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The Liquidity State Dependence of Monetary Policy Transmission

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Abstract

We show that monetary policy shocks move long-term government bond yields only when market liquidity is high and arbitrageurs are well capitalized. This *liquidity state dependence* operates entirely through real term premia, not expectations. Using novel transaction-level data on the US Treasury market, we find that arbitrageurs trade about 40% more duration during FOMC meetings in high-liquidity periods. We propose ways of enriching standard term-structure models to rationalize our evidence that constraints on arbitrage capital suppress transmission. The results introduce new empirical moments for theories of limits to arbitrage, and underscore the role of liquidity conditions in shaping the effectiveness of conventional monetary policy.

Keywords: monetary policy, long-term real rates, limited arbitrage, segmented markets

JEL Classification: E43, E44, E52, G12

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1 Introduction

Monetary policy influences economic activity through its impact on short- and long-term interest rates, with the latter linked to the former by no-arbitrage conditions (Woodford, 2003). A large literature shows that limits to arbitrage—arising from capital or risk constraints on intermediaries—can weaken these links. Yet little is known about whether such frictions systematically shape the strength of monetary policy transmission along the yield curve. We ask: does the impact of short-rate shocks on long-term bond yields vary with market liquidity and the availability of arbitrage capital?

Using aggregate time-series data, we show that monetary policy shocks move long-term bond yields only in high-liquidity states, when arbitrageurs are better capitalized. In these periods, a 1 percentage point shock to the 1-year nominal forward rate raises the 10-year forward by about 0.4 percentage points, with statistically significant effects persisting out to 15 years. This is an even stronger degree of monetary non-neutrality than documented in the previous literature.[1] In contrast, the response beyond five years is close to zero in low-liquidity states. The state dependence operates entirely through real rates—and within those, real term premia—with no effect on inflation compensation.

The effects are highly persistent: in high-liquidity states, the impact on long-term real rates remains statistically significant for more than three months after the shock, and passes through to mortgage rates. These results suggest that the availability of arbitrage capital shapes not only financial-market transmission but also real economic outcomes.

To arrive at these results, we identify monetary policy shocks using high-frequency changes in interest rate futures around Federal Open Market Committee (FOMC) announcements, following Nakamura and Steinsson (2018). Liquidity states are defined using the yield-curve noise measure of Hu et al. (2013), which captures deviations from a smooth yield curve and is tightly linked to the availability of arbitrage capital. We show that this measure is better explained by proxies for arbitrage capital, such as fixed-income arbitrage hedge fund returns, than by alternative candidates such as macroeconomic conditions or

[1] See, for example, Nakamura and Steinsson (2018), where the reaction of the 10-year nominal forward rate is statistically indistinguishable from zero.

volatility. This evidence makes clear that the state-dependent transmission we uncover is closely tied to arbitrageurs' capacity to intermediate.

To link these aggregate results to trading behavior, we use transaction-level data on the US Treasury market from MiFID II reporting by UK-based institutions. We identify counterparties as arbitrageurs or other traders based on regulatory categories and trading patterns, following the preferred-habitat framework (Vayanos and Vila, 2021). Arbitrageurs trade about 40% more long-end duration (11–30 years) around FOMC meetings when liquidity is high—providing direct evidence that arbitrage activity drives the state dependence. We also document that some investors display upward-sloping demand for duration, consistent with the idea that "reach-for-yield" behavior (Hanson and Stein, 2015) among certain preferred-habitat investors contributes to the positive term-premium response.

Taken together, the evidence introduces liquidity state dependence as a distinct empirical fact—related to, but not captured by, existing frameworks such as Hanson and Stein (2015) or Kekre et al. (2024). These authors respectively emphasize the roles of commercial banks and arbitrageurs' wealth, but neither framework on its own generates the patterns we document. This is why the results pose a challenge for standard preferred-habitat models. In particular, single-risk-factor preferred-habitat models struggle to generate the observed combination of (i) positive term premia in high-liquidity states; and (ii) stronger long-end responses when arbitrageurs are better capitalized. We show that extending the Vayanos and Vila (2021) framework to include demand risk can reconcile these patterns.[2]

Our mechanism also has important policy implications. It predicts an asymmetry between conventional and unconventional monetary policy: while QE has larger effects in illiquid markets, conventional policy is most effective when markets are liquid, because arbitrageurs are the key agents transmitting short-rate shocks to the long end. The framework also offers a new explanation for why monetary policy tightenings are often more powerful than easings, as easings tend to occur when arbitrageurs' capital constraints are most binding.

[2]We complement this with a 2-period, 2-bond model building on Kekre et al. (2024) that captures the same core intuition through transaction costs. See Appendix A for the full model derivation and discussion.

Taken together, our aggregate and micro evidence introduces a new dimension to state-dependent monetary policy transmission. The findings highlight the role of financial market structure in shaping the pass-through from short- to long-term rates and open new avenues for research on the interaction between monetary policy, risk premia, and limits to arbitrage.

Related Literature Our paper contributes to several strands of research in macroeconomics and finance.

First, we build on a large literature studying the transmission of monetary policy to long-term rates using high-frequency identification, with key contributions from Hanson and Stein (2015), Nakamura and Steinsson (2018) and Kekre et al. (2024).[3] Similar to Nakamura and Steinsson (2018) and Kekre et al. (2024), we use high-frequency-identified monetary policy shocks, while following Hanson and Stein (2015) in analyzing bonds with maturities above ten years and decomposing yields into expectations and term premia using an arbitrage-free term structure model. Prior work finds large, and sometimes puzzling, reactions of long-term real rates to short-term nominal rates. Our contribution is to show that these reactions are even larger than previously documented and concentrated on specific days—those when market liquidity is high.

Second, our interpretative framework builds on the preferred-habitat model of Vayanos and Vila (2021) and the extension of Kekre et al. (2024), which first highlighted the empirical disconnect in the term premia response. We contribute by analytically showing a tension in generating the observed liquidity state dependence in models without demand risk.

Third, our finding that specific classes of hedge funds are the marginal agent in pricing long-term bonds is consistent with the intermediary segmentation evidence of Siriwardane et al. (2025). Ray et al. (2024) also study state-dependent monetary transmission, but focus on unconventional policy; we focus on conventional policy.

Fourth, our emphasis on risk premia connects to recent work showing their importance in monetary transmission, including Bauer et al. (2023), Kashyap and Stein (2023), and

[3] See also Kuttner (2001), Cochrane and Piazzesi (2002), Gürkaynak et al. (2005b) and Gertler and Karadi (2015) for other seminal contributions.

Pflueger and Rinaldi (2022). In contemporaneous work, Nagel and Xu (2024) show that the impact of monetary policy on equity markets is driven entirely by its effect on bond yields. We add to this literature by showing that risk premia are also central for the transmission of conventional monetary policy to long-term yields.

Finally, we contribute to the macroeconomic literature on asymmetric monetary policy effects. Evidence of macroeconomic state dependence—dating back to Keynes—has recently been strengthened by studies such as Tenreyro and Thwaites (2016), Angrist et al. (2018), Barnichon and Matthes (2018) and Debortoli et al. (2023). We propose a complementary mechanism to downward nominal wage rigidity (Debortoli et al., 2023), loss aversion (Santoro et al., 2014), and firm financial constraints (Perez-Orive et al., 2024): reduced arbitrage capital can impair transmission to the long end of the yield curve, helping explain why monetary tightenings are often more powerful than easings.

2 Data and Methodology

2.1 Data

Our baseline analysis uses publicly available aggregate time-series data for the United States (US), described below. We also introduce the transaction-level dataset used for our analysis in Section 6.

Bond Yields. We use daily nominal yields from Gürkaynak et al. (2007), and real and inflation compensation components from Gürkaynak et al. (2010) available from the Federal Reserve Board.[4] Availability of real yields is the main constraint on the starting date, which is why all of our analysis is from 2000 onwards. We use instantaneous forward

[4]The data can be downloaded from the Federal Reserve website. We use the original dataset of Nakamura and Steinsson (2018) (available in their replication package on this website) in our baseline analysis to increase comparability with their results. In the different extensions we subsequently consider, we extend their original dataset with more recent data. However, this approach has the drawback that the data vintage for real interest rates used in Nakamura and Steinsson (2018) differs from the most recent vintage available on the website of the Federal Reserve Board due to subsequent revisions to the underlying methodology. We assess the robustness of our results to the choice of different data vintages in the Appendix.

rates at 1-year steps with maturities spanning up to 20 years ahead.

Bond Market Liquidity. We use the yield curve noise measure of Hu et al. (2013) as our baseline proxy for liquidity conditions in the US Treasury market. This is motivated by the fact that this proxy is intuitively related to limits to arbitrage capital (see Hu et al. (2013) and Vayanos and Wang (2013)), is not based on any particular segment of the yield curve, and has been shown by Hu et al. (2013) to capture aggregate liquidity conditions better than other popular measures. This makes this measure conceptually appealing as our baseline proxy.[5] We discuss in Section 2.3 how we identify high and low liquidity states. In Section 4.1, we explore potential drivers of the yield curve noise by relating it to observable proxies of arbitrage capital, business cycles, and other measures of market stress and liquidity.

Monetary Policy Shocks. In our baseline results we use the high-frequency measure of monetary policy surprises of Nakamura and Steinsson (2018), which uses the first principal component of the unanticipated change over the 30-minute window around scheduled FOMC announcements in various interest rates.[6] We extend this shock series to the most recent sample using the data provided by Acosta (2022). We show in Section 8.1 that our results are robust to the choice of alternative measures of monetary policy shocks. We follow Nakamura and Steinsson (2018) in restricting the sample to exclude all announcements taking place between July 2008 and June 2009 to ensure that our results are not driven by anomalous liquidity conditions in the Treasury market during the height of the Global Financial Crisis. We only depart from them by focusing on forward rates and extending the maturity breakdown of bond yields by including all the 1-year instantaneous

[5]Another benefit from using the yield curve noise rather than focusing directly on proxies for arbitrage capital is that it is available in real time and can be easily computed using widely available bond prices. Moreover, it is also robust to the changing importance over time of different arbitrageurs for bond markets, which may affect the relevance of specific arbitrage capital proxies.

[6]Specifically, Nakamura and Steinsson (2018) use the following five interest rate derivative contracts: the Fed funds futures maturing the next FOMC meeting and the one immediately after, and three-month eurodollar futures at horizons of two, three, and four quarters.

forwards from the 2-year forward up to 20 years.[7]

Macro and Financial Controls. We include in our analysis a number of observable proxies for risk, volatility, uncertainty, business cycle and arbitrage capital to explore the mechanism underlying our main results. For indicators related to volatility, uncertainty and liquidity, we use the VIX index from CBOE; the MOVE index from ICE BAML; the TED spread from FRED; a value-weighted measure of bid-ask spread in Treasuries based on CRSP data; a proxy for the on-the-run premium; the Pástor and Stambaugh (2003) liquidity measure; the risk aversion and uncertainty indices from Bekaert et al. (2022); the interest rate uncertainty index by Istrefi and Mouabbi (2018); and the interest-rate skewness measure of Bauer and Swanson (2023). Our business cycle indicators are the ADS real-time business cycle index by Aruoba et al. (2009) , available from the Philadelphia Fed website; the real-time unemployment rate used in Bauer and Chernov (2024); and the purchasing-manager index (PMI) from Markit.[8] For the arbitrage capital proxies, we consider the intermediary leverage measure of He et al. (2017); and the Barclays' hedge-fund return aggregate index and sub-indices for hedge funds specializing in different strategies such as fixed-income arbitrage, convertible arbitrage or multi-strategy (see Table D5 in the appendix section).

Secondary Market Transaction Data. We use the MIFID II database. This is a detailed transaction-level dataset, maintained by the Financial Conduct Authority in the United Kingdom, which provides information for almost all secondary market transactions on execution time, transaction price and quantity, as well as the International Securities Identification Number (ISIN), the Legal Entity Identifier (LEI) of both counterparties, and buyer-seller flags among other information.[9] The dataset covers virtually all transactions

[7]This is the most complete breakdown possible in our dataset. Focusing on forwards on such an extended maturity spectrum provides a comprehensive account of yield curve dynamics, and allows greater comparability of our results with Hanson and Stein (2015) and Kekre et al. (2024).

[8]These three macro variables are shown by Berge and Jordà (2011) to be among the best predictors of business cycles. The advantage of using the PMI relative to other macro indicators, including the ADS index, is that it is not subject to revisions.

[9]Further information on the MIFID II dataset can be found in the Reporting Guidelines: ESMA 2016.

where one of the counterparties involved in the trade is a UK-based institution. In this paper, we focus on US Treasury bond transactions between 2018 and 2022.[10] We complement the trade-level data with the Daily CRSP US Treasury Dataset. We collect information on duration, coupon rate, end of-day price, and amount outstanding for all the bonds in our dataset. We restrict our analysis to nominal coupon bonds with at least 1 year left to maturity. We do so because inflation-protected securities and floating-rate notes are distinct assets with a distinct investor clienteles.

2.2 Methodology

To measure the transmission of monetary policy, we run the following regression:

$$\Delta f_{i,t}^{(\tau)} = \alpha + \gamma_i^{(\tau)} \cdot mps_t + \varepsilon_t, \tag{2.1}$$

where t is the date of a scheduled FOMC announcements, $\Delta f_{i,t}^{(\tau)}$ is the daily change in the forward rate of denomination $i \in \{n, r, \pi\}$ (for nominal, real and inflation, respectively) and maturity τ, and mps_t is the high-frequency monetary policy shock. The coefficients $\gamma_i^{(\tau)}$ for $\tau \in (2, 20)$ trace out the estimated impact of the monetary policy shocks mps_t on the denomination i forward yield curve from the 2-year to the 20-year horizon. We depart from Nakamura and Steinsson (2018) by using forward rather than spot rates, as forward rates allow for a better understanding of the behaviour of the yield curve by maturity.[11]

We extend this baseline specification to allow for an heterogeneous transmission of monetary policy shocks across liquidity states. To do so, we interact the monetary policy surprise with indicator functions capturing whether the yield curve noise measure, our

[10] We are the first to focus on US Treasury data in the UK MIFID II dataset. For applications using UK Gilt bond transactions see Czech et al. (2021) and Pinter et al. (2024), and Jurkatis et al. (2023) for an application using UK corporate bonds.

[11] Forward rates offer a cleaner maturity decomposition since the spot rate of maturity τ at time t is simply the average of all the consecutive forward rates covering the period between t and τ. Forward rates therefore offer a cleaner measure of transmission to different parts of the curve since they don't include averages involving shorter-term rates. We do however show how our results translate into spot rates and reproduce Nakamura and Steinsson (2018) results for comparability. See Figure C1 and Table D13 in the appendix.

proxy for liquidity, on the day prior to a given FOMC announcement was below (HighLiq_{t-1}) or above (LowLiq_{t-1}) its median level across all announcements.[12] This yields the regression:

$$\Delta f_{i,t}^{(\tau)} = \alpha + \gamma_{i,hl}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \gamma_{i,ll}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon_{i,t}^{(\tau)} . \tag{2.2}$$

Our parameters of interest, $\gamma_{i,hl}^{(\tau)}$ and $\gamma_{i,ll}^{(\tau)}$, are therefore estimated on the same number of announcements. Each coefficient measures the degree of monetary policy transmission to bond yields under different liquidity states. This setting nests the baseline specification (2.1) in which the impact of monetary policy shocks is assumed constant over the entire estimation sample, corresponding to the coefficient restriction $\gamma_{i,hl}^{(\tau)} = \gamma_{i,ll}^{(\tau)}$.

To quantify the economic and statistical significance of the state-dependence (the difference in high vs. low liquidity estimates) we also estimate the related specification:

$$\Delta f_{i,t}^{(\tau)} = \alpha + \gamma_{i,ll}^{(\tau)} \cdot mps_t + \gamma_{i,h-l}^{(\tau)} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \varepsilon_t^{(\tau)}, \tag{2.3}$$

where $\gamma_{i,h-l}^{(\tau)}$ captures the incremental reaction of bond yields to monetary policy shocks on days of higher liquidity.

2.3 Identifying Liquidity States

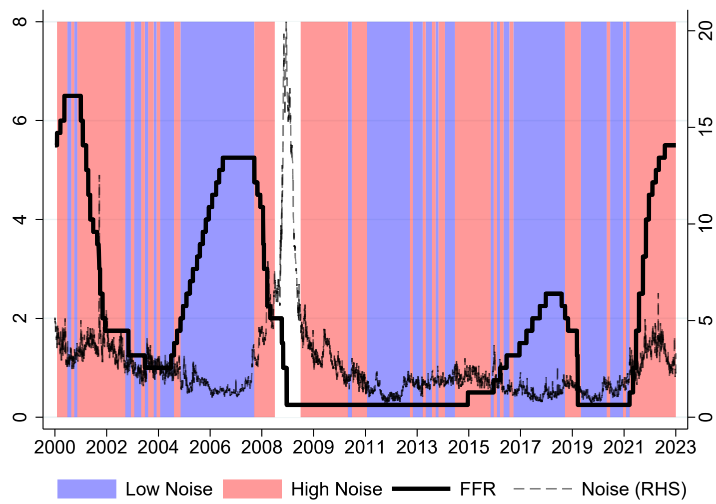
We identify high and low liquidity states by classifying FOMC meetings according to whether the yield curve noise measure of Hu et al. (2013) on the day *before* a given meeting was below or above its median level across all meetings. As the noise measure is trending over our sample,[13] we follow the approach of Cooper and Priestley (2009) and remove

[12]Using a dummy rather than the continuous variable is consistent with the intermediary asset pricing view of He and Krishnamurthy (2018) that frictions in intermediation affects the equilibrium in a non-linear fashion.

[13]One concern is that the supply of Treasuries may systematically affect the noise measure. For example an increase in the number of bonds outstanding may decrease the yield-curve fitting precision and hence increase noise. In Table D3 of the appendix, we report summary statistics on the input into the noise measure. While the number of bonds outstanding has increased, the fitting error captured by the noise measure has not. If anything, the noise seems to be trending down, in contrast to the supply of bonds which has trended up. The trend could be partly explained by introduction of electronic trading since early 2000s.

a quadratic trend as well as a linear trend from it in all our results. This detrending is conservative as our results are stronger in magnitude when using the raw noise measure. Another concern is that the noise could be systematically correlated with the monetary policy cycle. Figure 1 plots the time series of the raw yield-curve noise, the Fed Fund Rate (FFR) and the identified liquidity states based on the detrended noise. They key take-away from this figure is that the yield curve noise does not appear to be systematically correlated with the monetary policy cycle. Similarly, one may worry about the persistence of this variable. Figure 1 shows that liquidity switches between states relatively frequently.

FIGURE 1. High- and Low-Noise States and the Fed Fund Rate



Note: the black line is the Fed fund target rate (in %), the black dashed line is the yield curve noise (in bps, RHS). Areas shaded in blue are periods classified as Low Noise (High Liquidity), whereas areas shaded in red are periods classified as High Noise (Low Liquidity). A FOMC meeting is classified as High (Low) Noise if the level of the noise measure the day before the meeting is above (below) its median level across all FOMC meetings. We detrend the noise measure using a linear-quadratic trend estimated over the entire sample. The inter-meeting period carries the same classification as the last FOMC meeting. The sample is January 2000 to December 2023. The area in white is the height of the global financial crisis, July 2008 - July 2009, which we exclude from our analysis. The Fed fund target rate is from FRED (series: *DFEDTAR* spliced with the upper limit of the Fed fund target range *DFEDTARU* from December 2008 onwards), the yield curve noise is from Hu et al. (2013).

Table 1 reports descriptive statistics of key observables for the whole sample and the high- and low-liquidity subsamples. There are a total of 152 FOMC meetings in our sample (2000-2019, excl. the Global Financial Crisis).[14] By construction, they are evenly

[14]Recently Hu et al. (2013) have updated the noise series, and Acosta (2022) and Jarociński and Karadi

split into high and low liquidity states and we expect low liquidity states to coincide with worse macroeconomic conditions. This prior is somewhat confirmed, with a significantly higher incidence of recessions during low liquidity periods but no significant difference in inflation across liquidity states.[15] There is a slight easing bias for the changes in the Fed fund rate during low liquidity periods, but no significant difference in the *sign* of the monetary policy shocks between the two liquidity states, with positive and negative shocks almost evenly split. However, there might still be differences in the distribution of policy shocks between the two regimes, for instance due to a more aggressive easing of the monetary policy stance in periods of stressed financial markets, when liquidity is low.

To ensure our results are not driven by the differences in the distribution of monetary policy shocks across high and low liquidity FOMC meetings, we re-scale the monetary policy shocks in each state separately when estimating regressions (2.2) and (2.3). The shocks have unit variance and a 1pp impact on the 1-year nominal forward rate in the respective liquidity states, therefore ensuring that the results are directly comparable across states and are not driven by subsample characteristics. Using the raw monetary policy shocks results in even larger differences in point estimates on the short end of the curve, while retaining similar differences at medium- and long-term horizons.[16]

Figure C8 in the appendix shows the time series of monetary policy shocks in high and low liquidity states, before and after the normalization. See also Figures C9 and C10 for scatterplots of the relationship between changes in real forward rates and the monetary policy shocks in high and low liquidity states.

(2020) have updated the monetary policy shock series to allow us to extend the analysis through 2023. Our main results are unchanged in this longer sample.

[15]The unemployment rate is significantly higher during high liquidity periods. However, Table D4 in the appendix shows that this is not the case when we use the detrended noise measure to identify the liquidity states—as it is the case in our main analysis.

[16]Our main results are also present when we just standardize the monetary policy shocks instead, ensuring they have unit variance and zero mean in each liquidity regime.

TABLE 1. Summary Statistics Across Liquidity States and the Macroeconomy

	Pooled		High Liquidity		Low Liquidity		Diff.
	Mean	SD	Mean	SD	Mean	SD	p-value
Inflation	1.75	0.36	1.78	0.38	1.73	0.34	0.41
Unemployment Rate	5.79	1.79	6.52	2.12	5.06	0.95	0.00
Recession	0.06		0.01		0.11		0.02
MP Shock	-0.00	0.03	0.00	0.03	-0.01	0.03	0.08
Positive MPS	0.54		0.58		0.50		0.33
Negative MPS	0.46		0.42		0.50		0.33
FFR	1.90	1.90	1.74	1.95	2.05	1.85	0.32
Hike	0.14		0.18		0.11		0.17
Ease	0.11		0.04		0.17		0.01
No Change	0.75		0.78		0.72		0.46
Slope (10Y-2Y)	1.27	0.92	1.40	1.00	1.14	0.82	0.09
AAA-Treasury	1.53	0.41	1.54	0.43	1.52	0.38	0.71
Observations	152		76		76		152

Note: The table shows summary statistics based on the raw noise measure. The High and Low Liquidity periods are identified based on whether the noise measure on the day before a scheduled FOMC meeting is below or above its median level across all meetings. The sample period is 01/01/2000 - 31/12/2019, excluding all FOMC meetings taking place between July 2008 and June 2009. The monetary policy shocks (MPS) series is the shock from Nakamura and Steinsson (2018), as updated by Acosta (2022). Hike, Ease and No Change are defined based on monthly changes in the effective Fed fund rate. Recessions are monthly NBER recession dates. Unemployment rate is the real-time vintage civilian unemployment rate from Bauer et al. (2023). Inflation is the Personal Consumption Expenditures Excluding Food and Energy (PCEPILFE) from FRED. The last column ('Diff.') reports the p-value of a test of equality in means between the High Liquidity and Low Liquidity samples.

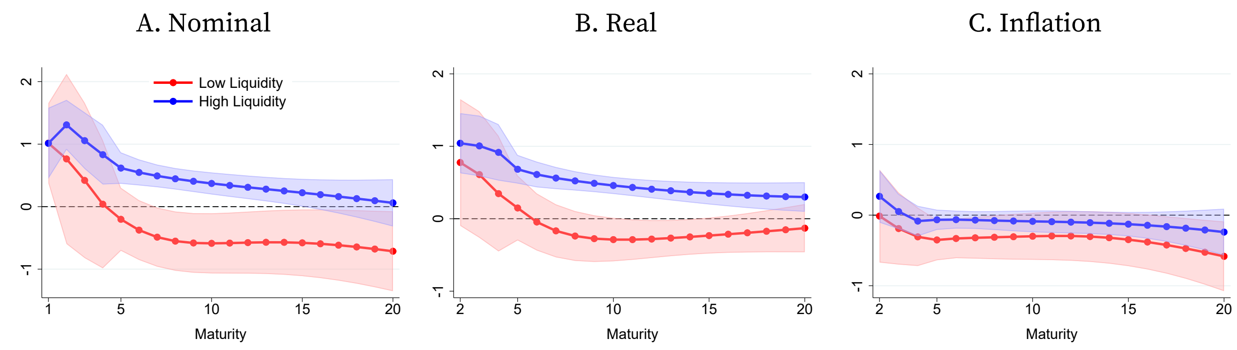
3 The Liquidity State Dependence of Monetary Policy Transmission

This section contains the main results of the paper: the liquidity state dependence in the response of forward rates to monetary policy shocks; the role of expectations and term premia; persistence; and real-economy transmission through mortgage rates.

3.1 Main Result

Figure 2 shows that monetary policy transmission differs sharply by liquidity state. In high-liquidity states (blue curve, Panel 2A), a 1-pp shock to the 1-year nominal forward raises the 10-year forward by about 0.4 pp, with statistically significant effects out to 15 years. In low-liquidity states, the response fades to zero by the 5-year point and turns slightly negative.[17]

FIGURE 2. The Liquidity State Dependence: The Response of Forward Rates



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), scaled to have unit variance in each liquidity state and normalized so that its impact on the 1-year nominal forward rate equals 100bps in each liquidity state separately. The monetary policy shock series is interacted with dummies for the liquidity states, which group FOMC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations. Regression results for the 2, 3 and 4-year forward rates are based on a sample size of 74 observations (starting in 2004).

The sign reversal in nominal forward rates under low liquidity is consistent with the interpretation that arbitrage constraints weaken the pass-through from short to long maturities. When arbitrageurs are capital-constrained, they do not take the offsetting positions needed to transmit short-rate changes to the long end, leaving long-term bond prices—and hence spot yields—largely unchanged.[18] Given the rise in short-term yields

[17]We are not the first to document that long-term forward rates turn negative following monetary policy shocks. In an earlier sample, Gürkaynak et al. (2005b) document the same phenomenon. In a more recent sample, Kekre et al. (2024) find results similar to ours.

