Bank Lending Survey (BLS)[2], the TLTRO-III programme has supported credit provision. Moreover, banks have indicated that TLTRO-III had a net easing impact on the terms and conditions offered to borrowers and a positive net impact on their lending volumes. The Eurosystem's interventions together with the contribution of Governments, which implemented several policy measures to support credit provision, such as debt moratoria and public guarantees, protected bank-based credit flows.[3]

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[1] Any views expressed in this paper are the authors' and do not necessarily represent those of the Bank of Italy. We are grateful to Luigi Cannari, Patrizia Ceccacci, Gioia Cellai, Alberto Locarno, Franco Panfili, Stefano Siviero and one anonymous referee for valuable comments and suggestions. We also thank Paola Antilici, Stefania Bacchetta, Marco Luca and Gianluca Mosconi for comments on a previous version of this paper.

[2] See ECB, 2020a; ECB, 2020b; ECB, 2020c.

[3] In the case of Italy, debt moratoria for SMEs were introduced by Decree Law 18/2020 ("Cure Italy" decree) and measures related to new loans backed by public guarantees (via the Central Guarantee Fund or the public agency SACE) by Decree Law 23/2020 ("Liquidity Decree").

The effectiveness of TLTRO-III was further supported by the temporary capital relief measures introduced by ECB Banking Supervision, the European Banking Authority (EBA), and the National Competent Authorities (NCAs).[4]

The Eurosystem also adopted a package of temporary collateral easing measures to increase the availability of eligible collateral and to allow counterparties to participate in liquidity providing operations, such as the TLTRO-III.[5] The measures collectively supported the provision of bank loans especially by easing the conditions at which credit claims were accepted as collateral. At the same time, the Eurosystem increased its risk tolerance, particularly by lowering collateral valuation haircuts for all assets consistently.[6] As part of additional credit claims scheme (ACC), Bank of Italy included as eligible collateral new loans backed by public guarantees and portfolios of consumer loans.

This paper addresses the interaction between LCR, the composition of the collateral pool, bank characteristics and lending activity. There is a fundamental relationship between LCR, the role of the Eurosystem as liquidity provider and its collateral framework. Since central bank reserves are treated as HQLA, banks can fulfil the LCR requirement by borrowing from the Eurosystem against eligible non-HQLA collateral. We use the liquidity transformation rate (LTR), an indicator recently proposed by Hartung (2020), to calculate the amount of net HQLA that a bank generates pledging specific assets as collateral with the Eurosystem, instead of keeping them unencumbered. LTR can be calculated in a granular way, at the level of individual asset, by comparing the haircuts and the Eurosystem eligibility criteria with those enacted in the LCR regulation. It can also be aggregated at bank level, allowing to compare the extent of liquidity transformation over time and cross-section.

Our empirical analysis is focused on Italian banks. For these banks, we have calculated the LTR on a monthly basis for the period from October 2015 to January 2022. We focus on the time interval following the outbreak of the pandemic.

The contribution of this paper is twofold. Firstly, we analyse how bank characteristics correlate with the LTR. Our aim is to understand whether counterparties with low (high) financial soundness have a high (low) liquidity transformation rate or if, rather, the latter is the result of an efficient liquidity management, where the most liquid assets remain available, e.g. to be used in the repo market. In this regard, we conduct a panel regression at bank level, where the independent variables can be classified into six categories: (i) size; (ii) efficiency; (iii) liquidity; (iv) capital adequacy; (v) riskiness and (vi) opportunity cost of participating in refinancing operations. The main finding of our analysis is that variables relating to banks' liquidity and efficiency have an impact on their liquidity transformation rate, but we do not find any link with financial soundness indicators. Results show the absence of a

[4] See the ECB Banking Supervision press release entitled "ECB Banking Supervision provides temporary capital and operational relief in reaction to coronavirus", 12 March 2020. In addition, see the blog post by Andrea Enria entitled "Flexibility in supervision: how ECB Banking Supervision is contributing to fighting the economic fallout from the coronavirus", 27 March 2020.

[5] The range of eligible collateral can vary considerably across time and central banks; the Eurosystem already accepted one of the broadest set of assets as collateral for its refinancing operations, including non-HQLA assets such as credit claims or "own used" securities, i.e. issued by an entity with which the bank that holds the collateral has close links.

[6] See L. de Guindos, I. Schnabel, "Improving funding conditions for the real economy during the COVID-19 crisis: the ECB's collateral easing measures" (ECB Blog, 22/04/2020) and P.R. Lane, "The monetary policy response to the pandemic emergency" (ECB Blog, 01/05/2020).

systematic credit risk transfer from credit intermediaries to the central bank, supporting the view that central banks can provide liquidity without absorbing undue risks onto their balance sheets.

Our study is closely related to Fecht *et al.* (2016) and de Roure and McLaren (2020). In the context of German and British banks, respectively, they seek evidence of "systemic arbitrage", where riskier banks take up more credit from the central bank and pledge riskier collateral assets. The former, who use data on German banks from 2006 to 2010, find evidence of this relationship, so they argue that the ECB collateral framework does not price the correlation risk between counterparty and collateral, which would otherwise be priced in private markets. The latter find no evidence of such an arbitrage opportunity in the UK context.

With respect to these two papers, we broaden the analysis by considering other bank characteristics (i.e. asset encumbrance) and by taking into account the introduction of the LCR regulatory requirement and its possible interaction with the choices of banks regarding assets pledged as monetary policy collateral. A number of papers has recently studied the relationship between assets pledged as collateral with the Eurosystem and liquidity regulatory requirement. Hartung (2020) presents the liquidity transformation rate (LTR), a new measure for assets' liquidity profile, at a level of individual asset, at bank level and for individual euro area countries. He finds that banks follow a hierarchical approach in managing their collateral pools, preferring to pledge with the Eurosystem first less liquid assets and, successively, more liquid assets, such as government bonds. However, the author does not carry out an econometric analysis to verify the existence of a relation between LTR and bank characteristics. Kedan and Ventula Veghazy (2021) compare banks' demand for central bank reserves before and after the introduction of the LCR in 2015. They find that banks with low LCR increased their demand for central bank reserves more than those with high LCR. Schmidt (2019) shows that, in countries without liquidity requirement prior to the introduction of the LCR, banks have pledged less liquid collateral with the Eurosystem after the introduction of the harmonized requirement.

Secondly, the paper investigates how LTR correlates with credit supply, at individual bank level. The intuition is that if a bank pledges as collateral a non-HQLA asset to obtain central bank liquidity, both its liquidity transformation rate and its LCR rise; therefore, the bank could become more willing to engage in activity that can reduce the LCR, such as lending to the real economy. Our findings confirm this hypothesis: banks with high LTR increase their lending to non-financial firms and households more than the ones with low LTR, suggesting that the broad range of eligible collateral in the euro area may have helped the provision of credit to the real economy in recent years and in particular during the pandemic. In this way, we contribute to the literature regarding the impact on the real economy of the degree of liquidity of the assets pledged with the central bank.

Gocheva *et al.* (2022) have drawn similar findings in a recent paper. Their analysis suggests that attractively priced central bank credit operations in which a broad range of less liquid assets are accepted as collateral can provide strong incentives for banks to take actions that reduce their LCRs. Such actions could include the provision of additional credit.

More in general, we also contribute to the empirical assessment of the transmission of unconventional monetary policy. After the onset of the COVID-19, we find that collateral relaxation measures may have contributed to the growth of credit supply. By temporarily expanding the set of assets eligible as collateral, Eurosystem's measures ensured that the banking sector retained access to ample central bank liquidity at favorable terms.

Related literature includes Barthélémy *et al.* (2017), who show that an increase in the share of illiquid assets pledged with the Eurosystem is associated with greater resilience of banks' lending activity (with reference to largest euro area banks between 2011 and 2014). Carpinelli and Crosignani (2020) analyse the transmission of the three-year VLTRO in Italy from December 2010 to June 2012 and find that the eligibility of new assets as collateral at the central bank helped banks to restore their credit supply, by supporting their access to VLTRO. Chan *et al.* (2018) show that the key driver of the VLTROs' effectiveness was the maturity extension of ECB lending to banks in combination with allowing banks to use loans to firms as collateral. Choi *et al.* (2021) build a model that incorporates maturity transformation and collateral circulation. They show that it can be optimal, for the central bank, to lend against low-quality collateral since it improves liquidity and the functioning of markets. Other studies that are focused on the impact of the TLTROs on the amount of credit granted to non-financial private corporations include Esposito *et al.* (2020), Andreeva and Garcia-Posada (2019). Altavilla *et al.* (2020) find that the TLTRO-III programme complemented by supervisory authorities' interventions has been able to mitigate the adverse impact of COVID-19 on loans growth.

Finally, for banks with the same business model, the liquidity transformation rate can be considered as an indicator of banks' efficiency in the liquidity management process, measuring their ability to minimize the cost of liquidity as well as optimize compliance with liquidity regulatory constraints. High values of LTR could suggest that banks are willing to engage in activity supporting the real economy, such as the provision of loans. In a similar vein, Albanese and Ciocchetta (2021) show the importance of organizational efficiency variables in supporting credit supply. The authors find that these variables resulted more important than banks' balance sheet characteristics in explaining bank lending in Italy during the pandemic.

The remaining part of the paper is organized as follows. Section 2 focuses on the LTR indicator, analysing its composition, trend and distribution from October 2015 to January 2022. In section 3 we present the results of the econometric analyses about the correlation between LTR and bank characteristics; section 4 focuses on how the level of liquidity transformation rate has an impact on bank lending. Section 5 finally concludes.

## 2. The liquidity transformation rate: composition, trend and distribution

The liquidity transformation rate (LTR), introduced by Hartung (2020), indicates how much HQLA a bank obtains by pledging an asset as collateral with the Eurosystem.[7] Such transformation is possible thanks to different haircuts between LCR regulation and the Eurosystem collateral framework. In order to calculate the LTR, it is necessary to derive a quantitative measure at a granular level, starting from each individual asset $j$ at time $t$ with its related haircuts (equation 1). Successively, the liquidity transformation rate can be computed for each bank or jurisdiction $i$ by aggregating the results (equation 2).

[7] The rate can be computed by using either the mobilised or the encumbered collateral. In this work, we refer to the mobilised collateral.

$$LTR_{j,t} = 1 - \frac{HQLA_{j,t}^{LCR}}{CVAH_{j,t}^{ECB}} = 1 - \frac{1-h_{j,t}^{LCR}}{1-h_{j,t}^{ECB}} = \frac{h_{j,t}^{LCR}-h_{j,t}^{ECB}}{1-h_{j,t}^{ECB}} \quad (1)$$

$$LTR_{i,t} = 1 - \frac{\sum_j HQLA_{i,j,t}^{LCR}}{\sum_j CVAH_{i,j,t}^{ECB}} \quad (2)$$

The term $HQLA^{LCR}$ denotes the value of an asset in terms of liquidity requirements after applying the asset-specific LCR-haircut($h_{j,t}^{LCR}$)[8], while the term $CVAH^{ECB}$ represents the collateral value of that asset according to the haircuts of the Eurosystem collateral framework($h_{j,t}^{ECB}$). For instance, LTR equals to 0.6 implies that, for each euro of mobilised assets, on average EUR 0.6 of additional HQLA is generated.

We can look over two polar cases in order to better understand the functioning of the LTR: if an asset does not generate HQLA in terms of LCR regulation (i.e. it has a haircut equal to 100%) but it is accepted as collateral in the monetary policy pool, the LTR is equal to one (numerator of the second term is zero), while if the two haircuts are identical, the liquidity transformation rate is zero (the second term is equal to one). The larger the difference between two haircuts, the higher is the liquidity transformation rate of the specific asset. However, the liquidity transformation rate can be negative since the LCR-haircut could be lower than the Eurosystem-haircut, such as for government bonds.[9]

Therefore, the ratio HQLA/CVAH represents the opportunity cost of mobilising and, eventually, encumbering a specific asset in the Eurosystem; banks have an incentive to mobilise assets in the monetary policy pool taking into consideration an ascending order of liquidity, firstly pledging non-HQLA assets with limited utilization in the financial markets. This approach allows the banking system to make liquidity management more efficient by minimizing liquidity costs and those associated with the fulfilment of liquidity requirements. Large banks with a diversified business model are more likely to carry out this strategy than small or specialised banks, also considering the relevance of the information technology system for the pledging and monitoring of credit claims in

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8 The LCR is computed according to the following formula: LCR=Liquidity buffer/(Outflows-min(Inflows; 75%×Outflows))
where outflows are calculated by multiplying the outstanding balances of various categories or types of liabilities and off-balance sheet commitments by the rates at which they are expected to run off or be drawn down in a specified stress scenario. Inflows are calculated by multiplying the outstanding balances of various categories of contractual receivables by the rates at which they are expected to flow in under the scenario up to an aggregate cap of 75% of outflows.
LCR regulation requires that the liquidity buffer consists of assets of extremely high liquidity and credit quality, or level 1 assets, and assets of high liquidity and credit quality, or level 2 assets, further dividing the latter into level 2A and level 2B assets according to the different levels of liquidity. Level 1 assets include coins and banknotes, reserves held in the central bank and which can be withdrawn at any time during stress period (free central bank reserves, therefore excluding compulsory reserves), very high quality government bonds and covered bonds; level 2 assets include covered bonds of lower credit quality, ABS and corporate debt securities.
Each of these asset categories is subject to specific haircuts, which are summarised in Grandia *et al.* (2019) and range from 0% for central bank reserves and central government bonds to 50% for eligible corporate bonds with rating between BBB+ and BBB-.

