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The Sector Liquidity Timing Ability of Bond Mutual Funds

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ABSTRACT

We investigate whether bond mutual fund managers exhibit market liquidity timing skills in the U.S. corporate bond market. At the portfolio level, we find only weak evidence that bond funds adjust their overall market exposure in anticipation of changes in corporate bond market liquidity. In contrast, when liquidity timing is examined through sector allocation strategies across investment grade, high-yield, and mortgage-backed securities (MBS) sectors, we find strong evidence of high-yield sector liquidity timing ability—fund managers overweight high-yield bonds as corporate bond market liquidity improves. Using individual fund level analysis, we find that top-ranked bond funds demonstrate market liquidity timing skills with respect to both the overall market and all three sectors. Bootstrap analyses indicate that these liquidity timing skills of bond fund managers are unlikely to be driven by luck. Moreover, we find evidence of persistence in sector liquidity timing ability over time, especially for high-yield sector timing. Finally, these sector liquidity timing strategies help predict future fund performance.

JEL Classification: G11, G23

1 | Introduction

There has been an extensive literature on equity mutual fund performance. By comparison, bond mutual fund managers have received less attention despite bond funds playing an increasingly important role in investors' portfolios. At the year-end of 2024, the total net assets of US bond funds were around 5.07 trillion dollars,[1] which accounted for 18% of the mutual fund total net assets (Investment Company Institute 2025).

Early studies document that bond funds underperform relevant benchmarks on average (Blake et al. 1993; Elton et al. 1995; Ferson et al. 2006; Huij and Derwall 2008). More recently, Cici and Gibson (2012) do not find evidence that bond fund managers possess selectivity skill in choosing corporate bonds. However, Huang et al. (2025) provide evidence that many bond mutual fund managers exhibit skills. Taken together, these findings may suggest that the contribution of active bond fund management is more likely driven by timing ability rather than security selection.

In this study, we investigate the liquidity timing ability of bond mutual funds in corporate bond markets. We focus on liquidity timing for several reasons. First, market liquidity is closely linked to bond mutual fund performance, particularly for funds holding illiquid assets. Goldstein et al. (2017) find that when market liquidity is low, investor outflows impose substantially larger return costs on bond funds. As investor flows influence fund performance and hence manager compensation, fund managers are incentivized to adjust asset allocation according to market liquidity conditions. If fund managers can anticipate changes in market liquidity, they may adjust their portfolio exposures to market liquidity to mitigate losses and enhance performance. Second, the asset pricing literature has identified market liquidity as an important state variable for bond pricing. For example, Lin et al. (2011) find that the liquidity risk factor is priced in corporate bond returns and show that the average return on bonds with high sensitivities to aggregate liquidity exceeds that for bonds with low sensitivities by about 4% annually. Finally, while market returns exhibit little persistence and are therefore difficult to predict, market liquidity—like market volatility—tends to be more persistent. As a result, market liquidity may be easier for fund managers to time than market returns.

Building on the Blake et al. (1993) multifactor model for bond fund performance evaluation, we develop two liquidity timing models for bond mutual funds under the framework of Treynor and Mazuy (1966). The first model focuses on overall market liquidity timing, while the second model focuses on sector-level liquidity timing ability.

Our first liquidity timing model measures funds' exposure to the overall bond market, similar to the model developed by Cao, Simin, and Wang (2013) for equity mutual funds. Using a sample of US bond mutual funds that have substantial corporate bond holdings, including corporate, high-yield, and diversified bond funds, we construct equally-weighted portfolios of funds based on fund characteristics and apply our model to examine the liquidity timing skills of these fund portfolios. When all bond funds are included in the portfolio construction, the results show little evidence of liquidity timing for the overall corporate bond market, which is consistent with the findings of Chen et al. (2010).

This finding contrasts with prior research on equity funds (Cao, Simin, and Wang 2013), which provides evidence of the broad market liquidity timing ability of all groups of equity fund managers. Compared to the centralized stock market, bond markets are decentralized and operate through segmented over-the-counter (OTC) trading. When anticipating corporate bond market liquidity fluctuations, bond funds may not simply adjust their exposure to the broad bond market. Instead, they may adjust their exposure to specific bond sectors, and models that account only for the overall bond market may fail to capture sector liquidity timing skills. Therefore, we develop a new multi-sector liquidity timing model to identify bond mutual funds' sector liquidity timing ability, which is conceptually similar to the style liquidity timing ability observed in equity mutual funds (Bazgour et al. 2017).

This sector liquidity timing model further explores fund managers' liquidity timing skills for bond sectors, that is, the investment grade, high-yield, and mortgage-backed securities (MBS) markets. These sector liquidity timing strategies turn out to be important but have not been explicitly examined in previous studies, such as Chen et al. (2010) and Li et al. (2017). We model fund exposures to bond sectors as a linear function of corporate bond market liquidity conditions, which allows us to assess a fund's exposure to each individual bond sector. Notably, we find that the full sample of bond funds exhibits high-yield sector liquidity timing ability. When the liquidity in the corporate bond market increases, bond fund managers tilt their portfolio weights towards high-yield bonds, and vice versa.

