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Liquidity and monetary transmission: a quasi-experimental approach

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Abstract

In the face of lower real interest rates, central bank balance sheets are likely to remain larger relative to pre-crisis levels, resulting in greater banking system liquidity. However, there is little evidence on the impact of higher liquidity on credit supply and the monetary transmission mechanism in the 'new normal'. We exploit a novel dataset on bank liquidity positions arising from a unique regulatory regime and combine it with a highly-detailed, loan-level administrative dataset on UK mortgages. Using the design of quantitative easing auctions as an instrument for liquidity to address endogeneity, we find that more liquid banks charge slightly higher mortgage interest rates, and pass on significantly less changes in risk-free rates. We explain this through bank behaviour that attempts to preserve net interest margins in the face of holding low-yielding liquidity. Consistent with this, we find excess liquidity leads to reaching-for-yield responses in banks' mortgage risk-taking. Additionally, the results shed light on the optimal mix between (un)conventional monetary policy tools. Policies that boost bank net interest margins are more likely to help the transmission of risk-free rates to lending rates.

Key words: Bank liquidity, interest rate pass-through, monetary policy.

JEL classification: E52, E58, G21.

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1 Introduction

In order to counter the zero lower bound during the Great Recession, monetary policymakers worldwide purchased assets via quantitative easing (QE) programs. However, persistently low natural interest rates suggest that unconventional monetary policies (asset purchases or other unconventional tools) are likely to be a part of the standard future monetary policy toolkit (Bernanke, 2020). In turn, the large increase in liquidity in the banking system relative to pre-crisis levels — mainly in the form of central bank reserves — could remain in the 'new normal'. What implications does this have for bank lending behaviour, and in particular, where banks have to satisfy new Basel 3 liquidity requirements?

This paper focuses on an important spillover for monetary policy: the transmission of risk-free rates to lending rates. This is a mainstay of the transmission of *conventional* monetary policy, as well as channels of QE that reduce longer-term risk-free rates.[1] To the best of our knowledge, this paper is the first to explicitly empirically analyse the interaction of asset purchases with interest rate pass-through behaviour of banks – long accepted to be a key part of the monetary transmission mechanism (MTM) (Bernanke and Blinder, 1992).

This development interacts with the gradual implementation of global bank liquidity requirements, which are seen as beneficial for making bank runs less likely. Intuitively, one may expect banks with more surplus liquid assets created by QE to lend more freely, as they may be less concerned about breaching requirements. However, there is a countervailing effect: if banks target a given net interest margin (NIM), they may charge higher loan rates to compensate for the low return on liquid assets. This would reduce credit supply.

Using an instrumental variables (IV) identification strategy that exploits the design of the Bank of England's QE purchases to isolate exogenous variation in bank-specific liquidity, we find that banks with more excess liquidity pass-on less of changes in risk-free rates. This suggests that the increase in liquidity may have weakened interest rate pass-through in the mortgage market.[2] This effect is economically significant – we estimate that the increase in bank liquidity over the ILG regime (2010-15) may

[1] The signalling channel of QE operates by committing monetary policy to low rates for extended periods of time. Studies listed in the next section have also found that QE reduces risk premia on long-term risk-free rates.

[2] We define excess liquidity as holdings of liquid assets over and above requirements.

have reduced pass-through by 28 bps of every 100bps that would have been passed-through previously. We also find these banks charge higher loan rates, suggesting they reduce credit supply. This implies the NIM-targeting effect dominates, but this 'direct' effect is small relative to other benchmarks, such as the estimated effects of higher capital requirements. We estimate the increase in liquidity raised mortgage rates by just 15 bps – which is comparable to a 1pp change in the countercyclical capital buffer (Benetton et al., 2017). The difference here is that this change occurs slowly over more than five years, whereas the countercyclical buffer can change by 1pp within a year. [3]

Furthermore, our mortgage-level dataset also enable us to show that banks attempt to reach-for-yield, as the reduction in pass-through by more liquid banks predominantly occurs in the lower risk categories. This risk-shifting behaviour is consistent with NIM-targeting behaviour: banks increase rates on the safer, lower-yielding mortgages, but also do not contract supply to riskier mortgages, shifting their portfolio to these higher yielding mortgages.

At this point, it is important to emphasise that this result speaks purely on the *interaction* between conventional monetary policy and QE, and not on the efficacy of the policies themselves (which have other direct effects). Other unconventional policies, such as funding schemes that boost NIMs, could also be more successful in complementing traditional interest rate policies. Instead, we see this paper as informative of how interest rate pass-through could operate in a reserve-rich environment as central bank balance sheets remain larger relative to pre-crisis levels.

A key contribution of this paper is the combination of three highly granular datasets: on bank liquidity positions, loan-level mortgages, and transaction-level QE auctions. The UK is uniquely suited to analysing this topic as the UK had the Individual Liquidity Guidance (ILG) regime, which was active from June 2010 until the introduction of the EU Liquidity Coverage Ratio in October 2015. The regulatory returns from this regime enable us to build a novel dataset on effective net liquidity positions.

This dataset further distinguishes this paper from the literature for two reasons. Firstly, we can net off repurchase agreements (repos), which are commonly used by large banks and distort their true liquidity position relative to what is simply reported

[3] As we explain further in Section 3.2, the mechanisms we describe are more likely to affect rate cuts, which are the more interesting and policy-relevant case. Furthermore, it is feasible that the effects that we describe here affect other types of interest-bearing bank lending, such as to corporates. We focus here on the mortgage market due to granularity of available data and its importance in the monetary transmission mechanism.

on their balance sheets. Secondly, we differentiate the effect between simple liquid asset holdings and excess liquidity (over and above requirements). As we show later in the paper, the effect is very different between the two. As previous papers analysing the impact of bank liquidity on lending typically only observe liquid asset holdings, such as Kashyap and Stein (2000) and Jiménez et al. (2012), they are unable to make these two distinctions. Furthermore, we complement the branch of literature on liquidity shocks not only with the matching of highly detailed datasets, but also with examining bank loan price behaviour in response to risk-free rates, rather than quantities. The latter is important in today's environment, as the vast majority of central banks no longer target money supply, but set a baseline policy rate instead.

We use instrumental variables to identify the causal effect, as banks' liquidity position may be correlated with time-varying unobservables. For example, changing risk appetite over time may affect both liquidity choice and mortgage rates. We therefore build on Jiménez et al. (2012) by generating exogenous variation in bank liquidity. The IV comes from the Bank of England's transaction-level QE auction data, as in Butt et al. (2014). Asset purchases were performed with large gilt holders (such as pension funds) through competitive auctions. If their bid was successful, the Bank of England would exchange their gilts for reserves in the form of a bank deposit. Some banks, therefore, received extra reserves outside their control as it depended on their clients' desire to sell gilts in QE auctions. Thus, this boost to their liquidity should be exogenous to both funding and lending decisions.

We combine our novel liquidity data with a large loan-level administrative dataset – the Product Sales Database (PSD) – containing the near-universe of originated UK residential mortgages since 2005, from Benetton et al. (2017).[4] While the importance of the credit channel of monetary policy is long-established (Bernanke and Blinder, 1992), our focus on the focus on the mortgage market is warranted by recent literature. Cloyne et al. (2020) finds that the vast majority of the consumption response to monetary policy is driven by mortgagors, while owner-occupiers' consumption is unresponsive. To the extent that the mortgage market affects house prices, Bahaj et al. (2020) finds that directors' home values create collateral effects on aggregate firm investment as large as corporate property, providing another channel how this paper's results affects the MTM. Additionally, our highly granular dataset allows us to control for loan-level risk factors, such as the Loan-to-Value (LTV) ratios and borrower

[4]We thank the authors for allowing access to their dataset. For an extensive description of the cleaning and matching procedure, see the appendices.

incomes. The rich set of loan-level variables also improves the precision of our results relative to using bank-level data.

Furthermore, our highly detailed loan-level data helps deal with other demand-side sources of endogeneity. For example, credit demand shocks may be correlated with bank liquidity. We use time fixed effects to absorb economy-wide demand effects. Additionally, our results are robust to including postcode-month fixed effects, which should control for local demand shocks. Distinguishing the effects of credit demand and supply shocks is the main focus of Jiménez et al. (2012), who use loan-application level data from the Spanish credit registry. The cornerstone of our paper is instead on identifying causal effect of liquidity to credit supply.

2 Relation to the literature

This paper is closest to the empirical literature on the QE effects on bank lending, which has largely focused on the US implementation of QE. Rodnyansky and Darmouni (2017) finds that banks more affected by QE1 and QE3 increased their lending by 2-3% more than their counterparts. However, QE2 – which focused solely on Treasuries rather than mortgage-backed securities – did not have any significant impact. Chakraborty, Goldstein, and Mackinlay (2019) similarly find that mortgage-backed securities (MBS) purchases increased mortgage origination, but lowered commercial lending. Treasury purchases, on the other hand, had negligible effects on lending. In our 2010-15 sample, the UK implementation of QE exclusively purchased government bonds. We find statistically significant effects of QE-driven liquidity on credit supply, but have limited economic significance, and thus fully consistent with these papers. A recent relevant UK study also reports similar findings on the limited effects of QE on bank lending activity (Giansante et al., 2020).

We emphasise instead how the additional liquidity interacts with the transmission of risk-free rates to lending rates. Butt et al. (2014), whose IV we use, focus on quantities rather than loan pricing behaviour. From the relatively instability of non-bank deposits, they do not find changes in credit supply from a QE-driven rise in liquidity. We benefit from a much greater detail in liquidity and loan-level data (they only used central bank reserves and aggregated lending volumes). Likewise, Jiménez et al. (2012) run similar interest rate pass-through regressions as we do, but only observed the balance sheet holdings of liquid assets. The literature of the overall effects on QE

– often on the term premia or signalling effects – is extensive.[5]

There is an established literature on how liquidity shocks affect credit supply – often referenced as the bank lending channel. Kashyap and Stein (2000) suggest less liquid banks reduced credit supply to contractionary open market operations that reduces aggregate liquidity. Similarly, Khwaja and Mian (2008) find quantities respond to bank liquidity shocks, but not loan prices. Likewise, using exposure to wholesale markets during the 2008 crisis, Dagher and Kazimov (2015) show more affected banks contracted credit supply by more. Gatev and Strahan (2006) demonstrate that banks act as a hedge to a liquidity shock in the commercial paper market, as bank deposits flow in during stressed conditions. The extensive work on liquidity shocks include Peek and Rosengren (2000), Paravisini (2008), Puri et al. (2011), Cornett et al. (2011), and others.

Another proximate branch of literature looks at how risk-taking behaviour of financial institutions responds to QE. Chodorow-Reich (2014) demonstrates how money market funds with higher costs and some pension funds reached-for-yield in response to the Fed's QE1 and QE2, and Di Maggio and Kacperczyk (2017) find money market funds invested in riskier asset classes. Kurtzman et al. (2018) reach a similar conclusion that banks loosened credit standards to asset purchases, although with a complementary net-worth channel instead.

Additionally, key relevant papers from the interest rate pass-through literature include Bianchi and Bigio (2014), who have a structural model of the banking sector and a core mechanism of banks' liquidity management. The model predicts the aforementioned channels to either a shock to the discount window rate or the interest on reserves. Meanwhile the reduced form approaches, such as Gambacorta (2008), and more recently Banerjee et al. (2013), show that pass-through varies on the capital and liquidity positions of banks.