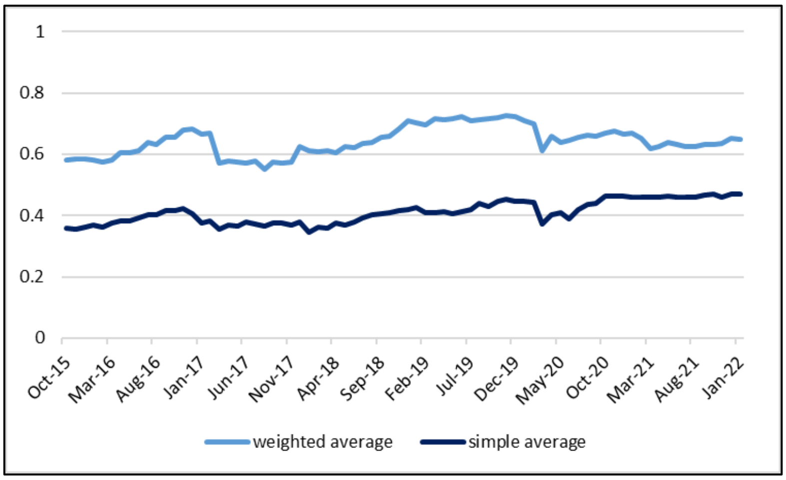
9 In this case, a situation of distress in the financial markets could generate difficulties to fulfil LCR requirements for those banks having LCR above but close to 100% if they had to participate at the monetary policy operations. Under the perspective of easing the functioning of monetary policy, the derogation from compliance to LCR regulation, granted by the ECB Banking Supervision during the pandemic, can be positively evaluated.

the collateral pool. As refinancing with the Eurosystem increases, it is however plausible that the liquidity transformation rate will decrease, because banks will encumber more liquid assets.

In periods of excess liquidity, banks register high LCR and the liquidity transformation process becomes less crucial to fulfil liquidity requirements. The easing of the collateral framework incentivizes banks to pledge credit claims that would otherwise be unused on balance sheets in order to obtain liquidity to expand lending. In fact, the appraisal of the loans at their nominal value allows banks to stabilise the level of the collateral pool, especially in the event of tensions in the financial markets, when the prices of securities fall.

Figure 1 presents the trend of liquidity transformation rate of the Italian banking system from October 2015 to January 2022, which ranges between 0.60 and 0.75 if calculated as weighted average[10] and between 0.34 and 0.47 if calculated as simple average of LTRs at individual bank level. At the end of January 2022, liquidity transformation rate is 0.65 as weighted average and 0.47 as simple average.

**Figure 1 – LTR time series of the Italian banking system**




Source: Eurosystem and Bank of Italy

The trend of liquidity transformation rate is strictly correlated to LCR and to the composition of the collateral pool. In this regard, in the same period the average LCR of the Italian banking system rose from about 150% to over 200%[11], against a regulatory minimum of 100%[12], despite the increase of the net cash outflows over a 30-day stress scenario (denominator of the LCR; Figure 1A in Appendix). Such trend is mainly due to the extraordinary measures promoted by the Eurosystem to support liquidity; the increase in customer deposits also contributed. These measures favoured the increase of the liquidity buffer (numerator in the LCR formula), which consists of approximately 90% of level 1 assets, mostly government bonds and central bank reserves.

[10] The calculus of the weighted average is obtained considering the ratio between the sum of values in terms of liquidity requirements (after applying the asset-specific LCR-haircut) of assets mobilized in the monetary policy pool by Italian counterparties and the sum of collateral values of those assets (after applying the haircuts of the Eurosystem collateral framework). The value for Italian banks is in line with those of other euro area countries (see Hartung, 2020).

[11] The LCR of the Italian banking system is calculated as the ratio between the sum of the liquidity buffers and the sum of the net cash outflows of all Italian banks.

[12] It should be noted that, as part of the measures in response to the pandemic, the possibility of operating temporarily with LCR levels below 100% has been introduced. The minimum LCR under the CRR was: 60% from 1 October 2015, 70% from 1 January 2016, 80% from 1 January 2017 and 100% from 1 January 2018.

In 2017 and 2018, the liquidity buffer steadily fluctuated around an average of €400 billion, while in 2019 it was close to €500 billion due to an increase in both government bonds and central bank reserves. After the outbreak of the pandemic, the liquidity buffer significantly rose up to €720 billion in December 2021 as a result of the growing central bank reserves held by the counterparties (from €115 billion in March 2020 to €425 billion in December 2021 – see Figure 2A.a).[13]

During the last two years, the composition of Italian banks' liquidity buffer has considerably changed on aggregate: the weight of government bonds declined from 62% to 32%, while the weight of central bank reserves rose from 23% to 59% (see Figure 2A.b).[14]

The other factor influencing the LTR is the composition of the monetary policy pool. After an initial increase following the TLTRO-II.4 allotment in March 2017, monetary policy pool remained substantially stable until February 2020 (Figure 3A), at around €300 billion. Successively, in correspondence with the increase of the recourse by banks to the monetary policy refinancing following the outbreak of the COVID-19[15], there were two significant rises of the monetary policy pool in March 2020 (€55 billion) and in April 2020 (€40 billion). In the first case, the increase is mainly due to the encumbrance of government bonds, while in the second case it is attributable to the extraordinary measures adopted to ease the eligibility requirements and the risk-control criteria.[16] More specifically, the haircuts-reduction resulted in an automatic rise in the value of the collateral of approximately €36 billion. The extension of the Additional Credit Claims (ACC) by the Bank of Italy led to an increase in the use of these assets in the following months, once the banks had adapted their internal procedures; in addition, the new measures helped to incentivize 15 counterparties to start pledging bank loans. In correspondence with the TLTRO-III.7 allotment in March 2021[17], the monetary policy pool reached a new peak at around €500 billion. After an initial pledge of government bonds, the counterparties partially replaced this type of asset with bank loans, which consequently became the most representative asset class of the collateral pool. Most of the bank loans were pledged under the ACC temporary scheme.

From March 2020 to January 2022, weighted average LTR raised from 0.61 to 0.65 (simple average from 0.37 to 0.47). Albeit the increment in April 2020 was due to the reduction of haircuts, in the following months the increasing LTR tells us how banks have modified the composition of the mobilised collateral preferring less liquid assets in terms of LCR regulation.

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13 It should also be noted that the two-tier system (TTS) introduced in October 2019 exempt a part of banks' holdings of excess liquidity from the negative deposit facility rate (currently equal to -0.50%). The maximum amount of the reserves that are exempted is six times the minimum reserve requirement for each bank; the remuneration rate for the exempt tier is zero per cent.

14 In the period January 2017-December 2021 available government bonds and central bank reserves represent, on average, 87% of the liquidity buffer.

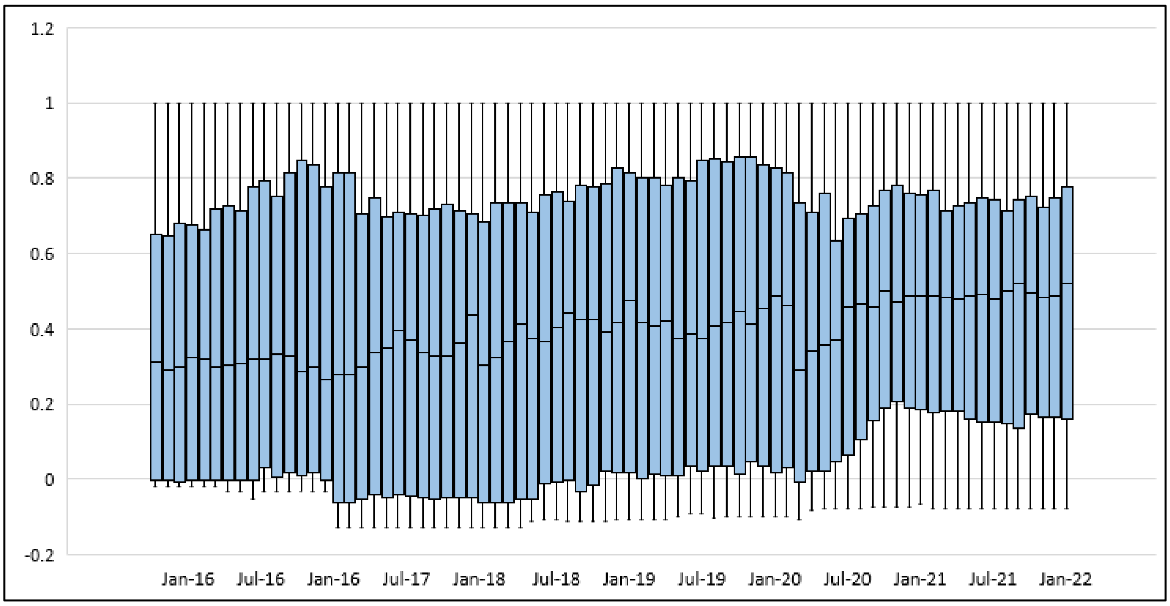
15 The rise was facilitated by both the easing of the conditions of TLTRO-III programme and additional LTROs, carried out in response to the pandemic.

16 In March 2020, the Eurosystem reduced haircuts of all eligible assets (debt securities and bank loans) by 20 per cent. At the same time, it decided to decrease both the additional haircuts applied to covered bank bonds allocated in own use and the haircuts for securities valued at theoretical price. A further reduction in haircuts was also applied, on a permanent basis, only to bank loans. The Bank of Italy has extended its additional credit claims scheme (ACC), including, from 25 May 2020, loans covered by public guarantees issued by the public agency SACE and the Central Guarantee Fund for SMEs on the basis of Decree Law 23/2020 ("Liquidity decree"). From 17 June 2020, Italian counterparties can also pledge portfolios of consumer loans as collateral.

17 The TLTRO-III.7 led to a substantial net injection of liquidity of approximately €74 billion.

Figure 2 illustrates the box-plot of the LTR time series, which represents for each month the LTR distribution of the counterparties, dividing it in four quartiles. With the exception of the period following the outbreak of the pandemic, about 25% of Italian banks record negative LTRs and 50% of them rarely exceed the value of 0.4, while the LTRs of the last quartile are usually between 0.75 and 1. With reference to the entire sample period, the monthly average of the median (0.39) is lower than that of the aggregate LTR (0.64)[18], therefore we can affirm that large banks tend to record high LTR while small and medium-sized banks are likely to be included in the first two quartiles of the distribution. This evidence is consistent with the fact that large banks, having a wide asset-spectrum including "own used" covered bonds and asset-backed securities (issued by an entity with which the bank that holds the assets has close links), can generate much more liquidity transformation, while small banks mainly manage government bonds that have a negative LTR.

**Figure 2 – *Box-plot* of LTR time series**




Source: Eurosystem and Bank of Italy

Note: in the figure the light-blue rectangles represent the two central quartiles of the distribution (25% -50% and 50% -75%) while the horizontal bar that separates them is the value of the median. The lower and upper bars represent the min-25% quartile and the 75% -max quartile, respectively.

In April 2020, the extraordinary measures that relaxed the collateral eligibility requirements and risk control criteria had an immediate effect on the LTR distribution with a considerable increase of its mean from 0.61 in April 2020 to 0.66 in May 2020. In particular, the reduction of haircuts determined a raise in the value of the collateral pool even though its composition remained unchanged. Also in the following months, the LTR distribution showed some variations; the first and second quartiles are noteworthy since their upper bounds increased until their historical maximum values, respectively 0.20 in November 2020 and 0.51 in September 2020.