To assess heterogeneity in liquidity timing skills across funds, we further evaluate the sector liquidity timing ability of mutual fund managers at the individual fund level, and we find evidence of high-yield, investment grade, and MBS sector timing for a range of funds, even after controlling for false discoveries. Our bootstrap analysis suggests these sector liquidity timing skills are due to managerial skills rather than purely sampling variation, that is, luck. Overall, our findings demonstrate that liquidity timing models that focus only on overall market exposure may lead to misidentification of liquidity timing, especially for bond mutual funds.

Given that bond funds' sector exposures may vary for other reasons, we conduct a wide range of additional tests to gain deeper insights into sector liquidity timing among bond funds. First, considering that large funds' sales of assets can simultaneously affect market liquidity, we perform subsample analyses for small funds whose trades are less likely to impact overall market liquidity, thereby mitigating concerns about simultaneity bias. We further use liquidity innovations to control for contemporaneous fund trading and investor common flows. Second, because OTC bond markets are less liquid, especially in the high-yield segment, bond funds may face constraints related to dealers' intermediation capacity, which can limit their ability to adjust sector exposures. To address this concern, we further examine sector liquidity timing, controlling for intermediation capacity constraints. Finally, we conduct additional tests using alternative timing model specifications, extra risk factors, and different liquidity measures. Overall, our findings are robust across these analyses.

The study also contributes to a better understanding of the economic value of liquidity timing strategies and active management in bond funds. We provide evidence that fund managers persistently time the corporate bond market liquidity, and this persistence generates abnormal returns (alpha) to some extent. Using the standard portfolio-sort approach, we construct decile portfolios based on the liquidity timing coefficients and hold these portfolios for 6, 12, 24, and 36 months. After each holding period, we calculate their returns and rebalance these portfolios, and the time-series returns are regressed on the corresponding liquidity timing models. Consistent with our portfolio-level results showing little evidence of market-wide liquidity timing, we find no evidence of skill persistence for the overall market factor. However, we do find evidence of persistence in liquidity timing skills for investment grade, high-yield, and MBS factors. The evidence is particularly strong for high-yield sector liquidity timing skills, regardless of the holding period. We then evaluate these portfolio returns using the performance model of Blake et al. (1993) to assess the out-of-sample performance. The results provide some evidence of positive out-of-sample alpha for the high-yield, investment grade, and MBS sectors. Additionally, we find some significant alphas in the spread portfolio, which is the difference between the top and bottom decile portfolios. For example, the spread portfolio sorted by investment grade sector liquidity timing coefficients generates a statistically significant alpha of 1.92% per annum when the holding period is 6 months. Overall, when combining results on persistence in liquidity timing skills and alpha generation, we find that bond fund managers enhance fund returns by tilting portfolio weights towards specific bond categories in anticipation of corporate bond market liquidity changes. However, the contribution of liquidity timing strategies to bond fund returns remains weaker than that of equity funds.

Our study differs from previous research by not relying on a single liquidity proxy. Instead, we employ multiple liquidity measures to ensure that our findings are not driven by any specific proxy choice. For example, Li et al. (2017) use the corporate bond spread, defined as the difference between the par yields on a fixed-rate corporate bond and a corresponding fixed-rate government bond with matching maturities, as a measure of overall bond market liquidity, while Chen et al. (2010) define the fixed-income market liquidity as the yield difference between 3-month nonfinancial corporate commercial paper rates and the 3-month Treasury yield. In our study, we select a set of liquidity measures that have been originally developed and tested in stock markets and have been shown to effectively capture variations in bond liquidity. These liquidity measures are selected following Schestag et al. (2016), who provide a comprehensive benchmarking study of the liquidity measures in corporate bond markets. To the best of our knowledge, this is the first market liquidity timing paper that uses high-frequency intraday data from the Trade Reporting and Compliance Engine (TRACE) database to capture time-series market-wide liquidity changes in the corporate bond market. Our observation period spans from July 2002 to September 2021, making this one of the most extensive liquidity timing studies to date. We are unaware of any other liquidity timing study that employs TRACE data on such a large scale. Therefore, a key contribution of our paper is the investigation of the liquidity timing ability of bond funds in the US corporate bond market using the most comprehensive liquidity data source.

The rest of the paper is organized as follows: Section 2 reviews related literature, then Section 3 describes the fund data, liquidity proxies, and how to construct market-wide liquidity. Sections 4 and 5 report the liquidity timing results at the portfolio and individual levels, respectively. Section 6 reports the results of the persistence and performance tests. In Section 7, we provide several further robustness tests, and Section 8 concludes.

2 | Literature Review

Timing ability reflects a fund manager's use of superior information about future market movements and is conceptually distinct from security selection skill. Timing is closely related to asset allocation, as it involves adjusting portfolio exposures across asset classes or risk factors in response to expected market conditions, whereas selectivity refers to the ability to identify and choose superior securities within a given asset class. Since the seminal work of Treynor and Mazuy (1966), the market timing ability of investment fund managers has been extensively studied.