This paper is also closely related to the literature on the effects of liquidity regulations on credit supply. Our results are consistent with theoretical papers predicting limited 'direct' impacts (on credit supply, rather 'indirect' on pass-through) from liquidity requirements. Miller and Sowerbutts (2018) argue that investors should recognise more liquid banks are less likely to fail from runs, therefore reduce the risk premium on their funding. This should offset some of the cost from holding more

[5] A small selection include: Joyce et al. (2011), Krishnamurthy and Vissing-Jorgensen (2011), Gagnon et al. (2011), Christensen and Rudebusch (2012), Bauer and Rudebusch (2014), Churm et al. (2015), Eser and Schwaab (2016), Lloyd (2018), Christensen and Krogstrup (2019) and many others.

liquidity, leading to a modest overall effect. In addition, liquidity requirements may not be costly, as raising liquidity relaxes risk-weighted capital requirements (Boissay and Collard, 2016; Roger and Vlcek, 2011). Similarly, empirical studies find little direct impact on retail lending. Banerjee and Mio (2018) study UK banks under the ILG regime, finding no change in retail lending. Bonner and Eijffinger (2016) find similar results for Dutch banks subject to the LCR. A recent paper by Reinhardt et al. (2020) that use a similar liquidity dataset constructed in conjunction with this paper find larger effects, but on cross-border lending.

In a New Keynesian setup, Brunnermeier and Koby (2019) find that the reversal rate – the rate where lower policy rates become contractionary – rises when banks are required to hold more liquidity. Thus, *ceteris paribus* the pass-through of policy rates becomes weaker when banks are more liquid. Much like to the NIM targeting hypothesis, bank profitability is the key mechanism. When the fall in net interest income (from a policy rate cut) is sufficiently large, bank net worth suffers which reduces banks' ability to intermediate funds to borrowers. This mechanism also exists in Horst and Neyer (2019), where excess reserves created from QE is costly if negative interest rate policies are implemented. Moreover, Gigineishvili (2011) finds bank behaviour that attempt to protect NIMs: there is weaker adjustment of lending rates in response to changes market rates in countries with lower NIMs.

Finally, there is a literature predicting liquidity regulations may affect the MTM through central banks' ability to control short-term money market rates. Duffie and Krishnamurthy (2016), Bech and Keister (2017) and a technical paper by ECB (2013) argue that liquidity regulations could increase short interest rate volatility, reducing the power of monetary policy. We leave this particular channel for future research.

3 Background on Liquidity Requirements

3.1 The UK Liquidity Regime

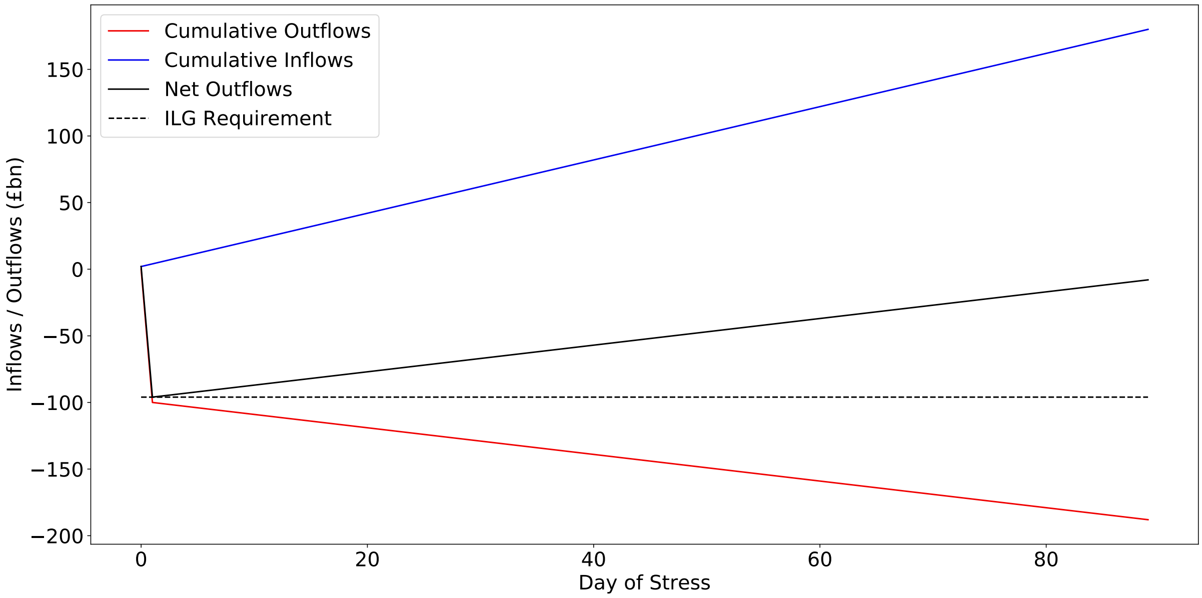
From June 2010 until October 2015, UK banks and building societies were subject to the Individual Liquidity Guidance (ILG) regime.[6] Banks reported the maturity breakdown of their entire balance sheet to the Prudential Regulatory Authority (PRA).

[6]There was no serious or binding liquidity regulations pre-2010, and the EU Liquidity Coverage Requirement (LCR) came into force in October 2015.

The maturity reporting was very granular over a short time horizon. For the first 90 days, banks had to report the volume of each product that would mature every day.[7] This allowed for detailed modelling of banks inflows and outflows over those 90 days.

The PRA applied inflow and outflow rates ("stress factors") to each product. For example, the stress factors for short term wholesale funding and retail deposits were 100% and 10-20%, respectively, depending on their characteristics. A bank's total outflows and inflows were the sum of the products multiplied by their stress factor. On any given day, a bank's cumulative net outflows were the cumulative outflows minus inflows. A bank's ILG requirement was given by their worst day of cumulative net outflows over the 90 day time horizon. Figure 1 provides a stylised example of a bank with high initial net outflows, followed by net inflows thereafter. Their ILG requirement is given by their cumulative net outflows on day 1 of the stress.[8]

Figure 1: Stylised calculation of ILG requirement from net outflows



Banks had to hold a buffer of high quality liquid assets (HQLA) to cover their ILG requirement. The ratio of their HQLA to requirement was called the ILG ratio:

[7] Banks reported the maturity structure of their balance sheet beyond 90 days, in larger time buckets, but it was not relevant for calculating their liquidity requirement.

[8] In addition to the mechanical requirement from banks' balance sheets, supervisors applied "add-ons" to bank-specific liquidity risks. Balance sheets often did not capture these risks well, such as derivative margin calls and participation in settlement systems. Add-ons were set at banks' liquidity reviews, which occurred annually for large banks and every 3 years for small banks.

$$\text{ILG ratio} = \frac{\text{HQLA}}{\text{ILG requirement}} \geq X\% \tag{1}$$

This setup is similar to the Basel 3 LCR. However, there are some crucial differences:

- Under the ILG regime, banks only had to hold HQLA to cover 50% of their requirement. Banks must now meet 100% of their LCR. [9]
- Banks can hold a much wider range of HQLA under LCR than the ILG regime, where only reserves or AAA-rated government bonds were allowed.
- The ILG regime was modelled off a 90 day stress, whereas the LCR is 30 days.
- The LCR is a snapshot of banks' liquidity position on day 30 of a stress. The timing of inflows and outflows before day 30 are irrelevant to banks' compliance. However, the ILG regime had more granular timing reporting, and banks had to be liquid *on each day* of the stress up to day 90.

As banks only had to cover 50% of their requirement, we define their "distance" as:

$$\text{Distance} = \text{HQLA} - 0.5 \times \text{ILG requirement} \geq 0 \tag{2}$$

An added complexity with the ILG regime was pre-positioned collateral (PPC) at the Bank of England's liquidity facilities. From 2012-15, banks were allowed to use PPC to meet some of their ILG requirement.[10] Many banks opted to do so because PPC-eligible assets, such as mortgages and corporate loans, generally yielded more than HQLA. While we add a control for the extent of PPC usage, as we go into detail later, our identification strategy uses exogenous variation in the reserves component of HQLA instead and thus, PPC usage should not affect our results.

3.2 How might banks respond to liquidity shocks?

In Section 1, we outlined two hypotheses for how banks may respond to tighter liquidity requirements. They predict different outcomes for mortgage rates, hence the importance of empirical analysis for deciding which is dominant.

[9] The EU LCR was phased in under a transition path. Banks had to meet 80% of their requirement initially and this was phased up to 100% by January 2018.

[10] Banks had to meet some other conditions too, such as a 7% capital ratio, in order to use PPC. The amount they could use also varied between 10% and 20% of their ILG requirement.

Hypothesis 1 is that banks could target a net interest margin (NIM). Liquid assets generally have lower yields, so banks with more surplus liquidity could compensate this by charging higher mortgage rates.

NIM-targeting has a similar implication for pass-through. Suppose there is a policy rate cut, which reduces risk-free rates and then bank funding costs. Banks should pass this on through lower mortgage rates, which would increase loan supply. However, banks with more surplus liquidity are less able to do so, if NIM-targeting behaviour incentivises them to charge higher mortgage rates. A fall in the yield of the HQLA asset holdings (driven by the same fall in risk-free rates) would also further enhance this channel. Therefore, banks with more distance from their requirement should pass through less of their changes in funding costs.

Hypothesis 2 is that banks are concerned about breaching liquidity requirements. When a bank wants to create a mortgage, they must create a deposit in order to fund the loan. In the presence of liquidity requirements, they must hold liquidity against this deposit, which is costly. The bank's internal treasury could be expected to pass on this cost to higher mortgage rates through their funds transfer pricing (FTP) mechanisms. Therefore, a positive liquidity shock which increases distance from requirements should induce the bank charge lower mortgage rates.

This FTP mechanism also affects pass-through. Again, suppose there is a policy rate cut that reduces bank funding costs. We expect them to pass this on through lower mortgage rates, which would increase credit supply. However, they again need to hold liquidity against funding for these loans. Therefore, banks with more distance from their requirement have greater ability to expand credit supply, and thus pass through more of their changes in funding costs.

Note that these mechanisms are likely to be more relevant for rate cuts, rather than hikes. A credit supply contraction driven by a rate hike reduces liquidity requirements from the reduction of deposits created from reduced loan-making activities, so liquidity requirements are not more binding for less or more liquid banks (given their one-sided nature), like they are for rate cuts. A rise in funding costs might compound the pressure of low-yielding liquidity on NIM targets, leading to stronger upward pass-through – but this could be attenuated by higher yields on the liquid assets from the higher risk-free rates. Nevertheless, we argue that interactions with rate cuts are the more interesting and relevant case for monetary policymakers. Reductions in pass-through in rate hikes can easily be compensated with more rate hikes, but is more difficult to do with rate cuts close to the lower bound in a low natural real rate environment. We discuss this further in the Section 6, where other tools like bank funding schemes could be useful in reinforcing pass-through.

4 Data and Specification

4.1 Bank Data

Our main source of bank data is the FSA047 and FSA048 regulatory returns, which were used to monitor compliance with the ILG regime. Jointly developed alongside Reinhardt et al. (2020), this is the first academic paper to make use of them so we provide detail in this section. Large banks were required to submit these returns weekly, and small banks monthly. We therefore aggregate data from large banks to monthly frequency. This matches our other bank-level data.

