The Impact of Quantitative Tightening on Credit Supply*

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Abstract

We use two years of Quantitative Tightening (QT) in post-Covid UK and confidential loan-level data to test conflicting predictions about the impact of QT on credit supply. We present evidence that QT reduces lending through a liquidity self-insurance motive. When a bank's reserve holdings (self-insurance) fall due to QT, its lending declines relative to that of other banks. This reflects a threefold adjustment in banks' balance sheets. On the asset side, banks rebalance away from loans towards lower-yielding but more liquid securities. On the liabilities side, banks shift away from wholesale deposits towards more stable, albeit costlier, longer-term funding sources. However, within asset classes with the same liquidity risk, banks reallocate towards higher-yielding assets, thereby increasing interest rate risk. The effects of QT are symmetrically opposite to those observed during Quantitative Easing (QE). Consequently, QE does not necessarily result in a ratcheting up in liquidity risk-taking.

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1 Introduction

Central banks' ability to influence the economy ultimately rests on their role in supplying reserves to banks.[1] Over the past two years, the supply of reserves has shrunk as central banks including the Federal Reserve and ECB have started to reverse the balance sheet expansion initiated after the GFC and Covid. In this paper, we ask how the reserves shrinkage from this "Quantitative Tightening" affects bank lending. This is ultimately an empirical question. If lower self-insurance in the form of reserves holdings increases banks' liquidity risk exposure, banks could respond by curtailing their exposure to illiquid assets including loans. But if banks remain able to *borrow* reserves from other banks or the central bank (Acharya and Rajan, 2024), or if QT simultaneously shrinks banks' exposure to flighty deposits and therefore demand for reserves (Lopez-Salido and Vissing-Jorgensen, 2023), QT might not affect lending.

In this paper, we present evidence that QT reduces bank lending through a liquidity self-insurance mechanism.[2] When banks' reserve holdings reduce due to QT, they respond by curtailing lending to the real economy. In line with a self-insurance motive, reductions in bank lending come along with a broader rebalancing in the liquidity risk from banks' assets and liabilities. In particular, banks rebalance their assets towards more liquid securities, and they rebalance their liabilities towards longer-term funding. And in line with an attempt to mitigate the cost of that rebalancing, within asset classes with similar liquidity risk, banks shift towards higher assets with higher interest rate risk and therefore yield.

To obtain these results, we examine QT at the Bank of England (BoE). The BoE was among the first central banks to start shrinking its balance sheet after Covid-19, starting in February 2022. With two-and-a-half years of accumulated evidence and around £200 billion of reserves shrinkage, the UK therefore provides a good laboratory.[3]

[1] In line with this, changes in reserves supply associated with conventional monetary policy partly transmit to the economy by impacting bank lending. Over time, scholars have emphasised different mechanisms behind this bank lending channel (Bernanke and Blinder, 1992; Drechsler *et al.*, 2017; Bianchi and Bigio, 2022).

[2] Following Holmstrom and Tirole (2011), we refer to liquidity self-insurance to draw a contrast with liquidity *co-insurance* (through participation in interbank markets). In the latter case, banks address liquidity risk by pooling it with other banks rather than by holding reserves on their balance sheet. Yet another possibility to insure against liquidity risk is to rely on *public insurance* (e.g. borrowing liquidity from the central bank).

[3] The BoE had bought £895 billion of assets – mostly UK government bonds ("gilts") - across five rounds of QE between 2009 and 2020. These purchases were financed by the creation of new reserves held by commercial banks.

This set-up has three extra key benefits for identification. First, we have access to confidential monthly loan-level data on UK banks' mortgage lending. This allows us to control for confounding changes in credit demand. Second, we can also exploit granular monthly regulatory data on the liquidity and maturity profile of banks' assets and liabilities. This allows us to understand the mechanism underpinning banks' response. Third, unlike in pre-Covid US and Euro Area, reserves are exempt from leverage requirements through our sample. We can therefore focus on the liquidity effect of reserves while ignoring leverage effects.[4]

To test the lending impact of QT, we construct a monthly panel for all UK banks engaged in retail lending. The sample starts in 2020, when bank-level data begins and shortly before an unprecedented round of QE following the Covid-19 outbreak. The sample ends in March 2024 with the latest available data. We thus cover around two years when reserves increase with QE, and around two-and-a-half years when reserves shrink through QT. The data allows us to alternate between two main dependent variables: monthly changes in lending volumes (across different loan categories), and changes in the price of individual mortgages.

To identify the causal impact of QT, the key challenge is to isolate variation in reserves holdings across time and banks that is plausibly unrelated to banks' lending decisions (other than through the mechanism of interest). *In the aggregate*, the supply of reserves available to banks is set by the central bank. When the central bank sells (or does not reinvest) government bonds, total reserves held by commercial banks mechanically shrink. This effect is credibly exogenous to any individual bank because central banks' QT decisions are based on aggregate economic or financial market factors.[5] And we can control for these confounding factors via time fixed effects.[6]

How *individual banks*' reserves holdings are affected by changes in aggregate reserves sup-

Initially, the BoE implemented QT by ceasing to reinvest maturing gilts on its balance sheet. From November 2022, it also started selling gilts through auctions. QT was halted for around two months starting in October 2022, when the BoE bought long-dated gilts to address the fallout from liquidity stress in UK pension funds. See section 4.

[4]Diamond *et al.*, (2024) find that the inflow of reserves into banks' balance sheet during post-GFC QE crowded out bank lending in the US. They attribute this to balance sheet costs from holding reserves, likely due to leverage requirements. Theoretical models by Martin *et al.*, (2016) and Williamson (2019) explicitly integrate such costs.

[5]In the UK, QT was not aimed at tightening the stance of monetary policy. Instead, it was aimed at avoiding a ratcheting up in the size of the central bank's balance sheet over time.

[6]The aggregate supply of reserves could also shrink due to banks' own decisions, e.g. if banks repay loans from the central bank. However, our results are robust to only exploiting changes in reserves supply due only to shrinkage in BoE's government bond holdings.

ply can also largely reflect exogenous factors. In the UK context, a majority of government bonds sold (or not reinvested) by the central bank are bought by nonbank financial institutions (NBFIs).[7] In that case, typically, the nonbank's deposit at a bank shrinks. As a result, this bank loses reserves *by the nonbank's choice*.[8]

However, the *net* effect of QT on banks' reserves holdings can also depend on banks' own decisions. In some cases, such response could be part and parcel of the mechanism we try to identify. For instance, to respond to the loss in self-insurance (reserves), banks might attract new deposits and thus reserves. And if this is costly, banks might need to cut lending. However, another threat to identification is that banks' response reflects alternative, unobservable drivers of lending. For instance, banks with lower lending opportunities might put less effort to attract funding and reserves. These banks could also be more inclined to buy bonds from the central bank (and thus lose reserves, all else equal). Empirically, such responses could introduce a positive correlation between lending and reserves holding. OLS regressions could thus fail to isolate the self-insurance mechanism of interest.

To address these challenges, our empirical approach has two key pillars. First, we follow Acharya *et al.*, (2023) and construct an instrumental variable (IV) for changes in reserve holdings. Second, we use this IV not only on bank-level lending data but also to loan-level data. This enables us to control for remaining challenges from unobserved demand-side factors.

The instrument for reserves is in the spirit of a "shift-share" IV. The idea is to predict a bank's change in reserves by interacting i) plausibly exogenous changes in aggregate reserves supply (the "shift" dimension), and ii) pre-determined exposure ("beta") to these changes (the "share" dimension). To measure the shift dimension, we track changes in aggregate supply of reserves induced by QE or QT decisions by the BoE in a given month. And for the share dimension, we measure each bank's share of aggregate reserves over the year before the QE or QT decision. The higher a bank's share, the more this bank's reserve holdings are expected

[7] Overall, available evidence suggests that nonbank financial institutions (NBFIs) have seen the largest net increases in gilt holdings over the QT period in the UK, and not banks (Kaminska *et al.*, 2025).

[8] In Acharya and Rajan (2024), banks are assumed to be broker-dealers that are able to decide which fraction of bonds sold by the central banks to buy themselves vs. leave to nonbanks. However, our sample does not include dealer entities (see section 5.)

to decline as the central bank reduces the aggregate supply of reserves. As Acharya *et al.*, (2023) argue, this share is likely to reflect relatively stable underlying factors related to banks' clienteles or their centrality in the interbank network. In line with this, our headline results are largely unchanged when we measure shares more than a year before t.

Since the IV varies across banks and time, we can control for confounding macroeconomic developments (via time fixed effects) and unobserved bank heterogeneities (via bank fixed effects). In our loan-level regressions, we can address further confounding demand-side factors by including a more extensive set of fixed effects, including: borrower location-time, loan type-time and borrower type-time fixed effects.

Equipped with this set-up, we test two key conflicting hypotheses about the reserves shrinkage effect of QT on lending. One hypothesis is that when banks' reserves holdings (liquidity self-insurance) shrink, they curtail their liquidity risk exposure. One option to do so would be to reduce their exposure to illiquid assets including loans.[9] A second hypothesis is that lending is unaffected by reserves' shrinkage. For instance, banks might be confident that they can make up for lost reserves if/when needed by borrowing reserves from other banks or the central bank (Acharya and Rajan, 2024; Acharya *et al.*, 2023).[10] Alternatively, if QT simultaneously extinguishes nonbank deposits, this could reduce the bank's demand for reserves (Lopez-Salido and Vissing-Jorgensen, 2023), thus obviating the need to cut lending. This could be the case if banks view nonbank deposits as particularly flighty.

Our key results are in line with the first hypothesis. When a bank's reserves holdings fall by 10%, the bank's loan volume falls by around 4%, and its mortgage spreads increase by around 4.4 basis points. As we augment the Acharya *et al.*, (2023) specification and saturate our loan-level regressions with extra fixed effects to further control for loan demand, the estimated

[9] In the UK, mortgage loans are largely illiquid: only a small fraction are securitised (Chavaz and Elliott, 2023). UK banks are not subject to reserve requirements. To manage their liquidity risk from mismatches between their assets and liabilities however, banks hold liquid assets (whether because of regulatory requirements or self-imposed targets). Since QE, reserves have formed a large fraction of UK banks' liquid assets.

