BANCO CENTRAL DE RESERVA DEL PERÚ

The Liquidity Premium Channel of Monetary Policy

Piero Garcia *

* Banco Central de Reserva del Perú.

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The Liquidity Premium Channel of Monetary Policy*

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Abstract

This paper studies how exogenous liquidity shocks transmit from central bank balance-sheet operations to bank contract pricing. Using real-time liquidity forecasts from the Central Reserve Bank of Peru (BCRP), I identify reserve-supply shocks from forecast errors in the calibration of daily open market operations. The main analysis quantifies how these shocks affect financial conditions in the banking sector by estimating the dynamic response of lending and deposit spreads relative to safe yields of comparable maturity. I find that a positive liquidity shock to financial institutions generates a sizable and persistent compression of spreads, driven by declines in bank credit and deposit rates while safe yields respond little, consistent with a reduction in the liquidity premia embedded in bank contracts. The results are robust across alternative maturities, liquidity measures, model specifications, and alternative approaches to the measurement of liquidity shocks. These findings imply that balance-sheet and liquidity management policies can influence the effective stance of monetary policy not only through the level of short-term rates, but also through the pricing of liquidity risk that shapes bank spreads and borrowing costs.

Keywords: liquidity premium, monetary policy, non-conventional policy, interbank market, interest rates.

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†Piero Garcia: Central Reserve Bank of Peru (e-mail: piero.garcia@bcrp.gob.pe)

1 Introduction

Since the global financial crisis, central banks have expanded the use of balance-sheet policies, leading to persistently high levels of bank reserves and a shift toward abundant-liquidity regimes. This transformation has placed bank liquidity at the core of monetary transmission, as emphasized by a growing theoretical literature in which reserve supply affects the pricing of short-term funding and propagates to bank credit and deposit markets (Afonso and Lagos, 2015; Bech and Monnet, 2016; Siklos and Stefan, 2021; Bianchi and Bigio, 2022; Bianchi et al., 2023; Engel and Yeung, 2023). However, direct empirical evidence on how exogenous liquidity fluctuations transmit to the pricing of bank contracts remains scarce.

This paper studies the effects of reserve-supply shocks on bank interest rate spreads. A central implication of recent models is that changes in reserves alter banks' liquidity risk and the associated premia embedded in lending and deposit rates (Bianchi and Bigio, 2022; Bigio and Sannikov, 2021). An increase in reserves reduces the probability of liquidity shortfalls, compressing liquidity premia and lowering spreads relative to safe yields. Quantifying this mechanism provides a direct, price-based measure of monetary transmission.

To identify exogenous variation in reserve supply, the paper exploits real-time liquidity forecasts from the Central Reserve Bank of Peru (BCRP). Forecast errors in the calibration of daily liquidity operations generate unanticipated fluctuations in aggregate reserves that are orthogonal to contemporaneous macroeconomic and financial conditions. This approach isolates a liquidity-driven transmission channel operating through bank balance sheets.

The empirical analysis uses instrumental-variable local projections to estimate the dynamic effects of liquidity shocks on lending and deposit spreads relative to safe yields. The results show that positive liquidity shocks lead to economically large and persistent declines in bank spreads. Following an increase in reserves, both lending and deposit spreads compress gradually, with peak effects after several weeks. This adjustment is driven primarily by declines in bank rates, while safe yields respond only weakly. Consistent with the liquidity effect literature, the identified shock also reduces the overnight interbank rate on impact.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and institutional setting. Section 4 presents descriptive evidence. Section 5 outlines the empirical strategy. Section 6 provides supporting evidence from the interbank market. Section 7 reports the main results, and Section 8 presents robustness checks. Section 9 concludes.

2 Related Literature

This article relates to several strands of the literature on banking, finance, macroeconomics, and monetary economics. A large body of work studies whether liquidity risk is priced in financial assets, giving rise to a liquidity premium. The dominant empirical approach identifies valuation differences across securities with similar cash flows but different liquidity characteristics. The evidence shows that a time-varying liquidity premium is embedded in fixed-income yields (Warga, 1992; Longstaff, 2002; Gómez-Puig, 2006; de Jong and Driessen, 2012; Fontaine and Garcia, 2012; Güler et al., 2017; Andreasen et al., 2021), currency returns (Fukuta and Saito, 2002; Brunnermeier et al., 2008; Siklos and Stefan, 2021), interbank interest rates (Eisenschmidt and Tapking, 2009; Baglioni and Monticini, 2010; Drehmann and Nikolaou, 2013; Alexius et al., 2014; Abbassi et al., 2017; Bechtel et al., 2023), option prices (Deuskar et al., 2011), and equity returns (Gibson and Mougeot, 2004; Franzoni et al., 2012; Elgammal et al., 2016). Related work also studies the optimal supply of liquid assets (Holmström and Tirole, 1998; Angeletos et al., 2023).

Rather than focusing on cross-sectional liquidity differences across assets, this article studies shocks to the liquidity position of financial institutions. Following Drehmann and Nikolaou (2013), bank liquidity is defined as the ability to meet payment obligations with immediacy, while liquidity risk reflects the probability of failing to do so over a given horizon.[1] Prior to the global financial crisis, liquidity considerations were largely viewed as second-order for monetary policy transmission, due to a Modigliani–Miller irrelevance result: once the policy rate is set, balance sheet operations do not affect market rates in frictionless environments (Wallace, 1981; Curdia and Woodford, 2011).

This view has been challenged by a growing literature on monetary policy implementation and interbank market frictions. In the canonical framework of Poole (1968), liquidity shocks generate excess reserves and motivate the use of standing facilities. Building on this insight, Afonso and Lagos (2015) and Bech and Monnet (2016) develop models in which idiosyncratic liquidity shocks determine banks' reserve positions, while search and matching frictions govern interbank trading. In these models, liquidity shocks affect market tightness in the interbank market and generate systematic movements in the overnight interbank rate: positive (negative) liquidity shocks exert downward (upward) pressure on interbank rates.

Recent general-equilibrium models extend these mechanisms to broader interest-rate dynamics. Bianchi and Bigio (2022) shows that liquidity shocks spill over from the interbank market to retail credit and deposit markets by altering the liquidity premium embedded in lending and borrowing rates. In this framework, open market operations

[1] Funding liquidity and market liquidity are closely linked, as banks supply market liquidity and their ability to do so depends on their access to funding (Brunnermeier and Pedersen, 2009).

affect not only the level of short-term rates but also interest rate spreads, effectively operating as a distinct policy instrument (Bigio and Sannikov, 2021). Related results arise in alternative modeling environments: Benigno and Nisticò (2017) and Del Negro et al. (2017) show that shocks to asset resaleability increase liquidity premia and that central bank liquidity provision—often implemented through non-conventional balance sheet policies—mitigates these effects.

On the empirical side, the causal identification of liquidity shocks has been most extensively studied in the context of the U.S. interbank market. Seminal work by Hamilton (1997) exploits forecast-based instruments for reserve supply and shows that exogenous increases in reserves significantly lower the federal funds rate. More recently, Afonso et al. (2024) documents that this liquidity effect is state-dependent: the sensitivity of the interbank rate to liquidity shocks is stronger in scarce-reserve environments and weakens as reserves become abundant, consistent with a flattening demand curve for reserves.

The declining sensitivity of interbank rates in high-liquidity environments reflects lower liquidity risk. As excess reserves increase, the number of reserve suppliers rises while the number of borrowers falls, relaxing market tightness (Fuhrer, 2018). This reduces the probability of liquidity shortfalls and compresses liquidity premia (Bianchi and Bigio, 2022). In the limit, abundant reserves give rise to floor-type operating systems in which interbank rates converge to the policy floor and become insensitive to liquidity shocks (Baglioni, 2024). Conversely, balance sheet contractions, as observed during episodes of quantitative tightening, can reintroduce liquidity risk and amplify rate volatility (Acharya et al., 2023; Acharya and Rajan, 2024). Consistent with this view, liquidity disruptions in September 2019 pushed the federal funds rate above the FOMC target range (Afonso et al., 2021).

Alternative identification strategies exploit quasi-natural experiments. In interbank markets, Abbassi et al. (2017) shows that the introduction of free intraday overdrafts lowers rates on collateralized loans, consistent with a liquidity premium. Hryckiewicz and Kozlowski (2018) documents that liquidity imbalances affect banks' liquidity positions and credit supply, while Fuhrer et al. (2017) show that assets qualifying as high-quality liquid assets under Basel III command a yield premium. In banking markets, crisis-based evidence shows that banks with more stable funding maintain lending, while more liquidity-constrained banks contract credit (Cornett et al., 2011; Kapan and Minoiu, 2014). Cross-bank liquidity shocks induced by external events further confirm that liquidity shortages reduce credit supply (Khwaja and Mian, 2008; Schnabl, 2012).

The literature also provides reduced-form evidence that liquidity premia shape yields and spreads. Krishnamurthy and Vissing-Jorgensen (2012) show that changes in the supply of U.S. Treasuries affect a wide range of yield spreads, reflecting their money-like liquidity and safety properties. Similarly, Lee (2020) finds that increases in narrow money

is associated to reductions in spreads between liquid and illiquid assets. The liquidity premium of near-money assets is closely linked to short-term interest rates, indicating a high elasticity of substitution between money and near-money instruments (Nagel, 2016).

This article also relates to the literature on non-conventional balance sheet policies. Following the global financial crisis, a large literature studied the effects of LSAP programs, typically emphasizing market segmentation and portfolio balance channels (Gertler and Karadi, 2013; Carlstrom et al., 2017; Adrian et al., 2025). Event-study evidence shows that these policies significantly affected interest rates and asset prices (Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011; Mamaysky, 2018). Macroeconomic studies find robust effects on output and inflation (Fabo et al., 2021; Kim et al., 2020), with similar conclusions obtained under alternative identification schemes (Baumeister and Benati, 2013; Gambacorta et al., 2014; Weale and Wieladek, 2016).

Despite this extensive literature, an important gap remains in causally quantifying how liquidity shocks spill over to *bank contract pricing*. While empirical work has established that reserve-supply innovations affect overnight interbank rates through the classic *liquidity effect*, modern theory emphasizes that these liquidity shocks can spillover to bank credit and deposit markets through a non-conventional margin, as liquidity risk is priced in interest rate spreads over safe yields (Bianchi and Bigio, 2022).

In this context, empirical evidence that isolates a plausibly exogenous liquidity shock and exploits it to quantify the dynamic response of lending and deposit spreads remains unexplored. This paper addresses this gap by leveraging real-time liquidity forecasts produced by the Central Reserve Bank of Peru. Forecast errors arising from daily liquidity management generate exogenous variation in the supply of reserves, which the paper uses to trace the propagation of liquidity shocks to the financial system through retail interest rates and their spreads relative to safe yields.

3 Data

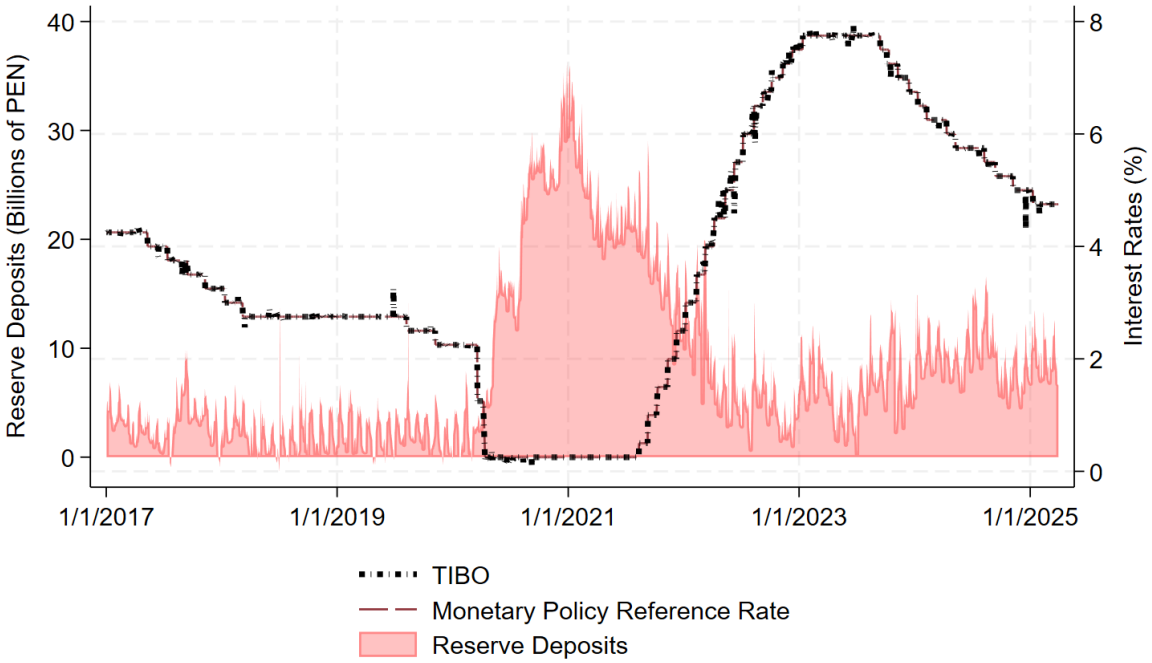
The liquidity position of a financial institution is defined by its holdings of liquid assets, including money, central bank reserves, and near-money instruments such as Treasury bonds (Nagel, 2016). In Peru, the regulatory authority, Superintendencia de Banca, Seguros y AFP (SBS), classifies as liquid assets: currency, reserve deposits at the Central Reserve Bank of Peru (BCRP), deposits at domestic and foreign banks, Treasury bonds, and Certificates of Deposit issued by the BCRP (CD BCRP), among others.