The FSA047 reports the contractual maturity of *non-retail* products maturing within 90 days. Banks must fill out a separate column for each day and a row for each granularly-defined product.[11] This is the main source for our outflow data, which makes up most of banks' ILG requirements. Additionally, the FSA048 reports the contractual maturity of *retail* products maturing within 90 days, and the maturity for all products after 90 days. The calculation of a bank's mechanical ILG requirement only requires maturities up to 90 days within the stress window. However, some of the longer term items are relevant for calculating firm-specific 'add-ons'.

The FSA048 also includes data on banks' liquid asset buffers, which consisted of reserves and AAA government bonds. These items did not have to be held on balance sheet – banks could use repurchase agreements (repos) to meet their requirement (provided the repo term exceeds the 90 day stress horizon). This is a major advantage of using regulatory returns, rather than balance sheet data, to estimate banks' liquidity positions. Balance sheets may give a misleading picture if repos are extensively used.

We complement the regulatory returns with internal data on banks' stress factors and add-ons at monthly frequency. This allows calculation of the firm-specific ILG requirement in each period. Changes in banks' add-ons were relatively rare, as they usually changed only at banks' liquidity reviews.

We also have additional balance sheet items from Bank of England internal data.

[11] Figure 8 and 9 in the appendices shows a sample of the template.

These datasets are used to publish monthly aggregate statistics,[12] but we have access to the bank-level confidential data. This provides us with controls for banks' total assets, capital requirements and capital resources.[13]

Our final bank-level dataset is from QE auctions between banks and the Bank of England. These provide us with reserve-creation data at each bank, and therefore our IV. Section 4.5 discusses in more detail our identification strategy using QE.

Table 1: Bank-specific characteristics

Variable	Units	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
ILG ratio	%	0.628	0.179	0.501	0.622	0.700
Capital req.	%	0.109	0.021	0.089	0.106	0.123
Capital resources	%	0.186	0.049	0.151	0.176	0.201
QE / assets	%	0.0003	0.001	0	0	0
Liquid assets / assets	%	0.189	0.096	0.114	0.139	0.285
ILG req. / assets	%	0.313	0.151	0.201	0.241	0.453
Distance / assets	%	0.033	0.043	0.001	0.035	0.063
log(total assets)	log(£)	25.772	1.194	25.986	26.093	26.300

4.2 Mortgage Data

The mortgage data is from the Product Sales Database (PSD), which is owned by the Financial Conduct Authority (FCA). It records at origination every regulated residential UK mortgage since 2005. Our sample is from 2010-15, when the ILG regime was only active (or binding after its announcement) during this period. This yields a sample of over three million mortgages after matching with the ILG data.[14]

The PSD has a very wide range of loan-level characteristics, which is useful for two reasons.[15] Firstly, we can directly control for loan risk, which may be correlated with both interest rates and liquidity requirements. Second, controls such as borrower age should improve our precision, even if they are likely uncorrelated with liquidity

[12]See https://www.bankofengland.co.uk/statistics/tables.

[13]Capital resources is defined as the sum of Common Equity Tier 1 (CET1), Additional Tier 1 (AT1) and Tier 2 capital.

[14]There are many more banks in the PSD sample relative to the the regulatory data. However, these banks are very small and account for only 2.4% of mortgages.

[15]Further summary statistics of categorical variables could be found in the appendices.

requirements.[16] Our mortgage data also includes borrower location, given by their postcode. This allows us to control for regional demand shocks, which could threaten our identification if correlated with bank liquidity. We run specifications with different fixed effects structures to deal with this.

Table 2: Mortgage-level characteristics: Continuous variables

Variable	Units	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Interest rate	%	3.324	1.040	2.590	3.190	3.980
Risk weight	%	0.145	0.118	0.055	0.107	0.209
Mortgage term	Years	22.111	7.699	16	23	27
log(loan val)	log(£)	11.737	0.649	11.346	11.756	12.155
log(property val)	log(£)	12.276	0.583	11.881	12.231	12.612
log(gross income)	log(£)	10.770	0.567	10.386	10.733	11.112
Impaired status	0/1	0.002	0.048	0	0	0

We merge the bank-level liquidity data to the PSD. We then filter to include only the ILG ratios between zero and two. ILG ratios outside this range are likely reporting errors, as banks typically held much less than 200% of their ILG requirements. This only removes 0.7% of the PSD sample, so outliers were rare and typically very small banks.

4.3 Macro and Funding Cost Data

A large proportion of the UK mortgage market consists of fixed rate mortgages. A fairly typical contract in the sample is a fixed rate mortgage, which resets to a variable rate (usually very uncompetitive, so most households re-mortgage to a different deal) after two years. Therefore, banks use the two-year swap rate (based on overnight indexed swap contracts on SONIA rates) as the risk-free reference rate, which will also be our primary risk-free rate. We also have unsecured funding spreads for the Big 6 banks, which is a common proxy for their marginal funding source as they can raise wholesale funding quickly.

[16]The full set of mortgage level controls we use is: Loan to Value ratio (LTV) bands, Loan to Income ratio (LTI) bands, property value, loan value, mortgage term, risk weight, mortgage rate type (fixed or variable), repayment type (capital and interest, or interest only), borrower gross income, income basis (sole vs joint income), borrower age, borrower type (re-mortgagor, home-mover, or first time buyer), region of the UK (NUTS1), whether their income has been verified, whether the loan is impaired.

Table 3: Aggregate/regional macroeconomic variables

Variable	Units	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Unemployment rate	%	6.956	1.721	5.800	6.500	8.500
2y swap rate	%	0.700	0.259	0.499	0.710	0.840
12m house price growth	%	3.999	5.000	0.530	3.440	7.239
log(house sales)	log(#)	8.820	0.547	8.535	8.920	9.215

We use time fixed effects to deal with aggregate macroeconomic shocks. However we complement these specifications with regional economic controls,[17] to deal with local demand shocks.

4.4 Specification

Our baseline specification is the following, with i mortgages, j banks, t months and q quarters:

$$r^L_{ijt} = \beta_1 r^S_t + \beta_2 dist_{jt} + \beta_3 r^S_t \times dist_{jt} + \zeta(x^1_{jt}, x^2_{ij}) + \alpha_j + \alpha_t + \epsilon_{ijt} \tag{3}$$

where r^S_t is the two-year swap rate at time t. $dist_{jt}$ is bank j's distance from their liquidity requirement in month t. This is normalised by their total assets. x^1_{jt} is a vector of bank-specific controls and x^2_i is a vector of mortgage-specific controls. α_j and α_t are bank and month fixed effects, respectively.

However given our fixed effect structure, note that the first term $\beta_1 r^S_t$ drops out of the regression. This is acceptable as our main coefficient of interest is β_3, which determines whether distance from liquidity requirement affects pass-through of funding cost changes. $\beta_3 > 0$ would suggest more liquid banks pass through more of their changes in funding costs. $\beta_3 < 0$ would suggest more liquid banks pass through less of their changes in funding costs.

Another treatment effect of interest is the direct effect of tougher liquidity requirements, which would be calculated as $\beta_2 + \beta_3 \times \overline{swap}$. If this number is positive, then it suggests more liquid banks charger higher interest rates, and vice versa if negative. We could compare this result with Banerjee and Mio (2018), who found no effect of liquidity requirements on retail lending volumes and rates.

[17] We have regional unemployment, house prices and house sales

We use the two-year swap rate as the key interest rate r_t^S. We argue that this is reasonable as banks use swap rates as risk-free benchmark in their funds transfer pricing curves (Cadamagnani et al., 2015). Another advantage of this is that we do not lose any banks from the sample. However, we do not have any cross-sectional variation in funding costs, therefore our time dummies α_t cause the swap rate to drop out. This prevents us from estimating the absolute level of pass-through, but we can still estimate the effect of liquidity on pass-through (the interaction term). As an extension, we add bank-specific funding cost measures as a robustness check.[18] β_2 and β_3 with swap rates remain our coefficients of interest, however, as monetary policy primarily affects risk-free rates.

As discussed in the next section, it is difficult to make causal claims with OLS due to potential endogeneity. We therefore appeal to IV specifications to generate exogenous variation in liquidity.

4.5 Identification Strategy

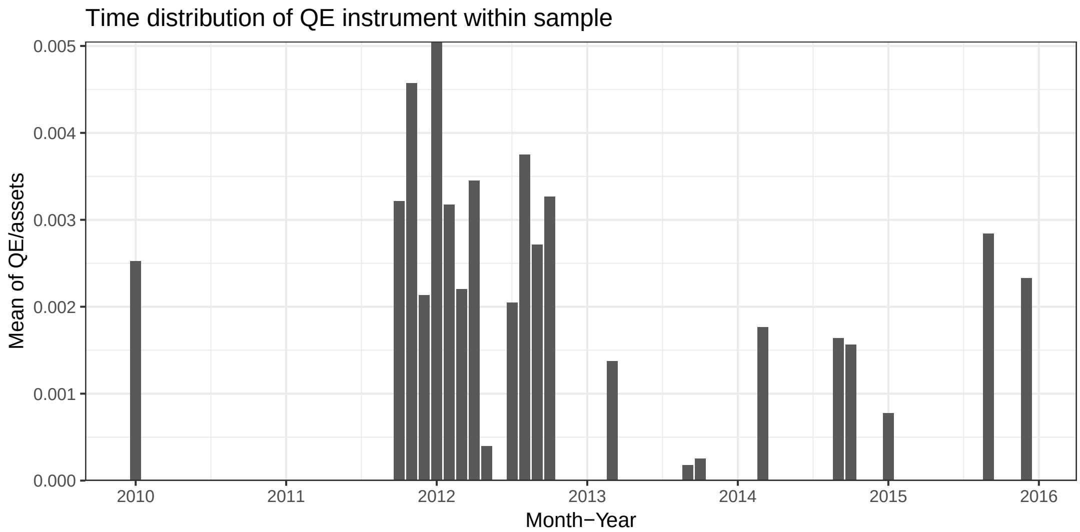
There are multiple potential sources of endogeneity in the banks' liquidity requirements. For example, changes in liquid buffers could result from changing risk appetite over time affecting both liquidity choice and mortgage rates. There may also be measurement error in trying to proxy how tough banks' requirements were from their ILG requirements, because their supervisors or own internal requirements may have actually held them to a different standard. This would be unobservable in our data. We therefore want to generate some exogenous variation (i.e. outside of the individual banks' control) in banks' liquidity using IV.

Our IV is QE asset purchases from the Bank of England. When the Bank of England performed QE purchases, large gilt holders (such as insurance funds) would submit bids in an auction. If their bid was accepted, their gilt was exchanged for a deposit at a client bank. This added both an asset (reserves), and a liability (the deposit itself), to the bank's balance sheet. QE is likely to be endogenous to credit (mortgage) market conditions. However, note that given our fixed effects structure (bank and month), we only need QE's *allocation across banks* to be exogenous.

We instrument for $dist_{jt}$ and the interaction term $r_t^S \times dist_{jt}$ with QE_{jt} and $r_t^S \times QE_{jt}$ (and two lags of each instrument), where QE_{jt} measures the amount of QE reserves received by bank j in period t. We normalise QE_{jt} by total assets, as we also do for the

[18]This restricts the sample to the Big 6 for whom we have CDS spreads.

Figure 2: Aggregated time-series variation of QE purchases in matched sample



*Note: As this is only the PSD-matched sample, this is a **not** an exhaustive sample of all QE purchases. Several other (investment) banks took part in the auction, but they do not have significant (if any) mortgage portfolios.*

endogenous variable $distance_{jt}$. This necessary normalisation could be problematic as it can, in theory, create artificial co-movement between the instrument and the endogenous variables. This would inflate our first stage F-statistics. However, in a battery of robustness tests in Section 5.4, we design a placebo test for the IV to show that this is *not* the case.