[10] Banks could not view interbank or central bank borrowing as perfect substitutes for different reasons. Whereas reserves can always be used to meet liquidity outflows, to do so securities must be posted as collateral or sold into secondary markets. For instance banks could worry about interbank borrowing or securities market liquidity being impaired during stresses. In theory, they could also worry about stigma attached to borrowing from the central bank, although this seems less relevant in the UK context given the Bank of England's open for business approach (Saporta, 2024).

impact of QT *increases* by around 60%. This effect is broadly symmetric across QE and QT. And when we estimate separate coefficients for the effect of changes in reserves during the QE and QT periods, this coefficient increases by another 25%. These results are robust to a battery of robustness checks. This includes lagging banks' share of aggregate reserves (the cross-sectional dimension of our IV) by more than a year to mitigate potential correlation with unobserved drivers of lending such as lending opportunities.

To further explore the liquidity self-insurance mechanism, we exploit granular monthly bank-level information on the nature and maturity of banks' assets and liabilities. In line with our hypothesis, we find that when banks' reserve holdings go down, the share of their assets in the form of loans (i.e. illiquid assets) decreases, whereas the share of securities (i.e. typically liquid assets) goes up. Further, the share of banks' securities in the form of (non-reserves) highly liquid securities increases, whereas the share of lower-liquidity securities falls.

Another way for banks to adjust for the loss of liquidity self-insurance is via the composition of their funding. In line with our hypothesis, banks respond to the reduction in their reserve holdings by increasing the share of liabilities in the form of relatively stable retail funding, which is typically covered in large parts by deposit insurance. In contrast, the proportion of relatively less stable (typically uninsured) retail and non-retail funding falls. Further, banks respond to reserves outflows by lengthening the maturity of their retail funding – consistent with an attempt to further make funding more stable.

Together, our results suggest that banks respond to QT by rebalancing their assets and liabilities in a way that offsets the loss in liquidity self-insurance. All else equal, however, this rebalancing has the potential to reduce the profitability of banks' assets, and increase the cost of their funding. One way for banks to offset this effect is to rebalance towards assets with a similar liquidity profile but relatively higher yield. Our results confirm this effect: banks respond by increasing the maturity of their loans and securities, whereas the maturity of lower-quality assets does not change.

Relation to existing literature Our key contribution is to document novel implications for bank lending and risk-taking from the reserves-induced impact of QT through a liquidity-self

insurance mechanism. QT is an increasingly important and debated central bank policy for which direct evidence is only starting to accrue. So far, a majority of empirical studies of QT focus on the effect on bond yields and other asset prices (Du *et al.*, 2024; D'Amico and Seida, 2024; Lloyd and Ostry, 2024).

Our findings complement two recent studies of the effect of QT on the (US) banking system, but that focus on implications other than lending. First, Acharya *et al.*, (2023) study the effect of QE/QT (before Covid) on liquidity supply by banks, whereas we focus on bank lending for QE/QT after Covid. They find that during QE, US banks issued more corporate credit lines and demand deposits. Banks did not reverse this during QT, leaving the banking system more exposed to liquidity risk. We find that during QT, banks reverse the increase in lending (and deposit-taking) driven by QE. Banks more exposed to QT also reduce liquidity exposure by rebalancing the composition and maturity of their asset and liabilities. Second, Lopez-Salido and Vissing-Jorgensen (2023) study the implications of QT for the central banks' control over short-term interest rates. Similarly to us, they emphasise the link between QT and banks' demand for reserves.

A related paper by Altavilla *et al.*, (2023) focuses on evaluating different monetary policy implementation frameworks for the ECB and what this implies for QT strategy. As part of this, they document a positive empirical relationship between lending and non-borrowed reserves at the aggregate and firm level - in line with our findings. Similarly to us, they emphasise the precautionary role of reserves. We focus on QT transmission rather than operating frameworks. By studying broader effects on banks' behaviour, we shed light on the mechanism that underlies the effect on lending.

Our results also complement research on the bank lending impact of QE in pre-Covid US. Rodnyansky and Darmouni (2017) find that QE only boosts lending when the Fed purchases Mortgage-Backed Securities (MBS) and not only Treasuries. This suggests that this effect is not due to the impact of QE on reserves holdings, unlike in our paper. Diamond *et al.*, (2024) find that reserves inflows from QE crowd out bank lending. They attribute this effect to balance sheet costs of holding reserves e.g. due to leverage requirements. We study a context where

reserves are exempt from these requirements; we can therefore focus on the impact of reserve holdings on liquidity constraints. Christensen and Krogstrup (2019) show that changes in aggregate reserves from QE lead banks to rebalance their bond portfolios, whereas we focus on rebalancing in banks' lending and funding. In line with our results, Kandrac and Schlusche (2021) find a positive link between reserves and lending during QE.[11]

Our paper adds to extensive research on the bank lending channel of conventional monetary policy. This research proposes that monetary policy tightening lowers the quantity of commercial bank funding or increases its costs, and that banks cut lending in response.[12] In Bianchi and Bigio (2022), tighter monetary policy reduces bank lending because when the aggregate supply of reserves fall, it becomes more costly for banks to borrow reserves from other banks to meet liquidity outflows. This mechanism stresses *co-insurance* against liquidity risk, whereas ours centers on *self-insurance*. Since QT reduces reserves held by banks, and borrowing reserves from other banks or the central bank is an imperfect substitute for holding reserves, QT makes it more costly to insure against liquidity risk. In particular, must devote a larger share of their assets to low-yielding securities, and must finance their assets with stickier but costlier funding. Similarly to other recent characterisations of the bank lending channel of conventional policy (Drechsler *et al.*, 2017), our mechanism does not rely on reserve requirements. Instead, reserves matter because of their unique role for liquidity risk management.[13]

[11] Butt *et al.*, (2015) found no effect from early Bank of England QE on bank lending. Also see Giansante *et al.*, (2022). Our results are in line with Kumhof and Salgado-Moreno (2024). In their model, QT makes bank lending (and the corresponding creation of deposits) by banks more costly via its effect on the supply of reserves.

[12] In Bernanke and Blinder (1992), when the central bank conducts open markets operations to tighten policy, this drains reserves and deposits away from banks. Since outsiders are unable to observe the value of bank assets, banks are unable to raise funding to make up for the loss in loanable funds. Alternatively, banks must replace the lost funding with more expensive funding – for instance as insured deposits must be replaced by uninsured "managed liabilities'' (Stein, 1998).

[13] Altavilla *et al.*, (2022) find that when the ECB reduced the negative interest rate on a portion of banks' reserves ("tiering"), this unfroze the interbank market. Ex-ante reserve-poor banks borrowed more reserves, and increased lending. Our mechanism is consistent, but emphasises liquidity *self-insurance* (reserves holdings) rather than *co-insurance* (reserves borrowings).

2 Data

2.1 Data Sources

To evaluate the impact of QT on bank lending, we use two main datasets. First, to understand the effect on loan prices, we use data on mortgage lending from Product Sales Database (PSD), a confidential regulatory dataset collected by the UK Financial Conduct Authority (FCA). We focus on mortgages because the data is particularly granular and comprehensive. The PSD covers all residential mortgages originated in the UK on a loan-by-loan basis. And for each loan, we observe a range of variables including: the name of the lender; the borrower income, age, credit history, and type (first-time buyer, home mover, refinancer); the property location and type; and the mortgage origination date, size, initial interest rate, fixation period, loan-to-value (LTV) ratio, loan-to-income (LTI) ratio, and term.

Unlike the US Home Mortgage Disclosure Act (HMDA) dataset, PSD does not report loan sales. However, the overwhelming majority of UK mortgages are retained during our sample period (Chavaz and Elliott, 2023). UK mortgages also typically have a short "fixation period'' (typically 2 to 5 years). After this period, the interest rate switches to a "standard variable rate'' that significantly exceeds the original interest rate; the vast majority of borrowers therefore refinance at this point (Cloyne *et al.*, 2019). Unlike in the US, borrower characteristics play little role in the pricing of mortgages in the UK. Instead, pricing is based almost entirely on the fixation period and LTV ratio (Robles-Garcia, 2019). Rates available for different combinations of fixation period and LTVs are published transparently by all banks, and contracted mortgage rates are similar to advertised rates. We drop any adjustable-rate mortgage from the sample.

Second, to understand the effect of QT on credit volumes, we use a confidential regulatory monthly panel dataset covering all UK-regulated banks collected by the Prudential Regulatory Authority (PRA 110). This data gives us information about loan volumes broken down by borrower groups and maturity. The dataset also contains rich information on banks' other assets and liabilities. For each asset and liability category, we observe the outstanding balance and maturity. Important categories include e.g. High Quality Liquid Assets (HQLA) and

other securities, and a range of funding instruments (deposits, bonds, etc.). We exploit this information to control for confounding bank characteristics, as well as to identify how banks adjust the liquidity and maturity of their balance sheet.[14]

To construct controls for bank profitability and capitalization, we use two additional confidential regulatory reporting datasets collected each quarter by the BoE: FinRep (financial reporting) and CoRep (common reporting). FinRep reports accounting data on assets, liabilities, equity and statement of profit and loss. CoRep covers different aspects of bank risk used to calculate regulatory Basel II capital requirements.

2.2 *Sample*

Our sample starts in January 2020, when the PRA 110 data becomes available. The sample ends in March 2024 (for PRA110 data) and June 2024 (for PSD data) – the latest available data at the time of writing. In practice, our baseline regressions only use data from January 2021. This is because our independent variable is the year-on-year change in a bank's reserve balances. The remaining baseline sample covers 13 months during which the reserves expamd with QE and then stay flat, and 26 – 29 months during which reserves shrink with QT (more details in section 4). However, our results are robust to considering the three-months change in lending as dependent variables and therefore start the dataset in April 2020 already.