For the purpose of isolating liquidity shocks, this paper focuses on a specific subset of liquid assets: reserve deposits held at the BCRP (in the following, also referred to as banking system or interbank market liquidity). From a daily liquidity management perspective, banks primarily rely on these reserve deposits to meet reserve requirements

and absorb liquidity shocks. Unlike other assets, the aggregate variation of alternative liquid instruments in the banking system is limited, as it depends on the issuance and maturity of securities by the Treasury or the central bank. Crucially, reserve deposits are directly linked to the identification strategy proposed in this paper, which exploits central bank forecast errors in liquidity operations (see Section 5.2). This variable is observed at a daily frequency and retrieved from BCRP internal archives.

The overnight average interbank interest rate ($TIBO_t$)[2] and the monetary policy reference rate are obtained from BCRP's public data archives (BCRPData) and are available daily for the period 2017:1–2025:3 (Figure 1).

Figure 1: Daily Monetary Policy Rate, Banking System Reserve Liquidity, and Overnight Interbank Rate (TIBO)



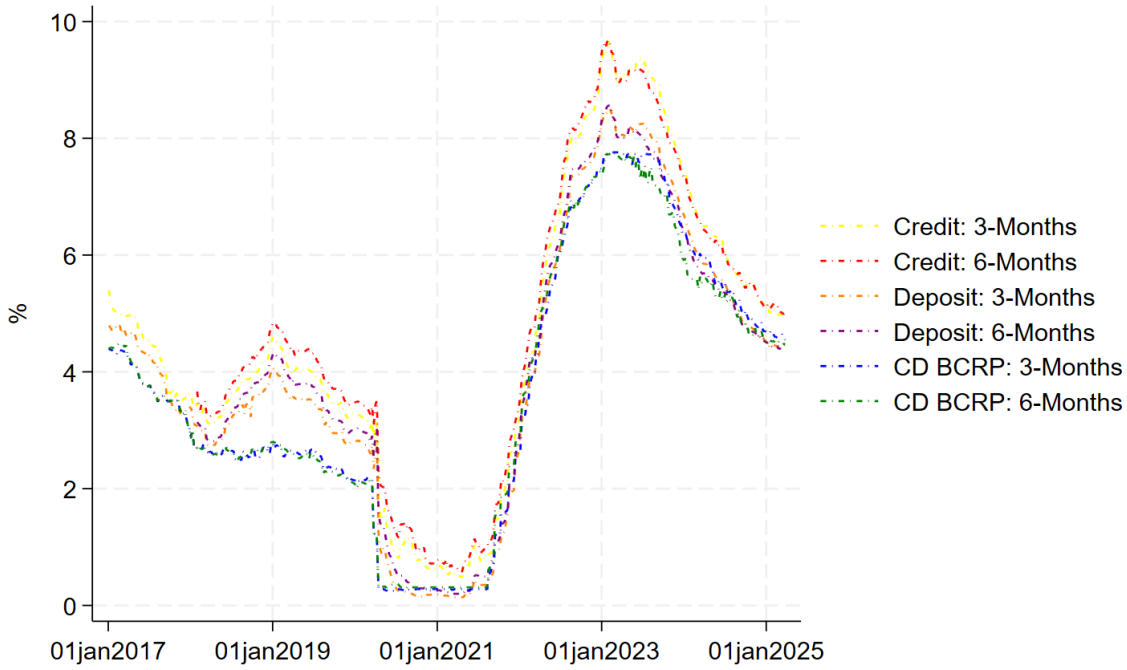
To control for the size of the banking system, the total volume of bank liabilities subject to liquidity requirements (TOSE) is used to normalize reserve holdings. This measure accounts for both the banking system's size and the volume of legally required reserves. This variable is retrieved from BCRPData over the period 2017:1–2025:3, on monthly frequency.

Interest rate data cover prime lending and deposit rates, which capture transactions

[2]The TIBO is the weighted average interest rate of uncollateralized one-day loans among private commercial banks in domestic currency. Outliers are excluded to ensure representativeness. See BCRP (2023) for technical details. The TIBO reflects prevailing supply and demand conditions in the interbank market.

with the most creditworthy clients and reduce contamination from risk premia. Weekly observations are obtained from internal BCRP archives and span maturities of 3 and 6 months. The 3-month series covers the period 2017:1–2025:3, while the 6-month series is available from 2018:1–2025:3. To construct interest rate spreads, weekly yields on BCRP Certificates of Deposit with maturities of 3 and 6 months are also collected over 2017:1–2025:3 (see Figure 2).

Figure 2: Prime Credit and Deposit Interest Rates and CD BCRP yields
(Percent)



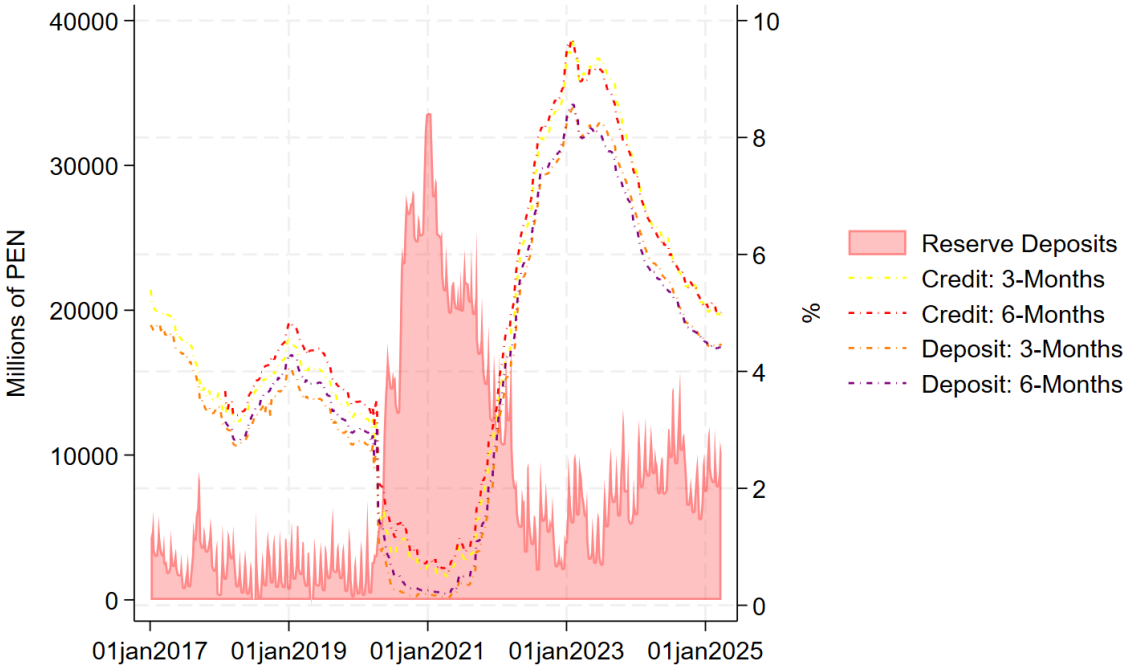
4 Descriptive Evidence

This section provides descriptive evidence on how system-wide liquidity conditions co-move with bank interest rate pricing. In the presence of liquidity-management frictions, the availability of liquid funds affects the shadow cost of meeting payment obligations and the compensation required to bear liquidity risk. As a result, higher (lower) liquidity should be associated with lower (higher) bank rates and, in particular, with lower (higher) spreads of bank rates over yields on safe assets. The purpose of this section is to document these patterns in the data and to quantify their reduced-form dynamics. Causal identification is developed in the main analysis.

Over the period of analysis, the data display a robust negative association between banking system reserve liquidity and corporate prime lending and deposit rates at maturities

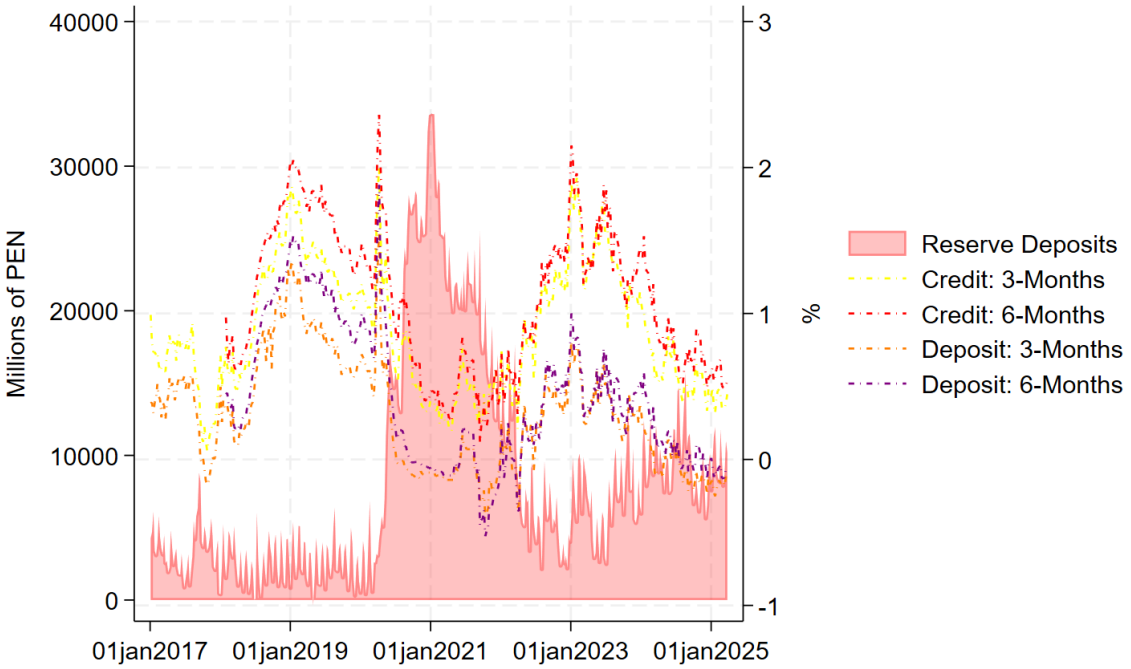
between 3 and 12 months. Periods of abundant liquidity coincide with lower prime rates, whereas periods of tighter liquidity coincide with higher prime rates. Across maturities in this segment, the correlations range from approximately -0.57 to -0.49.

Figure 3: Reserve Liquidity and Prime Interest Rates



Because nominal bank rates may co-move with policy expectations and time-varying risk premia, I also examine spreads of corporate prime rates relative to yields on safe assets of comparable maturity. Specifically, I consider spreads over BCRP certificates of deposit (CD BCRP), which incorporate information about the level and expectations of the policy rate as well as term premia. Using prime rates helps minimize the role of credit risk premia, as these contracts are extended to the highest-rated corporate clients. Over the same period, the negative association persists—and strengthens—when using spreads: correlations between reserve liquidity and prime spreads lie in the range -0.65 to -0.51 for maturities between 3 and 12 months.