[18]We show in Figure C1 in the appendix that estimates of the reaction of nominal spot rates to monetary policy shocks are indeed not statistically significant beyond the 2-year maturity, with point estimates close to zero from around 7 years.

after a short-rate shock, long-end forwards must then fall mechanically to keep spot yields flat. This mechanism, developed formally in Section 5, captures the core of the liquidity-state dependence: long-term yields respond to monetary policy shocks only when market liquidity is high and arbitrageurs have the capacity to intermediate.

Panel 2B reports our second key result. In high-liquidity states, a monetary policy shock significantly raises real forward rates at all maturities out to 20 years; in low-liquidity states, the response is negligible. In other words, monetary non-neutrality is present only when liquidity is high. Using the difference-in-coefficients specification in (2.3) (Table 9, row "Diff"), we reject equality of the high- and low-liquidity coefficients at nearly all maturities.

Panel 2C repeats the exercise for inflation compensation (breakeven inflation). We find no significant differences between liquidity states, confirming that the state dependence in transmission operates through real rates rather than expected inflation.

These results are robust to a wide range of checks, including alternative sample periods and monetary policy shock measures (Section 8). The liquidity state dependence is not an artifact of the data or sample period used by Nakamura and Steinsson (2018).[19] Nor is it driven by unconventional monetary policy operations during and after the global financial crisis.

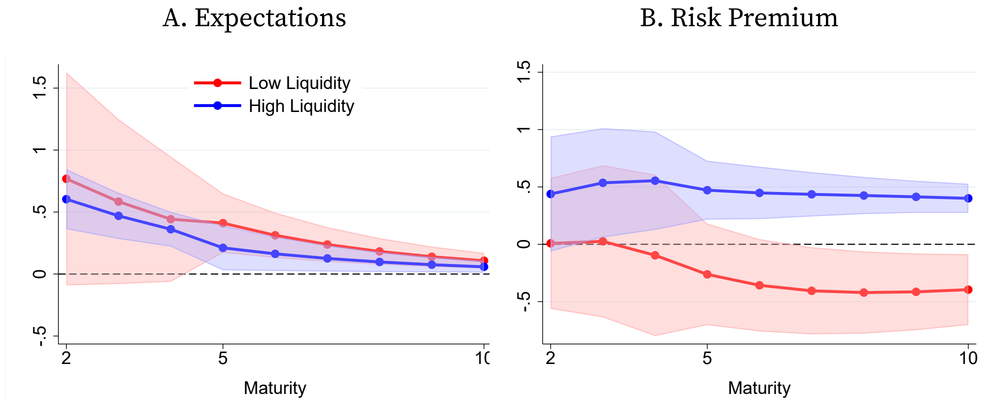
3.2 The Role of Risk Premia vs Expectations

Just like we can decompose nominal rates into a real and an inflation component, we can decompose any rate (nominal, real or inflation compensation) into an expectation component and a risk premium component. Nakamura and Steinsson (2018), using the model-based decomposition of Abrahams et al. (2016), attribute movements in real rates to expectations—consistent with a "Fed information effect" in which policy changes reveal private information. Hanson and Stein (2015), by contrast, argue that real-rate changes reflect shifts in term premia, based on forecasting regressions rather than a structural

[19] Table D13 in the appendix also replicates the baseline results from Nakamura and Steinsson (2018) to facilitate comparability.

decomposition.[20] For comparability with Nakamura and Steinsson (2018), we use the Abrahams et al. (2016) decomposition, and verify robustness using alternative approaches from Kim and Wright (2005) and d'Amico et al. (2018) (Section 8).[21]

FIGURE 3. Decomposing the Response of Real Forward Rates



Note: the figure plots the OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) estimated separately for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 10]$, together with 95% confidence intervals based on robust standard errors. Panels A and B show estimates for respectively the expectation hypothesis (*EH*) and risk premium (*RP*) components, which are based on the model decomposition estimated by Abrahams et al. (2016). We follow Nakamura and Steinsson (2018) by grouping the term premia, liquidity premium and model error into a single risk premium component. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), scaled to have unit variance and normalized so that its impact on the 1-year nominal forward rate equals 100bps in each liquidity state. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2004 to 19/03/2014, excluding those taking place between July 2008 and June 2009.

Figure 3 shows that monetary policy shocks move expectations (Panel 3A), but the response is nearly identical across liquidity states—so expectations cannot account for the state dependence. In contrast, the risk-premium component moves sharply only in high-liquidity states (Panel 3B), fully explaining the liquidity-state dependence of the real-rate response.

These results are consistent with elements of both Nakamura and Steinsson (2018) and

[20] Kekre et al. (2024) also point to the term premia moving but they do not provide a direct test using real term premia estimates. Instead, they infer from the U-shaped response of real rates to monetary policy shocks they document that the term premia component must be driving the response of long-term rates. We do not find evidence of a U-shaped response.

[21] We thank Min Wei for sharing with us a finer 1-year instantaneous forward maturity decomposition than is available online, to allow us to match our regression design and compare with Abrahams et al. (2016).

Hanson and Stein (2015). Like Nakamura and Steinsson, we find a significant expectations channel, especially in high-liquidity states. But, consistent with Hanson and Stein, we also find a substantial term-premium component—present only in high-liquidity states—which explains why the pooled-sample analysis in Nakamura and Steinsson detects no term-premium effect. While both channels operate, it is the term-premium component that drives the liquidity-state dependence.

In Section 5, we show how the sign and magnitude of this state dependence constrain the assumptions in preferred-habitat models such as Vayanos and Vila (2021) and connect to the framework in Kekre et al. (2024). In Section 6, we present transaction-level evidence consistent with the "reach-for-yield" behavior described by Hanson and Stein (2015).

3.3 Persistence

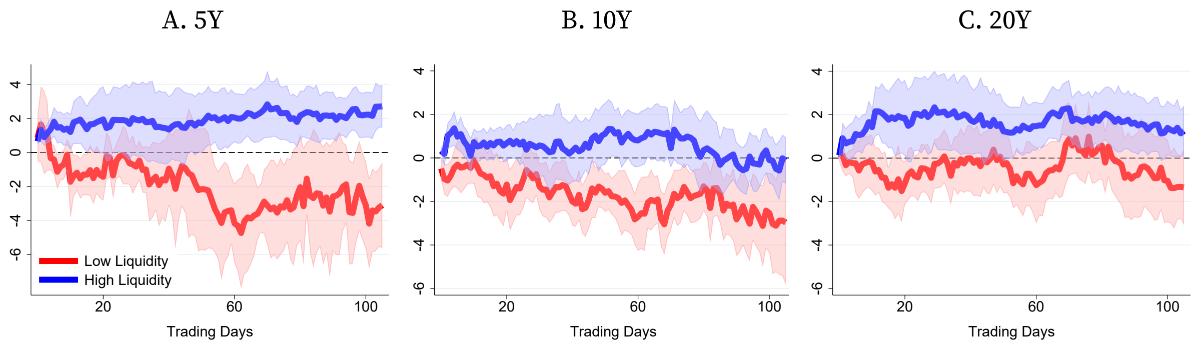
A natural question is whether the liquidity state dependence we document is short-lived. We find it is not: the effects persist for more than a quarter after the initial shock. To examine this, we extend the specification in Equation (2.2) to

$$f^{(\tau)}_{r,t+h} - f^{(\tau)}_{r,t-1} = \alpha_h + \gamma^{(\tau)}_{r,h,hl} \cdot [mps_t \times \mathbb{1}_{\text{HighLiq}_{t-1}}] + \gamma^{(\tau)}_{r,h,ll} \cdot [mps_t \times \mathbb{1}_{\text{LowLiq}_{t-1}}] + \epsilon^{(\tau)}_{r,t+h}, \tag{3.4}$$

where the left-hand side variable measures the cumulative change over an horizon of h days after the announcement.

Figure 4 shows the results for real forward rates in the baseline sample. In high-liquidity states, the initial increase in real forwards after a positive shock remains statistically significant for up to three months. The effects are strongest over the first month for intermediate maturities of 5 and 10 years, and the cumulative change after three months is significant for the 5-year and 20-year forwards. In low-liquidity states, by contrast, responses are muted: most estimates are indistinguishable from zero, and the 5-year and 10-year forwards even show a significant cumulative decline after three months.

FIGURE 4. Persistence of the Liquidity State Dependence on Real Forward Rates



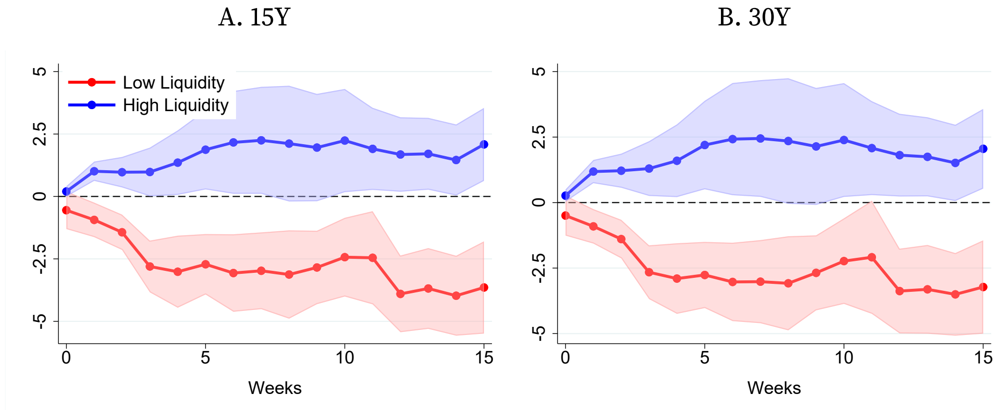
Note: the figure shows estimates of $\gamma^{(\tau)}_{r,h,hl}$ and $\gamma^{(\tau)}_{r,h,ll}$ in regression (3.4) for real forward rates with maturities of 5 (Panel A), 10 (Panel B), and 20 years (Panel C) at horizons ranging from 1 to 122 trading days after the announcement, together with 90% confidence intervals based on Newey-West standard errors with 10 lags. High Liquidity and Low Liquidity refer to the subset of scheduled FOMC announcements for which the level of the noise measure the day before the meeting is below (resp. above) its median level across all FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations on which the policy news shock is computed and each regression is estimated.

3.4 The Response of Mortgage Rates

So far, our analysis has focused on the benchmark (risk-free) government bond yield curve. The persistence of the liquidity-state-dependent effects suggests that they may have implications for the real economy. In a frictionless world, changes in government yields would pass through one-for-one to other borrowing rates and to risky asset prices. If, as our interpretation suggests, larger yield responses occur in high-liquidity states because arbitrage is less constrained, then such pass-through would also be more complete in those periods. To test this prediction, we examine the response of mortgage rates, given the central role of housing finance in the monetary transmission mechanism.

Figure 5 reports the estimated responses of U.S. fixed-rate mortgage rates in our baseline sample. Consistent with our main findings, monetary policy transmission to mortgage rates is strongly liquidity-state-dependent: in high-liquidity states, mortgage rates rise significantly following a short-rate shock, with the high–low difference remaining large and statistically significant over a three-month horizon.

FIGURE 5. The Response of Mortgage Rates



Note: the figure shows the OLS estimates for $\gamma^{(\tau)}_{h,hl}$ and $\gamma^{(\tau)}_{h,ll}$ using 15Y and 30Y mortgage rates respectively in regression (3.4) together with 90% confidence intervals based on Newey-West standard errors with 10 lags, where High (res. Low) Liquidity corresponds to the subset of scheduled FOMC announcements for which the level of the noise measure the day before the meeting is below (resp. above) its median level across all FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations on which the policy news shock is computed and each regression is estimated.

4 Liquidity State Dependence and Arbitrage Capital: Empirical Evidence

In Section 3, we documented that monetary policy shocks have much larger effects on long-term yields in high-liquidity states than in low-liquidity states. We now investigate whether this "liquidity state dependence" is linked to the availability of arbitrage capital, as suggested by the yield curve noise measure of Hu et al. (2013).

Section 4.1 examines which variables best explain changes in yield curve noise. Section 4.2 then re-estimates the baseline regressions from Section 3 using proxies for arbitrage capital in place of yield curve noise as the conditioning variable. We also test other potential drivers that are not directly related to arbitrage capital and document that they fail to replicate the liquidity state dependence.

4.1 Arbitrage Capital Can Explain Liquidity

We begin by exploring the different mechanisms that could explain the liquidity state dependence by analyzing how factors with a clear economic interpretation can account for the variations in liquidity (captured by the yield curve noise). Motivated by the intermediary asset pricing literature—e.g. He and Krishnamurthy (2012, 2013), Brunnermeier and Sannikov (2014)—we consider a host of variables proxying for broad market conditions (including volatility, liquidity and stress), uncertainty, the business cycle, and arbitrageurs' capital. In these models, arbitrage capital and macroeconomic outcomes are jointly determined, resulting in many of these variables potentially having a significant correlation with liquidity.

To proxy for broad market conditions, we include the option-implied equity volatility VIX index, the option-implied bond volatility MOVE index, TED spread, and the risk-aversion index proposed by Bekaert et al. (2022). Following Berge and Jordà (2011), we include the macroeconomic variables that best capture the state of the business cycle, including the real-time ADS index by Aruoba et al. (2009), the purchasing-manager index (PMI), and initial jobless claims. To proxy for uncertainty we use the index proposed by Bekaert et al. (2022), the interest rate skewness measure of Bauer and Chernov (2024) and the interest rate uncertainty measure of Istrefi and Mouabbi (2018). Lastly, we proxy for arbitrageurs' capital using the intermediary leverage factor of He et al. (2017) and the Barclays' hedge-fund return aggregate index and sub-indices for hedge funds specializing in different strategies. These include three macro strategies, four specialized strategies and four equity strategies.

We regress monthly changes in yield curve noise on each variable separately, then within-category, and finally across all categories combined. Hedge fund results appear in Table D5, and the broader set in Table D6. Table 2 summarizes the best-performing variables.

In line with the recent evidence of asset market segmentation in Siriwardane et al. (2025), we find that fixed-income arbitrage (FIA) returns have one of the highest univariate explanatory power amongst all hedge-fund returns (R^2 of 35%). FIA is also one of the only

TABLE 2. What Explains the Yield Curve Noise?

	Monthly Changes in Noise								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔMOVE	0.02***							0.01***	
	(4.24)							(3.59)	
ΔUnemp.		0.14***						0.10***	
		(2.68)						(2.95)	
ΔUnc.			0.71**					-0.32	
			(2.44)					(-1.27)	
ΔLev.				1.43***				0.59*	
				(3.90)				(1.93)	
FIA Ret.					-0.41***		-0.18***	-0.17***	-0.32***
					(-7.95)		(-3.02)	(-2.63)	(-4.84)
ConvArb Ret.						-0.45***	-0.32***	-0.32***	-0.05
						(-5.35)	(-3.38)	(-2.82)	(-0.77)
Adj. R^2	15.94	2.53	16.10	16.35	34.52	40.89	43.47	50.77	18.76
N	205	240	240	240	240	240	240	205	239

Note: The dependent variable is the monthly change in the yield curve noise measure, obtained by averaging daily observations over a given month. We use the following specification $\Delta \text{Noise}_t = \alpha + \beta \Delta X_t + \epsilon_t$, where X_t is a vector of explanatory variables. We use the MOVE index obtained from the CBOE as liquidity proxy; initial jobless claims obtained from the Bureau of Labor Statistics as business cycle proxy; the uncertainty index from Bekaert et al. (2022); the broker-dealer leverage factor of He et al. (2017) (Δ Lev.), and Barclay's fixed-income arbitrage (FIA Ret.) and convertible-arbitrage (ConvArb Ret.) return indices for arbitrage capital proxies. All dependent variables are standardized to ease comparison. The sample covers from 01/2000 to 12/2019, corresponding to a sample size of 240 observations, except otherwise noted. Newey-West standard errors with 36 lags are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

two hedge fund strategies to remain statistically significant when all the other subindices are included in the regression. The other significant subindex is the convertible arbitrage (CA) one, which has an even higher univariate explanatory power (R^2 of 41%), consistent with the results in Mitchell et al. (2007) which link convertible arbitrage returns to slow moving capital. To separate the information content of the fixed-income arbitrage versus convertible-arbitrage returns, we use the AR(1) innovations for each in explaining changes in noise (see column 9 of Table 2).[22] This exercise suggests that fixed-income arbitrage may be more important once we account for the predictable component in each series.

Overall, proxies for arbitrage capital explain variation in liquidity even when controlling for other plausible drivers. The evidence points to a specific role for fixed-income arbitrageurs, rather than hedge funds in general, in maintaining low yield curve noise.

[22] Table D7 in the appendix presents the results for the variables in the other categories.

4.2 Arbitrage Capital State Dependence

We next test whether proxies for arbitrage capital can replicate the liquidity state dependence in monetary policy transmission documented in Section 3. For each proxy, we classify FOMC meetings as "high" or "low" based on whether the variable's value the day before the meeting is above or below its sample median (month before for monthly data). We then re-estimate the baseline regression (2.2) separately by state, scaling the monetary policy shock to have unit variance and a 1pp effect on the 1-year nominal forward in each subsample.

Table 3 reports results for arbitrage capital proxies. Panel A replicates our baseline results for the extended 2000–2019 sample. FIA returns produce a high–low difference in real forward rate responses that closely matches our baseline yield curve noise results (Panel B). Convertible arbitrage returns, despite explaining noise levels, do not replicate the high–low gap at maturities beyond 10 years. Broker-dealer leverage (He et al., 2017) comes closer but with weaker significance.

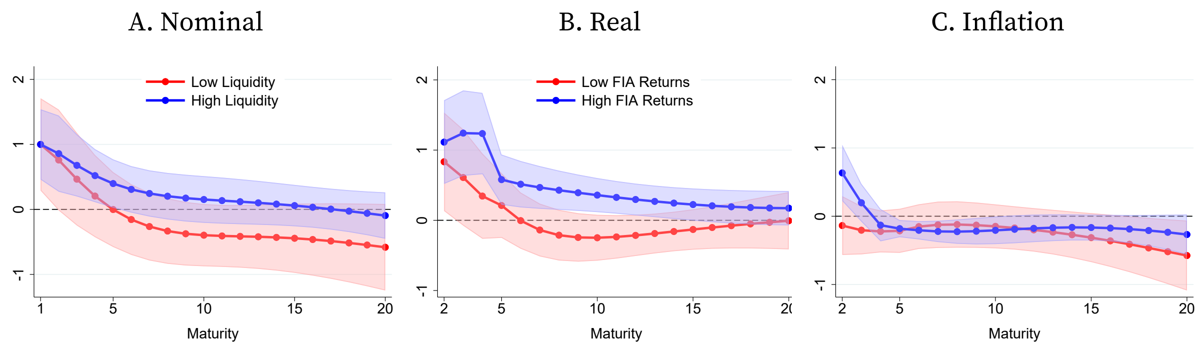
Table 4 reports results for other non-macroeconomic variables. The TED spread and the interest rate skewness measure of Bauer and Chernov (2024) capture some state dependence at shorter horizons (up to 10 years), but neither matches FIA returns at the long end. Moreover, neither survives robustness checks such as excluding easing meetings or extending the sample period.[23] This reinforces that our baseline measure and FIA returns capture a specific form of liquidity tied to arbitrage capital.

Figure 6 visualizes the conditioning on FIA returns. The pattern is similar to Figure 2: in periods following high FIA returns, real forwards respond strongly to policy shocks; after low returns, responses are muted. The effect is even more pronounced in the extended sample (Figure C6 in the appendix).

Finally, we test other potential liquidity proxies—Treasury bid–ask spreads, on-the-run premiums, and the Pástor and Stambaugh (2003) factor—and find that none reproduce the state dependence, despite capturing other aspects of market liquidity (Table D10 in

[23] See Tables D8 and D9 in the appendix for results excluding all FOMC meetings where the target rate was reduced. We show in Section 7 that this exercise is an important robustness test to control for potential confounding effects from macroeconomic state dependence in the transmission of monetary policy.

FIGURE 6. The Liquidity State Dependence: Conditioning on Arbitrage Returns



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for each forward maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), scaled to have unit variance and normalized so that its impact on the 1-year nominal forward rate equals 1pp in each liquidity state. Each regression is estimated separately for each maturity and liquidity state. A given FOMC meeting is grouped in the High (Low) FIA returns state if the value of the hedge fund return index in the month prior to the meeting is above (below) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the coefficients in the High-Liquidity state (high FIA returns), while the red line represents the coefficient estimates in the Low-Liquidity state (low FIA returns) FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations. Regression results for the 2, 3 and 4-year forward rates are based on a sample size of 74 observations (starting in 2004).

the appendix). This suggests that the relevant notion of liquidity in our baseline is closely linked to the availability of arbitrage capital.

5 Liquidity State Dependence and Arbitrage Capital: Theory

The empirical results reveal a pronounced state dependence in monetary policy transmission: in high-liquidity states, long-term forward rates often overshoot in response to short-rate shocks, whereas in low-liquidity states the reaction is muted or slightly negative. We now ask whether standard theories of the term structure—particularly models featuring limits to arbitrage—can account for these patterns.

We base our discussion on the preferred-habitat model of Vayanos and Vila (2021) (hereafter VV), a benchmark framework for analyzing the interaction between bond supply, preferred-habitat demand, arbitrageur risk-taking capacity, and term premia. Our focus is on how variation in arbitrageurs' risk-bearing capacity can generate the liquidity state dependence we document. An alternative possibility is that the effect arises from state dependence in preferred-habitat demand—or from both channels. We discuss this alternative only briefly, as our empirical evidence is more directly supportive of the arbitrage-capital channel.

We begin with the single-risk-factor version of VV (Section 3 of their paper), in which short-rate risk is the only priced risk. In this setting, there is a tension between the model's predictions and our empirical findings: without demand risk, the sign of the term premium is independent of arbitrageurs' risk-bearing capacity, making it difficult to jointly match the state dependence in forwards and in term premia shown in Section 3. Moreover, such models cannot generate yield-curve noise when arbitrageurs are active in the market.

We then introduce demand risk, as in Section 4 of VV. This extension can reconcile the model's predictions with the empirical facts by allowing the sign and magnitude of term premia to vary with arbitrageurs' risk-bearing capacity. It also naturally rationalizes both the existence of yield-curve noise and its variation over time as arbitrage capital fluctuates.

We conclude the section by outlining the economic intuition behind the resulting state dependence, emphasizing its implications for the transmission of conventional versus unconventional monetary policy, and suggesting directions for future work on the role of demand risk in shaping yield-curve dynamics.

5.1 Vayanos and Vila (2021) model without demand risk

Throughout we will use the original VV notation and results, where arbitrageurs' risk-bearing capacity is driven by the coefficient of risk aversion. To relate this to arbitrageurs' capital, in the Appendix B we augment the model in VV with variable arbitrage capital in the form of a variable mass of identical arbitrageurs present in the market at each point in time. As number of arbitrageurs increases, total arbitrage capital increases, leading to higher risk-bearing capacity, which is equivalent to lowering the CARA coefficient of risk-aversion, which is what we do below.[24]

In the equilibrium without demand risk, where preferred habitat exogenous demand is fixed, VV show that equilibrium yields are an affine one-factor model, with forward rates given by:[25]

$$f_t^{(\tau)} = e^{-\kappa_r^* \tau} r_t + C'(\tau) \,, \tag{5.5}$$

$$\kappa_r^* = \kappa_r + a\sigma_r^2 \int_0^T \alpha(\tau) A(\tau)^2 d\tau \,, \tag{5.6}$$

where τ is the maturity; κ_r^* and κ_r are the degree of mean-reversion of the short-rate process under the risk-adjusted and actual measure, respectively; a is the CARA risk-aversion coefficient of arbitrageurs; σ_r^2 is the volatility of short-rate shocks; and $\alpha(\tau)$ is the negative of the price-elasticity of preferred habitat investors' demand.[26]

The response of the forward rate and term premium component to a monetary policy (short-rate) shock are given by:[27]

$$\frac{\partial f_t^{(\tau)}}{\partial r_t} = e^{-\kappa_r^* \tau} \tag{5.7}$$

$$\frac{\partial TP_t^{(\tau)}}{\partial r_t} = \frac{\partial f_t^{(\tau)}}{\partial r_t} - \frac{\partial \mathbb{E}_t r_{t+\tau}}{\partial r_t} = e^{-\kappa_r^* \tau} - e^{-\kappa_r \tau} \tag{5.8}$$

The key for liquidity state dependence and sign of term premium is the relation between

[24]Modeling a varying number of arbitrageurs present in the market does not need to be literal. It could equally proxy for different levels of arbitrageur capital allocated to this market, entry of arbitrageurs in the spirit of slow-moving capital, changes in risk-bearing capacity of arbitrageurs driven by time-varying risk aversion, wealth effects or exogenous changes in funding constraints. While the underlying frictions are different, for our purposes the equilibrium outcomes are isomorphic and equivalent to varying the risk aversion parameter directly.

[25]See Proposition 1 in VV.

[26]Preferred-habitat investor of type-τ demand only bonds with maturity τ, with their demand given by $Z_t^{(\tau)} = -\beta(\tau) - \alpha(\tau) \log P_t^{(\tau)}$. The demand for bond-$\tau$ has an inelastic component ($\beta(\tau)$) and an elastic one that depends on the current price $P_t^{(\tau)}$, where $\alpha(\tau)$ is the negative of the price-elasticity. The model discussed in this section $\beta(\tau)$ is fixed, so only risk in the model comes from short-rate uncertainty.

[27]See Proposition 2 in VV.

the degree of short-rate mean-reversion under the risk-adjusted measure (κ_r^*) and actual measure (κ_r). The sign of term premium is given by the sign of $\kappa_r^* - \kappa_r$, while the magnitude of forward reaction is driven by κ_r^* only. A higher κ_r^* raises both the response of forwards and the term premium, but whether that comes with positive or negative term premium depends on $\kappa_r^* - \kappa_r$.