Our baseline mortgage sample contains ca. 2 million loans originated by 64 different banks. For consistency across regressions, we drop any bank in the bank-time panel dataset banks that is not present in the mortgages dataset (PSD). This excludes e.g. banks focused on wealth management or investment banking. The UK banking market is concentrated, with the six biggest banks accounting for approximately 80% of total mortgage lending during our sample. Of these, five banks are eligible to participate in QE and QT auctions. This will typically occur through these banks' investment banking entity. Under UK ring-fencing regulation, this

[14]PRA 110 data is available at weekly frequency for the largest banks with total assets equal to or greater than €30 billion, but only at monthly frequency for the majority of smaller banks. To preserve cross-sectional variation, we use the monthly version. Data is collected at the subsidiary level. This matters for the six largest banks, which must separate their retail and investment banking businesses into separate subsidiaries under the so-called ring-fencing regulation (Chavaz and Elliott, 2023). In this case, we use data from the retail subsidiary, given our focus on lending. However, our headline results are robust to using aggregated group-level data instead.

entity must be separated from the entity that engages mainly in retail activities. Since we're mainly interested in the effect of QT on lending to the real economy, we include in our sample the retail entity of such conglomerates and not the investment-banking entity. Tables I and II report summary statistics for the monthly bank panel and loan-level dataset, respectively.

3 Quantitative Tightening in the UK

Figure 1 illustrates the dramatic build up the BoE's balance sheet since 2006. At this time, the balance sheet hovered around £100 million pounds – around 1% of UK GDP. UK banks therefore held a very small amount of central bank reserves. At its peak in 2022, the BoE balance sheet had swollen to ca. £1 trillion. The lion share of this increase was the product of £895 billion of asset purchases intended to stimulate the economy after the GFC (2009, 2010, 2012), Brexit referendum (2016), and Covid pandemic (2020) while the policy rate was close to zero. This QE mainly took the form of purchases of UK government bonds ("gilts'') financed by the issuance of interest-bearing central bank reserves held by banks (Busetto *et al.*, 2022). Below, we further explain the mechanics of QE and QT for central bank, nonbank, and bank balance sheets.

The round of QE launched after Covid and covered in our dataset was particularly dramatic, with a combined £450 billion of purchases commissioned in three stages between March and November 2020. As a result, the BoE's Asset Purchase Facility (APF) – the facility created to hold the assets purchased under QE – kept increasing until the start of 2022. At this point, the BoE kept the APF unchanged by reinvesting maturing gilts.[15]

In August 2021, with the economy rebounding and inflation rising above the 2% target, the BoE's Monetary Policy Committee (MPC) announced its strategy for reducing the stock of purchased assets. QT would not be used to tighten the stance of monetary policy. Instead, the primary instrument would be the policy rate ("Bank Rate'') – judged to be an operationally easier and better understand tool. However, QT would still proceed "in the background", in

[15]To a lesser extent, the BoE balance sheet also increased with the Term Funding Scheme with special incentives for SME (TFSME). The TFSME was launched in March 2020 to stimulate credit supply to SMEs by offering banks access to long-term funding depending on their lending to SMEs. TFSME loans peaked a little under £200 billion in 2021 In robustness checks, we show that the creation of reserves via the TFSME cannot explain our results.

order to prevent the balance sheet from ratcheting up over time, and to increase flexibility to use QE in the future (Bailey *et al.*, 2020). Specifically, when Bank Rate would reach 0.5%, the BoE would start QT by ceasing to reinvest maturing assets. And when Bank Rate would reach 1%, the MPC would consider starting active sales of purchases assets.[16]

In order not to disrupt gilt market functioning, QT would be implemented in a "gradual and predictable'' way. QT could also be amended or reversed e.g. in case of market stress. The target for reduction in the stock of purchased assets would be set on a yearly basis, and would mainly be determined by circumstances in financial markets. In contrast, Bank Rate decisions are made every six weeks and are dictated by the macroeconomic outlook. Keeping QT "in the background" would also ensure that QT would not be seen as a signal for the future stance of policy, therefore shutting down the signalling channel that can play a large part in the transmission of QE. For our purpose, this strategy has the benefit of mitigating concerns around confounding macroeconomic developments that typically complicate identification of conventional monetary policy shocks.

QT started in February 2022, when Bank Rate reached 0.5% and the MPC voted to cease reinvest maturing assets in the APF. At this time, the Fed and ECB had not started QT. In August 2022, the MPC set an indicative target to reduce the APF by £80 billion over 12 months starting in October 2022. This target was achieved despite the BoE's intervention in September and October 2022.[17] In September 2023, the MPC voted to reduce the stock of purchased assets by £100 billion over the next year. At the time of writing, this target had been achieved, with APF assets around £658 billion – a little more than £200 billion less than at its peak.

To maintain interest rate control and guard against any financial stability risk from the shrinkage of central bank reserves due (mainly) to QT, in 2022 the BoE created a new facility allowing banks to borrow reserves from the BoE at Bank Rate. However this Short-Term Repo (STR) facility was little used until recently. Therefore, in the UK context, there was no force to counter the decline in aggregate reserves supply from QT. In contrast, in the US, QT after Covid

[16] See Bank of England Monetary Policy Report August 2021, p12-13.

[17] To restore financial stability after the incoming government's "mini-budget'' announcement, the BoE delayed gilt sales and instead conducted temporary purchases of gilts. Around the start of 2023, these purchases had been reversed, and gilt sales were resumed.

was countered to a significant degree by large increases in the Fed's Overnight Reverse Repo Facility, as well as (more temporarily) by borrowings from the emergency lending facilities put in place after the 2023 turmoil in the US banking system.

4 QT and the banks: mechanics and hypotheses

4.1 Mechanical effect of QT on banks

To motivate our hypothesis, we start by explaining the mechanical impact of QT on the balance sheets of banks and the central bank. For simplicity, we consider the case when QT is implemented via active sales of government bonds by the central banks. However, the key insights are exactly similar in the case where the central bank implements QT by ceasing to reinvest maturing assets on its balance sheet. In practice, when a government bond matures, the treasury issues a new bond in replacement. Overall therefore, this operation has the exact similar impact on the balance sheets of banks and the central bank (Ihrig *et al.*, 2017).

Figure 2 shows stylised balance sheets of the central bank (left-hand side) and bank (right-hand side). When the central bank sells a bond, its assets shrink, and this is matched by an equivalent reduction of its liabilities in the form of reserves. Since reserves can only be held by banks, this is matched by an equivalent reduction in banks' reserves holdings.

Most typically, in the context of UK QT, this would be matched by an equivalent reduction in banks' liabilities in the form of deposits from insurance companies and pension funds (ICPFs). This is because ICPFs are the most common end-buyer of bonds sold by the central bank. When an ICPF purchases a bond, its deposit balance at its bank is likely to fall. In turn, the reserve balance of this bank at the central bank shrinks by the same amount.[18]

Figure 3 illustrates the mechanical implications of QT when the central bank sells bonds to a bank rather than to ICPFs. The effect on the central bank balance sheet is exactly similar: the reduction in bond holdings is matched by a fall in reserves. However, the effect on banks is different. To pay for the bond, the bank reduces its reserve balance. Therefore, it ef-

[18]This would not be the case if the ICPF holds the bond through a repo rather than buying it outright.

fectively swaps bonds for reserves, leaving the size of its balance sheet as well as its liabilities unchanged. Available evidence for the UK suggests that this case is not prevalent: banks are not usual end-buyers for QT bonds.

4.2 Hypothesis development

Our key focus is to test how the shrinkage in banks' reserves holdings from QT affects bank lending via a liquidity self-insurance mechanism. Supplying loans and liquidity in the form of demandable deposits and credit lines exposes banks to liquidity risk - i.e. the risk not being able to meet liquidity outflows. To address this risk, banks hold a buffer of liquid assets that can be readily monetized (Kashyap *et al.*, 2002). We refer to such holdings as *self-insurance* (Holmstrom and Tirole, 2011). This contrasts with co-insurance (via interbank markets) and public insurance (via borrowing from the central bank and other public entities).

Reserves are the most liquid asset available to banks because they can directly be used to settle outflows. By shrinking the supply of reserves, QT reduces banks' liquid assets holdings. In itself, all else equal, this increases banks' liquidity risk exposure. To rebalance their exposure, one possibility is for banks to reduce their exposure to illiquid assets. In the UK context, where securitization is very rare, such assets includes both corporate loans and mortgages.

However, how much this hypothesis should verify in practice should depend on two assumptions. First, QT must push a bank's reserves holdings below the level it wants to hold given its risk exposure. This assumption could e.g. be violated if during QE, a bank had seen substantial inflows of deposits (and therefore reserves), and the bank had not increased in liquidity risk-taking in a commensurate way (e.g. because it considered these newly created deposits as too flighty). Relatedly, a bank might view its liquidity risk as unchanged by QT if the decline in reserves is matched by a decline in deposits viewed as particularly flighty.[19]

A second key assumption is that borrowing reserves is not a perfect substitutes for holding reserves outright. Banks can usually borrow reserves from other banks (through interbank markets) or from the central bank (through standing or exceptional lending facilities). Typ-

[19] In Lopez-Salido and Vissing-Jorgensen (2023) for instance, banks' demand for reserves depends on their deposit-taking.

ically, banks borrow reserves by posting assets like securities and (some) loans as collateral, subject to haircuts. Even if QT lowers reserves holdings, banks might not feel compelled to reduce lending if they remain confident that their ability to borrow reserves is unchanged (Acharya *et al.*, 2023). This could e.g. be the case if banks do not expect freezes in the functioning of interbank markets. QT could also leave banks with more securities holdings, and therefore greater ability to post these as collateral to borrow reserves (Acharya and Rajan, 2024). Alternatively, banks could be indifferent in borrowing reserves from the central bank, e.g. because there is no stigma effect.