Figure 4: Reserve Liquidity and Prime Spreads over CD BCRP Yields

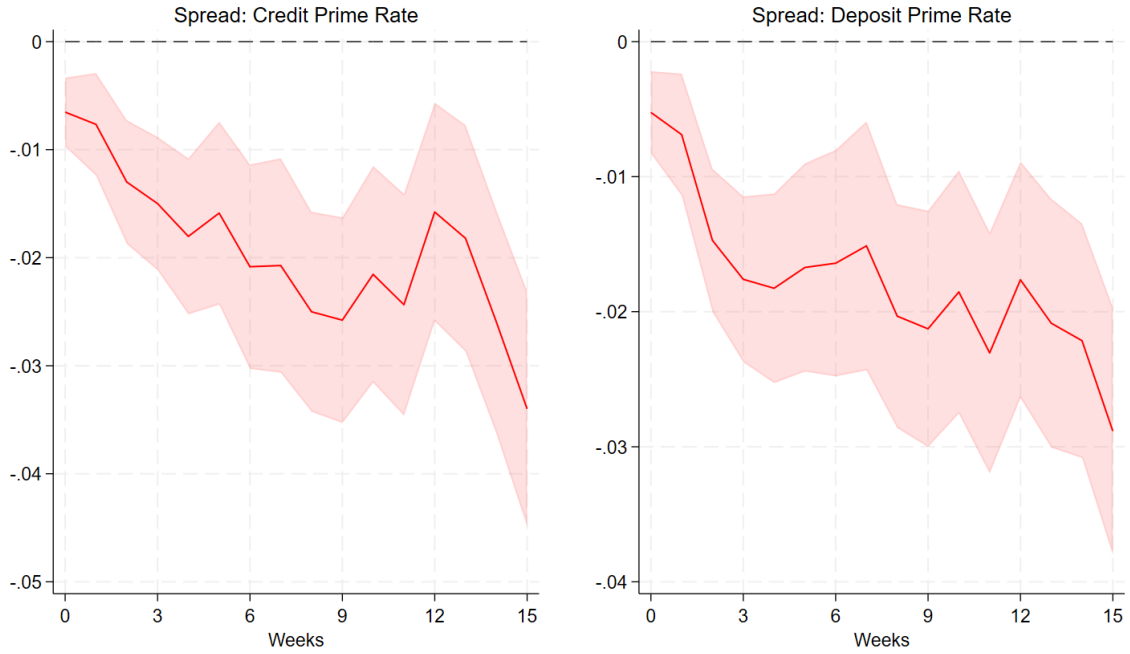


To summarize the dynamics in a simple reduced-form way, I estimate standard local projections (Jordà, 2005)[3] for prime spreads, treating innovations to reserve liquidity as exogenous for the purpose of this preliminary exercise. This assumption is strong—liquidity and interest rates are jointly determined in equilibrium—so the resulting impulse responses should be interpreted as descriptive benchmarks rather than causal effects.

Figure 5 reports the implied responses of 3-month prime lending and deposit spreads to a positive innovation in reserve liquidity. The impulse responses indicate a sustained and gradually strengthening decline in spreads over the horizon, with no evidence of mean reversion back to zero. For both lending and deposit rates, spreads fall steadily following the shock, with the magnitude of the response increasing over time and reaching peak effects at longer horizons. Quantitatively, a liquidity innovation of PEN 1 billion is associated with peak reductions in prime spreads of approximately 0.03 percentage points. Overall, the reduced-form evidence points to a persistent negative association between reserve liquidity and prime spreads, providing a descriptive benchmark for the causal analysis based on instrumental-variable local projections.

[3]The model specification is described in Section 5. The estimation mirrors the baseline setup but omits the external instrument; the IV-based results are reported in the main analysis.

Figure 5: Impulse Responses for Spreads: 3-month Prime Rate Minus 3-month CDBCRP
OLS Specification



* The IRF displays 68% confidence bands

5 Empirical Strategy

5.1 Empirical Model

To quantify the dynamic causal effect of liquidity shocks on retail interest rates and their spreads, I employ an Instrumental Variables Local Projections (IV-LP) framework (Jordà et al., 2015; Stock and Watson, 2018):

$$\Delta_h R_t = \gamma_h + \beta_h \Delta L_t + Z_t' \delta_h + \varepsilon_{t+h}, \tag{1}$$

Where $\Delta_h R_t$ is the cumulative change in the studied retail interest rate or spread of interest over horizon h, ΔL_t is the first-difference of the level of reserve deposits of the banking system held at the central bank, Z_t' is the vector of control variables and ε_{t+h} is the perturbation term. In the benchmark case, the model is specified in its long-difference form. Although long-differences and levels specifications are asymptotically equivalent, the former has been proven robust to potential small sample bias, becoming the preferred specification in applied work. In contrast to the VAR literature, the literature on LP has not yet determined a consensus on lag selection strategies. As this methodology is less

vulnerable to lag-selection related bias, and in order to maintain parsimony, the lag order is set to 12 for all included variables, where weekly data is employed (Jordà and Taylor (2025)).

As the model features potential endogeneity issues, I instrument ΔL_t using BCRP's daily forecast errors of the banking system's level of reserve assets in the interbank market (FE_t) (see an explanation of the identification strategy in Section 5.2). This variable is argued to satisfy the necessary conditions to be employed as an instrument in the LP framework, as stated in Stock and Watson (2018). On one hand, the fulfillment of the relevance condition is formally tested at each step. On the other hand, Section 5.2 discusses the fulfillment of the lead-lag exogeneity assumption.

Besides lagged variables, all specifications include a standard set of macroeconomic and financial controls to account for cyclical conditions, inflationary pressures, global risk sentiment, and the slope of the domestic yield curve. Short-term monetary conditions are captured by the interbank interest rate, while real activity is proxied by year-on-year GDP growth. Inflation dynamics are controlled for using core inflation, defined as consumer price inflation excluding food and energy components. To account for global financial conditions and risk appetite, I include the VIX index. Finally, I control for the slope of the yield curve using two complementary measures: the spread between 12-month and 3-month CD BCRP yields, and the spread between 3-month and 1-month prime rates. Together, these controls absorb conventional macro-financial influences on interest rates and bank pricing, helping isolate the effects of liquidity innovations operating through non-conventional channels.

5.2 Identification Strategy

Identifying exogenous variation in liquidity is challenging because reserve supply, interest rates, and macro-financial conditions are jointly determined. Government debt issuance, central bank operations, and global financial factors all influence the supply of liquid assets, making observed liquidity conditions endogenous to market outcomes (Nagel, 2016; Brunnermeier et al., 2024).

This paper isolates exogenous liquidity shocks using forecast errors from the Central Reserve Bank of Peru (BCRP). In its daily liquidity management framework, the central bank conducts open market operations to align the overnight interbank rate with the policy rate. This requires forming real-time projections of end-of-day reserves based on expected autonomous factors and the estimated demand for reserves. Policy interventions are then calibrated to offset predictable fluctuations in liquidity.

The key identification insight is that deviations from these projections represent unanticipated liquidity innovations. I define the forecast error as the difference between realized and projected end-of-day reserves, FE_t. By construction, FE_t captures variation in re-

serve supply that is orthogonal to systematic policy actions and predictable liquidity flows, providing a high-frequency source of exogenous shocks.

The endogenous variable is the level of reserves available prior to central bank intervention, L_t. I instrument L_t using FE_t. This mapping exploits the intertemporal structure of reserve accounting: unexpected innovations to end-of-day liquidity translate into next-day opening reserve positions, shifting the initial tightness of the interbank market. Since intraday rate formation depends on the distribution of liquidity across banks, this initial condition governs the pricing of liquidity risk and the resulting interest rate spreads (Bianchi and Bigio, 2022).

The validity of the instrument relies on three conditions. First, relevance follows from the mechanical link between forecast errors and subsequent reserve positions. Second, contemporaneous exogeneity holds because FE_t reflects unanticipated deviations from the central bank's information set and is therefore orthogonal to shocks affecting market outcomes within the same period. Third, lead-lag exogeneity is satisfied because forecast errors are constructed using only information available at time t; in addition, all specifications include lagged forecast errors to account for potential persistence.

For an IV-LP framework, the instrument must satisfy three conditions (Stock and Watson, 2018):

1. Relevance Condition: FE_t must be correlated with the endogenous liquidity variable, L_t. This is formally tested in the first-stage regression.

2. Contemporaneous Exogeneity: FE_t should not be correlated with shocks to the dependent variables at time t.

3. Lead-Lag Exogeneity: The instrument must be unrelated to all shocks at leads and lags. On one hand, by construction, FE_t is based solely on information available up to day t, and future shocks cannot predict it. On the other hand, the possibility that past shocks influence current forecast errors is analyzed in Section 8.

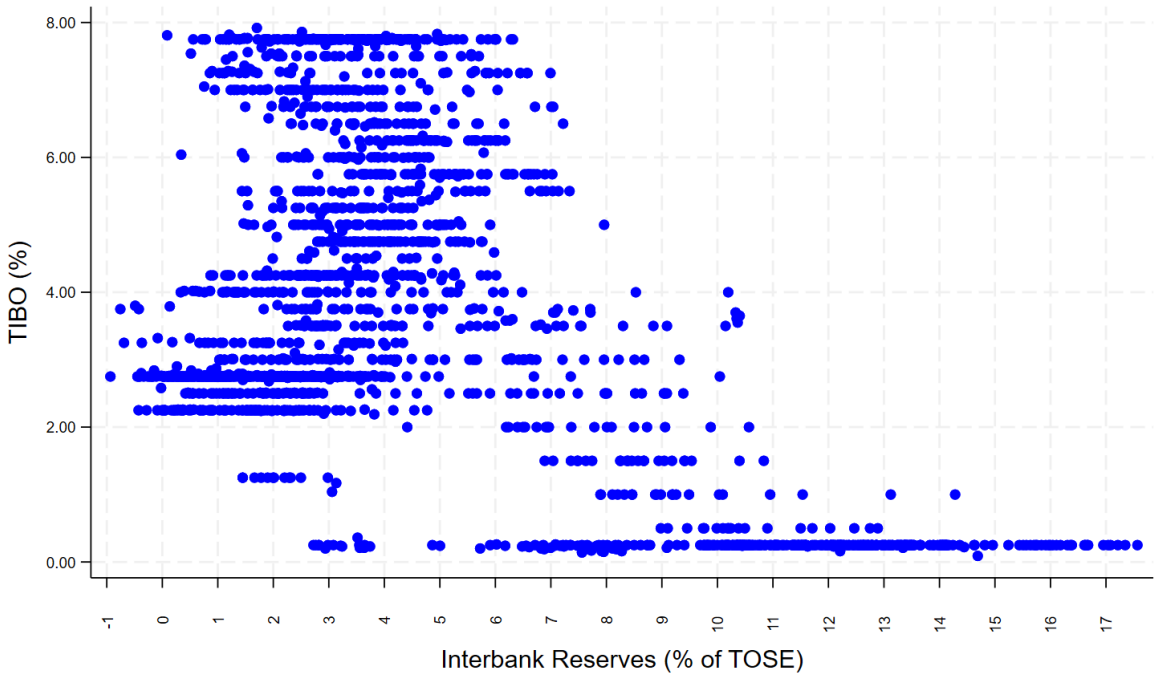
Hamilton (1997) pioneered the use of central bank liquidity forecast errors to identify interbank liquidity shocks. More recent studies (Afonso et al., 2024) extend this approach, typically relying on proxies generated from time-series models to mimic central bank forecasts. While practical, these proxies may imperfectly capture actual forecast errors. In contrast, this paper constructs the first real-time daily measure of BCRP's liquidity forecast errors, allowing for a more precise identification of liquidity shocks. Importantly, this strategy is also the first to apply such an instrument to study the propagation of liquidity shocks to wider financial markets.

6 Mechanism Validation: Interbank Liquidity Effect

The reduced-form evidence motivates the causal analysis that follows. A standard approach in the liquidity-effect literature is to identify exogenous reserve-supply shocks using forecast errors and validate them in the interbank market, where liquidity is priced at the shortest horizon. Following Hamilton (1997) and subsequent work (Afonso et al., 2024; Smith and Valcarcel, 2023), I use central bank liquidity forecast errors as an external instrument for reserve supply. In the Peruvian context, the instrument is constructed from the BCRP's daily forecast errors in the calibration of open market operations (see Section 5.2). This subsection provides a benchmark validation by testing whether the identified innovation is priced as a liquidity shock in the interbank market.

Figure 6 plots interbank reserves (as a percentage of TOSE) against the overnight interbank rate (TIBO). While these equilibrium observations are not informative about causality, the negative association is consistent with a liquidity effect: higher reserves are associated with lower overnight rates. However, reserve levels are endogenous to policy actions, anticipated flows, and banks' behavior. The empirical analysis therefore relies on the forecast-error instrument to isolate exogenous variation in reserve supply.