Existing studies primarily focus on equity fund managers' ability to time market returns (Treynor and Mazuy 1966; Henriksson and Merton 1981; Jagannathan and Korajczyk 1986; Jiang 2003) and their ability to time market return volatility (Busse 1999; Fleming et al. 2001). Related work also examines timing with respect to factor or style returns (Chen et al. 2013; Swinkels and Tjong-A-Tjoe 2007) and systematic return coskewness (Wattanatorn and Padungsaksawasdi 2020). The evidence is mixed in terms of return timing. Earlier studies using annual or monthly data often document a pattern of perverse market return timing ability. Studies that find no or negative timing abilities include Treynor and Mazuy (1966), Chang and Lewellen (1984), Henriksson and Merton (1981), Graham and Harvey (1996), Ferson and Schadt (1996), Becker et al. (1999), Jiang (2003), and Elton et al. (2012). In contrast, Bollen and Busse (2001) and Mamaysky et al. (2008) find significant evidence of market timing ability using daily data, and Jiang et al. (2007) report similar results based on a holding-based approach. In addition, Busse (1999) and Fleming et al. (2001) provide evidence on volatility timing abilities.

Studies of bond fund returns have documented a similar pattern of perverse market timing ability in earlier studies across different groups of bond funds. For example, Boney et al. (2009) examine timing ability in a sample of high-quality corporate bond funds using the quadratic programming technique pioneered by Sharpe (1992) and find negative market timing ability on average. Recent studies, however, find supportive evidence of the market timing ability of bond mutual funds by applying the holding-based measure of Jiang et al. (2007). Huang and Wang (2014) examine the market timing ability of a sample of government bond funds using their Treasury securities holdings. They show some positive timing ability, but only at a 1-month forecasting horizon. By incorporating a larger sample of different kinds of bond mutual funds, Moneta (2015) finds neutral evidence of timing ability on average, and the subgroup of multi-sector funds showed positive timing ability. It is comforting to see that there is evidence of positive timing ability that uses portfolio-holding information.

Aside from market return timing, other perspectives have also been developed recently on bond fund managers' market timing abilities. Cici and Gibson (2012) study the characteristic timing ability of corporate bond funds, using a decomposition methodology that Wermers (2000) applied to equity funds. Specifically, they report that high-yield bond funds are able to time bond characteristics (duration and credit ratings), but investment grade bond funds are not able to time these characteristics. Chen et al. (2010) evaluate the ability of bond funds to time nine common factors related to bond markets. They extend the Treynor and Mazuy (1966) specification of market timing by controlling for potential non-timing-related sources of nonlinearity, including passive timing, interim trading, stale pricing, and public information. They report overall neutral to weakly positive timing among bond funds.

More recently, researchers have turned their attention to investigating whether fund managers are able to time aggregate market liquidity. Cao, Chen, et al. (2013) and Cao, Simin, and Wang (2013) investigate the market liquidity timing ability (hereafter simply referred to as liquidity timing) of equity-focused mutual funds and hedge funds from the new perspective of market liquidity. Managers of these funds may adjust their exposure to systematic risk based on the forecast of liquidity level. Using this liquidity timing strategy, funds increase their exposure to the market during times of high liquidity while reducing it during times of low liquidity. Their findings support the idea that fund managers are capable of predicting liquidity levels and reducing their market exposure when aggregate liquidity is expected to be low. Bodson et al. (2013) and Foran and O'Sullivan (2017) further confirm the liquidity timing ability using the US and UK equity fund samples, respectively. Furthermore, using a nonparametric method, Yin et al. (2024) suggest that large funds tend to be more successful at timing market liquidity in these two markets. Using mutual fund data from an emerging market (Thailand), Wattanatorn et al. (2020) show that fund managers can time market-wide liquidity within a higher-moment framework.

There is mixed evidence of liquidity timing ability in the fixed-income market. Li et al. (2017) study the market liquidity timing ability of debt-oriented hedge funds and find evidence of liquidity timing ability for the fixed-income market for all debt-oriented hedge fund categories. In contrast, Chen et al. (2010) examine the market-wide liquidity timing for bond mutual funds using market timing models controlling for non-timing related linearities, and find only neutral to weak positive liquidity timing.

3 | Data and Liquidity Proxies

3.1 | Bond Fund Data

We obtain our data on US bond mutual funds from Morningstar. Our sample includes only taxable mutual funds, excluding municipal and money market funds. Additionally, index funds are excluded from our sample because they replicate benchmark index performance and are unlikely to exhibit any timing ability by design. In order to increase the size of our sample, we include both domestic and overseas bond funds that invest in the US fixed-income market. For both types of funds, we retain only share classes with a USD base currency.[2] For these share classes, net asset values and returns are calculated and reported directly in USD. Because both US-domiciled onshore and non-US offshore funds in our sample primarily hold USD-denominated corporate bonds and all returns are expressed in USD, differences arising from currency conversion or currency hedging are unlikely to materially affect our results.

We select funds with substantial holdings of corporate bonds and regroup these funds into three categories: corporate bond funds, high-yield bond funds, and diversified bond funds. Corporate bond funds focus on investment grade corporate bonds in US dollars, while high-yield bond portfolios concentrate on lower-quality bonds. Diversified bond funds invest primarily in various kinds of investment grade US fixed-income issues, including government, corporate, and securitized debt. Although corporate and diversified bond funds mainly invest in investment grade bond securities, they may still hold a limited portion of lower-rated or high-yield bonds; conversely, high-yield bond funds may include a small allocation to higher-quality bonds for diversification or risk management purposes. Detailed bond fund categories can be found in the Appendix S1.