In this simple model, the risk-bearing capacity of arbitrageurs, captured by risk-aversion coefficient a and short-rate uncertainty (σ_r^2), determines the magnitude of the difference, whereas the sign of preferred habitat demand elasticity ($-\alpha$) will determine the sign of term premium.[28] If we assume downward sloping demand ($\alpha > 0$, as assumed by VV) then the term premium is always negative, whereas if we assume upward sloping demand ($\alpha < 0$) then the term premium is always positive.[29] But for a given sign of the term premium, the absolute size of the term premium is driven by arbitrageurs' risk bearing capacity: a higher risk bearing capacity leads to a higher magnitude of the term premium. This is at the heart of the tension in matching the liquidity state dependence: in the data, in periods where arbitrageurs' risk-bearing capacity is higher (high liquidity state) a higher response in forward is driven by a higher and positive term premium component, with no or even negative term premium component for long maturity forwards in periods where arbitrageurs' risk-bearing capacity is lower (low liquidity state). Without state dependence in preferred habitat demand it is not possible to generate a higher term premium when arbitrageurs' risk-bearing capacity is lower.

Therefore, while we can generate a positive term premium in the simple one-factor model of VV by introducing reach-for-yield investors as in Hanson and Stein (2015), this would lead to a counterfactual higher forward curve reaction in low liquidity states.[30] We

[28]Since $\left(a, \sigma_r^2, A(\tau)^2\right) \geq 0$, the sign of $\kappa_r^* - \kappa_r = a\sigma_r^2 \int_0^T \alpha(\tau)A(\tau)^2 d\tau$ is determined by sign of α.

[29]To better understand the role played by price elasticity, consider how preferred-habitat investors react to short-term interest rate shocks. They decrease (increase) their demand for long-term bonds in response to a positive (negative) shock to short-term rates, which implies that arbitrageurs have to increase (decrease) their holding of long-term bonds, for which they require a higher (lower) term premium. This mechanism is also present in Kekre et al. (2024), with the difference that the endogenous wealth effect could still dominate and deliver a positive term-premium response to a positive short-rate shock even when preferred-habitat investors have negative price elasticity for their demand.

[30]This same tension applies to other ways of generating positive term premium in extensions of VV, such as Jansen et al. (2024), which do so by introducing cross-elasticities in preferred habitat demand, or

can only generate the correct state dependence in the reaction of forwards with negative term premium responses in both states, driven by a less negative term premium response in high liquidity states.

5.2 Vayanos and Vila (2021) model with demand risk

When the exogenous demand from preferred habitats is not fixed, short-rate risk is no longer the only risk factor. This leads to qualitatively different behavior by arbitrageurs, as trading in long term bonds exposes them to more demand risk. This additional risk can potentially reconcile the liquidity state dependence with theory as a function of arbitrageurs' risk-bearing capacity.[31]

VV show that in the presence of demand risk factors, the transmission of monetary policy to the forward yield curve will be as before if arbitrageurs' risk-bearing capacity is sufficiently high, albeit muted relative to the counterfactual of no demand risk due to hedging motives introduced by demand risk. So when arbitrageurs are less constrained there would be either positive or negative term premium response to monetary policy, depending on price elasticity of demand. However, if arbitrageurs' risk-bearing capacity is sufficiently low, VV show that the response of forward curve inverses beyond an intermediate maturity, as the hedging demand dominates. This would lead to opposite sign of term premium in long-term forward rates.

Therefore if the term premium sign is positive in the absence of demand risk, because of upward-sloping demand curve, then when arbitrageurs are sufficiently well capitalized we should observe a positive response of the entire forward curve in response to short-rate shocks with a positive term premium component. But irrespective of the sign of the term premium in the absence of demand risk, if arbitrageurs' risk-bearing capacity is

Kekre et al. (2024), who add endogenous wealth. Without state dependence in demand, or some additional state-dependence in Kekre et al. (2024), such as arbitrageurs becoming more myopic in low liquidity states (captured by higher per period death probability), then both models would generate higher positive term premium in periods of low arbitrageur risk-bearing capacity.

[31]The discussion here is based on Section 4 of VV, in the discussion in Section 4.2 and Proposition 5. We also draw on the more detailed discussion of the effect of increasing the number of demand risk factors in the earlier working paper version Vayanos and Vila (2009).

sufficiently low relative to demand risk, then we should observe a muted reaction in the forward curve with an inflection beyond short maturities. This combination matches the liquidity state dependence evidence if high (low) liquidity states correspond to high (low) arbitrageur risk-bearing capacity.

Vayanos and Vila (2009) also discuss how as the number of demand factors increases, the yield curve becomes increasingly localized, as arbitrageurs find it harder to hedge demand risk for a given risk-bearing capacity. This could potentially explain the existence of yield curve noise obtained from fitting smoothed yield curves to the individual bond data, and why the noise would rise when arbitrageurs are more constrained, such as in the global financial crisis. The presence of multiple demand risk factors can therefore potentially explain both the liquidity state dependence and noise itself as a function of arbitrageur capital.

5.3 Intuition: Interest Rate versus QE State Dependence

At first glance, our finding that term premia rise when arbitrage-capital constraints are looser may seem to contradict the core intuition of intermediary asset pricing and limits-to-arbitrage theories (Vayanos and Vila, 2021; Kekre et al., 2024). In those models, tighter constraints typically increase the compensation required for holding risk. The key to reconciling our evidence with these models lies in understanding their comparative statics, and in contrasting the predicted responses to conventional (short-rate) and unconventional (QE/QT) policy shocks.

Short-rate shocks In response to a short-rate shock, arbitrageurs will only trade long-term bonds to the extent that the change in short-term rates makes the trade attractive, i.e. offer sufficient expected excess returns to compensate for the additional risk of trading long term bonds in response to change in expected short-rates. This is why arbitrageurs will react less to a given change in short-term rates when they are more capital-constrained and there is background risk in the form of demand risk, as they are reluctant to be exposed to the additional demand risks when trading long-term bonds. Therefore, long-term yields will only react to the extent that arbitrageurs are willing to trade in response to the monetary policy shock.[32] When long-term yields do not change, the term premium component automatically offsets the change in the expectation component, as observed in the low liquidity state.

QE shocks In the case of a QE shock, the arbitrage capital state dependence is more intuitive, and not dependent on demand risk. Here, asset purchases by the central bank (QE) reduce the supply of bonds, hence arbitrageurs have to hold less risk in equilibrium. Therefore, the yield curve reaction will be bigger when arbitrageurs are more constrained, as shown in Ray et al. (2024) and Guimaraes and Vlieghe (2024). Short-rate shocks, on the other hand, do not automatically imply larger/smaller positions by arbitrageurs,[33] it only affects their risk if they choose to trade across the yield curve.

6 Inspecting the Mechanism: Evidence from Transaction Data

In this section, we use a granular transaction-level dataset to provide *direct* evidence on the mechanism behind the liquidity state dependence, as well as on the sign of the term premia. This dataset covers actual trading by all market participants in the UK. As a by-product, we observe a fraction of US Treasury trading whenever one party is UK based. One caveat is that our dataset covers a shorter sample period (2018-2022). Nonetheless, the richness of our transaction-level data can help answering many questions that have proven elusive in the literature. We provide an overview of the dataset and summary statistics in Appendix C.

[32] When the demand of preferred habitat investors is price inelastic, there is no reaction of long-term yields in response to short-rate shocks in the absence of arbitrageurs.

[33] It only leads to exogenous changes in their position to the extent that they accommodate changing bond demand from price-elastic preferred habitat investors. This is why the price elasticity of these investors is key to the sign of the term premium in VV, why it impacts the parameter region that delivers positive term premia in Kekre et al. (2024), and why introducing cross-maturity elasticities as in Jansen et al. (2024) can also lead to positive term premia.

We document two main results using this dataset. In Section 6.1, we show that arbitrageurs are responsible for substantially higher trading volumes around high-liquidity FOMC meetings. This is particularly pronounced at longer maturities, directly matching our aggregate empirical evidence in Section 3. This finding is consistent with low noise periods capturing periods of diminished constraints on arbitrageurs, corroborating the findings in Section 4.

In Section 6.2, we provide evidence supporting the existence of reach-for-yield investors, that is investors whose demand for long-term bonds increases when the yield curve steepens, as suggested in Hanson and Stein (2015) and Hanson et al. (2021). The presence of reach-for-yield investors is one of the leading explanations for the overreaction of the forward rate.

6.1 Arbitrageurs' Trading Around FOMC Meetings

We expect periods where the level of the yield curve noise is low to be associated with more arbitrage activity. In particular, we should observe arbitrageurs becoming *increasingly* more active in those periods and at longer maturities, consistent with the noise measure proxying for constraints on the availability of arbitrage capital and the mechanism for the liquidity state dependence introduced in Section 5.

We calculate the gross volume by trader i in sector s at time t in bond b as $y^{(b)}_{i,s,t}$. We scale this quantity by the duration of bond b at time t, denoted $d^{(b)}_t$, to adjust for the risk associated with the trade and define the total duration traded as $f^{(b)}_{i,s,t} = y^{(b)}_{i,s,t} \cdot d^{(b)}_t$. For scaling purposes we divide it by the gross duration traded across all the bonds by trader i on the same date t. This way, our measure captures the relative amount of trading in different maturity buckets:

$$\tilde{f}^{(b)}_{i,s,t} \equiv \frac{f^{(b)}_{i,s,t}}{\sum_b f^{(b)}_{i,s,t}}.$$

In Appendix C.1, we develop an algorithm to identify arbitrageurs based on their trading behaviour. In line with our prior, we find that arbitrageurs concentrate among hedge funds, followed by asset managers and some banks.

In a second step, we collapse arbitrageurs' daily trading volumes into a single observation per maturity bucket m. We have four maturity buckets: short ($1-3\,y$), intermediate ($4-7\,y$), medium-long ($7-10\,y$) and long ($11-30\,y$). We denote $\tilde{f}^{(m)}_{arb,t}$ the total gross duration traded by arbitrageurs on bonds in maturity bucket m at time t. We are interested in comparing arbitrageurs trading in high and low liquidity states. We average their trading on FOMC days $t \in \{\mathrm{H}, \mathrm{L}\}$, where "H" denotes a high-liquidity FOMC day and "L" a low-liquidity one:

$$\tilde{f}^{(m)}_{arb,k} = \frac{1}{T_{\mathrm{k}}} \sum_{t \in T_{\mathrm{k}}} \tilde{f}^{(m)}_{arb,t}, \qquad k \in H, L$$

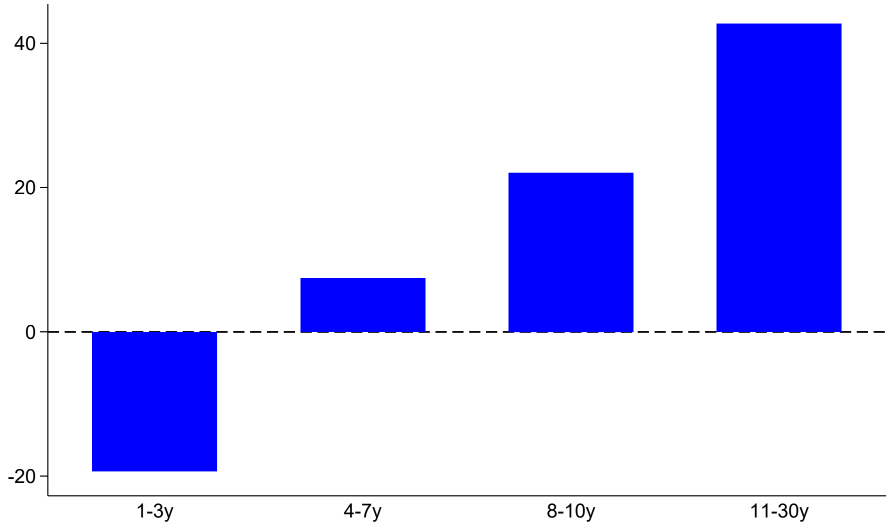
We then take the growth rate of gross duration traded across high- and low-liquidity FOMC meetings for each maturity bucket m:

$$g^{m}_{arbs,h-l} = \frac{\tilde{f}^{(m)}_{arb,h}}{\tilde{f}^{(m)}_{arb,l}} - 1, \tag{6.9}$$

Under our hypothesis that arbitrageurs trade relatively more of longer-duration bonds around FOMC meetings where they are less constrained (high-liquidity meetings), we should see $g_{arbs,h-l} > 0$ for larger m. Figure 7 shows the values of the measure of growth in traded duration across maturity buckets for arbitrageurs. They increase their trading activity when liquidity is high, as evidenced by the fact that $g_{arbs,h-l}$ is monotonically increasing across maturity buckets, trading around 40% more duration at the long-end of the curve ($11-30\,y$) when liquidity is high.[34] These patterns are consistent with the liquidity state dependence of monetary policy being driven by higher arbitrageur trading.

[34] This pattern is robust to computing the growth measure only on FOMC meeting days (as shown in Figure 7), or using a 2-day window or 3-day window, as well as to excluding individual investors that do not trade in at least 5 or 15 of the FOMC meetings in our sample.

FIGURE 7. Arbitrageurs' Trading on High- vs Low-Liquidity FOMC Meetings



Note: the figure plots $g_{arb,h-l}$, the growth rate in duration traded on high relative to low liquidity FOMC meetings, as defined in equation (6.9). The algorithm to identify arbitrageurs is explained in Appendix C.1. The sample period is 01/01/2018 - 31/12/2022, excluding the Covid crisis 01/03/2020 - 30/05/2020.

The takeaway from this subsection is that arbitrageurs are more active when liquidity is high. This could be for a number of reasons, from decreased risk aversion, exogenous investor inflows, unexpected positive returns to slack funding constraints. We do not take a stance on the reason why, but we note that all of those are consistent with diminishing limits to arbitrage.

6.2 The Presence of Reach-for-Yield Investors

Hanson and Stein (2015) show that the presence of reach-for-yield investors could explain a positive term premia coefficient in response to monetary policy shocks. These investors buy (sell) long-term bonds when the term spread increases (decreases), and this could account for the reaction of long-term bonds to monetary policy shocks. Hanson and Stein (2015) stress that this is not a prediction that is specific about monetary policy shocks, but a behaviour that should be observed on any day. They find that banks increase their duration following an increase in the yield spread, consistent with their hypothesis. We test this hypothesis below for banks and other sectors.

We begin by repeating an exercise analogous to that of Hanson and Stein (2015), asking whether when short-term yields go down relative to long-term yields, certain traders purchase more long-term bonds. To test this, we exploit the rich panel cross-section in our data and run the following specification separately for each sector s:

$$\tilde{q}_{i,s,t}^{(b)} = \alpha_i + \alpha_s + \alpha_b + \alpha_y + \beta_s \cdot \Delta\mathrm{TERM}_{t-1} + \varepsilon_{i,s,b,t},$$

where $\tilde{q}_{i,s,t}^{(b)}$ is the *net* duration purchased by trader i in sector s at time t on bond b, scaled by the gross duration traded across all the bonds by trader i on the same date t; $\Delta\mathrm{TERM}_{t-1}$ is the lagged daily change in term spread, the difference between the 10-year nominal spot yield and the 2-year nominal spot yield; and α_i, α_s, α_b, α_y are trader, sector, bond and year fixed effects respectively.[35]

Below we restrict our attention to sectors traditionally suspected of displaying upward-sloping demand curves, such as banks (Hanson and Stein, 2015), insurance companies (Domanski et al., 2017), pension funds (Greenwood and Vayanos, 2010) and foreign officials. We call those reach-for-yield sectors following Hanson et al. (2021).[36]

Our main result is in Table 5.[37] We find evidence that following an increase in term spread, reach-for-yield traders are net buyers of duration, consistent with the results of Hanson and Stein (2015). The inclusion of fixed effects does not impact the sign or magnitude of the estimated coefficients, as can be seen from columns (2) to (5). It is possible that while the aggregate net duration purchased increases, it may reflect purchases of large quantities of short-maturity bonds. To test whether this is the case, we interact the term spread with a dummy consisting of three maturity buckets: $1-3\,y$, $4-10\,y$ and $11-30\,y$.

[35]We also run the regression on short-term and long-term yields separately and cannot reject the hypothesis that the coefficients are equal and with opposite signs, validating the hypothesis that they trade based on the term spread.

[36]In the appendix, we consider all the sectors and find empirical support for the inclusion of those sectors. We find limited evidence of reach-for-yield behaviour for asset managers and no significant evidence for hedge funds.

[37]Table D11 in the appendix repeats the same regression split by sector.

In column (6) we find that purchases are concentrated in longer-maturity bonds.

$$\tilde{q}_{i,s,t}^{(b)} = \alpha_i + \alpha_s + \alpha_b + \alpha_y + \sum_{\tau'} \beta_s^{(\tau')} \cdot \left[\mathbb{1}_{\tau=\tau'} \times \Delta\text{TERM}_{t-1}\right] + \varepsilon_{i,s,t}^{(b)},$$

A second question concerns whether this behaviour differs on FOMC days. To test this, we interact the term spread with two dummies: one for FOMC meeting days and one for post-FOMC meeting days. Column (7) presents the results. We find that the reach for yield is not different on FOMC days, with statistically insignificant estimated interaction coefficients for FOMC days. In other words, the reach-for-yield behaviour is a permanent feature of those investors, as advocated by Hanson and Stein (2015).

The presence of reach-for-yield investors is consistent with a positive price-elasticity for preferred-habitat investors in VV. The evidence from transaction data therefore supports the mechanism in Section 5 in explaining the sign of the state-dependent term premia response to monetary policy shocks documented in Section 3.

7 Liquidity and the Macroeconomy

In this section we examine how the liquidity state dependence relates to previously documented macro state-dependence and what our evidence implies for conventional versus unconventional monetary policy.

7.1 Which State Matters: Liquidity or the Macroeconomy?

Could the liquidity state dependence be driven by the state of the business cycle?[38] We argue below that the liquidity state dependence may partly explain some of the macro state dependence recently documented in addition to playing a separate role.

We first consider the business cycle aspect of the macro state dependence, which posits that monetary policy has weaker macroeconomic effects during recessions. To check whether this can explain our results we repeat our main exercise excluding all FOMC meetings during periods identified as NBER recessions. This exercise is shown in panel A of Table 6, and our main results are unaffected. As an alternative in Panel B of Table 6, we repeat the analysis excluding periods of slowing activity—defined as FOMC meetings taking place in periods where the latest value of the PMI index has fallen below 50. Results are consistent with our main conclusion, although with a slightly weaker significance. This may be explained by lower statistical power as we are reducing our sample size by roughly 20%.

We then consider whether the sign of the monetary policy stimulus (i.e. easings vs tightenings) is associated with the macroeconomic state dependence. We document in Panel C of Table 6 a stark asymmetry in the pass-through of monetary policy shocks to the yield curve depending on the outcome of the policy decision.[39] While the transmission seems to be the comparable when there is no change in the policy target rate (*Hold*) or when it is raised (*Hike*), there is no significant transmission when the policy rate is cut (*Ease*).[40]

The liquidity state dependence could therefore be linked to easing cycles, as almost

[38]A number of studies have found evidence for a macroeconomic state dependence of monetary policy effects using novel nonlinear methods; see e.g. Tenreyro and Thwaites (2016), Angrist et al. (2018), Barnichon and Matthes (2018) and Debortoli et al. (2023). Their focus is on a lower-frequency analysis of macroeconomic outcomes, and different identification strategies for monetary policy shocks. Therefore, their results are not directly comparable to ours.In addition, only Angrist et al. (2018) consider the impact of monetary policy shocks on the yield curve.

[39]In results not reported, we show that the sign of the monetary policy shock itself does not lead to asymmetric responses in forward yields. This suggests that the sign-state dependence in the different macro studies could be strongly driven by the policy shock identification, and how it correlates with actual policy changes.

[40]This is in line with the results documented in Angrist et al. (2018) for the period before the Global Financial Crisis.

all the FOMC meetings associated with cuts in the Fed funds target rate took place during low liquidity periods (see Figure 1). To check this directly, we exclude all FOMC meetings where the target rate was reduced and re-estimate the regression for the liquidity state dependence. The results in Panel D of Table 6 suggest that the liquidity state dependence is not completely driven by the weaker transmission of monetary policy shocks during easing cycles, as the stronger transmission to long-term yields is still present when we exclude the easing meetings.[41] We believe this is compelling evidence that the liquidity state dependence we have documented is *not* about easing cycles or recessions.

As a final robustness check, we run a 'horse race' between liquidity and the business cycle indicators considered in Section 4. Since the main hypothesis based on the above analysis is that the stronger (weaker) transmission in the high (low) liquidity state may simply be driven by the high (low) state of the macroeconomy, we modify the specification in (2.2) to incorporate a high liquidity state dummy and a high macroeconomic state dummy. The results are shown in Table 7 and suggest that the larger response of forward yields beyond 5 years—the essence of the liquidity state dependence we have uncovered—is entirely explained by the high liquidity state even when we control for the high macroeconomic state. The results are unaffected by the choice of the business cycle indicator.

Our results can thus potentially offer an explanation for the weaker transmission of monetary policy during easing periods. The unresponsiveness of yields during easing cycles can also explain why durable goods and business investment react by much less in recessions, as shown by Tenreyro and Thwaites (2016). Our results identify arbitrage capital as a mechanism to rationalize these pieces of evidence. As arbitrageurs tend to be more constrained in recessions when monetary policy is trying to provide stimulus, the yield curve reaction is muted and therefore has a smaller impact on durable goods consumption and business investment, which are more sensitive to longer-term rates than to the short-term policy rate.

[41] In the appendix we repeat this exercise for both the Nakamura and Steinsson (2018) sample and the extended sample using Acosta (2022) data, using either the yield curve noise measure or FIA returns to define the states, and show our main results are unchanged (see Figures C5 and C7 in the appendix).

7.2 Conventional Policy, QE and Market-Maker of Last Resort

We highlighted that our theoretical framework for the liquidity state dependence (see Section 5) clearly distinguishes between the role of arbitrage capital in transmitting short-term interest rate shocks, such as conventional monetary policy shocks, and quantity shocks, such as QE or market maker of last resort (MMLR) purchases. We have thus far focused on our evidence for liquidity state dependence assuming it captures conventional monetary policy effects. In this section we show evidence supporting this interpretation and draw out some implications for the conduct of monetary policy.

Our results are virtually unchanged when we exclude all the QE-related dates identified by Cieslak and Schrimpf (2019) (see Panel A of Table 8). All point estimates for the LSAP shocks of Swanson (2021) are very similar across liquidity states, with no sign of state dependence. These results suggest that our main conclusions regarding the liquidity state dependence are not influenced by the QE/LSAP operations implemented since the Global Financial Crisis.

Policy Implications. King (2019) has shown that the effect of QE in the VV model is drastically reduced in the presence of the zero lower bound on interest rates. This is due to the lower volatility of interest rates, which dampens the risks associated with holding long-term bonds. This is at odds with the fact that the Fed and other central banks have mostly resorted to QE during periods where the lower bound constraint on short-term interest rates was binding.

Our results may offer an explanation for why QE may be preferred when markets are illiquid, such as in crisis periods, while conventional interest rate policies are preferred when markets are liquid in "normal" times. Guimaraes and Vlieghe (2024) document that the dampening effect from the lower bound is more than offset by the larger effect from reduced risk-bearing capacity of arbitrageurs in stressed markets. Relevant illustrations include the period following the collapse of Lehman Brothers, and the dash-for-cash episode at the onset of Covid.[42] As a result, bond purchase programmes, either for monetary

[42]The use of bond purchases for financial stability purposes during the UK LDI crisis in September 2022

policy (QE) or financial stability purposes (MMLR), become more potent during periods of market stress when arbitrage capital is severely constrained. Our results show that conventional monetary policy becomes less potent during these periods, explaining why asset purchases may be a preferred tool during episodes of market stress.

8 Additional Robustness Tests for our Main Empirical Results

8.1 Alternative Monetary Policy Shocks

Previous studies on monetary policy transmission through the yield curve have adopted different definitions for the measurement of shocks. Hanson and Stein (2015) use the daily change in 2-year yields on FOMC announcement days. Nakamura and Steinsson (2018) use changes over 30-min windows around the announcement, and argue that their identification accounts for the difference in the results relative to Hanson and Stein (2015). The more recent literature has increasingly focused on high-frequency measures similar to Nakamura and Steinsson (2018) as a way to mitigate the additional background noise in measures based on daily changes. Refinements include the exclusion of days when changes in equity prices suggest the presence of an information effect (Jarociński and Karadi, 2020), ensuring that shocks are orthogonal to public information available at the time of the monetary policy decision (Bauer and Swanson, 2023; Karnaukh and Vokata, 2022), and decomposing shocks into federal funds rate, forward guidance and LSAP shocks (Swanson, 2021).[43]

The robustness results are summarized in Table 9, which shows the point estimates for low and high liquidity states estimated using regression (2.2) for different measures of

(Alexander et al., 2023) reinforces the argument of a preference for bond purchases in distressed markets as interest rates were not constrained by the ELB during this episode.

[43]This is the terminology proposed by Swanson (2021). The LSAP shocks, however, are nearly identical before and after 2009 except for 3 dates (March 2009, and two Taper Tantrum dates), which suggests that assigning these shocks to LSAP operations may be misleading and they should rather be considered as "curve twist" shocks. The first two shocks correspond to what others (Gürkaynak et al., 2005b) have referred to as short-rate and path shocks.

monetary policy shocks (mps) and sample periods. As before, our focus is on evidence of liquidity state dependence in long maturity forwards, as by construction (due to our normalization, see Section 2.3) there is little difference at short maturities.

We start by extending the sample period, while keeping the same shock series. Panel A of Table 9 shows the baseline Nakamura and Steinsson (2018) results discussed in Section 3, while Panel B shows the estimates with the same shock and the sample extended through 2019, using the series provided by Acosta (2022).

In Panel C, we consider the extended sample but exclude the component of the Nakamura and Steinsson (2018) shocks that can be explained by the same variables used in Bauer and Swanson (2023) and the lagged noise measure. The evidence for liquidity state dependence is unaffected by the different sample choices.[44]

In Panel D of Table 9, we consider the alternative monetary policy surprise measures of Jarociński and Karadi (2020). This shock series is constructed to exclude announcement days for which the comovements between changes in interest rates and changes in stock prices suggest the presence of an information effect. The results with the Jarociński and Karadi (2020) shocks, also used in Kekre et al. (2024), confirm our baseline results using the Nakamura and Steinsson (2018) shocks, with similar magnitude in the extended sample.

