Quantitative Tightening: The Bank Liquidity-Duration Nexus*

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Abstract

Quantitative Tightening (QT) drains liquidity from the banking system on a large scale, typically at times of increasing interest rates. We show that QT's transmission is shaped by banks' joint management of liquidity and interest rate (duration) risk. Using post-Covid UK as a laboratory, we find that in response to QT-induced reserves outflows, banks reduce the quantity of lending but extend its duration. We reconcile these findings in a model where managing liquidity risk can be costly in terms of forgone duration exposure. Our results highlight a knock-on effect between two bank vulnerabilities central to the 2023 banking turmoil. Importantly, we find that access to central bank liquidity facilities can help ease the effects of QT.

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In 2022, major central banks have embarked on unprecedented Quantitative Tightening (QT), draining substantial liquidity in the form of central bank reserves from the banking system. In parallel, central banks have hiked interest rates at an unusually rapid pace. The 2023 US banking turmoil highlighted the potential for adverse interactions between banks' exposure to liquidity and interest rate risk, culminating in the collapse of Silicon Valley Bank.

This paper connects these issues by empirically documenting how QT transmits to credit supply via banks' joint management of liquidity and interest rate risk. Using confidential loan-level data from post-Covid UK, we show that this interaction leads to unexpected effects on bank lending: QT lowers the quantity of lending, but lengthens its duration. This response is part of a broader rebalancing of bank balance sheets towards lower liquidity transformation, but higher maturity transformation.

At the origin of these effects is QT's impact on bank liquidity holdings. When the central bank shrinks its bond holdings (typically via bond sales to nonbanks, in the UK), banks mechanically lose reserves – their most liquid assets. In response, banks cut lending and rebalance towards more liquid (but lower-yielding) assets and stickier (but costlier) funding - consistent with managing liquidity risk. Yet, banks simultaneously extend the maturity of remaining assets with the same liquidity risk, consistent with boosting duration and thus expected profits.

These contrasting effects on quantity and maturity are hard to reconcile with standard bank lending channel or money multiplier theories. To formalise our interpretation, we add an interest rate risk management problem and QE/QT to a model of liquidity risk management (Sundaresan and Xiao, 2024). In line with our findings, the model suggests that if QT tightens liquidity constraints, banks face a trade-off between the liquidity benefits of cutting lending, and the cost in terms of forgone duration exposure and therefore expected profits. Consistent with this trade-off, we find stronger lending cuts for banks with lower initial Liquidity Coverage Ratios (LCR) and greater frictions in borrowing reserves from the central bank.

Our findings add new insights to the body of evidence starting to emerge about QT. Beyond effects on asset prices and money markets (Du *et al.*, 2024), QT can affect credit supply as well as banks' liquidity and maturity transformation through a liquidity-duration channel.

Understanding these interactions is important because QT drains liquidity from banks, often during periods of rapid interest rate increases. By curbing liquidity risk-taking when central banks withdraw liquidity, banks can escape the "liquidity dependence" associated with QE (Acharya and Rajan, 2024). Meanwhile, by curbing lending while shifting the remaining credit towards longer-term (fixed rate) loans, QT can reduce credit supply but also shield remaining borrowers from rising interest rates. This provides a novel spillover between central banks' balance sheet and interest rate policies. It also suggests that balance sheet policies not only affect the quantity of duration held by the private sector (Vayanos and Vila, 2021), but also its allocation between banks and nonbanks.

Looking beyond QT, our results establish novel spillovers between liquidity and interest rate risk management. The 2023 banking turmoil underscored a negative feedback loop between these risks: sharp increases in interest rates lowered the value of banks' long-term bond portfolios, triggering deposit outflows (Drechsler *et al.*, 2023; Jiang *et al.*, 2024). Instead, we show that banks' efforts to mitigate liquidity risk from QT can lead them to boost the duration exposure of their remaining assets.

Another central contribution of our study is to demonstrate that banks' ability to access central bank liquidity — particularly through pre-positioned collateral — can offset some of the contractionary effects of QT on lending. Our empirical analysis shows that banks with more pre-positioned collateral with the Bank of England, and thus easier access to central bank liquidity, are less likely to cut lending in response to QT-induced reserve outflows. This finding suggests that access to central bank liquidity relaxes banks' need to hold liquid assets to manage liquidity risk, allowing them to sustain credit supply even as reserves are drained.

The Bank of England (BoE) initiated QT early among major central banks, reducing its bond holdings by ca. £315 billion since 2022 - around a third of peak holdings. Unlike the Federal Reserve, the BoE both actively sells some bonds and lets other mature. The additional bond supply is typically absorbed by nonbank financial institutions (NBFIs) (Kaminska *et al.*, 2025). Bond transactions are settled in reserves. And unlike in the US (Anbil *et al.*, 2024), UK reserves can only be held by banks. Therefore, QT mechanically shrinks banks' reserves.

All else equal, reserve outflows increase banks' liquidity risk (Kashyap *et al.*, 2002). However, QT could simultaneously *lower* liquidity risk by draining flighty nonbank deposits (Blickle *et al.*, 2025). In any case, banks might not respond to reserves outflows if they have "excess" liquidity (Lopez-Salido and Vissing-Jorgensen, 2023), or if they view *borrowed* reserves (from banks or the central bank) as a perfect substitute for *owned* reserves (Acharya and Rajan, 2024).

Our model tackles these ambiguities by formalising how QT's impact depends on banks' initial liquidity positions and deposits flightiness. To ground the model in reality, we also derive critical values for initial liquidity and deposit flightiness under which QT deteriorates banks' LCR. In our model, when the conditions are met for QT to reduce bank liquidity, banks respond by cutting lending. Since this reduces interest rate exposure below optimal levels, banks extend the maturity of their remaining assets (loans or securities).

The UK regulatory framework has several benefits for identifying mechanisms related to bank liquidity. Since reserves are exempted from leverage requirements since 2016 in the UK, we can ignore the leverage channel that has been found to drive the lending impact of US QE (Diamond *et al.*, 2024). Moreover, unlike US and euro-area banks, UK banks are not subject to reserve requirements; our findings therefore cannot reflect a traditional bank lending channel (Bernanke and Blinder, 1992). In contrast, all banks in our sample face a modern form of liquidity constraint imposed by the LCR. This is not the case for smaller US banks - precisely the banks that seem most prone to "liquidity dependence" due to QE (Acharya et al., 2023).

UK data has two further advantages for identification. First, we can use confidential loan-level data for the universe of mortgage originations, and thus control for confounding changes in credit demand. Second, to shed further light on the mechanism at play, we can use confidential panel data on the composition and maturity of banks' assets and liabilities, LCR, and collateral positions with the BoE. Our sample covers around one year of reserve expansion under QE (2021-2022) and two-and-a-half years of contraction under QT (2022-2024).

Our preferred specification uses mortgage-level regressions to estimate how loan rates respond to changes in reserves holdings during QE/QT, and how this varies with loan duration. The main identification challenge is to isolate sources of variation in banks' reserve holdings plausibly unrelated to banks' lending.

QT provides two such sources. First, QT mechanically shrinks banks' *aggregate* reserves holdings, and central bank QT decisions are based on economy-wide factors that can be absorbed by time fixed effects. Second, the impact on *individual banks* depends on which agents absorb the bond supply brought by QT, and thus (likely) draw down their bank deposits. In turn, this depends on portfolio management decisions by a myriad of potential investors, and these decisions are plausibly exogenous to bank lending, and difficult to predict.

However, a remaining challenge is that in the data, changes in banks' reserves holdings could reflect not only the exogenous impact of QT, but also any endogenous responses by banks to that impact. To address that challenge, we use a three-pillar approach.

The first pillar is to use a "shift-share"-type instrumental variable (IV) for changes in reserves holdings, expanding on Acharya et al. (2023). The shift dimension captures changes in the aggregate supply of reserves by the central bank. The share dimension captures the sensitivity ("beta") of a bank to these changes. To measure this, we compute each bank's share of aggregate reserves, measured in the past. Overall, the IV thus captures a simple accounting identity: the higher its share of reserves, the more a bank stands to lose reserves as the central bank shrinks the supply of reserves. While the IV could also predict outflows of deposits, reserves and deposit outflows should have exactly opposite effects on lending. Therefore, we can let the regression results determine which effect dominates.

Since we focus on the cross-sectional impact of QT, the exogeneity of reserves shares is crucial for the IV to provide identification (Goldsmith-Pinkham *et al.*, 2020). Even if shares are pre-determined, they are not randomly distributed. To mitigate endogeneity, we alternatively calculate reserves shares as rolling averages or as constants measured before the start of the sample and of post-Covid QE. The cross-correlations between these measures exceed 95%. Reserves shares thus seem to reflect highly persistent bank characteristics (e.g. business models or depositor mix), rather than any transient effect of post-Covid QE/QT.

Still, a key concern is that lagged shares correlate with a bank's lending opportunities. Therefore, our second pillar is to include a range of fixed effects controlling for multiple dimensions of loan demand - including postcode-time, borrower type-month, and mortgage product-time fixed effects. Since we also exploit *loan-level* heterogeneities in terms of maturity, we can also include bank-time fixed effects, thus controlling for any unobserved difference in lending opportunities (or other confounders) across banks within the same month.

The third pillar is to include additional interacted controls for alternative mechanisms that could violate the exclusion restriction. This includes e.g. controlling for bank size, exposure to bond valuation losses due to rising interest rates, and monetary policy surprises.

Our key estimates indicate a sizeable credit supply reduction. When a bank's reserve holdings fall by 10%, its mortgage spreads increase by around 4.4 basis points. The effect strengthens when the range of fixed effects expands. Consistent with our model, the effect diminishes with mortgage maturity; maturities beyond five years (the 75th percentile of the distribution) are virtually unaffected. Banks thus reduce the quantity of lending but shift their remaining lending towards longer maturities. Longer maturities increase banks' duration exposure without reducing their liquidity ratio, since the LCR framework treats all asset maturities beyond 30 days identically.

We find an entirely consistent result using our second dataset – a confidential monthly bank-level panel. The more a bank loses reserves due to QT, the more its lending volume falls and the more the average maturity of its loans increases.

Using this dataset, we uncover a broader balance sheet rebalancing consistent with our preferred mechanism. On the asset side, when banks lose reserves, the share of their assets in the form of loans (i.e. illiquid assets) decreases, whereas the share of securities goes up. Further, the mix of securities shifts towards highly liquid securities, away from less liquid ones. On the liabilities side, the composition shifts towards relatively stable (typically insured) retail funding, away from relatively less stable (typically uninsured) retail and non-retail funding. Banks also lengthen the maturity of their retail funding – consistent with further reducing liquidity risk. Banks' LCRs are unresponsive to reserve outflows, consistent with the liquidity risk impact of QT being neutralised. In contrast, the maturity gap between banks' assets and liabilities increases, consistent with the *net* duration of banks' remaining assets increasing.

Finally, we document cross-sectional heterogeneity that further supports our preferred mechanism. The lending impact of QT is concentrated among banks with below-average initial LCRs, consistent with other banks having "excess" liquidity when QT started. The impact of QT is also weaker for banks with more assets "pre-pledged" as collateral with the BoE, which should therefore have easier access to central bank liquidity if and when needed. This finding is in line with the idea that access to central bank liquidity relaxes banks' needs to hold liquid assets to manage liquidity risk (Sundaresan and Xiao, 2024).

Contribution to existing literature We contribute to the literature on the transmission of central bank policies through the banking system.

We add to an emerging literature about QT. Existing studies focus on implications for asset prices (Du *et al.*, 2024; D'Amico and Seida, 2024; Lloyd and Ostry, 2024) or money market dynamics (Lopez-Salido and Vissing-Jorgensen, 2023; Anbil *et al.*, 2024).

Closer to us, Acharya et al. (2023) find that US banks respond to reserve inflows due to (pre-Covid) QE by increasing deposit-taking and credit line issuance. However banks do not reverse this behaviour when they lose reserves during QT. The authors argue that this is because banks remain confident in being able to *borrow* reserves from other banks or the central bank. Our focus is on lending rather than deposit-taking and credit lines. Our granular data allows us to consider multiple ways in which banks can adjust liquidity risk – e.g. through the composition of securities portfolios and funding. We also find that the lending impact of QT is concentrated on banks closer to the LCR constraint. In contrast, smaller US banks were not subject to the LCR, and these banks appear the most prone to maintain liquidity risk-taking despite QT. Our results thus suggest that liquidity requirements incentivise banks to rely on their own liquidity - in line with the LCR's intent. At the same time however, banks boost the duration exposure of remaining assets. This finding echoes evidence that liquidity requirements can increase credit risk-taking (Bosshardt *et al.*, 2024).[1]

Our results also add to the literature on the effect of QE on banks. Mechanisms empha-

[1]Burlon *et al.*, (2025) study the impact of central bank balance sheet reduction driven by banks' repayment of long-term loans to the ECB, rather than by central bank bond sales as in our study.

sized by existing literature include banks' ability to sell Mortgage-Backed Securities to the central bank (Rodnyansky and Darmouni, 2017; Chakraborty *et al.*, 2020), the creation of flighty deposits (Blickle *et al.*, 2025; Darst *et al.*, 2025), or the balance sheet costs of holdings reserves (Diamond *et al.*, 2024). Closer to us, other studies highlight that reserve creation due to QE can affect banks through portfolio balance, money multiplier dynamics, or liquidity management (Christensen and Krogstrup, 2019; Kandrac and Schlusche, 2021; Altavilla *et al.*, 2023; Altavilla *et al.*, 2025a).[2] We emphasise the joint role of liquidity and interest rate risk management.

Our results shed new light on the role of interest rate risk for the transmission of central bank policies and for financial stability. QE increases bond prices by transferring duration risk away from private investors (Vayanos and Vila, 2021). Transmission of monetary policy is known to depend on the interest rate risk exposure of both banks (Gomez *et al.*, 2021) and households (Di Maggio *et al.*, 2017). We show that QT can affect the distribution of duration risk between borrowers and banks. This is because banks increase the supply of longer-term fixed-rate loans, for which interest rate risk is borne by banks rather than borrowers. Research inspired by the 2023 US banking turmoil highlights how interest rate risk (via exposure to bond valuation losses when interest rates rise rapidly) can spill over into liquidity risk (via outflows of uninsured deposits) (Drechsler *et al.*, 2017; Choi *et al.*, 2023; Jiang *et al.*, 2024). We emphasise another spillover: neutralising the liquidity risk associated with withdrawal of central bank liquidity entails higher duration exposure for remaining bank assets.