In order to be consistent with the start date of the TRACE database, our fund sample starts in July 2002 and ends in September 2021. We only include bond funds with at least 36 monthly observations. The final sample includes 851 unique bond funds, among which there are 64 corporate bond funds, 158 high-yield funds, and 629 diversified funds. We also distinguish survivors from non-survivors. As of September 2021, 536 funds are still alive, with the remaining 315 being defunct. Fund returns are measured as total monthly returns net of management fees.

Table 1 reports summary statistics of fund characteristics for our bond mutual fund sample. Fund age is defined as the number of years between the last return date and the inception date when the fund is first offered. Fund size is the total net assets (TNA, in millions of dollars) of a mutual fund. The normalized monthly flow (in percentage) is defined as $\text{flow}_t = \frac{\text{TNA}_t - \text{TNA}_{t-1}(1+R_t)}{\text{TNA}_{t-1}}$, where TNA_t is the TNAs at the end of month t and R_t is the return in month t. Fund size, turnover ratio (%), net expense ratio (%), and monthly fund flows (%) are first averaged over time for each fund and then averaged across funds within each fund category.

On average, bond mutual funds have an age of 17.7 years, total net assets of 2101 million, an annual net expense ratio of 0.66%, an annual turnover ratio of 125%, and monthly flows of 1.40%. Among fund categories, high-yield funds, on average, have the highest net expense ratios, while diversified funds have the highest turnover ratios.

We construct equally weighted portfolios of corporate, high-yield, diversified, non-survivor, survivor, and all bond funds and then compute the monthly time-series returns for these portfolios. From the summary statistics in Table 1, high-yield funds have the highest returns and volatility among the three bond categories. Compared with defunct funds, surviving funds, on average, have higher returns and volatility.

3.2 | Liquidity Proxies

Our liquidity measures are calculated using data from two primary sources, TRACE Standard and TRACE Enhanced from the Financial Industry Regulatory Authority (FINRA).[3] In July 2002, TRACE was introduced to improve transparency in the

TABLE 1 | Summary statistics of bond funds.

Fund categories	Nobs	Fund size ($million)	Turnover (%/year)	Net expense (%/year)	Flow (%)	Age (years)	Return (%)	Std Dev (%)
Corporate	64	898.39	89.47	0.62	1.42	13.87	0.405	1.423
High-Yield	158	1144.03	89.45	0.86	0.81	18.17	0.589	2.285
Diversified	629	2668	141.27	0.59	1.61	18.31	0.272	0.744
Non-survivor	315	336.74	113.12	0.42	3.84	2.21	0.269	0.913
Survivor	536	2356.14	126.22	0.67	1.05	20.07	0.377	1.032
All fund	851	2101.04	125.35	0.66	1.40	17.73	0.341	0.963

Note: This table reports summary statistics of mutual fund characteristics. Fund age is defined as the number of years between the fund's inception date and the last return observation date. Fund size is measured by total net assets (TNA). Fund size (in millions of dollars), turnover ratio (%), net expense ratio (%), and monthly fund flows (%) are first averaged over time for each fund and then averaged across funds within each fund category. For each category—corporate, high-yield, diversified, non-survivor, survivor, and all bond funds—we form equally weighted portfolios and compute monthly time-series returns. The final two columns report the time-series mean (%) and standard deviation (%) of monthly portfolio returns.

over-the-counter corporate bond market containing transaction information such as price, time, and size. In addition to the TRACE Standard, the TRACE Enhanced offers uncapped volume data and buy-sell side information for all trades in the US corporate bond market. TRACE currently covers the vast majority of corporate bond trades in the US fixed-income market. The only trades omitted are those executed on exchanges, most through the NYSE's Automated Bond System.

Our sample includes corporate bond transaction records from July 2002 to September 2021. We exclude trading in government agency bonds, securitized products including asset-backed securities and mortgage-backed securities, and corporate bonds or securitized products falling under Rule 144a of the Securities Act of 1933. It is important to note that raw data from an intraday database requires careful cleaning prior to analysis. Following the cleaning procedure described in Dick-Nielsen (2009, 2014), we delete duplicates, reversals, and same-day corrections of trades. In addition, we remove agency transactions, where an introducing broker buys bonds from an executing broker and passes them to a customer.[4] To measure bond liquidity, we employ four liquidity measures, including buy-sell spread, high-low spread (Corwin and Schultz 2012), interquartile range, and the Amihud (2002) price impact. We obtain the daily yield, trading volume, and prices (including daily high, low, buy, sell, close, average, 25th percentile, and 75th percentile) from intraday data. Details of liquidity proxies are described in the Appendix S1.

We first calculate daily liquidity using these liquidity proxies. The monthly liquidity proxy is calculated as the time-series average of daily liquidity within each month.[5] In order to reduce outliers and possible data errors, we require bonds to have at least ten daily observations in a given month when calculating the monthly liquidity measures. In each month, for each liquidity measure, we compute the market-wide liquidity as the cross-sectional average of the measure across individual bonds.

We then use the principal component analysis (PCA) method to extract latent market liquidity factors across these four market liquidity measures. Each liquidity measure is standardized to avoid our latent market factor being driven by a particular liquidity measure. We extract the first three principal components across liquidity measures and use the first principal component to represent latent market-wide liquidity. Table 2 shows the factor loadings for the first three principal components and summary statistics of our market liquidity measures. The latent liquidity factor (PC1) explains 89.4% of the variation in four market liquidity measures.