We use QE as an IV because the reserves banks received should mechanically increase their distance from requirement. The reserves from QE fully count as liquid assets. However, banks only had to hold *at most* 50% of them to cover the corresponding deposit, as shown in Equation 2. We therefore depart from Butt et al. (2014), who instrument other financial corporations (OFCs) deposits (the non-banks who sold gilts). We instrument distance as this is the actual variable banks had to monitor when they were bound by liquidity requirements.

Our first stage F-statistics are higher than Butt et al. (2014) find for their endogenous variable. Butt et al. (2014) suffer from a weak instrument problem when instrumenting OFC deposits, but QE remains a strong predictor of distance even when including month fixed effects. There could be two reasons: (1) OFC deposits are more noisy, and (2) their regression is bank-level, while ours is mortgage-level. The latter puts more weight on larger banks, who have issued more mortgages, but are also more likely to have participated in QE operations. As Figure 2 shows, there is also plenty of time-series variation in the instrument. The chart plots the *average* QE purchases, normalised by the bank's total assets, *conditional* on QE purchases happening at that bank in a given month. The sample captures the last month of QE1, all of QE2 and QE3, and various (smaller) re-investments that happen in between the major asset purchasing rounds as the gilts mature.

Butt et al. (2014) highlight concerns about instrument relevance, as these OFC deposits are potentially 'flighty'. The OFCs that sold the gilts could rebalance their portfolio towards other assets, and thus the extra liquidity that QE creates is too transitory to have meaningful impact on relaxing their liquidity position relative to requirements. Indeed, portfolio rebalancing was expected to be the main stimulative channel that asset purchases of government bonds has on the real economy (Joyce et al., 2012). Christensen and Krogstrup (2019) use the interesting case of the Swiss National Bank's QE program which only purchased short-term bills, and yet found effects on long-term yields. This was mainly reflected in reduced term premiums, consistent with portfolio balance effects.[19]

To examine this concern, we estimate the impulse responses of the distance variable to a QE shock, via local projections:

$$\text{Bank-level:} \qquad distance_{j,t+h} = \alpha_j + \alpha_t + \beta_h QE_{j,t} + \varepsilon_{j,t} \tag{4}$$

$$\text{Mortgage-level:} \qquad distance_{i,j,t+h} = \alpha_j + \alpha_t + \beta_h QE_{j,t} + \zeta(x^1_{jt}, x^2_{ij}) + \varepsilon_{i,j,t} \tag{5}$$

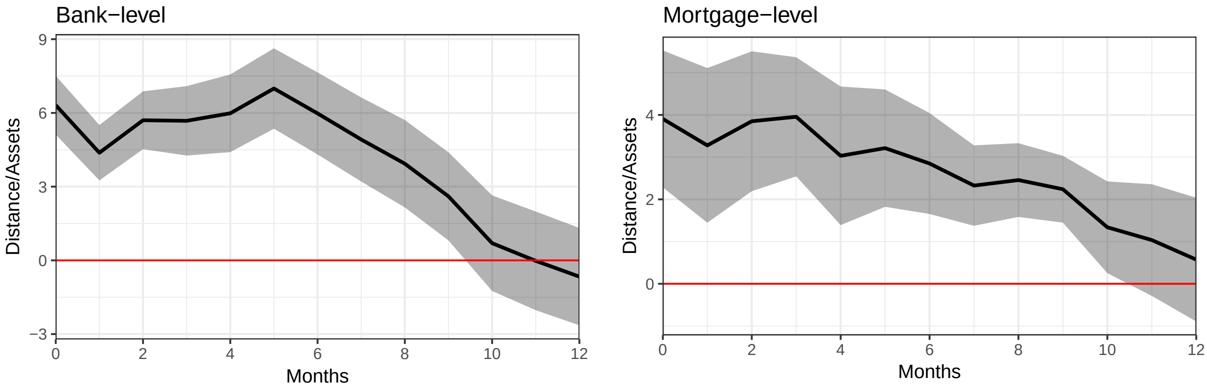
for each horizon $h = \{0, 1, \ldots, 12\}$. We perform this at the bank- and mortgage-level. The latter weights towards the true sample in the second-stage regression. Both sets of local projections have bank and month fixed effects. We also add the same controls $\zeta(x^1_{jt}, x^2_{ij})$ as in the baseline specification for the mortgage-level estimates, but we add no controls for the bank-level. As we argue later on in this section, having no controls should not affect the consistency of the estimate, as the shock is plausibly exogenous.

The impulse responses eventually drift down to zero, as predicted by the portfolio rebalancing channel. However, the instrument (statistically significantly) relaxes the liquidity constraint on impact, and fairly persistently afterwards. The first-stage *F*-statistics of the regressions reported in Section 5 also suggest that the instrument is sufficiently strong.

The primary threat to instrument exogeneity is that QE is designed to stimulate the economy, which is potentially endogenous to banks' lending decisions. However, our

[19] If the effect was through signalling, the fall in yields would appear in the expected rates component instead.

Figure 3: Local projection of distance variable to a QE shock



Note: Shaded areas are 68% confidence intervals. The left chart is an unweighted bank-level panel regression with bank and month FEs in the matched sample. No additional controls are added, and the intervals use Driscoll-Kraay standard errors. The right chart is the mortgage-level regression, with the same additional controls as the regression in Section 5.1 below, and also with bank and month FEs. We use standard errors clustered at the bank-level.

month fixed effects structure should control for the macro environment, so we simply require that the *allocation* of QE across the banks is uncorrelated with their lending decisions. Using the same arguments as Butt et al. (2014), we argue that this is indeed the case for two reasons.

Firstly, the decision to execute the QE transaction to sell a particular gilt is made by the OFCs, rather than the bank itself. The QE transaction is simply executed though the bank. Thus, it is highly unlikely that QE gilt sales at a particular bank are endogenous to their lending.

Secondly, the two possible methods that the QE transactions were conducted also safeguards against endogeneity. First, the OFC directly makes an offer via its bank to the QE auction. These transactions have no balance sheet risk for the executing bank, and are typically carried out by the bank without commission to build or maintain relationships with OFC clients. The consequence is that there would be no price competition to carry out such transactions. Alternately, banks could agree to purchase gilts that OFCs would like to sell, then later bid at an QE auction. This involves balance sheet risk for the bank (and thus expect to be compensated for), but it is unlikely that this decision would be affected by the mortgage business line of the bank.

Additionally, these OFCs are likely to be clients of larger banks, and thus the instrument may be correlated with bank characteristics. Having bank fixed effects should address the (time-invariant) differences across different banks in how they pass-on changes in funding costs. Nevertheless, there is still variation even within the Big 6 lenders in the mortgage markets, and the results are robust to restricting the sample to only these banks.

5 Results

5.1 Baseline Results

Table 4 presents results from our baseline specifications. Columns 1 and 2 are the OLS specifications, the latter with month fixed effects. Columns 3 and 4 are our QE IV specifications, again the latter with month fixed effects. All specifications include firm fixed effects and the controls discussed in Section 4.4. We report standard errors clustered at a bank-level.[20]

Our OLS results with month FEs suggest no direct effect from liquidity as the coefficient is not significant. The coefficient on the liquidity – swap rate interaction is negative and significant, suggesting banks with more surplus liquidity pass through less of their changes in funding costs. However, due to potential endogeneity (discussed in Section 4.5), we cannot interpret the OLS results as causal.

Our baseline IV results (from Column 4) show that banks with more surplus liquidity charge statistically significantly higher mortgage rates. This provides support for the NIM-targeting hypothesis: more liquid banks need to compensate for the low return on liquid assets by charging higher mortgage interest rates.

Similarly, the IV specifications all show that banks with more surplus liquidity pass through less of their changes in risk-free rates. Coefficients on the interaction term are negative and significant at the 1% level across all specifications. Again this supports the NIM-targeting hypothesis. Suppose there is an interest rate cut: banks want to expand their credit supply by cutting mortgage rates, but more liquid banks could be less able to do because they need to maintain their NIM with higher mortgage rates.

Table 4 shows our results are robust to adding month fixed effects, which removes the threat of endogeneity from monetary policy feedback. We use only the variation

[20]The robustness section includes two-way clustered standard errors (at a bank and month level). We opt to use bank-level clustering as when computing the first-stage F-statistics, we encounter some of the large-sample, many fixed effects, numerical approximation issues as documented in Cameron et al. (2011) with multi-way clustering. Nevertheless, the main conclusions on statistical significance do not change with two-way bank-month clustering.

Table 4: Baseline results

	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)
Pass-through and liquidity				
$swap_t$	0.389^{***}		0.817^{***}	
	(0.061)		(0.150)	
$liquidity_{jt}$	3.885^{**}	1.519	4.459	3.797^{***}
	(1.794)	(0.924)	(5.978)	(1.110)
$liquidity_{jt} \times swap_t$	-3.621^{***}	-1.565	-14.800^{**}	-3.095^{***}
	(1.135)	(0.969)	(6.632)	(0.982)
Selected mortgage characteristics				
$\log(loan\_val_i)$	-0.103^{***}	-0.104^{***}	-0.104^{***}	-0.103^{***}
	(0.020)	(0.018)	(0.024)	(0.018)
$\log(property\_val_i)$	-0.186^{***}	-0.165^{***}	-0.186^{***}	-0.165^{***}
	(0.031)	(0.033)	(0.030)	(0.033)
$\log(gross\_income_i)$	0.053^{***}	0.063^{***}	0.047^{***}	0.063^{***}
	(0.019)	(0.020)	(0.017)	(0.020)
$mortgageterm_i$	0.006^{**}	0.006^{**}	0.005^{*}	0.006^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
$riskweight_i$	0.418	0.900^{*}	0.442	0.898^{*}
	(0.597)	(0.530)	(0.613)	(0.541)
Selected bank controls				
$capitalrequirements_{jt}$	2.835^{*}	0.653	8.703^{***}	-0.261
	(1.447)	(0.869)	(3.125)	(0.729)
$capitalresources_{jt}$	-1.718	-0.420	-2.722^{*}	-0.498
	(1.257)	(0.425)	(1.474)	(0.454)
$\log(totalassets_{jt})$	-0.241	0.022	1.229	-0.011
	(0.431)	(0.246)	(1.132)	(0.264)
Regional macroeconomic conditions controls				
$unemp_{rt}$	0.235^{***}	0.009	0.210^{***}	0.008
	(0.028)	(0.006)	(0.024)	(0.005)
$\log(housesales_{rt})$	-0.538^{***}	0.216^{**}	-0.434^{***}	0.200^{***}
	(0.059)	(0.085)	(0.118)	(0.077)
$housepricegrowth_{rt}$	0.008^{**}	0.004	-0.013	0.003
	(0.004)	(0.003)	(0.009)	(0.003)
Additional bank, region, mortgage controls	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Month FE	N	Y	N	Y
F-stat: Liquidity			110.77	30.77
F-stat: Interaction			24.11	17.35
Observations	3,204,180	3,204,180	3,192,346	3,192,346

Standard errors clustered around banks $\quad {}^{*}p < 0.1$; ${}^{**}p < 0.05$; ${}^{***}p < 0.01$

Note: The additional mortgage-specific controls are loan-to-value bands, loan-to-income bands, loan advance type, single or dual income basis, borrower age, fixed or variable rate type, repayment type (interest only, or also with principal), region, income verification status, loan impairment status. The additional bank-level control is the amount of pre-positioned collateral.

in QE across banks, rather than the average level of QE. The QE instrument is highly relevant with a first stage F-statistic of ≈ 30 on the liquidity variable.[21]

Our baseline results have a wide range of bank-level and mortgage-level controls. They also have a standard fixed-effects setup, with both bank and month fixed effects. The latter will soak up aggregate macroeconomic shocks. However, it is possible that regional demand shocks may differentially affect both mortgage rates and more liquid banks. Table 5 presents results from our attempts to control for regional activity.