Looking beyond QE/QT, our evidence provides a reason why central bank policies can affect bank lending. Existing explanations for the bank lending channel of (conventional) monetary policy include reserve requirements (Bernanke and Blinder, 1992), frictions in access to external funding (Stein, 1998), deposit market power (Drechsler *et al.*, 2017) or interbank market dynamics (Bianchi and Bigio, 2022). Instead, we emphasise the joint role of bank liquidity and interest risk, and document opposite effects on the quantity and maturity of lending.

[2] Relatedly, Altavilla *et al.*, (2025b) find that unfreezing the Euro Area interbank market and therefore allowing banks to *borrow* reserves stimulated bank lending.

1 Data Sources and Sample

Data Sources We employ two main datasets. First, to assess QT's effect on loan pricing, we use comprehensive and granular loan-level mortgage data provided by the Product Sales Database (PSD). This confidential regulatory dataset from the UK Financial Conduct Authority covers all UK residential mortgages on a loan-by-loan basis. It reports key variables including lender identity, borrower characteristics (income, age, credit history, borrower type), property details (location and type), and detailed mortgage terms (origination date, loan amount, initial interest rate, fixation period, loan-to-value (LTV), loan-to-income (LTI) ratios, and term).

The UK and US mortgage data and markets differ in several ways. Unlike the US Home Mortgage Disclosure Act (HMDA) data, the PSD does not include loan sales information. However, loan sales or securitizations are rare in the UK during our sample period (Chavaz and Elliott, Forthcomming). UK mortgages have relatively short maturities (generally 2-5 years).[3] Unlike in the US, pricing primarily depends on the fixation period and LTV buckets. The interest rates on mortgages with different combinations of fixation period and LTV, and the corresponding eligibility criteria, are published online and in specialised media. As long as borrowers meet these criteria, other variables such as credit scores do not affect pricing (Robles-Garcia, 2019).

Second, we use confidential regulatory panel data (PRA 110) collected by the Prudential Regulation Authority (PRA). This data covers all UK-regulated banks monthly and tracks banks' liquidity risk through detailed breakdowns of asset and liability volumes and maturities.[4] This includes different categories of loans and securities, and a wide array of funding instruments (e.g., deposits, bank-issued bonds). We use this data to measure reserve holdings (our main explanatory variable), lending and deposit volumes, and other bank-level controls.

We augment these datasets with two confidential quarterly datasets collected by the BoE

[3]We compute the maturity using the so-called fixation period. During this period, the initial fixed interest rate holds. Afterwards, rates revert to prohibitive standard variable rates, prompting near-universal refinancing.

[4]The data is weekly only for the largest banks (assets exceeding £30 billion). The data is collected at the subsidiary level. When banks have both retail and investment banking subsidiaries, we use the former given our focus on mortgage lending.

to construct controls for bank profitability and capitalisation: Financial Reporting (FinRep) and Common Reporting (CoRep). FinRep provides detailed accounting data, including asset, liability, equity positions, and income statements. CoRep offers comprehensive information on various bank risks used to compute Basel II capital requirements.

Sample Our dataset begins in January 2020, when PRA 110 coverage starts. It ends in March 2024 (PSD) and June 2024 (PRA 110) with the latest available data. Since our key explanatory variable is the year-on-year changes in banks' reserves, our main regressions begin in January 2021, covering 10 months of aggregate reserves increase under QE and 26–29 months of decreases due to QT. Our key results hold when considering three-month changes in reserves, thus including more QE observations.

The baseline mortgage sample contains approximately 2 million loans originated by 64 banks. For consistency across regressions, we restrict our sample to banks present in both the bank-level and loan-level datasets. This excludes lenders not regulated by the PRA (e.g. wealth managers or branches of foreign banks). The UK banking market is highly concentrated: the top six banks account for roughly 80% of mortgage lending in our sample. Five of these banks operate both investment banking and retail banking subsidiaries. These subsidiaries are legally separate under the UK ring-fencing regulation. Since we focus on lending to the real economy, we only include retail subsidiaries. Summary statistics for the loan-level and bank-level datasets are reported in Tables I and II.

2 Quantitative Tightening in the UK

Figure 1 illustrates the scale of QE and QT in the UK. It plots total assets in the Bank of England's Asset Purchase Facility (APF), which holds assets bought for QE. Between 2009 and the start of QT in 2022, total assets increase from around £100 billion to £1 trillion. This expansion reflects £895 billion in purchases of UK government bonds ("gilts") across five QE rounds responding to the Global Financial Crisis (2009), Eurozone crisis (2011-12), Brexit referendum (2016), and Covid pandemic (2020). These purchases were financed by creating interest-bearing reserves held by banks (Busetto *et al.*, 2022).

Given data availability, our analysis focuses on QE/QT programs initiated since 2020. The Bank's Monetary Policy Committee (MPC) announced £450 billion in gilt purchases in March, June and November 2020, in response to the economic impact of Covid.[5] As a result, the APF expanded until November 2021 before stabilising.

The Bank started monetary policy tightening in December 2021, using Bank Rate as the primary active tool. In February 2022, with the policy rate reaching 0.5%, the MPC initiated QT by stopping reinvestment of maturing bonds. In November 2022, the Bank also started outright sales of gilts.[6]

The MPC's stated rationale for QT was not to tighten monetary policy, but to prevent the balance sheet from ratcheting upwards over time - potentially constraining future QE capacity. QT was designed to proceed ”in the background”, independent of changes in the macroeconomic outlook, while the policy rate remained the primary instrument of monetary policy.

Starting in September 2022, each year the MPC announced annual targets for the reduction in gilt holdings - beginning with £80 billion target for 2022. Every quarter, calendars of auctions to achieve these targets are then announced. Bonds auctioned by the Bank can only be bought by a selected group of dealer banks authorised by the UK Debt Management Office (DMO). Although dealers can purchase bonds for themselves, in most cases they act as intermediaries for end-buyers, e.g. their nonbank clients. By the end of our sample, QT had reduced APF holdings, and thus aggregate reserves, by over £200 billion - a ca. 20% reduction in reserves.

3 QT and bank lending: hypotheses

To motivate our hypothesis, we first outline the mechanical effects of QT on the balance sheets of banks, and then discuss how this could affect lending in theory. Our focus is on the impact of QT *operations*, i.e. sales or passive run-offs of government bonds held by the central bank. A separate question is the effect of QT *announcements* - see e.g. Du *et al.*, (2024) for asset price

[5] Alongside gilts, the Bank also announced and purchased £10bn sterling denominated corporate bonds, bringing the total stock of corporate bonds held by the Bank to £20 billion.

[6] Gilt sales were postponed during the September-October 2022 gilt market interventions following liability-driven investor fire sales (Hauser, 2022). The Bank also sold £20 billion in corporate bonds. The corporate bond sales programme commenced in May 2022 and concluded with the final transactions in June 2023.

impacts. While announcements could also affect bank lending via general-equilibrium effects, these effects do not directly affect banks' balance sheets, and are absorbed by time fixed effects in our regressions.

3.1 Mechanical effect of QT operations

For brevity, we focus on the case where the central bank sells government bonds. However the insights are similar when the central bank instead ceases to reinvest maturing bonds. In that case, as bonds mature, the Treasury typically issues new bonds, with similar effects on central bank and bank balance sheets (Ihrig *et al.*, 2017).

Figure 2 illustrates stylised balance sheets for the central bank and banks. When the central bank sells bonds, its assets decline. Since transactions with the central bank are settled with reserves, central banks' liabilities in the form of reserves shrink one-for-one. And since only banks can hold reserves (in the UK), banks' reserve holdings must also shrink one-for-one.

In addition to reserves holdings, QT necessarily affects another part of banks' balance sheet. The nature of this simultaneous effect depends on who is the *end-buyer* of bonds sold by the central bank. (The *primary* buyer is always a (broker-dealer) bank, since in the UK these are the only counterparties allowed to transact with the BoE. However banks can be mere intermediaries for the end-buyer).

Figure 2 illustrates a first scenario, where the end-buyer is a bank. Banks swap reserves for bonds, leaving their balance sheet size unchanged. Evidence suggests that this scenario is not dominant in our sample. Kaminska *et al.*, (2025) document that bonds sold in BoE QT auctions are mainly purchased by non-bank financial institutions ("NBFIs"). In line with this, earlier UK and US evidence suggests that during QE, it is NBFIs' government bond holdings that decrease rather than banks' (Carpenter *et al.*, 2015; Joyce et al., 2017).

Figure 3 illustrates the second, empirically dominant scenario where bonds are bought by NBFIs. To finance this purchase, the NBFI draws down its deposit at its bank. To settle the transaction, the central bank draws down this bank's reserves. Overall, QT therefore reduces the bank's holding of reserves and deposits, and its balance sheet size shrinks.[7] Our simple theoretical model allows to analyse the joint effect of these simultaneous impacts.

3.2 *Theory: QT, lending and liquidity and interest rate risk management*

How should QT operations affect bank lending, and what role do banks' liquidity and interest rate (duration) risk management play in that context? To formalise these mechanisms, we start from an existing model of bank liquidity management and add a role for interest rate risk and QT. This section provides a brief description; appendix C gives further modelling details.

The model's key insight is that QT can trigger a knock-on effect between liquidity and interest rate risk management, with opposite effects on the volume and maturity of lending. If QT worsens banks' liquidity ratios, restoring liquidity can force banks to shrink lending and therefore balance sheet size. This pushes banks below their preferred total interest rate exposure, leading them to extend the maturity of remaining assets. However, these effects only materialise under specific conditions for (i) the flightiness of deposits drained by QT, (ii) banks' initial liquidity ratios, and (iii) banks' access to borrowed reserves. Therefore, QT's effect is likely to be heterogenous empirically.

Framework We start from the bank liquidity risk management model by Sundaresan and Xiao (2024). This model has three periods ($t = 0, 1, 2$) and is designed to capture a short-term liquidity stress as embedded in the Liquidity Coverage Ratio (LCR). Banks hold a mix of loans and liquid assets, funded with deposits. At $t = 1$, a fraction a of deposits is withdrawn. At t=0, banks choose their asset mix and deposit volume. Liquid assets are costless to liquidate but yield less; loans are costly to liquidate but yield more. Banks hold enough liquid assets to satisfy a liquidity constraint, i.e. liquid assets must cover expected deposit outflows.

In our model, at $t = 1$, banks additionally face an interest rate shock. At this point, the level of interest rates is revealed, and this affects the value of banks' assets. At $t = 2$, all assets must be sold at market prices. At $t = 0$, banks must also choose the maturity of loans and

[7] This would generally also be the case if bond purchases are funded through repos rather than bank deposits. Repo funding would likely come from money market funds (Anbil *et al.*, 2024). In turn, the money market fund's bank deposit would likely shrink, reducing its bank's reserves and deposits.

liquid assets. Interest rate risk creates an additional trade-off. The longer an asset's maturity, the more its value falls if interest rates rise, but the higher its yield is (a form of term premium).

In the model, assets' liquidity and interest rate risk exposures are separate. The liquidity of assets does not affect their sale value at $t = 2$. Conversely, the maturity of assets does not affect their liquidation value at $t = 1$. This separation matches the logic of the LCR framework. The LCR forces banks to hold enough liquid assets to meet outflows over a *30-day* stress period. However, most banks' asset maturities extend well beyond 30 days. To satisfy the LCR, what matters is whether an asset can be liquidated easily, not its maturity. For instance, a government bond counts similarly towards HQLA whether its maturity is one or 15 years. And a mortgage counts as fully illiquid regardless of maturity. However, these differences in maturities clearly involve substantially different interest rate risk.

Impact of QT At $t = 0$, QT exogenously reduces banks' liquid assets and deposits one-for-one. Banks then optimise. The initial effect of QT on the bank's liquidity ratio depends on the withdrawal probability of the deposits drained by QT (a). For QT to affect liquidity, a must be below 100%. If instead $a = 100\%$, the negative liquidity impact from reserve outflows is fully offset by the positive effect of lower exposure to withdrawal risk.

To restore its liquidity, the bank must either increase its liquid asset holdings or cut lending. In the first scenario, the bank adjusts the composition of its liquid assets, but lending, balance sheet size, and total asset duration are unchanged. In the second scenario, reducing lending shrinks the balance sheet, pushing total interest rate risk exposure below the bank's preferred level. To restore that level, banks must increase the maturity of their remaining assets. Since asset maturity and liquidity are separate, liquidity risk is unchanged.[8]

Discussion The model suggests that QT can lead banks to reduce lending (or asset) volumes while extending asset maturities, under specific conditions. First, the impact of reserves and

[8] In appendix C, we derive the theoretical conditions under which banks chose either option. Cutting lending is the preferred option when QT follows a QE program that is large relative to a bank's initial liquid assets. In that case, banks are unable to maintain a constant ratio of liquidity holdings to deposits by shedding existing liquid assets. Instead to maintain that ratio, banks expand lending (and therefore deposit-taking). This pushes liquid asset holdings above its profit-maximising level. This means that when banks subsequently lose reserves during QT, restoring liquidity by increasing liquid asset holdings is not optimal, and banks instead cut lending.

deposits drainage must not offset each other (i.e. $a < 1$), so that QT deteriorates banks' liquidity. This assumption matches policymaker commentary, which suggests that QT should worsen banks' liquidity (Sveriges Riksbank, 2024; European Banking Authority, 2025). This assumption also matches the fact that central banks like the BoE have deployed new lending facilities to meet additional bank demand for reserves due to QT (Saporta, 2024).

In appendix B, we derive the conditions under which QT worsens banks' LCR, as authorities seem to think. QT worsens the LCR when the withdrawal probability of drained deposits falls below the inverse of the bank's initial LCR ($a < \frac{1}{LCR_0}$). We assess how likely this condition is met, given assumed outflows rates in the LCR rulebook, and depending on starting LCRs. The condition is likely to be met for banks with starting LCR below the sample median. More broadly, the lending effect of QT should decrease with banks' initial LCR.

In line with the LCR derivation, our model suggests that the lending impact of QT should decrease with the bank's initial liquidity holdings. In the model, QT can only affect lending if it leads banks to breach their preferred ratio of liquid assets to deposits. Otherwise, banks let their ratio shrink. This further suggests that the lending effect of QT should decrease with banks' initial liquid asset holdings (relative to deposits).

Even if QT increases liquidity risk, banks could undo reserve outflows by borrowing reserves from other banks or the central bank (Acharya and Rajan, 2024). Therefore, another key assumption is that banks view borrowed reserves as an imperfect substitute for owned reserves. This is likely to be the case for several reasons. Borrowing reserves usually requires encumbering collateral assets and is subject to haircuts. Interbank markets can freeze and be tepid during QE periods. And borrowing from the central bank might carry stigma effects. Regardless, the effect of QT should be weaker for banks with better access to borrowed reserves.