Figure 1 plots the time series of corporate bond market illiquidity using various liquidity measures. As shown in Figure 1, market illiquidity increased significantly during the 2008 global financial crisis and the COVID-19 pandemic in the US. All these liquidity measures are proxies for market illiquidity, so we multiply them by −1 to represent market liquidity in the following analysis.

Figure 2 plots the time series of innovations in market liquidity (the latent factor) estimated from an AR(2) process, which represents the unpredictable component of market liquidity. The series remains close to zero under normal market conditions, indicating that large unexpected liquidity shocks are rare. However, it exhibits pronounced negative spikes during major systemic crises, most notably in September–October 2008 and March 2020, reflecting sudden and severe liquidity disruptions during these periods.

TABLE 2 | Summary of liquidity measures.

Panel A: Principal component analysis

Liquidity	PC1	PC2	PC3
Buy-sell spread	15.25	−1.56	2.62
High-low spread	15.22	−2.92	−0.50
Interquartile range	15.17	−2.75	−1.86
Amihud impact	13.09	8.41	−0.30
Eigenvalue	3.58	0.37	0.04
% variance explained	89.4%	9.2%	1.1%

Panel B: Summary of liquidity measure

Liquidity	Nobs	Mean	Std Dev	Min	25th	50th	75th	Max
Buy-sell spread	231	0.011	0.005	0.003	0.007	0.011	0.014	0.033
High-low spread	231	0.006	0.004	0.002	0.004	0.006	0.008	0.023
Interquartile range	231	0.007	0.004	0.002	0.004	0.006	0.009	0.029
Amihud impact	231	391.2	149.5	181.7	286.5	344.9	463.5	953.6
Latent liquidity	231	2.38E-17	0.064	−0.090	−0.048	−0.011	0.029	0.290

Note: This table provides the results of principal component analysis (PCA) and summary statistics of our liquidity measures. Panel A reports the PCA loadings for the first three principal components (PC1- PC3) constructed from four liquidity measures, including the buy–sell spread, high–low spread, interquartile range, and Amihud (2002) price impact. Principal components are computed from standardized variables. Panel B provides the summary statistics of liquidity measures, including buy-sell spread, high-low spread, interquartile range, Amihud (2002) price impact, and the latent market liquidity factor (PC1) from the PCA.

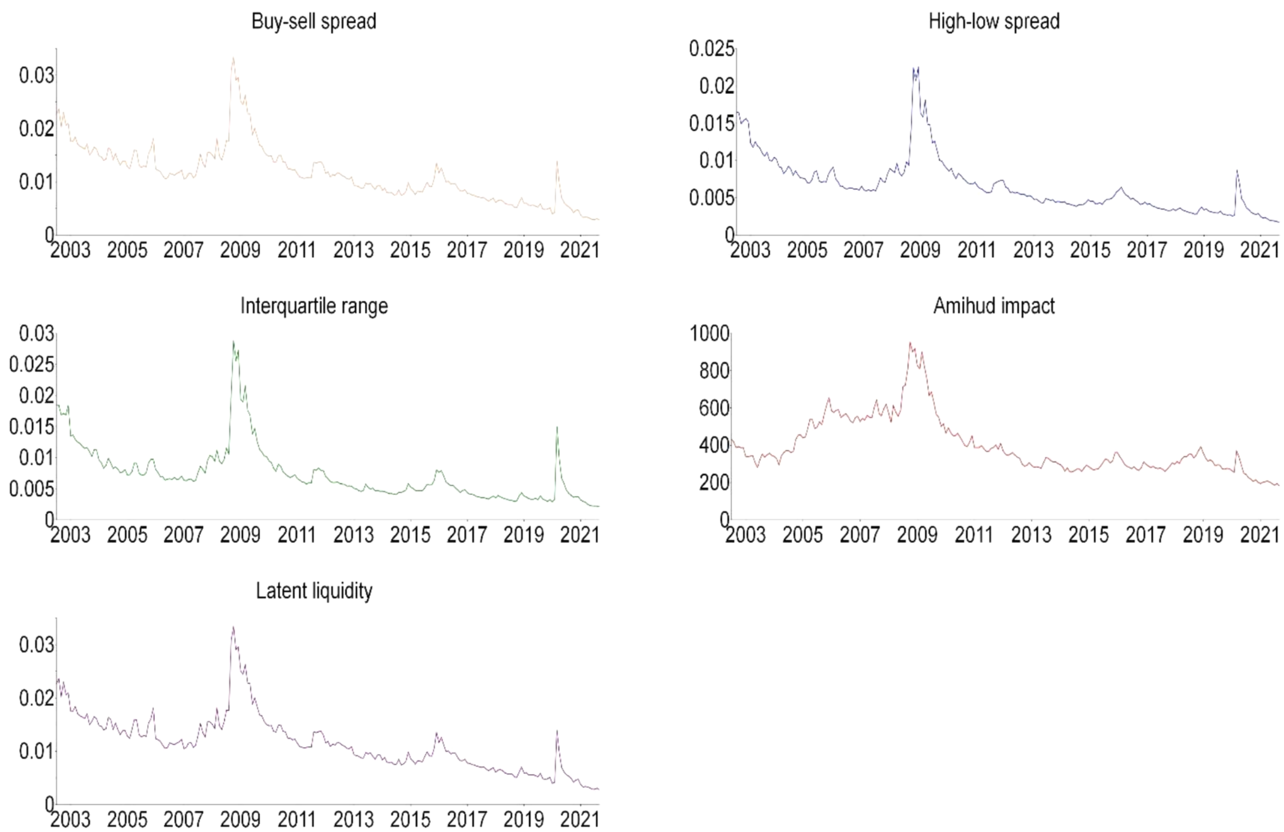

FIGURE 1 | Time series of corporate bond market illiquidity. [Colour figure can be viewed at wileyonlinelibrary.com].