While our focus in the effect of QT on liquidity constraints, in theory the effect of QT on reserves holdings could also affect lending through capital constraints. Since reserves are riskless, QT does not affect risk-weighted capital. However, if QT lowers the size of banks' balance sheet, it lowers leverage. And if there are costs to maintaining a large, levered balance sheet, QT could reduce the cost of adding new loans to the balance sheet (Martin *et al.*, 2016; Diamond *et al.*, 2024).[20] Unlike in the US and Euro Area however, in the UK reserves had been excluded from leverage ratio requirements since 2016 already.[21] That said, QT could still lower market-based leverage. And in theory, this could reduce asymmetries of information vis-a-vis bank creditors and therefore bank's funding costs. In practice, however, it's unclear that this effect would be significant since reserves are riskless.[22]

[20] Martin *et al.*, (2016) show that in a frictionless banking system without reserve requirements, the amount of reserves is irrelevant for banks' lending decisions: only the return on reserves (the opportunity cost of lending) matters - not their quantity. However, when there are balance sheet costs, more reserves can lower lending. In the model by Diamond *et al.*, (2024), higher reserves can either crowd out lending (by tightening leverage ratios) or crowd it in (by relaxing liquidity ratios). Their estimated structural model for the US suggests that in the aggregate, the first effect dominates.

[21] In the US and Euro Area, reserves were temporarily exempted from some leverage requirements during Covid.

[22] A potential alternative channel that would predict a similar impact on lending as the self-insurance mechanism is through the reserves-induced effect of QT on bank profitability. All else equal, reserves shrinkage reduces the share of low-yielding assets on banks' balance sheets, increasing profitability. In turn, if banks have a preference for stable profitability over time, this could lower the incentive to increase lending to offset the negative profitability impact of large reserve holdings. Banks e.g. have a preference for stable profits in Drechsler *et al.*, (2021). In line with, Miller and Wanengkirtyo (2020) find that banks experiencing larger reserve inflows from QE (and therefore higher pressures on their profitability) lowered mortgage rates.

5 Identification

To assess the bank lending impact of QT via the shrinkage in reserves, we estimate the relationship between a bank's lending and reserves holdings in a panel set-up. Our approach builds on the strategy developed by Acharya *et al.*, (2023) to understand the effect of QT on liquidity supply by US banks. But we modify it in different ways, in particular to further control for unobservable changes in credit demand.

Specifically, we run variants of the two following baseline regressions:

$$\Delta(LoanVolume)_{i,t} = \beta \cdot \Delta(Reserves)_{i,t} + B \cdot Controls + \epsilon_{i,t}, \tag{1}$$

$$Spread_{i,l,t} = \beta \cdot \Delta(Reserves)_{i,t} + B \cdot Controls + \epsilon_{i,l,t}. \tag{2}$$

The first dependent variable $\Delta(Lending)_{i,t}$ is the yearly change in (log) lending by bank i during month t. Our second dependent variable $\Delta(Rate)_{i,l,t}$ is the interest rate charged for loan l by bank i during month t. In both models, our key explanatory variable is $\Delta(Reserves)_{i,t}$, defined as the yearly change in this bank's (log) reserves holdings. Our focus is on identifying β, which captures the relationship between the changes in reserves holdings and lending.

The key empirical challenge is to isolate QT-induced variation in reserves holdings that is plausibly driven by factors endogenous to individual banks' lending decisions. Key exogenous drivers are twofold.

First, in the aggregate, in our context, changes in reserves supply from QT are determined by central bank decisions, and these decisions are credibly exogenous to any individual bank's lending behaviour. As discussed in section 3, in the UK, QT is aimed to mitigate a ratcheting up in the central bank balance sheet, and not to adjust the stance of monetary policy to changes in the macroeconomic outlook. In turn, the pace of QT (i.e. the quantity of bonds sold or not reinvested) is set every year by the BoE's MPC based primarily on considerations around gilt market liquidity. Finally, each quarter, the BoE announces how bond sales will be allocated across individual auctions for the coming quarter. Again, these decisions are based on con-

siderations around gilt market liquidity (Ramsden, 2023). Clearly, gilt market liquidity could correlate with aggregate factors that might have a more direct impact on lending, e.g. changes in interest rates. However, we can control for any such factor with time fixed effects.[23]

Second, variation in reserve holding *across banks* (for a given aggregate supply of reserves) are determined in large part by decisions by bank's nonbank depositors. In particular, by deciding whether to purchase assets sold or not reinvested by the central bank, nonbanks effectively decide whether to draw down on their deposit balances at banks. In turn, these nonbank decisions determine the extent to which banks lose reserves (all else equal). And these decisions should reflect nonbanks' optimal portfolio allocation calculations rather than any consideration around their bank's lending behaviour.[24]

Incidentally, the role of depositor decisions also means that overall, banks should struggle to predict the impact of QT on their own reserves holdings. To a large extent, banks should be able to predict the overall pace of QT, and its allocation across auctions. After all, the BoE and MPC explicitly aim for QT to be "gradual and predictable". However, how a given quantum of QT should mechanically affect individual banks' reserves holdings should be much harder to predict, since it depends in large part on the decisions of individual nonbank depositors across all banks.

Clearly, the *net* change in banks' reserve holdings will also depend on endogenous responses by banks to the mechanical first-round effect of QT. However, some of these reactions might be part and parcel of the mechanism we try to identify, rather than being alternative

[23] Aggregate reserves supply could also be driven by redemptions (or maturation) or central banks loans to banks. In particular, in the UK, the BoE had launched a Term Funding Scheme (TFS) after the Brexit referendum in 2016; the TFS was then expanded in 2020 after the Covid outbreak. In parallel to reductions in BoE bond holdings, in late 2022 the stock of loans to banks under the BoE's Term Funding Scheme (TFS) also started to decline as TFS loans matured or were redeemed (Ramsden, 2023). However our results are similar if we measure changes in reserves supply using changes in BoE securities holdings only, rather than using aggregate reserves.

[24] In Acharya and Rajan (2024), banks are assumed to be broker-dealers. They can decide which fraction of bonds sold by the central banks to buy themselves vs. leave to nonbank clients. In that case, the extent of reserves lost through bond purchases by nonbanks could be partly determined by banks themselves. And if that determination reflected motives correlated with lending decisions, this could bias our results. However there are no dealer entities in our sample (see section 2). A small number of large banks in our sample are part of conglomerates that also include dealers. But since we're interested in retail lending, we only include the entity within these conglomerates that engages in retail activities, and not the one that engages in investment-banking activities. Under so-called ring-fencing legislation, these entities are strictly separated from each other (Chavaz and Elliott, 2023). In addition, in practice, nonbanks can buy bonds from any dealer - not only from the dealer they bank with. Therefore, banks in our sample are unlikely to be able to exert significant influence over their depositors' decisions to buy bonds from the central bank, and if any, this is unlikely to reflect motives around retail lending.

explanations. For instance, if a bank loses reserves because its depositors buy bonds, it might respond by borrowing reserves from other banks (or from the central bank). It could also respond by attracting new deposits and therefore reserves, as we document in section 7. If doing so is costly, it could also cut lending.

However, a more concerning possibility is that banks' response reflects motives other than our self-insurance mechanism of interest. In particular, if a bank has lower lending opportunities, it might be less inclined to try and attract new funding when it loses deposits and reserves, or to resist these outflows e.g. by raising deposit rates. Such a bank might also be more likely to buy bonds from the central bank, given the higher yield. Empirically, much like our mechanism of interest, these demand-side mechanisms would induce a positive correlation between lending and reserves holdings.

To address these challenges, we use a two-pronged approach. First, we follow Acharya *et al.*, (2023) and predict changes reserves by using an instrument composed of plausibly exogenous to banks' contemporaneous lending behaviour. Second, we use loan-level data and add fixed effects in the spirit of Khwaja and Mian (2008) to further evacuate unobserved demand-side confounding factors.

5.1 Instrumental variable

Following Acharya *et al.*, (2023), we construct the following instrument for reserves:

$$Predicted(\Delta(Reserves)_{i,t}) = \Delta(AggregateReserves)_t \times BankExposure_{i,t}. \tag{3}$$

The instrument is in the spirit of a "shift-share" IV. It interacts two plausibly exogenous dimensions outlined above. First, on the time-series ("shift") dimension, $\Delta(AggregateReserves)_t$ captures year-on-year changes in aggregate reserves supplied by the central bank. Second, on the cross-sectional ("share") dimension, $BankExposure_{i,t}$ captures the extent to which a bank should be exposed to a given change in aggregate reserves supply for pre-determined reasons. To proxy for this, $BankExposure_{i,t}$ is defined as the share of all reserves held by bank i's,

averaged over the last 12 months, i.e.:

$$BankExposure_{i,t} = \frac{1}{12}\sum_{k=1}^{12}\frac{Reserves_{i,t-k}}{AggregateReserves_{t-k}}. \quad (4)$$

At a high level, the greater the fraction of aggregate reserves held by a bank, the more its reserve holdings are expected to decrease as the central bank reduces the supply of reserves. And since this fraction is pre-determined, this rules out any reverse causality between lending and $BankExposure_{i,t}$.

In addition to being pre-determined, as Acharya *et al.*, (2023) argue, in a period following QE $BankExposure_{i,t}$ is likely to be driven by nonbank depositors' behaviours rather than by banks' own choices. In particular, the more a bank's nonbank depositors sell bonds to the central bank during QE, the higher the share of aggregate reserves created by QE should be held by this bank (all else equal). In turn, each bank's exposure to nonbank deposits should reflect long-standing business model factors rather than contemporaneous factors.

A remaining challenge is that $BankExposure_{i,t}$ nonetheless correlates with unobserved factors that might affect lending. For instance, for a given exposure to nonbank deposits a bank' reserve holdings might correlate with past or expected lending opportunities. To mitigate this risk, our loan-level regressions include a host of fixed effect to control for demand (more below). We also verify that our results are robust to measure $BankExposure_{i,t}$ further back in the past to mitigate any correlation with current lending.