4 Identification

To estimate how QT-induced reserves outflows affect lending, our preferred specification is:

$$Spread_{i,l,t} = \beta \cdot \Delta(Reserves)_{i,t} + \gamma \cdot \Delta(Reserves)_{i,t} \times Maturity_{i,l,t} + B \cdot Controls + \epsilon_{i,l,t}. \quad (1)$$

where $Spread_{i,l,t}$ is bank i's rate for loan l in month t net of the maturity-matched risk-free (OIS) rate. $\Delta(Reserves)_{i,t}$ is the year-on-year change in bank i's log reserves holdings for every month t. A negative estimate for β would indicate that reserve outflows are associated with higher spreads, i.e. a reduction in loan supply. $Maturity_{i,l,t}$ is the loan's maturity, in years. A positive estimate for γ would suggest that the loan supply reduction weakens with maturity, i.e. banks shift remaining lending towards longer maturities.

4.1 *Identification challenge*

The empirical challenge is isolating QT-induced changes in $\Delta(Reserves)$ that are plausibly exogenous to lending *except through our mechanism of interest*.

QT provides two sources of such variation. First, QT exogenously shrinks the *aggregate* stock of reserves held by banks. The BoE implements QT by letting bonds mature or selling bonds (section 2). The timing of bond run-offs is determined by the maturity profile of bonds bought during QE, years before QT began. In turn, the timing of bond sales reflects the BoE's auctions schedule. This schedule is based on aggregate market liquidity considerations (Ramsden, 2023). These factors could affect lending but are absorbed by time fixed effects in regressions.

Second, the effect of QT operations on *individual* banks' reserves should depend on a chain of investor decisions unlikely to be correlated with bank lending, or predictable to the bank. Which bank loses reserves depends on who absorbs the additional bond supply caused by QE. Bonds sold by the BoE are generally bought by NBFIs, not banks (Kaminska *et al.*, 2025). If the buyer settles the purchase with its bank deposit, the buyer's bank generally loses reserves to the seller's bank.[9] However the buyer could sell the bond to another nonbank. This second buyer could also simultaneously issue another bond to households. (A pension fund could e.g. sell life insurance bonds to clients). In any case, each decision along this chain should reflect investors' portfolio optimisation rather than any consideration around their bank's lending.[10]

[9] Another possibility is that the buyer borrows funding from the repo market (Anbil *et al.*, 2024). In turn, the repo funding would likely come from money market funds. Therefore, in that case, it's the money market fund's bank that would likely lose reserves and deposits.

[10] In Acharya and Rajan (2024), banks can affect the supply of bonds available to other investors because banks first determine the quantity of auctioned bonds they retain for themselves. This mechanism does not apply to

While the direct effect of QT operations on banks' reserves can thus be largely exogenous, data does not allow to isolate that direct impact. Our explanatory variable $\Delta(Reserves)$ captures the change in a bank's reserves *in a given month*. This change could not only reflect the direct impact of QT in this month, but also any banks' endogenous response to that impact.

Such response might not threaten identification if it reflects our mechanism of interest. For instance, if a bank loses reserves due to QT and this increases its perceived liquidity risk, the bank may respond by raising deposit rates to attract deposits and therefore reserves. The bank could also respond by buying bonds. If these responses are costly and banks must reduce lending, this would be a manifestation of our preferred mechanism.

However a more concerning possibility is that banks' responses could reflect alternative mechanisms. In particular, banks' response to reserve outflows could reflect their (unobserved) lending opportunities. This might generate spurious correlations between reserves and lending. We address these challenges through three complementary pillars: (i) an instrumental variable (IV) approach, (ii) granular fixed effects and (iii) controls to address violations to the exclusion restriction.

4.2 *Instrumental variable*

Our first pillar is to use an IV for changes in reserves. The IV provides a first pass against reverse causality and omitted variable concerns. In particular, the IV allows to isolate variation in reserve holdings that is due to mechanical, pre-determined factors and therefore not directly affected by lending decisions at t. Since the IV is not randomly distributed however, we complement it with granular fixed effects (pillar two), and additional controls (pillar three).

Building on Acharya et al. (2023), we start from the following shift-share IV for $\Delta(Reserves)_{i,t}$:

$$Predicted(\Delta(Reserves)_{i,t}) = \Delta(Aggregate\,Reserves)_t \times BankExposure_i. \quad (2)$$

the banks in our sample, which only comprise commercial banks and not dealers. The UK ring-fencing regulation strictly separates retail banking entities (our focus) from investment banking activities within conglomerates (Chavaz and Elliott, Forthcomming).

Shift-share (or Bartik) IVs provide identification by using differential exposure to common shift(s). In our context, the shifts correspond to the sequence of QT (and QE) operations by the BoE. $\Delta(Aggregate\ Reserves)_t$ is defined as the year-on-year changes in reserve supply by the BoE. The "share" component measures the bank-specific sensitivity to these shifts. It is defined as the share of all reserves held by bank i:

$$Bank\ Exposure_i = \frac{Reserves_i}{Aggregate\ Reserves_t}. \tag{3}$$

As usual with shift-shares, the IV reflects an accounting identity rather than any economic theory. Since reserves can only be held by banks (in the UK), the change in total reserves (the shift) must equal the sum of changes in reserve holdings across all banks. The share dimension turns that identity into a simple assumption: the higher its share of reserves, the more a bank's reserves stands to shrink when total reserves contract. Thus, the IV helps to isolate variation in reserves holdings due to mechanical factors not directly affected by banklending at t.

For shift-shares IV to provide identification and meet the exclusion restriction, the shift *or* the share dimension must be exogenous to the outcome of interest (Borusyak *et al.*, 2025). Since we focus on the *bank-level* impact of QT, the exogeneity of shares is key in our case.

As long as they are measured before t, shares cannot be directly affected by lending at t. Still, a key concern is that if lending decisions are serially correlated, shares could still correlate with banks' (unobserved) lending opportunities - directly or via confounding factors. However, shares must be exogenous *conditional on controls* in the regressions (Goldsmith-Pinkham *et al.*, 2020). In other words, shares must be uncorrelated with the error term in equation 1 - ie they should only affect lending through changes in reserves - once controls have been partialled out. This is why we complement the IV approach (our pillar one) with a rich set of fixed effects (pillar two) and controls (pillar three) to control for multiple unobserved dimensions of loan demand and other threats to the exclusion restriction (more in Section 4.3).

To further strengthen the exogeneity of reserves shares, we also experiment with alternative ways to measure $Bank\ Exposure_i$. Acharya et al. (2023) use a rolling average of shares, i.e. $\frac{1}{12}\sum_{k=1}^{12}\frac{Reserves_{i,t-k}}{AggregateReserves_{t-k}}$. For comparability, we start with the same approach. Using rolling shares measured closely before t is likely to increase the *relevance* of the instrument, i.e. its correlation with $\Delta Reserves_t$. However, this approach increases concerns about the exclusion restriction, e.g. if shares correlate with low-frequency changes in unobserved lending opportunities. Therefore, we alternatively measure shares at a fixed point in the past and keep them constant. We measure shares either at one point in time (before the sample starts and therefore before the start of post Covid QE), or at two points (before the start of post-Covid QE and QT, respectively). We also use a rolling average measured further back in time, i.e. $\frac{Reserves_{i,t-13}}{AggregateReserves_{t-13}}$.

All these measures of reserves shares yield similar results for our key regressions. This is not surprising: cross-correlations between these measures are between 94% and 99%. Since some of these measures are calculated before post-Covid QE/QT, these correlations indicate that the treatment exposure (i.e. shares) is not affected by the treatment itself (i.e. post-Covid QE/QT). Instead, reserves shares seem to reflect highly persistent characteristics of banks.[11]

Since reserves outflows are likely to coincide with deposit outflows, mechanically the IV could also predict outflows of deposits. However, as our model clarifies, reserves and deposit outflows have exactly opposite effects on liquidity risk, and therefore on lending. Therefore, we can let the regression results determine which effect dominates. We consistently find that QT leads to less lending, which suggests that the reserves effect dominates.[12]

4.3 *Fixed effects*

Our second pillar exploits loan-level granularity to use an extensive set of fixed effects to control for unobserved changes in loan demand, in the spirit of Khwaja and Mian (2008). Bor-

[11]Since the first round of QE in 2009, the UK banking system has been in an abundant-reserves regime. In such a regime, there is little trading of reserves between banks. Therefore, banks have limited control over their reserves holdings. Instead, bank's depositor clientele is a key driver of reserves accumulation during (pre-Covid) QE years. Agents that are net sellers of bonds to the central bank during QE years are likely to be sophisticated agents such as NBFIs. In return, these agents are likely to accumulate deposits. Therefore, a bank's reserves share is likely to increase with its exposure to such sophisticated clients, e.g. reflecting the bank's own sophistication.

[12]This is consistent with the mechanics of LCR framework. Reserves add to the LCR one-for-one, whereas deposits reduce the LCR by a factor between 0 and 1, depending on the assumed outflow rate. The impact of reserves thus dominates unless the entire mix of drained deposits had an outflow rate of 1. This is highly unlikely in practice (in the UK context), as we discuss in more details in appendix B).

rower location (postcode)-time fixed effects absorb geographical variation in credit demand. Product-time fixed effects (where products combine LTV buckets and maturities) control for shifting demand across mortgage types. In the UK, unlike in the US, mortgage pricing is based almost exclusively on mortgage maturities and LTV (Robles-Garcia, 2019). Therefore, product fixed effects absorb nearly all variation relevant to pricing. Borrower type-time fixed effects absorbed differences in loan demand across first-time borrowers, refinancers and movers. Bank-product fixed effects capture confounding supply-side factors, such as specialisation by banks into specific mortgage segments.

Finally, in some specifications we include bank-month fixed effects. This means that identification only rests on heterogeneities in the maturity of loans offered by the same bank in a given period. Mechanically however, these fixed effects absorb any unobserved difference in lending opportunities (and other confounding factors) across banks and periods.

4.4 Controls

We include a range of controls to deal with threats to the exclusion restriction not addressed by fixed effects. In all regressions we control for loan characteristics, including amount, LTI and LTV ratios, term, maturity, and a credit impairment indicator. Following Acharya et al. (2023), we also include time-varying controls for the bank's size (log total assets), capitalisation (equity over total assets), profitability (total income over total assets), and (log) reserves lagged by a year.

In robustness checks, we add further interacted controls designed to capture alternative supply-side factors that could violate the exclusion restriction. In particular, we interact Δ *Aggregate Reserves*$_t$ (the shift dimension of our IV) with bank characteristics that could correlate with reserve holdings, including bank size and capitalisation, and holdings of government bonds. The latter control addresses the potential effect of monetary policy tightening and QT on banks' asset valuation (Jiang *et al.*, 2024). We also interact $Bank\ Exposure_i$ (the share dimension of our IV) with time-varying factors that could correlate with the change in aggregate reserves. In particular we control for changes in conventional monetary policy, using high-frequency identified shocks (more details below).

5 Main results

5.1 Baseline loan-level regressions

Table IV presents baseline results using loan-level data, for different variants of equation 1. The dependent variable is the spread between mortgage rates and maturity-matched risk-free rates. The cross-sectional dimension of the IV is measured via rolling averages of banks' reserve shares. In robustness checks below, we instead measure shares before the start of the sample (and of post-Covid QE) and hold them constant, to further ensure exogeneity.

Column 1 reports results from a basic OLS regression. Higher reserve outflows are associated with higher loan spreads, and therefore a contraction in credit supply. Column 2 reports the first stage of the two-stage least squares (2SLS) regression. The instrument appears to be relevant: banks with higher (predetermined) shares of aggregate reserves lose more reserves when total reserves shrink. Column 3 presents second-stage 2SLS results, which are consistent with OLS. The Kleibergen-Paap statistic (114.7) indicates that the instrument is strong.

That reserve outflows are associated with a contradiction in lending supply is consistent with the liquidity risk management motive in our model. Our model also makes clear that reserves outflows could come along with outflows of deposits, which in itself *improves* banks' liquidity. If that effect dominated empirically however, we should find that QT is associated with more lending, not less lending.

The key estimate *increases* as we add more conservative controls and fixed effects. Column 4 adds borrower and loan characteristics (loan size, borrower age, LTI and LTV ratios, maturity and a dummy for impaired credit history). Column 5 adds bank-product and product-time fixed effects. Column 6 is our most stringent specification, with borrower type-time and location-time fixed effects absorbing unobserved variation in credit demand along borrower type and geographical dimensions. The most stringent specification (column 6) yields the largest estimate. Addressing confounding changes in credit demand thus strengthens rather than attenuates the estimated effect of QT.

The economic magnitudes are substantial. Our most conservative specification (column 6) suggests that a 10% decline in a bank's reserves increases loan spreads by around 4.4 basis points — roughly 10% of the standard deviation in spreads (see Table I). For perspective, Joyce and Lengyel (2024) find that when a QT program of comparable magnitude is announced, UK government bond yields rise by 7 basis points.[13] Typically, loan rates paid by borrowers correspond to the sum of government bond yields plus the spread charged by banks. Therefore, the effect of QT on loan spreads makes a substantial addition to household borrowing costs, on top of costs due to higher government bond yields.

In column 7, we interact $\Delta Reserves_{i,t}$ with $Maturity_{i,l,t}$. In line with our prior, the estimate is positive. In other words, the increase in spreads associated with reserve outflows is smaller for longer-maturity mortgages. Banks thus reduce credit supply less for longer-maturity mortgages, tilting lending towards more duration. Since our regressions include product-time fixed effects, this result cannot be explained by a shift in the demand for loans of different maturities.

Alternative specifications Table V reports results for nine variants of our most stringent specification (column 7 of Table VII). Column 1 reproduces this specification for comparison.

We first modify the main explanatory variable. Column 2 measures $\Delta(Reserves)_{i,t}$ using three-month rather than twelve-month changes; column 3 lags $\Delta(Reserves)_{i,t}$ by one month to further guard against reverse causality. Results are unchanged.

We then modify the instrument. In column 4, the 'shift' element $\Delta(Aggregate\ Reserves)_t$ is measured through changes in the size of the BoE facility that housed assets purchased for QE (APF) rather than changes in aggregate reserves. This strips out variation in reserves due to the Term Funding Scheme with additional incentives for SME (TFSME) program. Introduced in response to the Covid-19 pandemic, this program aimed to encourage bank lending by offering long-term funding to banks on a voluntary basis. Therefore, changes in TFSME borrowing

[13] Whereas we test the impact of QT *operations* on banks, Joyce and Lengyel (2024) test how gilt yields respond to UK government debt auction *announcements*. Their estimate considers a 10% decline to central bank bond holdings. It captures the impact on bonds with maturity of 3.5-years - the average maturity of mortgages in our sample.

could be endogenous to changes in bank lending. Results are unchanged.