Figure 6: Reserves and the interbank interest rate



To quantify the interbank liquidity effect using an external instrument, I follow Hamilton (1997) and related work (Afonso et al., 2024; Smith and Valcarcel, 2023) and estimate the bivariate specification

$$TIBO_t = \beta_0 + \beta_1 L_t + \varepsilon_t, \tag{2}$$

where $TIBO_t$ denotes the day-t average overnight interbank interest rate and L_t is the level of banking system reserves, expressed in billions of PEN.[4] Because L_t may be jointly determined with $TIBO_t$, I instrument L_t with the BCRP's daily forecast errors of the banking system's closing liquidity, denoted FE_t (see Section 5.2 for details on timing and identification).

The corresponding first-stage is

$$L_t = \alpha_0 + \alpha_1 FE_t + \mu_t. \tag{3}$$

Table 1 reports the benchmark IV estimates for the interbank market. The 2SLS coefficient on opening liquidity is negative and statistically significant, implying that a positive reserve-supply innovation lowers the overnight interbank rate—consistent with the classic liquidity effect documented in the interbank literature (Hamilton, 1997; Afonso et al., 2024). Appendix B reports rolling IV estimates, showing that the liquidity effect remains negative across subsamples and varies in intensity over time, in line with the state-dependent patterns emphasized in recent work (Afonso et al., 2024). Overall, these results support interpreting the forecast-error series as isolating reserve-supply innovations that are priced as liquidity shocks at the shortest horizon.

[4]The literature often focuses on the opportunity cost of holding reserves. In the U.S., this object is typically measured as the overnight interbank rate net of the interest rate on reserves. In Peru, reserve balances held at the central bank do not earn interest, so the relevant opportunity cost is given by the interbank rate itself.

Table 1: Mechanism validation in the interbank market: liquidity effect

	(A) 2SLS (IV)	(B) First stage	(C) OLS (benchmark)
LI_t	-0.219^{***}		-0.137^{***}
	(0.0516)		(0.0043)
FE_t		0.00129 ***	
		(0.0002	
Constant	5.670^{***}	8.902 ***	4.933^{***}
	(0.468)	(0.171)	(0.0660)
Observations	2,056	2,056	2,056
R^2	0.129	0.016	0.204

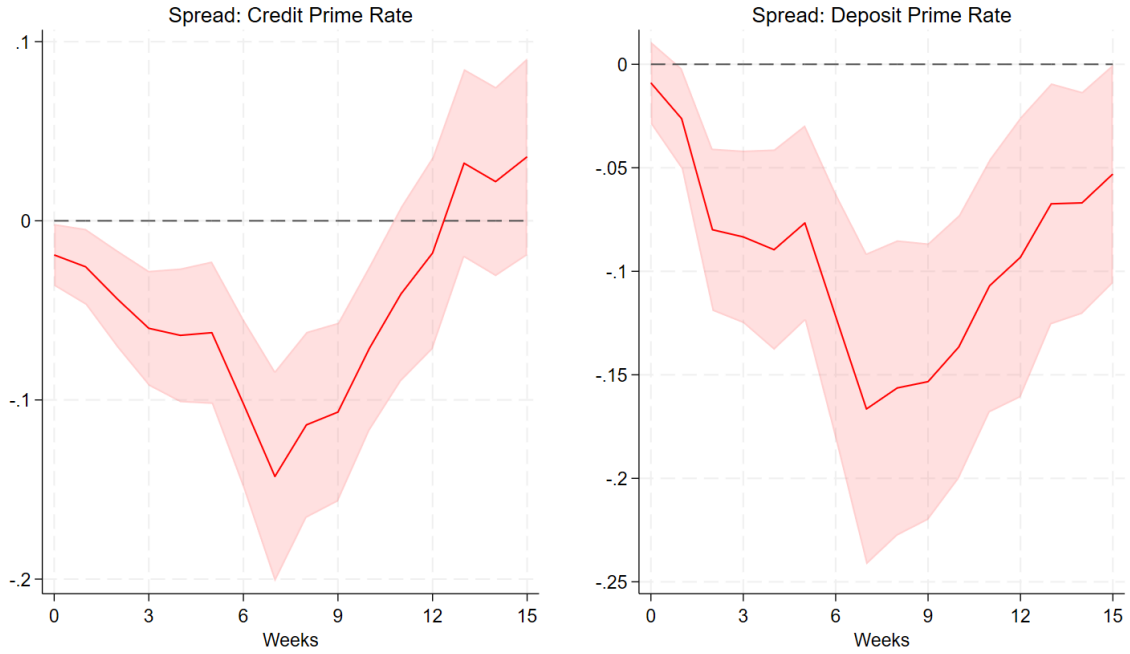
Notes: Column (A) reports 2SLS estimates of equation (2), instrumenting LI_t with contemporaneous FE_t. Column (B) reports the first-stage regression in equation (3). Column (C) reports the corresponding OLS estimates. The liquidity shock is normalized to a one-billion PEN increase in reserves, so estimated coefficients measure responses to a PEN 1 billion exogenous liquidity innovation. Standard errors are reported in parentheses. *** denotes significance at the 1% level.

7 Main Results

This section quantifies the causal effect of reserve-supply shocks on bank contract pricing. Using the BCRP forecast-error instrument, I estimate IV local projections for spreads between prime lending and deposit rates and safe yields of comparable maturity (CD-BCRP). Focusing on spreads isolates movements in bank pricing from common variation in policy expectations and term premia.

Figure 7 reports the responses of 3-month prime credit and deposit spreads to a one-billion PEN increase in reserves. The shock leads to a statistically significant and persistent compression of both spreads. The response is hump-shaped, peaking around week 7, with declines of approximately 0.17 percentage points. IV estimates are substantially larger than their reduced-form counterparts, consistent with attenuation from endogeneity and measurement error in observed reserve movements. In particular, realized liquidity reflects both policy responses and anticipated flows, biasing reduced-form estimates toward zero.

Figure 7: Impulse Responses for Spreads: 3-month Prime Rate Minus 3-month CDBCRP
IV Specification



Notes: The figure reports impulse responses for 3-month prime credit and deposit spreads, measured as the spread between 3-month prime lending (deposit) rates and the 3-month CDBCRP rate. The liquidity shock is identified using the benchmark IV-LP specification. Shaded areas denote 68 percent confidence intervals.

The results are consistent with a liquidity-premium channel of monetary policy. An increase in reserves reduces the shadow value of liquidity and the compensation required to price liquidity risk in bank contracts (Bianchi and Bigio, 2022). While the interbank literature shows that such shocks lower overnight rates (Hamilton, 1997; Afonso et al., 2024), the evidence here shows that they also propagate to bank pricing, generating sizable and persistent movements in lending and deposit spreads.

These magnitudes are economically meaningful and align with broader evidence that liquidity is priced in financial markets. Prior work documents liquidity premia in money markets (Abbassi et al., 2017), in the pricing of high-quality liquid assets (Fuhrer et al., 2017), and in credit supply responses to bank liquidity shocks (Khwaja and Mian, 2008). The results here provide a price-based counterpart: reserve-supply shocks shift the terms at which banks price credit and deposits relative to safe yields.

Finally, the findings complement the literature on balance-sheet policies. Unlike most QE evidence—focused on term premia and portfolio balance effects on longer-term yields (Gertler and Karadi, 2013; Carlstrom et al., 2017; Gagnon et al., 2011; Mamaysky, 2018; Fabo et al., 2021)—the identification strategy isolates reserve-supply innovations and

traces their effects on bank spreads. This provides direct evidence on a liquidity-based transmission channel operating through the pricing of bank liabilities and assets (Bigio and Sannikov, 2021; Bianchi and Bigio, 2022).

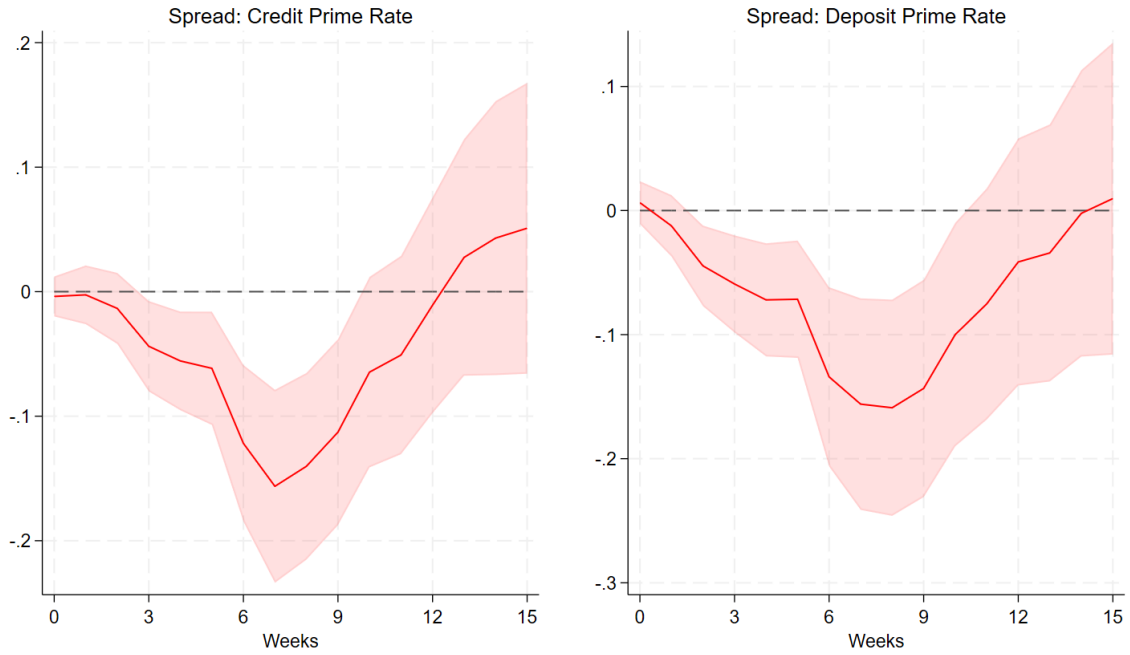
8 Robustness

8.1 Interest Rates

As a robustness check, this subsection examines the response of bank interest rates in levels. Figure 8 reports IV local-projection estimates for 3-month prime lending and deposit rates following a reserve-supply shock of PEN 1 billion. Both rates decline on impact and display persistent, hump-shaped dynamics, closely mirroring the responses of spreads in Figure 7.

The similarity between level and spread responses indicates that spread compression is primarily driven by a repricing of bank contracts rather than by movements in the benchmark yield. Lending and deposit rates move in the same direction as spreads, consistent with a direct effect of liquidity shocks on banks' pricing decisions.

Figure 8: Impulse Responses for 3-month Prime Interest Rates

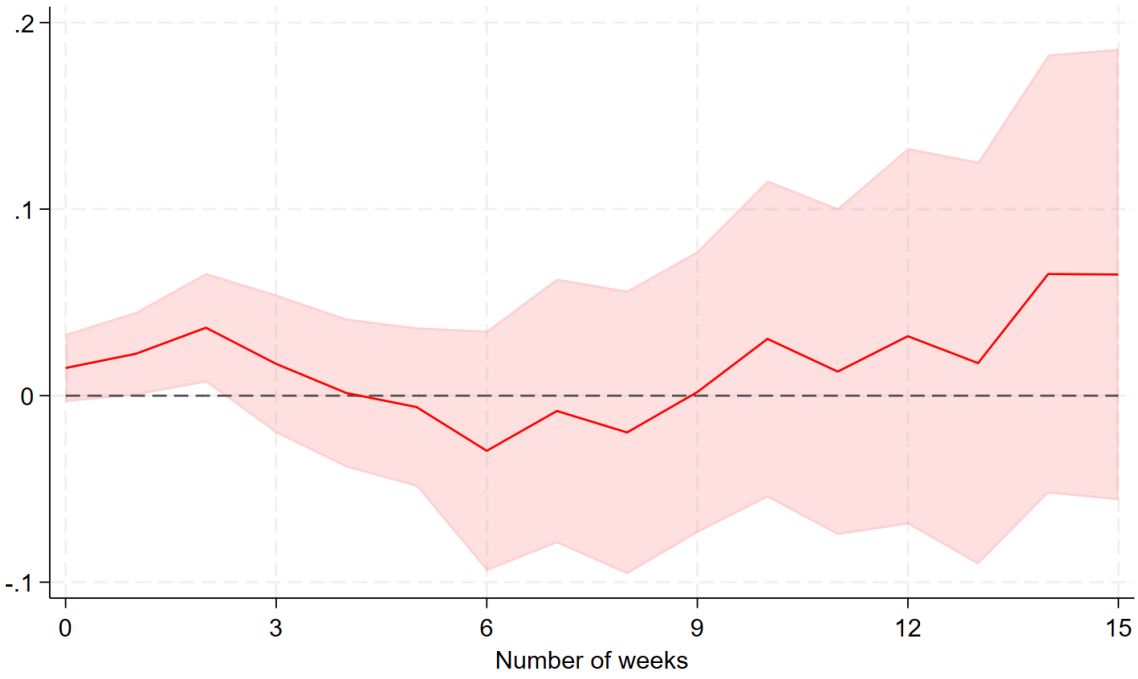


Notes: The figure reports impulse responses for 3-month prime credit and deposit interest rates. The liquidity shock is identified using the benchmark IV-LP specification. Shaded areas denote 68 percent confidence intervals.