The effects of the interventions adopted by Bank of Italy and the European Central Bank (ECB) after the outbreak of COVID-19 are evident by dividing the distribution of the LTR into two intervals. From October 2015 to March 2020, the upper bound of the first quartile remains at values close to 0,

[18] The aggregate LTR of the entire banking system can be interpreted as a weighted average.

while, starting from April 2020, it gradually increases until a level above 0.15. The median, in the last 16 months, remains at its maximum values of the historical series as well.

## 3. Empirical analysis: determinants of the LTR

### *3.1 Variables and data*

In this section, we describe the variables used in the econometric analysis to identify which bank characteristics contribute more to determine the liquidity transformation rate (LTR).

According to the literature (see Fecht *et al.*, 2016, and de Roure and Mc Laren, 2020), we divide the variables identified to describe bank characteristics into six categories: size, efficiency, liquidity, financial health, riskiness and opportunity cost of participating in central bank credit operations.

We consider the size as a qualitative variable, which groups banks into four classes based on total assets.[19] For the efficiency category, we use both the variable ROA (return on asset) and a proxy of bank digitalization. The former is measured as the ratio between annualized earnings and total assets. Banks with high ROAs should achieve considerable LTRs. For the latter, we use a proxy based on banks'expenses for information technology (IT) adoption. Indeed, Branzoli *et al.* (2021) show that bank IT costs are positively correlated with both a higher likelihood of offering digital services and engaging in innovative processes. Following these authors, we measure banks' level of IT adoption using yearly costs for the automatic processing of data, reported in banks' income statements. These costs include expenses incurred for the purchase of hardware and software, gross wages paid to IT specialists and the outsourcing of IT services to external providers. We normalize these costs by banks' total assets. The conjecture is that banks with higher IT costs should be more efficient in the liquidity management process compared to the others, also considering the relevance of the IT system for the pledging and monitoring of credit claims in the collateral pool.

As liquidity explanatory variables, we consider several indicators in order to capture the peculiarities of the funding structure of Italian banks: LCR, Eurosystem refinancing over total asset, asset encumbrance, asset encumbrance eligible, variation of sight deposits, strength index on the bond market and the net debt position on the repo market. As described in the previous paragraph, LCR is a coverage index that aims at ensuring that an intermediary maintains an adequate stock of available HQLA to meet any liquidity needs over 30 days in a stressful scenario. In a hypothetical context in which the central bank manages the monetary policy under a structural liquidity deficit and banks have a LCR close to the regulatory threshold, banks would have greater incentives to carry out the liquidity transformation, pledging loans or less liquid assets to the central bank collateral pool. The high operating costs associated with the mobilization toward central bank of these activities would be more than offset by the missed cost of violating the regulatory requirement. In this context, a negative relationship between LCR and LTR is plausible. However, in the period considered in our analysis almost all banks have recorded, on average, high LCRs (much larger than the regulatory

[19] The classes are based on four groups: (1) banks with total assets of less than or equal to 3,626 billion; (2) banks with a value of total assets between 3,626 and 21,532 billion; (3) banks with a value of total assets between 21,532 and 182,052 billion; (4) banks with total assets greater than 182,052 billion.

threshold), also as a result of the ECB's unconventional monetary policy operations. Therefore, the incentive to minimize the use of HQLA in central bank credit operations has been low.

Eurosystem refinancing over total assets shows how much of a bank's balance sheet is financed by the central bank. Banks that have a high refinancing ratio should have low LTRs. This result would be in line with that one found by Hartung (2020). The author finds that if banks want to take up more central bank credit, they pledge additional collateral, which may differ from that previously used. The banks, on average, follow a hierarchical approach, mobilizing first less liquid assets; only at a later stage and when their recourse to refinancing operations rise, they pledge with the Eurosystem more liquid assets, such as government bonds. This implies a reduction of the liquidity transformation rate.

The asset encumbrance ratio (AE) and the asset encumbrance eligible ratio (AEE) both provide a measure of the share of assets tied up in funding transactions, but the second one considers only the subset of assets eligible for monetary policy operations. They can be computed according to the following formulas:

$$AE = \frac{Encumbered\ assets + collateral\ received\ and\ reused}{Total\ assets + Total\ collateral\ received}$$

$$AEE = \frac{Encumbered\ eligible\ assets + eligile\ collateral\ received\ and\ reused}{Total\ eligible\ assets + Total\ eligible\ collateral\ received}$$

From the liquidity risk point of view, the analysis of the encumbrance is important since the scarce availability of unencumbered collateral means that the bank has low financing capacity in stressful situations. The relationship between AE and LTR should be positive: banks that have high levels of AE use to pledge less liquid assets, such as loans or retained ABS, as collateral with the Eurosystem, which determine high LTRs.

On the contrary, since the AEE is calculated on a small subset of assets (those eligible for monetary policy)[20], high values indicate that the marketable assets, such as government bonds, are more used as monetary policy guarantees than the others. This implies that, on average, high AEE should correspond to low LTR.

Then, we consider a variable related to the variation of sight deposits, which is calculated as a weighted average of deposits' monthly changes during the previous 12 months, with a greater weight ($w_s$) for the most recent data.

$$Sight\ deposits\ change = \sum_{t=1}^{T} \sum_{s=0}^{11} \Delta\ sight\ deposits_{t-s} * w_s \qquad w_s = q^s, \quad q = 0.9$$

[20] It should also be borne in mind that the AEE ratio is affected by the difficulty of classifying loans among available assets eligible for monetary policy; in fact, loans are usually considered by the reporting banks as not eligible until they are pledged in the monetary policy pool. For example, consider two banks A and B, which have the same balance sheet composition: 100 million of government bonds and 100 million of loans and the same amount of encumbered assets (equal to 150 million). In particular, bank A has encumbered to the monetary policy collateral pool 50 million of government bonds, 50 million of loans and 50 million of loans as underlying of covered bonds pledged as collateral for monetary policy operations. Its AEE is 75%. The bank B has encumbered 100 million of government bonds and 50 million of loans as underlying of covered bonds pledged as collateral for monetary policy operations. In this case, its AEE is 100%, since loans are not considered eligible assets until they are pledged.

This allows to capture their temporal evolution, obtaining a proxy of the depositors' confidence level toward a bank.

We compute the strength index on the bond market as the difference between net issues[21] and bonds falling due in the following 12 months, where both the measures are reported on a monthly base, over total outstanding bonds:

$$Strength\ index\ on\ the\ bond\ market\ = \frac{net\ issues - maturing\ bonds}{total\ outstanding\ bonds}$$

Low values of the indicator denote banks that have greater difficulties in raising funding on the bond market.

When for a bank these two latter indicators (variation of sight deposit indicator and strength index on the bond market) decrease, the incentive to encumber less liquid assets as monetary policy collateral pool rises, with a consequent increase in its LTR.

The net debt position on the repo market is given by the difference between the repo positions (liquidity obtained by the bank against collateral on the market) and the reverse repo positions (liquidity provided by the bank in exchange for collateral). The increase in the net debt position, which implies a greater use of government bonds as collateral on the repo market, should correspond to a rise in the LTR.

Financial health is captured by capital ratios (CET1 Ratio, Tier 1 Ratio and Total Capital Ratio), while banks' riskiness is measured by their Non-Performing Loan (NPL) Ratio. The latter provides a measure of the write-downs on loans that banks may face, and which will have future effects on their profitability and capital ratios. A negative (positive) and significant relationship between capital ratios (NPL ratio) and LTR would prove the existence of a "systemic arbitrage", in which riskier banks pledge with the Eurosystem less liquid collateral assets.[22]

We calculate the opportunity cost of participating in central bank refinancing operations as the difference between the yield on unsecured Italian bank bonds on the secondary market and the cost of Eurosystem refinancing (taking into account the interest rate of the TLTROs). The greater this difference, the more advantageous for banks to participate in refinancing operations rather than issuing bonds.

Finally, we add as explanatory variable the average haircut of the monetary policy collateral pool to take into account the changes in LTR that occur automatically in correspondence with changes in the monetary policy collateral haircuts, e.g. the easing of the risk control framework by the ECB occurred in April 2020 after the outbreak of the COVID-19.

[21] Net issues are monthly equivalent values of quarterly data moving averages.
[22] Nyborg's (2016) study of central bank collateral frameworks introduced the concept of systemic arbitrage. See Nyborg (2015) for a summary. Fecht *et al.* (2016) resumed it.

In the annex, Table 1A reports some summary statistics for each of the variables used, while Table 2A shows their correlation matrix. From the analysis of the correlation matrix, it results that, as expected, AE and AEE are correlated, while other variables show low pairwise correlation.

The sources of bank-level data are both supervisory reports harmonized at European level, i.e. Common Reporting (COREP, containing information on capital adequacy and risk-specific information) and Financial Reporting (FINREP, which includes balance sheet items and detailed breakdowns of assets and liabilities by product and counterparty), as well as other datasets from supervisory and monetary policy reporting.[23] Monetary policy reporting provides both the composition of the collateral pool pledged by each Italian bank with the Eurosystem and the volume of refinancing operations of each bank. The dataset includes the composition of each pool at the security or loan level. Regarding the refinancing operations, we construct a monthly series of the stock of refinancing of each bank, taking into account early repayments. We also use data from MTS Repo and market data from Bloomberg.

The econometric analysis is based on monthly data for the period from October 2015 to January 2022.[24] October 2015 represents the date of entry into force of the LCR requirement at the European Union level. The dataset comprises 89 banks and banking groups, equal to 93% of the total assets of the Italian banking system. They represent the complete set of counterparties that pledge collateral to the monetary policy pool.[25]

### *3.2 Panel analysis*

This section analyses the relationship between the liquidity transformation rate and the variables that summarize banks' characteristics. Our aim is to understand whether there are systemic incentives for some counterparties to use specific collateral assets rather than others. In this regard, we conduct panel regressions on the data described in the previous section. The model specification is the following:

$$\begin{aligned}LTR_{i,t} = {} & \propto_i + \beta_1 size_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 \frac{IT\ expenses}{Total\ Asset}_{i,t-1} + \beta_4 LCR_{i,t-1} + \beta_5 \frac{ECB\ Refinancing}{Total\ Asset}_{i,t-1} \\ & + \beta_6 AE_{i,t-1} + \beta_7 AEE_{i,t-1} + \beta_8 Sight\ deposit\ change_{i,t-1} \\ & + \beta_9 Fragility\ Index\ bond\ market_{\ i,t-1} \\ & + \beta_{10} \frac{Net\ debt\ position\ MTS\ Repo}{Total\ Asset}_{i,t-1} + \beta_{11} CET1\ Ratio_{i,t-1} + \beta_{12} NPL\ Ratio_{i,t-1} \\ & + \beta_{13} Opportunity\ Cost_{t-1} + \beta_{14} Average\ haircut_{t-1} + \varepsilon_{i,t}\end{aligned}$$

All explanatory variables are lagged. The term $\propto_i$ represents the fixed effect at the level of single bank, invariant over time.

Table 3A reports the results. The first two columns of the table show the coefficients of the linear panel regression with fixed effects at bank level, where the t-statistics is calculated based on standard

[23] We use banks data at the highest degree of consolidation.

[24] To get the monthly equivalent for variables available only on a quarterly basis, we kept the last value constant.

[25] Only Cassa Depositi e Prestiti and Poste Italiane are excluded from the analysis.

errors clustered at bank level.[26] Column 2 shows the results of the model by adding the fixed temporal effects to take into account events that have an impact on the LTR and that are not invariant over time.

Since the dependent variable LTR follows a mixed distribution, where there are several observations that take values equal to 1 and a continuous distribution for values less than 1, Tobit models can be a valid estimation approach. Therefore, column 3 reports the coefficients of the panel Tobit regression; specifically, we apply the Mundlak - Chamberlain correction (Mundlak, 1978, and Chamberlain, 1984), as proposed by Wooldridge (2013), which allows for accommodating the correlation between the unobserved effects and the explanatory variables.[27]

In a second specification of the model, we eliminate the variable AEE, given its correlation with the variable AE. With the aim to take into account the existence of any non-linearity in the relationship with the LTR, we proceed in the following way: i) we add the squared LCR variable; ii) we interact the refinancing on total assets with a dummy variable, which takes the value equal to 1 if the size of the bank's assets is less than the median. The results are shown in Table 4A, where in the first three columns we exclude all the non-significant variables, except for capital ratios and the NPL ratio. In this way, we can test if the capital ratios and the NPL ratio eventually become significant when the specification of the model varies. Finally, the fourth column of Table 4A reports the panel Tobit regression without the capital ratio variable.