Columns 5-7 modify the 'share' element ($Bank\,Exposure_{i,t}$). Instead of a rolling average between $t-12$ and t, column 5 calculates reserve share at $t-13$, eliminating overlap with our twelve-month dependent variable. To further mitigate potential correlations between reserve shares and unobserved lending opportunities, we then use time-invariant shares. In column 6, shares are measured in January 2020 - prior to the start of the sample and before the onset of post-Covid QE. In columns 7, shares are measured in January 2020 for the QE part of the sample, and in January 2022 for the QT period (February 2022 onwards). The key results remain. This is not surprising because cross-correlations between share measures are between 94% and 99%. As discussed in section 4.2, this suggests that reserve shares reflect long-lasting characteristics, rather than the transient effect of post-Covid QE/QT.

Next, we address remaining threats to the exclusion restriction. This restriction requires that the instrument, $\Delta(AggregateReserves)_t \times BankExposure_{i,t}$, does not affect bank lending through channels other than through the endogenous explanatory variable $\Delta(Reserves)_{i,t}$.

Columns 8-10 address the concern that $Bank\,Exposure_{i,t}$ correlates with bank confounding characteristics that could affect banks' response to QT. As a first pass, column 8 adds time fixed effects interacted with an indicator for the largest six banks. These banks dominate the mortgage market and stand out in terms of size and sophistication. Column 9 interacts $\Delta(Aggregate\,Reserves)_t$ with the bank's size, capitalisation, return-on-assets and government bond holdings. The latter variable controls for the possibility that QT affects interest rates and therefore bond values. Results are unchanged.[14]

Column 10 addresses the concern that $\Delta(AggregateReserves)_t$ correlates with confounding changes in conventional monetary policy. Although the BoE explicitly decouples QT decisions from monetary policy decisions (Section 2), QT implementation partly coincided with changes in the policy rate. The exclusion restriction could be violated if these changes affects banks depending on characteristics correlated with $Bank\,Exposure_{i,t}$. Additionally, this column addresses the concern that our results reflect the confounding effect of QT *announcements* on

[14] In unreported results, we find that results are unchanged when size is measured as a bank's total assets over total banking system assets.

interest rates (Du *et al.*, 2024), rather than the effect of QT *operations* on reserves.

To control for conventional monetary policy and QE/QT announcements, we use the three monetary policy shock series identified by Braun *et al.*, (2024) using high-frequency financial market reactions to monetary policy communications. The first two series capture changes in current policy rates and in expected future rates. The third series captures changes in expected QE or QT. We interact each factor with $Bank\ Exposure_{i,t}$. Our estimates persist.

Finally, column 11 adds bank-month fixed effects. The explanatory variable $\Delta Reserves_{i,t}$ drops. However the estimate for $\Delta Reserves_{i,t} \times Maturity_{i,l,t}$ remains similar. This provides further comfort that our results do not reflect heterogeneity in loan demand (or other confounders) across banks - all the more since heterogeneity in demand across loan maturities is controlled for via product-time fixed effects.

Table VI estimates our key coefficients separately for the QE (Jan 2021-Jan 2022) and QT periods (Feb 2022 onwards), for all specifications in Table V. This is to ensure that our results hold also when focusing only on the QT period. For both coefficients, the QT-specific estimates remain significant across all specifications. The QE-specific coefficients generally have the same sign as the QT coefficients, but are statistically weaker. This is perhaps because the sample covers only the tail end of post-Covid QE, limiting statistical power.[15]

5.2 *Bank-level regressions*

To further assess robustness, Table VII tests our key hypotheses using bank-level rather than loan-level data. We estimate:

$$\Delta(Loan\ Volume)_{i,t} = \beta \cdot \Delta(Reserves)_{i,t} + B \cdot Controls + \epsilon_{i,t}, \tag{4}$$

The dependent variable is the year-on-year change in log lending by bank i during month t. Following Acharya et al. (2023), we include time fixed effects, bank controls, and a dummy

[15]Between the sample start and the beginning of QT, the BoE did not announce new QE purchases, although reserves still increased by ca. £150bn as the BoE implemented previously announced purchases.

for the largest six banks.[16] Since these regressions cannot include additional fixed effects, they may not fully control for changes in credit demand. One advantage, however, is that each bank contributes the same number of observations, whereas loan-level data are skewed towards large lenders. Bank-level regressions thus capture the effect of QT for a representative bank.

The results are consistent with the loan-level findings. OLS (column 1) and IV (column 3) specifications suggest that reserve outflows are associated with lower lending volumes. To enhance comparability with our loan-level results, column 5 focuses on retail lending volumes (the data does not enable us to isolate mortgage volumes), and column 6 weights observations by banks' mortgage market shares. Estimates remain similar. Column 7 uses as dependent variable the weighted average maturity of loans. The results suggest that banks respond to QT by increasing loan maturity - in line with the previous loan-level results.

Results in Table VIII show that the key estimates holds in the same set of robustness tests used for the loan-level regressions. In the next section, we use this bank-level dataset to show the reduction in lending is part of a broader balance sheet rebalancing.

6 Mechanism

The previous section establishes that QT-induced reserve outflows lead banks to lower the supply of lending, while extending its maturity. These patterns are consistent with our theoretical framework where the effect of QT on banks is shaped by their joint management of liquidity and interest rate risk (Section 3.2).

Our empirical set-up allows to rule out several alternative explanations. Any impact of QT on interbank market dynamics (Bianchi and Bigio, 2022) would be picked up by time fixed effects. Any impact of QT on banks' bond holdings should not depend on these banks' reserves holdings; this impact should also materialize when QT is announced – not when QT operations are conducted (Du *et al.*, 2024). Leverage effects (Diamond *et al.*, 2024) cannot explain our results since reserves are exempt from leverage requirements in our sample.[17]

[16] Acharya et al. (2023) instead include a dummy for broker-dealer banks. Our sample only includes commercial banks, not dealers. However, the six largest banks have subsidiaries active as gilt market dealers.

[17] Even if swapping reserves for bonds can increase leverage, this mechanism cannot explain why banks simul-

Other existing theories can only explain part of our findings. A money multiplier mechanism e.g. as embedded in bank lending channel theories (Bernanke and Blinder, 1992) would predict lower lending quantity when reserves shrink, but are silent about effects for loan maturity. The model of Drechsler *et al.*, (2021) could explain why banks respond to QT by increasing asset duration, but does not give a role to reserves or liquidity risk management.[18] A reserve-driven portfolio balance channel (Christensen and Krogstrup, 2019) implies that QT should lead banks to *shorten* asset maturity – opposite to our findings. If QT mainly affected banks by reducing their exposure to flighty deposits (Blickle *et al.*, 2025; Darst *et al.*, 2025), banks would respond by *increasing* their exposure to illiquid asset such as (in the UK) loans.

This section provides additional support for our preferred interpretation using bank-level data. Although identification is less conservative than with loan-level data, bank-level data allows us to capture key aspects of banks' balance sheets and risk management. First, we show that balance sheets rebalance in a way consistent with our model. Second, we find that the effect of QT on lending varies cross-sectionally with banks' liquidity risk exposure and ability to access central bank reserves.

6.1 Balance sheet rebalancing

6.1.1 Rebalancing towards more liquid assets

We begin with the asset side. We classify banks' assets into loans (illiquid in the UK) and securities (liquid). We further divide securities into liquid and relatively less liquid categories, following the LCR framework.[19] Reserves are included in neither category.

We estimate how the share of each asset categories (loans, securities, liquid securities and less liquid securities) over total assets varies with reserve outflows induced by QT. To do so,

taneously rebalance their liabilities, or why QT's effect of lending varies with banks' liquidity, as we show below.

[18] In their model, banks have a preference for stable income in order to hedge the fixed costs of operating their deposit franchise. This motive could explain why banks increase the duration of their assets, insofar as shrinking lending to manage liquidity risk puts downward pressure on profitability.

[19] This framework requires banks to hold enough HQLA to cover 30-days liquidity outflows. "Level 1" HQLA include claims on sovereigns and quasi-sovereign entities without credit risk and with a liquid market. "Level 2" HQLA include corporate bonds, commercial paper and residential mortgage backed securities with high credit ratings. Level 1 HQLA contribute one-for-one towards LCR requirements, whereas level 2 securities are subject to a haircut of 15% to 50%.

we use specification 4 estimated using the same IV approach as above and include the set of controls and fixed effects from Acharya et al. (2023).

Table IX reports the results. When reserve holdings fall, the share of banks' assets in the form of loans decreases (column 1), whereas the share of securities increases (column 2). Within securities, the share of higher-quality (relatively more liquid) securities increases (column 3), whereas the share of lower-quality (less liquid) securities decreases (column 4). Banks thus systematically shift their portfolios toward more liquid assets.

6.1.2 Rebalancing towards more stable funding

Although our model is silent about banks' liabilities, in practice banks can also reduce liquidity risk by shifting toward more stable funding. We classify liabilities into four categories: core retail deposits (held by individuals and SMEs below critical balance thresholds), non-core retail deposits (from individuals with larger balances and larger SMEs), non-retail deposits (deposits from larger corporates and financial institutions) and bonds.[20] Contractually, bonds provide the most stable funding, with maturities typically of several years. Behaviourally, however, some types of deposits can also provide long-term funding. Accordingly, the LCR framework treats core retail deposits as the most stable, largely because they are typically fully insured. Non-core retail deposits and non-retail deposits, on the other hand, are considered relatively less stable and therefore face higher outflow rates (between 10% and 20%.).

Table X confirms that QT-induced reserve losses lead banks to tilt their funding mix toward more stable sources: the share of core retail deposits increases (column 1), whereas the share of less stable retail deposits and non-retail deposits falls (columns 2 and 3). The share of bonds also increases though not significantly (column 4), perhaps due to the small sample.

To shed further light, Table XI analyses the weighted-average maturity of these four liabilities categories. In line with our previous findings, the results suggest that banks seek to lock in longer-term funding to further reduce liquidity risk. Specifically, in response to reserve outflows, banks lengthen the maturities of core retail deposits (column 1), non-core retail de-

[20] We again use LCR framework definitions. Non-core ("other") retail deposits include those meeting specific criteria, including a balance in excess of £500'000, or being accessible exclusively via online banking platforms.

posits (column 2) and bonds (column 4). One exception is wholesale deposits, where maturity shortens (column 3).

6.1.3 Rebalancing towards longer-duration assets

Section 5 finds that in response to QT, banks rebalance credit supply towards longer-term loans. Here, we test whether this pattern reflects a broader rebalancing towards longer-duration assets, consistent with our model. To do so. we examine how the weighted-average maturity of the other three asset categories considered in section 6.1.1 respond to reserve outflows. Increasing maturity would not weaken banks' liquidity ratios because within each category, all assets receive identical LCR treatment irrespective of their maturity (as long as it exceeds the LCR's 30-day horizon). Table XII confirms that reserve outflows are associated with higher maturities for securities (column 2), and higher-quality securities (column 3).

6.1.4 Effect on overall risk metrics

Finally, we test how higher-level bank risk metrics respond to QT. Our model suggests that banks respond to reserve outflows by neutralising the impact on their liquidity risk. To test this idea, in column 1 of Table XIII we use as dependent variable the bank's LCR at time t. The results confirm that LCRs do not respond significantly to QT. This is in line with the idea that banks lose liquidity via reserve shrinkages, but gain liquidity via more liquid securities, less illiquid loans, and stickier funding. The results are also consistent with UK banks LCRs' striking stability between 2020 and 2024, despite the large fluctuations in reserves holdings (Figure 4). This indicates that banks prefer stable LCRs even when far in excess of the 100% minimum requirement. We return to this idea in section 6.3.

Our model also suggests that the opportunity costs of neutralising the effect of QT on liquidity leads banks to increase the maturity of remaining assets. To test this idea, in column 2 we use as dependent variable the weighted-average maturity of all assets. Column 3 uses the difference between the weighted-average asset and liabilities maturity - a common proxy of interest rate risk. The results confirm that asset maturity and the asset-liabilities maturity gap increase in response to QT - as our model predicts.[21]

6.2 *Cross-sectional heterogeneity in liquidity ratios*

To further support our mechanism, we exploit variation in banks' initial liquidity ratios. In our model, banks are less likely to cut lending if their liquidity ratio remains above their preferred level despite QT - e.g. if banks enter QT with "excess" reserves due to QE. Our LCR derivation (in appendix B) also concludes that QT is more likely to shrink LCRs and therefore lead to lending cuts when starting LCRs are low. We test this idea in two ways.

First, we interact $\Delta(Reserves)_{i,t}$ with $LCR\ Distance_{i,2020}$ - defined as the bank's LCR buffer over the 100% minimum requirement, as measured in January 2020 (before our sample starts). As shown in Table II, the median LCR distance is around 130 percentage points, with substantial variation across banks. In line with our prior, the results in Table XIV show that higher LCR is associated with a weaker lending response to reserve outflows (column 1).

Why does the LCR matter even when it exceeds the 100% minimum requirement? Cross-country evidence suggests that banks prefer to hold large excess LCR, suggesting that the LCR binds well beyond the minimum requirement (Bonner and Eijffinger, 2016). Similarly in our sample, LCRs are stable despite large-scale fluctuations in reserves holdings (Figure 4). This preference for stable LCR could e.g. reflect requirements for banks to disclose LCRs on a quarterly basis, or a desire to avoid triggering supervisory scrutiny (Mathur *et al.*, 2023). In any case, our results are in line with regulatory views that banks were reluctant to use up their LCR buffer during Covid (Saporta, 2022). In particular, the Basel Committee on Banking Supervision (2022) report points to evidence of "banks taking ... action to bolster liquidity... including by cutting some lending" during that period.

Second, we calculate a cruder liquidity ratio capturing the idea that banks' demand for reserves depends on their exposure to deposit outflows (Lopez-Salido and Vissing-Jorgensen, 2023). Specifically, we use the ratio of a bank's reserves to non-retail deposits, which are more flight-prone in a stress. A higher ratio implies lower liquidity risk. In line with our prior, a

[21] Our data does not allow to test whether banks simultaneously change their interest rate risk management through interest rate swaps - see e.g. Vuillemey (2019).

higher ratio weakens the lending response to reserve outflows (column 2 of Table XIV).