Figure 9 reports the response of the 3-month CDBCRP rate. The effect is small, short-

lived, and only marginally significant at short horizons. Taken together, these results show that liquidity shocks operate primarily through bank-level repricing, with limited transmission through the risk-free benchmark. This pattern is consistent with a liquidity-premium channel in which reserve-supply innovations reduce the shadow cost of liquidity and compress the premia embedded in bank lending and deposit rates (Bianchi and Bigio, 2022; Bigio and Sannikov, 2021).

Figure 9: Impulse Responses for 3-month CD BCRP



Notes: The figure reports impulse responses for 3-month CD BCRP yield. The liquidity shock is identified using the benchmark IV-LP specification. Shaded areas denote 68 percent confidence intervals.

8.2 Imperfect Information

A potential concern in high-frequency identification is that the instrument may exhibit serial correlation, not because it embeds systematic policy stance, but because information is processed gradually in the presence of noisy signals and informational rigidities. Miranda-Agrippino and Ricco (2021) emphasize that commonly used high-frequency monetary policy instruments may conflate true policy shocks with information revealed through policy actions. In such environments, learning frictions can induce persistence and predictability in measured surprises, even when policy actions themselves are not predictable.

In their framework, the relevant innovation corresponds to the component of the policy signal that is orthogonal to past information, that is, the surprise net of predictable dynamics arising from gradual learning and signal extraction. This "time-to-learn" logic

implies that serial dependence in high-frequency measures does not necessarily reflect systematic policy behavior, but rather the presence of informational frictions.

Motivated by this insight, I implement a pre-whitening robustness check for the forecast-error instrument. Specifically, I model the liquidity forecast error as an autoregressive process,

$$FE_t = \sum_{p=1}^{p} \rho_p \, FE_{t-p} + u_t,$$

where p denotes the lag order and ranges from 1 to 12, and define the innovation component as the residual u_t. This residual removes the predictable component of the forecast error and isolates the unanticipated innovation that is most closely aligned with the notion of a true liquidity shock. I then re-estimate the main IV local projection specifications using u_t as the external instrument. This exercise is intended as a robustness check: while the baseline identification relies on the contemporaneous forecast error, the pre-whitened instrument tests whether the results are sensitive to serial dependence in the raw series.

Table 2: AR(p) regressions for forecast errors (FE_t): incremental lag order

	(1) AR(1)	(2) AR(2)	(3) AR(3)	(4) AR(4)	(5) AR(5)	(6) AR(6)	(7) AR(7)	(8) AR(8)	(9) AR(9)	(10) AR(10)	(11) AR(11)	(12) AR(12)
$L.FE$	0.349***	0.357***	0.358***	0.333***	0.308***	0.318***	0.307***	0.316***	0.321***	0.314***	0.303***	0.300***
	(0.0735)	(0.0753)	(0.0767)	(0.0714)	(0.0815)	(0.0764)	(0.0756)	(0.0758)	(0.0781)	(0.0753)	(0.0757)	(0.0755)
$L2.FE$		-0.0189	-0.0475	-0.0319	-0.0292	0.0134	0.0229	0.0358	0.0301	0.0470	0.0462	0.0412
		(0.0684)	(0.0785)	(0.0583)	(0.0584)	(0.0563)	(0.0569)	(0.0582)	(0.0581)	(0.0587)	(0.0595)	(0.0625)
$L3.FE$			0.0806*	-0.0345	-0.0322	-0.0370	-0.0113	-0.0240	-0.0300	-0.0455	-0.0346	-0.0349
			(0.0463)	(0.0486)	(0.0501)	(0.0537)	(0.0538)	(0.0524)	(0.0534)	(0.0565)	(0.0536)	(0.0542)
$L4.FE$				0.320***	0.294***	0.291***	0.288***	0.255***	0.261***	0.245***	0.236***	0.241***
				(0.0686)	(0.0671)	(0.0673)	(0.0658)	(0.0711)	(0.0743)	(0.0716)	(0.0671)	(0.0707)
$L5.FE$					0.0770	0.120*	0.120*	0.122*	0.135*	0.153*	0.145*	0.141*
					(0.0802)	(0.0711)	(0.0712)	(0.0724)	(0.0772)	(0.0810)	(0.0819)	(0.0812)
$L6.FE$						-0.143**	-0.114**	-0.117**	-0.119**	-0.0827	-0.0703	-0.0735
						(0.0565)	(0.0535)	(0.0537)	(0.0528)	(0.0619)	(0.0633)	(0.0634)
$L7.FE$							-0.0863	-0.120*	-0.119*	-0.124**	-0.103*	-0.0966
							(0.0611)	(0.0640)	(0.0645)	(0.0606)	(0.0625)	(0.0662)
$L8.FE$								0.110**	0.127**	0.130**	0.126**	0.137**
								(0.0488)	(0.0615)	(0.0585)	(0.0578)	(0.0600)
$L9.FE$									-0.0501	-0.00469	-0.0000693	0.00212
									(0.0818)	(0.0734)	(0.0730)	(0.0732)
$L10.FE$										-0.136**	-0.110**	-0.108**
										(0.0545)	(0.0534)	(0.0523)
$L11.FE$											-0.0829	-0.0683
											(0.0601)	(0.0586)
$L12.FE$												-0.0457
												(0.0636)
Constant	10.60	11.71	10.98	7.815	7.453	7.342	7.991	7.346	7.677	8.931	9.256	9.763
	(26.08)	(26.60)	(25.51)	(23.70)	(24.63)	(22.93)	(22.73)	(23.13)	(23.08)	(23.09)	(23.57)	(24.09)
Observations	428	427	426	425	424	423	422	421	420	419	418	417
Prob > F	2.77e-06	1.44e-05	3.53e-05	1.25e-07	2.66e-07	9.51e-11	2.70e-10	1.26e-10	0	0	0	0

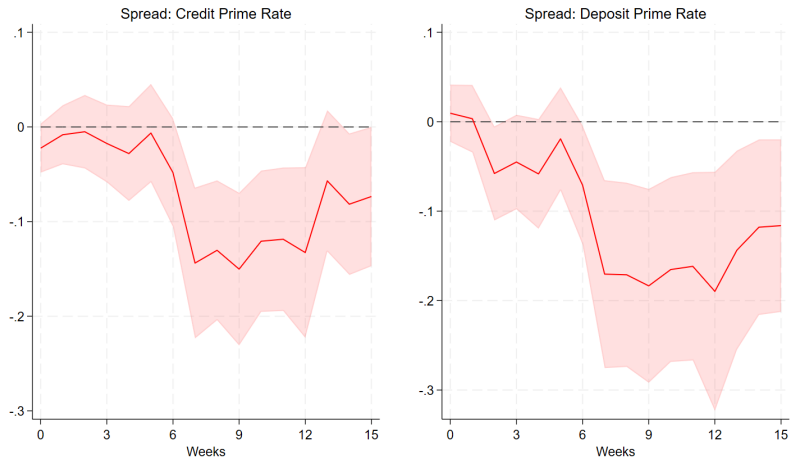
Notes: Each column reports an OLS regression of FE_t on an incremental set of its own lags, $FE_t = \alpha + \sum_{\ell=1}^{p} \phi_\ell FE_{t-\ell} + u_t$. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors are heteroskedasticity- and autocorrelation-consistent (HAC), computed using the Newey–West estimator.

Table 2 reports AR(p) estimates for the forecast error with incrementally increasing lag order. The results indicate statistically significant persistence at short horizons, with a large and highly significant first lag and additional significant dynamics at selected higher lags. This pattern implies that a non-trivial fraction of the raw forecast-error series is predictable from its own past, consistent with gradual information processing and operational noise. Importantly, Appendix C shows that the residual component u_t no longer displays serial correlation, supporting its interpretation as the unanticipated innovation in liquidity conditions. Treating this residual as the relevant shock follows closely the argument in Miranda-Agrippino and Ricco (2021), who emphasize that identification should rely on the unpredictable component of high-frequency measures once informational rigidities are acknowledged.

Figure 10 reports the IV-LP impulse responses of credit and deposit spreads to a liquidity shock identified from the pre-whitened residual of the forecast error. The shock is calibrated to correspond to a one-billion PEN liquidity innovation. The responses of credit and deposit spreads remain negative and economically sizable, but differ from the benchmark specification in their short-run dynamics. In particular, the effects are not statistically significant during the first few weeks following the shock. Instead, the response emerges with a delay, becoming statistically significant only at medium horizons. Once the effect materializes—around weeks 6 to 7—it strengthens sharply and reaches magnitudes comparable to those observed in the baseline results, before gradually unwinding.

This delayed but pronounced response suggests that serial correlation in liquidity forecast errors may influence the timing of the estimated effects, reinforcing early responses in the benchmark specification. After purging this component, liquidity shocks continue to exert a strong and persistent impact on bank pricing conditions, albeit concentrated at medium horizons. Importantly, the qualitative conclusion remains unchanged: unexpected increases in aggregate liquidity lead to a sustained compression of credit and deposit spreads, consistent with a liquidity-premium channel operating through bank-level repricing rather than immediate mechanical adjustments.

Figure 10: Liquidity Forecast Errors Before and After Serial-Correlation Purging



Notes: The figure reports impulse responses of credit and deposit spreads to a liquidity shock obtained from the serially uncorrelated residual of the liquidity forecast error. Shaded areas denote 68 percent confidence intervals.

8.3 Liquidity measures

The benchmark results measure liquidity shocks in levels (PEN), which is natural given the reserve-supply interpretation of the instrument. However, levels may mechanically reflect changes in the scale of the banking system over time. Following the money-market literature, an alternative is to normalize reserves by a size-related aggregate, which yields a scale-free measure of liquidity conditions (Afonso et al., 2024). This subsection assesses whether the spread responses are robust to measuring liquidity as a ratio rather than in monetary units.

8.3.1 Liquidity as % of TOSE

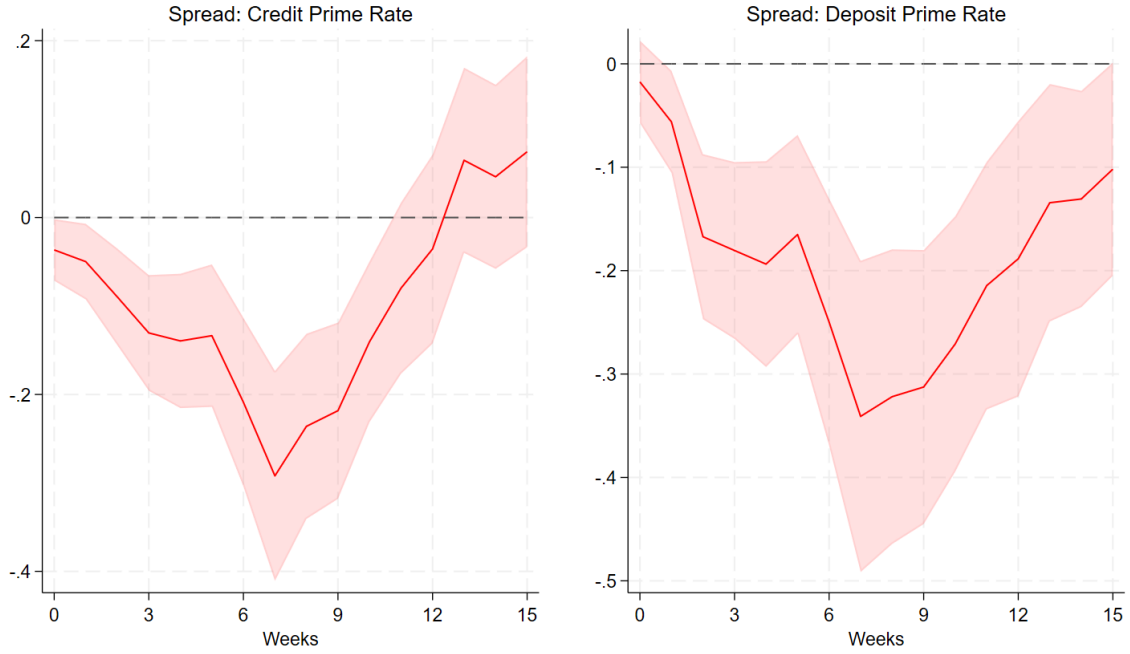
Figure 11 reports IV local-projection responses when liquidity is measured as reserves normalized by TOSE. The qualitative results remain unchanged: an increase in liquidity leads to a significant and persistent compression of both prime lending and deposit spreads relative to the 3-month CDBCRP rate.