Tables 3A and 4A show that large banks have higher liquidity transformation rate; the coefficient of ROA, which is a measure of the bank efficiency, is positive and significant in the Tobit panel regressions, indicating that as banks improve efficiency, their LTRs increase. This result is also confirmed by the positive and significant coefficient of IT expenses in the Tobit panel regressions. This confirms the conjecture that more digitalized banks (as measured by our proxy based on IT expenses) tend to use their assets as collateral more efficiently.

Banks with high LCR show substantial liquidity transformation rate, but we find a negative and significant coefficient for the squared LCR variable (see Table 4A). These results suggest a concave non-linear relationship between LCR and LTR: this finding implies that banks with liquidity ratios close to the regulatory threshold are not more “aggressive” than the other banks in exploiting the differences between the haircuts and the eligibility criteria of the Eurosystem collateral framework and those laid down in the LCR regulation.[28] As a *caveat*, it should be emphasized that in recent years almost all banks have recorded LCRs much higher than the regulatory threshold.

We find that banks with high ratio of Eurosystem refinancing over total assets have low LTR, confirming the findings by Hartung (2020), according to which banks mobilize collateral with the

[26] Statistical significance at the 1%, 5% and 10% levels is indicated by ***, **, and * respectively.

[27] The Mundlak test conducted on Tobit regression rejects the null hypothesis of the absence of correlation between fixed effects at bank level, invariant over time, and explanatory variables. This result recommends using the panel Tobit function (which in statistical software packages, as Stata, is applicable only for the case of random effects) with the Mundlak - Chamberlain correction as suggested by Wooldridge, which allows for loosening the restrictive hypotheses of random effects.

[28] In a second set of estimates, we use the variable *log(LCR-regulatory minimum)*. This variable allows to capture directly whether banks with liquidity ratios close to the regulatory threshold are more or less “aggressive” than the other banks. The results, available on request, confirm that these banks have not higher LTRs than the others.

central bank following a hierarchical approach: first, they pledge less liquid assets and then, if they increase participation in the central bank credit operations, they use more liquid assets. To verify whether this result is always true, even for small-sized banks, we examine the existence of non-linearity in the relationship between Eurosystem refinancing and LTR. The Eurosystem refinancing over total assets is interacted with a dummy variable that assumes value 1 if bank's assets are less than the median. The results show that the coefficient is negative and significant for the large banks, while it is positive and significant (in the Tobit panel regressions) for the small banks. The presence of fixed operating costs for loans' mobilization and subsequent monitoring, including those incurred to install adequate information technology systems, influences the propensity of counterparties to use them as collateral with the central bank. Therefore, small banks will be willing to bear these costs only if their ratio between refinancing and total assets increases.

The relationship between asset encumbrance and LTR is positive and significant: banks that have high AE levels use less liquid assets, such as loans, either as underlying assets for securitization and covered bond issues or as collateral with the Eurosystem.

As expected, the relationship between AEE and LTR is negative. Given that the AEE is calculated on a restricted subset of assets (those eligible as guarantee for monetary policy operations), a high value indicates that very liquid assets (such as, for example, government bonds) are used as collateral more than the others, resulting in low LTRs.

Banks that have greater difficulties in borrowing on the bond market (i.e. measured by low values of the strength bond market indicator) have an incentive to take up credit from the central bank. If they face difficulties in issuing bonds, they will be incentivized to find alternative funding, and taking action to use, as collateral with the central bank, less liquid assets. As a result, we find a negative and significant coefficient in the linear panel regressions; negative but not significant in the Tobit panel regressions.

The coefficients of the sight deposit changes as well as those of the net debt position on repo market are not significant.

Turning to the variables linked to banks' financial health and riskiness, we do not find significant relationships in almost all specifications. Using the CET1 Ratio as a measure of financial health, the relationship with the LTR is not significant. As robustness checks, we also use the TIER1 Ratio and Total Capital Ratio, obtaining similar results. With regard to the relationship between NPL Ratio and LTR, Table 3A shows that the coefficient is not significant; on the contrary, Table 4A reports a negative and significant relationship in the Tobit panel regressions once the other not-significant variables have been eliminated. While this evidence is suggestive of the absence of a systematic transfer of credit risk from the private sector to the central bank, we also conducted a further analysis on the riskiness of pledged assets in the collateral pool to confirm that widening the range of eligible collateral does not imply the absorption of undue risk in central bank's balance sheet. In this sense, we assessed looking forward the riskiness of pledged assets. The analysis shows that the rating of marketable assets pledged in the collateral pool by Italian banks remained substantially unchanged, on average, from year t to year t+1, over the period 2015-2022. These findings support the idea that central banks can provide liquidity, even against a wider range of eligible collateral, without absorbing undue risk in their balance sheets. Offering this form of liquidity transformation can help improve liquidity in financial markets, preserving financial stability as well.

As expected, the relationship between the average haircut of the monetary policy pool and the LTR is negative: reductions in haircuts, such as those that occurred in April 2020 to tackle the pandemic, led to an automatic increase in LTR for all banks.

### *3.3 COVID-19 period*

The aim of this subsection is to answer the following questions: did the impact on the liquidity transformation rate of variables relating to bank efficiency and liquidity diminish after the COVID-19 outbreak? Did the effect of the financial health and the riskiness variables change?

Firstly, we run panel regressions with bank fixed effects and standard errors clustered at the bank level over the period following the outbreak of the COVID-19 pandemic (from March 2020 to January 2022). The results, reported in Table 5A, are broadly consistent with the hypothesis that also in the COVID-19 period banks in better liquidity and efficiency conditions have higher liquidity transformation rate, with the same degree of statistical significance as in the previous section.

The CET1 ratio coefficient is positive but not significant, confirming that banks with low capital ratios do not carry out more liquidity transformation. The NPL ratio shows a positive and significant coefficient in case of panel Tobit regressions.[29]

Secondly, as a robustness check, to the estimates on the entire sample we add variables interacting with a dummy that take the value equal to 1 in correspondence with the period following the spread of COVID-19 and zero otherwise. In this way, we can better appreciate the differences in the significance of the variables. The results are substantially confirmed. Table 6A shows that over the COVID-19 period the coefficient on the variable associated with the CET1 ratio is positive and significant in almost all regressions. This shows that over the COVID-19 period the finding of the absence of systematic credit risk transfer from counterparties to central banks is strengthened. Furthermore, we also find that the coefficients related to efficiency variables (ROA, IT expenses) are positive and significant in Tobit regressions, which may reflect the fact that banks with both high ROA and IT expenses used their assets as collateral more efficiently during the pandemic.

### *3.4 Robustness check*

As highlighted in the previous subparagraphs, we consider in the estimates as explanatory variable the average haircut of the monetary policy collateral pool in order to take into account the changes in LTR that occur automatically in correspondence with changes in the monetary policy collateral haircuts. However, this could not be sufficient to fully separate the impact of bank characteristics on

[29] On average, in recent period the riskiness of Italian banks, measured by the NPL Ratio, diminished compared to previous years, also thanks to NPLs' massive disposals.

LTR from that of contemporaneous changes in the ECB haircut policy (holding bank characteristics constant).

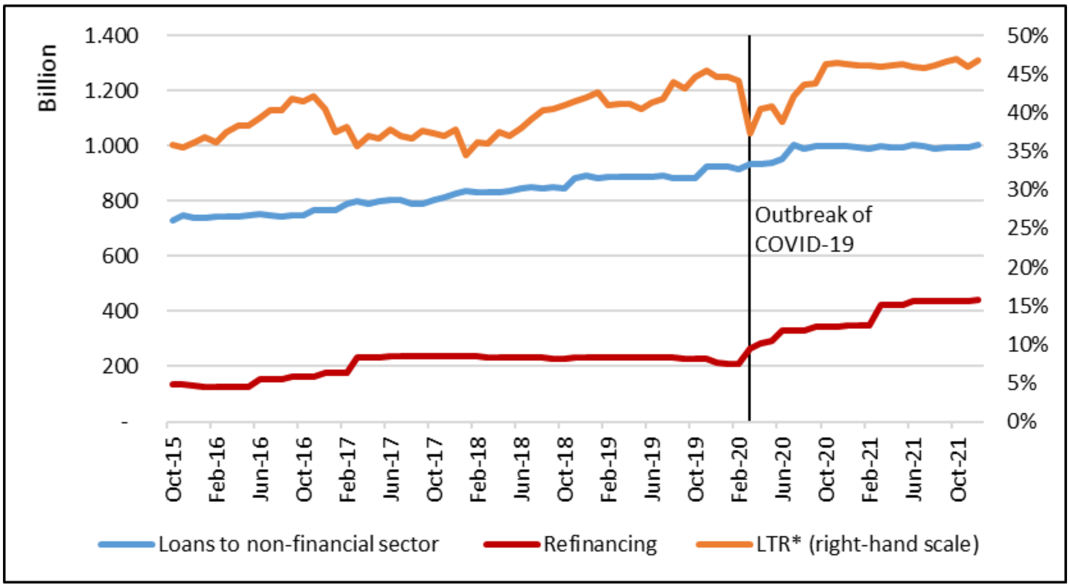
To fully dispel this concern, we run a robustness analysis on the sub-period from February 2017 to February 2020, where the ECB collateral framework was substantially constant. Specifically, the haircut policy of the Eurosystem collateral framework from October 2015 to January 2022 has been changed only twice: one at the beginning of 2017 and another in April 2020. Results, reported in Table 7A, confirm the hypothesis that banks in better liquidity conditions have higher liquidity transformation rate, while banks with low capital ratios do not carry out more liquidity transformation. Furthermore, the NPL ratio coefficient is negative and significant.

## 4 Liquidity transformation rate and bank lending

### *4.1 The relationship between LTR and credit supply*

Loans to non-financial sector have been rising over the entire sample period and in particular after the outbreak of COVID-19 (Figure 3).

**Figure 3 – Credit dynamics, Eurosystem refinancing and LTR**




Source: Eurosystem and Bank of Italy. (*) Simple average.

It is likely that the composition of the collateral pools pledged with the central bank and its interaction with the criteria laid down in the LCR regulation matter for the supply of bank loans to the economy. We are interested in determining whether the liquidity transformation rate is not neutral on banks' lending behavior. We can identify at least four reasons, already appeared in previous papers (i.e. Barthélémy *et al.*, 2017, Gocheva *et al.*, 2022), supporting this conjecture.

Barthélémy *et al.* (2017) show that, in periods of market tensions, a bank with a low liquidity transformation rate (a collateral pool mainly composed of marketable assets) is more exposed to market volatility: when the market prices decrease, the value of the assets as collateral drops. This is the same mechanism highlighted by Kiyotaki and Moore (1997), and defined as financial accelerator. By contrast, a bank with high LTR pledges in the collateral pool also non-marketable assets and so it is more insured against price variations, given that credit claims are less pro-cyclical since their valuation only depends on their default probability. The intuition is that, in periods of market tensions, a bank with a collateral pool less exposed to market fluctuations has a greater propensity to take actions such as the provisions of loans, compared to the other banks.

Furthermore, when easing the conditions at which credit claims are accepted as collateral, the central bank is relaxing the borrowing constraint of banks (Ahn *et al.*, 2016); therefore, banks become more willing to grant loans to the real economy. Since selling credit claims is costly and lengthy, as this requires securitizing them in the form of asset-backed securities or covered bonds, it results relatively simpler posting them as collateral for central bank refinancing operations. On the contrary, marketable assets have the alternative to be used also as repo on the securitized interbank market or to be sold quickly. Pledging credit claims has an opportunity cost lower than that associated to marketable securities.

Third, when a bank receives credit from the central bank using non-HQLA assets as collateral, both its LTR and LCR increase. Our hypothesis is that in this case banks become more willing to engage in activity that could reduce their LCR, such as lending to the real economy. In this regard, we follow Gocheva *et al.* (2022), whose analysis, focused on the euro area after the onset of the COVID-19, shows that banks that get strong LCR boosts from central bank credit tend to increase the provision of lending to the real economy.