6.3 Cross-sectional heterogeneity in access to central bank liquidity

Our model abstract from potential substitutes to holding reserves for managing liquidity risk. One such substitute could be to *borrow* reserves from the central bank. This possibility is not accounted for in the LCR, since the LCR is designed to encourage banks to *self*-insure against liquidity risk (Stein, 2013). In practice however, access to central bank funding could mitigate banks' need to manage their own liquidity, relaxing the trade-off between liquidity holdings and lending (Sundaresan and Xiao, 2024).

To proxy for this access, we measure UK banks' pre-positioning of collateral with the BoE. UK banks are encouraged to pre-position collateral in order to reduce operational frictions that could hamper their ability to borrow from the BoE if and when needed - in particular in terms of central banks' ability to evaluate collateral values in a timely way. These frictions are likely particularly significant for loan collateral, since unlike securities loans do not have directly observable market value. In line with this idea, the bulk of pre-positioned assets in the UK consist of mortgages. While pre-positioning has been discussed prominently in recent policy debates (Hanson *et al.*, 2024; Acharya et al., 2024), to the best of our knowledge, there is no empirical evidence on its role in the transmission of QT.

To fill that gap, we use confidential BoE data for the value of each bank's pre-positioned collateral, net of any haircut (measured before the start of the sample), and we interact this measure with our main coefficient $\Delta(Reserves)_{i,t}$. The results in column 3 of Table XIV confirm that banks with more pre-positioned collateral respond less to reserve outflows.

7 Conclusion

As major central banks make progress in winding down their balance sheet and therefore draining reserves from the banking system, understanding the transmission mechanisms of QT becomes critical. Evidence is only starting to emerge. In this paper, we contribute to expanding this evidence by documenting how Quantitative Tightening (QT) transmits through banks via a joint liquidity-duration risk management motive. Understanding this interaction is important because QT shrinks liquidity in the banking system, typically at a time of rapid increases in interest rates.

Our key findings are the following. In response to reserve outflows driven by QT, banks cut lending and rebalance their balance sheet towards more liquid assets and stickier funding - consistent with a liquidity risk management mechanism. In doing so, banks neutralise QT's impact on their liquidity ratios. However, since liquid assets are typically lower-yielding and stable funding is typically more expensive, this rebalancing puts bank profitability under pressure. Consistent with an attempt to mitigate that effect, within asset categories with the same liquidity risk, we find that banks shift towards assets that have the same liquidity but a higher duration and therefore yield. These findings are consistent with a simple model where banks jointly optimise liquidity and interest rate risk-taking. The model highlights a trade-off between the liquidity benefits of cutting lending, and the costs in terms of forgone exposure to duration and therefore expected profit.

Our results can inform quantitative assessments of QT's macroeconomic impact. Beyond established channels working through financial markets and asset prices, these models could incorporate channels working through banks' liquidity holdings. Since QT affects the supply of short-term vs. long-term (fixed rate) loans, these models could also incorporate a spillover between QT and exposure to increases in interest rates among banks and borrowers - and therefore between central banks' balance sheet and interest rate policies. Beyond QT, our results point to knock-on effects between liquidity and interest rate risk-taking in the banking system. These effects can inform ongoing discussions about regulatory options to bolster bank liquidity in the wake of the Silicon Valley Bank and Credit Suisse failures.

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A Figures and Tables

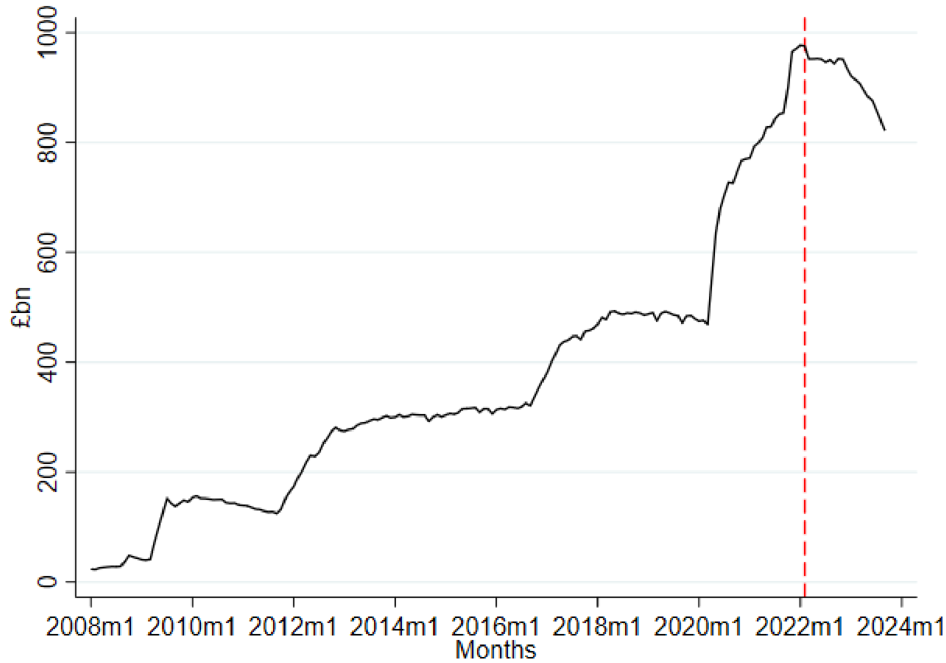


FIGURE 1: Total assets held in the Bank of England's Asset Purchase Facility (APF). The red dashed vertical line indicates the start of QT.

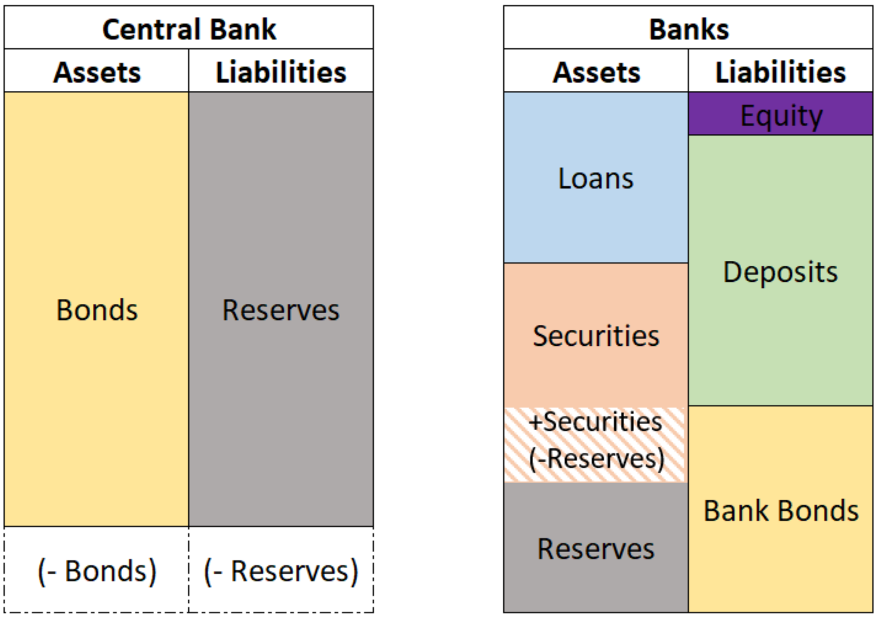


FIGURE 2: Effect of quantitative tightening (via the sale of a bond by the central bank to a commercial bank) on the stylised balance sheet of the central bank (left) and a commercial bank (right)

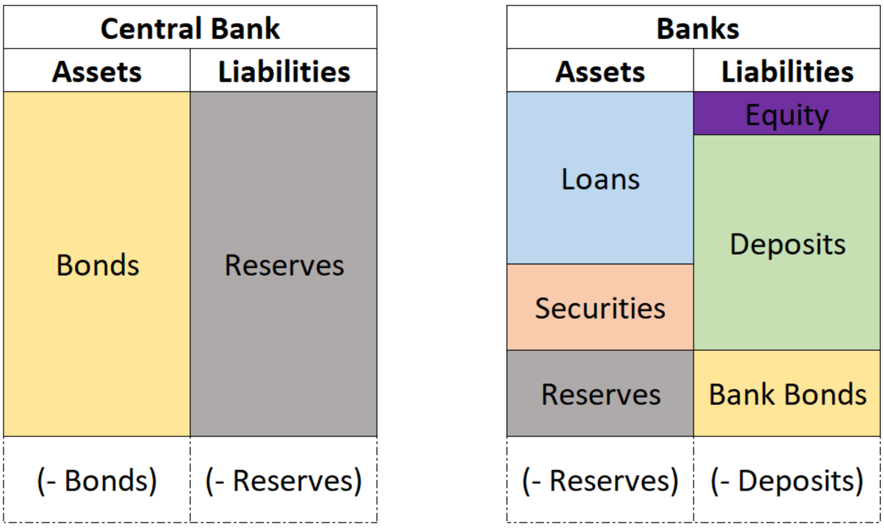


FIGURE 3: Effect of quantitative tightening (via the sale of a bond by the central bank to a nonbank agent) on the stylised balance sheet of the central bank (left) and a commercial bank (right)

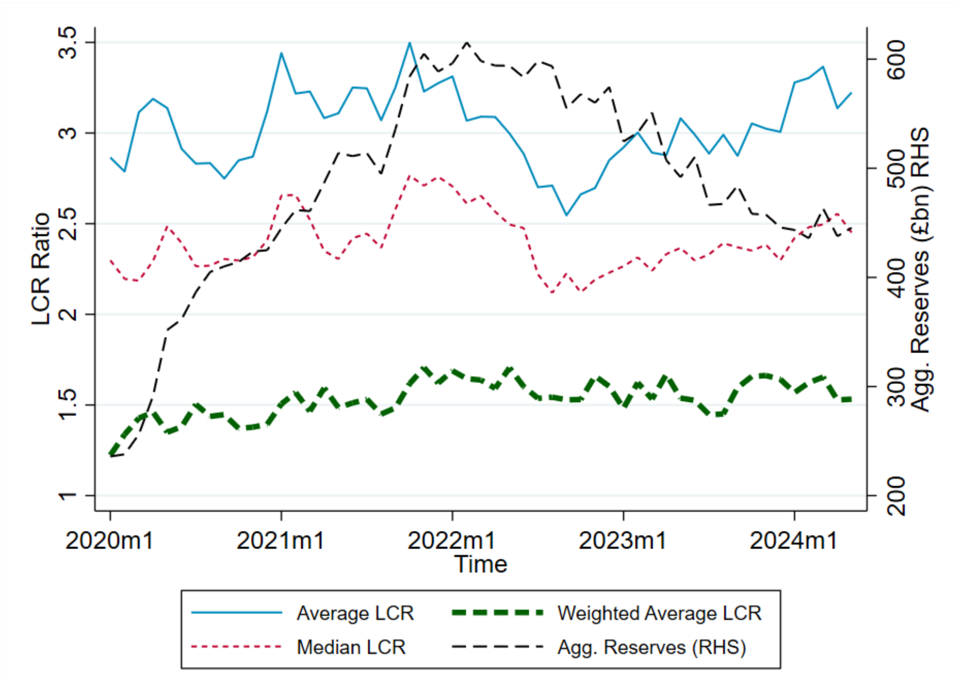


FIGURE 4: UK bank's Liquidity Coverage Ratio (LCR; y-axis) and aggregate central bank reserves (x-axis).

TABLE I: Summary statistics: Mortgage-level dataset

	Mean	Median	StDev	p.25	p.75
Interest rate spread (%)	0.51	0.48	1.34	-0.31	1.38
Borrower age (years)	39.22	38.00	10.16	31.00	46.00
Ln(loan amount)	11.91	12.01	0.85	11.51	12.46
Loan-to-income ratio (LTI)	2.90	3.10	1.32	1.98	3.96
Loan-to-value ratio (LTV)	59.25	66.06	26.67	39.58	81.82
Term (months)	299.59	300.00	103.52	228.00	384.00
Impaired credit history indicator	0.00	0.00	0.04	0.00	0.00
Maturity (fixation period; years)	3.77	5.00	1.73	2.00	5.00
Bank size (£billion)	263.40	274.42	139.96	260.78	308.75
Return on Assets (%)	0.11	0.11	0.12	0.07	0.18
Capitalisation (CET1 ratio)	0.19	0.16	0.08	0.15	0.23
Big-6 indicator	0.80	1.00	0.40	1.00	1.00
Observations	2,412,248				

Notes: This table reports summary statistics for variables included in the main mortgage-level dataset.

TABLE II: Summary statistics: Monthly bank panel

	Mean	Median	StDev	p.25	p.75
Total loans (£bn)	38.66	2.71	95.44	0.99	18.82
of which: retail loans (£bn)	25.49	1.80	70.32	0.74	7.46
Total HQLA excl. reserves (£bn)	2.13	0.11	6.92	0.00	0.83
of which: Liquid Assets (£bn)	1.71	0.08	6.03	0.00	0.53
of which: Less liquid assets (£bn)	0.42	0.00	1.35	0.00	0.15
Total liabilities (£bn)	38.08	2.48	96.67	0.70	14.31
Total deposits (£bn)	32.09	2.18	84.23	0.64	10.70
of which: core retail (£bn)	15.19	0.79	44.45	0.30	3.39
of which: non-core retail (£bn)	7.43	0.71	18.68	0.13	4.41
of which: non-retail (£bn)	9.43	0.11	29.02	0.01	1.30
Bonds (£bn)	1.45	0.00	3.91	0.00	0.60
Bank size (£bn)	57.73	2.54	147.11	0.73	15.95
Return on assets (%)	0.09	0.08	0.51	0.03	0.18
Capitalisation (CET1 ratio)	0.19	0.17	0.07	0.15	0.21
Big-6 indicator	0.08	0.00	0.28	0.00	0.00
LCR Distance_{2020}	1.866	1.292	1.949	0.626	1.945
Reserves / Non-retail deposits	5.273	2.0922	10.043	0.742	8.789
Pre-positioned assets / Total assets	0.0537	0.0440	0.0610	0.000	0.0834
Observations	2,904				

Notes: This table reports summary statistics for the variables included in the main bank-month panel dataset.