Quantitatively, a 1 percentage point increase in reserves as a share of TOSE generates a pronounced hump-shaped decline in spreads over the 15-week horizon. The responses build up gradually, reaching their largest magnitudes around week 7, and subsequently unwind at a slow pace. Both the timing and persistence of the effects closely mirror those observed in the benchmark specification, reinforcing the stability of the estimated transmission mechanism.

Normalizing reserves by TOSE strengthens the interpretation that the estimated spread

responses reflect variations in liquidity conditions rather than mechanical changes in the scale of bank balance sheets or market size. By expressing liquidity in relative terms, this specification confirms that the effects are driven by shifts in the availability of liquid resources vis-à-vis outstanding financial liabilities, lending further support to the liquidity-premium channel emphasized in the baseline analysis.

Figure 11: Impulse Responses for Spreads: 3-month Prime Rate Minus 3-month CDBCRP
Liquidity as % of TOSE



Notes: The figure reports impulse responses for 3-month prime credit and deposit spreads, measured as the spread between 3-month prime lending (deposit) rates and the 3-month CDBCRP rate. The liquidity shock is identified using the benchmark IV-LP specification, normalizing the endogenous variable to be measured as a percentage of TOSE. Shaded areas denote 68 percent confidence intervals.

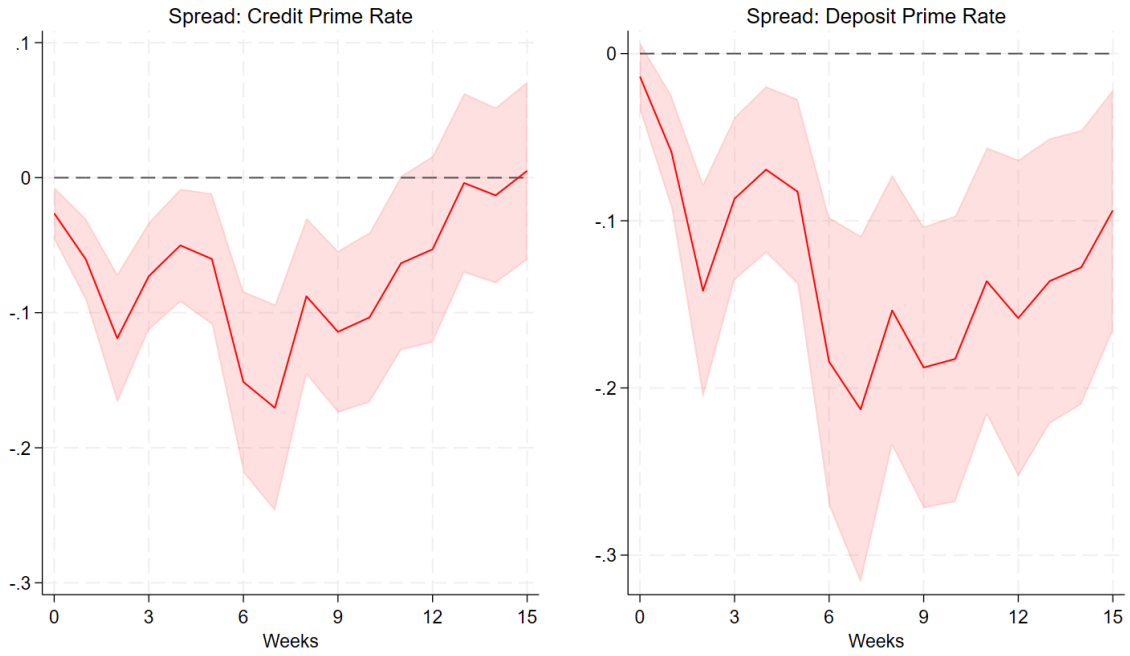
8.4 Alternative Maturity

The baseline results focus on 3-month interest rate spreads, which correspond to a central segment of prime bank contracts. This subsection assesses the robustness of those findings by examining whether the effects of liquidity shocks extend to longer contract maturities. To this end, I estimate IV local projections for prime credit and deposit spreads at the 6-month horizon, benchmarked against CDBCRP yields of matching maturity. As in the baseline specification, the liquidity shock is normalized to correspond to a one-billion PEN exogenous increase in reserves.

Figure 12 reports the impulse responses of 6-month prime credit and deposit spreads.

Both spreads display a clear and statistically significant compression following a liquidity shock. The dynamic pattern closely resembles the 3-month benchmark: spread compression builds up over the first several weeks, reaches its maximum around weeks 6 to 8, and subsequently unwinds gradually. The magnitude and persistence of the responses at the 6-month maturity are comparable to those estimated in the baseline specification, indicating that the effects of reserve-supply shocks are not confined to very short-term contracts.

Figure 12: Impulse Responses for Spreads: Credit Prime Rate Minus CDBCRP
Maturity: 6 months



Notes: The figure reports impulse responses of bank spreads constructed from 6-month maturity prime credit and deposit contracts, benchmarked against CDBCRP rates of matching maturity. Impulse responses are estimated using the IV local projection framework. Shaded areas denote 68 percent confidence intervals.

8.5 Model Specification: Long-Differences vs Levels

The benchmark IV local-projection specification is estimated in long differences. This modeling choice is standard in applied work, as level-based local projections may suffer from finite-sample distortions and accumulate small specification errors over longer horizons (Jordà and Taylor, 2025). Estimating the model in long differences helps mitigate these issues and yields more stable inference when the dependent variable exhibits high persistence.

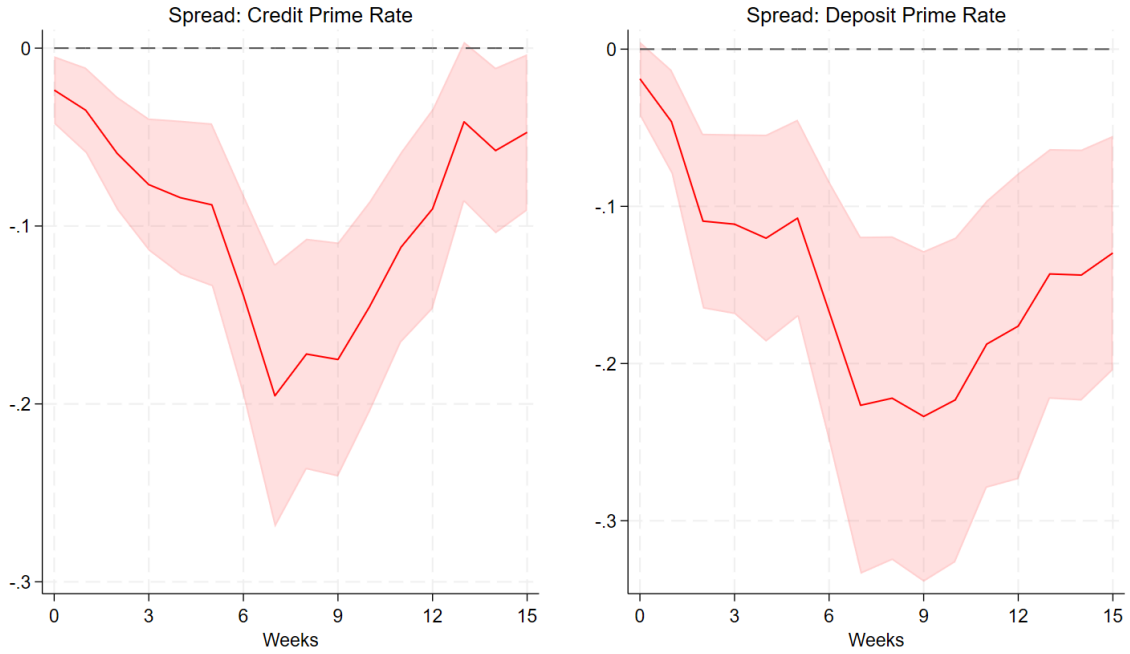
As a robustness check, I re-estimate the spread responses using a levels specification. Figure 13 reports the resulting impulse responses for 3-month prime lending and deposit spreads relative to the 3-month CDBCRP rate, using the same IV-LP framework and a liquidity shock normalized to a one-billion PEN exogenous increase in reserves.

The results are qualitatively unchanged. Liquidity shocks continue to generate a statistically significant and persistent compression of both prime lending and deposit spreads. The dynamic pattern closely mirrors the benchmark long-difference specification: spread compression builds up over the first several weeks, reaches its maximum around weeks 6 to 8, and subsequently unwinds only gradually while remaining negative over the 15-week horizon. Although levels estimates tend to display slightly larger point responses—consistent with the greater persistence of level variables—the timing and overall shape of the impulse responses remain remarkably similar across specifications.

Overall, the close correspondence between long-difference and level-based estimates indicates that the main results are not driven by the choice of outcome transformation. Instead, the findings reflect a robust transmission of liquidity shocks into bank pricing conditions, supporting the interpretation that reserve-supply innovations compress credit and deposit spreads through a persistent liquidity-premium channel.

Figure 13: Impulse Responses for Spreads: 3-month Prime Rate Minus 3-month CDBCRP

Levels Specification



Notes: The figure reports impulse responses for 3-month prime credit and deposit spreads, measured as the spread between 3-month prime lending (deposit) rates and the 3-month CDBCRP rate. The liquidity shock is identified using the benchmark IV-LP specification expressed in its levels form, instead of its long-differences form. Shaded areas denote 68 percent confidence intervals.

8.6 Large Shocks

A final robustness exercise addresses the concern that central banks may operate with implicit tolerance bands around their liquidity forecasts, treating small projection errors as operationally trivial. Under this view, only sufficiently large forecast errors would reflect meaningful and unanticipated disruptions in the level of liquidity available to the banking system.

To test whether the baseline results are driven by such large liquidity shocks, I construct an alternative instrument that isolates atypically large forecast errors. Specifically, the new instrument equals the original liquidity forecast error whenever its realization lies below the 25th percentile or above the 75th percentile of its empirical distribution, and is set to zero otherwise. This transformation effectively filters out moderate forecast deviations and retains only large, tail events, which are more likely to fall outside the central bank's tolerance range and to carry economic significance for banks' liquidity management.

Figure 14 reports the resulting IV local-projection impulse responses for 3-month prime

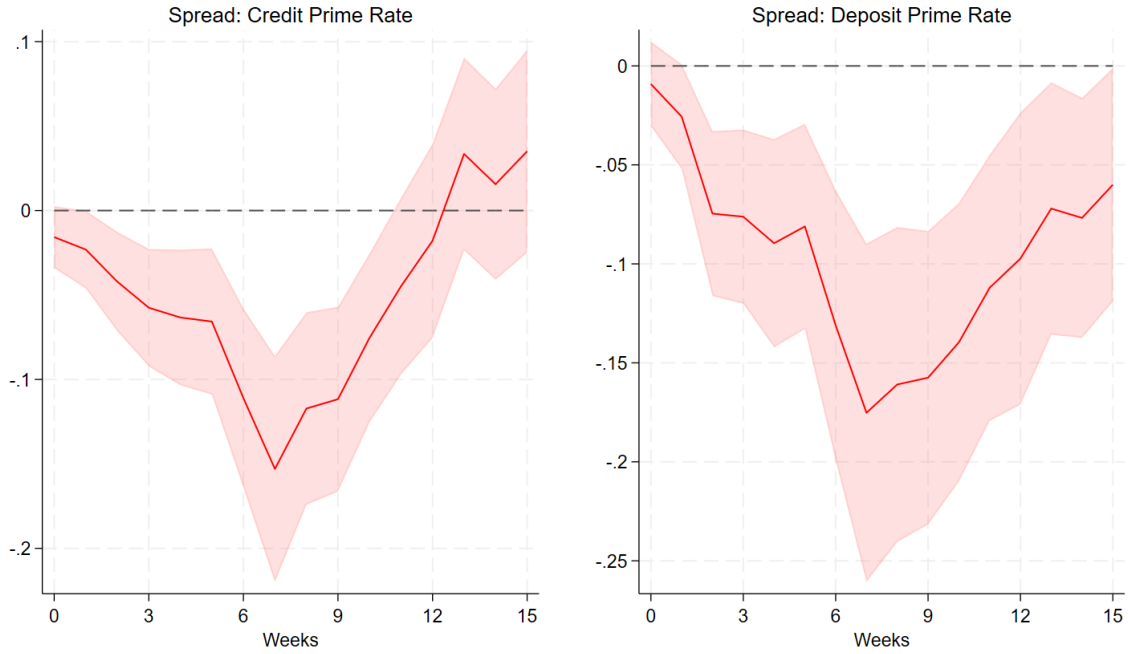
lending and deposit spreads relative to the 3-month CDBCRP rate. Despite the sharper identification and the reduced effective variation in the instrument, the qualitative results remain intact. Large liquidity shocks generate a pronounced and persistent compression of both credit and deposit spreads. The dynamic pattern closely resembles the benchmark specification: spread compression builds up over the first several weeks, reaches its maximum around weeks 6 to 8, and then gradually unwinds while remaining negative over the medium-term horizon.