Finally, for banks with the same business model, the liquidity transformation rate can be considered as an indicator of banks' efficiency in the liquidity management process, i.e. minimizing the cost of liquidity as well as optimizing compliance with regulatory constraints. High values of LTR could thus suggest that banks are proactive in participating in monetary policy operations and in supporting the real economy through the provision of loans. Albanese and Ciocchetta (2021) show the importance in supporting credit supply of organizational efficiency variables, such as the use of technology to interact with potential applicants for new loans and the adoption of advanced methods to assess the prospective borrowers' credit risk. The authors find that these variables resulted more important than banks' balance sheet characteristics in explaining bank lending in Italy during the COVID-19.

To test these hypotheses on our sample of 87 Italian banks[30] from October 2015 to January 2022, we regress the loans to the non-financial sector (households and non-financial corporations)[31] on the liquidity transformation rate. We are primarily interested in determining whether the coefficient of this variable is significantly greater than zero, i.e. whether a bank's ability to realize high value of LTR is associated with its lending to the economy.

We estimate the following panel equation:

[30] Compared to the analysis of the previous paragraph, we exclude two banks with insufficient observations in the dataset.

[31] In particular, we consider logarithm of the total outstanding loans to non-financial corporations and households, excluding loans for house purchase purposes.

$$
\begin{aligned}
Log\ loans_{i,t} = &\propto_i \\
&+ \beta_1 LTR_{i,t-1} + \beta_2 LogRefinancing_{i,t-1} + \beta_3 CET1\ Ratio_{i,t-1} + \beta_4 NPL\ Ratio_{i,t-1} \\
&+ \beta_5 \Delta GDP_t + \beta_6 LTR_{i,t-1} \times \Delta GDP_t + \varepsilon_{i,t}
\end{aligned}
$$

All explanatory variables are lagged, except macroeconomic variables. The term $\propto_i$ represents the fixed effect at the level of single bank, invariant over time. The coefficient $\beta_1$ measures to what extent banks with high LTRs expand their lending more than those with low LTRs. The coefficient $\beta_2$ assesses whether the level of Eurosystem's credit obtained by a bank plays an additional role in determining lending decisions. We also consider the quality of banks by including the CET1 Ratio and the NPL Ratio. We control for contemporaneous loan demand and, more in general, the co-movements of supply and demand by adding macroeconomic controls to the analysis (changes in Italian GDP, industrial production and business confidence) as well as their interaction with LTR[32]. Residuals are clustered at the bank level to allow for heterogeneity in the distribution of shocks. To account for the inertia in loan creation, we also include in one specification of the model the lagged dependent variable as an explanatory variable.

We estimate the equation both on the entire sample and on the period following the COVID-19 outbreak. Tables 8A (based on entire period) and 9A (based on the sub-period February 2020 – January 2022) report the regression estimates in which we introduce one explanatory variable after another. The results show that a high LTR is associated with a significant increase in loans to the economy, both in the entire sample and in the COVID-19 period. We also find a positive relation between the total volume of Eurosystem's credit obtained by a bank and its granted loans; specifically, the correlation is significant in the COVID-19 period. Banks that pledge more illiquid assets against central bank reserves are those that increased lending to the economy the most.

In the entire sample, variables included to consider the quality of banks (CET1 Ratio and NPL Ratio) do not have statistically significant coefficients. Macroeconomic variables have positive and statistically significant coefficients: a growth of these variables is related to an expansion of granted loans, as expected. The interaction with LTR is significant only for the industrial production variable, while the LTR variable remains significant in all the specifications. In this way, we can exclude that the increase in loans by high LTR banks is driven solely and fully by the demand side of the market.

To exploit better the relation between loans and LTR for bank-month period observations with positive liquidity uptake from the Eurosystem, we also estimate the Heckman selection model. This approach combines a selection mechanism focused on positive Eurosystem liquidity uptakes with a panel regression of loans on the LTR and the time fixed effects. We also control for the quality of banks by including the CET1 Ratio and the NPL Ratio. As before, residuals are clustered at the bank level to allow for heterogeneity in the distribution of shocks at the bank level. The selection equation is:

[32] In detail, GDP data are at constant price, seasonally adjusted; industrial production is a constant price value index, seasonally adjusted and the business confidence is an indicator seasonally adjusted. The source of data is the Italian National Institute of Statistics (ISTAT) and data are obtained by Refinitv Datastream. Quarterly Italian GDP data are reported on a monthly basis by applying the cubic spline technique.

$$z_{i,t} = \gamma' w_{i,t} + u_{i,t}$$

The regression model is:

$$y_{i,t} = \beta' x_{i,t} + \varepsilon_{i,t} \text{ estimated if } z_{i,t} = 1$$

where $(u_{i,t}, \varepsilon_{i,t})$ are assumed to be bivariate normal [0, 0, 1, $\sigma_{\varepsilon}$, $\rho$].

The variable $z_{i,t}$ takes value equal to 1 if $z^{*}_{i,t} > 0$ and equal to 0 if $z^{*}_{i,t} = 0$, with *Prob* ($z_{i,t} = 1$) = $\Phi(\gamma' w_{i,t})$ e *Prob* ($z_{i,t} = 0$) = $1 - \Phi(\gamma' w_{i,t})$, respectively. Variable $z_{i,t} = 1$ indicates that the bank *i* on time *t* has positive liquidity uptake (takes credit) from the Eurosystem ($z^{*}_{i,t} > 0$) and $\Phi$ is the standardized normal cumulative distribution function.

In the selected sample with $z_{i,t} = 1$:

$$E[y_{i,t} | z_{i,t} = 1] = \beta' x_{i,t} + \rho \sigma_{\varepsilon} \lambda(\gamma' w_{i,t})$$

where $\lambda$ is the inverse Mills ratio. [33] The model is estimated by maximum likelihood, which provides consistent, asymptotically efficient parameter estimates (Greene, 2018).

The selection equation includes additional variables that are not in the regression model, namely LCR, and variation of sight deposits. As before, we run the model over the entire sample period and over the COVID-19 period. The results are reported in Table 10A.

The findings are broadly consistent with the hypothesis that exists a connection between banks' ability to realize high value of LTR and their lending to the real economy.

### *4.2 The collateral relaxation measures*

In this subsection we analyse the role of collateral eligibility for the transmission of central bank liquidity provisions in the period following the outbreak of the COVID-19. In order to participate to the expansionary injections of liquidity proposed by the ECB, banks needed to have sufficient availability of eligible collateral. This constraint is relaxed if new assets become eligible to be pledged at the central bank or collateral valuation haircuts are lowered. As described before, Eurosystem introduced relevant measures that effectively eased the collateral requirements.

We evaluate the impact of these measures on the amount of credit granted to non-financial sector. First, we investigate if banks showing high LTRs before the pandemic have been more inclined to grant loans to the real economy than others. We consider the level of LTR as of February 2020. The intuition is that banks with high LTRs might have had a greater propensity to exploit the collateral relaxation measures decided by the Eurosystem, compared to banks with low LTRs, because they have probably already pledged a large portion of their non-marketable assets in the collateral pool. Thus, these banks should have been the main beneficiaries of the new measures. In the estimates, we consider a dummy variable equal to 1 if LTR of a bank *i* is greater than 0.40 as of February 2020.

[33] The inverse Mills ratio is the ratio of the probability density function to the complementary cumulative distribution function (the latter also called survival function).

The value of 0.40 represents the median of the historical distribution.[34] Our choice is to use banks' LTR as a source of heterogeneity and to focus on those one that actively participate to the monetary policy. For this reason we interact the LTR variable with a second dummy that takes value equal to 1 for banks that have a positive Eurosystem refinancing uptake in the period following the outbreak of COVID-19 and zero otherwise.

Indeed, after the announcement of collateral easing measures, lending patterns of TLTRO-III participating banks with a high value of LTR markedly diverged from those of other banks. The former banks experienced a sharp increase in outstanding total credits (see Figure 4A).

We estimate the following triple-interaction model:

$$Log\ loans_{i,t} = \propto_i + \beta_1 I(LTR_i) \times I_{TLTRO-III_i} \times I_{COLL\ RELAXATION} + \beta_2 CET1\ Ratio_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is the log outstanding amount of credit granted by bank *i* at time *t*. As described before, the variable $I(LTR_i)$ is a dummy variable; $I_{TLTRO-III}$ is a dummy equal to one for banks that have a positive Eurosystem refinancing uptake in the period following the outbreak of COVID-19 and equal to zero for the non-participating banks. $I_{COLL\ RELAXATION}$ is a dummy equal to 1 in the period following the introduction of collateral relaxation measures by the Eurosystem (t > April 2020). We include the CET1 Ratio as control variable for the quality of banks and bank fixed effects to absorb any bank time-invariant characteristic.

We show the estimation results in Table 11A. The estimated triple interaction term suggests that banks with high LTR have contributed to the growth of credit supply more than the other banks in the period following the Eurosystem's collateral measures.[35]

These findings are consistent with the idea that in the COVID-19 period Eurosystem, by injecting liquidity against a wider range of eligible collateral, has supported the provision of credit to the real economy. The collateral easing measures in response to the pandemic have been an essential cornerstone to avoid a credit crunch, contributing to the growth of credit supply, especially for "constrained" banks (with high LTR or low LCR). By temporarily expanding the set of assets eligible as collateral, Eurosystem's measures ensured that the banking sector would have retained access to ample central bank liquidity at favorable terms (i.e. during TLTRO-III). The revised collateral framework has thus created a supportive environment for banks to continue lending to the real economy.

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[34] As a robustness check, we also consider the value in correspondence of the 60th percentile. Results are reported in Table 11A.

[35] Since we introduce bank and time fixed effects, the dummies $I(LTR_i)$ and $I_{TLTRO-III_i}$ and the double interaction $I(LTR_i) \times I_{TLTRO-III_i}$ are dropped, because of collinearity. In a second set of estimates, we use LCR as measure of banks' exposure to the collateral easing interventions, considering the level of the variable as of February 2020. The intuition is that banks with low level of LCR (which have scarce HQLA collateral, for a given level of net cash outflows) might have benefited more from the collateral relaxation decided by the Eurosystem compared to banks with high LCR. The results, available on request, show that banks with low LCR, which were more constrained before the introduction of collateral relaxation measures, have contributed to the growth of credit supply more than the other banks.

## 5 Conclusions

This paper focuses on the interaction between the liquidity coverage ratio (LCR), the composition of the collateral pool, bank characteristics, and lending activity. Counterparties can increase HQLA to achieve their LCR requirement by pledging with the Eurosystem non-HQLA assets as collateral and receiving central bank reserves in return. The liquidity transformation rate (LTR), introduced by Hartung (2020), is a synthetic measure that indicates how much HQLA a bank can obtain by pledging an asset as collateral with the Eurosystem.

In this study, we have analysed how bank characteristics correlate with the liquidity transformation rate, using data at bank level. The econometric analysis, conducted on the Italian banking system in the period October 2015 - January 2022, shows the existence of statistically significant relationships between the liquidity transformation rate and banks' liquidity and efficiency. In particular, we find a concave non-linear relationship between LCR and LTR, which implies that banks with liquidity ratios close to the regulatory threshold are not more "aggressive" than the other banks in exploiting the differences between the haircuts and the eligibility criteria of the Eurosystem collateral framework and those laid down in the LCR regulation. As a *caveat*, it should be emphasized that in recent years almost all banks have recorded LCRs much higher than the regulatory threshold. Furthermore, it emerges that banks with high ROA and high IT expenses (measures of efficiency) used more efficiently their assets as collateral, reporting high values of LTR. These results are broadly confirmed also in the COVID-19 period.

If we consider the entire sample we do not find any correlation with financial soundness indicators, but we obtain mixed results over the COVID-period, where, in some specifications of the model, LTR shows a positive and significant correlation with both CET1 Ratio and NPL Ratio.

Overall, we find no evidence of credit risk transfer from banks to the central bank. This supports the view that central banks can provide liquidity and relax the collateral framework without absorbing undue risks onto their balance sheets, even in situations of market stress. Offering this form of liquidity transformation can improve liquidity in financial markets supporting financial stability as well.

In this paper, we have also investigated how LTR is related to credit supply. We find that banks that pledged more illiquid assets against central bank reserves are those that increased their lending to the economy the most. There are at least four reasons to explain this result. First, a bank pledging non-marketable assets in the collateral pool is more insured against price variations, given that credit claims are less pro-cyclical, since their valuation only depends on their default probability (Barthélémy *et al.*, 2017). Second, accepting credit claims as collateral, the central bank relaxes the borrowing constraint of banks (Ahn *et al.*, 2016). Third, when a bank receives credit from the central bank posting non-HQLA assets as collateral, both its LTR and LCR increase. This bank may become more willing to take actions, such as the provision of additional credit to the real economy, that bring its LCR back to the starting value (Gocheva *et al.*, 2022). Fourth, the liquidity transformation rate can be considered as an indicator of banks' efficiency in the liquidity management process, i.e. minimizing the cost of liquidity as well as optimizing compliance with regulatory constraints: efficient banks are more inclined to provide credit (Albanese and Ciocchetta, 2021).