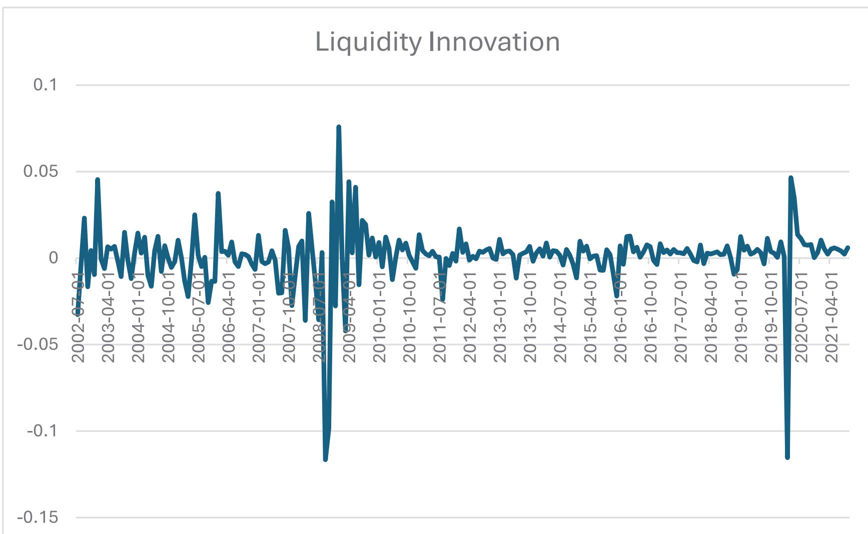

FIGURE 2 | Time series of corporate bond market liquidity innovations. [Colour figure can be viewed at wileyonlinelibrary.com].

4 | Empirical Analysis

4.1 | Liquidity Timing in the Overall Bond Market

We begin our analysis by considering the Blake et al. (1993) model to explain the time series of bond fund returns:

$$r_{p,t} = \alpha_p + \beta_{m,p}\text{MKT}_t + \beta_{\text{hy},p}HY_t + \beta_{\text{mbs},p}\text{MBS}_t + \varepsilon_{p,t} \quad (1)$$

where $r_{p,t}$ is the excess return of fund p in month t, ***MKT*** is a proxy for the excess return of the overall bond market, ***HY*** is a proxy for the return from holding low-grade bonds, and ***MBS*** is a proxy for the return of mortgage-backed securities that have option-like characteristics (prepayment risk). We use the 1-month Treasury bill rate from the Ken French library as our proxy for the risk-free rate. MKT_t is calculated as the excess return on the Bloomberg US Universal Index in month t. The Bloomberg US Universal Index covers taxable bonds denominated in US dollars. HY_t and MBS_t

are the excess returns of the Bloomberg US Corporate High Yield Index and the Bloomberg US MBS Index, respectively.

To account for liquidity timing, we follow the liquidity timing literature (Cao, Chen, et al. 2013; Cao, Simin, and Wang 2013) to create a time-varying market beta.[6] Specifically, the market beta is expressed as a linear function of market liquidity in excess of its time series average.

$$\beta_{m,p} = \beta^0_{m,p} + \theta_{m,p}\left(L_{m,t} - \overline{L}_m\right) \tag{2}$$

where $L_{m,t}$ is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measure. We use the average liquidity estimate over the previous 36 months as a proxy for the mean liquidity. This specification is also consistent with models of market return timing (Treynor and Mazuy 1966) and market volatility timing (Busse 1999), which specify time-varying market beta as a linear function of market returns or market volatility.

Substituting Equations (2) into (1) generates our three-factor liquidity timing model:

$$\begin{aligned} r_{p,t} = \alpha_p + \beta^0_{m,p}\text{MKT}_t + \theta_{m,p}\left(L_{m,t} - \overline{L}_m\right)\text{MKT}_t \\ + \beta_{\text{hy},p}HY_t + \beta_{\text{mbs},p}\text{MBS}_t + \varepsilon_{p,t} \end{aligned} \tag{3}$$

The coefficient $\theta_{m,p}$ measures the liquidity timing ability of bond fund managers. A significant and positive $\theta_{m,p}$ indicates that mutual fund managers correctly anticipate high (low) corporate bond market liquidity and increase (decrease) market exposure accordingly. Conversely, if $\theta_{m,p}$ is significant and negative, bond fund managers perversely increase (decrease) market exposure when market liquidity is expected to be low (high).

We study the liquidity timing ability of bond mutual funds using portfolios of bond funds. In addition to an equally weighted portfolio of all funds, we analyse portfolios grouped by investment style, as well as portfolios of surviving and non-surviving funds. Our aim is to examine whether liquidity timing skill depends on the fund's investment style or its survival status.