While confidence bands widen—as expected given the focus on tail realizations—the estimated responses remain economically meaningful and statistically significant at medium horizons. This evidence suggests that the baseline results are not driven by marginal or operationally irrelevant forecast errors. Instead, the spread compression is primarily associated with large, abnormal liquidity shocks that plausibly escape central bank tolerance bands and materially affect banks' funding conditions.

Taken together, this exercise reinforces the interpretation that reserve-supply shocks influence bank pricing through a liquidity-premium channel. Even when attention is restricted to unusually large forecast errors, unexpected increases in liquidity lead to a sustained repricing of bank credit and deposit contracts, rather than merely reflecting noise or minor deviations around an operational target.

Figure 14: Impulse Responses for Spreads: 3-month Prime Rate Minus 3-month CDBCRP

Levels Specification



Notes: The figure reports impulse responses for 3-month prime credit and deposit spreads, measured as the spread between 3-month prime lending (deposit) rates and the 3-month CDBCRP rate. The liquidity shock is identified using the benchmark IV-LP specification, relying on an alternative definition of the instrument used to capture large liquidity shocks. Shaded areas denote 68 percent confidence intervals.

9 Conclusions

This paper studies how exogenous liquidity shocks transmit from central bank balance-sheet operations to bank contract pricing and, ultimately, to financial conditions relevant for the effective stance of monetary policy. Leveraging real-time liquidity forecasts from the Central Reserve Bank of Peru, the empirical design identifies reserve-supply shocks from forecast errors in daily liquidity management, providing plausibly exogenous variation in banks' reserve balances.

The core finding is that unexpected increases in reserve supply generate economically meaningful and persistent compression in bank lending and deposit spreads relative to safe yields. Following a positive liquidity shock, bank spreads decline gradually and remain compressed over several weeks, with peak effects occurring at medium horizons. Decompositions show that this adjustment is driven primarily by a repricing of bank lending and deposit rates themselves, while yields on safe assets respond only weakly and temporarily. This pattern is consistent with a reduction in the liquidity premia embedded

in bank contracts when liquidity risk declines.

Evidence from the interbank market provides benchmark mechanism validation. The same reserve-supply innovations identified in the main analysis lower the overnight interbank rate on impact, reproducing the classic liquidity effect emphasized in the monetary implementation literature. Together, these results demonstrate that reserve-supply shocks are priced at both very short horizons—through overnight rates—and at longer horizons, through the spreads embedded in retail banking contracts.

The findings contribute to a growing literature that emphasizes liquidity as a distinct channel of monetary transmission. While traditional analyses focus on policy-rate adjustments and much of the non-conventional policy literature highlights portfolio balance or segmentation effects operating through longer-term yields, this paper shows that liquidity management can shift financial conditions by altering the pricing of liquidity risk faced by banks. In this sense, reserve-supply policies operate as a complementary instrument that affects borrowing costs even when safe yields remain largely unchanged.

Overall, the results highlight that reserve-supply conditions are not only central to monetary policy implementation in money markets, but also to the broader transmission of monetary policy through bank credit and deposit pricing. Understanding this liquidity-premium channel is therefore crucial for assessing how balance-sheet and liquidity tools shape the effective stance of monetary policy, particularly in environments where reserves fluctuate meaningfully and banks' liquidity management plays a central role.

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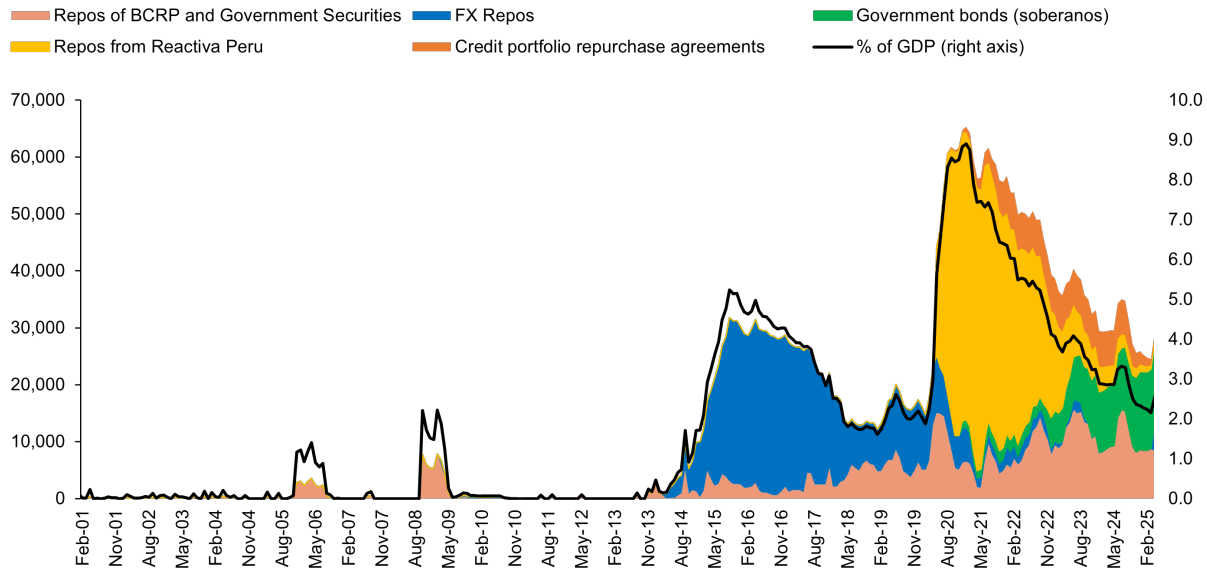
A Balance of BCRP Injection Operations

Figure 15 shows the outstanding balance of liquidity injection operations conducted by the BCRP, disaggregated by instrument. The stacked areas represent the contribution of different facilities—repos, FX repos, government securities, Reactiva Perú operations, and credit-portfolio repurchase agreements—while the right axis reports the aggregate balance as a percentage of GDP. The figure highlights substantial time variation in both the scale and composition of liquidity provision, with a sharp expansion and diversification of instruments after 2020.

Figure 15: Balance of BCRP Injection Operations



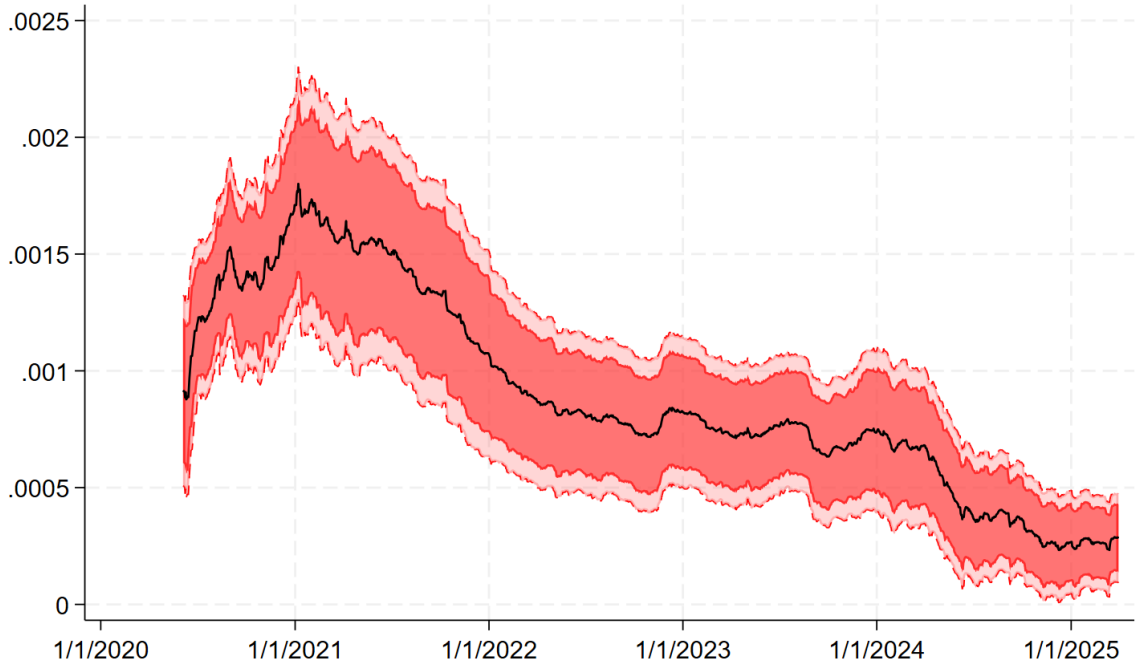
* Millions of PEN

B Liquidity Effect: Rolling Regressions

Theoretical insights and previous evidence suggesting a nonlinear demand curve for interbank reserves (Smith and Valcarcel, 2023; Afonso et al., 2024) imply that a full sample linear estimate of the liquidity effect could be misleading. To address this obstacle, I implement rolling IV regressions of Equation (2) with a 1250-business-day window (approximately five years), which balances sample size with the relevance of the instrument. In this exercise, liquidity is redefined as reserves normalized by TOSE, so that variation in liquidity is expressed relative to the size of the banking system size rather than in absolute levels.

Figure 16 reports rolling first-stage estimates and shows that forecast errors are a strong predictor of opening liquidity throughout the sample, supporting instrument relevance across subsamples.

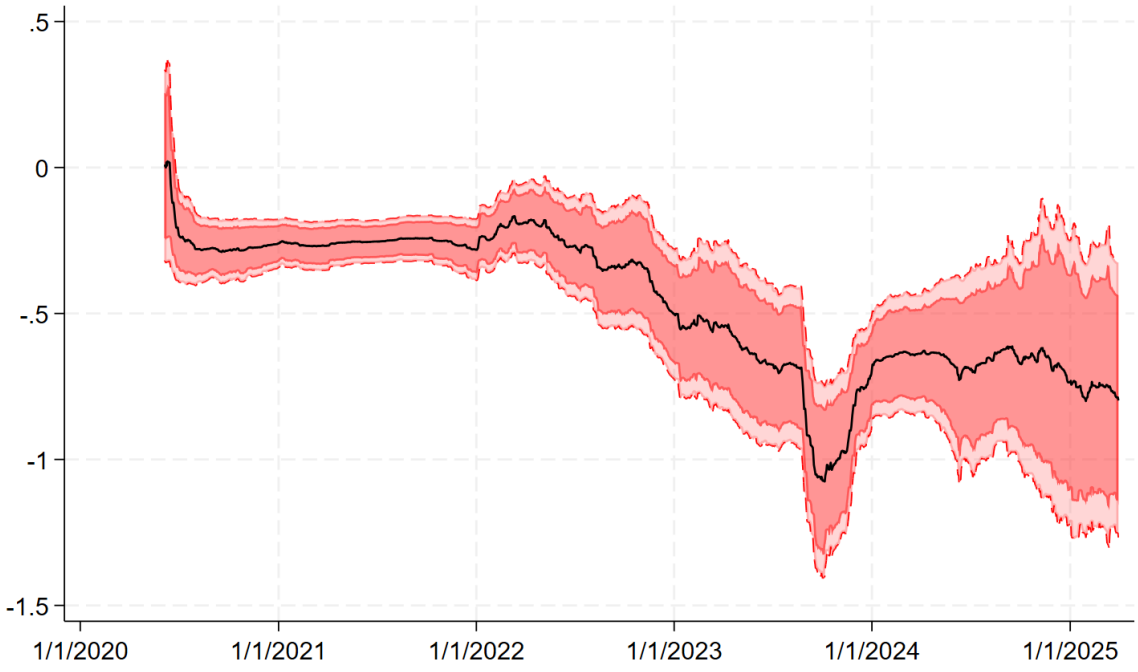
Figure 16: First-Stage Rolling Coefficient



* Confidence intervals at 95% and 99% are shown

Figure 17 plots the rolling IV estimates of the liquidity effect. With the exception of the earliest windows, the estimated liquidity effect is negative and statistically significant at the 1% level. After being relatively stable around -0.37 percentage points, the effect becomes more volatile from early 2022 onward, reaching a minimum close to -1 pp. by late 2023. It then partially reverts and remains around -0.75 pp. toward the end of the sample. Interpreted at the latest estimates, a 1 pp. increase in reserves as a share of TOSE reduces the overnight interbank rate by about 0.75 pp. in absolute value.