5.2 Fixed effects and controls

Our models include a range of additional fixed effects and controls to mitigate the risk that the different dimensions of our IV affect lending through other channels than changes in reserves holdings.

Our key explanatory variable varies across banks and time. This allows us to include time fixed effects. This controls for confounding aggregate developments that might drive the central bank's decision on the pace of QT, and therefore correlate with $\Delta(AggregateReserves)_t$.[25]

[25]These fixed effects also control for any aggregate impact of QT, e.g. via impacts on gilt yields and therefore in-

We also include bank fixed effects to control for unobserved business model factors that might correlate with $BankExposure_{i,t}$. 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. We also include a dummy for the largest bank.[26]

When we use loan-level data, we can use a much more extensive set of controls fixed effects to control for unobserved changes in the demand for loans. Starting with controls, we can include a range of characteristics reported in our PSD dataset: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan maturity (in months) and fixation period (in years), and a dummy for borrowers with impaired credit history. Turning to fixed effects, we include borrower location-time fixed effects, to control for changes in credit demand across geographies in the sprit of Khwaja and Mian (2008). And to control for unobserved changes in credit demand across different types of mortgages and borrowers, we include loan type-time and borrower type-time fixed effects.

In robustness checks, we address residual challenges to the exclusion restriction by additionally interacting $\Delta(AggregateReserves)_t$ (the first dimension of our IV) with our extra bank controls (size, capitalisation). We add interactions between $BankExposure_{i,t}$ (the second dimension of our IV) and proxies for confounding time-series developments such as changes in conventional monetary policy.

6 Main results

6.1 Baseline regressions

Our key results using the monthly bank panel are reported in Table III. The dependent variable is the change in banks' lending volumes. Table IV reports findings for the mortgage-level regressions, where the outcome variable is the interest rate on individual mortgages. In columns

terest rates in the economy. However the timing of this impact should not coincide with the timing of QT auctions, unlike our mechanism of interest. These fixed effects will also control for any effect of QT on interbank markets and therefore banks' ability to borrow reserves.

[26] In contrast Acharya et al. includes a dummy for any broker-dealer. Our approach is equivalent in spirit since outside the six largest UK banks, no UK included in our dataset is active as gilt market dealer.

1-4 of both tables, we report results for different variations of models 1 and 2, with the set of fixed effects and controls following Acharya *et al.*, (2023).

In column 1, we start by reporting OLS results. For both dependent variables, declines in reserves holdings are associated with decreases in credit supply. Specifically, fewer reserves is associated with lower loan volumes (Panel A) and higher mortgages (Panel B). In column 2, we report the first stage for our two-stage least square (2SLS) regression. The instrument has a positive and highly significant relationship with our key endogenous explanatory variable $\Delta(Reserves)_{i,t}$. In other words, a bank's reserves holdings declines significantly when the central bank shrinks the supply of reverses, and when this bank has higher pre-determined exposure to changes in aggregate reserves.

Column 3 shows the second stage of the 2SLS regression, where $\Delta(Reserves)_{i,t}$ is instrument by $Predicted(\Delta(Reserves)_{i,t})$. The results are consistent with the OLS results. Specifically, when reserve holdings decline, banks' loan volumes falls, whereas their mortgage rates goes up. Across both models, the IV coefficients for these estimates are around 2.5 larger than the OLS estimates. In other words, when we exploit only plausibly exogenous variation in reserve holdings rather than all the variation, we find a stronger impact on lending. As we discussed in section 4, this could reflect the possibility for banks to offset some of the mechanical (exogenous) impact of QT on their reserve balances, e.g. by borrowing reserves or raising new funding. Our IV ensures that such endogenous responses do not bias our estimates. Finally, in column 3, we estimate our key coefficient of interest (β) separately for the period where changes in aggregate reserves is mainly driven by QE and by QT.

In the final columns of Panel A, we report two additional results that help to bridge the gap to our loan-level regressions in Panel B. A first difference is that our bank panel regressions consider total lending, whereas loan-level regressions only use mortgages. In column 5, we therefore use as dependent variable the change in retail rather than total lending. (The data does not allow us to isolate the share of retail lending in the form of mortgages). Results are similar in statistical and economic significance. A second difference is that each bank has (roughly) the same number of observations in the bank panel; in contrast in the loan-level re-

gressions, banks that lend more get more observations. This matters because the UK banking market is concentrated, with the main six banks accounting for x% of mortgage lending in our sample. Therefore, in column 6 we report results estimated via IV weighted least squares. Results are similar, if not somewhat smaller. This could indicate a weaker bank lending channel for larger banks, consistent with these banks finding it easier to adjust to the loss of liquidity from QT (eg by raising new funding).

A remaining challenge is that our results could be driven by unobservable changes in credit demand. Therefore, in columns 5-8 of Panel B, we go past the Acharya *et al.*, (2023) set-up and increasingly saturate our loan-level regressions with additional controls and fixed effects. In column 5, we add our controls for borrower and loan characteristics. In column 6, we add a set of additional fixed effects that have become usual in studies of PSD (Chavaz and Elliott, 2023). Specifically, we include bank-product fixed effects (to account for heterogeneities in lending specialisation across banks) and product-time fixed effects (to account for changes in the demand for different mortgages over time). In column 7, we further saturate the model to control even more finely for changes in credit demand over time across borrower groups (via borrower group-time fixed effects) and geographies (via location-time fixed effects). Our results remain significant across these changes. In fact, as we make the specification increasingly conservative by adding fixed effects, our main coefficient becomes significantly larger.

Our results could reflect not only the impact of reserves outflows due to QT, but also reserves inflows from the unprecedented 2020 QE program in response to Covid. And importantly, Acharya *et al.*, (2023) find that in the US context, banks expand credit lines during QE, but the reverse is not true during QT. Although we study the supply of credit and not credit lines, we therefore separately estimate the link between reserves and lending in the QE and QT periods. Results are reported in column 4 of Panel A and columns 4 and 8 of Panel B. The results confirm that the bank lending channel is significant during the QT period (for our loan-level regression, this is visible in our more conservative regression (column 8) and not for the less tight bank-level regression (column 4).

Looking across the different specifications, the estimates point to an economically sizable

relationship. When a bank's reserves holdings fall by 10%, the bank's loan volume falls by around 4%, and its mortgage rates increase by around 4.4 basis points. When we only consider the impact of reserves outflows driven by QT (and not that of reserves inflows from QE), the estimated impact on mortgage rates increases by around 20%.

6.2 Robustness

In Tables V and VI, we report the results from ten different modifications of our baseline regressions, which we apply consistently to the monthly panel regressions and loan-level regressions, respectively. Column 1 reports the baseline results for ease of reference.

First, we test the robustness of our results to using different measures of our dependent variables $\Delta(Reserves)_{i,t}$. In column 2, we lag the variable by one month to provide additional reassurance against reverse causality concerns. In column 3, we consider the three-months rather than twelve-moths change in reserves. Results are largely unchanged.

Next, we explore additional controls to guard against challenges to the exclusion restriction that our baseline set of controls and fixed effects might not fully address. In particular, one concern is that our instrument $\Delta(AggregateReserves)_t \times BankExposure_{i,t}$ could affect bank lending through channels other than its effect on our endogenous explanatory variable $\Delta(Reserves)_{i,t}$. For instance $BankExposure_{i,t}$ could be correlated with a range of bank characteristics that might also affect how it reacts to QT. To rule out this possibility, in column 5 we additionally interact our bank controls (size, capitalisation, profitability) with the time-series factor of our instrument, $\Delta(AggregateReserves)_t$. In addition, in column 6, we also interact this factor with the ratio of the bank's total assets to aggregate total assets in our sample. This provides further comfort against the possibility that the cross-sectional dimension of our instrument $BankExposure_{i,t}$ is correlated with confounding size-related factors.

Another potential challenge to the exclusion restriction is if changes in the aggregate supply of reserves (the time-series dimension of our instrument) are correlated with changes in conventional monetary policy, and if these changes impact on bank lending vary with bank characteristics correlated with $BankExposure_{i,t}$. In section 3, we have shown that QT decisions

should not be based on the macroeconomic outlook, whereas policy rate decisions should. In practice, however, QT unfolded in parallel to the progressive hikes in Bank Rate design to bring inflation back to target. To test whether this drives our result, in column 11 we add controls for changes in conventional policy. To isolate changes in monetary policy from confounding macroeconomic developments, we use estimates of UK monetary policy shocks by Braun *et al.*, (2024). Monetary policy surprises are identified based on the high-frequency (intraday) reaction of bond yields and interest rate futures to monetary policy news. The estimates capture separately changes to the current level of policy rates ($Target_t$) and to its expected future level ($Path_t$). Results are unchanged.

Finally, we evaluate the robustness of our IV approach. In column 7, we start by modifying our measure for the aggregate change in reserves (the time-series dimension of our IV). Specifically, instead of using changes in aggregate reserves, we use changes in the size of the Asset Purchase Facility (APF) – the facility that housed the asset purchased during the BoE's QE programs (see section 3). The benefit if this approach is to exclude changes in aggregate reserves driven by changes in borrowings (and redemptions) from the TFSME scheme launched to stimulate lending after Covid. Results are unchanged.

Next, we modify our measure for banks' exposure to changes in reserves (the cross-sectional dimension of our IV). Our baseline approach follows Acharya *et al.*, (2023) by using the ratio of a bank's reserves to aggregate reserves averaged over the past 12 months. To further ensure that this variable is exogenous, in column 8 we instead measure the ratio 13 months before t. This means that there is no overlap between our IV and dependent variable, which is also measured as a year-on-year change. Since measuring this ratio at one point in time could introduce noise, in column 9, we measure the ratio as an average over the periods t-13 to t-18. Our results are unchanged.