TABLE III: Banks' shares of aggregate reserves: cross-correlations

	$\frac{1}{12}\sum_{k=1}^{12}\frac{Reserves_{i,t-k}}{Aggr\ Reserves_{t-k}}$	$\frac{Reserves_{i,Jan2020}}{Aggr\ Reserves_{Jan2020}}$	$\frac{Reserves_{i,Jan2020/22}}{Aggr\ Reserves_{Jan2020/22}}$	$\frac{Reserves_{i,t-13}}{Aggr\ Reserves_{t-13}}$
$\frac{1}{12}\sum_{k=1}^{12}\frac{Reserves_{i,t-k}}{Aggr\ Reserves_{t-k}}$	1			
$\frac{Reserves_{i,Jan2020}}{Aggr\ Reserves_{Jan2020}}$	0.992	1		
$\frac{Reserves_{i,Jan2020/22}}{Aggr\ Reserves_{Jan2020/22}}$	0.986	0.984	1	
$\frac{Reserves_{i,t-13}}{Aggr\ Reserves_{t-13}}$	0.990	0.988	0.993	1
Observations	70			

Notes: This table reports cross-correlations between variants of $Bank\ Exposure_i$ - the share dimension of the IV for $\Delta Reserves$. In the first row, shares are measured as rolling averages between $t-1$ and $t-12$. In the second row, shares are measured before in January 2020, before the sample and post-Covid QE starts. In the third row, shares are measured before in January 2020 for the QE period, and in January 2022 (before the start of QT) for the QT period. In the fourth row, shares are measured at $t-13$. We calculate cross-correlations by including one observation per bank. For rolling measures (rows one and four), we use the sample mean for a given bank.

TABLE IV: QT and bank lending: main results (mortgage-level dataset)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator:	OLS	IV (Stage 1)			IV (Stage 2)		
Dependent variable:	$Spread_{i,l,t}$	$\Delta(Reserves)_{i,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$
$\Delta(Reserves)_{i,t}$	-0.110*		-0.274**	-0.244*	-0.411**	-0.442***	-0.658***
	(0.0621)		(0.132)	(0.125)	(0.154)	(0.132)	(0.153)
$Predicted(\Delta(Reserves)_{i,t})$		7.182***					
		(0.671)					
$\Delta(Reserves)_{i,t} \times Maturity_{i,l,t}$							0.0637**
							(0.0331)
Observations	2,078,542	1,985,418	1,985,418	1,985,418	1,984,445	1,944,640	1,939,453
R^2	0.608	0.766	0.00973	0.149	0.0457	0.0132	0.0133
Kleibergen-Paap			114.7	114.8	30.40	37.73	17.48
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	No	No	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Month Fixed Effects	No	No	No	No	Yes	Yes	Yes
Product x Bank Fixed Effects	No	No	No	No	Yes	Yes	Yes
Location x Month Fixed Effects	No	No	No	No	No	Yes	Yes
Borrower Type x Month Fixed Effects	No	No	No	No	No	Yes	Yes

Notes: This table reports the results of OLS (column 1) and 2SLS (columns 2-7) regressions using a mortgage-level dataset. The main dependent variable $Spread_{i,l,t}$ is the interest rate on mortgage l originated by bank i during month t, minus the maturity-matched reference (OIS) rate. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $Predicted(\Delta(Reserves)_{i,t})$ is the instrument for $\Delta(Reserves)_{i,t}$, defined as $\Delta(Aggregate\,Reserves)_t \times Bank\,Exposure_{i,t}$. $Bank\,Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\,Reserves_{t-k})$. $Maturity_{i,l,t}$ is the mortgage maturity, in months. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. Loan controls include: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan term (in months) and maturity (fixation period; in years), and a dummy for borrowers with impaired credit history. Product fixed effects are dummies for all combinations of loan maturity and LTV buckets. Location fixed effects are dummies for postcodes. Borrower types are dummies for first-time buyers, house movers, and refinancers. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Standard errors clustered by banks and month are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE V: QT, bank lending, and loan maturity: robustness checks (mortgage-level dataset)

Dependent variable: $Spread_{i,l,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta(Reserves)_{i,t}$	-0.658***	-1.409***	-0.697***	-0.665***	-0.578***	-0.571***	-0.551***	-0.646***	-0.781***	-0.425***	
	(0.153)	(0.423)	(0.184)	(0.187)	(0.169)	(0.171)	(0.166)	(0.110)	(0.176)	(0.147)	
$\Delta(Reserves)_{i,t} \times Mat_{i,l,t}$	0.0637**	0.216**	0.0679**	0.0395	0.0980**	0.102**	0.0983**	0.0756**	0.0595*	0.0832**	0.0615**
	(0.0312)	(0.0810)	(0.0329)	(0.0340)	(0.0416)	(0.0463)	(0.0427)	(0.0331)	(0.0314)	(0.0329)	(0.0261)
Observations	1,939,453	2,489,450	1,876,832	1,861,049	2,033,902	2,032,527	2,033,902	1,939,453	1,939,453	1,939,453	1,939,359
R^2	0.0133	-0.0102	0.0118	0.00766	0.0186	0.0191	0.0195	0.0143	0.00696	0.0244	0.0210
$\Delta(Reserves)$ variant	-	Δ^{3m}	$t-1$	-	-	-	-	-	-		
IV variant	-	-	-	APF	$t-13$	Jan 20	Jan 20/22	-	-	-	-
Bank and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 x Month FE	No	No	No	No	No	No	No	Yes	No	No	No
$\Delta Aggr\ Res.\times$ bank contr.	No	No	No	No	No	No	No	No	Yes	No	No
$Bank\ Exp.\times$ mon. shocks	No	No	No	No	No	No	No	No	No	Yes	No
Bank x Month FE	No	No	No	No	No	No	No	No	No	No	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly mortgage-level dataset. The main dependent variable $Spread_{i,l,t}$ is the interest rate on mortgage l originated by bank i during month t, minus the maturity-matched reference (OIS) rate. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Aggregate\ Reserves)_{i,t})$, defined as $\Delta(Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_t)$ - except in columns 5-7. $Maturity_{i,l,t}$ is the mortgage maturity, in months. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. In column 2, $\Delta(Reserves)$ is the change in reserves over the last three months. In column 3, $\Delta(Reserves)$ is the lagged year-on-year change in reserves. In column 4, $\Delta(Aggregate\ Reserves)$ is the year-on-year change in the BoE's Asset Purchase Facility. In column 5, $Bank\ Exposure_{i,t}$ is measured at $t-13$. In column 6, $Bank\ Exposure_{i,t}$ is measured in January 2020. In column 7, $Bank\ Exposure_{i,t}$ is measured in January 2020 for the QE period, and February 2022 for the QE period. Loan controls include: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan term (in months) and maturity (fixation period; in years), and a dummy for borrowers with impaired credit history. Product fixed effects are dummies for all combinations of loan maturity and LTV buckets. Location fixed effects are dummies for postcodes. Borrower types are dummies for first-time buyers, house movers, and refinancers. Monetary policy shocks are three shock series estimated by Braun *et al.*, (2024) based on high-frequency financial market response to monetary policy communications. The sample includes all banks active in domestic mortgage lending. Standard errors clustered by banks and month are in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE VI: QT, bank lending, and loan maturity: robustness checks (loan-level regressions)

Dependent variable: $Spread_{i,l,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta(Reserves)_{i,t} \times QE_t$	-0.0987	0.119	-0.687	-0.323**	2.563	0.0461	0.0461	-1.697	0.487	0.487	
	(0.137)	(1.099)	(3.050)	(0.131)	(8.017)	(0.224)	(0.224)	(10.12)	(0.371)	(0.371)	
$\Delta(Reserves)_{i,t} \times QT_t$	-1.007**	-2.392*	-1.251*	-0.513**	-1.173**	-0.759**	-0.785**	-0.743**	-1.066**	-0.785**	
	(0.415)	(1.231)	(0.677)	(0.201)	(0.452)	(0.368)	(0.311)	(0.319)	(0.501)	(0.311)	
$\Delta(Reserves)_{i,t} \times Mat_{i,l,t} \times QE_t$	0.00666	-0.0149	-0.0421	-0.0266	0.150	0.0193	0.0193	0.430	0.0552	0.0552	0.0032
	(0.0260)	(0.511)	(0.204)	(0.0307)	(0.436)	(0.0408)	(0.0408)	(2.322)	(0.0390)	(0.0390)	(0.0315)
$\Delta(Reserves)_{i,t} \times Mat_{i,l,t} \times QT_t$	0.113**	0.304**	0.0967**	0.120**	0.105**	0.0942**	0.0880**	0.0929**	0.120**	0.0880**	0.0733*
	(0.0469)	(0.137)	(0.0417)	(0.0482)	(0.0453)	(0.0464)	(0.0388)	(0.0432)	(0.0589)	(0.0388)	(0.0379)
Observations	1,939,097	2,009,494	1,876,479	1,861,049	1,939,097	2,032,151	2,033,526	2,033,526	2,031,646	2,033,476	1,939,008
$\Delta(Reserves)$ variant	-	Δ^{3m}	$t-1$	-	-	-	-	-	-	-	-
IV variant	-	-	-	APF	$t-13$	Jan 20	Jan 20/22	-	-	-	-
Bank and loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location x Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower x Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 x Month Fixed Effects	No	No	No	No	No	No	No	Yes	No	No	No
$\Delta AggrRes.\times$ bank controls	No	No	No	No	No	No	No	No	Yes	No	No
$Bank\ Exp.\times$ mon. shocks	No	No	No	No	No	No	No	No	No	Yes	No
Bank x Month FE	No	No	No	No	No	No	No	No	No	No	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly loan-level dataset. $Spread_{i,l,t}$ is the interest rate on mortgage l originated by bank i during month t, minus the maturity-matched reference (OIS) rate. $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$, except in columns 5-7. QE_t and QT_t are dummies for the Jan 2021-Jan 2022 and Feb 2022-onwards periods, respectively. $Maturity_{i,l,t}$ is the mortgage maturity, in months. Bank controls include a bank's: size (log total assets); capitalisation; profitability (total income over total assets); (log) reserves lagged by a year; and a big-6 banks dummy. In column 2, $\Delta(Reserves)$ is the change in reserves of the last three months. In column 3, $\Delta(Reserves)$ is lagged by one month. In column 4, $\Delta(Aggregate\ Reserves)$ is the year-on-year change in the BoE's Asset Purchase Facility. In columns 5 and 6, $Bank\ Exposure_{i,t}$ is measured at $t-13$ and January 2020, respectively. In column 7, $Bank\ Exposure_{i,t}$ is measured in January 2020 for the QE period, and February 2022 for the QE period. Loan controls include: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan term (in months) and maturity (fixation period; in years), and a dummy for borrowers with impaired credit history. Product fixed effects are dummies for combinations of loan maturity and LTV buckets. Location fixed effects are dummies for postcodes. Borrower types are dummies for first-time buyers, house movers, and refinancers. Monetary policy shocks are three shock series from Braun *et al.*, (2024). Standard errors clustered by banks and month in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE VII: QT and bank lending: main results (monthly bank panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator:	OLS	IV (Stage 1)		IV (Stage 2)		WLS	IV (Stage 2)
Dependent variable:	$\Delta(Loans)_{i,t}$	$\Delta(Reserves)_{i,t}$	$\Delta(Loans)_{i,t}$	$\Delta(Loans)_{i,t}$	$\Delta(Retail\ Loans)_{i,t}$	$\Delta(Loans)_{i,t}$	$\Delta(Loans)_{WAM}$
$\Delta(Reserves)_{i,t}$	0.169***		0.424***		0.383***	0.244***	-0.0662*
	(0.0109)		(0.0580)		(0.0705)	(0.0158)	(0.0362)
$Predicted(\Delta(Reserves)_{i,t})$		5.848***					
		(0.483)					
$\Delta(Reserves)_{i,t} \times QE_t$				0.489***			
				(0.0751)			
$\Delta(Reserves)_{i,t} \times QT_t$				0.430***			
				(0.0745)			
Observations	2776	2740	2740	2740	2740	2201	2740
R^2	0.320	0.265	-0.140	-0.0582	-0.0615	0.149	0.2518
Kleibergen-Paap			43.99	20.97	43.99	129.9	43.99
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of OLS (column 1), 2SLS (columns 2-5 and 7) and WLS (column 6) regressions using a monthly bank-level panel dataset. The dependent variable is indicated in the top row. $\Delta(Loans)_{i,t}$ is the year-on-year change in (log) loan volume by bank i during month t. The WAM subscript refers to the weighted average maturity of the variable. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year (log) change in reserves holdings by bank i during month t. $Predicted(\Delta(Reserves)_{i,t})$ is the instrument for $\Delta(Reserves)_{i,t}$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise. Controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

Table VIII: QT and bank lending: robustness checks (monthly bank panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable: $\Delta(Loan)_{i,t}$										
$\Delta(Reserves)_{i,t}$	0.424***	0.315***	0.399***	1.008**	0.334***	0.459***	0.451***	0.441***	0.405***	0.399***
	(0.0580)	(0.0383)	(0.0582)	(0.441)	(0.0319)	(0.0818)	(0.0707)	(0.0677)	(0.0539)	(0.0491)
Observations	2740	3415	2742	2740	2740	2750	2464	2776	2723	2772
R^2	-0.140	-0.391	-0.176	-0.329	0.108	-0.0263	-0.238	-0.205	-0.0809	-0.0665
Kleibergen-Paap	43.99	43.20	43.83	17.14	133.2	20.03	25.34	24.16	66.54	69.55
$\Delta(Reserves)$ variant	-	Δ^{3m}	$t-1$	-	-	-	-	-	-	
IV variant	-	-	-	APF	$t-13$	Jan 20	Jan 20/22	-	-	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 x Month Fixed Effects	No	No	No	No	No	No	No	Yes	No	No
$\Delta AggrRes. \times$ bank controls	No	No	No	No	No	No	No	No	Yes	No
$Bank\,Exp. \times$ mon. shocks	No	No	No	No	No	No	No	No	No	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable $\Delta(Loan)_{i,t}$ is the year-on-year change in total (log) loans held by bank i during month t. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$, except in columns 5-7. Controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. In column 2, $\Delta(Reserves)$ is the change in reserves of the last three months. In column 3, $\Delta(Reserves)$ is the lagged year-on-year change in reserves. In column 4, $\Delta(Aggregate\ Reserves)$ is the year-on-year change in the BoE's Asset Purchase Facility. In column 5, $Bank\ Exposure_{i,t}$ is measured at $t-13$. In column 6, $Bank\ Exposure_{i,t}$ is measured in January 2020. In column 7, $Bank\ Exposure_{i,t}$ is measured in January 2020 for the QE period, and January 2022 for the QT period. Monetary policy shocks in column 10 are three shock series estimated by Braun *et al.*, (2024) based on high-frequency financial market response to monetary policy communications. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE IX: QT and bank lending: mechanism (asset-side)