Column 1 shows the baseline results from Table 4. Column 2 modifies the FE structure by interacting the region fixed effects with the month fixed effects. The variation used here is comparing the mortgage rates by more or less liquid banks within the same region and month. This should account for any regional demand effects. Column 3 further deepens the FE structure by using month-postcode combinations, and thus absorbs postcode specific demand effects.[22]

We have the same pattern of results after each method of controlling for regional demand shocks – a positive direct impact of liquidity and negative impact on pass-through. Column 3 is likely our best-identified specification, as we are using only the variation in mortgage rates within a given postcode *and* time period. Therefore, demand shocks within a given postcode would have to be correlated with liquidity in order to bias our results. Moreover, they would have to be correlated with specifically the variation in liquidity generated by the QE IV, which is unlikely.

5.2 Buffers vs Requirements

Banks may treat the liquidity needed to meet their requirement differently to surplus liquidity above the requirement. Unlike previous papers, we have data on both liquid asset holdings *and* liquidity requirements so we can analyse this question. Table 6 shows these results. Column 1 presents results from our baseline specification, where our liquidity variable is distance. In Column 2 we re-specify the liquidity variable to banks total liquid assets, rather than their distance. Column 3 re-specifies the liquidity variable to just the liquidity needed to meet regulatory requirements.

[21] Like Butt et al. (2014), the first-stage falls dramatically when month FEs are added – suggesting that there is a significant time-series variation in QE purchases, that are soaked up by month FEs. However, unlike their paper, our instrument remains highly relevant.

[22] The mean number of mortgages per 3-digit postcode is 1,783, and the median is 1,552. The combination between postcode-month fixed effects generates just over individual 200,000 fixed effects.

Table 5: Controlling for Regional Demand

	Time/Area FE		
	Month	Month-Region	Month-Postcode
	(1)	(2)	(3)
Pass-through and liquidity			
$liquidity_{jt}$	3.797***	3.880***	3.707***
	(1.110)	(1.105)	(1.079)
$liquidity_{jt} \times swap_t$	−3.095***	−3.161***	−3.023***
	(0.982)	(0.961)	(0.927)
Selected mortgage characteristics			
$\log(loan\_val_i)$	−0.103***	−0.103***	−0.104***
	(0.018)	(0.018)	(0.017)
$\log(property\_val_i)$	−0.165***	−0.163***	−0.158***
	(0.033)	(0.033)	(0.032)
$\log(gross\_income_i)$	0.063***	0.062***	0.063***
	(0.020)	(0.020)	(0.021)
$ageborrower_i$	0.0005	0.0005	0.0004
	(0.001)	(0.001)	(0.001)
$mortgageterm_i$	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)
$riskweight_i$	0.898*	0.901*	0.896*
	(0.541)	(0.543)	(0.515)
Selected bank controls			
$capitalrequirements_{jt}$	−0.261	−0.295	−0.304
	(0.729)	(0.724)	(0.669)
$capitalresources_{jt}$	−0.498	−0.514	−0.505
	(0.454)	(0.455)	(0.424)
$\log(totalassets_{jt})$	−0.011	−0.003	−0.010
	(0.264)	(0.262)	(0.245)
Regional macroeconomic conditions controls			
$unemp_{rt}$	0.008		
	(0.005)		
$\log(housesales_{rt})$	0.200***		
	(0.077)		
$housepricegrowth_{rt}$	0.003		
	(0.003)		
Additional bank, region and mortgage controls	Y	Y	Y
Bank FE	Y	Y	Y
F-stat: Liquidity	30.77	30.26	29.34
F-stat: Interaction	17.35	17.23	19.97
Observations	3,192,346	3,192,346	3,192,346

Standard errors clustered around banks — $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note: The additional mortgage-specific controls are loan-to-value bands, loan-to-income bands, loan advance type, single or dual income basis, fixed or variable rate type, repayment type (interest only, or also with principal), region, income verification status, loan impairment status. The additional bank-level control is the amount of pre-positioned collateral.

Table 6: Buffers vs Requirements

	Liquidity measure		
	Distance	Liquid Assets	Requirements
	(1)	(2)	(3)
Pass-through and liquidity			
$liquidity_{jt}$	3.797***	1.947**	0.412
	(1.110)	(0.791)	(0.434)
$liquidity_{jt} \times swap_t$	−3.095***	−0.860**	−1.345*
	(0.982)	(0.366)	(0.747)
Selected mortgage characteristics			
$\log(loan\_val_i)$	−0.103***	−0.104***	−0.102***
	(0.018)	(0.018)	(0.018)
$\log(property\_val_i)$	−0.165***	−0.164***	−0.167***
	(0.033)	(0.033)	(0.034)
$\log(gross\_income_i)$	0.063***	0.063***	0.065***
	(0.020)	(0.020)	(0.021)
$ageborrower_i$	0.0005	0.0005	0.0004
	(0.001)	(0.001)	(0.001)
$mortgageterm_i$	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)
$riskweight_i$	0.898*	0.959*	0.855*
	(0.541)	(0.562)	(0.476)
Selected bank controls			
$capitalrequirements_{jt}$	−0.261	−0.034	−1.811
	(0.729)	(0.782)	(1.620)
$capitalresources_{jt}$	−0.498	−0.318	−0.066
	(0.454)	(0.420)	(0.530)
$\log(totalassets_{jt})$	−0.011	−0.040	−0.221
	(0.264)	(0.175)	(0.234)
Regional macroeconomic conditions controls			
$unemp_{rt}$	0.008	0.007	0.009
	(0.005)	(0.005)	(0.006)
$\log(housesales_{rt})$	0.200***	0.194**	0.244**
	(0.077)	(0.076)	(0.100)
$housepricegrowth_{rt}$	0.003	0.003	0.004
	(0.003)	(0.003)	(0.004)
Additional bank, region, mortgage controls	Y	Y	Y
Bank and month FE	Y	Y	Y
F-stat: Liquidity	30.77	9.41	11.45
F-stat: Interaction	17.35	36.86	15.94
Observations	3,192,346	3,192,346	3,192,346

Standard errors clustered around banks $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note: The additional mortgage-specific controls are loan-to-value bands, loan-to-income bands, loan advance type, single or dual income basis, fixed or variable rate type, repayment type (interest only, or also with principal), region, income verification status, loan impairment status. The additional bank-level control is the amount of pre-positioned collateral.

There is indeed some evidence that banks treat surplus liquidity differently than liquidity needed to meet requirements. Column 3 shows no significant impact of the liquidity needed to meet requirements on either mortgage pricing or pass-through. This may be because banks' treasuries recognise the costs associated with breaching liquidity requirements. Therefore, transfer pricing does not appear to penalise it, unlike the treatment of surplus liquidity. Moreover, the insignificant results are not driven by ballooning standard errors, but near-zero and precisely estimated coefficients. The standard errors actually become smaller when we re-specify the distance variable to required liquidity.

The results from Column 2 with just liquid assets are qualitatively the same as the baseline result.[23] Both the direct and indirect effects of total liquidity are still positive and significant at the 5% level. However, the magnitudes are significantly smaller. This is consistent with the results in Column 3 – that banks do not penalise the liquidity needed to satisfy requirements – as Column 2 is effectively an average between Columns 1 and 3. This implies that total liquidity affects pass-through less than surplus liquidity. At this point, it is important to stress that the identification strategy is not well-suited to study the impact of liquidity *regulations* on credit supply or pass-through, as we use liquidity variation driven by QE rather than regulations. This question would need an understanding how banks react to higher liquidity requirements. We refer the reader to Reinhardt et al. (2020), a complementary study that uses an identification strategy that exploits exogenous variation in requirements (though they primarily look at cross-border lending).

Nevertheless, our results are fully consistent with other empirical studies of liquidity requirements, which find little direct impact on retail lending. Banerjee and Mio (2018) also studied UK banks under the ILG regime. While they found banks raised their liquid assets in response, they find no change in retail lending. Bonner and Eijffinger (2016) find similar results for Dutch banks subject to the LCR. Furthermore, both studies also only use bank-level data, which masks risk-shifting effects that require more granular data. This result highlights the importance of using liquidity data that can distinguish between liquid asset holdings and requirements. This is ever more important in today's Basel 3 environment, as banks' liquidity management practices must take into account of these requirements. The vast majority of the literature on liquidity, while equipped with excellent loan-level data that allows a sat-

[23] To iterate, the liquid assets here includes any repo positions the bank may have over the 90-day horizon.

urated fixed effects structure for credit supply-demand identification, do not observe liquidity requirements nor liquidity positions net of repos.

5.3 Risk-taking behaviour

The NIM-targeting hypothesis implies that banks should respond to higher liquidity requirements by charging higher loan rates. If the treasury is simply trying to maintain a headline NIM, they may shift into riskier loans ("risk shifting"). This would imply that while higher liquidity holdings reduce banks' liquidity risk, it may also raise their assets' credit risk. They do so contracting the credit supply of lower risk loans (by increasing the interest rate charged), while maintaining supply for the higher risk (which are naturally higher yielding) loans. In other words, the risk 'term' structure of loans become flatter — the rise in interest rates for a given increase in a mortgage's riskiness, is reduced.

To analyse this, we use the 'reduced form' regression (that is, using QE as a regressor directly, as opposed to as an instrument). It is easier to use the reduced form regression, as it becomes more difficult to specify the first stage if we interact the distance variable further.[24] While it becomes more difficult to map the result quantitatively to the liquidity measures, but the direction of the coefficients are still informative as given our arguments for QE's exogeneity remain valid.

$$\begin{aligned} r^L_{ijt} = \beta_2 QE_{jt} + \beta_3 r^S_{jt} \times QE_{jt} + \zeta(x^1_{jt}, x^2_{ij}) + \alpha_j + \alpha_t + \\ \sum_{k=1}^{K-1} \beta^k_4 QE_{jt} \times LTVband^{(k)}_i + \sum_{k=1}^{K-1} \beta^k_5 r^S_{jt} \times QE_{jt} \times LTVband^{(k)}_i + \epsilon_{ijt} \end{aligned}$$

We use LTV bands as our main measure of risk for several reasons. Firstly, the UK mortgage market is strongly segmented in LTV bands, thus the impact of liquidity may be heterogeneous across these separate markets. The LTV bands also gives rise to natural thresholds for the regression, unlike other measures like risk weights. Secondly, we find highly non-linear and non-monotonic effects that would unlikely be captured by a simple interaction with the LTV level. The natural thresholds then naturally lead to allow us to examine these non-linear effects. Lastly, and related to the market segmentation reason, the rise in riskiness (as measured by risk weights) as

[24]We would need many separate first stages as there are many LTV buckets, which are our risk measure.