We then consider measures of monetary policy shocks that are orthogonalized relative to different information sets. In Panel E, we use the shocks proposed by Bauer and Swanson (2023), which are orthogonalized with respect to selected macroeconomic variables. In Panel F, we use the shocks proposed by Karnaukh and Vokata (2022), who orthogonalize the shock series with respect to growth survey forecasts. Both confirm our main results, with slightly less significant estimates for the Bauer and Swanson (2023) shocks. When using the individual shocks from Swanson (2021) only the forward guidance (FG) shock has any statistically significant state-dependence (Panel G), with estimates similar to those using the Nakamura and Steinsson (2018) shocks.

[44]We note that the effects on mortgage rates documented earlier also hold in the extended sample.

8.2 Alternative Yield Decompositions

In Section 3.2, we used the yield curve decomposition of Abrahams et al. (2016) for comparability with Nakamura and Steinsson (2018). Here we confirm that the main stylised fact of the state dependence being primarily driven by the term premia is robust to alternative model decompositions and sample choices.

In Table 10 we first consider the joint real-nominal decomposition of d'Amico et al. (2018), shown in Panel B. The results confirm the importance of the real term premia in explaining the liquidity state dependence. They also suggest a role for the expectation component, though the statistical evidence for the latter is weaker.

We also consider the nominal decompositions of Kim and Wright (2005) and Adrian et al. (2013), shown respectively in Panels C and D. Both decompositions confirm the strong evidence of term-premium state dependence, with the differences for the expectation components not statistically different from zero at conventional levels.

8.3 Evidence from the UK

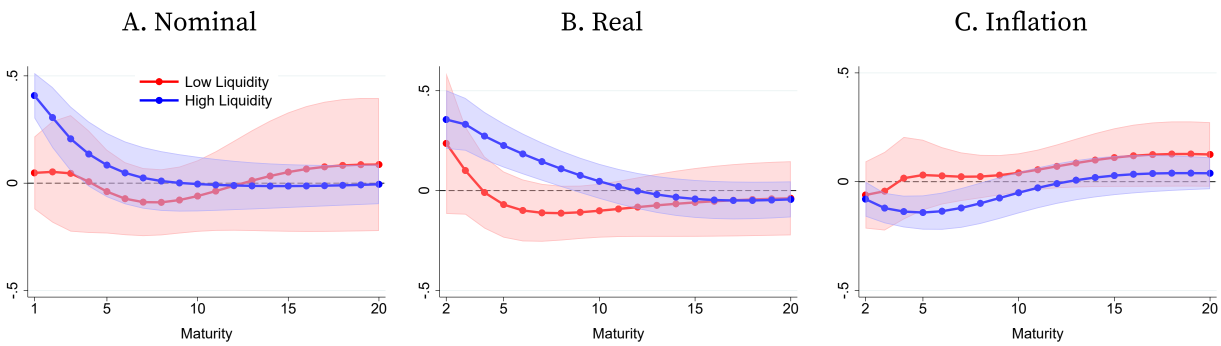
We now turn to the results using UK data (see Section D.5 for a description of the UK data). This exercise allows us to investigate whether we find any evidence of a liquidity state-dependent transmission of monetary policy in other countries than the US.

Figure 8 shows the results using all the Bank of England MPC announcements for the sample 2000-2024.[45] While we find qualitatively similar results overall, in particular the reduced pass-through in low liquidity states, there are a two quantitative differences.

First, even at the very short end the pass-through of monetary policy shocks is severely impaired in low-liquidity periods in the UK. For the US, the response of the 1-year nominal forward rate was smaller in low liquidity states, but it was still highly statistically significant (with t-stats over 4). This allowed us to normalize the shocks separately in high and low liquidity states to emphasize the differential maturity response. For the UK, even the 1-year nominal forward rate does not respond to monetary policy shocks, with point estimates

[45] Here we show the full sample available, which includes data through June 2024. In Section D.5 in the appendix, we show results corresponding to the same samples as the ones used for the US.

FIGURE 8. The Liquidity State dependence in the UK



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) estimated separately for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the UK equivalent of the monetary policy shock series of Nakamura and Steinsson (2018) introduced in Braun et al. (2024), namely the 1st principal component of the high-frequency surprises in the first four quarterly futures contracts around regularly scheduled MPC announcements. The monetary policy shock series is interacted with dummies for the liquidity states, which group MPC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state MPC meetings. The sample includes all regularly scheduled MPC meetings from 01/01/2000 to 30/06/2024, excluding those taking place between July 2008 and June 2009 and between March and May 2020. This corresponds to a sample size of 244 observations.

close to zero and t-stats well below 1. Because of this, we do not normalize UK shocks.

Second, we find a very similar pattern of state-dependence for the real forward curve as found for the US. Unlike for the US, we also find that the response of inflation forwards is state-dependent, with a significant negative response in inflation forwards of short to medium maturities to policy shocks in the high-liquidity state. This state-dependent reaction of inflation forwards partly offsets the larger impact on real forwards in the full sample, leaving the nominal forward reaction closer across liquidity states, though the pattern in each of its components is clearly state dependent.[46]

[46] Figure C13 shows that the liquidity state dependence in the UK is more pronounced in the post-GFC sample.

9 Conclusions

This paper brings together two previously separate literatures—on the high-frequency identification of monetary policy shocks and on the role of financial intermediaries—to study how market liquidity, arbitrage capital, and investor demand shape monetary policy transmission along the yield curve.

Our main finding is that when Treasury market liquidity is high, short-rate shocks have large and persistent effects on long-maturity yields; when liquidity is low, the pass-through vanishes beyond five years. Using both aggregate and transaction-level data, we trace this state dependence to the capital position of arbitrageurs, who intermediate the transmission from the short end to the long end. This evidence implies that market functioning is not merely a financial stability concern but a central determinant of the efficacy of conventional monetary policy. It also rationalizes the use of bond purchases in distressed markets—when arbitrage capital is scarce—and of interest rate policy in normal times, as well as the tendency for monetary policy easings to be less effective than tightenings.

On the theory side, the results are difficult to reconcile with preferred-habitat models driven solely by short-rate risk. They instead point to an important role for demand risk and to a subtle interaction between arbitrage capital and the demand elasticity of other investors—illustrated by the presence of reach-for-yield behavior in the micro data.

Taken together, the paper shows that monetary transmission is a joint product of policy, market structure, and investor composition. Accounting for this interaction is essential for understanding when and why monetary policy shocks have strong effects on long-term interest rates.

TABLE 3. Liquidity State Dependence Conditioning on Arbitrage Capital Proxies

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Sorting on the yield curve noise measure from Hu et al (2013)											
High Liquidity	1.02***	0.53***	0.27*	0.15	1.16***	0.68***	0.37***	0.27**	0.17	-0.15	-0.10	-0.12
	(3.88)	(4.17)	(2.51)	(1.19)	(4.61)	(5.85)	(4.28)	(2.91)	(0.94)	(-1.92)	(-1.38)	(-1.42)
Low Liquidity	0.98*	-0.09	-0.62**	-0.64**	1.75*	0.34	-0.24	-0.23	-0.39	-0.43**	-0.37*	-0.41*
	(2.48)	(-0.34)	(-2.85)	(-2.74)	(2.61)	(1.34)	(-1.60)	(-1.73)	(-1.21)	(-2.79)	(-2.39)	(-2.42)
Diff.	0.926	0.032	0.000	0.004	0.416	0.233	0.001	0.003	0.156	0.113	0.123	0.130
	B. Sorting on fixed-income arbitrage (FIA) hedge fund returns											
High FIA ret.	0.97**	0.48*	0.16	0.09	1.49***	0.66***	0.40**	0.25*	0.44*	-0.18**	-0.23*	-0.16
	(3.31)	(2.58)	(1.02)	(0.61)	(4.09)	(3.55)	(3.22)	(2.36)	(2.20)	(-3.00)	(-2.42)	(-1.89)
Low FIA ret.	1.09*	-0.12	-0.63**	-0.72**	1.57**	0.32	-0.41*	-0.31	-0.47	-0.44*	-0.22	-0.41*
	(2.48)	(-0.44)	(-2.69)	(-2.76)	(2.83)	(1.16)	(-2.23)	(-1.86)	(-1.91)	(-2.40)	(-1.34)	(-2.21)
Diff.	0.823	0.074	0.006	0.008	0.899	0.296	0.000	0.005	0.006	0.184	0.942	0.229
	C. Sorting on convertible arbitrage (CA) hedge fund returns											
High CA ret.	0.91**	0.38*	0.01	-0.02	1.69**	0.59**	0.24	0.14	0.12	-0.21*	-0.23*	-0.16
	(3.23)	(1.98)	(0.05)	(-0.12)	(3.33)	(2.99)	(1.76)	(1.14)	(0.50)	(-2.24)	(-2.06)	(-1.55)
Low CA ret.	1.10*	0.09	-0.30	-0.44	1.30**	0.43	-0.08	-0.08	-0.15	-0.34**	-0.22	-0.35*
	(2.61)	(0.32)	(-1.34)	(-1.90)	(3.20)	(1.71)	(-0.50)	(-0.58)	(-0.67)	(-2.86)	(-1.79)	(-2.55)
Diff.	0.708	0.380	0.282	0.146	0.544	0.611	0.139	0.239	0.423	0.398	0.961	0.274
	D. Sorting on the broker-dealer leverage factor from He et al (2017)											
Low BD Lev.	0.81***	0.31*	0.08	0.00	1.37***	0.49***	0.22*	0.18	0.30	-0.18*	-0.14	-0.17*
	(3.50)	(2.19)	(0.56)	(0.02)	(5.62)	(3.40)	(2.19)	(1.83)	(1.27)	(-2.45)	(-1.78)	(-2.24)
High BD Lev.	1.63*	0.10	-0.74*	-0.83*	2.01**	0.67	-0.27	-0.33	-0.39	-0.57**	-0.48*	-0.50
	(2.27)	(0.21)	(-2.32)	(-2.27)	(2.89)	(1.45)	(-1.00)	(-1.47)	(-1.27)	(-2.74)	(-2.30)	(-1.95)
Diff.	0.282	0.662	0.021	0.033	0.388	0.709	0.088	0.041	0.096	0.078	0.137	0.225

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panel A defines the states as in our baseline, using the yield curve noise measure of Hu et al. (2013). Panels B and C use respectively the fixed-income arbitrage (FIA) and convertible arbitrage hedge fund return indices from Barclays to define the state. FOMC meetings are grouped into the high (low) liquidity state if the value of the hedge fund return index in the month prior to the meeting is above (below) its median level across all meetings. Panel D uses the broker-dealer leverage factor of He et al. (2017) as the state variable, with FOMC meetings grouped into the high (low) liquidity state if the value of the leverage factor on the day before the meeting is below (above) its median level across all meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE 4. Liquidity State-Dependence with Alternative Conditioning Variables for the States

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Sorting on the MOVE index											
Low MOVE	1.09***	0.27	-0.20	-0.26	1.07***	0.66**	-0.05	-0.16	0.03	-0.40**	-0.15	-0.11
	(4.11)	(1.06)	(-1.01)	(-1.35)	(3.91)	(3.00)	(-0.26)	(-0.78)	(0.21)	(-2.74)	(-1.22)	(-0.75)
High MOVE	1.06**	0.30	-0.06	-0.14	1.07**	0.50*	0.14	0.12	-0.10	-0.21*	-0.21*	-0.26*
	(3.32)	(1.29)	(-0.34)	(-0.70)	(3.16)	(2.46)	(0.99)	(0.92)	(-0.51)	(-2.33)	(-2.28)	(-2.35)
Diff.	0.942	0.930	0.626	0.667	0.992	0.590	0.427	0.255	0.620	0.277	0.720	0.414
	B. Sorting on the VIX index											
Low VIX	1.10***	0.45**	0.03	-0.02	1.01***	0.69***	0.14	0.04	0.09	-0.24**	-0.11	-0.06
	(7.36)	(3.00)	(0.23)	(-0.13)	(5.07)	(5.00)	(1.19)	(0.37)	(0.74)	(-3.06)	(-1.79)	(-0.80)
High VIX	0.76*	0.06	-0.23	-0.32	1.20*	0.31	0.04	0.03	-0.32	-0.25*	-0.27*	-0.35*
	(2.42)	(0.28)	(-1.02)	(-1.43)	(2.33)	(1.59)	(0.28)	(0.22)	(-1.11)	(-2.15)	(-2.16)	(-2.60)
Diff.	0.345	0.152	0.338	0.261	0.728	0.123	0.639	0.951	0.218	0.958	0.271	0.073
	C. Sorting on the TED spread											
Low TED	1.07***	0.55***	0.25*	0.13	1.91***	0.75***	0.30**	0.20	-0.06	-0.20*	-0.05	-0.06
	(4.13)	(3.75)	(2.09)	(1.10)	(4.31)	(4.88)	(2.74)	(1.82)	(-0.18)	(-2.38)	(-0.69)	(-0.85)
High TED	0.85*	-0.27	-0.78***	-0.78**	1.19**	0.12	-0.26	-0.22	-0.12	-0.39*	-0.52**	-0.56**
	(2.04)	(-1.10)	(-3.63)	(-3.09)	(2.72)	(0.51)	(-1.66)	(-1.63)	(-0.50)	(-2.51)	(-3.25)	(-3.10)
Diff.	0.648	0.005	0.000	0.001	0.252	0.029	0.004	0.018	0.879	0.272	0.007	0.012
	D. Sorting on the risk aversion index from Bekaert et al (2022)											
Low RA	1.03***	0.37*	-0.01	-0.07	0.99***	0.65***	0.14	0.08	0.06	-0.28**	-0.15*	-0.14*
	(6.67)	(2.55)	(-0.08)	(-0.54)	(5.04)	(4.87)	(1.25)	(0.72)	(0.48)	(-3.26)	(-2.44)	(-1.99)
High RA	0.83**	0.13	-0.20	-0.28	1.25*	0.36	0.04	0.01	-0.26	-0.23*	-0.24	-0.29*
	(2.66)	(0.58)	(-0.89)	(-1.26)	(2.38)	(1.79)	(0.29)	(0.07)	(-0.90)	(-2.03)	(-1.94)	(-2.12)
Diff.	0.575	0.389	0.480	0.434	0.661	0.260	0.627	0.719	0.339	0.766	0.531	0.378
	E. Sorting on the interest rate skewness measure from Bauer and Chernov (2024)											
Low IR Skew	1.02*	-0.07	-0.49*	-0.51*	1.82**	0.37	-0.14	-0.14	-0.41	-0.44**	-0.35*	-0.37*
	(2.46)	(-0.25)	(-2.52)	(-2.50)	(2.78)	(1.39)	(-0.88)	(-0.97)	(-1.34)	(-2.71)	(-2.35)	(-2.60)
High IR Skew	1.04***	0.53***	0.17	0.03	1.21***	0.68***	0.30**	0.20	0.26	-0.15*	-0.13	-0.16
	(3.87)	(3.91)	(1.01)	(0.18)	(4.87)	(5.73)	(2.82)	(1.79)	(1.38)	(-2.15)	(-1.41)	(-1.41)
Diff.	0.967	0.047	0.011	0.047	0.388	0.288	0.029	0.073	0.087	0.113	0.217	0.260
	F. Sorting on the uncertainty index from Bekaert et al (2022)											
Low Uncert.	0.92**	0.28	-0.12	-0.17	1.24***	0.45*	0.14	0.08	0.22	-0.17*	-0.26**	-0.25**
	(3.17)	(1.39)	(-0.80)	(-1.32)	(5.33)	(2.27)	(1.27)	(0.81)	(1.20)	(-2.47)	(-2.93)	(-2.84)
High Uncert.	1.13**	0.23	-0.16	-0.27	1.70**	0.63*	0.04	0.00	-0.38	-0.40*	-0.20	-0.27
	(2.79)	(0.79)	(-0.55)	(-0.92)	(2.67)	(2.31)	(0.20)	(0.00)	(-1.26)	(-2.59)	(-1.35)	(-1.56)
Diff.	0.671	0.886	0.900	0.759	0.506	0.595	0.674	0.713	0.120	0.178	0.723	0.919
	G. Sorting on the interest rate uncertainty measure from Istrefi and Mouabbi (2018)											
Low IR Unc.	1.14***	0.53**	-0.04	-0.08	1.35***	0.78***	0.16	-0.01	-0.20	-0.24*	-0.20	-0.08
	(5.48)	(2.75)	(-0.31)	(-0.70)	(5.65)	(4.44)	(1.24)	(-0.05)	(-1.15)	(-2.03)	(-1.77)	(-0.75)
High IR Unc.	0.78**	0.13	-0.11	-0.20	0.89*	0.34	0.08	0.08	0.12	-0.21*	-0.19	-0.27*
	(2.68)	(0.67)	(-0.53)	(-0.99)	(2.58)	(1.94)	(0.59)	(0.63)	(0.46)	(-2.38)	(-1.84)	(-2.40)
Diff.	0.334	0.158	0.788	0.650	0.277	0.082	0.706	0.649	0.315	0.813	0.962	0.223

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panel A defines states based on the MOVE index; Panel B uses the VIX index; Panel C uses the TED spread; Panel D conditions the states on the risk aversion index from Bekaert et al. (2022); Panel E conditions on the interest rate skewness measure from Bauer and Chernov (2024); Panel F on the uncertainty index from Bekaert et al. (2022); and Panel G on the interest rate uncertainty measure from Istrefi and Mouabbi (2018). The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE 5. Reach-for-Yield Traders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔTERM_{t-1}	0.228***	0.184**	0.184**	0.225***	0.223***		0.240***
	(3.940)	(3.213)	(3.213)	(3.953)	(3.982)		(3.958)
1-3y $\times$ ΔTERM_{t-1}						0.004	
						(0.075)	
4-10y $\times$ ΔTERM_{t-1}						0.319***	
						(4.224)	
11-30y $\times$ ΔTERM_{t-1}						0.308**	
						(2.994)	
FOMC (t) $\times$ ΔTERM_{t-1}							-0.299
							(-0.972)
Post-FOMC (t+1) $\times$ ΔTERM_{t-1}							-0.144
							(-0.937)
Constant	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***
	(10.582)	(51.829)	(51.829)	(51.100)	(55.497)	(55.568)	(55.349)
Trader FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes	Yes
R^2	0.00	0.06	0.06	0.07	0.07	0.07	0.07
N	328,886	328,489	328,489	328,489	328,489	328,489	328,489

Note: the table reports the result of regressing the net duration purchased on lagged changes in the term spread, defined as the 10-year nominal spot yield minus the 2-year nominal spot yield. Reach-for-yield traders are traders belonging to one of the following sectors: banks, insurance companies, pension funds or foreign official sector. The sample period is 01/01/2018 - 31/12/2022, excluding the Covid crisis 01/03/2020 - 30/05/2020.

TABLE 6. Liquidity State Dependence, Business Cycles and Monetary Policy Cycles

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. LSD excluding NBER recessions											
High Liquidity	1.05***	0.54***	0.27*	0.15	1.18***	0.68***	0.37***	0.26**	0.18	-0.14	-0.10	-0.12
	(3.87)	(4.21)	(2.46)	(1.17)	(4.75)	(5.84)	(4.27)	(2.91)	(1.00)	(-1.81)	(-1.43)	(-1.47)
Low Liquidity	1.39**	0.09	-0.61*	-0.68*	2.16*	0.63	-0.14	-0.20	-0.54	-0.54*	-0.46*	-0.47*
	(2.73)	(0.24)	(-2.06)	(-2.29)	(2.42)	(1.72)	(-0.69)	(-1.10)	(-1.71)	(-2.59)	(-2.43)	(-2.10)
Diff.	0.549	0.267	0.007	0.014	0.297	0.900	0.025	0.027	0.061	0.078	0.082	0.150
	B. LSD excluding periods of slowing activity (PMI<50)											
High Liquidity	1.35***	0.47*	0.10	0.02	1.20***	0.71***	0.27*	0.17	0.12	-0.25*	-0.17*	-0.15
	(7.46)	(2.54)	(0.67)	(0.12)	(5.00)	(4.42)	(1.98)	(1.31)	(0.68)	(-2.21)	(-2.01)	(-1.61)
Low Liquidity	1.28*	0.05	-0.63	-0.78*	1.68*	0.73	-0.24	-0.34	-0.21	-0.68***	-0.40	-0.43
	(2.05)	(0.11)	(-1.72)	(-2.13)	(2.25)	(1.56)	(-1.01)	(-1.63)	(-1.03)	(-5.75)	(-1.84)	(-1.76)
Diff.	0.917	0.429	0.074	0.054	0.538	0.970	0.069	0.044	0.234	0.010	0.332	0.294
	C. Monetary policy cycle (by direction of change in Fed funds target rate)											
Hold	1.57***	0.64**	0.05	-0.07	1.55***	0.93***	0.25	0.12	0.10	-0.29*	-0.20	-0.20
	(8.72)	(3.17)	(0.30)	(-0.40)	(4.48)	(4.85)	(1.65)	(0.96)	(0.49)	(-2.38)	(-1.89)	(-1.48)
Hike	1.32***	0.39	-0.20	-0.18	1.58***	0.56*	0.26	0.16	-0.18	-0.17	-0.46*	-0.34
	(3.57)	(1.19)	(-0.75)	(-0.69)	(3.67)	(2.12)	(1.32)	(0.62)	(-0.49)	(-0.83)	(-2.39)	(-1.94)
Ease	0.35	0.04	0.02	-0.07	0.34	0.23	0.10	0.10	-0.09	-0.19	-0.08	-0.17
	(0.98)	(0.20)	(0.08)	(-0.28)	(0.75)	(1.36)	(0.61)	(0.60)	(-0.23)	(-1.87)	(-0.71)	(-1.49)
	D. LSD excluding all Ease FOMC meetings (when Fed funds target rate was reduced)											
HighLiq_{NoEase}	1.36***	0.58**	0.15	0.06	1.05***	0.72***	0.33**	0.21	0.26	-0.14	-0.18	-0.15
	(8.91)	(3.28)	(1.07)	(0.44)	(5.32)	(5.05)	(2.67)	(1.80)	(1.53)	(-1.25)	(-1.94)	(-1.35)
LowLiq_{NoEase}	2.23***	0.63	-0.57	-0.68	3.71***	1.36**	-0.01	-0.14	-0.85*	-0.73**	-0.56*	-0.54
	(4.48)	(1.34)	(-1.19)	(-1.39)	(5.34)	(2.90)	(-0.02)	(-0.46)	(-2.06)	(-3.01)	(-2.11)	(-1.62)
Diff.	0.099	0.927	0.156	0.152	0.000	0.196	0.391	0.288	0.018	0.031	0.181	0.279

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panels A, B and D define the states as in our baseline, using the yield curve noise measure of Hu et al. (2013). Panel A drops from the sample of all regularly scheduled FOMC meetings between 01/01/2000 and 31/12/2019 (excluding those taking place between July 2008 and June 2009) the ones taking place during periods identified as NBER recessions. Panel B, excludes FOMC meetings taking place during periods of slowing activity, defined as periods where the latest value of the PMI index has fallen below 50. Panel D excludes all the FOMC meetings where the Fed funds target rate was reduced. Finally, Panel C reports the OLS coefficient estimates from regression (2.1) estimated separately on the subset of FOMC meetings where the Fed funds target rate was maintained (*Hold*), increased (*Hike*), or reduced (*Ease*). Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE 7. State Dependence Horse Race: Liquidity versus Business Cycles

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. State dependence with high liquidity and high PMI											
mps	0.92*	-0.10	-0.60**	-0.63**	1.74*	0.31	-0.23	-0.21	-0.40	-0.42**	-0.37*	-0.42*
	(2.32)	(-0.41)	(-2.72)	(-2.63)	(2.57)	(1.22)	(-1.48)	(-1.60)	(-1.23)	(-2.68)	(-2.33)	(-2.38)
$\mathbb{1}_{HighLiq} \times mps$	-0.17	0.55	0.95***	0.84**	-0.69	0.23	0.66***	0.54**	0.44	0.32	0.29	0.29
	(-0.32)	(1.78)	(3.79)	(2.93)	(-0.81)	(0.78)	(3.61)	(3.21)	(1.08)	(1.75)	(1.57)	(1.42)
$\mathbb{1}_{HighPMI} \times mps$	0.61	0.20	-0.18	-0.13	0.16	0.30	-0.14	-0.14	0.18	-0.11	-0.04	0.01
	(1.58)	(0.76)	(-0.87)	(-0.57)	(0.26)	(1.31)	(-0.83)	(-0.83)	(0.54)	(-0.75)	(-0.28)	(0.06)
	B. State dependence with high liquidity and high ADS											
mps	0.96*	0.01	-0.57*	-0.63*	1.90*	0.41	-0.21	-0.20	-0.31	-0.39*	-0.36*	-0.42*
	(2.21)	(0.05)	(-2.35)	(-2.31)	(2.55)	(1.46)	(-1.22)	(-1.37)	(-0.74)	(-2.34)	(-2.11)	(-2.16)
$\mathbb{1}_{HighLiq} \times mps$	0.04	0.66*	0.91***	0.80**	-0.62	0.36	0.63***	0.50**	0.54	0.30	0.28	0.29
	(0.07)	(2.37)	(3.85)	(3.07)	(-0.87)	(1.31)	(3.63)	(3.21)	(1.36)	(1.76)	(1.62)	(1.54)
$\mathbb{1}_{HighADS} \times mps$	0.05	-0.29	-0.15	-0.04	-0.27	-0.19	-0.10	-0.07	-0.13	-0.10	-0.05	0.02
	(0.12)	(-1.24)	(-0.77)	(-0.21)	(-0.54)	(-0.91)	(-0.66)	(-0.43)	(-0.47)	(-0.74)	(-0.38)	(0.15)
	C. State dependence with high liquidity and low unemployment											
mps	0.93*	-0.10	-0.47*	-0.38	1.60	0.31	-0.12	-0.06	-0.50	-0.41*	-0.35*	-0.32
	(2.33)	(-0.37)	(-2.10)	(-1.64)	(1.95)	(1.14)	(-0.86)	(-0.45)	(-1.63)	(-2.43)	(-2.08)	(-1.89)
$\mathbb{1}_{HighLiq} \times mps$	0.03	0.61*	0.93***	0.87**	-0.65	0.33	0.65***	0.55**	0.51	0.29	0.28	0.33
	(0.06)	(2.13)	(3.57)	(3.08)	(-0.85)	(1.13)	(3.47)	(3.25)	(1.21)	(1.61)	(1.56)	(1.61)
$\mathbb{1}_{LowUne} \times mps$	0.09	0.03	-0.27	-0.51*	0.24	0.07	-0.23	-0.33**	0.18	-0.04	-0.04	-0.18
	(0.24)	(0.13)	(-1.49)	(-2.61)	(0.29)	(0.29)	(-1.71)	(-2.70)	(0.51)	(-0.27)	(-0.29)	(-1.20)

Note: the table shows the estimated OLS coefficients in a modified specification of regression (2.3), for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. The specification incorporates a dummy capturing the high-liquidity state and a dummy capturing the high macroeconomic state. In both cases, the states are identified in the same way as in the baseline analysis, based on whether the value of the conditioning variable before a given FOMC meeting is above its median level across all meetings. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), as well as interaction terms with the dummy state variables. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity. Panel A defines the macroeconomic states using the purchasing-manager index (PMI); Panel B uses the real-time ADS index by Aruoba et al. (2009); and Panel C uses initial jobless claims as the macro state variable. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE 8. Is Liquidity State Dependence About Conventional or Unconventional Monetary Policy?