Finally, we have analysed the role of collateral easing measures, enacted by the ECB in the period following the outbreak of the COVID-19, in the transmission of central bank liquidity provisions. Our findings show that the collateral relaxation measures contributed to the growth of credit supply, especially for "constrained" banks (with high LTR or low LCR). By temporarily expanding the set of assets eligible as collateral, Eurosystem's measures ensured that the banking sector would have retained access to ample central bank liquidity at favorable terms, creating a supportive environment for banks to continue lending to the real economy.

Recently the Eurosystem has scaled back its monetary policy refinancing, following some TLTROs' repayments by the banks. In the next future, excess liquidity in the financial system is expected to decline, driven by monetary policy tightening. Pandemic collateral easing measures introduced in April 2020 are gradually going to phase out, in three steps between July 2022 and March 2024. This gradual phasing out allows ample time for the Eurosystem's counterparties to adapt. In any case, these dynamics should not lead a change in the banks' behavior with reference to the use as collateral of assets with high LTRs. Banks that incurred in relevant expenses for the adoption of IT systems for the pledging and monitoring of credit claims in the collateral pool should continue to use loans as a collateral asset. In a context of reduction of both the collateral pool and excess liquidity in the financial system, banks could find convenient to remove part of the government bonds from the monetary policy pool and to use them as repo in the market, continuing to keep loans in the pool.

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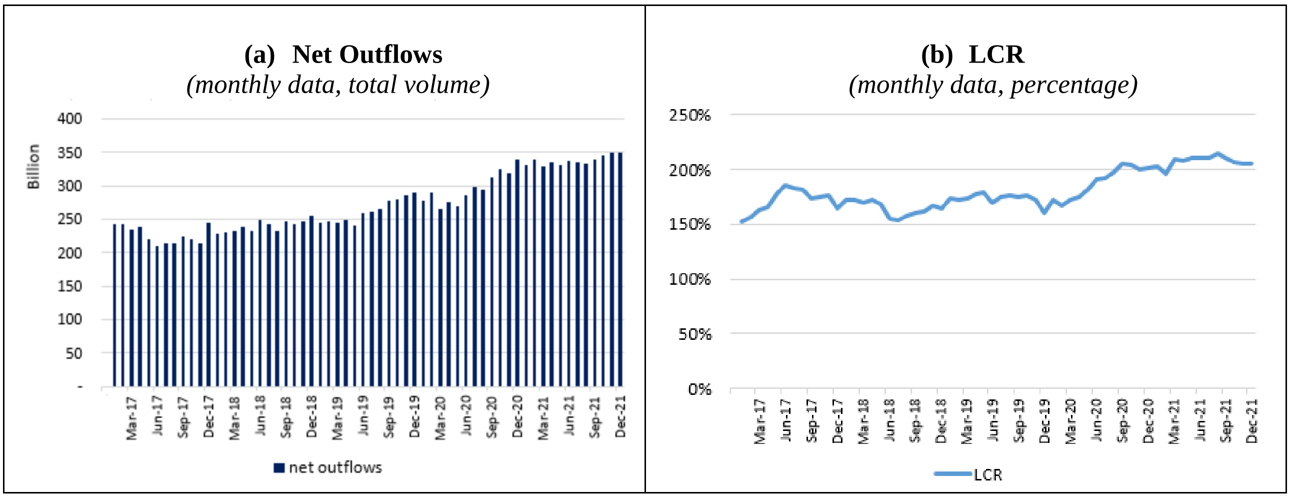
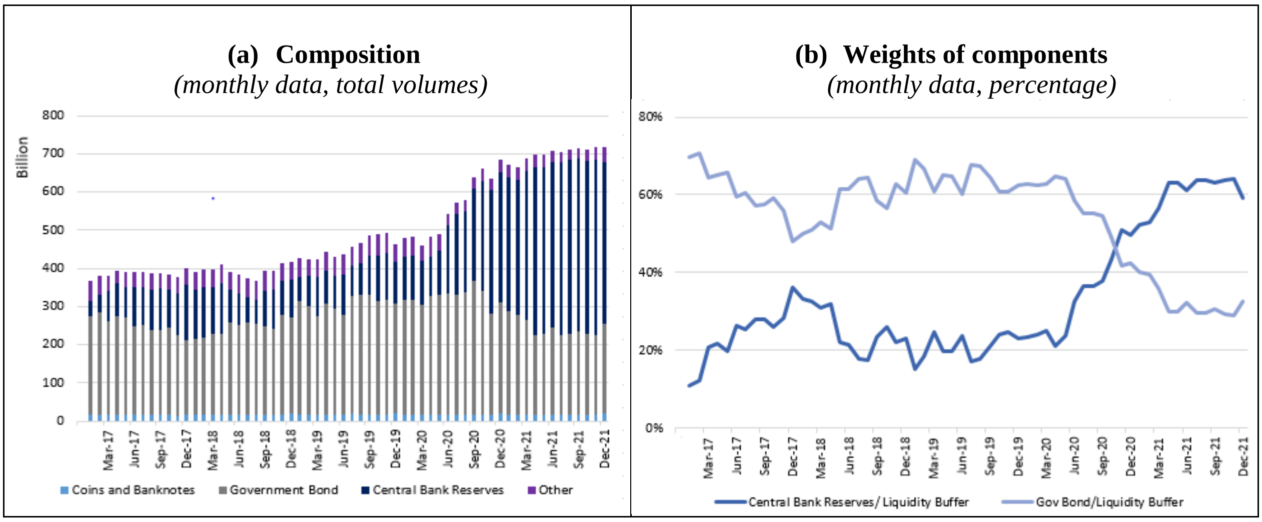
## Tables and figures

### Figure 1A – Net outflows and time-trend of LCR



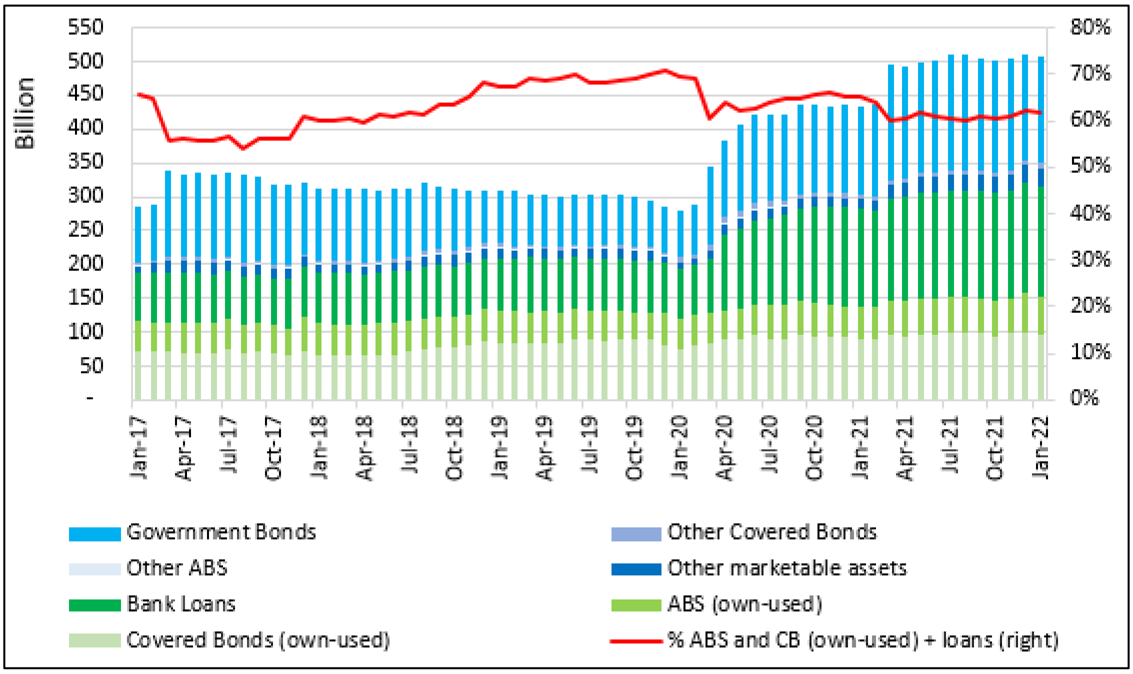

Source: supervisory reports, harmonized at European level (consolidated for groups, individual for banks not belonging to a group).

### Figure 2A – Liquidity buffer, composition and trend



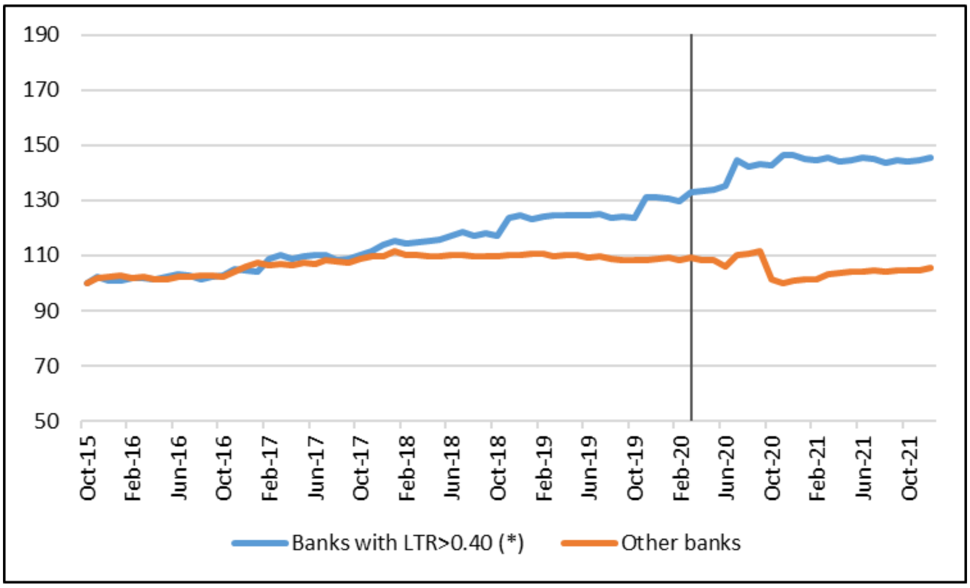

Source: supervisory reports, harmonized at European level (consolidated for groups, individual for banks not belonging to a group).

**Figure 3A – Monetary policy collateral pool, time trend and composition**
*(monthly data, value after haircut)*




Source: Eurosystem and Bank of Italy.

**Figure 4A – Loans to non-financial sector of banks with high LTR**
*(monthly data; indices: 31 October 2015=100)*




Source: Eurosystem and Bank of Italy. (*) Banks with LTR>0.40 as of February 2020 and with a positive Eurosystem refinancing uptake in the period following the outbreak of COVID-19 pandemic.