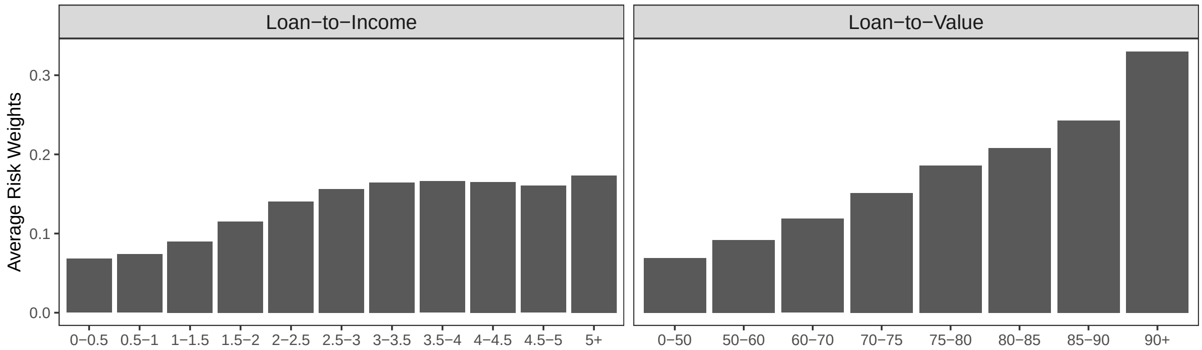


Figure 4: Average risk weights by LTI bands (left) and LTV bands (right)

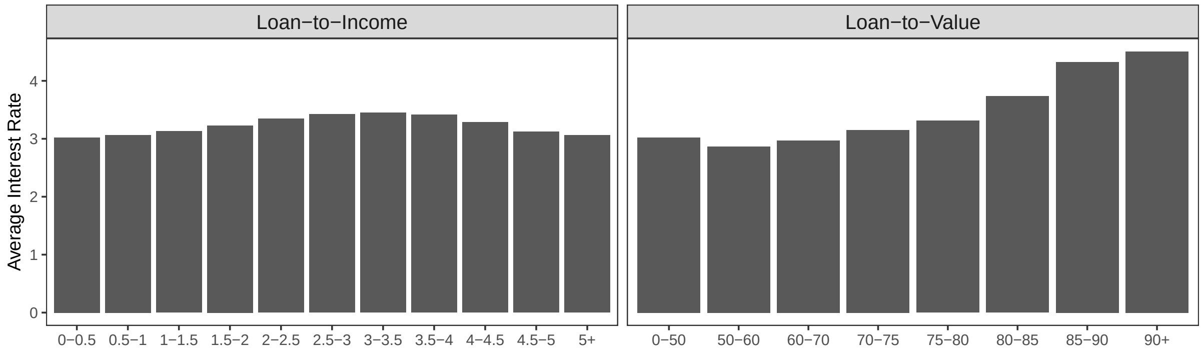


Figure 5: Average interest rates by LTI bands (left) and LTV bands (right)

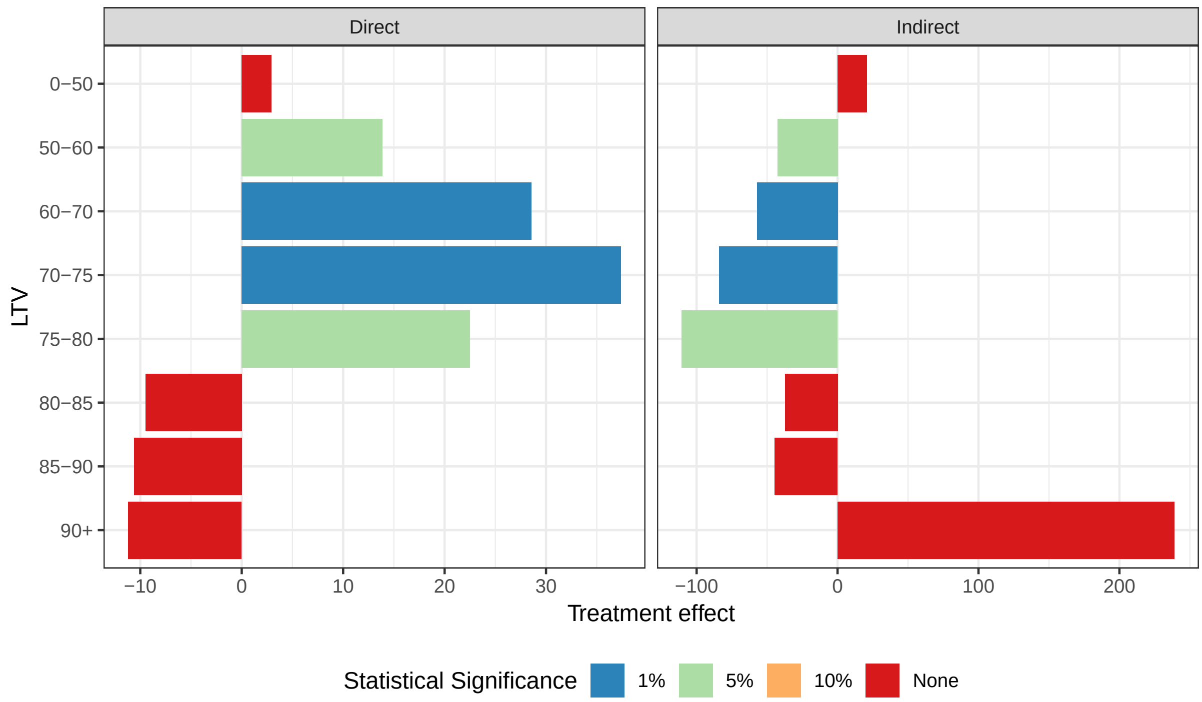
you increase LTV bands is much stronger when compared to LTI bands (Figure 4).[25] This would give us the most variation in riskiness to help identify the heterogeneous effects of liquidity across the risk spectrum.

If the β_4 coefficients associated with lower LTV ratios were *positive*, that would provide further evidence that banks with more liquidity charge higher interest rates on less risky loans, thereby risk-shifting towards higher risk lending. Likewise, if the β_5 coefficients associated with lower LTV ratios were *negative*, this suggests that the reduction in the pass-through from risk-free rates were concentrated in the lower risk loans. Figure 6 shows the results of this analysis: on the left, we show $\beta_2 + \beta_4$ (the direct effect of liquidity, at a given LTV band), and on the right $\beta_3 + \beta_5$ (the indirect effect). The colour codes also indicate the statistical significance from a Wald test of the sum of the respective coefficients.[26] Note that for ease of interpretation of the direct effect, we run a regression without the $r^S_{jt} \times QE_{jt}$ and $r^S_{jt} \times QE_{jt} \times LTVband_i$

[25]Reflective of the same reason, Figure 5 shows that average interest rates barely increase in higher LTI bands, but they do with LTV bands.

[26]The full regression coefficients can be found in the appendix.

Figure 6: Interactions between QE_{jt} (left) and $QE_{jt} \times r_t^F$ (right) with LTV bands



terms first, and then run the full regression for the indirect effects.

Figure 6 show that the main results that we find – both on the direct and indirect effects – are concentrated particularly in the lower LTV ratios (between 50% to 80%). This leads to two channels on how banks attempted to increase their net interest margins. Firstly, banks tightened credit supply in these lower-risk loans by increasing their interest rates, composing around 48% of mortgage lending in our sample, directly helping to increase their NIMs. Secondly, they did not correspondingly tighten supply in higher LTV mortgages.[27] This also helps to increase NIMs as these higher-risk mortgages are already higher-yielding mortgages. Therefore, this constitutes some indirect evidence of risk-shifting, as this behaviour is consistent with substitution towards higher risk assets.[28]

This mechanism – the flattening of the risk structure of interest rates – can be seen as a form of a risk-taking channel of liquidity-increasing unconventional monetary policy. It is known that the main transmission channel of QE would be through

[27] In fact, the regressions indicate a slight expansion in credit supply in these higher risk loans, albeit they are statistically insignificant.

[28] Direct evidence would require a credit registry: the probability of banks granting higher risk loans would be higher.

portfolio rebalancing of non-banks and policy signalling mechanisms, rather than through increasing bank lending per se (Joyce et al., 2012; Haldane et al., 2016). Because of time fixed effects, we do not examine the potential effects of QE on risk-free rates through the policy signalling channel (which only has time-series variation). Instead, the evidence presented in this paper uses cross-sectional variation, which show that pass-through in higher LTV mortgages is *relatively* higher than those with lower LTVs. This risk taking channel occurs through the creation of liquidity in the presence of NIM-targeting incentives of banks.

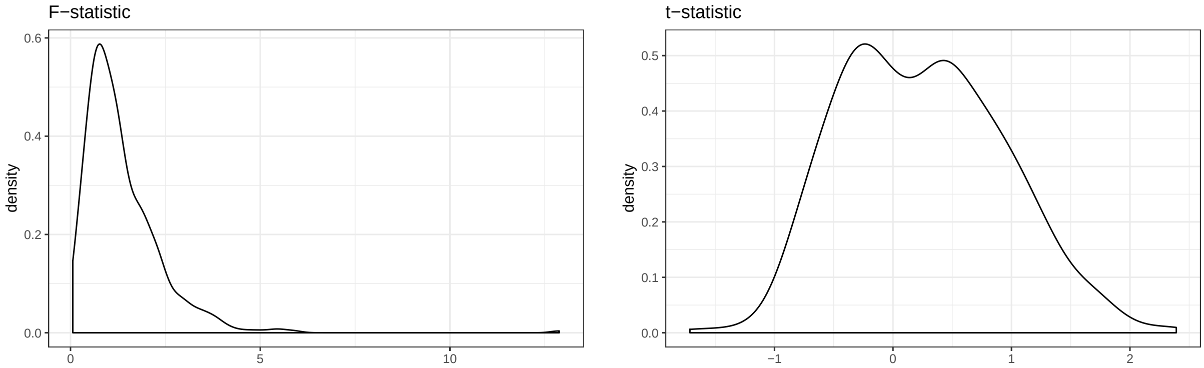
This result appears to be consistent with the reaching-for-yield responses of money market funds to QE (Di Maggio and Kacperczyk, 2017; Chodorow-Reich, 2014). In response to the low interest rates and administrative costs, money market funds invested in riskier asset classes in an attempt to avoid waiving fees. This reaction attenuated the negative impact on profitability. Kurtzman et al. (2018) also found similar results, which used the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). Banks with greater exposure to mortgage-backed securities (MBS) (which was subsequently purchased through QE) loosened lending standards after QE1 and QE3. However, this primarily occurred through a net-worth channel instead, as the Federal Reserve's QE program pushed up on the prices of banks' MBS holdings. This mechanism is somewhat different as the MBS were purchased directly from banks, where the Bank of England's asset purchases were from non-bank financial institutions – and thus had no effect on net worth. Therefore, our reaching-for-yield mechanism of QE-driven liquidity creation and its interaction to banks' liquidity management is complementary to Kurtzman et al. (2018).

5.4 Robustness: First Stage Relevance Placebo Test

Our instruments seem highly relevant as the first stage F-statistics from Table 4 greatly exceed the critical values from Sanderson and Windmeijer (2016). However, we scale both our liquidity measure (the endogenous variable) and our instruments by total assets as a necessary normalisation. Therefore, changes in total assets could drive a spurious relationship between these variables that is from the normalisation.

To analyse this issue, we design a placebo test. We replace the QE instrument with a placebo random variable that mimics the statistical properties of the IV. Firstly, we draw a sequence of zeros and ones, with the probability of drawing a zero equal

Figure 7: Distribution of results from placebo regressions



to their proportion in the sample (80.4%).[29] Second, we replace the ones with a normally-distributed random variable that has the same mean and variance of the QE instrument (*conditional on* the QE instrument being strictly positive). If the placebo regressions produce high F-statistics, this would indicate that changes in total assets are driving the instrument relevance, rather than a true predictive relationship between the IV and endogenous variable.