	(1) $\Delta\%(Loans)$	(2) $\Delta\%(Securities)$	(3) $\Delta\%$(Liquid Sec)	(4) $\Delta\%$(Less Liquid Sec)
Panel A				
$\Delta(Reserves)_{i,t}$	0.212***	-0.0566***	-0.0559***	0.0185*
	(0.0406)	(0.0122)	(0.0193)	(0.0106)
Observations	2740	1984	1841	1251
Kleibergen-Paap	43.99	33.01	26.13	40.98
Panel B				
$\Delta(Reserves)_{i,t} \times QE_t$	0.0658	-0.104***	-0.113***	-0.00703
	(0.0427)	(0.00468)	(0.00789)	(0.00858)
$\Delta(Reserves)_{i,t} \times QT_t$	0.147***	-0.0453***	-0.0404***	0.000692
	(0.0300)	(0.0104)	(0.00968)	(0.00847)
Observations	2740	1984	1841	1251
Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable is indicated in the top row. $\Delta\%$ refers to the year-on-year percentage point change in the variable in parenthesis. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise. Controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE X: QT and bank lending: mechanism (liabilities-side)

	(1) $\Delta\%$(Core Retail)	(2) $\Delta\%$(Non-core Ret)	(3) $\Delta\%$(Non-Retail)	(4) $\Delta\%(Bonds)$
Panel A				
$\Delta(Reserves)_{i,t}$	-0.0883***	0.112***	0.0304***	-0.0105
	(0.0214)	(0.0205)	(0.00896)	(0.00882)
Observations	2547	2713	2511	1305
Kleibergen-Paap	35.02	37.99	42.19	139.6
Panel B				
$\Delta(Reserves)_{i,t} \times QE_t$	-0.261***	0.154***	0.0779***	-0.0110**
	(0.0242)	(0.0369)	(0.0189)	(0.00419)
$\Delta(Reserves)_{i,t} \times QT_t$	-0.115***	0.140***	0.0176**	-0.0123
	(0.0150)	(0.0266)	(0.00865)	(0.0180)
Observations	2547	2713	2511	1305
Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable is indicated in the top row. $\Delta\%$ refers to the year-on-year percentage point change in the variable in parenthesis. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE XI: QT and bank lending: mechanism (funding maturity)

	(1) $\Delta(\text{Core Retail})_{WAM}$	(2) $\Delta(\text{Non-core Ret})_{WAM}$	(3) $\Delta(\text{Non-Retail})_{WAM}$	(4) $\Delta\ (\text{Bonds})_{WAM}$
Panel A				
$\Delta(Reserves)_{i,t}$	-0.761***	-0.713**	1.357**	-1.001**
	(0.260)	(0.288)	(0.556)	(0.461)
Observations	2547	2707	2511	1305
Kleibergen-Paap	35.02	38.12	42.19	139.6
Panel B				
$\Delta(Reserves)_{i,t} \times QE_t$	1.166***	-0.441	3.140*	-1.338**
	(0.253)	(0.266)	(1.733)	(0.639)
$\Delta(Reserves)_{i,t} \times QT_t$	-0.848**	0.0461	1.558***	-1.521***
	(0.337)	(0.0499)	(0.229)	(0.478)
Observations	2547	2707	2511	1305
Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable is indicated in the top row. Δ refers to the year-on-year change in the log of the variable in parenthesis. The subscript WAM stands for weighted average maturity. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE XII: QT and bank lending: mechanism (asset-side maturity)

	(1) Δ (Loans)$_{WAM}$	(2) Δ (Securities)$_{WAM}$	(3) Δ(Liquid Sec)$_{WAM}$	(4) Δ (Less liquid Sec)$_{WAM}$
Panel A				
$\Delta(Reserves)_{i,t}$	-0.0662*	-0.667**	-0.684***	0.219
	(0.0362)	(0.259)	(0.223)	(0.406)
Observations	2740	1874	1710	1205
Kleibergen-Paap	43.99	33.42	24.30	38.46
Panel B				
$\Delta(Reserves)_{i,t} \times QE_t$	0.218	0.0419	-0.531	0.432*
	(0.202)	(0.195)	(0.492)	(0.253)
$\Delta(Reserves)_{i,t} \times QT_t$	-0.134***	-0.0956	-0.318	0.778
	(0.0209)	(0.249)	(0.292)	(0.759)
Observations	2740	1874	1710	1205
Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable is indicated in the top row. Δ refers to the year-on-year change in the log of the variable in parenthesis. The subscript WAM stands for weighted average maturity. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE XIII: QT and bank lending: effect on risk metrics

	(1) Δ (Liquidity Coverage Ratio)	(2) $\Delta(\text{Total Assets})_{WAM}$	(3) Δ (Assets$_{WAM}$ - Liabilities$_{WAM}$)
$\Delta(Reserves)_{it}$	0.469	-0.171**	-0.156*
	(0.686)	(0.0728)	(0.0864)
Observations	2587	2734	1271
R^2	0.0431	0.270	0.126
Kleibergen-Paap	40.81	139.6	72.34
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel dataset. The main dependent variable is indicated in the top row. Δ refers to the year-on-year change in the log of the variable in parenthesis. The subscript WAM stands for weighted average maturity. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year change in (log) reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\ Reserves)_t \times Bank\ Exposure_{i,t}$. $Bank\ Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\ Reserves_{t-k})$. Bank controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE XIV: QT and bank lending: heterogenities across banks (monthly bank panel)

	(1)	(2)	(3)
Estimator:		IV (Stage 2)	
Dependent variable:		$\Delta(Loans)_{i,t}$	
$\Delta(Reserves)_{i,t} \times QE_t$	0.0828***	-1.011	0.499***
	(0.0237)	(0.720)	(0.0741)
$\Delta(Reserves)_{i,t} \times QT_t$	-0.0174	0.0817	0.408***
	(0.2019)	(0.120)	(0.0636)
$\Delta(Reserves)_{i,t} \times LCR\,Distance_{i,2020} \times QE_t$	-0.294***		
	(0.0297)		
$\Delta(Reserves)_{i,t} \times LCR\,Distance_{i,2020} \times QT_t$	-0.400*		
	(0.217)		
$\Delta(Reserves)_{i,t} \times \frac{Reserves_{i,2020}}{Deposits_{i,2020}} \times QE_t$		-3.647**	
		(1.523	
$\Delta(Reserves)_{i,t} \times \frac{Reserves_{i,2020}}{Deposits_{i,2020}} \times QT_t$		-0.641***	
		(0.208)	
$\Delta(Reserves)_{i,t} \times Pledged\,Collateral_{i,2020} \times QE_t$			-0.0527**
			(0.0256)
$\Delta(Reserves)_{i,t} \times Pledged\,Collateral_{i,2020} \times QT_t$			-0.0488***
			(0.0136)
Observations	2,587	2, 561	2,740
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Big-6 Fixed Effects	Yes	Yes	Yes

Notes: This table reports the results of 2SLS regressions using a monthly bank-level panel dataset. The dependent variable $\Delta(Loans)_{i,t}$ is the year-on-year change in (log) loan volume by bank i during month t. The main explanatory variable $\Delta(Reserves)_{i,t}$ is the year-on-year (log) change in reserves holdings by bank i during month t. $\Delta(Reserves)_{i,t}$ is instrumented by $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Aggregate\,Reserves)_t \times Bank\,Exposure_{i,t}$. $Bank\,Exposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{i,t-k}/Aggregate\,Reserves_{t-k})$. $LCR\,Distance_{i,2020}$ is the difference between the bank's Liquidity Coverage Ratio and the minimum 100% LCR requirement in January 2020. QE_t and QT_t are 1 during the QE (Jan 2021-Jan 2022) and QT (Feb 2022 on) periods, respectively, and 0 otherwise, respectively. Controls include a bank's: size (log total assets); capitalisation (equity over total assets); profitability (total income over total assets); (log) reserves lagged by a year; and a dummy for the largest six banks. The sample covers the 2021-2024 period and includes all banks active in domestic mortgage lending. Driscoll-Kraay standard errors (with a 12-month lag length) clustered by time are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

B The Impact of QT on the LCR

The Liquidity Coverage Ratio (LCR) is designed to ensure that banks maintain a sufficient amount of high-quality liquid assets (HQLA) to survive a 30-day period of significant liquidity stress.[22] The LCR is defined as follows:

$$LCR = \frac{HQLA}{Outflows_{30days} - Inflows_{30days}}. \tag{5}$$

The numerator is the stock of HQLA like sovereign bonds and reserves. The denominator captures the bank's expected cash outflows over a 30-day horizon, net of expected cash inflows. *Outflows* are calculated by applying regulatory "outflow rates" to different categories of liabilities. For instance, retail deposits have a low outflow rate because they are seen as less likely to run during a stress. Inflows include e.g. expected cash inflows from reverse repos, securities borrowing, maturing loans, and interest payments. Banks are required to maintain an LCR above 100%, i.e. HQLA must exceed expected net outflows during the 30 day stress.

B.1 Analytical solution

As discussed in section 3, QT operations shrink banks' holdings of reserves and deposits one-for-one. Reserve outflows unambiguously lower HQLA, and therefore the LCR. However, lower deposits reduce expected outflows, improving the LCR. The net impact of QT on the LCR therefore depends on the relative strength of these countervailing effects.

In general, central banks and regulators expect QT to worsen banks' liquidity position (Bank of Canada, 2022; European Banking Authority, 2025; Sveriges Riksbank, 2024). In line with this idea, central banks expect QT to lead banks to borrow more liquidity from the central bank (Schnabel, 2024), and some central banks like the Bank of England have introduced new lending facilities explicitly designed to meet this additional demand (Saporta, 2024).

We now derive the assumptions under which QT lowers the LCR, as authorities seem to think. We show that the net LCR impact depends on (i) the assumed outflow rate of deposits drained by QT, and (ii) the bank's starting LCR level.

Let N denote the stock of deposits drained by QT - i.e. the deposits used for purchases of

[22] The LCR was introduced as part of the Basel III reforms following the 2008 financial crisis. The UK Prudential Regulation Authority (PRA) began phasing in the LCR requirement in October 2018.

bonds sold by the central bank; let k denote the assumed outflow rate for these deposits. Let R represent the stock of deposits not drained by QT, with an assumed outflow rate m. In general, deposits drained by QT should be flightier than other deposits, by revealed preference (Blickle *et al.*, 2025). Therefore we assume that $0 < m < k < 1$. This plays no role for our conclusions, but helps to restrict the analysis to a realistic subset of cases.

The starting LCR can then be re-written as:

$$LCR_0 = \frac{HQLA}{N \times k + R \times m - Inflows} \tag{6}$$

For simplicity, we set $Inflows$ to zero. QT can only have a negligible impact on inflows, since they mainly come from e.g. pre-existing loans.

How does the LCR change after a round of QT? Let δ denote the QT-induced reduction in central bank reserves. This reduction comes along with a same-size reduction in deposits. Therefore, the new LCR ratio becomes:

$$LCR_1 = \frac{HQLA - \delta}{(N - \delta) \times k + R \times m} \tag{7}$$

The net effect of QT on the LCR is therefore given by:

$$\Delta(LCR) = \frac{\delta[k \times HQLA - (N \times k + R \times m)]}{(N \times k + R \times m - \delta \times k)(N \times k + R \times m)} \tag{8}$$

Under what conditions can $\Delta(LCR)$ be negative, as authorities seem to think? Note first that the denominator can only be positive, since it is capturing a product of two positive (expected cash outflow) terms.[23] Therefore, given the numerator, $\Delta(LCR)$ can only be negative if $k \times HQLA > (N \times k + R \times m)$. We can rewrite this condition as:

$$k \times [\frac{HQLA}{N \times k + R \times m)}] < 1. \tag{9}$$

The central expression within brackets corresponds to the starting LCR (LCR_0). Therefore, the condition for the LCR impact to be negative further simplifies to:

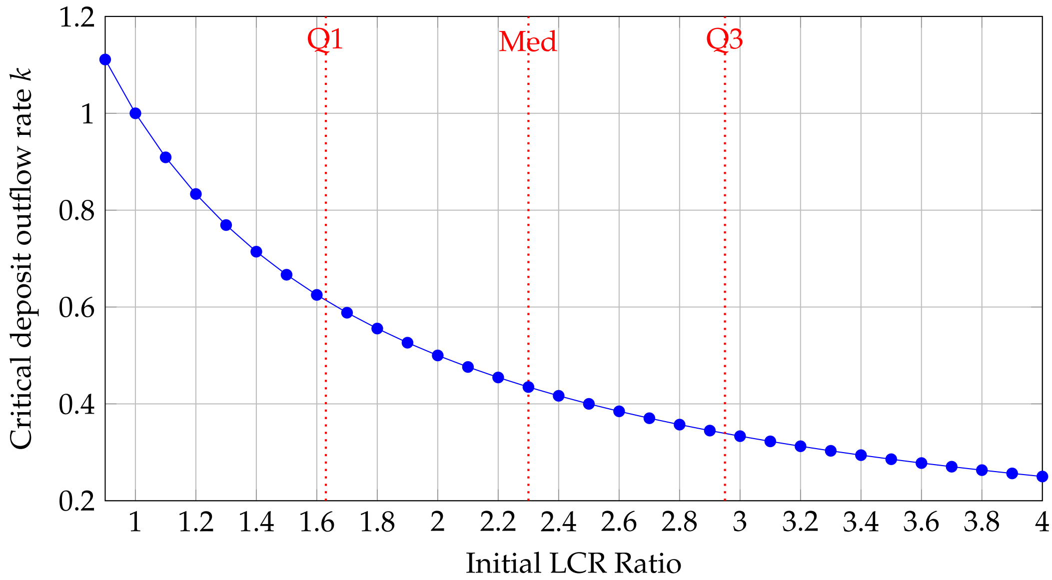
$$k < \frac{1}{LCR_0}. \tag{10}$$

[23] The denominator would still be positive if we relaxed the assumption that $Inflows$ are zero, because the LCR framework caps inflows at 75% of total outflows.

This condition makes clear that the LCR impact hinges on two key parameters: k - the outflow rate associated with deposits drained by QT - and the starting LCR, LCR_0. When $k < \frac{1}{LCR_0}$, the LCR falls. When $k = \frac{1}{LCR_0}$, the LCR is unchanged. And if $k > \frac{1}{LCR_0}$, the LCR increases. We now discuss how likely it is that QT lowers the LCR given the LCR of banks in our sample, and the assumed deposit ouflow rates in the LCR framework.

B.2 How likely is it that QT lowers the LCR?

For illustration, Figure 5 depicts the threshold value for k below which QT lowers the LCR, depending on the starting LCR. The dashed red vertical lines show the 25th, 50th, and 75th percentile of the starting LCR in the sample. For these banks, the critical level of k is around 60%, 45%, and 35%, respectively.



Notes: This chart plots the critical deposit outflow rate k below which QT lowers the LCR (y-axis). The x-axis plots the initial LCR ratio. The red dotted vertical bars plot the 25th percentile, median and 75th percentile levels of starting LCR in the regression sample, respectively.