Finally, to further explore IV robustness, in column 10 we define $BankExposure_{i,t}$ as the ratio of bank i's deposits from insurance companies and pension funds (ICPFs) over aggregated ICPF deposits in our sample (averaged over the last twelve months). As we discuss in section 3, ICPFs are the main end-buyer of bonds sold (or not reinvested) by the central bank under

QT. And to buy these bonds, an ICPF would dip into its deposit balance at a bank. Therefore, all else equal, a bank with a larger share of ICPF deposits could expect a stronger reserve outflow from QT. One challenge in implementing this idea is that our dataset does not allow us to fully ascertain in which category a bank classifies ICPF deposits. In any case, our results are in line with baseline results – although statistical significance dips below 10% in our loan-level regression – consistent with this proxy being potentially noisy.

7 Mechanism

In the previous section, we have established that when banks loose reserves due to QT, they curtail lending. This is consistent with the idea that reserve outflows reduce the liquidity of banks' assets, and that banks respond by illiquid assets such as loans. Reverses are the most liquid asset that banks can hold to insure against liquidity risk, and unlike government bonds they do not carry any interest rate risk. In contrast, unlike in the US, UK mortgages are largely illiquid since only a very small fraction of mortgages are securitised or sold). Put otherwise, QT increase banks' exposure to liquidity risk, and this makes issuing new loans more costly – in line with the model by Kumhof and Salgado-Moreno (2024).

In this section, we further explore the mechanism that underpin this "bank lending channel''. To do so, we exploit the granularity of information on bank balance sheets in our bank-time panel dataset and test how banks adjust the composition and maturity profile of their assets and liabilities. In particular, we test whether this response is consistent with an attempt to adjust to the liquidity impact of reserves outflows from QT.

The tables reporting our results in the main text of this paper exploit fluctuations in reserves holdings during both the (Covid-era) QE and the ensuing QT. In appendix tables, however, we repeat all the tests while estimating separate coefficients for the QE and QT period. All the results reported in the main text are consistent when only considering the QT period.

7.1 Rebalancing towards more liquid assets

To start with, we study the response in the composition of banks' assets. We separate two main asset classes: loans (typically illiquid) and securities (typically liquid). We then break down securities into higher-quality securities (most liquid) and lower-quality securities (relatively less liquid).[27] (Reserves are included in neither of these categories). We then study how the share of a bank's total assets in the form of each of these categories fluctuates with reserve outflows from QT.

Table VII reports our results. In line with our hypothesis, we find that when banks loose reserves, the share of their assets in the form of loans decreases (column 1). Therefore, banks do not only respond to reverse outflows by reducing their stock and flow of loans (as seen in Section 6), but also by shifting the composition of their assets away from loans. By contrast, when banks loose reserves, the share of their assets in the form of securities goes up (column 2). In addition, reserve outflows also lead banks to increase the share of higher-quality (relatively more liquid) securities (column 3), whereas the share of lower-quality (relatively less liquid) securities is unchanged (column 4).

Note that, although lower-quality securities have high credit ratings, we cannot completely rule out that there are small differences in credit risk with higher-quality securities. However, it is not clear why reserve outflows would lead banks to shift the credit risk profile of their assets towards (presumably) relatively safer securities. In contrast, there is a material difference in the treatment of the two groups for liquidity requirements, and a clear rationale for banks faced with reserve outflows to want to increase their exposure to securities with a more favourable regulatory treatment.

[27] To separate high-quality and lower-quality securities, we use the Basel Liquidity Coverage Ratio (LCR) framework. High-quality securities (or "level 1'' assets) include claims on sovereigns and quasi-sovereign entities without credit risk and a liquid market. Lower-quality securities ("level 2'') include corporate bonds, commercial paper and residential mortgage backed securities with high credit ratings. Reflecting the difference in the liquidity of the two categories, level 1 securities count fully towards LCR requirements, whereas level 2 securities are subject to a haircut of 15% to 50%.

7.2 *Rebalancing towards more stable funding*

Another way for banks to lower their liquidity risk exposure after losing reserves from QT is to adjust the profile of their liabilities towards relatively more stable funding sources. To test this idea, we exploit detailed breakdown of banks liabilities into different categories reported in our bank-month panel. Specifically, we focus on four non-overlapping categories of funding: i) core retail deposits (deposits from individuals and SMEs below critical balance thresholds), non-core retail deposits (deposits from individuals with larger balances and larger SMEs), non-retail deposits (deposits from larger corporates and financial institutions) and bonds.[28]

Of these categories, bonds are the most stable in contractual terms, with maturities typically of several years. Behaviourally, however, deposits can also be stable. In line with this, the Basel LCR framework assigns a relatively low "outflow rate" to deposits, depending on the type of deposits. Core retail deposits are considered the most stable, largely because these deposits are typically fully covered by deposit insurance. In contrast, non-core retail deposits and non-retail deposits are considered relatively less stable and therefore are given relatively larger outflow rates. Therefore, if banks seek to make their funding more stable, we expect them to favour stable retail deposits and debt, at the expense of less stable retail deposits and non-retail deposits.

The results reported in Table VIII confirm this hypothesis. When a bank faces reserves outflows from QT, the share of its liabilities in the form of core retail deposits increase (column 1). In contrast, the share of less stable retail deposits and non-retail deposits falls (columns 2 and 3). And like the share of stable deposits, the share of debt instruments increases. Note however that this effect is not statistically significant to conventional levels. This could possibly reflect the fact that our sample is almost halved in that case due to a large number of missing information from smaller banks. Overall, however, the results indicate that banks pivot away from less stable funding and towards more stable funding, in line with our hypothesis.

In addition to changing the composition of its liabilities, a bank that seeks to reduce its

[28] To separate core and non-core retail deposits, we use the Basel LCR framework. Non-core ("other") retail deposits include deposits fulfilling a range of criteria, including a balance in excess of €500'000, and access through internet only. Generally these deposits should be assigned an outflow rate between 10% and 20%.

liquidity risk could also lengthen the maturity of its funding within different categories. To test this idea, we exploit the fact that our bank-month panel also reports the weighted average maturity across the different funding categories. For consistency, we focus on the same four categories of liabilities, and report results in Table IX. In line with our hypothesis, higher outflows of reserves from QT are associated with an increase in the maturity of core deposits (column 1), non-retail deposits (column 2), and bonds (column 4). In contrast, the maturity of non-retail deposits falls when reserve outflows increase (column 3). The data is not granular enough to explore the drivers of this result. However, changes in non-retail deposits are likely to partly reflect changes in ICPF deposit balances when ICPFs buy bonds sold (or not reinvested) by the central bank. Speculatively, therefore, this result could indicate that ICPF balances had relatively longer maturities than other forms of non-retail funding.

7.3 Risk shifting

Together, our results suggest that banks respond to QT by rebalancing towards more liquid assets, and towards more stable funding – consistent with an attempt to offset the negative impact of reserve outflows for their liquidity. All else equal, however, this rebalancing also has the potential to reduce the profitability of banks. This is because more liquid assets tend to have lower yields, and more stable funding tends to be – generally – more costly.[29]

One way for banks to offset the cost of the rebalancing without compromising its benefit for liquidity is to shift towards relatively higher-yielding assets within a given asset liquidity bucket. To test this idea, and for consistency, we return to the four asset categories from section y. Instead of considering the proportion of these asset classes, however, we examine how their average maturity varies with reserves outflows from QT. Generally, within a given category, longer-maturity assets will carry higher yields. If banks seek to increase profits within a category, we would therefore expect maturities to lengthen with reserves outflows from QT.

Table X reports the results. The findings are in line with our hypothesis. The more reserves flow out of a bank during QT, the more this bank's lengthens the maturity of its loan book (col-

[29] Core retail deposits typically bear low interest rates due convenience or deposit insurance. At the margin, however, banks would need to increase rates to attract new deposits. And since banks typically struggle to discriminate new and existing deposits, this could increase the cost of retail funding across the board.

umn 1) The same is true for securities (column 2), and for higher-quality securities within the securities bucket (column 3). In contrast, the maturity of lower-quality securities is unchanged (column 4). By pivoting towards longer-maturity securities and loans, all else equal, a bank can chase higher yields, without compromising its liquidity ratios. This is because, within a given asset class, the Basel LCR framework does not set different haircuts depending on the asset's liquidity or maturity.

7.4 Implications for liquidity risk

The results in the previous sections suggest that banks more exposed to reserves outflows from QT tend to increase interest rate-risk taking. In contrast, Acharya *et al.*, (2023) emphasise that QT can increase banks' liquidity risk. They observe that during QE (pre-Covid), US banks respond to reserves inflows by expanding liquidity supply (credit lines and demandable deposits). When reserves flow out during QT, they do not scale back liquidity supply. They conjecture that even if banks lose reserves, they remain confident in their ability to borrow reserves if needed.[30]

Our paper is not directly comparable because we study post-Covid UK and mainly focus on lending. That said, we find that the expansion in lending by banks more exposed to reserves inflows during QE is reversed during QT. In Appendix table XII, we find that this is also true of deposit-taking. We also consider a broader range of levers that banks can use to lower liquidity risk during QT. In particular, we find that banks more exposed to outflows increase their holdings of liquid assets, and to stickier funding. Using information on the maturity of each liability types (rather than just comparing demand and time deposits), We find that maturity of different funding sources increase with QT. In other words, overall, we do not find that QE creates "liquidity dependence".

Abstracting from differences in approaches, what explains these different findings? In the post-Covid UK context, regulation or market discipline might have been sufficient for banks to internalize externalities from higher liquidity risk-taking on aggregate financial stability. In

[30] In Acharya and Rajan (2024), this is because when banks do not lose nonbank deposits from QT, they swap bonds for reserves with the central bank. In turn, bonds can be used as collateral to borrow reserves from other banks or the central bank.

our sample, all banks are subject to Liquidity Coverage Ratio (LCR) regulation. In contrast, when QT started in the US (2014), LCR was only being phased in, and applied to a lesser extent to smaller banks. And indeed, Acharya *et al.*, (2023) find that it's these smaller banks that increased liquidity risk-taking during QE years, and not larger banks. Individually, small banks might also have fewer incentives to internalise the negative externalities from lower liquidity self-insurance. The higher concentration of the UK banking system might help to correct this effect. Another possibility is that post-Covid, banks were less confident in their capacity to borrow reserves, eg having seen the September 2019 US money market turmoil. Banks could also have been more prudent about the flightiness of uninsured deposits, having observed the September 2023 US banking turmoil.