## Table 1A – Descriptive Statistics

| | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| LTR | 0.4143 | 0.3795 | -0.1299 | 1.0000 |
| size | 1.7753 | 0.9244 | 1.0000 | 4.0000 |
| ROA | 0.0017 | 0.0051 | -0.0012 | 0.0084 |
| IT expenses | 0.0020 | 0.0026 | 0.0000 | 0.0247 |
| LCR | 2.6947 | 1.6478 | 0.5436 | 6.1383 |
| Refinancing / Total asset | 0.1102 | 0.0839 | 0.0000 | 0.5555 |
| AE | 0.2436 | 0.1490 | 0.0000 | 0.8480 |
| AEE | 0.5255 | 0.2683 | 0.0000 | 1.0000 |
| Sight deposits change | 0.0122 | 0.0593 | -0.3126 | 3.1581 |
| Strength index bond market | -0.1359 | 4.0627 | -18.2335 | 2.7016 |
| Net debt position on repo / Total assets | 0.0211 | 0.0599 | -0.1388 | 0.4782 |
| CET1 Ratio | 0.1704 | 0.1155 | -0.0709 | 1.2414 |
| NPL Ratio | 0.1131 | 0.0904 | 0.0000 | 0.8540 |
| Opportunity cost | 0.0140 | 0.0050 | 0.0075 | 0.0290 |
| Monetary policy haircut (average) | 0.1900 | 0.0342 | 0.1319 | 0.2314 |

## Table 2A – Correlation Matrix

| | LTR | size | ROA | IT expenses | LCR | Refinancing / Total asset | AE | AEE | Sight deposits change | Strength index bond market | Net debt position on repo / Total assets | CET1 Ratio | NPL Ratio | Opportunity cost | Monetary policy haircut (average) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LTR | 1 | | | | | | | | | | | | | | |
| size | 0.3379 | 1 | | | | | | | | | | | | | |
| ROA | -0.0873 | 0.0161 | 1 | | | | | | | | | | | | |
| IT expenses | -0.0159 | -0.0813 | -0.0376 | 1 | | | | | | | | | | | |
| LCR | -0.18 | -0.2637 | 0.1219 | 0.1702 | 1 | | | | | | | | | | |
| Refinancing / Total asset | -0.1026 | -0.1299 | 0.0852 | -0.2407 | 0.0323 | 1 | | | | | | | | | |
| AE | 0.3155 | 0.1569 | -0.067 | -0.2216 | -0.0713 | 0.4283 | 1 | | | | | | | | |
| AEE | 0.159 | 0.1393 | -0.0869 | -0.1509 | -0.0906 | 0.3912 | 0.7029 | 1 | | | | | | | |
| Sight deposits change | -0.0271 | -0.0302 | 0.0174 | -0.0017 | 0.0152 | 0.0006 | 0.0059 | -0.0418 | 1 | | | | | | |
| Strength index bond market | 0.0401 | -0.0083 | 0.063 | 0.0120 | 0.0212 | 0.0225 | 0.0192 | -0.0185 | 0.0023 | 1 | | | | | |
| Net debt position on repo / Total assets | 0.1156 | 0.0851 | 0.1671 | -0.0703 | -0.1153 | -0.1399 | 0.1648 | 0.0584 | 0.0077 | -0.0276 | 1 | | | | |
| CET1 Ratio | -0.1512 | -0.1728 | 0.0203 | 0.0655 | 0.2633 | 0.1943 | 0.0789 | -0.0083 | 0.0183 | -0.0013 | -0.1058 | 1 | | | |
| NPL Ratio | -0.0465 | -0.0783 | -0.281 | 0.0262 | -0.0087 | -0.073 | -0.1066 | 0.0932 | 0.0172 | -0.0482 | -0.1164 | -0.1089 | 1 | | |
| Opportunity cost | 0.0118 | 0.0132 | -0.0156 | 0.0069 | 0.0356 | 0.0726 | 0.0555 | 0.0031 | -0.0098 | -0.0083 | -0.0037 | -0.0021 | -0.1024 | 1 | |
| Monetary policy haircut (average) | -0.0382 | -0.0232 | -0.0471 | 0.0139 | -0.1236 | -0.2103 | -0.0692 | -0.052 | -0.0204 | -0.0429 | 0.0589 | -0.0441 | 0.1435 | -0.1795 | 1 |

## Table 3A– Panel regressions on LTR

| *Dep. Variable: LTR* | (1) | (2) | (3) |
|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Tobit Panel with Mundlak – Chamberlain correction |
| L. size | 0.0843 | 0.0628 | 0.0705*** |
| | (0.0599) | (0.0563) | (0.0133) |
| L. ROA | 1.5179 | 1.4782 | 1.4967** |
| | (2.8318) | (2.9252) | (0.7382) |
| L. IT expenses | 7.3904 | 6.9227 | 7.7575*** |
| | (7.1387) | (6.6769) | (2.3946) |
| L.LCR | 0.0129* | 0.0111* | 0.0101*** |
| | (0.0066) | (0.0064) | (0.0024) |
| L. Refinancing / Total Asset | -0.6137*** | -0.6438*** | -0.7702*** |
| | (0.2087) | (0.2021) | (0.0607) |
| L.AE | 0.6233*** | 0.5670*** | 0.6286*** |
| | (0.1689) | (0.1665) | (0.0403) |
| L.AEE | -0.2528*** | -0.2384*** | -0.2564*** |
| | (0.0769) | (0.0747) | (0.0192) |
| L. Sight deposits change | -0.0386 | -0.0424 | -0.0045 |
| | (0.0437) | (0.0451) | (0.0565) |
| L. Strength index bond market | -0.0006*** | -0.0006*** | -0.0006 |
| | (0.0001) | (0.0001) | (0.0006) |
| L. Net debt repo position / Total Asset | 0.0918 | 0.2061 | 0.0848 |
| | (0.2490) | (0.2375) | (0.0825) |
| L.CET1 Ratio | -0.0097 | -0.0192 | 0.0015 |
| | (0.0760) | (0.0757) | (0.0474) |
| L.NPL Ratio | -0.0980 | -0.0139 | -0.0219 |
| | (0.2313) | (0.2476) | (0.0464) |
| L.Opportunity cost | 0.5529 | 2.2700 | |
| | (1.0390) | (8.9388) | |
| L. Average haircut | -0.6616** | -2.7448 | -3.2877*** |
| | (0.2612) | (2.2876) | (0.8321) |
| Bank Fixed effects | Yes | Yes | No |
| Time Fixed effects | No | Yes | Yes |
| *Number of banks* | 87 | 87 | 87 |
| *Observations* | 5,836 | 5,836 | 5,836 |
| *Overall variance* | 0.1747 | 0.1739 | 0.1801 |
| *Panel level variance* | 0.3238 | 0.3269 | 0.3030 |
| *Bayesian Information Criterion* | -3855.047 | -3354.395 | -1264.292 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 4A – Panel regressions on LTR with a subset of variables

| *Dep. Variable: LTR* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Tobit Panel with Mundlak – Chamberlain correction | Tobit Panel with Mundlak – Chamberlain correction |
| L. ROA | | | 1.8034** | 1.8186** |
| | | | (0.7467) | (0.7455) |
| L. IT expenses | | | 7.7805*** | 7.8798*** |
| | | | (2.4099) | (2.4077) |
| L.LCR | 0.0542** | 0.0407* | 0.0280*** | 0.0273*** |
| | (0.0261) | (0.0234) | (0.0092) | (0.0092) |
| L.LCR$^2$ | -0.0054* | -0.0037 | -0.0025* | -0.0024* |
| | (0.0032) | (0.0028) | (0.0013) | (0.0013) |
| L. Refinancing / Total Asset | -0.7235** | -0.8189*** | -1.0110*** | -1.0092*** |
| | (0.2768) | (0.2795) | (0.0841) | (0.0840) |
| L. Refinancing / Total Asset × Dummy banks<median | 0.0156 | 0.1217 | 0.2923*** | 0.2905*** |
| | (0.3076) | (0.3112) | (0.0883) | (0.0883) |
| L.AE | 0.2795*** | 0.2510*** | 0.2845*** | 0.2840*** |
| | (0.0940) | (0.0907) | (0.0308) | (0.0308) |
| L. Strength index bond market | -0.0003*** | -0.0004*** | | |
| | (0.0001) | (0.0001) | | |
| L.CET1 Ratio | -0.0752 | -0.0746 | -0.0275 | |
| | (0.0778) | (0.0782) | (0.0478) | |
| L.NPL Ratio | -0.1588 | -0.0971 | -0.1079** | -0.1079** |
| | (0.2298) | (0.2421) | (0.0469) | (0.0467) |
| L. Average haircut | -0.5651** | -1.5347 | -1.5019* | -1.4907* |
| | (0.2521) | (1.2099) | (0.8800) | (0.8800) |
| Dummy banks<median | -0.1388** | -0.1343** | -0.1626*** | -0.1633*** |
| | (0.0588) | (0.0619) | (0.0174) | (0.0174) |
| Bank Fixed effects | Yes | Yes | No | No |
| Time Fixed effects | No | Yes | Yes | Yes |
| *Number of banks* | 89 | 89 | 87 | 87 |
| *Observations* | 5,986 | 5,986 | 5,846 | 5,846 |
| *Overall variance* | 0.1770 | 0.1764 | 0.1817 | 0.1818 |
| *Panel level variance* | 0.3285 | 0.3315 | 0.3361 | 0.3377 |
| *Bayesian Information Criterion* | -3753.26 | -3238.53 | -1200.79 | -1217.95 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 5A – COVID-19 period: panel regressions on LTR

| *Dep. Variable: LTR* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Tobit Panel with Mundlak – Chamberlain correction | Tobit Panel with Mundlak – Chamberlain correction |
| L. ROA | | | 8.0912*** | 8.0484*** |
| | | | (1.3376) | (1.3331) |
| L. IT expenses | | | 26.3973*** | 26.4611*** |
| | | | (4.5326) | (4.5299) |
| L.LCR | 0.1316** | 0.1160** | 0.1093*** | 0.1090*** |
| | (0.0543) | (0.0527) | (0.0178) | (0.0178) |
| L.LCR$^2$ | -0.0168** | -0.0144** | -0.0134*** | -0.0134*** |
| | (0.0075) | (0.0072) | (0.0023) | (0.0023) |
| L. Refinancing / Total Asset | -0.6968*** | -0.9519*** | -0.9295*** | -0.9261*** |
| | (0.1801) | (0.2180) | (0.1245) | (0.1244) |
| L. Refinancing / Total Asset × Dummy banks<median | 0.3391 | 0.0570 | 0.0032 | 0.0047 |
| | (0.2234) | (0.2576) | (0.1262) | (0.1257) |
| L.AE | 0.2676* | 0.2824* | 0.2820*** | 0.2837*** |
| | (0.1573) | (0.1677) | (0.0562) | (0.0559) |
| L. Strength index bond market | 0.1028* | 0.0971* | | |
| | (0.0548) | (0.0545) | | |
| L.CET1 Ratio | 0.1039 | -0.0856 | -0.0554 | |
| | (0.2256) | (0.2301) | (0.1489) | |
| L.NPL Ratio | 0.2730 | 0.4181 | 0.4657*** | 0.4692*** |
| | (0.4018) | (0.4434) | (0.0977) | (0.0974) |
| L. Average haircut | -0.8923*** | -1.5068*** | -1.3558*** | -1.3493*** |
| | (0.2062) | (0.3431) | (0.2717) | (0.2711) |
| Dummy banks<median | -0.0705* | -0.0510 | -0.0678*** | -0.0676*** |
| | (0.0419) | (0.0499) | (0.0190) | (0.0190) |
| Bank Fixed effects | Yes | Yes | No | No |
| Time Fixed effects | No | Yes | Yes | Yes |
| *Number of banks* | 84 | 84 | 82 | 82 |
| *Observations* | 1,835 | 1,835 | 1,798 | 1,798 |
| *Overall variance* | 0.1123 | 0.1108 | 0.1135 | 0.1135 |
| *Panel level variance* | 0.3397 | 0.3415 | 0.2873 | 0.2885 |
| *Bayesian Information Criterion* | -2836.655 | -2752.750 | -1715.579 | -1729.746 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 6A – Panel regressions on LTR with focus on COVID-19 period