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. excluding QE dates using Nakamura & Steinsson (2018) shocks, extended sample (2000-2019)											
High Liquidity	0.99***	0.48***	0.27*	0.13	1.11***	0.64***	0.36***	0.26**	0.16	-0.16*	-0.09	-0.13
	(3.81)	(4.09)	(2.47)	(0.99)	(4.59)	(5.98)	(4.09)	(2.79)	(0.88)	(-2.05)	(-1.27)	(-1.53)
Low Liquidity	0.97*	-0.11	-0.65**	-0.69**	1.73**	0.32	-0.26	-0.24	-0.39	-0.43**	-0.39*	-0.44**
	(2.49)	(-0.43)	(-3.05)	(-3.02)	(2.64)	(1.30)	(-1.74)	(-1.88)	(-1.20)	(-2.80)	(-2.50)	(-2.66)
	B. using LSAP shocks from Swanson (2021), extended sample (2000-2019)											
High Liquidity	-1.79*	-2.57**	-1.44**	-1.41**	-1.04	-1.93*	-1.14**	-0.53	-0.75	-0.64*	-0.30	-0.87
	(-2.12)	(-3.01)	(-2.89)	(-2.84)	(-0.71)	(-2.12)	(-3.03)	(-1.63)	(-0.90)	(-2.03)	(-0.56)	(-1.44)
Low Liquidity	-5.85**	-6.97***	-4.76**	-4.85*	-4.20	-5.28**	-2.52*	-2.19	-1.66	-1.70*	-2.23*	-2.66*
	(-2.80)	(-4.23)	(-2.71)	(-2.57)	(-1.56)	(-3.24)	(-2.28)	(-1.96)	(-1.02)	(-2.48)	(-2.59)	(-2.38)
Diff.	0.074	0.019	0.071	0.080	0.303	0.075	0.236	0.155	0.618	0.164	0.060	0.162

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). The independent variable in Panel A is the monetary policy shock series of Nakamura and Steinsson (2018); and the unconventional monetary policy shock (LSAP) series of Swanson (2021) in Panel B. In both cases, the shock series is interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Panel A further excludes QE-related dates identified in Cieslak and Schrimpf (2019). Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 9. Robustness of Liquidity State-Dependence: Different Shocks and Samples

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Nakamura & Steinsson (2018) shocks, original sample (2000-2014)											
High Liquidity	1.31***	0.62***	0.37***	0.22	1.04***	0.68***	0.46***	0.35***	0.27	-0.07	-0.09	-0.13
	(6.42)	(4.83)	(4.14)	(1.98)	(4.93)	(6.79)	(7.70)	(4.49)	(1.40)	(-0.91)	(-1.13)	(-1.46)
Low Liquidity	0.76	-0.20	-0.59*	-0.58*	0.78	0.15	-0.29	-0.23	-0.01	-0.35*	-0.30	-0.35
	(1.10)	(-0.79)	(-2.39)	(-2.13)	(1.74)	(0.65)	(-1.89)	(-1.84)	(-0.04)	(-2.39)	(-1.76)	(-1.81)
Diff.	0.473	0.006	0.001	0.010	0.609	0.035	0.000	0.000	0.487	0.092	0.278	0.320
	B. Nakamura & Steinsson (2018) shocks, extended sample (2000-2019)											
High Liquidity	1.32***	0.53***	0.27*	0.15	1.16***	0.68***	0.37***	0.27**	0.17	-0.15	-0.10	-0.12
	(6.30)	(4.17)	(2.51)	(1.19)	(4.61)	(5.85)	(4.28)	(2.91)	(0.94)	(-1.92)	(-1.38)	(-1.42)
Low Liquidity	1.36	-0.09	-0.62**	-0.64**	1.75*	0.34	-0.24	-0.23	-0.39	-0.43**	-0.37*	-0.41*
	(1.89)	(-0.34)	(-2.85)	(-2.74)	(2.61)	(1.34)	(-1.60)	(-1.73)	(-1.21)	(-2.79)	(-2.39)	(-2.42)
Diff.	0.956	0.032	0.000	0.004	0.416	0.233	0.001	0.003	0.156	0.113	0.123	0.130
	C. Nakamura & Steinsson (2018) shocks residualized for economic news and lagged noise, extended sample (2000-2019)											
High Liquidity	1.25***	0.44***	0.17	0.04	1.10***	0.57***	0.27*	0.23*	0.15	-0.12	-0.10	-0.20*
	(5.34)	(3.52)	(1.29)	(0.24)	(4.79)	(4.90)	(2.39)	(2.19)	(0.87)	(-1.72)	(-1.35)	(-2.16)
Low Liquidity	1.63*	-0.08	-0.72**	-0.76**	1.97**	0.42	-0.27	-0.27	-0.34	-0.50*	-0.45*	-0.50*
	(2.05)	(-0.27)	(-3.07)	(-2.94)	(2.78)	(1.47)	(-1.30)	(-1.48)	(-0.75)	(-2.43)	(-2.17)	(-2.57)
Diff.	0.648	0.116	0.001	0.008	0.247	0.641	0.023	0.019	0.317	0.084	0.107	0.159
	D. Jarocinski & Karadi (2020) shocks, extended sample (2000-2019)											
High Liquidity	1.80***	0.58***	0.37*	0.24	1.69**	0.74***	0.51***	0.41**	0.10	-0.15	-0.14	-0.17
	(3.69)	(3.54)	(2.25)	(1.15)	(2.67)	(4.49)	(5.22)	(3.24)	(0.31)	(-1.53)	(-1.04)	(-1.14)
Low Liquidity	1.25	-0.25	-0.72**	-0.76**	1.52	0.05	-0.30	-0.28	-0.28	-0.31	-0.42*	-0.48*
	(1.22)	(-0.85)	(-3.04)	(-2.67)	(1.94)	(0.19)	(-1.71)	(-1.88)	(-0.58)	(-1.50)	(-2.04)	(-2.33)
Diff.	0.633	0.016	0.000	0.005	0.869	0.046	0.000	0.001	0.531	0.502	0.252	0.224
	E. Bauer & Swanson (2023) shocks, extended sample (2000-2019)											
High Liquidity	0.97***	0.38**	0.11	-0.00	0.84***	0.50***	0.22*	0.18	0.14	-0.12	-0.11	-0.18*
	(5.10)	(3.27)	(0.93)	(-0.01)	(4.58)	(4.84)	(2.19)	(1.83)	(0.98)	(-1.71)	(-1.73)	(-2.17)
Low Liquidity	1.57	-0.18	-0.91**	-1.01**	2.04*	0.56	-0.32	-0.37	-0.48	-0.73***	-0.59*	-0.64**
	(1.90)	(-0.48)	(-2.89)	(-3.01)	(2.57)	(1.62)	(-1.30)	(-1.59)	(-1.15)	(-3.61)	(-2.57)	(-2.64)
Diff.	0.486	0.146	0.003	0.006	0.144	0.879	0.044	0.031	0.168	0.005	0.046	0.076
	F. Karnaukh & Vokata (2022) shocks, extended sample (2000-2019)											
High Liquidity	1.19***	0.62***	0.38***	0.23*	0.96***	0.69***	0.47***	0.33***	0.22	-0.07	-0.09	-0.10
	(5.77)	(4.72)	(4.07)	(2.13)	(5.14)	(6.31)	(7.09)	(4.36)	(1.26)	(-0.97)	(-1.19)	(-1.08)
Low Liquidity	0.58	-0.65*	-1.10**	-1.00*	0.59	-0.31	-0.62**	-0.53*	-0.01	-0.35	-0.49*	-0.47
	(0.69)	(-2.09)	(-3.28)	(-2.59)	(0.98)	(-1.07)	(-2.70)	(-2.59)	(-0.02)	(-1.76)	(-2.22)	(-1.73)
Diff.	0.507	0.000	0.000	0.003	0.573	0.002	0.000	0.000	0.607	0.194	0.099	0.210
	G. Swanson (2021) FG shocks, extended sample (2000-2019)											
High Liquidity	1.14***	0.61***	0.24***	0.19*	0.97***	0.68***	0.37***	0.27***	0.17	-0.07	-0.13	-0.08
	(8.17)	(4.24)	(3.55)	(2.52)	(4.06)	(5.25)	(5.76)	(4.57)	(1.26)	(-0.95)	(-1.97)	(-1.02)
Low Liquidity	1.67***	0.67**	-0.11	-0.25	1.76***	0.87***	0.02	-0.08	-0.08	-0.19	-0.14	-0.17
	(4.96)	(2.68)	(-0.60)	(-1.32)	(5.99)	(4.33)	(0.20)	(-0.64)	(-0.50)	(-1.64)	(-1.18)	(-1.47)
Diff.	0.141	0.827	0.082	0.033	0.038	0.442	0.012	0.010	0.241	0.403	0.996	0.561

Note: The dependent variable in each regression is the one-day change in forward rates, over all regularly scheduled FOMC meetings. The independent variables are high-frequency identified shocks interacted with dummies partitioning the sample according to the liquidity state. FOMC meetings are grouped into the high (low) liquidity state if the value of the detrended yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. High Liquidity (Low Liquidity) refers to the OLS estimates of $\gamma^{(\tau)}_{hl,t}$ ($\gamma^{(\tau)}_{ll,t}$) in specification (2.2) . Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). All shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Panel A reports the estimates using the Nakamura and Steinsson (2018) shocks in their original sample (2000-2014). Panel B repeats the same exercise using the extended sample (2000-2019) using the Nakamura and Steinsson (2018) shocks extended by Acosta (2022). Panel C uses the same shocks as Panel B but excludes the component that can be explained by the same variables used in Bauer and Swanson (2023) and the lagged noise measure. Panel D uses the shock series from Jarociński and Karadi (2020) in the extended sample. Panel E uses the Bauer and Swanson (2023) orthogonalized shocks. Panel F uses the shock series from Karnaukh and Vokata (2022) in the extended sample. Panel G uses the forward guidance (FG) shock from Swanson (2021) in the extended sample. The extended sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 10. Decomposing the Forward Rate: Expectation Hypothesis vs Risk Premium

	Nominal						Real					
	Expectations			Term Premium			Expectations			Term Premium		
	2Y	5Y	10Y	2Y	5Y	10Y	2Y	5Y	10Y	2Y	5Y	10Y
	A. Abrahams, Adrian, Crump & Moench (2016)											
High Liquidity	0.71***	0.26*	0.07*	0.60***	0.36**	0.30**	0.60***	0.21*	0.06*	0.44	0.47***	0.40***
	(5.98)	(2.56)	(2.53)	(3.88)	(2.79)	(2.89)	(4.91)	(2.29)	(2.41)	(1.71)	(3.61)	(6.18)
Low Liquidity	0.76	0.44**	0.13**	-0.00	-0.64**	-0.71**	0.77	0.41**	0.11**	0.00	-0.27	-0.40*
	(1.70)	(3.32)	(3.33)	(-0.00)	(-3.07)	(-2.92)	(1.76)	(3.36)	(3.35)	(0.02)	(-1.18)	(-2.52)
Diff.	0.909	0.291	0.282	0.096	0.000	0.000	0.735	0.213	0.245	0.289	0.007	0.000
	B. D'Amico, Kim & Wei (2018)											
High Liquidity	0.64***	0.38***	0.22***	0.43***	0.28**	0.26***	0.47***	0.27***	0.15***	0.32***	0.23**	0.20***
	(7.10)	(7.00)	(5.87)	(5.18)	(2.82)	(3.61)	(8.41)	(7.02)	(5.96)	(5.09)	(2.90)	(3.67)
Low Liquidity	0.74**	0.18	0.02	0.26	-0.06	-0.22	0.66**	0.17	0.02	0.19	-0.02	-0.15
	(2.67)	(1.44)	(0.29)	(0.82)	(-0.38)	(-1.44)	(3.37)	(1.92)	(0.35)	(0.84)	(-0.15)	(-1.38)
Diff.	0.722	0.157	0.038	0.608	0.077	0.005	0.348	0.282	0.041	0.578	0.103	0.006
	C. Kim & Wright (2005)											
High Liquidity	0.53***	0.29***	0.15***	0.79***	0.25*	0.12						
	(7.40)	(7.43)	(7.19)	(5.50)	(2.57)	(1.18)						
Low Liquidity	0.52*	0.21**	0.09*	0.84	-0.29	-0.70***						
	(2.26)	(2.62)	(2.02)	(1.66)	(-1.62)	(-3.74)						
Diff.	0.976	0.391	0.196	0.925	0.009	0.000						
	D. Adrian, Crump & Moench (2013)											
High Liquidity	0.92***	0.74***	0.60***	0.21*	0.09	0.01						
	(9.22)	(4.53)	(4.31)	(2.31)	(1.39)	(0.06)						
Low Liquidity	1.36**	1.22***	0.96***	-0.17	-0.53***	-0.85***						
	(3.35)	(4.74)	(4.47)	(-1.07)	(-4.10)	(-4.84)						
Diff.	0.320	0.131	0.171	0.039	0.000	0.000						

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ll, hl\}$ for the expectation and term premium components of each forward maturity $\tau \in [2, 5, 10]$, together with robust standard errors. Diff. reports the p-value of a test of equality of means between High- and Low-liquidity periods using (2.3). The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A uses the joint real-nominal model decomposition of Abrahams et al. (2016); Panel B uses the joint real-nominal model decomposition of d'Amico et al. (2018); and Panels C and D use respectively the model decomposition of nominal rates from Kim and Wright (2005) and Adrian et al. (2013). The sample covers all regularly scheduled meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. The decomposition of Abrahams et al. (2016) in Panel A covers from 01/01/2000 to 19/03/2014. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

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Appendix

A Two-periods and Two-bonds Preferred-habitat Model

A.1 Model Setup

Our model follows closely Kekre et al. (2024) analytical model. Time is discrete and runs forever.

Assets– There is a short rate r_t that evolves exogenously according to an AR(1) process:

$$r_{t+1} = \bar{r} + (1 - \kappa_r)(r_t - \bar{r}) + \sigma_r \varepsilon_{t+1}, \tag{A1}$$

where $\varepsilon_{t+1} \sim N(0, 1)$, $\sigma_r, \bar{r} > 0$ and $\kappa_r \in (0, 1)$.[47] There are two assets: a zero-coupon bond maturing next period, and another zero-coupon bond maturing in two periods, *the long bond*. Each bond at maturity pays 1 unit of the numeraire. The price of the one-period bond is pinned down by the exogenous short rate:

$$P_t^{(1)} = e^{-r_t},$$

The long bond has price P_t, determined endogenously in equilibrium.

Note that the (log) holding-period return of the two-period bond is given by:

$$r_{t+1}^{(2)} = -r_{t+1} - \log P_t,$$

since next period the two-period bond becomes a one-period bond, its price will be $P_{t+1}^{(1)} = e^{-r_{t+1}}$.

[47] We are going to normalize $\sigma_r = 1$.

It is useful to define the forward rate:[48]

$$f_t = -\log P_t - r_t. \tag{A2}$$

Agents– There are two types of agents: arbitrageurs and preferred-habitat investors. Arbitrageurs are risk averse and we describe them in more detail in Section A.2. Preferred-habitat investors have exogenous demand for the long bond as in Vayanos and Vila (2021):

$$z_t = -\alpha \log P_t - \theta_t, \tag{A3}$$

where the first term ($\alpha \log P_t$) is a price-elastic component of demand while the second term (θ_t) is a demand shock.

Market clearing– the storage technology is in perfectly elastic supply so that its price is always the short rate. The long bond is zero net supply:

$$x_t + z_t = 0, \tag{A4}$$

this means that any demand coming from preferred-habitat investors (z_t), has to be absorbed by the arbitrageurs (x_t).

A.2 The Arbitrageurs

Arbitrageurs have constant absolute risk aversion (CARA) utility with risk-aversion coefficient ϕ. They effectively maximize:

[48] Recall the definition of the (log) forward rate: $r_t + f_t = y_t^{(2)}$. The left-hand side is the return of a rollover strategy that invests for one period at the (known) short-rate r_t and reinvest next period at f_t. The right-hand side is the return from holding the two-period bond until maturity, that is its yield to maturity. Substituting in $\log P_t = -y_t^{(2)}$ completes the proof.

$$\max_{x_t} U(x_t) \equiv \mathbb{E}_t\big(W_{t+1}\big) - \frac{\phi}{2}\mathbb{Var}_t\big(W_{t+1}\big), \tag{A5}$$

subject to the budget constraint:

$$W_{t+1} = W_t r_t + x_t(r_{t+1}^{(2)} - r_t). \tag{A6}$$

A.3 Equilibrium

The first-order condition for the long bond, x_t, is:

$$\mathbb{E}_t r_{t+1}^{(2)} - r_t = \phi \mathbb{Var}_t(r_{t+1}^{(2)}) x_t, \tag{A7}$$

Using the process for the short rate in (A1), we obtain

$$-\kappa_r \bar{r} - (1 - \kappa_r) r_t - \log P_t - r_t = \phi x_t,$$

rearranging yields

$$\log P_t = -\kappa_r \bar{r} - (2 - \kappa_r) r_t - \phi x_t.$$

By market clearing arbitrageurs are the mirror image of preferred-habitat investors, $x_t = -z_t$, hence

$$\begin{aligned} \log P_t &= -\kappa_r \bar{r} - (2 - \kappa_r) r_t + \phi z_t, \\ &= -\kappa_r \bar{r} - (2 - \kappa_r) r_t - \phi(\alpha \log P_t + \theta_t), \end{aligned}$$

$$= \frac{1}{1 + \alpha\phi}(-\kappa_r \bar{r} - (2 - \kappa_r) r_t - \phi\theta_t),$$

The first two terms reflect the fundamental value, and the expectations hypothesis implied by the short-rate process. The last term is a risk premium. Suppose that $\theta_t > 0$, then preferred-habitat investors are selling long bonds, which in turn means the arbitrageurs will need to hold them. This is risky because shocks to the short rate could cause volatility in wealth. Crucially, how risky this trade is depends also on other factors. In particular, the price is scaled by the preferred-habitat price elastic response through the denominator $(1 + \alpha\phi)^{-1}$. As the short rate changes, so does the price-elastic component of preferred-habitat demand in equation (A3). Depending on the sign of α, it could amplify or dampen risk. We will return to this point later as it will turn out to be an important feature of the liquidity state dependence.

Plugging in the budget constraint (A6) into the arbitrageurs' objective (A5) yields:

$$\max_{x_t} x_t(\mathbb{E}_t(r^{(2)}_{t+1}) - r_t) - \frac{\phi}{2} x_t^2 \mathbb{Var}_t(r^{(2)}_{t+1}),$$

Using the process for the short rate in (A1), we obtain

$$\begin{aligned}
\mathbb{E}_t(r^{(2)}_{t+1}) &= -\bar{r} - (1 - \kappa_r)(r_t - \bar{r}) - \log P_t, \\
&= -\kappa_r \bar{r} - (1 - \kappa_r) r_t - \log P_t, \\
\mathbb{Var}_t(r^{(2)}_{t+1}) &= \mathbb{Var}_t(r_{t+1}), \\
&= 1
\end{aligned}$$

We now derive the reaction of the forward rate to a short rate shock. To do so, we differentiate the forward rate in (A2) with respect to the short rate:

$$\frac{\partial f_t}{\partial \varepsilon_{r,t}} = -\frac{\partial \log P_t}{\partial \varepsilon_{r,t}} - 1 \tag{A8}$$

$$= \frac{(2-\kappa_r)}{1+\alpha\phi} - 1 \tag{A9}$$

$$= \frac{1-\kappa_r}{1+\alpha\phi} - \frac{\alpha\phi}{1+\alpha\phi} \tag{A10}$$

A.4 The Model with Wealth Effects

We follow Kekre et al. (2024) and assume logarithmic utility and use their second-order Taylor expansion to yield the following first-order condition (equation (14) in their paper):

$$\mathbb{E}_t r^{(2)}_{t+1} - r_t + \frac{\sigma^2_r}{2} \approx \frac{x_t}{W_t}$$

This equation replaces the first-order condition (A7), while we use the same equations and procedure to obtain the reaction of the forward rate as in the baseline model.

A.5 The Effect of a Monetary Shock on the Term Premium

The forward rate overreaction, or equivalently the increase in term premium is:

$$\frac{\partial TP_t}{\partial \varepsilon_{r,t}} = \frac{\partial f_t}{\partial \varepsilon_{r,t}} - (1-\kappa_r) > 0, \tag{A11}$$

in other words, the forward rate ($\partial f_t / \partial \varepsilon_{r,t}$) increases by more than the expectations hypothesis, $(1-\kappa_r)$.

In turn, the reaction of the forward rate to a short-rate shock, $\varepsilon_{r,t}$ is given by

$$\frac{\partial f_t}{\partial \varepsilon_{r,t}} = -\frac{\partial \log P_t}{\partial \varepsilon_{r,t}} - 1, \tag{A12}$$

Each model is characterized by a different economic mechanism underlying the change in forward rate. We will now examine the response of the forward rate (and term premium) in a number of models, and whether they are able to generate the state dependence.

Model without wealth effect (Vayanos and Vila, 2021):

$$\frac{\partial TP_t}{\partial \varepsilon_{r,t}} = \frac{1-\kappa_r}{1+\alpha\phi} - \frac{\alpha\phi}{1+\alpha\phi} - (1-\kappa_r),$$
$$= -\frac{\alpha\phi}{1+\alpha\phi}(2-\kappa_r),$$

note that $\kappa_r \in (0,1)$ so that the sign of the term premia response depends on α. If $\alpha > 0$, then the forward rate underreacts. If instead there is reach for yield, $\alpha < 0$ then the forward rate overreacts.[49] As arbitrageurs become less risk averse, a decrease in ϕ, the overreaction diminishes.

Model with wealth effect (Kekre et al., 2024):

$$\frac{\partial TP_t}{\partial \varepsilon_{r,t}} = \frac{1-\kappa_r-\frac{1}{W_t}\alpha}{1+\frac{1}{W_t}\alpha} + \frac{\frac{1}{W_t}x_t}{1+\frac{1}{W_t}\alpha}e^{-\xi}\omega - (1-\kappa_r), \tag{A13}$$
$$= -\frac{\frac{1}{W_t}\alpha}{1+\frac{1}{W_t}\alpha}(2-\kappa_r) + \frac{\frac{1}{W_t}x_t}{1+\frac{1}{W_t}\alpha}e^{-\xi}\omega, \tag{A14}$$

the first term captures the main channel of Vayanos and Vila (2021), while the wealth effect is captured by the second term. If the second term dominates, then there is overreaction. Varying wealth (W_t) generates the opposite state dependence than in our empirical findings. If instead we interpret high noise periods as periods where arbitrageurs are more myopic (an increase in ξ) then this could help switch from overreaction to underreaction.

[49] We assume throughout that $\alpha\phi < 1$.

B Equivalence between Changes in Risk Aversion and Arbitrage Capital

We consider an extension of Vayanos and Vila (2021) where we introduce arbitrage capital in tractable way. We assume that there is a continuum of arbitrageurs, indexed by i and total mass n.

Agents. The market is populated by two types of agents: a mass n of myopic arbitrageurs, indexed by $i \in [0, \ldots, n]$ and preferred-habitat investors. We treat the mass n of arbitrageurs as a parameter but can be endogenized through a participation cost, inattention or financial constraints. Preferred-habitat investor type-τ lives only in maturity τ, demanding an exogenous amount $Z_t^{(\tau)}$.

Arbitrageur i maximizes mean-variance utility (CARA):

$$U_{i,t} = \mathbb{E}_t(dW_{i,t}) - \frac{a}{2}\mathbb{V}_t(dW_{i,t})$$

subject to the the budget constraint

$$dW_{i,t} = W_{i,t} r_t dt + \int_0^T X_{i,t}^{(\tau)} \left(\frac{dP_t^{(\tau)}}{P_t^{(\tau)}} - r_t dt\right) d\tau, \tag{A15}$$

where $dP_t^{(\tau)}/P_t^{(\tau)}$ is the return on a bond with maturity τ, purchased at time t and sold an instant later at $t + dt$.

Market Clearing. Since bonds are in zero net supply, market clearing requires:

$$\int_0^n X_{i,t}^{(\tau)} dF + Z_t^{(\tau)} = 0. \tag{A16}$$

Since arbitrageurs are symmetric $X_{i,t}^{(\tau)} = X_t^{(\tau)}$, which implies a total demand of nX_t, so that by market clearing (A16)

$$nX_t^{(\tau)} + Z_t^{(\tau)} = 0. \tag{A17}$$

Equilibrium The first-order condition of trader i for bond with maturity τ is

$$\mu_t^{(\tau)} - r_t = -a\sigma_r^2 A^{(\tau)} \int_0^T X_{i,t}^{(\tau)} A^{(\tau)} d\tau.$$

Using the fact that arbitrageurs are symmetric, and market clearing yields:

$$\mu_t^{(\tau)} - r_t = \frac{a}{n}\sigma_r^2 \int_0^T Z_t^{(\tau)} (A^{(\tau)})^2 d\tau,$$

which shows that varying the mass of arbitrageurs in the market is isomorphic to varying risk aversion. The more arbitrageurs are in the market, the lower per-capita risk, which pushes down bond risk premium.