We perform 500 replications of the placebo regression, then plot the distribution of the first stage F-statistics (Figure 7). The median F-statistic is around 1, suggesting that the placebo is a weak instrument and that changes in total assets do not drive our strong first stage. We also provide test statistics of the coefficient on the liquidity variable (β_2) from the second stage regressions. These are centred close to 0, showing our results would not hold with irrelevant IVs.

5.5 Other Robustness

Table 10 shows results from our tests of specification robustness. Column 1 lags the independent variables by a period to check whether our results could be driven by some form of reverse causality. Columns 2 and 3 restrict the sample to the Big 6 UK banks, who account for around 80% of mortgages. In Column 3, we also control for firm-specific funding cost shocks, measured by their 5y unsecured funding spread.[30] Column 4 interacts the swap rate with all our control variables, to check

[29]The high percentage of zeros is also a defence against the normalisation driving the high first stage F-statistics. If QE is zero, the normalised QE instrument will also be zero and therefore the normalisation drives no variation in most observations.

[30]We use the same series as Cadamagnani et al. (2015). It is the secondary market spreads for five-year euro senior unsecured bonds (where available, if not, we use the nearest maturity as a proxy). As

the pass-through effect is not driven by something other than liquidity (with the exception of LTV bands, which we discuss extensively in the previous subsection why that matters). Our main results are robust to all these specification changes, further supporting the NIM-targeting hypothesis.

6 Economic Significance and Policy Implications

We have shown that our results are statistically significant, but for policy relevance we also need to analyse their economic significance. We use results from Column 1 of Table 6 as this is our baseline specification. In this section, we also discuss the main policy takeaways from our results.

Firstly, the increase in liquidity from the start to the end of the sample raised mortgage rates by 15 bps. In comparison, the same impact could be generated by just a 1.3pp increase in capital requirements (Benetton et al., 2017), or 1.1pp increase (Meeks, 2017). These are modest changes relative to the increase in capital requirements since the crisis. This is also a result reminiscent of other studies that find little to no effects on bank lending by QE that focused on U.S. Treasuries (Rodnyansky and Darmouni, 2017; Chakraborty et al., 2019).[31]

However, the impact of liquidity on pass-through may be much larger. We estimate that the increase in liquidity in the same period of time reduced pass-through by 28pp. In other words, banks now pass-through 28 bps less of a 100 bps cut in swap rates, relative to what they have done previously. Note that as we fully absorb the time series variation in favour of cleaner identification, we do not estimate the absolute level of pass-through.[32]

Nevertheless, we are still able to arrive at useful conclusions for the conduct of monetary policy, and in particular, the interaction of conventional and unconventional monetary policies. With natural real rates that are likely to remain depressed, unconventional monetary policies could be used more often around the zero lower bound (Bernanke, 2020). Our results indicate that the rise of liquidity of banks' balance sheets

the euro money markets are far more liquid than in sterling, UK banks typically tap the euro market as their marginal funding source. Thus, we think that this would be the best measure of their *marginal* costs.

[31] They find stronger effects on bank lending by Federal Reserve's QE1 and QE3, which focused more on mortgage-backed securities.

[32] Other identification strategies that do not remove the time series variation but isolate monetary policy shocks are needed.

may have significantly weakened pass-through of risk-free rates to mortgage rates – an important component of the credit channel of monetary policy, and especially to consumption behaviour (Cloyne et al., 2020). It is worthwhile re-emphasising that this paper does *not* imply QE policies were counter-productive. The liquidity-creation effect of QE simply do not appear to reinforce the transmission of conventional monetary policy, but other studies have demonstrated QE's effectiveness from its direct effects through policy signalling and reducing term premia instead.

However, even if interest rate pass-through is *ceteris paribus* weaker via the increase in bank liquidity, the mechanism that we find most consistent with the results – NIM targeting behaviour – also suggest that other unconventional policies such as bank funding schemes that lower the cost of funds and increase NIMs can reinforce interest rate pass-through. Examples of these policies include the European Central Bank's targeted longer-term refinancing operations (TLTROs) and the Bank of England's Term Funding Scheme (TFS, and more recently, TFSME – with additional incentives for small- and medium-sized enterprises), amongst others.

A question remains on the link between QE and bank liquidity, beyond the mechanical relationship we previously described. Could the build-up of liquidity over the ILG regime be simply preparations for a tougher LCR regime? We do not think that is the complete story. At first glance the LCR appears tougher, requiring banks hold 100% of requirements, instead of 50% in the ILG. However, the ILG's criteria for HQLA is much stricter (only central bank reserves and AAA-rated sovereign bonds) than the LCR. Additionally, while the LCR requires banks to have sufficient liquidity *at the end* of the 30-day stress window, the ILG required that banks be liquid for *every single day* of a 90-day stress window. Furthermore, Chart D in the December 2019 *Financial Stability Report* shows that continued to build on liquid asset buffers far above 100% since 2016 (Bank of England, 2019).[33] This is alongside the asset purchases in the August 2016 stimulus package, subsequent to the UK's EU membership referendum.

Another possibility is that liquidity management practices became more conservative. Arnould and Lallour (2019) argue disclosure requirements create incentives to build liquidity buffers far above requirements, from the perception that liquid asset buffers are partially unusable in times of stress. However, QE purchases still affect aggregate liquidity, on top of any liquidity banks themselves choose to hold. If portfolio balancing happens (OFCs buying another asset after selling the government bonds),

[33]There is a slight dip since 2019, but the *Report* attributes it to methodological changes, which resulted in banks reclassifying some deposits into higher outflow categories.

the reserves simply end up at another bank. Thus, our main conclusion remains the same – the liquidity created from asset purchases and from a large central bank balance sheet further adds to aggregate bank liquidity, and leads to the effects on interest pass-through we have described.

7 Conclusion

In this paper, we estimate the impact of higher liquidity of the banking system on pass-through of risk-free rates to lending rates. The UK's unique post-crisis regime is ideal for such analysis: we were able to combine a novel dataset on UK banks' post-crisis liquidity requirements with granular near-universal data on UK residential mortgages originated since 2005 and transaction-level QE auction data. Previous papers analysing liquidity typically did not have data on the requirements themselves.

We believe we have identified causal impacts of bank liquidity. We have a strong IV to generate variation in liquidity that should be unrelated to both local demand shocks and omitted variables. Furthermore, our IVs affect different banks in different time periods, allowing us to control directly for aggregate shocks with regional and time fixed effects. Our results are consistent across different fixed effects structures and specifications of our independent variable.

Our main finding is that higher post-crisis liquidity has weakened the pass-through of risk-free rates to lending rates. Taking the rise in liquidity at the sample, banks passed through 28 bps less of a 100bps rate cut, relative to what they would have done in the past. Therefore, interest rate pass-through for a part of the credit channel may be less effective *relative to pre-crisis*. We also find that the higher liquidity has raised mortgage interest rates, but only modestly relative to other benchmarks (such as the credit supply effects of higher capital requirements). We estimate the rise in liquidity within the sample period has raised rates by 15 bps. Furthermore, we find that the effects on credit supply and interest rate pass-through to be in liquidity over and above requirements, and not on the requirements themselves.

A particularly interesting result is that excess liquidity encourages reaching-for-yield behaviour. Banks with more low-yielding liquidity shift their portfolio towards riskier, higher-yielding mortgages, by contracting the supply of lower risk, lower-yielding mortgages. This is consistent with the explanation that banks attempt to preserve their net interest margins. From this result, an indirect – but important –

monetary policy takeaway is that policies that increase bank profits appear to increase pass-through of risk-free rates to lending rates. Funding schemes that provide banks with relatively low-cost funding, achieve exactly that.

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A Example templates of FSA047 and FSA048 forms

Figure 8: Sample of FSA047 return

FSA047
Daily Flows
Part 1 - Memo Items

		B	C	...	*n*
		Date + 1	Date + 2	...	*Date + n*
1	Non-dated capital resources				
2	Bank of England liquidity facilities				
3	Other central bank liquidity facilities				
4	Prior period's peak intra-day collateral used for UK settlement and clearing systems				
5	Prior period's peak intra-day collateral used for settlement and clearing systems outside the UK				

Part 2 - Security, transferable whole-loan and commodity flows

		A	B	...	*n*
		Date + 1	Date + 2	...	*Date + n*
6	Liquid asset buffer-eligible securities			...	
7	Other high quality central bank, supranational and central government debt			...	
8	US GSE/GSA securities			...	
9	Own-name securities and transferable whole-loans			...	
10	High quality asset-backed securities			...	
11	High quality covered bonds				
12	Securities issued by group entities			...	
13	High quality corporate bonds (UK credit institutions)			...	
14	High quality corporate bonds (non-UK credit institutions)			...	
15	High quality corporate bonds (excluding credit institutions)			...	
16	Equities included in major indices			...	
17	Other securities and commodities			...	

Figure 9: Sample of FSA048 return

		A	B	C	D	E	F	G	H	I	J
Part 2 - Security, transferable whole-loan and commodity flows		Unencumbered position	Open maturity	<= 2 weeks	2 weeks <=1 month	> 1 month <= 3 months	> 3 months <= 6 months	> 6 months <= 1 year	> 1 year <= 2 years	> 2 years <= 5 years	> 5 years
6	Liquid asset buffer-eligible securities										
7	Other high quality central bank, supranational and central government debt										
8	US GSE/GSA securities										
9	Own-name securities and transferable whole-loans										
10	High quality asset-backed securities										
11	High quality covered bonds										
12	Securities issued by group entities										
13	High quality corporate bonds (UK credit institutions)										
14	High quality corporate bonds (non-UK credit institutions)										
15	High quality corporate bonds (excluding credit institutions)										
16	Equities included in major indices										
17	Other securities and commodities										
Part 3 - Wholesale asset cash flows		Non defined maturity	Repo/Reverse with open maturity								
18	Designated money market funds										
19	Liquid asset buffer-eligible central bank reserves and deposits										
20	Lending to group entities										
21	Lending to UK credit institutions										
22	Lending to non-UK credit institutions										
23	Own account security cash flows										
24	Notional flows of own-name securities and transferable whole-loans										
25	Reverse repo (items reported in line 6)										
26	Reverse repo (items reported in lines 7 and 8)										
27	Reverse repo (items reported in lines 10 and 11)										
28	Reverse repo (items reported in lines 13, 14 and 15)										
29	Reverse repo (items reported in line 16)										
30	Reverse repo (items reported in lines 9, 12 and 17)										
Part 4 - Other asset cash flows											
31	Non-retail lending exposures										
32	Retail lending exposures										
33	SSPE asset cash flows										

B PSD data definitions and cleaning

B.1 Cleaning procedure

The raw loan level data from the PSD requires extensive cleaning to be useful in our specification. We use a similar procedure to Benetton et al. (2017). First, we remove all lenders who are not banks or building societies as they are not subject to liquidity regulation. Around 25% of mortgages have missing interest rates because, for some of the sample period, reporting interest rates was optional. We therefore remove these observations too. We exclude some lenders entirely, because they had merger activity either during or shortly after the crisis.[34] We also exclude some unusual mortgage types, because they belong to very diffferent markets to classic owner-occupier mortgages.[35] Finally we winsorised some key variables according to prior definitions, as reporting issues led to some extreme values. This removed less than 1% of the sample in total.