Figure 17: Liquidity Effect: IV Rolling Regressions



* Confidence intervals at 95% and 99% are shown

C Serial Correlation in Forecast Errors' Residuals

Table 3: AR(p) regressions for pre-whitened forecast errors (FE_u12): incremental lag order

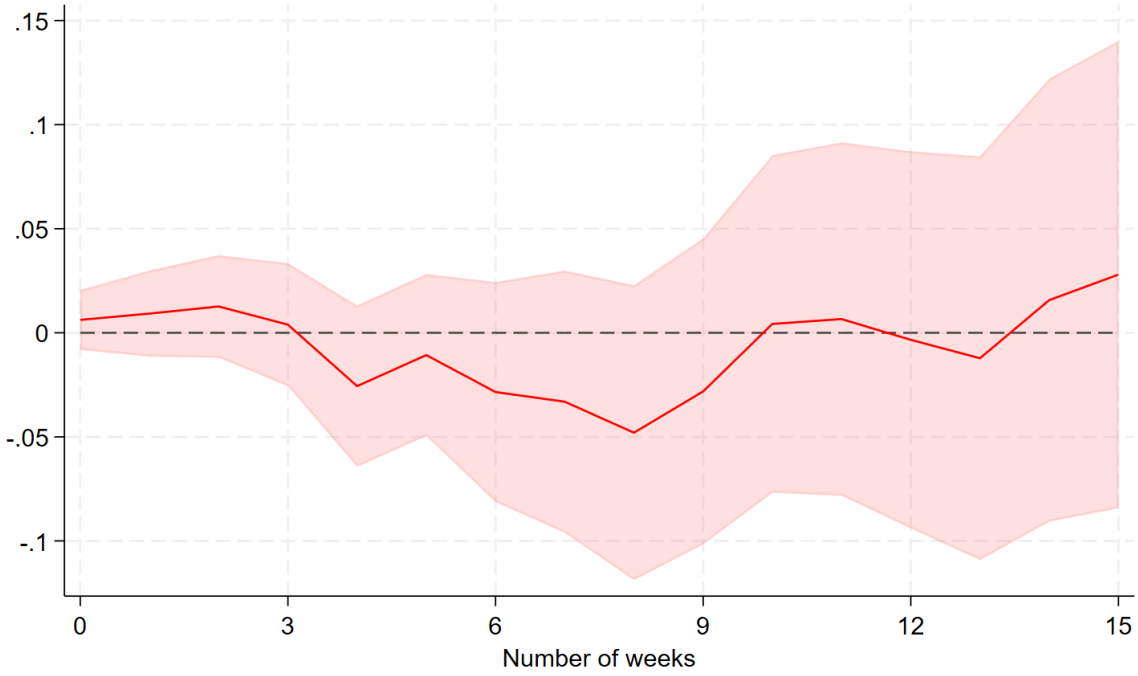
	(1) AR(1)	(2) AR(2)	(3) AR(3)	(4) AR(4)	(5) AR(5)	(6) AR(6)	(7) AR(7)	(8) AR(8)	(9) AR(9)	(10) AR(10)	(11) AR(11)	(12) AR(12)
$L.FE_u12$	0.00189	0.00200	0.00262	0.00385	0.00418	0.00451	0.00408	0.00395	0.00412	0.00473	0.00412	0.00385
	(0.0737)	(0.0733)	(0.0734)	(0.0733)	(0.0735)	(0.0738)	(0.0741)	(0.0744)	(0.0744)	(0.0745)	(0.0745)	(0.0745)
$L2.FE_u12$		0.00696	0.00646	0.00573	0.00463	0.00383	0.00419	0.00410	0.00488	0.00490	0.00551	0.00534
		(0.0616)	(0.0613)	(0.0606)	(0.0609)	(0.0617)	(0.0622)	(0.0624)	(0.0624)	(0.0623)	(0.0623)	(0.0629)
$L3.FE_u12$			0.0167	0.0169	0.0170	0.0178	0.0169	0.0170	0.0176	0.0173	0.0173	0.0167
			(0.0594)	(0.0590)	(0.0598)	(0.0602)	(0.0610)	(0.0614)	(0.0615)	(0.0617)	(0.0614)	(0.0617)
$L4.FE_u12$				0.0216	0.0213	0.0210	0.0219	0.0216	0.0209	0.0205	0.0202	0.0204
				(0.0660)	(0.0659)	(0.0659)	(0.0660)	(0.0656)	(0.0656)	(0.0653)	(0.0651)	(0.0646)
$L5.FE_u12$					0.0164	0.0165	0.0162	0.0163	0.0177	0.0183	0.0180	0.0185
					(0.0826)	(0.0824)	(0.0824)	(0.0824)	(0.0823)	(0.0825)	(0.0830)	(0.0830)
$L6.FE_u12$						0.00418	0.00431	0.00420	0.00257	0.00231	0.00290	0.00311
						(0.0706)	(0.0703)	(0.0702)	(0.0704)	(0.0710)	(0.0711)	(0.0714)
$L7.FE_u12$							0.00514	0.00515	0.00574	0.00676	0.00654	0.00673
							(0.0670)	(0.0670)	(0.0668)	(0.0668)	(0.0671)	(0.0673)
$L8.FE_u12$								0.00410	0.00380	0.00370	0.00471	0.00607
								(0.0689)	(0.0692)	(0.0697)	(0.0692)	(0.0703)
$L9.FE_u12$									-0.00217	-0.00187	-0.00196	-0.00229
									(0.0595)	(0.0591)	(0.0592)	(0.0590)
$L10.FE_u12$										-0.0159	-0.0156	-0.0151
										(0.0446)	(0.0447)	(0.0447)
$L11.FE_u12$											-0.0164	-0.0163
											(0.0664)	(0.0664)
$L12.FE_u12$												-0.0295
												(0.0606)
Constant	-0.199	0.164	-0.822	0.0217	-0.422	0.0265	0.513	0.619	-0.213	0.199	0.586	0.190
	(23.31)	(23.29)	(23.16)	(23.06)	(23.08)	(23.16)	(23.25)	(23.32)	(23.42)	(23.48)	(23.59)	(23.70)
Observations	416	415	414	413	412	411	410	409	408	407	406	405
Prob > F	0.980	0.994	0.994	0.992	0.996	0.999	1	1	1	1	1	1

Notes: Each column reports an OLS regression of FE_{u12t} on an incremental set of its own lags, $FE_t = \alpha + \sum_{\ell=1}^{p} \phi_\ell FE_{t-\ell} + u_t$. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors are heteroskedasticity- and autocorrelation-consistent (HAC), computed using the Newey–West estimator.

D Conventional Monetary Policy Neutrality

A key concern is whether the liquidity shock captured by our instrument is confounded with innovations to the conventional monetary stance. Table 4 provides direct evidence against such confounding: across specifications that regress weekly changes in the policy rate on contemporaneous and lagged forecast errors, the estimated coefficients are economically small and statistically indistinguishable from zero. Consistent with this reduced-form evidence, Figure 18 reports the impulse response of the policy rate to an instrumented liquidity shock and shows no systematic movement in the policy rate over the subsequent weeks; the response remains close to zero and the 68% confidence bands encompass zero throughout the horizon. Taken together, these results indicate that the identified liquidity shock operates largely through non-rate instruments, rather than through conventional adjustments in the policy rate.

Figure 18: Impulse Responses for Monetary Policy Rate



* The IRF displays 68% confidence bands

Table 4: Forecast Errors and Changes in the Policy Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Δ Policy Rate							
FE_t	1.56e-05						
	(2.35e-05)						
FE_{t-1}		2.24e-05					
		(1.45e-05)					
FE_{t-2}			2.13e-05				
			(1.83e-05)				
FE_{t-3}				4.94e-06			
				(1.64e-05)			
FE_{t-4}					-1.57e-05		
					(1.01e-05)		
FE_{t-5}						3.47e-06	
						(1.01e-05)	
FE_{t-6}							9.47e-06
							(9.85e-06)
Constant	0.000916	0.000808	0.000809	0.00109	0.00143	0.00112	0.00105
	(0.00729)	(0.00712)	(0.00718)	(0.00726)	(0.00730)	(0.00718)	(0.00715)
Observations	428	428	427	426	425	424	423
F-test p-value	0.508	0.123	0.244	0.763	0.123	0.732	0.337

Notes: Each column reports a separate regression of weekly changes in the policy rate on the forecast error (FE) at the indicated lag. All specifications are estimated using Newey–West heteroskedasticity and autocorrelation consistent standard errors with five lags. The reported estimates correspond to regressions of the form

$$\Delta\text{Policy Rate}_t = \alpha + \beta\, FE_{t-\ell} + u_t,$$

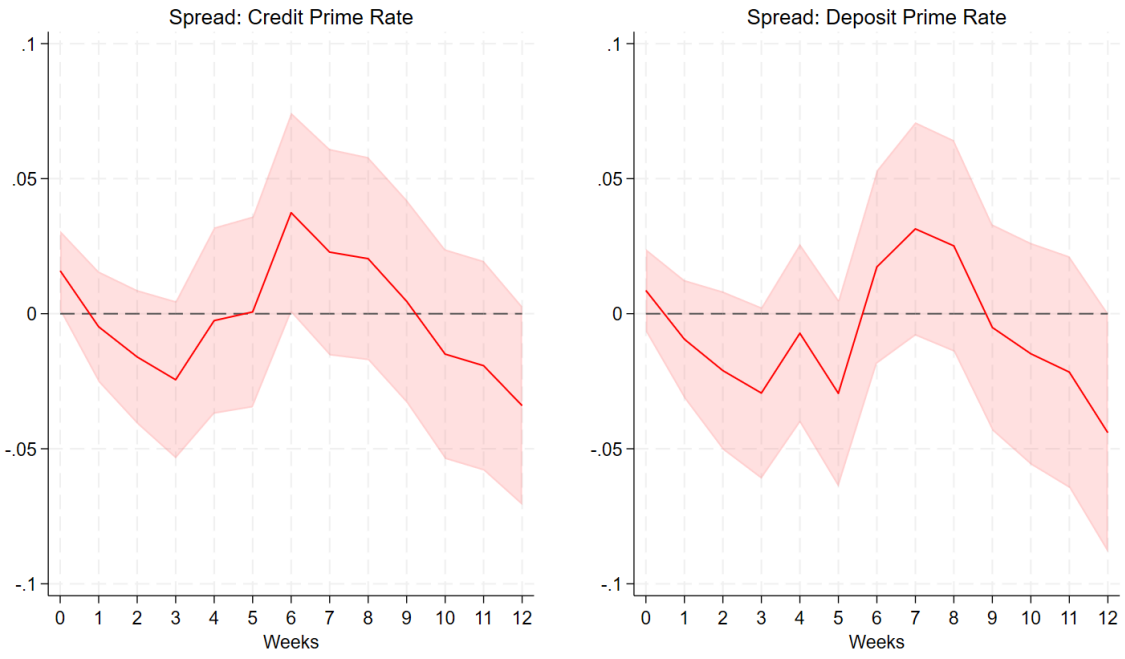
where ℓ denotes the lag reported in each column. Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

E Effect Anticipation

Figure 19 reports impulse responses of lagged bank spreads—evaluated 15 weeks prior—to a liquidity shock occurring at time t. The exercise serves as a falsification test of the identifying assumptions underlying the IV local-projection framework. In particular, it assesses whether the estimated liquidity shock exhibits anticipatory effects, that is, whether innovations dated at time t systematically predict movements in the dependent variables in the past.

The results show no evidence of such anticipation. For both credit and deposit spreads, the responses of lagged outcomes are statistically indistinguishable from zero across horizons, and display no systematic pre-trends. This pattern supports the lead–lag exogeneity assumption required for valid identification: future liquidity shocks do not affect current or past bank pricing conditions. More broadly, the absence of pre-responses reinforces the interpretation that the estimated dynamics reflect the causal propagation of unanticipated reserve-supply shocks, rather than reverse causality or predictable adjustments in bank spreads.

Figure 19: Impulse Responses for Lagged Spreads: 3-month Prime Rate Minus 3-month CDBCRP



* The IRF displays 68% confidence bands