C Transaction-level Data

The identities of the participants involved in trades are denoted by unique Legal Entity Identifiers (LEIs), which allow us to classify clients into different sectors. We focus our analysis on banks, asset managers, hedge funds, foreign officials (central banks and sovereign wealth funds) and insurance companies and pension funds (ICPFs). We develop a sectoral classification based on a text-based algorithm which we complement with the Bank of England's internal classification system. ICPFs in our sample include liability-driven investors (LDI) which are usually managed by asset managers. Our definition of hedge funds includes both discretionary and systematic funds featuring both macro and relative value strategies. Our definition of asset managers include both wealth and asset managers as well as other mutual funds. Foreign officials include foreign central banks, sovereign wealth funds and any state-owned entity operating in this market.

Panel A in Table D1 reports aggregate statistics on the dealer-to-client (D2C) segment. On an average day, we observe volumes of $728 millions in duration terms (using the dollar value of a basis point, or DV01, as unit), 958 transactions and an average trade size of $0.76 million of DV01. Our data covers 9227 unique clients trading in US Treasuries.

Panel B shows the same statistics broken down by maturity buckets. There is substantial trading across all maturities (number of trades), with a slight tilt toward the $4-7y$ bucket. The number of unique investors is roughly comparable across maturity buckets and, as expected, higher duration volumes are traded at longer maturities.

Panel C shows the sectoral composition of the market. Banks and hedge funds account for around 60% of the volumes in this market, followed by asset managers and foreign officials. Banks and asset managers trade more frequently but in smaller ticket size ($0.47 and $0.39 millions of DV01 respectively). Hedge funds and Foreign Officials trade in substantially larger ticket sizes.

Since our focus is on FOMC meetings, Panel A in Table D2 provides descriptive statistics around those events. Given the time-zone difference between the US and UK, the FOMC decision is usually released at 19.00pm UK time, which we take to be near market close in London. Due to the time-zone difference, we call the FOMC day, *Pre-FOMC* and the day after *Post-FOMC*. The remaining days are gathered under *no FOMC* days. On average, activity increases after FOMC events with both higher duration volumes traded and more transactions. It is worth noting that not everyone trades those events: of the 9227 unique identifiers, only 30 – 35% are active around FOMC events.

The main finding of our paper is that the Treasury market reaction to monetary policy surprises is fundamentally different depending on market liquidity conditions. To stay close in spirit to our evidence in Section 3, we define the same measure in our sample. Specifically, we use the updated noise measure of Hu et al. (2013) through 2022 and we compute its median level on the days before FOMC meetings taking place in the period 2018-2022. We define *Low Liquidity* FOMC meetings as those for which the value of the yield curve noise is above its median level, and *High Liquidity* meetings those for which the value of the noise measure is below its median level.[50] Panel B of Table D2 shows descriptive statistics for post-FOMC days split between High and Low liquidity meetings. On average, traded duration volumes are higher on high-liquidity FOMC meeting days, with slightly larger trade sizes. We also observe a larger pool of market participants (unique trader IDs), although this does not translate into a higher average number of transactions.

C.1 Identifying Arbitrageurs in the Data

The key question when bringing the theory to the data is who are the arbitrageurs. Previous studies have assumed that certain sectors carried out such activity: for example hedge funds and trading desks of large broker-dealers. We adopt a different approach and develop a new methodology to identify individual institutions whose trading behavior is consistent with arbitrage activities. Our paper is to our knowledge the first to attempt such an exercise using quantity data directly.[51] We can do so because of the frequency and granularity of our dataset, in which we observe the identities of both counterparties in every trade, which provides a considerable advantage relative to the existing literature.

Our measure ranks traders according to two criteria. First, how many maturities (markets) is the trader active in, as fixed-income arbitrage exploits price discrepancies *across* the curve. We operationalize this criteria by computing the standard deviation of the maturities traded (weighted by the notional). We denote the standard deviations of maturities traded by trader i over period t by $\sigma_{i,t}$. Second, we measure the amount of net duration risk exposure. Arbitrageurs are interested in exploiting price discrepancies between two different maturities while minimizing exposure to interest rate risk. We implement this measure by computing the *net* duration exposure of the combined trades. We denote the net duration exposure of trader i over period t as $d_{i,t}$. Since we are not interested in the direction of the exposure, e.g. whether it is a net long or net short, we take the absolute value. We also multiply by –1 so that an increase in duration will be penalized

[50] Results are nearly identical when we use the whole sample median to define High Liquidity and Low Liquidity FOMC meetings.

[51] Giese et al. (2024) perform a similar exercise, but focus on identifying preferred-habitat investors, and for that reason only consider the maturity range of different investors.

by our composite score. An important consideration is the time horizon (t) over which we compute the two measures. We experimented with different horizons (daily, weekly, monthly) and report the main results with a monthly window.

Each period, we rank traders across each of the two measures and combine them into a single composite index:[52]

$$I_{i,t} = R^{\sigma}_{i,t} * R^{d}_{i,t},$$

where $R^M_{i,t} \in [0, 1]$ is the (standardized) ranking of trader i at time t on metric $M = \{\sigma, d\}$. We take the average of the index over the entire sample and end up with a single score for each trader.

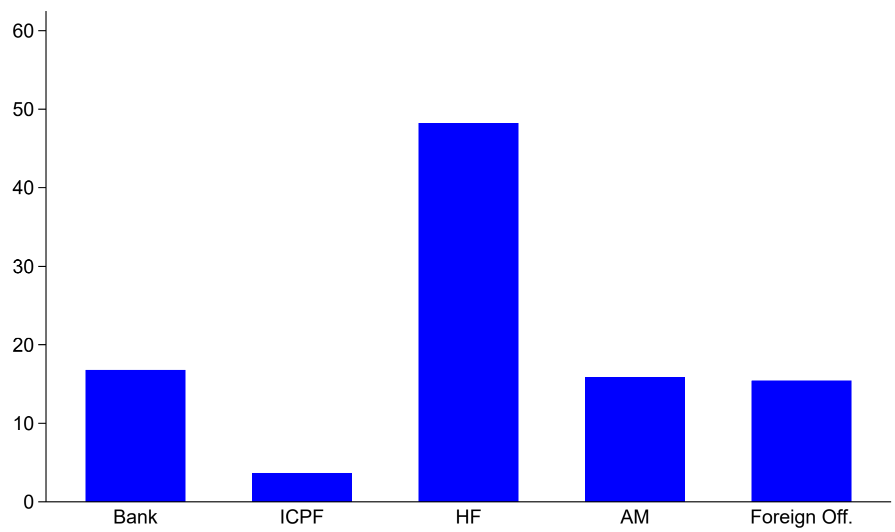
$$I_i = \frac{1}{N_i} \sum_{t=1}^{N_i} I_{i,t}$$

We then define arbitrageurs as those that score above the third tercile on the combined metric over the entire sample. This means they are the traders that both trade across more maturities while having smaller net duration exposure.

According to our measure, the majority of arbitrageurs are from the hedge fund sector (Figure C1), accounting for about 50% of total arbitrage volumes. The remaining share includes mostly banks and asset managers, which gives us confidence that our measure is picking up sophisticated institutional investors.

[52]We standardize the ranking of each measure between zero and one.

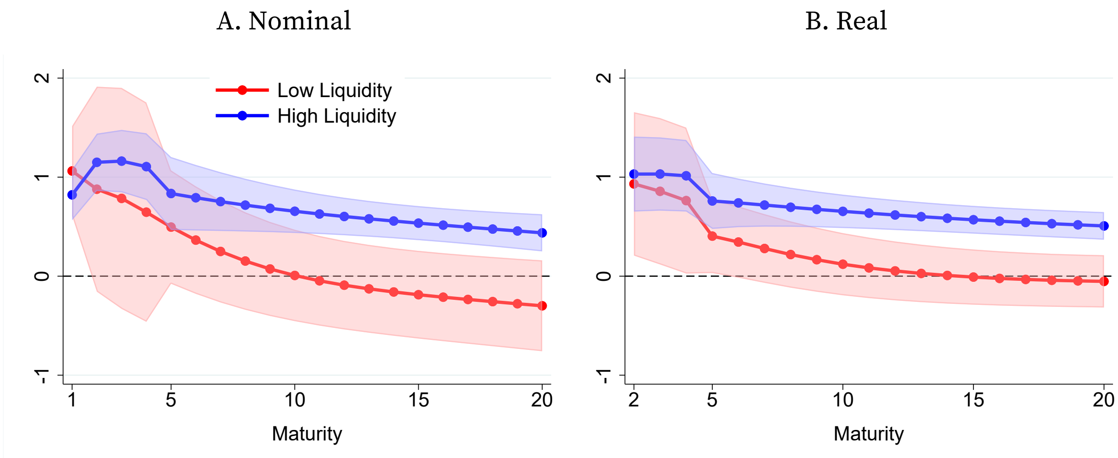
FIGURE C1. Traders Classified as Arbitrageurs Belong to These Sectors



Note: The figure plots the gross duration traded over the entire sample by traders belonging to different sectors (Bank, ICPF, HF, AM, Foreign Off.). The columns refer to traders that are classified as arbitrageurs by our algorithm explained in Appendix C.1, summing to 100%. The sample period is 01/01/2018-31/12/2022, excluding the Covid crisis (01/03/2020 - 30/05/2020).

D Additional Figures

FIGURE C1. The liquidity state dependence: The Response of *Spot* Rates

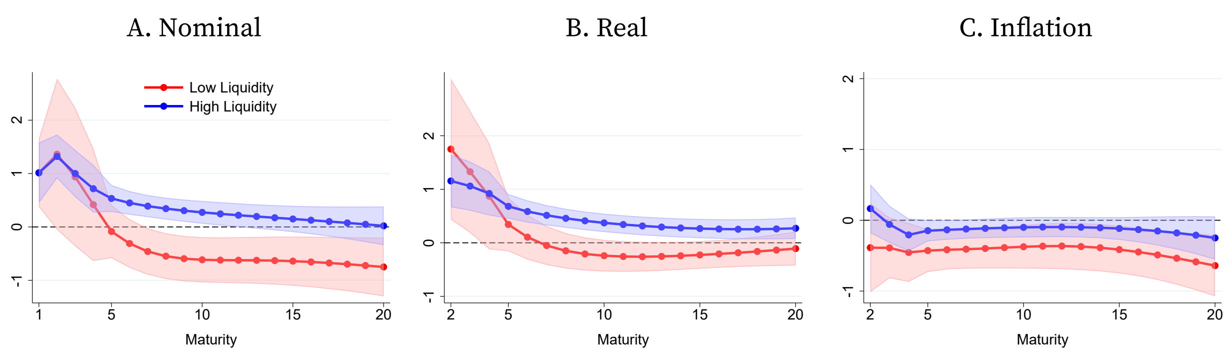


Note: the figure plots the OLS coefficient $\gamma_j^{(\tau)}$ in regression (2.2) estimated separately for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, using spot yields instead of forwards, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), scaled by the variance in each liquidity state and normalized so that its impact on the 1-year nominal spot rate is 100bps in each liquidity state separately. Panel A shows estimates for nominal spot rates. Panel B shows estimates for real spot rates. The blue line represents the OLS coefficient in the High-Liquidity state, while the red line represents the OLS coefficient in the Low-Liquidity state FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations. Regression results for the 2, 3 and 4-year forward rates are based on a sample size of 74 observations (starting in 2004).

D.1 Reproducing Section 3 with Extended Sample (2000 - 2019)

The charts below are equivalent to each chart in Section 3 but using the extended sample ending in December 2019 (instead of of our baseline sample ending March 2014, which was chosen for comparability with Nakamura and Steinsson (2018)). Our results are mostly unchanged.

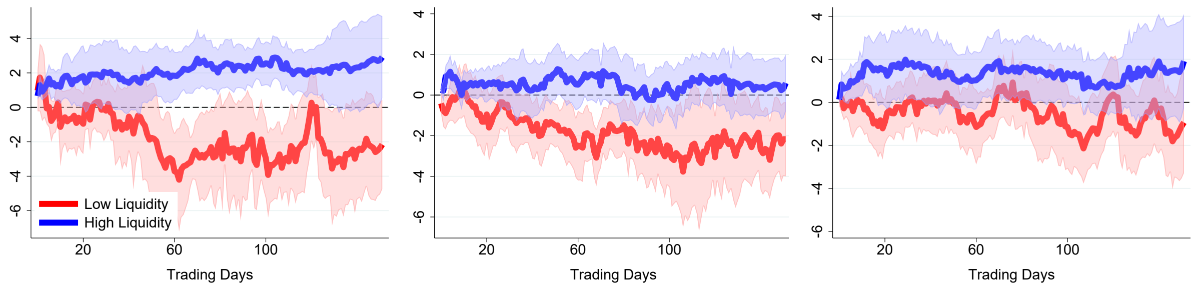
FIGURE C2. The liquidity state dependence - Extended Sample (2000 - 2019)



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018), scaled to have unit variance in each liquidity state and normalized so that its impact on the 1-year nominal forward rate equals 100bps in each liquidity state separately. The monetary policy shock series is interacted with dummies for the liquidity states, which group FOMC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state FOMC meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2019, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 152 observations. Regression results for the 2, 3 and 4-year forward rates are based on a sample size of 120 observations (starting in 2004).

FIGURE C3. Persistence of the liquidity state dependence on Real Forward Rates - Extended Sample (2000 - 2019)

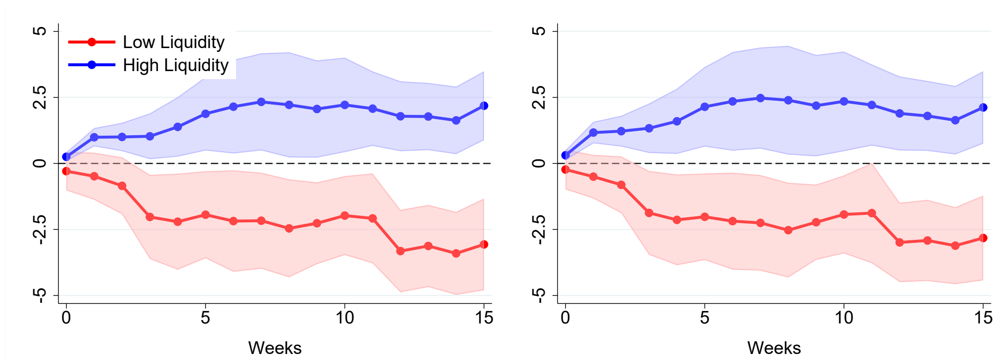
A. 5Y B. 10Y C. 20Y



Note: the figure shows estimates of $\gamma^{(\tau)}_{r,h,hl}$ and $\gamma^{(\tau)}_{r,h,ll}$ in regression (3.4) for real forward rates with maturities of 5 years (Panel A), 10 years (Panel B), and 20 years (Panel C) at horizons ranging from 1 to 152 trading days after the announcement, together with 90% confidence intervals based on Newey-West standard errors with 10 lags. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings.. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2019, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 152 observations on which the policy news shock is computed and each regression is estimated.

FIGURE C4. The Response of Mortgage Rates - Extended Sample (2000 - 2019)

A. 15Y B. 30Y

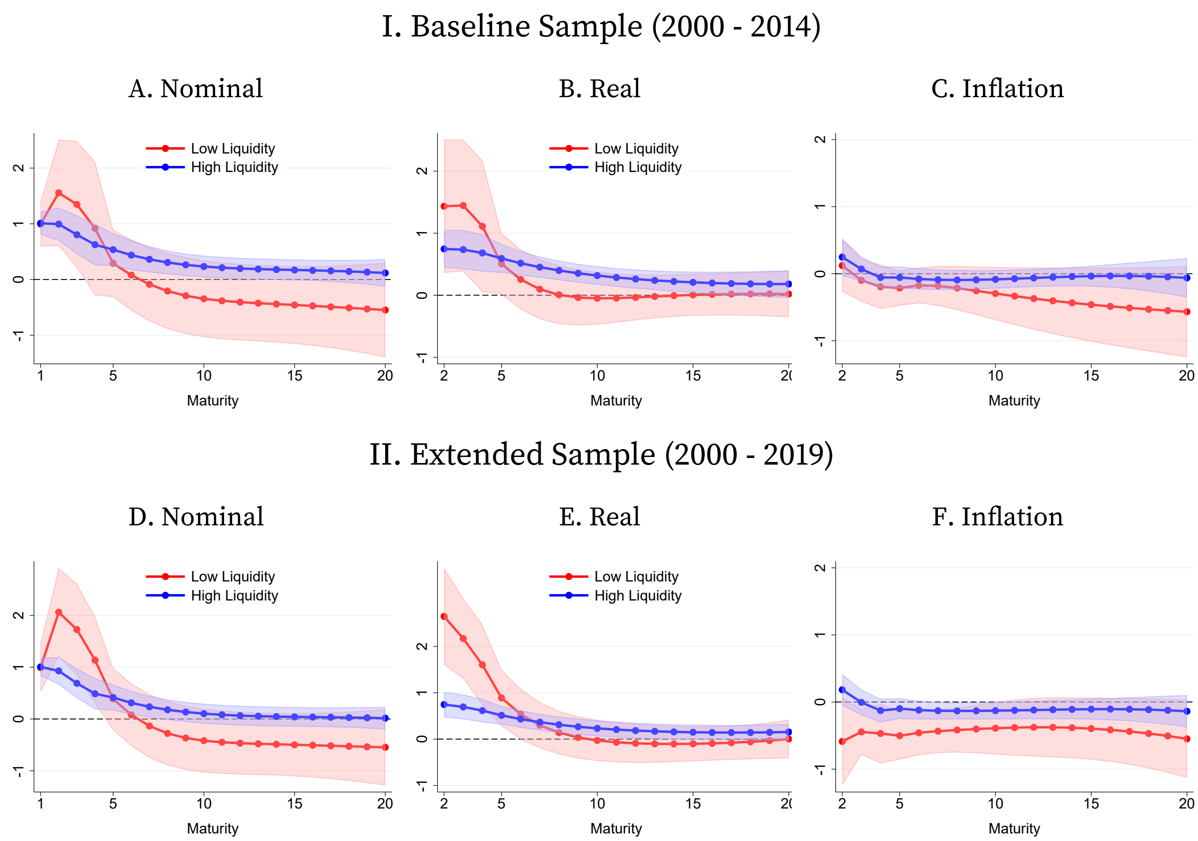


Note: the figures show the OLS estimates for $\gamma^{h}_{hl,\tau}$ and $\gamma^{h}_{ll,\tau}$ using 15-year and 30-year mortgage rates respectively in regression (3.4) together with 90% confidence intervals based on Newey-West standard errors with 10 lags. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2019, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 152 observations on which the policy news shock is computed and each regression is estimated.

D.2 Liquidity State Dependence Without Easing Meetings

Below we repeat the exercise in Section 3.1 where we exclude all meetings when FOMC eased and re-estimate our liquidity state dependence (i.e. partition the remaining sample and do the standardization/normalization within that subsample, for both the Nakamura and Steinsson (2018) sample and the extended sample using Acosta (2022) data.

FIGURE C5. The liquidity state dependence - Removing All FOMC Easing Meetings



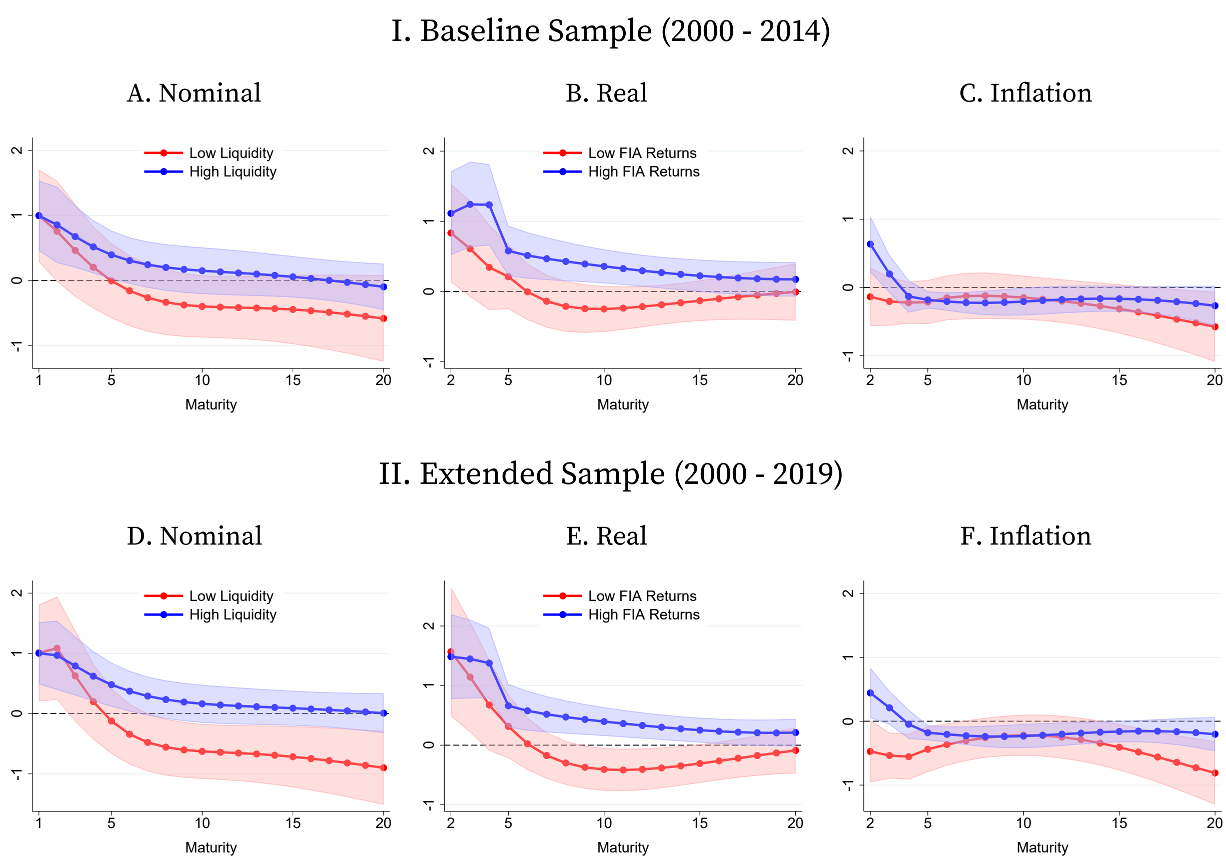
Note: The top panel is the equivalent to Figure 2 and the bottom panel to Figure C2, except that we exclude all FOMC meetings where the Fed funds target rate was reduced and re-estimate the liquidity state dependence following the same approach as before.

We can see that the main effect from removing all easing meetings is to increase the confidence intervals, which is natural given the drop in sample size. But there is now also a more pronounced overshoot in the short-term forwards in the 'Low Liquidity' state, and a slight reduction in significance and point estimates for the 'High Liquidity' estimates.

D.3 State Dependence Conditioning on FIA Returns – With and Without Easing Meetings

The first chart below reproduces Figure 6 in the top panel and the same exercise for the extended sample in the bottom panel (equivalent to Figure C2 but using the FIA returns as conditioning variable to define the states).

FIGURE C6. The liquidity state dependence Conditioning on Fixed-Income Arbitrage Returns

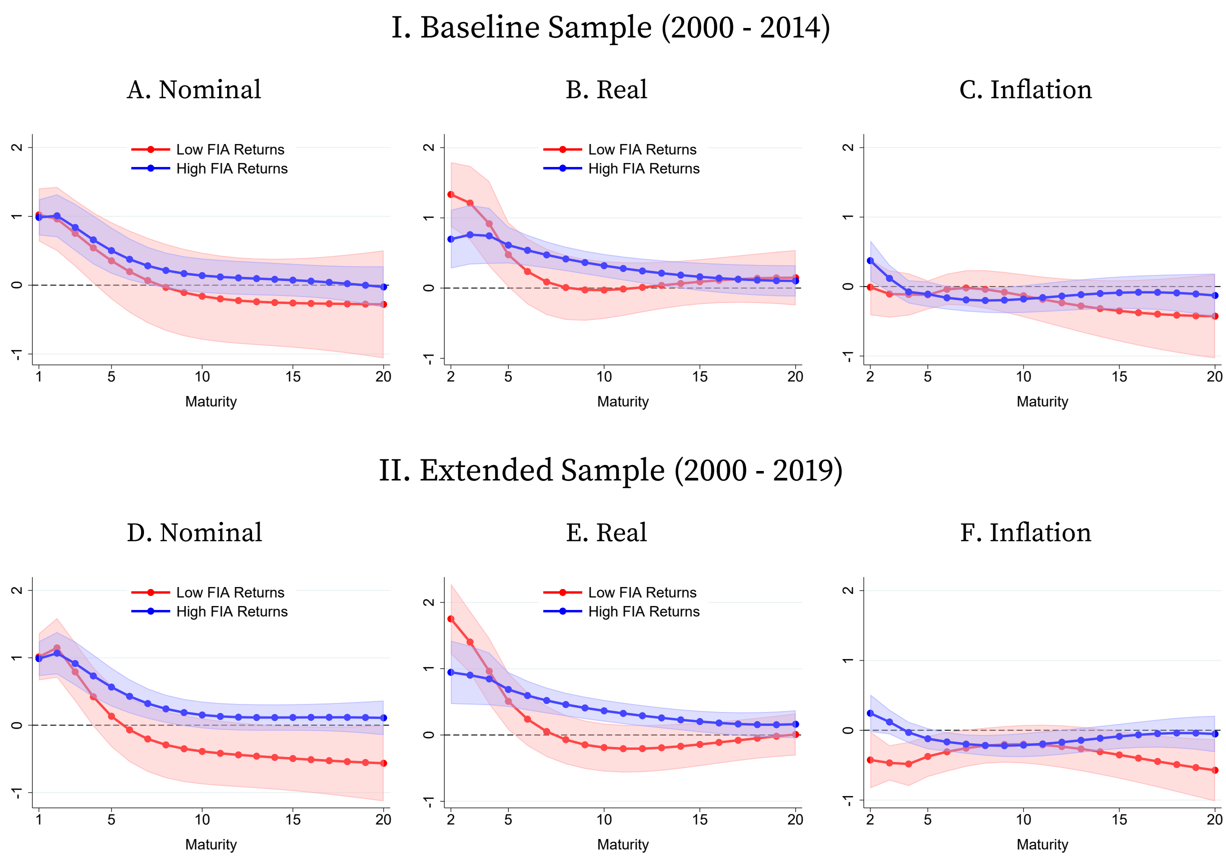


Note: Same as Figures 2 and C2 but using Fixed-Income Arbitrage hedge fund returns to determine the high and low states: a given FOMC meeting (excluding all easing meetings) is grouped in the High (Low) FIA returns state if the value of the hedge fund return index in the month prior to the meeting is above (below) its median level across all meetings.