We adjust some LTV bands because separate data on up-front fees is missing during much of the sample period. These are instead included in the value of the loan, but this will not be in the lender's real LTV calculation. Therefore we may miscalculate the true LTV. We adjust the LTV band thresholds to compensate: loans within the bottom 0.5 - 1% of a given band are actually moved into the band below.[36]

We next merge the PSD with several bank-level datasets. First, we estimate historic loan risk weights using a survey of IRB lenders conducted by the FCA. Each bank provides their historic average risk weight, aggregated by year and LTV band. For SA lenders, we use a lookup table form Basel 1 that assigns loans a risk weight based on their LTV. Capital ratios are from historic BoE regulatory returns, which are quarterly frequency. Liquidity ratios are also from regulatory returns, which we detail further in Section 3.1. These are weekly frequency for large firms and monthly for small firms, so we aggregate to monthly frequency for the large banks. There are some data quality issues with the liquidity returns, particularly during the earlier part of the ILG regime. We therefore winsorize these to exclude firms with implausibly extreme ILG ratios.

[34]These include Northern Rock, The Mortgage Works and UCB. Observations from Lloyd's Banking Group and TSB were excluded in the early part of the sample.

[35]We exclude lifetime mortagages, business mortages, council/social tenants buying, not known and other. The remaining categories are first-time buyers, home-movers and remortgagors.

[36]For example: we put a mortgage with LTV of 75.2% in the 70-75% band.

We match each loan to their closest bank-level variables and risk weight by date. The implicit assumption in doing so is that banks price mortgages based on their current state, rather than some forecast. In total, the cleaning and merging reduced our sample size from 14m to 3.2m. By far the biggest impacts were from missing data, excluding non-banks and excluding firms not subject to liquidity requirements.

B.2 Further PSD summary statistics

Table 7: Mortgage-level characteristics: LTV and LTI

	Units	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
LTV band						
0-50	0/1	0.26	0.44	0.00	0.00	1.00
50-60	0/1	0.11	0.32	0.00	0.00	0.00
60-70	0/1	0.15	0.35	0.00	0.00	0.00
70-75	0/1	0.11	0.31	0.00	0.00	0.00
75-80	0/1	0.11	0.31	0.00	0.00	0.00
80-85	0/1	0.10	0.30	0.00	0.00	0.00
85-90	0/1	0.12	0.32	0.00	0.00	0.00
90+	0/1	0.04	0.19	0.00	0.00	0.00
LTI band						
0-0.5	0/1	0.01	0.09	0.00	0.00	0.00
0.5-1	0/1	0.04	0.19	0.00	0.00	0.00
1-1.5	0/1	0.07	0.25	0.00	0.00	0.00
1.5-2	0/1	0.11	0.31	0.00	0.00	0.00
2-2.5	0/1	0.14	0.35	0.00	0.00	0.00
2.5-3	0/1	0.17	0.37	0.00	0.00	0.00
3-3.5	0/1	0.17	0.37	0.00	0.00	0.00
3.5-4	0/1	0.14	0.35	0.00	0.00	0.00
4-4.5	0/1	0.09	0.29	0.00	0.00	0.00
4.5-5	0/1	0.05	0.22	0.00	0.00	0.00
5+	0/1	0.01	0.12	0.00	0.00	0.00

Table 8: Mortgage-level: Categorical variables

	Units	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
NUTS1 Region						
East Anglia	0/1	0.04	0.20	0.00	0.00	0.00
East Midlands	0/1	0.06	0.23	0.00	0.00	0.00
London	0/1	0.15	0.36	0.00	0.00	0.00
North	0/1	0.04	0.20	0.00	0.00	0.00
North West	0/1	0.09	0.29	0.00	0.00	0.00

Northern Ireland	0/1	0.02	0.15	0.00	0.00	0.00
Scotland	0/1	0.07	0.25	0.00	0.00	0.00
South East	0/1	0.24	0.43	0.00	0.00	0.00
South West	0/1	0.09	0.28	0.00	0.00	0.00
Wales	0/1	0.04	0.20	0.00	0.00	0.00
West Midlands	0/1	0.08	0.26	0.00	0.00	0.00
Yorkshire Humber	0/1	0.08	0.27	0.00	0.00	0.00
Mortgagor type						
First time buyer	0/1	0.26	0.44	0.00	0.00	1.00
Home movers	0/1	0.38	0.49	0.00	0.00	1.00
Remortgagors	0/1	0.36	0.48	0.00	0.00	1.00
Rate type						
Discount	0/1	0.07	0.25	0.00	0.00	0.00
Fixed	0/1	0.76	0.43	1.00	1.00	1.00
SVR	0/1	0.04	0.20	0.00	0.00	0.00
Trackers	0/1	0.13	0.34	0.00	0.00	0.00
Repayment type						
Capital and interest	0/1	0.89	0.31	1.00	1.00	1.00
Interest only/endowment	0/1	0.01	0.07	0.00	0.00	0.00
Interest only/ISA	0/1	0.00	0.05	0.00	0.00	0.00
Interest only/pension	0/1	0.00	0.05	0.00	0.00	0.00
Interest only/unknown	0/1	0.08	0.27	0.00	0.00	0.00
Mixed	0/1	0.02	0.13	0.00	0.00	0.00
Not known	0/1	0.00	0.02	0.00	0.00	0.00
Income basis						
Joint income	0/1	0.50	0.50	0.00	0.00	1.00
Sole income	0/1	0.39	0.49	0.00	0.00	1.00
Unknown	0/1	0.12	0.32	0.00	0.00	0.00
Employment						
Employed	0/1	0.88	0.32	1.00	1.00	1.00
Other	0/1	0.01	0.12	0.00	0.00	0.00
Retired	0/1	0.01	0.10	0.00	0.00	0.00
Self-employed	0/1	0.09	0.29	0.00	0.00	0.00

C Further regression tables

Table 9: Reduced form regression – interactions with LTV bands

	(1)	(2)	(3)	(4)
QE_{jt}	2.925	-7.384	2.618	-9.086
	(7.988)	(19.455)	(7.819)	(18.442)
$QE_{jt} \times (50 \leq LTV \leq 60)$	10.954*	44.308***	11.187*	43.150***
	(6.170)	(8.693)	(5.852)	(7.561)
$QE_{jt} \times (60 \leq LTV \leq 70)$	25.637***	67.154***	26.017***	66.267***
	(7.955)	(19.198)	(7.673)	(17.749)
$QE_{jt} \times (70 \leq LTV \leq 75)$	34.440**	91.769**	34.122**	91.824***
	(15.537)	(37.351)	(14.802)	(34.093)
$QE_{jt} \times (75 \leq LTV \leq 80)$	19.586	89.920***	19.948*	92.754***
	(11.933)	(16.861)	(11.353)	(14.412)
$QE_{jt} \times (80 \leq LTV \leq 85)$	-12.390	18.369	-10.914	26.151
	(22.426)	(62.228)	(21.615)	(56.075)
$QE_{jt} \times (85 \leq LTV \leq 90)$	-13.545	20.826	-12.011	26.615
	(19.475)	(28.424)	(18.747)	(26.043)
$QE_{jt} \times (90 \leq LTV)$	-14.111	-167.121	-13.199	-156.199
	(21.955)	(157.901)	(20.702)	(150.123)
$r_t^s \times QE_{jt}$		20.623		23.346
		(33.949)		(31.479)
$r_t^S \times QE_{jt} \times (50 \leq LTV \leq 60)$		-63.202***		-60.669***
		(10.403)		(8.533)
$r_t^S \times QE_{jt} \times (60 \leq LTV \leq 70)$		-77.767**		-75.525***
		(30.311)		(27.977)
$r_t^S \times QE_{jt} \times (70 \leq LTV \leq 75)$		-104.513**		-105.344**
		(50.696)		(45.817)
$r_t^S \times QE_{jt} \times (75 \leq LTV \leq 80)$		-131.199***		-135.778***
		(29.546)		(26.255)
$r_t^S \times QE_{jt} \times (80 \leq LTV \leq 85)$		-57.908		-69.517
		(92.250)		(82.433)
$r_t^S \times QE_{jt} \times (85 \leq LTV \leq 90)$		-65.093		-73.139*
		(45.843)		(42.425)
$r_t^S \times QE_{jt} \times (90 \leq LTV)$		218.248		202.193
		(216.635)		(205.857)
Additional FEs	Y	Y	Y	Y
Additional controls	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Postcode-Month FE	N	N	Y	Y
No. of clusters	58	58	58	58
Observations	3,204,180	3,204,180	3,204,180	3,204,180

Standard errors are bank-level clustered $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note: The additional mortgage-specific controls are loan-to-value bands, loan-to-income bands, log(loan value), log(property value), log(gross income), borrower age, mortgage term, risk weight, loan advance type, single or dual income basis, borrower age, fixed or variable rate type, repayment type (interest only, or also with principal), region, income verification status, loan impairment status. The additional bank-level controls are capital requirements as a proportion of risk weighted assets, capital resources, log(total assets), and the amount of pre-positioned collateral. For (1) and (2), the additional NUTS1-level regional controls are regional unemployment, log(house sales) and 12m house price growth.

Table 10: Robustness

	Robustness			
	Lagged Distance	Big-6	Funding Cost	Swap Interaction
	(1)	(2)	(3)	(4)
Pass-through and liquidity				
$liquidity_{jt}$	3.047***	3.877***	5.904***	3.195***
	(1.159)	(1.058)	(1.823)	(1.204)
$liquidity_{jt} \times swap_t$	−2.516**	−3.737***	−5.004***	−2.213**
	(1.211)	(1.232)	(1.611)	(1.022)
Selected mortgage characteristics				
$\log(loan\_val_i)$	−0.103***	−0.088***	−0.089***	−0.091***
	(0.018)	(0.016)	(0.016)	(0.028)
$\log(property\_val_i)$	−0.165***	−0.170***	−0.169***	−0.204***
	(0.033)	(0.040)	(0.040)	(0.042)
$\log(gross\_income_i)$	0.062***	0.055**	0.055**	0.138***
	(0.020)	(0.026)	(0.025)	(0.046)
$ageborrower_i$	0.0005	0.001	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
$mortgageterm_i$	0.006**	0.004	0.004	0.007***
	(0.003)	(0.003)	(0.003)	(0.002)
$riskweight_i$	0.877*	0.291	0.257	0.699
	(0.526)	(0.397)	(0.394)	(0.686)
Selected bank controls				
$capitalrequirements_{jt}$	−0.110	−0.639	−1.882	−2.193
	(1.037)	(1.468)	(1.589)	(1.673)
$capitalresources_{jt}$	−0.361	−1.050*	−1.160**	0.217
	(0.484)	(0.569)	(0.528)	(0.464)
$\log(totalassets_{jt})$	−0.025	0.239	0.087	−0.096
	(0.289)	(0.242)	(0.186)	(0.189)
Regional macroeconomic conditions controls				
$unemp_{rt}$	0.008	0.004	0.005	0.009
	(0.006)	(0.003)	(0.004)	(0.008)
$\log(housesales_{rt})$	0.203**	0.130***	0.131***	0.203*
	(0.079)	(0.046)	(0.048)	(0.110)
$housepricegrowth_{rt}$	0.004	−0.001	−0.001	0.008
	(0.003)	(0.001)	(0.001)	(0.005)
Additional controls	Y	Y	Y	Y
Bank and Month FE	Y	Y	Y	Y
Observations	3,177,089	2,576,846	2,576,846	3,192,346

Note: *p<0.1; **p<0.05; ***p<0.01