Finally, could it be that in post-Covid UK, banks did not expect a central bank "liquidity put" to the same degree as banks in pre-Covid US? That does not sound compelling because the BoE has an explicit policy of supplying reserves "on demand". If anything, that policy has become even more explicit with QT - e.g. by encouraging banks to use the newly introduced Standing Repo facility (Saporta, 2024).

8 Conclusion

This paper provides evidence for the bank lending impact of Quantitative Tightening (QT) through a liquidity self-insurance motive. Over the past years, major central banks have started the process of unwinding their balance sheet. Yet, to date, evidence for impacts via banks is only starting to accrue, whereas there is more evidence on impacts via asset prices.

The mechanism we uncover is as follows. By curtailing the supply of reserves, QT shrinks the pool of liquid assets that banks can use to self-insure against liquidity risk. To adjust, banks rebalance their balance sheet away from illiquid assets in the form of loans, and towards liquid assets in the form of securities. Banks also rebalance towards more stable forms of funding. This rebalancing is the mirror image of that observed during QE, when banks increase lending and short-term funding. Therefore, QE does not need to create a ratcheting up in liquidity risk-taking.

However, since liquid assets are typically low-yielding and stable funding is typically more expensive, this QT-driven rebalancing is costly from the perspective of an individual bank. 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 interest rate risk and therefore yield.

Our results can inform attempts to quantify the macroeconomic impact of QT. In addition to better-established channels working through term premia, any such attempt should include a bank lending channel. Reductions in lending by reserve-depleted banks could be compensated by more lending by other banks, or by bond markets. In the aggregate, however, QT mechanically shrinks reserves supply. The loss of reserves is also concentrated on the largest banks.

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9 Figures and Tables

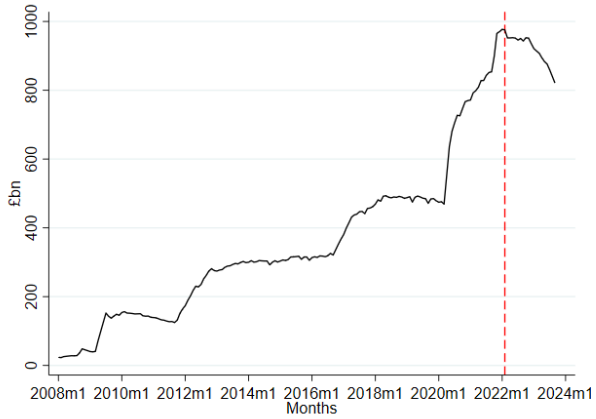


FIGURE 1: Total assets held in the Bank of England's Asset Purchase Facility (APF)

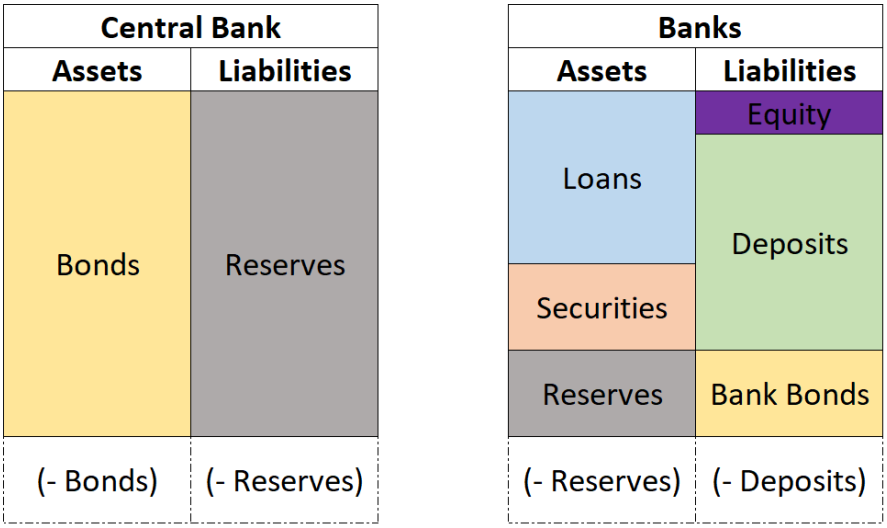


FIGURE 2: Effect of quantitative tightening (via the sale of a bond by the central bank to a nonbank agent) on the stylised balance sheet of the central bank (left) and a commercial bank (right)

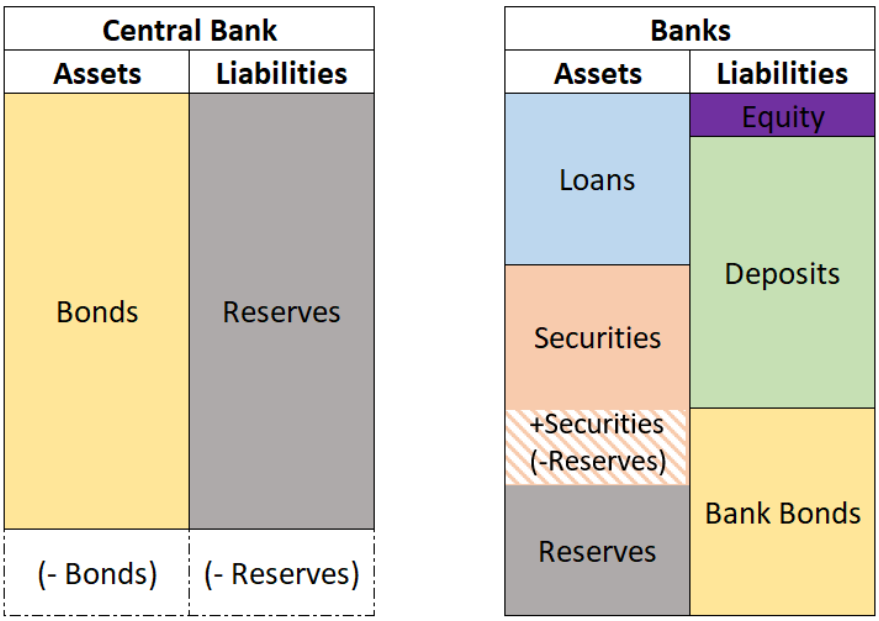


FIGURE 3: Effect of quantitative tightening (via the sale of a bond by the central bank to a commercial bank) on the stylised balance sheet of the central bank (left) and a commercial bank (right)

TABLE I: 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
ROA (%)	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
Observations	2,904				

Notes: This table reports definitions for the main bank-month variables of interest.

TABLE II: Summary statistics: Mortgage-level panel

	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
Maturity (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
Fixation period (years)	3.77	5.00	1.73	2.00	5.00
Bank Size (£bn)	263.40	274.42	139.96	260.78	308.75
ROA (%)	0.11	0.11	0.12	0.07	0.18
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 definitions for the main mortgage-level variables of interest.

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

Estimator:	(1) OLS	(2) IV (Stage 1)	(3)	(4) IV (Stage 2)	(5)	(6) WLS
Dependent variable:	$\Delta(Loans)_{i,t}$	$\Delta(Reserves)_{i,t}$	$\Delta(Loans)_{i,t}$	$\Delta(Loans)_{i,t}$	$\Delta(Retailloans)_{i,t}$	$\Delta(Loans)_{i,t}$
$\Delta(Reserves)_{i,t}$	0.169***		0.424***		0.383***	0.244***
	(0.0109)		(0.0580)		(0.0705)	(0.0158)
$Predicted(\Delta(Reserves)_{i,t})$		5.848***				
		(0.483)				
$\Delta(Reserves)_{i,t} \times QE_t$				0.321***		
				(0.0568)		
$\Delta(Reserves)_{i,t} \times QT_t$				0.421***		
				(0.0614)		
Observations	2776	2740	2740	2740	2740	2201
R-squared	0.320	0.265	-0.140	-0.0582	-0.0615	0.149
F-stat KP			43.99	20.97	43.99	129.9
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of OLS (column 1), 2SLS (columns 2-4) and WLS (column 5) regressions using a monthly bank-level panel dataset. The main 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. $Predicted(\Delta(Reserves)_{i,t})$ is the instrument for $\Delta(Reserves)_{i,t}$, defined as $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. QE and QT are one for the part of the sample when changes in aggregate reserves are driven by QE and QT, 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator:	OLS	IV (Stage 1)	IV (Stage 2)					
Dependent variable:	$Spread_{i,l,t}$	$\Delta(Reserves)_{i,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$	$Spread_{i,l,t}$
$\Delta(Reserves)_{i,t}$	-0.110*		-0.274**		-0.244*	-0.411**	-0.442***	
	(0.0621)		(0.132)		(0.125)	(0.154)	(0.132)	
$Predicted(\Delta(Reserves)_{i,t})$		7.182***						
		(0.671)						
$\Delta(Reserves)_{i,t} \times QE_t$				-0.319				-0.0709
				(0.217)				(0.167)
$\Delta(Reserves)_{i,t} \times QT_t$				-0.0589				-0.563**
				(0.144)				(0.277)
Observations	2078542	1985418	1985418	1985418	1985418	1984445	1944640	1944262
R-squared	0.608	0.766	0.00973	0.0142	0.149	0.0457	0.0132	0.0150
F-stat KP			114.7		114.8	30.40	37.73	
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	No	No	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time	No	No	No	No	No	Yes	Yes	Yes
Product x Bank FE	No	No	No	No	No	Yes	Yes	Yes
Location x Time FE	No	No	No	No	No	No	Yes	Yes
Borrower type x Time FE	No	No	No	No	No	No	Yes	Yes