We estimate the market liquidity timing model of Equation (3) using equally weighted portfolios for each investment style, as well as for surviving and non-surviving funds, in addition to all bond funds. These results are reported in Table 3. The Newey and West (1987) t-statistics with 2 lags are reported in parentheses.[7] At the aggregate level, there is little evidence that bond mutual funds positively time the bond market liquidity. For the portfolio of all bond funds, the liquidity timing coefficient is positive but not significant. We also find positive (though insignificant) liquidity timing ability for other subgroups of bond funds. In addition, both surviving and non-surviving funds exhibit positive (but their t-statistics are all insignificant) liquidity timing coefficients, suggesting the disappearance of non-surviving funds may be due to other factors rather than liquidity timing. For subgroups with different investment objectives, the model displays positive and significant liquidity timing for the portfolio of diversified bond funds. However, the evidence is weak when we control for alternative liquidity timing models (see Section 7.3). Overall, we find weak evidence of positive aggregate market liquidity timing in corporate bond markets.

TABLE 3 | Liquidity timing in the aggregate market.

	α_p	$\theta_{m,p}$	MKT	HY	MBS	R^2
Corporate	−0.05*	0.06	1.68***	0.11***	−0.75***	0.94
	(−1.75)	(0.07)	(14.30)	(4.68)	(−4.66)	
High-yield	−0.04*	0.56	−0.01	0.88***	−0.01	0.98
	(−1.72)	(0.59)	(−0.07)	(27.50)	(−0.05)	
Diversified	−0.04***	0.39**	0.78***	0.05***	−0.16***	0.95
	(−3.41)	(2.48)	(19.40)	(7.64)	(−3.28)	
Non-survivor	−0.07**	0.61	0.91***	0.12***	−0.42**	0.85
	(−2.36)	(1.16)	(5.94)	(5.60)	(−2.19)	
Survivor	−0.02*	0.47	0.67***	0.26***	−0.17**	0.98
	(−1.68)	(1.57)	(11.70)	(25.20)	(−2.35)	
All fund	−0.03**	0.56	0.74***	0.21***	−0.24**	0.96
	(−1.98)	(1.61)	(9.75)	(15.50)	(−2.47)	

Note: This table reports the regression results of the liquidity timing model:

$$r_{p,t} = \alpha_p + \beta^0_{m,p}\text{MKT}_t + \theta_{m,p}\left(L_{m,t} - \overline{\text{L}}_m\right)\text{MKT}_t + \beta_{\text{hy},p}\text{HY}_t + \beta_{\text{mbs},p}\text{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. MKT_t is the excess return on the Bloomberg US Universal Index in month t. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US *MBS* Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. The coefficient $\theta_{m,p}$ measures the liquidity timing ability of bond fund managers. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

4.2 | Liquidity Timing in Bond Sectors

4.2.1 | Multi-Sector Liquidity Timing Model

Cao, Chen, et al. (2013) and Cao, Simin, and Wang (2013) develop the liquidity timing model based on the notion that fund managers are capable of forecasting future market liquidity and weighting market exposure accordingly. The model in Equation (3) does not consider other liquidity timing opportunities in the various bond sectors. Compared with the centralized stock market, the bond markets are decentralized and segmented over-the-counter (OTC) markets. When anticipating corporate bond market liquidity fluctuations, bond funds may adjust their exposure to a specific bond sector. Models accounting for only the overall bond market risk factor are unlikely to identify sector liquidity timing skills. Therefore, ignoring sector liquidity timing strategies may result in misleading conclusions.

In order to examine liquidity timing opportunities across bond sectors, we relax the assumption of exposure to the overall bond market risk factors and extend the liquidity timing model to a multi-sector liquidity timing framework. We consider the variant of the Blake et al. (1993) model to explain the time series of bond fund returns in three bond sectors, including investment grade, high-yield, and MBS markets:

$$r_{p,t} = \alpha_p + \beta_{1,p} IG_t + \beta_{2,p} HY_t + \beta_{3,p} \mathrm{MBS}_t + \varepsilon_{p,t} \tag{4}$$

where IG is the excess return on the Bloomberg US Aggregate Index in month t. This index tracks the performance of investment grade, US dollar-denominated, fixed-rate taxable bond market. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. To account for liquidity timing opportunities across bond sectors, we follow the timing literature and allow the betas to be time-varying. That is, $\beta_{1,p} = \beta_{ig,p} + \theta_{ig,p}\left(L_{m,t} - \overline{L}_m\right)$,$\beta_{2,p} = \beta_{hy,p} + \theta_{hy,p}\left(L_{\mathrm{m,t}} - \overline{L}_m\right)$, and $\beta_{3,p} = \beta_{mbs,p} + \theta_{mbs,p}\left(L_{m,t} - \overline{L}_m\right)$. This assumption is motivated by Cao, Chen, et al. (2013) and Cao, Simin, and Wang (2013).