We now revisit the same exercise as in Section D.2 above using Fixed-Income Arbitrage hedge fund returns as the state variable instead of liquidity.

We can see that the main effect from removing all easing meetings is to increase the

FIGURE C7. The liquidity state dependence Conditioning on Fixed-Income Arbitrage Returns - Removing All FOMC Easing Meetings



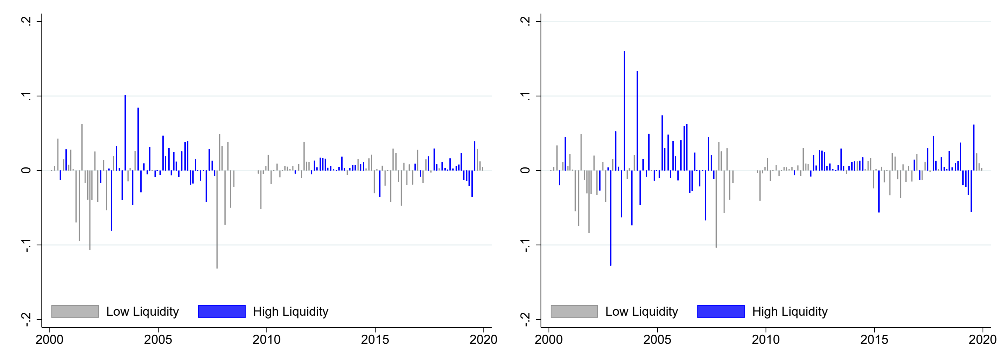
Note: Same as Figure C5 but using Fixed-Income Arbitrage hedge fund returns to determine the high and low states: a given FOMC meeting (excluding all easing meetings) is grouped in the High (Low) FIA returns state if the value of the hedge fund return index in the month prior to the meeting is above (below) its median level across all meetings.

confidence intervals, which is natural given the drop in sample size, particularly for the 'Low FIA returns' estimates. However the main qualitative stylized fact remains robust across these variations: the transmission of monetary policy shocks to longer maturity forward rates is significant only in 'High FIA returns' state. This even more clearly with FIA returns than when we condition on liquidity (proxied by yield curve 'noise').

D.4 Shocks by State and Scatter Plots

FIGURE C8. Monetary Policy Shocks By State

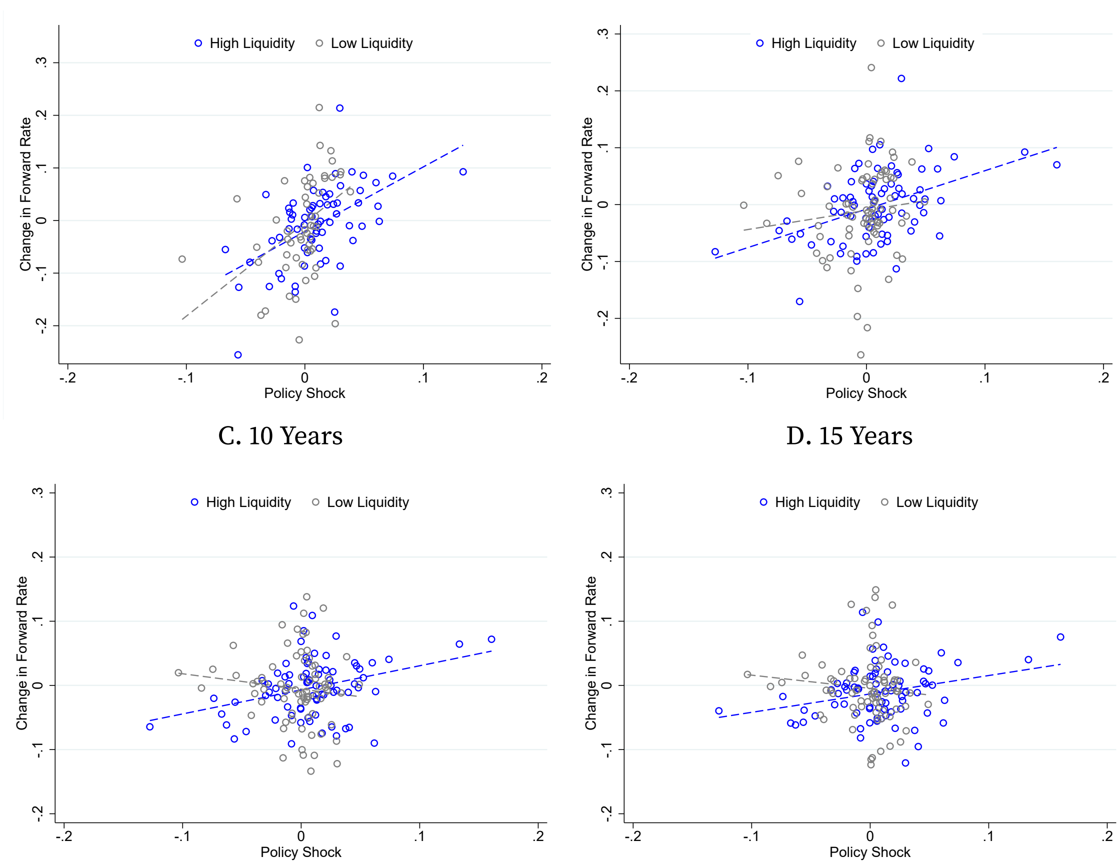
A. Raw Shocks B. Normalized Shocks



Note: the figures show time series of monetary policy shocks of Acosta (2022) on the left-hand side and divided by the standard deviation and scaled to have a 100bps impact on the 1-year nominal forward rate on the right-hand side. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. The sample covers the period 01/01/2000 - 31/12/2019, excluding the global financial crisis.

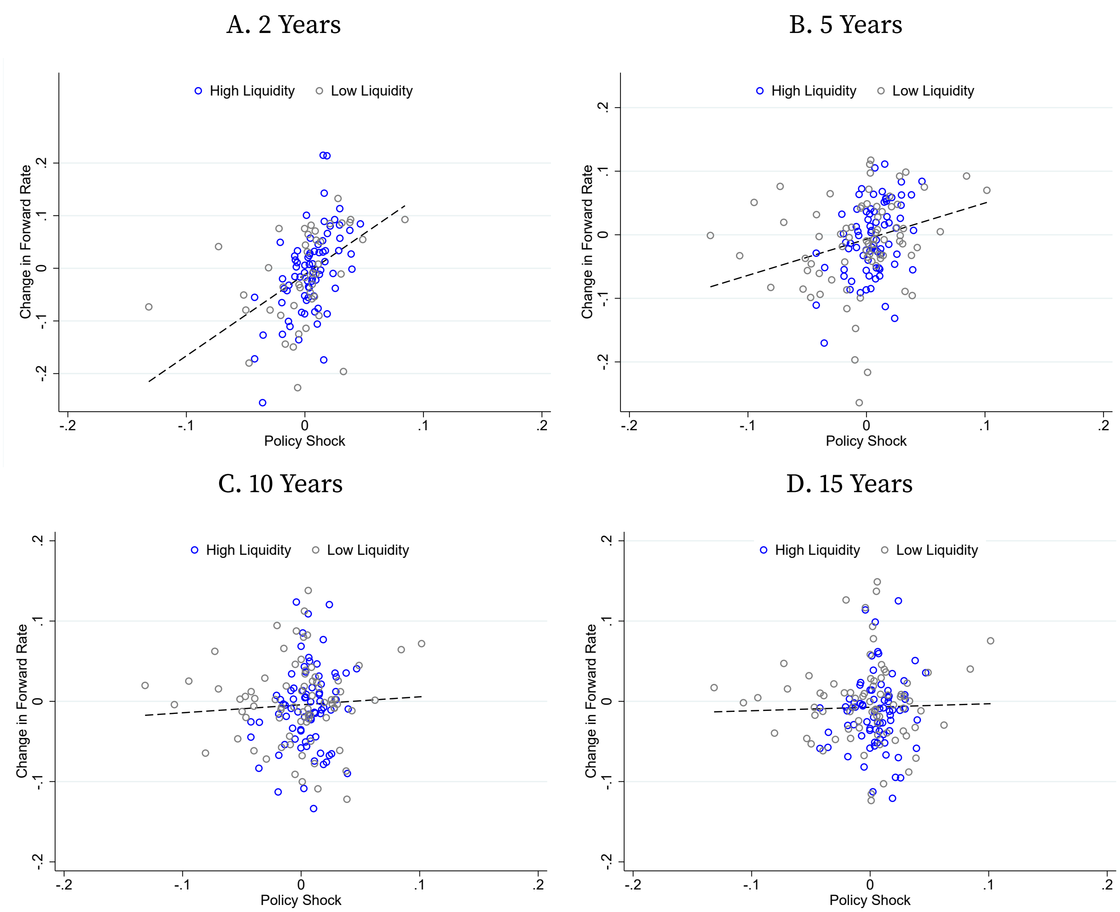
FIGURE C9. Normalized Policy Shocks vs Changes in Forward Rates

A. 2 Years | B. 5 Years | C. 10 Years | D. 15 Years



Note: The figure shows scatter plots of daily changes in real forward rates versus Nakamura and Steinsson (2018) policy shocks, divided by their standard deviation and scaled to have 100bps impact on the 1-year nominal forward rate, along with the line of best fit over the two samples. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. We use the raw (non-detrended) noise in this plot. The sample covers the period 01/01/2000 - 31/12/2019, excluding the global financial crisis.

FIGURE C10. Raw Policy Shocks vs Changes in Forward Rates



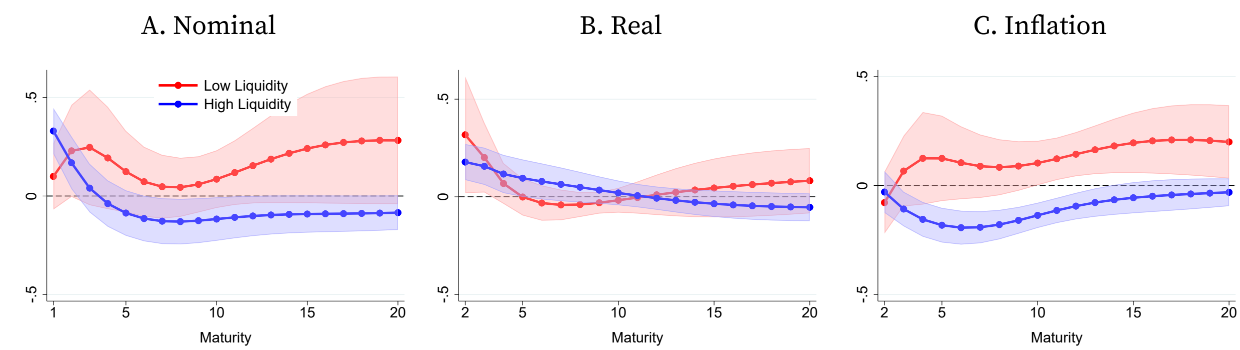
Note: The figure shows scatter plots of daily changes in real forward rates versus Nakamura and Steinsson (2018) policy shocks, along with the line of best fit over the pooled sample. FOMC meetings are grouped into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. We use the raw (non-detrended) noise in this plot. The sample covers 01/01/2000 - 31/12/2019, excluding the global financial crisis.

D.5 Liquidity State Dependence with UK Data

In this section we show the liquidity state dependence estimates for the UK using the same samples as used in the main text for the US.

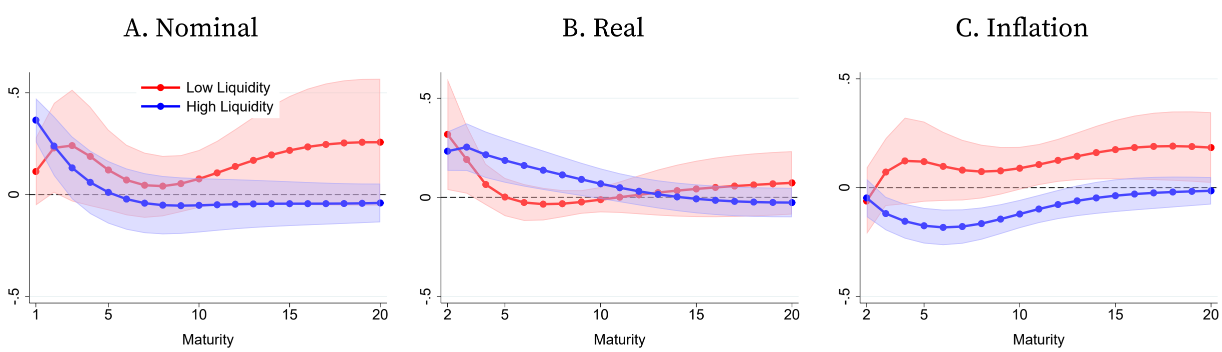
The measure of monetary policy shocks is the first principal component extracted from the high-frequency surprises in the the first four quarterly Short Sterling Futures contracts from Braun et al. (2024). As such, the monetary policy shocks incorporate information about the short-term target rate and the expected path of interest rates over the next few months, similar to the measure proposed by Nakamura and Steinsson (2018) for the US which we used in the main analysis. The yield curve noise is calculated using the Bank of England fitted yield curves, available at https://www.bankofengland.co.uk/statistics/yield-curves.

FIGURE C11. The liquidity state dependence in the UK - Baseline Sample (2000 - 2014)



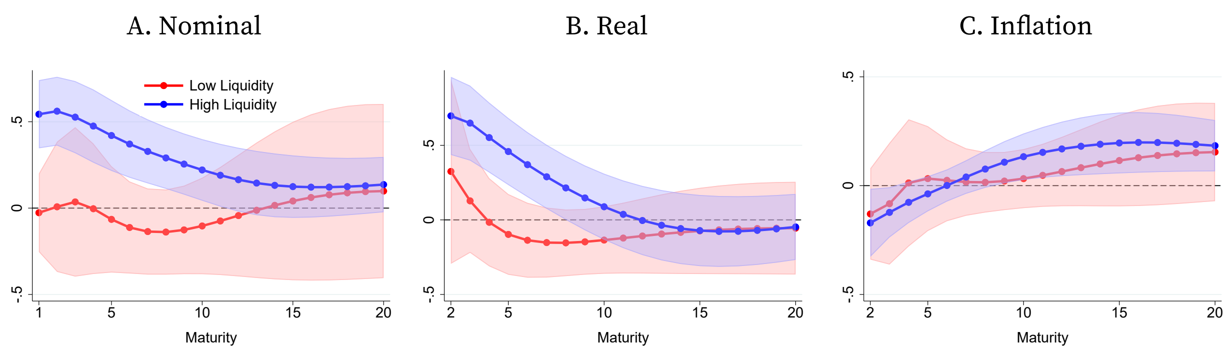
Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the UK equivalent of the monetary policy shock series of Nakamura and Steinsson (2018) introduced in Braun et al. (2024), namely the 1st principal component of the high-frequency surprises in the first four quarterly futures contracts around regularly scheduled MPC announcements. The monetary policy shock series is interacted with dummies for the liquidity states, which group MPC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state MPC meetings. The sample includes all regularly scheduled MPC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 158 observations.

FIGURE C12. The liquidity state dependence in the UK - Extended Sample (2000 - 2019)



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the UK equivalent of the monetary policy shock series of Nakamura and Steinsson (2018) introduced in Braun et al. (2024), namely the 1st principal component of the high-frequency surprises in the first four quarterly futures contracts around regularly scheduled MPC announcements. The monetary policy shock series is interacted with dummies for the liquidity states, which group MPC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state MPC meetings. The sample includes all regularly scheduled MPC meetings from 2000 to 2019, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 214 observations.

FIGURE C13. The liquidity state dependence in the UK - post-GFC sample (2009 - 2024)



Note: the figure plots the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2) for each liquidity state $j \in \{ll, hl\}$ and maturity $\tau \in [2, 20]$, together with 95% confidence intervals based on robust standard errors. The independent variable in each regression is the UK equivalent of the monetary policy shock series of Nakamura and Steinsson (2018) introduced in Braun et al. (2024), namely the 1st principal component of the high-frequency surprises in the first four quarterly futures contracts around regularly scheduled MPC announcements. The monetary policy shock series is interacted with dummies for the liquidity states, which group MPC meetings into the high (low) liquidity state if the value of the yield curve noise measure of Hu et al. (2013) on the day prior to the meeting is below (above) its median level across all meetings. Panel A shows estimates for nominal forward rates. Panel B shows estimates for real forward rates. Panel C shows estimates for inflation forward rates. The blue line represents the estimated coefficients in the High Liquidity state, while the red line represents the estimated coefficients in the Low Liquidity state MPC meetings. The sample includes all regularly scheduled MPC meetings from 01/07/2009 to 30/06/2024, excluding those taking place between March and May 2020. This corresponds to a sample size of 107 observations.

E Additional Tables

Table D1. Summary Statistics in Mifid

	Gross Dur	Pct	No. Trades	Pct	Trade Size	No. LEI
	Panel A: Full Sample					
	728		958		0.76	9227
	Panel B: By Maturity					
1-3y	60	0.08	219	0.23	0.28	5597
4-7y	174	0.24	263	0.27	0.66	5663
8-10y	205	0.28	247	0.26	0.83	5586
11-30y	294	0.40	235	0.24	1.25	4894
	Panel C: By Sector					
Bank	124	0.17	266	0.27	0.47	1018
ICPF	39	0.05	59	0.06	0.67	1134
HF	308	0.42	167	0.17	1.84	601
AM	123	0.17	315	0.32	0.39	3969
Foreign Off.	118	0.16	73	0.08	1.62	175

Note: The table shows summary statistics on the MIFID data. "Gross Dur" reports the daily average of gross duration traded, in millions. "Pct" reports the contribution of each sector to the total. "No Trades" reports the daily average number of transactions. "Pct" reports the contribution of each sector to the total number of trades. "Trade Size" reports the average traded size, in millions (duration). "No LEI" reports the count of total unique trader IDs. The sample period is 01/01/2018 - 31/12/2022, excluding the Covid crisis (01/03/2020 - 30/05/2020).

TABLE D2. Summary Statistics in Mifid: Specific Days

	Gross Dur	Pct	No. Trades	Pct	Trade Size	No. LEI
	Panel A: FOMC vs non FOMC					
	Volume	Pct	No. Trades	Pct	Trade Size	No. LEI
no FOMC	717	0.28	943	0.28	0.76	9076
Pre-FOMC	634	0.25	834	0.25	0.76	2618
Post-FOMC	1234	0.48	1607	0.47	0.77	3184
	Panel B: Post-FOMC High vs Low Noise					
High Noise	1084	0.35	1625	0.39	0.67	1730
Low Noise	1303	0.42	1599	0.38	0.81	2712

Note: The table shows summary statistics on the MIFID data. "Gross Dur" reports the daily average of gross duration traded, in millions of DV01. "Pct" reports the contribution of each sector to the total. "No Trades" reports the daily average number of transactions. "Pct" reports the contribution of each sector to the total number of trades. "Trade Size" reports the average traded size, in millions of DV01. "No LEI" reports the count of total unique trader IDs. Pre-FOMC refers to the day of the FOMC. We shift all trading occurring after the release of the FOMC statement, usually at 2pm, to the following day. The sample period is 01/01/2018 - 31/12/2022, excluding the Covid crisis (01/03/2020 - 30/05/2020).

TABLE D3. Summary Statistics: Input into the Yield-Curve Noise

	(1) 1990-2000	(2) 2001-2006	(3) 2007-2011	(4) 2012-2019
N Bonds	181	125	206	304
N Bonds 1-3Y (%)	64	65	56	56
N Bonds 3-7Y (%)	27	24	31	35
N Bonds 7-10Y (%)	9	12	13	9
Maturity (yrs)	2.70	2.74	3.25	3.16
Duration (yrs)	2.26	2.19	2.74	2.80
Age (yrs)	3.68	3.36	3.44	4.41
Price ($)	103.35	102.59	105.16	103.36
YTM (%)	5.88	3.31	1.82	1.28
Coupon (%)	6.34	3.97	3.09	2.02
Bid-Ask (bps)	0.06	0.03	0.03	0.04
Size ($ B)	12.81	21.69	26.87	35.05
Noise (mean)	3.29	2.47	4.47	1.62
Noise (p50)	3.13	2.33	3.10	1.62
Noise (p25)	2.43	1.63	2.22	1.24
Noise (p75)	3.96	3.16	4.86	1.92

Note: The table reports daily average of bonds feeding into the construction of the yield-curve noise measure of Hu et al. (2013). The source is the US CRSP Daily US Treasury dataset. Noise is from Jun Pan's website.

TABLE D4. Summary Statistics Across Liquidity States for Monetary Policy and the Macroeconomy

		Full sample	High Liquidity	Low Liquidity	Diff.
FOMC Meetings	Count	152	76	76	
	Recessions	9	0	9	0.002
	Hikes	70	47	23	0.003
	Ease	52	16	36	0.002
	No change	30	13	17	0.418
MP Shock (bps)	Positive	94	48	46	0.741
	Negative	58	28	30	0.741
	Mean	0.00	0.03	-0.04	0.000
	SD	0.14	0.10	0.16	0.000
	p25	-0.01	0.00	-0.06	
	p50	0.00	0.01	0.00	
	p75	0.03	0.08	0.01	
FFR (%)	Mean	0.25	0.86	-0.35	0.034
	SD	3.53	4.13	2.70	0.000
	p25	-1.29	-1.09	-1.37	
	p50	0.48	0.70	0.22	
	p75	1.89	2.70	1.18	
Core Inflation (%)	Mean	1.75	1.89	1.62	0.000
	SD	0.36	0.33	0.33	0.906
	p25	1.52	1.62	1.43	
	p50	1.72	1.88	1.60	
	p75	2.00	2.10	1.85	
Unemployment (%)	Mean	5.82	5.51	6.13	0.036
	SD	1.82	1.45	2.08	0.002
	p25	4.5	4.5	4.65	
	p50	5.35	5.15	5.45	
	p75	6.7	6.2	7.95	

Note: The table shows summary statistics based on the detrended noise measure, with monetary policy shocks rescaled by the standard deviations and normalized to have 100bps impact on the 1Y nominal forward rate in each respective sample. High Liquidity includes all the schedules FOMC meetings where the noise measure was below its median computed over the entire sample. The sample period is 01/01/2000 - 31/12/2019, excluding all FOMC meetings taking place between July 2008 and June 2009. The monetary policy shocks (MPS) series is the shock proposed by Nakamura and Steinsson (2018), as updated by Acosta (2022). Hikes, eases and no change are defined based on monthly changes in the effective Fed Fund Rate. Recessions are monthly NBER recession dates. Unemployment rate is the real-time vintage civilian unemployment rate from Bauer et al. (2023). Inflation is the Personal Consumption Expenditures Excluding Food and Energy (PCEPILFE) from FRED. The last column ('Diff.') reports the p-value of a test of equality between the High Liquidity and Low Liquidity sample.

TABLE D5. Explaining the Yield Curve Noise with Hedge Fund Returns

		Univ. R^2	(1)	(2)	(3)	(4)
	Aggregate HF Index	18.74				0.15
						(0.26)
Macro Strategies:	Fixed-Income Arb.	34.89	-0.26***			-0.19**
			(0.06)			(0.07)
	Multi-Strategy	29.20	-0.28**			-0.04
			(0.13)			(0.11)
	Global Macro	1.34	0.13*			0.06
			(0.08)			(0.05)
Specialized Strategies:	Convertible Arb.	40.83		-0.44***		-0.29***
				(0.09)		(0.07)
	Distressed	20.48		-0.03		0.08
				(0.06)		(0.07)
	Merger Arb.	10.48		-0.00		0.01
				(0.05)		(0.06)
	Event-driven	16.92		0.01		-0.06
				(0.06)		(0.14)
Equity Strategies:	Equity (Long Bias)	14.24			-0.54	-0.02
					(0.36)	(0.11)
	Equity (Long Short)	8.51			0.39	0.11
					(0.29)	(0.13)
	Equity (Market Neutral)	-0.21			0.00	0.02
					(0.06)	(0.05)
	Equity (European)	6.03			-0.12	0.05
					(0.07)	(0.07)
	Adj R^2		39.64	40.10	15.64	42.95
	N		240	240	240	240

Note: The dependent variable is the monthly change in the noise measure, obtained by averaging daily observations over a given month. We use the following specification $\Delta \text{Noise}_t = \alpha + \beta \Delta X_t + \epsilon_t$, where X_t is a vector of hedge fund returns from the Barclay Hedge Fund Return Index. All dependent variables are standardized to ease comparison. The column Univ. R^2 reports the adjusted R^2 of regressing the monthly change in noise on each hedge fund strategy separately. The period is from 01/2000 to 12/2019, corresponding to a sample size of 240 observations. Newey-West standard errors with 36 lags are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table D6. What Explains the Yield Curve Noise?