Notes: This table reports the results of OLS (column 1) and 2SLS (columns 2-8) regressions using a mortgage-level panel 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. QE and QT are one for the part of the sample when changes in aggregate reserves are driven by QE and QT, respectively, and 0 otherwise. Bank controls in columns 1-4 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. Controls in columns 1-4 additionally include: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan maturity (in months) and fixation period (in years), and a dummy for borrowers with impaired credit history. The sample covers the 2020-2024 period and includes all banks active in domestic mortgage lending. Standard errors clustered by banks are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE V: QT and bank lending: robustness checks (monthly bank panel)

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						$\Delta(Loans)_{i,t}$					
$\Delta(Reserves)_{i,t}$	0.424***			1.008**	0.340***	0.242***	0.481***	0.441***	0.408***	1.001***	0.416***
	(0.0580)			(0.441)	(0.0322)	(0.0325)	(0.0535)	(0.0677)	(0.0572)	(0.105)	(0.0374)
$\Delta^{3m}(Reserves)_{i,t}$		0.315***									
		(0.0383)									
$\Delta(Reserves)_{i,t-1}$			0.399***								
			(0.0582)								
$\Delta(Reserves)_{i,t} \times \text{Size}_{i,t-1}$					0.0270						
					(0.0182)						
$\Delta(Reserves)_{i,t} \times \text{ROA}_{i,t-3}$					0.0470***						
					(0.0136)						
$\Delta(Reserves)_{i,t} \times \text{Capital}_{i,t-3}$					0.0278						
					(0.0295)						
$\Delta(Reserves)_{i,t} \times \%(Size)_{i,t-1}$						1.241***					
						(0.417)					
$\text{Path}_{i,t-12} \times BankExposure_{i,t}$											2.432***
											(0.834)
$\text{Target}_{i,t-12} \times BankExposure_{i,t}$											0.407
											(0.663)
Observations	2740	3415	2742	2740	2740	2740	2464	2776	2407	1524	2740
R-squared	-0.140	-0.391	-0.176	-4.121	0.0884	0.237	-0.329	-0.205	-0.0770	-3.858	-0.112
F-stat KP	43.99	43.20	43.83	5.550	140.2	20.39	17.14	24.16	64.43	10.57	65.82
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 x Time FE	No	No	No	Yes	No	No	No	No	No	No	No
IV variant							APF	13M	13-18M	%(ICPF)	

Notes: This table reports the results of second-stage 2SLS regressions using a monthly bank-level panel 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 $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta(Reserves)_{i,t}$	-0.442***			-0.379***	-0.389***	-0.384***	-0.542**	-0.222***	-0.210***	-0.138	-0.344***
	(0.132)			(0.0750)	(0.125)	(0.0862)	(0.208)	(0.0708)	(0.0727)	(0.0954)	(0.109)
$\Delta^{3m}(Reserves)_{i,t}$		-0.551**									
		(0.248)									
$\Delta(Reserves)_{i,t-1}$			-0.475***								
			(0.161)								
$\Delta(Reserves)_{i,t} \times \text{Size}_{i,t-1}$					-0.106						
					(0.0733)						
$\Delta(Reserves)_{i,t} \times \text{ROA}_{i,t-3}$					0.0425						
					(0.0999)						
$\Delta(Reserves)_{i,t} \times \text{Capital}_{i,t-3}$					-0.0476						
					(0.0401)						
$\Delta(Reserves)_{i,t} \times \%(Size)_{i,t-1}$						-0.530					
						(1.043)					
$\Delta(Reserves)_{i,t} \times Exposure_{i,t}$											0.197
											(1.423)
$Target_{i,t-12} \times Exposure_{i,t}$											-3.135***
											(0.939)
Observations	1944640	2497511	1881599	1944640	1944640	1944640	1866105	2039567	1668678	1814093	1944640
R-squared	0.0132	0.00560	0.0112	0.0150	0.0166	0.0163	0.00612	0.0210	0.0198	0.0230	0.0197
F-stat KP	37.73	31.93	25.68	37.56	16.88	28.85	13.88	38.38	44.84	6.943	35.73
Bank and loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product x Time 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 Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower type x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Big-6 x Time FE	No	No	No	Yes	No	No	No	No	No	Yes	No
IV variant							APF	13M	13-18M	%(ICPF)	

Notes: This table reports the results of second-stage 2SLS regressions using a monthly loan-level panel 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 $Predicted(\Delta(Reserves)_{i,t})$, defined as $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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. Other controls include: (log) loan amount, loan-to-income (LTI) and loan-to-value (LTV) ratio, loan maturity (in months) and fixation period (in years), and a dummy for borrowers with impaired credit history. Standard errors clusterd by banks are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE VII: 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
F-stat KP	43.99	33.01	26.13	40.98
Panel B				
$\Delta(Reserves)_{i,t} \times QE$	0.0658	-0.104***	-0.113***	-0.00703
	(0.0427)	(0.00468)	(0.00789)	(0.00858)
$\Delta(Reserves)_{i,t} \times QT$	0.147***	-0.0453***	-0.0404***	0.000692
	(0.0300)	(0.0104)	(0.00968)	(0.00847)
Observations	2740	1984	1841	1251
Time FE	Yes	Yes	Yes	Yes
Controls	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE VIII: 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
F-stat KP	35.02	37.99	42.19	139.6
Panel B				
$\Delta(Reserves)_{i,t} \times QE$	-0.261***	0.154***	0.0779***	-0.0110**
	(0.0242)	(0.0369)	(0.0189)	(0.00419)
$\Delta(Reserves)_{i,t} \times QT$	-0.115***	0.140***	0.0176**	-0.0123
	(0.0150)	(0.0266)	(0.00865)	(0.0180)
Observations	2547	2713	2511	1305
Time FE	Yes	Yes	Yes	Yes
Controls	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE IX: 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) $\Delta(Bonds)_{WAM}$
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
F-stat KP	35.02	38.12	42.19	139.6
Panel B				
$\Delta(Reserves)_{i,t} \times QE$	1.166***	-0.441	3.140*	-1.338**
	(0.253)	(0.266)	(1.733)	(0.639)
$\Delta(Reserves)_{i,t} \times QT$	-0.848**	0.0461	1.558***	-1.521***
	(0.337)	(0.0499)	(0.229)	(0.478)
Observations	2547	2707	2511	1305
Time FE	Yes	Yes	Yes	Yes
Controls	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

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

	(1) $\Delta(Loans)_{WAM}$	(2) $\Delta(Securities)_{WAM}$	(3) $\Delta(\text{Liquid Sec})_{WAM}$	(4) $\Delta(\text{Less liquid Sec})_{WAM}$
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
F-stat KP	43.99	33.42	24.30	38.46
Panel B				
$\Delta(Reserves)_{i,t} \times QE$	0.218	0.0419	-0.531	0.432*
	(0.202)	(0.195)	(0.492)	(0.253)
$\Delta(Reserves)_{i,t} \times QT$	-0.134***	-0.0956	-0.318	0.778
	(0.0209)	(0.249)	(0.292)	(0.759)
Observations	2740	1874	1710	1205
Time FE	Yes	Yes	Yes	Yes
Controls	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

10 Appendix Tables

TABLE XI: QT and bank lending: mechanism (asset volumes)

Dependent variable:	(1) $\Delta(Loans)_{i,t}$	(2) $\Delta(Securities)_{i,t}$	(3) Δ(Liquid Sec)$_{i,t}$	(4) Δ(Less liquid Sec)$_{i,t}$
Panel A				
$\Delta(Reserves)_{i,t}$	0.424***	-1.065***	-0.961*	0.153
	(0.0580)	(0.223)	(0.505)	(0.359)
Observations	2740	1937	1797	1200
F-stat KP	43.99	34.85	28.52	55.14
Panel B				
$\Delta(Reserves)_{i,t} \times QE$	0.489***	-1.152***	-0.296**	-1.176***
	(0.0751)	(0.0932)	(0.115)	(0.108)
$\Delta(Reserves)_{i,t} \times QT$	0.430***	-1.117***	-1.061**	0.837
	(0.0745)	(0.269)	(0.423)	(0.792)
Observations	2740	1937	1797	1200
Time FE	Yes	Yes	Yes	Yes
Controls	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.

TABLE XII: QT and bank lending: mechanism (liability volumes)

Dependent variable:	(1) $\Delta(\text{Core Retail})_{i,t}$	(2) $\Delta(\text{Non-core Ret})_{i,t}$	(3) $\Delta(\text{Non-Retail})_{i,t}$	(4) $\Delta(Bonds)_{i,t}$	(5) $\Delta(\text{Sight})_{i,t}$	(6) $\Delta(\text{Time})_{i,t}$
Panel A						
$\Delta(Reserves)_{i,t}$	0.172***	0.869***	0.222	-1.178**	-0.0550	-1.618***
	(0.0310)	(0.0959)	(0.172)	(0.508)	(0.174)	(0.294)
Observations	2547	2713	2511	1305	2656	2656
Panel B						
$\Delta(Reserves)_{i,t} \times QE$	0.0141	1.338***	0.853***	-1.030	0.397*	-3.023***
	(0.211)	(0.130)	(0.166)	(0.612)	(0.207)	(0.213)
$\Delta(Reserves)_{i,t} \times QT$	0.0971**	1.020***	-0.166	-2.194***	0.406	-1.223***
	(0.0391)	(0.142)	(0.129)	(0.424)	(0.352)	(0.223)
Observations	2547	2713	2511	1305	2656	2656
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	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. 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 $\Delta(Reserves)_t \times BankExposure_{i,t}$. $BankExposure_{i,t}$ is defined as $\frac{1}{12}\sum_{k=1}^{12}(Reserves_{t-k}/Reserves_t)$. 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 2020-2024 period and includes all banks active in domestic mortgage lending. Robust standard errors are reported in parentheses. *, ** and *** indicate significance at 10, 5 and 1%.