| *Dep. Variable: LTR* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Linear Panel | Tobit Panel with Mundlak – Chamberlain correction |
| L. ROA | | | | 0.2299 |
| | | | | (0.8257) |
| L. IT expenses | | | | 7.9207*** |
| | | | | (2.4802) |
| L.LCR | 0.0406* | 0.0504** | 0.0435* | 0.0290*** |
| | (0.0232) | (0.0242) | (0.0234) | (0.0098) |
| L.LCR$^2$ | -0.0035 | -0.0052* | -0.0043 | -0.0023 |
| | (0.0028) | (0.0029) | (0.0028) | (0.0014) |
| L. Refinancing / Total Asset | -0.7272*** | -0.6969** | -0.7667*** | -0.9831*** |
| | (0.2758) | (0.2735) | (0.2878) | (0.0852) |
| L. Refinancing / Total Asset × Dummy banks<median | 0.0445 | 0.0254 | 0.0998 | 0.2665*** |
| | (0.3039) | (0.3051) | (0.3125) | (0.0893) |
| L.AE | 0.2783*** | 0.2774*** | 0.2579*** | 0.2896*** |
| | (0.0913) | (0.0914) | (0.0884) | (0.0307) |
| L. Strength index bond market | -0.0002** | -0.0002** | -0.0003*** | |
| | (0.0001) | (0.0001) | (0.0001) | |
| L.CET1 Ratio | -0.0572 | -0.0527 | -0.0602 | -0.0352 |
| | (0.0816) | (0.0821) | (0.0836) | (0.0480) |
| L.NPL Ratio | -0.1645 | -0.1963 | -0.1530 | -0.2545*** |
| | (0.2368) | (0.2351) | (0.2463) | (0.0531) |
| L. Average haircut | 0.1228 | -0.0501 | 0.0895 | 1.7919 |
| | (0.4161) | (0.3917) | (1.6414) | (1.2952) |
| L. ROA × Dummy COVID19 | | | | 5.7713*** |
| | | | | (1.2779) |
| L. IT expenses × Dummy COVID19 | | | | 15.3788*** |
| | | | | (2.7804) |
| L. LCR × Dummy COVID19 | 0.0357 | | | 0.0099 |
| | (0.0265) | | | (0.0203) |
| L. LCR$^2$ × Dummy COVID19 | -0.0065* | | | -0.0048* |
| | (0.0038) | | | (0.0027) |
| L. CET1 × Dummy COVID19 | 0.3148** | 0.2849** | 0.2173 | 0.3207*** |
| | (0.1397) | (0.1264) | (0.1331) | (0.0595) |
| L. NPL × Dummy COVID19 | 0.2465 | 0.2244 | 0.1769 | 0.3383*** |
| | (0.3372) | (0.3201) | (0.3405) | (0.0827) |
| Dummy banks<median | -0.1388** | -0.1298** | -0.1317** | -0.1587*** |
| | (0.0588) | (0.0533) | (0.0578) | (0.0174) |
| Dummy COVID-19 | -0.0545 | -0.0284 | | |
| | (0.0336) | (0.0355) | | |
| Bank Fixed effects | Yes | Yes | Yes | No |
| Time Fixed effects | No | No | Yes | Yes |
| *Number of banks* | 89 | 89 | 89 | 87 |
| *Observations* | 5,986 | 5,986 | 5,986 | 5,845 |
| *Overall variance* | 0.1761 | 0.1763 | 0.1761 | 0.1803 |
| *Panel level variance* | 0.3313 | 0.3309 | 0.3323 | 0.3335 |
| *Bayesian Information Criterion* | -3781.26 | -3780.46 | -3242.52 | -1251.76 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 7A – Panel regressions on LTR in the period February 2017 – February 2020

| *Dep. Variable: LTR* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Tobit Panel with Mundlak – Chamberlain correction | Tobit Panel with Mundlak – Chamberlain correction |
| L. ROA | | | 1.2614 | 1.2328 |
| | | | (1.0097) | (1.0096) |
| L. IT expenses | | | 46.4794*** | 45.9754*** |
| | | | (8.0746) | (8.0139) |
| L.LCR | 0.0511* | 0.0494* | 0.0524*** | 0.0516*** |
| | (0.0263) | (0.0249) | (0.0126) | (0.0125) |
| $L.LCR^2$ | -0.0052 | -0.0051 | -0.0054*** | -0.0054*** |
| | (0.0033) | (0.0032) | (0.0018) | (0.0018) |
| L. Refinancing / Total Asset | -0.2954 | -0.1787 | -0.7466*** | -0.7481*** |
| | (0.4652) | (0.4946) | (0.2172) | (0.2164) |
| L. Refinancing / Total Asset × Dummy banks<median | 0.0086 | -0.0234 | 0.4514** | 0.4490** |
| | (0.4736) | (0.4669) | (0.2107) | (0.2107) |
| L.AE | 0.1554* | 0.1271 | 0.2064*** | 0.2054*** |
| | (0.0928) | (0.0900) | (0.0455) | (0.0455) |
| L. Strength index bond market | 0.0002*** | 0.0001 | | |
| | (0.0000) | (0.0001) | | |
| L.CET1 Ratio | 0.0148 | 0.0288 | -0.0123 | |
| | (0.0783) | (0.0780) | (0.0532) | |
| L.NPL Ratio | -0.3560* | -0.2979 | -0.2320*** | -0.2449*** |
| | (0.2100) | (0.2348) | (0.0710) | (0.0702) |
| L. Average haircut | 0.7020 | -3.0619 | 1.1370*** | 1.1074*** |
| | (1.0451) | (4.9659) | (0.3870) | (0.3863) |
| Dummy banks<median | -0.1217* | -0.1157* | -0.1216*** | -0.1219*** |
| | (0.0633) | (0.0657) | (0.0340) | (0.0340) |
| Bank Fixed effects | Yes | Yes | No | No |
| Time Fixed effects | No | Yes | Yes | Yes |
| *Number of banks* | 87 | 87 | 85 | 85 |
| *Observations* | 2,795 | 2,795 | 2,725 | 2,726 |
| *Overall variance* | 0.1454 | 0.1456 | 0.1501 | 0.1501 |
| *Panel level variance* | 0.3601 | 0.3611 | 0.3345 | 0.3345 |
| *Bayesian Information Criterion* | -2865.401 | -2631.365 | -1606.853 | -1615.001 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 8A – Panel regressions on loans

| *Dep. Variable: Log loans* | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel |
| L.log(Loans) | | | | | | | 0.9868*** |
| | | | | | | | (0.0063) |
| L.LTR | 0.1411* | 0.1930** | 0.1754** | 0.1756** | 0.1755** | 0.1751** | 0.0061** |
| | (0.0739) | (0.0845) | (0.0688) | (0.0686) | (0.0688) | (0.0687) | (0.0024) |
| L.log(Refinancing) | | 0.0729 | 0.0852 | 0.0856 | 0.0853 | 0.0863 | -0.0014 |
| | | (0.0542) | (0.0515) | (0.0524) | (0.0515) | (0.0524) | (0.0020) |
| L.NPL Ratio | | | 0.7309 | 0.7343 | 0.7312 | 0.7345 | -0.0028 |
| | | | (0.6044) | (0.6040) | (0.6046) | (0.6046) | (0.0223) |
| L.CET1 Ratio | | | 0.1019 | 0.1040 | 0.1018 | 0.1042 | -0.0024 |
| | | | (0.2305) | (0.2308) | (0.2304) | (0.2312) | (0.0068) |
| Δlog(GDP) | | | | 380.387*** | | | -5.5835 |
| | | | | (138.0566) | | | (12.2189) |
| ΔIndustrial production | | | | | 0.1569*** | | |
| | | | | | (0.0529) | | |
| Δbusiness confidence | | | | | | 0.3972*** | |
| | | | | | | (0.1446) | |
| L.LTR × Δlog(GDP) | | | | 1.2643 | | | 0.0242 |
| | | | | (0.7716) | | | (0.0558) |
| L.LTR × ΔIndustrial prod. | | | | | 0.0014** | | |
| | | | | | (0.0007) | | |
| L.LTR × Δbusiness conf. | | | | | | 0.0004 | |
| | | | | | | (0.0005) | |
| Bank Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Number of banks* | 87 | 83 | 83 | 83 | 83 | 83 | 83 |
| *Observations* | 5,973 | 5,350 | 5,284 | 5,215 | 5,215 | 5,215 | 5,215 |
| *R-squared* | 0.1543 | 0.2800 | 0.3021 | 0.3025 | 0.3023 | 0.3016 | 0.9763 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 9A – Panel regressions on loans (month> February 2020)

| *Dep. Variable: Log loans* | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel |
| L.log(Loans) | | | | | | | 0.9193*** |
| | | | | | | | (0.0186) |
| L.LTR | 0.1013 | 0.1372* | 0.1447** | 0.1466** | 0.1460** | 0.1447** | 0.0045 |
| | (0.0789) | (0.0749) | (0.0701) | (0.0698) | (0.0700) | (0.0702) | (0.0077) |
| L.log(Refinancing) | | 0.1088** | 0.1101** | 0.1090** | 0.1104** | 0.1102** | 0.0019 |
| | | (0.0542) | (0.0542) | (0.0536) | (0.0540) | (0.0541) | (0.0041) |
| L.NPL Ratio | | | -0.1794 | -0.1617 | -0.1753 | -0.1803 | -0.0360 |
| | | | (0.4414) | (0.4514) | (0.4426) | (0.4454) | (0.0296) |
| L.CET1 Ratio | | | -0.8244 | -0.8410 | -0.8284 | -0.8244 | 0.0865* |
| | | | (0.6038) | (0.6044) | (0.6034) | (0.6040) | (0.0508) |
| Δlog(GDP) | | | | 4.1494** | | | 0.4677 |
| | | | | (1.9398) | | | (0.3285) |
| ΔIndustrial production | | | | | 0.0187** | | |
| | | | | | (0.0085) | | |
| Δbusiness confidence | | | | | | 0.2880** | |
| | | | | | | (0.1280) | |
| L.LTR × Δlog(GDP) | | | | 0.3769 | | | 0.0081 |
| | | | | (0.4237) | | | (0.0626) |
| L.LTR × ΔIndustrial prod. | | | | | 0.0010 | | |
| | | | | | (0.0006) | | |
| L.LTR × Δbusiness conf. | | | | | | -0.0001 | |
| | | | | | | (0.0002) | |
| Bank Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Number of banks* | 83 | 80 | 80 | 80 | 80 | 80 | 80 |
| *Observations* | 1,766 | 1,679 | 1,676 | 1,676 | 1,676 | 1,676 | 1,676 |
| *R-squared* | 0.1412 | 0.3217 | 0.3303 | 0.3311 | 0.3312 | 0.3303 | 0.9038 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

## Table 10A – Heckman selection model on loans

| | (1) Entire period | (2) Month > feb. 2020 |
|---|---|---|
| *Dep. Variable for Regression Equation: Log loans* | | |
| L.LTR | 2.0129*** | 1.7004*** |
| | (0.5033) | (0.6583) |
| L.NPL Ratio | -1.2918 | -8.6507* |
| | (2.1865) | (4.8527) |
| L.CET1 Ratio | -1.0230 | -10.2506* |
| | (1.2499) | (6.0026) |
| *Dep. Variable for Selection Equation: Positive liquidity uptake* | | |
| L.LTR | 0.1302 | 0.2415 |
| | (0.1614) | (0.1693) |
| L.NPL Ratio | 0.0628 | -1.1567 |
| | (0.7419) | (0.8906) |
| L.CET1 Ratio | 0.6222 | -0.5304 |
| | (0.4578) | (0.6046) |
| L.LCR | -0.0004 | 0.0062 |
| | (0.0045) | (0.0056) |
| L.Sight deposits change | 0.3695 | -0.8142* |
| | (0.4490) | (0.4873) |
| Ath.rho | -0.2825 | 1.6580*** |
| | (1.0189) | (0.4134) |
| Ln.sigma | 0.5719*** | 1.0027*** |
| | (0.1913) | (0.1370) |
| *Number of banks* | 89 | 84 |
| *Observations* | 5,805 | 1,757 |
| *Log pseudolikelihood* | -4728.991 | -1452.176 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1). Ath.rho estimates the inverse hyperbolic tangent of correlation between the regression equation residual and the selection equation residual, Ln.sigma estimates the logarithm of standard error of the residual in the regression equation.

## Table 11A – Panel regressions on loans with dummy LTR

| *Dep. Variable: Log loans* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| →Model: | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel | Linear Panel |
| dummy_collateral_relaxation × dummy_ECB_uptake>0 × dummy_LTR>50$^{th}$ perc. | 0.3046* | | 0.2582* | | 0.2355 | | 0.2835* | |
| | (0.1556) | | (0.1419) | | (0.1489) | | (0.1619) | |
| dummy_collateral_relaxation × dummy_ECB_uptake>0 × dummy_LTR>60$^{th}$ perc. | | 0.3250** | | 0.2770* | | 0.2547* | | 0.3042* |
| | | (0.1560) | | (0.1422) | | (0.1491) | | (0.1622) |
| L.CET1 Ratio | | | -0.4215 | -0.4253 | -0.4253 | -0.4292 | | |
| | | | (0.2843) | (0.2827) | (0.2638) | (0.2623) | | |
| Bank Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed effects | No | No | No | No | Yes | Yes | Yes | Yes |
| *Number of banks* | 87 | 87 | 87 | 87 | 87 | 87 | 87 | 87 |
| *Observations* | 6,053 | 6,053 | 5,973 | 5,973 | 5,973 | 5,973 | 6,053 | 6,053 |
| *Overall variance* | 0.2462 | 0.2463 | 0.2435 | 0.2436 | 0.2393 | 0.2394 | 0.2421 | 0.2422 |
| *Panel level variance* | 1.9911 | 1.9903 | 1.9836 | 1.9828 | 1.9830 | 1.9821 | 1.9908 | 1.9900 |
| *R-squared* | 0.1253 | 0.1243 | 0.1318 | 0.1309 | 0.1718 | 0.1710 | 0.1647 | 0.1637 |

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. *L* before variables denotes that they are lagged of order 1 (Lag 1).

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