FIGURE 5: Critical deposit outflow rate and initial LCR ratio

According to the Basel 3.1 rulebook, deposit outflow rates can range between 3% and 100%, depending on the assumed withdrawal probability during a 30-days stress period. The lowest outflow rate is assigned to retail deposits. NBFI deposits receive an outflow rate of 25% or 100% depending on whether they are operational or non-operational deposits. Operational deposits are those used for clearing, custody, or cash management activities. These deposits are generally essential for day-to-day financial operations and are not used for yield, so they are deemed less likely to run during a stress.

As discussed in section 3, the mix of deposits drained by QT depends on who absorbs the additional supply of bonds brought by QT. Empirical evidence suggests that for post-Covid UK, the initial buyer is likely to be an NBFI (Kaminska *et al.*, 2025). However NBFIs could subsequently sell the bond to other agents, or they could take other countervailing actions. For instance, insurance funds could take the opportunity of larger bond holdings (and therefore duration exposure) to sell additional life insurance products to households. In this case, the mix of drained deposits could be a mix of NBFI and retail deposits.

Figure 5 provides useful bookends. If drained deposits only include retail and operational NBFI deposits, then k would lie below the critical values below which QT lowers the LCR for virtually all banks, regardless of their starting LCR. If instead all drained deposits consist of non-operational NBFI deposits, then QT would not worsen the LCR for any bank. Both these cases are unrealistic. However they make it clear that the share of non-operational NBFI deposits is key. The lower this share, the more banks' LCRs should fall due to QT, even if their initial LCR is relatively high.[24]

The fact that authorities think that QT should generally lower banks' LCRs suggests that they do not think that drained deposits should mainly include non-operational deposits. In line with these ideas, Sveriges Riksbank (2024) finds that during QE, it is operational nonbank deposits that grow rather than non-operational deposits. There are two main reasons for this. First, the regulatory framework provides strong incentives for banks to classify NBFI deposits as operational. If instead banks classify NBFI as non-operational, their LCR is bound to shrink dramatically during large-scale and rapid QE programs (e.g. in March 2020). It is likely that this classification cannot be fully reversed at the banks' discretion during QT, since it is subject to supervisory scrutiny.[25] Second, the Basel rulebook definition (see above) includes financial market transactions as one admitted purpose of operational deposits, and this would naturally include e.g. bond transactions during QE and QT.

In any case, one clear prediction from the derivation is that QT is more likely to lower the LCR - and therefore to lead to lending cuts - for banks with relatively lower starting LCR. Our empirical evidence is in line with this idea.

[24]Figure 5 again provides illustrative examples. For a bank with a 25th percentile starting LCR, QT worsens the LCR if the mix of drained deposits e.g. includes a 50-50 share of non-operational and operational NBFI deposits. For a bank with a 50th percentile LCR, QT worsens the LCR if the mix includes e.g. an equal share of retail, non-operational and operational NBFI deposits or a 75%-25% mix of operational NBFI deposits and retail deposits.

[25]Since the definition of operational deposits is only qualitative, ultimately the classification depends on the bank's internal reporting practices and potentially on bank supervisors frameworks or views.

C Illustrative theoretical model

This section provides details on the framework discussed in Section 3.2. The framework highlights that if QT tightens liquidity constraints, banks face a trade-off between the liquidity benefit of cutting lending and the cost of forgone duration exposure and thus expected profits.

C.1 Set-up

Our core framework uses Sundaresan and Xiao (2024), who model the impact of liquidity requirements on banks' behaviour. We then add duration choice and QE/QT policies.

Core framework: Sundaresan and Xiao (2024)

Consider a three period model ($t = 0, 1, 2$). At $t = 0$, banks choose balance sheet size and composition: illiquid assets i (loans) and liquid assets l, financed by deposits d (where $i + l = d$). Illiquid assets yield return r, while liquid assets yield $r - p$, where p is a liquidity premium.[26] Liquidating illiquid assets at $t = 1$ incurs cost ϕ for the bank, with an externality on society η, whereas liquid assets can be liquidated costlessly.

Banks face convex deposit issuance costs $c(d) = \frac{1}{2}\delta d^2$. Banks pay a return $r - p$ on deposits. The premium p reflects the convenience associated with deposits (e.g. for transactions).

Liquidity risk arises from stochastic deposit withdrawals at $t = 1$. Specifically, a fraction a of depositors withdraw following a binary distribution: with probability $1 - \mu$, a fraction $a < 1$ withdraws (good state); with probability μ, all depositors withdraw (bad state). Banks with insufficient liquid assets ($l < ad$) must liquidate illiquid assets at the liquidation cost.

Under the regularity conditions, $\phi > p > \mu\phi$ and $\phi + \eta > p > \mu(\phi + \eta)$ banks do not hold only liquid assets or illiquid assets; instead banks hold liquid assets equal to expected withdrawals in the good state: $l = ad$. We call this condition the "liquidity constraint".

Extension: interest rate risk

We extend the framework to incorporate an interest rate risk management problem. At $t = 1$, an interest-rate shock $\varepsilon \sim (0, \sigma_\varepsilon^2)$ may realise. This shock affects all asset values depending on

[26] In Sundaresan and Xiao (2024), the liquidity premium is determined endogenously and is partly driven by the supply of liquid assets. QE/QT could therefore affect p. In our empirical analysis, however, this potential effect is absorbed by time fixed effects. For the model, we therefore treat p as given.

maturity: when, for example, rates rise, longer-maturity assets suffer larger valuation losses. For tractability, we assume banks are risk-averse with a CARA utility function.

In Sundaresan and Xiao (2024), assets differ only in liquidation costs, not maturity. This simplification is appropriate given their focus on short-term liquidity liquidity stress as embedded in the LCR, which focuses on a 30-day horizon. In practice, the overwhelming majority of bank asset maturities extend well beyond 30 days. Therefore, as long as maturity exceeds 30 days, maturity plays no role for the LCR. For instance a government bond counts fully towards HQLA regardless of its maturity. And loans count as fully illiquid regardless of their maturity. Clearly, however, these assets have different exposures to interest rate shocks.

Our model reflects the separation of liquidity and maturity in the LCR framework. Period $t = 1$ represents (in spirit) the 30-day LCR window: liquidity shocks materialise and illiquid assets can only be sold at a penalty ϕ. During this first period, assets differ only in their liquidity. Period $t = 2$ represents a longer horizon where all positions unwind at market prices, without liquidation penalties. The maturity of assets affects the market price at unwind, whereas their liquidity does not. We assume that this maturity can extend beyond $t = 2$, although we do not formally model longer horizons.

Asset maturity affects not only the sale value at $t = 2$, but also its yield. This creates a new trade-off: longer-maturity assets suffer larger valuation losses when interest rates rise, reducing their market value when sold. However, banks are compensated for bearing this duration risk through higher expected returns. We formalise this by assuming asset returns depend on maturity:

$$r(\tau) = \underline{r} + \beta\tau + \psi(\tau)\varepsilon, \tag{11}$$

where $\underline{r}$ denotes the return on a zero-maturity asset, $\beta > 0$ captures the term premium; ε is a mean-zero interest rate shock with variance σ_ε^2 and $\psi(\tau)$ governs duration sensitivity. For tractability, duration risk increases linearly with duration, i.e. $\psi(\tau) = \gamma\tau$ where $\gamma > 0$.[27]

To understand equation 11, consider the difference between a one and two-period government bond. Both bonds can be liquidated at no cost at $t = 1$. The one-period bond yields $\underline{r} + \beta - p$, compared to $\underline{r} + 2\beta - p$ for the two-period bond. However, if rates rise, the bond value falls by $2\gamma\varepsilon$ when liquidated. Banks balance these competing forces when choosing their optimal portfolio duration τ^*.

[27] Deposits are zero-maturity liabilities and still embed a liquidity premium and therefore cost $\underline{r} - p$.

Introducing QE and QT

We further extend Sundaresan and Xiao (2024) by incorporating central bank asset purchases (QE) and sales (QT). For simplicity, QE/QT is entirely exogenous. We only model the direct impact of QE/QT operations on banks, and abstract from any general-equilibrium effects (e.g., via changes in loan demand). This is because our empirical analysis only focuses on direct effects, whereas general equilibrium effects are captured by fixed effects.

At $t = 0$, banks learn about central bank QE/QT decisions and how these affect their starting balance sheets; they then optimise. QE/QT are implemented in line with the discussion in Section 3. Specifically, under QE, the central bank purchases bonds from non-banks, financed by new reserves. Banks' liquid assets and deposits thus increase one-for-one. QT has the opposite effect.

Let $\bar{l}$ and $\bar{d}$ denote the exogenous levels of liquid assets and deposits created by QE. Total holdings become $l = \tilde{l} + \bar{l}$ and $d = \tilde{d} + \bar{d}$, where $\tilde{l}$ and $\tilde{d}$ represent banks' endogenous choices, which adjust in order to optimise banks total liquid asset holdings and size. In the absence of exogenous liquid assets created by QE/QT, $\tilde{l}$ and $\tilde{d}$ would represent banks' optimal liquid asset holdings and size. Banks maximise risk-adjusted returns:

$$\begin{aligned} \max_{\tilde{d},\tilde{l},\tau}\ (\underline{r}+\beta\tau)i + (\underline{r}+\beta\tau-p)(\tilde{l}+\bar{l}) - (\underline{r}-p)(\tilde{d}+\bar{d}) - \frac{\delta}{2}(\tilde{d}+\bar{d})^2 \\ -\phi\mathbb{E}[\tilde{a}(\tilde{d}+\bar{d}) - (\tilde{l}+\bar{l})] - \frac{A}{2}(\tilde{d}+\bar{d})^2\gamma^2\tau^2\sigma_\varepsilon^2 \end{aligned} \tag{12}$$

subject to $i + l = d$ and $\tilde{l}, \tilde{d} \geq 0$, where A is the coefficient of absolute risk aversion.

Benchmark: No QE or QT

Without QE/QT ($\bar{l} = \bar{d} = 0$), banks choose the optimal balance sheet size $\tilde{d} = d^* = \frac{1}{\delta}\big[(1-a)(p-\phi\mu)\big]$. As discussed above, banks must also satisfy their liquidity constraint $l = ad$. When the balance sheet size is at its optimal level d*, liquid asset holdings are $\tilde{l} = l^* = ad^*$. In that case l not only satisfies the liquidity constraint but also maximises profits.

Banks choose optimal total duration risk exposure $\tau^* d^* = \frac{\beta}{\gamma^2\sigma_\varepsilon^2 A}$, where τ^* is the average duration of assets and d^* is total balance sheet size. Since the optimal size d^* is pinned down above, the optimal duration per asset τ^* adjusts inversely with balance sheet size to maintain constant total duration exposure.

These conditions formalise the notion that liquidity and duration choices are separate (absent QE/QT). Optimal liquidity depends on the balance sheet size (d) and the deposit outflow rate (a), and not on the asset maturity. Conversely, optimal duration does not depend on asset liquidity. Instead τ^* depends only on the balance sheet size - which together with τ^* determines the total exposure to interest rate risk ($\tau^* d^*$).

QT

QT simultaneously reduces banks' liquid assets and deposits. For QT to impact lending, one necessary condition is that it reduces the bank's liquidity to below its constraint, i.e. $l < ad$. That is, because of QT, liquidity holdings do not cover potential outflows any longer.

One reason this condition might not be met is if banks enter QT with a large liquid asset buffer above their constraint (i.e. $l > ad$). This could be the case if the preceding QE program had increased the bank's liquidity holdings to a point that it did not fully adjust its balance sheet until $l = ad$ was just met.[28] In that case, banks passively let liquid holdings and deposits fall towards $l = ad$. Lending is unaffected.

Another reason QT might not make the liquidity constraint bind is if the deposits drained during QT are fully flighty, i.e. they have a probability of withdrawals of 100% (Darst *et al.*, 2025). In that case, even if banks start with $l = ad$, the decline in l would be exactly equal to the decline in ad. Therefore, the liquidity constraint would still be satisfied.

If neither assumption are met, and QT pushes banks liquidity coverage below $l = ad$, then banks must react. In that case, banks face two options. First, banks could increase liquid asset holdings—e.g., by buying government bonds and crediting the seller's deposit. This would change the composition of banks' liquid assets, but lending and balance sheet size (and therefore asset duration) would be unchanged relative to before QT. Second, banks could restore $l = ad$ by reducing lending. This would shrink the bank's balance sheet size and overall duration exposure, all else equal. Therefore, under this second option, banks simultaneously lengthen the average maturity of remaining assets (τ^*) to restore optimal duration $\tau^* d^*$.

Formally, which option is chosen depends on whether QT leaves banks above or below their preferred (profit-maximising) level of liquid assets l^* and the corresponding balance sheet size d^*. If QT pushes their holdings of liquid assets below l^*, banks can simultaneously restore

[28] For instance this could be the case if increasing lending takes time.

$l = ad$ and l^* by increasing liquid assets, leaving lending and balance sheet size unchanged relative to before QT. However, if banks remain above l^* despite QT, then increasing liquid asset holdings is not profitable, and banks instead restore $l = ad$ by cutting lending and, hence, balance sheet size. This second scenario is more likely when QT follows a QE program that is large relative to a bank's pre-existing liquid assets. During QE, if the additional reserves holdings created are smaller than pre-existing liquid assets, the bank can maintain $l = ad$ by shedding existing liquid asset holdings. Otherwise, the only option is for banks to expand lending (and therefore d). This restores $l = ad$, but pushes l above the profit-maximising l^*.

Predictions Overall, the model suggests that QT *can* lead banks to shrink lending while increasing asset maturity —our key result (Section 5)—but only when the liquidity impact of losing reserves exceeds the offsetting reduction in deposit-related liquidity risk (captured by the condition $a < 1$). Second, this effect is less likely to materialise when banks have high liquidity coverage ($l > ad$), since reacting is not needed until l falls below ad.

Our model abstracts from banks' ability to borrow reserves from other banks or the central bank. While Sundaresan and Xiao (2024) show that such borrowing capacity can relax liquidity constraints, banks may not view borrowed reserves as perfect substitutes for owned reserves. Borrowing typically requires posting collateral subject to haircuts, interbank markets can freeze during stress periods, and central bank borrowing may carry stigma. In our context, these frictions mean that even with borrowing options available, QT can still affect lending behaviour—though the impact should be weaker for banks with better access to such facilities. This aligns with our empirical finding that QT's lending impact is weaker for banks with more assets pre-positioned at the BoE, which enhance banks' ability to borrow from the BoE.