		Univariate			By Block				Excl. Arbs	Arbs Only	All
		b	*t − stat*	R^2	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liq./Stress Proxies:	Δ VIX	0.62**	(2.37)	18.02	0.38				0.26		
					(1.00)				(0.84)		
	Δ MOVE	0.02***	(4.24)	15.94	0.01***				0.01***		0.01***
					(4.92)				(4.60)		(3.59)
	Δ TED	0.41***	(4.87)	7.63	0.03				-0.09		
					(0.16)				(-0.38)		
	Δ RA	0.39***	(8.77)	13.21	0.09				-0.01		
					(0.68)				(-0.05)		
Business Cycle Proxies:	Δ ADS	-0.10	(-1.18)	0.21		-0.07			-0.15*		
						(-1.02)			(-1.77)		
	Δ Unemp.	0.14***	(2.68)	2.53		0.16***			0.20**		0.10***
						(2.71)			(2.08)		(2.95)
	Δ PMI	-0.40	(-1.27)	5.16		-0.40			-0.25		
						(-1.26)			(-1.47)		
Uncertainty Proxies:	ISK	-0.13	(-1.23)	3.28			-0.09		-0.04		
							(-0.99)		(-0.74)		
	Δ Unc.	0.71**	(2.44)	16.10			0.63***		0.49***		-0.32
							(2.65)		(3.67)		(-1.27)
	Δ IR Unc.	0.27*	(1.66)	3.48			0.15***		0.06		
							(3.11)		(0.71)		
Arbitrageurs Proxies:	Δ Lev.	1.43***	(3.90)	16.35				0.49*			0.59*
								(1.81)			(1.93)
	FIA Ret.	-0.41***	(-7.95)	34.52				-0.15**		-0.18***	-0.17***
								(-2.58)		(-3.02)	(-2.63)
	ConvArb. Ret.	-0.45***	(-5.35)	40.89				-0.29***		-0.32***	-0.32***
								(-3.34)		(-3.38)	(-2.82)
	R^2				22.26	8.22	17.91	44.83	31.84	43.47	50.77
	N				205	240	226	240	191	240	205

Note: The dependent variable is the monthly change in the noise measure, obtained by averaging daily observations over a given month. We use the following specification $\Delta \text{Noise}_t = \alpha + \beta \Delta X_t + \epsilon_t$, where X_t is a vector of explanatory variables. As Liquidity Proxies we use: VIX obtained from CBOE, the T-Bill-Eurodollar spread (TED spread), and the index of risk aversion (*RA*) from Bekaert et al. (2022). As Business Cycle Proxies we use the ADS index from Aruoba et al. (2009) and initial jobless claims (ΔUnemp.) from the Bureau of Labor Statistics and the purchasing-manager index (*PMI*) from Markit. As Uncertainty proxies we use the interest-rate skeweness (ISK) from Bauer and Chernov (2024) and risk aversion (RA) from Bekaert et al. (2022). As Arbitrageurs Proxies we use intermediary factor of He et al. (2017) (Δ Lev.), Barclay fixed-income arbitrage returns (FIA Ret.) and convertible-arbitrage returns (ConvArb Ret.). All dependent variables are standardized to ease comparison. The period is from 01/2000 to 12/2019, corresponding to a sample size of 240 observations. Newey-West standard errors with 36 lags are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table D7. What Explains the Yield Curve Noise? Innovations

		Univariate			By Block				Excl. Arbs	Arbs Only	All
		b	$t-stat$	R^2	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liquidity Proxies:	ΔVIX	0.56**	(2.38)	14.50	0.15				0.06		
					(0.66)				(0.34)		
	ΔMOVE	0.03***	(4.21)	17.68	0.02***				0.02***		0.02***
					(3.59)				(4.81)		(2.73)
	ΔTED	0.40***	(4.67)	7.27	-0.01				-0.11		
					(-0.04)				(-0.45)		
	ΔRA	0.40***	(9.27)	14.07	0.20**				0.05		
					(2.21)				(0.39)		
Business Cycle Proxies:	ΔADS	-0.11	(-1.24)	0.31		-0.07			-0.12		
						(-0.99)			(-1.50)		
	ΔUnemp.	0.17**	(2.58)	3.17		0.17***			0.21**		0.17**
						(2.63)			(2.02)		(2.25)
	ΔPMI	-0.39	(-1.27)	5.12		-0.39			-0.28		
						(-1.23)			(-1.50)		
Uncertainty Proxies:	ISK	-0.18	(-1.52)	1.50			-0.08		0.00		
							(-0.93)		(0.07)		
	ΔUnc.	0.70**	(2.41)	15.48			0.63**		0.56***		0.22
							(2.54)		(3.18)		(1.56)
	ΔIR Unc.	0.31*	(1.69)	4.51			0.20***		0.11		
							(3.12)		(0.97)		
Arbitrageurs Proxies:	ΔLev.	1.43***	(3.90)	16.35				1.09***			1.01***
								(3.03)			(2.83)
	FIA Ret.	-0.34***	(-7.48)	18.95				-0.26***		-0.32***	-0.15**
								(-4.55)		(-4.84)	(-2.42)
	ConvArb. Ret.	-0.28***	(-4.55)	9.57				-0.03		-0.05	0.06
								(-0.63)		(-0.77)	(1.06)
	R^2				21.76	8.37	16.89	27.45	31.74	18.76	37.39
	N				204	239	225	239	190	239	204

Note: The dependent variable is the monthly change in the noise measure, obtained by averaging daily observations over a given month. We use the following specification $\Delta\text{Noise}_t = \alpha + \beta\Delta X_t + \epsilon_t$, where X_t is a vector of explanatory variables. As liquidity proxies we use: VIX obtained from CBOE and the T-Bill-Eurodollar spread (TED spread). As business cycle proxies we use the ADS index from Aruoba et al. (2009) and initial jobless claims (IJC). As uncertainty proxies, we use the interest-rate skeweness (ISK) from Bauer and Chernov (2024) and risk aversion (RA) from Bekaert et al. (2022). As arbitrageurs proxies we use broker-dealer leverage factor of He et al. (2017), Barclays' hedge fund returns index (HF Ret.) and its sub-index the fixed-income arbitrage returns (FIA Ret.). All dependent variables are standardized to ease comparison. The period is from 01/2000 to 12/2019, corresponding to a sample size of 240 observations. Newey-West standard errors with 4 lags are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table D8. Liquidity State Dependence Conditioning on Arbitrage Capital Proxies (Excluding All Easing FOMC Meetings)

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Sorting on the yield curve noise from Hu et al (2013)											
High Liquidity	0.97***	0.41**	0.10	0.04	0.75***	0.51***	0.23**	0.15	0.18	-0.10	-0.13	-0.11
	(8.92)	(3.28)	(1.07)	(0.44)	(5.33)	(5.05)	(2.67)	(1.79)	(1.53)	(-1.26)	(-1.95)	(-1.35)
Low Liquidity	1.49***	0.39	-0.42	-0.50	2.65***	0.89**	-0.03	-0.10	-0.59	-0.50**	-0.39	-0.40
	(4.31)	(1.27)	(-1.33)	(-1.60)	(4.95)	(2.86)	(-0.13)	(-0.52)	(-1.76)	(-2.78)	(-1.95)	(-1.68)
Diff.	0.151	0.934	0.118	0.106	0.001	0.252	0.287	0.241	0.038	0.046	0.218	0.254
	B. Sorting on fixed-income arbitrage (FIA) hedge fund returns											
High FIA ret.	1.07***	0.57***	0.15	0.11	0.95***	0.69***	0.36***	0.20*	0.24	-0.12	-0.21*	-0.09
	(6.70)	(3.88)	(1.51)	(1.15)	(3.88)	(5.13)	(4.41)	(2.49)	(1.78)	(-1.58)	(-2.44)	(-0.97)
Low FIA ret.	1.15***	0.13	-0.39	-0.49*	1.75***	0.51*	-0.19	-0.14	-0.43*	-0.38*	-0.20	-0.35*
	(5.09)	(0.57)	(-1.56)	(-2.02)	(6.47)	(2.32)	(-1.03)	(-0.86)	(-2.06)	(-2.52)	(-1.43)	(-2.04)
Diff.	0.771	0.113	0.046	0.024	0.028	0.485	0.007	0.065	0.009	0.132	0.932	0.182
	C. Sorting on convertible arbitrage (CA) hedge fund returns											
High CA ret.	1.04***	0.48*	-0.09	-0.09	1.13**	0.66***	0.20	0.12	0.00	-0.18	-0.29*	-0.20
	(5.23)	(2.23)	(-0.62)	(-0.65)	(3.33)	(3.46)	(1.48)	(0.93)	(0.00)	(-1.63)	(-2.51)	(-1.65)
Low CA ret.	1.10***	0.31	-0.05	-0.16	1.32***	0.56***	0.09	0.02	-0.07	-0.25*	-0.14	-0.18
	(6.61)	(1.96)	(-0.28)	(-0.86)	(5.37)	(3.81)	(0.66)	(0.18)	(-0.31)	(-2.37)	(-1.47)	(-1.49)
Diff.	0.838	0.530	0.881	0.760	0.634	0.665	0.544	0.580	0.794	0.680	0.312	0.892
	D. Sorting on the broker-dealer leverage factor from He et al (2017)											
Low BD Lev.	0.97***	0.41**	0.09	0.01	0.98***	0.57***	0.22**	0.18*	0.21	-0.16*	-0.13	-0.17*
	(7.06)	(3.35)	(0.82)	(0.06)	(5.63)	(5.68)	(2.76)	(2.26)	(1.43)	(-2.20)	(-1.72)	(-2.11)
High BD Lev.	1.45***	0.37	-0.40	-0.43	1.81***	0.74*	-0.02	-0.17	-0.36	-0.37*	-0.38*	-0.26
	(4.70)	(1.17)	(-1.44)	(-1.48)	(4.69)	(2.32)	(-0.10)	(-0.89)	(-1.56)	(-2.07)	(-2.14)	(-1.12)
Diff.	0.148	0.915	0.109	0.170	0.053	0.618	0.333	0.100	0.049	0.294	0.204	0.716

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ls, hs\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panel A defines the states as in our baseline, using the yield curve noise measure of Hu et al. (2013). Panels B and C use respectively the fixed-income arbitrage (FIA) and convertible arbitrage (CA) hedge fund return indices from Barclays to define the state. FOMC meetings are grouped into the high (low) liquidity state if the value of the hedge fund return index in the month prior to the meeting is above (below) its median level across all meetings. Panel D uses the broker-dealer leverage factor of He et al. (2017) as the state variable, with FOMC meetings grouped into the high (low) liquidity state if the value of the leverage factor on the day before the meeting is below (above) its median level across all meetings. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009 and every meeting the FOMC reduced the fed funds target rate. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE D9. Liquidity State-Dependence with Alternative Conditioning Variables for the States (Excluding All Easing FOMC Meetings)

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Sorting on the MOVE index											
Low MOVE	1.02***	0.35	-0.17	-0.23	0.93***	0.62**	-0.07	-0.17	0.09	-0.27*	-0.10	-0.06
	(4.17)	(1.50)	(-0.96)	(-1.24)	(3.64)	(2.85)	(-0.39)	(-0.87)	(0.72)	(-2.26)	(-0.96)	(-0.43)
High MOVE	1.13***	0.41**	-0.01	-0.09	1.21***	0.61***	0.22*	0.13	-0.10	-0.20*	-0.23*	-0.23
	(8.71)	(2.78)	(-0.07)	(-0.62)	(4.96)	(4.47)	(2.07)	(1.42)	(-0.50)	(-2.12)	(-2.48)	(-1.95)
Diff.	0.684	0.817	0.506	0.599	0.441	0.993	0.174	0.166	0.449	0.674	0.356	0.377
	B. Sorting on the VIX index											
Low VIX	1.11***	0.38**	-0.01	-0.08	0.99***	0.64***	0.10	-0.00	0.11	-0.26**	-0.11	-0.08
	(7.56)	(2.62)	(-0.09)	(-0.60)	(5.14)	(4.87)	(0.82)	(-0.01)	(0.91)	(-3.12)	(-1.89)	(-1.09)
High VIX	1.01***	0.38	-0.13	-0.19	1.64***	0.54*	0.18	0.14	-0.41	-0.16	-0.32*	-0.33
	(4.80)	(1.67)	(-0.60)	(-0.87)	(3.68)	(2.58)	(1.17)	(1.08)	(-1.32)	(-1.14)	(-2.06)	(-1.84)
Diff.	0.687	0.990	0.644	0.668	0.197	0.715	0.678	0.440	0.135	0.568	0.215	0.203
	C. Sorting on the TED spread											
Low TED	1.03***	0.50**	0.15	0.08	1.08***	0.68***	0.20*	0.13	0.10	-0.18*	-0.06	-0.05
	(6.24)	(3.31)	(1.39)	(0.78)	(4.25)	(4.76)	(2.02)	(1.42)	(0.59)	(-2.28)	(-0.88)	(-0.72)
High TED	1.25***	0.17	-0.49	-0.54*	1.69***	0.50*	0.02	-0.06	-0.26	-0.32	-0.51**	-0.48*
	(5.54)	(0.75)	(-1.90)	(-2.07)	(5.05)	(2.15)	(0.09)	(-0.33)	(-1.15)	(-1.93)	(-3.03)	(-2.37)
Diff.	0.417	0.231	0.025	0.031	0.151	0.496	0.409	0.368	0.211	0.425	0.013	0.047
	D. Sorting on the risk aversion index from Bekaert et al (2022)											
Low RA	1.01***	0.28	-0.05	-0.09	0.87***	0.56***	0.08	0.05	0.12	-0.27**	-0.12	-0.14
	(6.99)	(1.89)	(-0.33)	(-0.69)	(5.32)	(4.59)	(0.64)	(0.41)	(0.93)	(-2.95)	(-1.96)	(-1.83)
High RA	1.16***	0.49*	-0.09	-0.17	1.83***	0.65**	0.20	0.08	-0.35	-0.16	-0.29*	-0.25
	(5.37)	(2.20)	(-0.41)	(-0.79)	(4.33)	(3.05)	(1.28)	(0.59)	(-1.26)	(-1.22)	(-2.02)	(-1.44)
Diff.	0.559	0.448	0.876	0.771	0.042	0.704	0.553	0.859	0.148	0.507	0.309	0.585
	E. Sorting on the interest rate skewness measure from Bauer and Chernov (2024)											
Low IR Skew	1.31***	0.33	-0.18	-0.21	2.08***	0.74**	0.13	0.07	-0.45	-0.41*	-0.31*	-0.28*
	(4.33)	(1.29)	(-0.87)	(-1.20)	(5.00)	(2.89)	(0.64)	(0.36)	(-1.67)	(-2.25)	(-2.00)	(-2.00)
High IR Skew	1.09***	0.47**	-0.01	-0.10	0.93***	0.60***	0.16	0.07	0.21	-0.13	-0.17	-0.17
	(8.20)	(2.99)	(-0.04)	(-0.56)	(4.92)	(4.55)	(1.41)	(0.65)	(1.52)	(-1.83)	(-1.82)	(-1.31)
Diff.	0.496	0.638	0.511	0.638	0.015	0.626	0.885	0.989	0.041	0.170	0.440	0.549
	F. Sorting on the uncertainty index from Bekaert et al (2022)											
Low Uncert.	1.04***	0.44**	0.02	-0.04	1.05***	0.58***	0.16	0.07	0.21	-0.14	-0.14	-0.11
	(6.29)	(2.95)	(0.16)	(-0.29)	(5.03)	(4.48)	(1.54)	(0.69)	(1.35)	(-1.86)	(-1.80)	(-1.49)
High Uncert.	1.25***	0.36	-0.18	-0.25	1.66***	0.70**	0.13	0.06	-0.34	-0.34*	-0.30*	-0.31
	(5.53)	(1.49)	(-0.75)	(-1.07)	(4.43)	(2.97)	(0.69)	(0.37)	(-1.49)	(-2.24)	(-2.03)	(-1.65)
Diff.	0.454	0.804	0.485	0.445	0.173	0.654	0.882	0.938	0.066	0.257	0.338	0.344
	G. sorting on the interest rate uncertainty measure from Istrefi and Mouabbi (2018)											
Low IR Unc.	1.04***	0.56*	-0.06	-0.07	1.21***	0.64**	0.18	-0.06	-0.21	-0.09	-0.24	-0.01
	(3.69)	(2.11)	(-0.38)	(-0.49)	(3.70)	(2.62)	(1.01)	(-0.33)	(-0.80)	(-0.62)	(-1.64)	(-0.09)
High IR Unc.	1.10***	0.39**	-0.00	-0.10	1.23***	0.61***	0.16	0.14	0.11	-0.22*	-0.17	-0.24
	(7.46)	(2.65)	(-0.01)	(-0.59)	(5.16)	(4.72)	(1.49)	(1.52)	(0.74)	(-2.55)	(-1.89)	(-1.97)
Diff.	0.870	0.582	0.806	0.910	0.977	0.908	0.949	0.335	0.293	0.422	0.676	0.235

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ls, hs\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panel A defines states based on the MOVE index; Panel B uses the VIX index; Panel C uses the TED spread; Panel D conditions the states on the risk aversion index from Bekaert et al. (2022); Panel E conditions on the interest rate skewness measure from Bauer and Chernov (2024); Panel F on the uncertainty index from Bekaert et al. (2022); and Panel G on the interest rate uncertainty measure from Istrefi and Mouabbi (2018). The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009 and every meeting where the FOMC reduced the fed funds target rate. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE D10. Liquidity State-Dependence: Alternative Liquidity Proxies

	Nominal				Real				Inflation			
	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y	2Y	5Y	10Y	15Y
	A. Bid-Ask Spread											
High Bid-Ask	0.98***	0.33	-0.14	-0.17	1.12*	0.49	0.08	-0.07	-0.25	-0.37	-0.46	-0.43*
	(3.90)	(1.72)	(-0.76)	(-0.75)	(2.15)	(1.70)	(0.39)	(-0.35)	(-0.87)	(-1.61)	(-1.82)	(-2.02)
Low Bid-Ask	0.98***	0.51**	0.08	-0.07	-0.37	0.81*	0.17	0.13	1.34	-0.30	-0.07	-0.19
	(5.50)	(2.60)	(0.48)	(-0.55)	(-0.29)	(2.49)	(0.73)	(0.66)	(1.06)	(-0.89)	(-0.35)	(-0.98)
Diff.	0.980	0.500	0.379	0.714	0.298	0.442	0.760	0.464	0.241	0.855	0.228	0.408
	B. 10Y On-the-run Premium											
High On the Run	0.95***	0.48**	0.10	-0.04	-0.23	0.78**	0.20	0.10	1.18	-0.30	-0.10	-0.14
	(5.82)	(2.67)	(0.70)	(-0.36)	(-0.21)	(2.65)	(0.97)	(0.57)	(1.06)	(-1.02)	(-0.55)	(-0.83)
Low On the Run	1.05***	0.36	-0.25	-0.28	1.28	0.48	-0.16	-0.03	-0.38	-0.39	-0.55	-0.87*
	(3.54)	(1.56)	(-0.94)	(-0.87)	(1.66)	(1.09)	(-0.63)	(-0.11)	(-1.04)	(-1.07)	(-1.36)	(-2.28)
Diff.	0.768	0.697	0.245	0.490	0.279	0.559	0.262	0.688	0.201	0.847	0.305	0.082
	C. Pastor-Stambaugh (2003) Traded Factor											
High Pastor-Stambaugh	1.11***	0.64**	0.11	-0.04	1.15**	0.72**	0.27	0.28	-0.10	-0.04	-0.21	-0.44*
	(5.30)	(2.83)	(0.57)	(-0.26)	(3.24)	(3.09)	(1.29)	(1.24)	(-0.39)	(-0.27)	(-1.29)	(-2.09)
Low Pastor-Stambaugh	0.88***	0.18	-0.10	-0.12	-0.69	0.67	-0.01	-0.14	1.60	-0.53	-0.07	0.03
	(4.46)	(1.40)	(-0.86)	(-0.93)	(-0.50)	(1.81)	(-0.03)	(-0.99)	(1.14)	(-1.46)	(-0.32)	(0.16)
Diff.	0.423	0.074	0.353	0.718	0.199	0.907	0.369	0.117	0.232	0.216	0.637	0.086

Note: the table shows the estimated OLS coefficients $\gamma_j^{(\tau)}$ in regression (2.2), with $j \in \{ls, hs\}$ for each forward maturity $\tau \in [2, 5, 10, 15]$, together with robust standard errors. The independent variable in each regression is the monetary policy shock series of Nakamura and Steinsson (2018) interacted with dummies partitioning the sample according to the liquidity state. The shocks are scaled to have unit variance, and normalized to have an impact of 1pp on the 1-year nominal forward rate in each state. Each regression is estimated separately for each maturity and state variable. Panel A defines the liquidity states based on an aggregate measure of bid-ask spread computed from the daily CRSP Treasury dataset. Panel B defines liquidity states based on the 10-year on-the-run premium, computed from the 10-year constant maturity market yield from FRED relative to the 10-year yield from Gürkaynak et al. (2005a). Panel C defines liquidity using the traded liquidity factor from Pástor and Stambaugh (2003). The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 31/12/2019, excluding those taking place between July 2008 and June 2009. Robust t-stats are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

TABLE D11. Reach-For-Yield Sectors

	Bank	ICPF	HF	AM	FO
	b/t	b/t	b/t	b/t	b/t
1-3y $\times$ ΔTERM$_{t-1}$	-0.077	0.247	0.106	-0.020	0.056
	(-1.199)	(1.524)	(0.979)	(-0.346)	(0.505)
4-10y $\times$ ΔTERM$_{t-1}$	0.290***	0.282*	0.044	0.057	0.426*
	(3.338)	(2.063)	(0.685)	(1.046)	(2.493)
11-30y $\times$ ΔTERM$_{t-1}$	0.260*	0.571**	-0.053	0.148*	0.072
	(2.291)	(2.667)	(-0.534)	(1.965)	(0.600)
Trader FE	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R2	0.07	0.11	0.05	0.08	0.09
N	208,507	58,371	95,618	319,549	61,584

Note: The table reports the result of regressing the net duration purchased on lagged changed in term spread, defined as the 10Y nominal spot yield minus the 2Y nominal spot yield. The sample period is 01/01/2018 - 31/12/2022, excluding the Covid crisis 01/03/2020 - 30/05/2020.

TABLE D12. Predictable Components in Nakamura & Steinsson (2018)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Noise$_{t-1}$	-0.01*							-0.00
	(-2.39)							(-0.14)
FIA Ret$_{t-1}$		0.33						
		(0.85)						
Nonfarm Payrolls			-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
			(-0.07)	(-0.03)	(-0.36)	(-0.46)	(-0.64)	(-0.65)
Empl. Growth (12m)				0.00*	0.00*	0.00*	0.00*	0.00
				(2.61)	(2.51)	(1.99)	(2.32)	(1.87)
ΔS&P500					0.10	0.10	0.05	0.05
					(1.72)	(1.77)	(0.79)	(0.76)
ΔSlope						-0.01	-0.01	-0.01
						(-1.91)	(-1.40)	(-1.42)
Δlog Comm. Price							0.08	0.08
							(1.31)	(1.31)
ISK							0.03	0.02
							(1.50)	(1.34)
R^2	4.5	0.6	0	3.4	6.6	9.1	12.7	12.7
N	106	106	106	106	106	106	106	106

Note: each column report the OLS estimates of a regression of Nakamura and Steinsson (2018) shock series on macroeconomic releases, noise and fixed-income arbitrage returns. The residual from the full regression is used as a robustness check.

TABLE D13. The Liquidity State Dependence in Nakamura & Steinsson (2018)

	Baseline			Low noise			High noise			P-values		
	Nom.	Real	Inf.	Nom.	Real	Inf.	Nom.	Real	Inf.	Nom.	Real	Inf.
3M Treasury yield	0.67***			0.61***			0.69***			0.766		
	(0.14)			(0.16)			(0.19)					
6M Treasury yield	0.85***			0.74***			0.90***			0.475		
	(0.11)			(0.16)			(0.14)					
1Y Treasury yield	1.00***			1.48***			0.81***			0.007		
	(0.14)			(0.12)			(0.18)					
2Y Treasury yield	1.10***	1.06***	0.04	1.83***	1.69***	0.14	0.69*	0.70**	-0.01	0.034	0.034	0.715
	(0.33)	(0.24)	(0.18)	(0.23)	(0.32)	(0.33)	(0.41)	(0.29)	(0.20)			
3Y Treasury yield	1.06***	1.02***	0.04	1.92***	1.72***	0.20	0.57	0.62**	-0.05	0.018	0.021	0.482
	(0.36)	(0.25)	(0.17)	(0.27)	(0.33)	(0.28)	(0.43)	(0.29)	(0.20)			
5Y Treasury yield	0.73***	0.64***	0.09	1.68***	1.58***	0.10	0.34	0.26*	0.08	0.000	0.000	0.925
	(0.20)	(0.15)	(0.11)	(0.24)	(0.20)	(0.18)	(0.21)	(0.14)	(0.14)			
10Y Treasury yield	0.38**	0.44***	-0.06	1.24***	1.24***	0.00	0.03	0.11	-0.08	0.000	0.000	0.656
	(0.17)	(0.13)	(0.08)	(0.20)	(0.16)	(0.12)	(0.17)	(0.12)	(0.11)			
2Y Treasury inst. forward rate	1.14**	0.99***	0.15	2.25***	1.76***	0.49*	0.50	0.55*	-0.05	0.011	0.027	0.182
	(0.46)	(0.29)	(0.23)	(0.35)	(0.38)	(0.29)	(0.51)	(0.33)	(0.25)			
3Y Treasury inst. forward rate	0.82*	0.88***	-0.06	1.96***	1.77***	0.18	0.17	0.38	-0.21	0.009	0.012	0.193
	(0.43)	(0.32)	(0.15)	(0.45)	(0.42)	(0.20)	(0.44)	(0.31)	(0.19)			
5Y Treasury inst. forward rate	0.26	0.47***	-0.21**	1.17***	1.26***	-0.09	-0.12	0.15	-0.26**	0.001	0.001	0.353
	(0.19)	(0.17)	(0.08)	(0.30)	(0.25)	(0.13)	(0.19)	(0.17)	(0.11)			
10Y Treasury inst. forward rate	-0.08	0.12	-0.20**	0.58***	0.68***	-0.10	-0.34*	-0.10	-0.24*	0.002	0.000	0.490
	(0.18)	(0.12)	(0.09)	(0.18)	(0.12)	(0.13)	(0.20)	(0.13)	(0.13)			

Note: The first panel (Baseline) reports estimates of γ in regression (2.1). The second (Low noise) and third (High noise) panels respectively present parameter estimates for γ_1 and γ_2 in regression (2.2), corresponding to the subset of scheduled FOMC announcements for which the yield curve noise measure is below (resp. above) its median level. The last panel reports the p-values of the tests of equality between the coefficients estimates for low- and high-noise FOMC announcements. The dependent variable in each regression is the one-day change in the variable stated in the left-most column. The sample includes all regularly scheduled FOMC meetings from 01/01/2000 to 19/03/2014, excluding those taking place between July 2008 and June 2009. This corresponds to a sample size of 106 observations on which the policy news shock is computed and each regression is estimated. Regression results for the 2- and 3-year yields and forward rates are based on a sample size of 74 observations (starting in 2004). Robust standard errors are in parentheses. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

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