Considering liquidity timing opportunities in different bond sectors yields our multi-sector liquidity timing model:

$$\begin{aligned} r_{p,t} = {} & \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right) IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right) HY_t \\ & + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p} IG_t \\ & + \beta_{\mathrm{hy},p} HY_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t} \end{aligned} \tag{5}$$

The coefficients $\theta_{ig,p}$, $\theta_{hy,p}$ and $\theta_{mbs,p}$ measure liquidity timing ability with respect to IG, HY, and MBS factors, respectively. A positive (negative) timing coefficient indicates that the fund increases (decreases) its exposure to the factor as corporate bond market liquidity increases. We expect that bond fund managers have positive $\theta_{ig,p}$, $\theta_{hy,p}$ and negative $\theta_{mbs,p}$. That is, bond fund managers increase (decrease) their exposure to the investment grade and high-yield bonds (MBS sector) when overall corporate bond market liquidity increases.

As shown in Table 4, for the portfolio of all bond funds, the liquidity timing coefficients for the investment grade and MBS sectors are both insignificant, while the liquidity timing coefficient for the high-yield bond sector is statistically significant at the 5% level. That is, bond funds tend to increase their exposure to the high-yield bond sector as the overall corporate bond market liquidity increases. The high-yield timing coefficient of 0.28 implies that when aggregate market liquidity is one standard deviation (0.064 from Panel B of Table 2) above its mean, ceteris paribus, the average mutual fund portfolio's high-yield beta increases by approximately 0.018 (0.28×0.064). This represents about 6% of the baseline high-yield beta of 0.28 when aggregate liquidity is at its average level. In addition, the liquidity timing coefficients for the high-yield factor, $\theta_{hy,p}$, are significant for both surviving and non-surviving funds.

Among the subgroups of bond mutual funds, corporate bond funds show significant high-yield timing coefficients at the portfolio level. The high-yield timing coefficient is 0.53, with a t-statistic of 2.71. This result suggests that corporate bond funds become risk-seeking by holding more high-yield bonds when the overall corporate bond market liquidity increases and vice versa. Interestingly, the sector timing coefficient for high-yield bond funds is insignificant, suggesting that these funds may not adopt sector liquidity timing strategies at the portfolio level.

4.2.2 | Multi-Sector Liquidity Timing Using Sector-Specific Liquidity

In Section 4.2.1, we show that bond mutual funds exhibit high-yield liquidity timing ability in response to changes in aggregate corporate bond market liquidity. That is, bond funds adjust their exposures based on anticipated liquidity conditions in the overall corporate bond market. In practice, however, fund managers may rely on sector-specific liquidity conditions rather than aggregate market liquidity as their timing signal. Therefore, we replace aggregate corporate bond market liquidity with sector-specific liquidity measures for investment-grade, high-yield, and MBS markets in Equation (5). We calculate sector-level liquidity measures for the investment-grade and high-yield markets using the same methodology applied to aggregate corporate bond market liquidity, as described in Section 3.2. TRACE reports MBS trading data only from 2014 onward, resulting in a sample period shorter than our full analysis window. Therefore, we use the Roll (1984) spread of the Bloomberg MBS Index as a proxy for MBS sector liquidity.

In Table 5, we report the sector liquidity timing results using sector-specific liquidity measures. Compared to the baseline results based on aggregate liquidity in Table 4, we find weaker but still statistically significant evidence of high-yield sector liquidity timing for the portfolio of all funds. For corporate bond funds, the estimated high-yield liquidity timing coefficient is smaller in magnitude (0.44 vs. 0.53) than in the baseline specification, implying smaller beta adjustments relative to those based on aggregate market liquidity. In detail, for corporate bond funds, the high-yield beta increases by 0.027 (0.44×0.061) when high-yield sector liquidity is one standard deviation above its mean. By comparison, the high-yield beta increases by 0.034 (0.53×0.064, see Table 4) when aggregate corporate bond market liquidity is one standard deviation above its mean.

TABLE 4 | Liquidity timing in bond sectors.

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.09**	−1.07	0.53***	0.29	1.51***	0.29***	−0.72***	0.92
	(−2.51)	(−0.46)	(2.71)	(0.12)	(15.70)	(11.00)	(−5.79)	
High-Yield	−0.07***	1.27	0.31	−1.57	−0.05	0.91***	0.01	0.98
	(−3.64)	(0.62)	(0.99)	(−0.73)	(−0.79)	(41.50)	(0.16)	
Diversified	−0.04**	−0.34	0.01	1.08	0.68***	0.11***	−0.11**	0.94
	(−2.54)	(−0.47)	(0.25)	(1.56)	(18.00)	(10.90)	(−2.17)	
Non-survivor	−0.09***	−0.93	0.40***	1.44	0.73***	0.22***	−0.29**	0.82
	(−2.63)	(−0.57)	(2.62)	(0.82)	(7.12)	(7.05)	(−2.14)	
Survivor	−0.03**	0.00	0.18**	0.33	0.58***	0.32***	−0.13**	0.97
	(−1.97)	(−0.00)	(2.39)	(0.34)	(13.40)	(23.20)	(−2.25)	
All fund	−0.05**	−0.31	0.28***	0.69	0.63***	0.28***	−0.18**	0.94
	(−2.38)	(−0.27)	(2.60)	(0.60)	(11.60)	(16.10)	(−2.45)	

Note: This table reports the regression results of the multi-sector liquidity timing model:

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. The coefficients $\theta_{ig,p}$, $\theta_{hy,p}$ and $\theta_{mbs,p}$ measure liquidity timing abilities with respect to IG, HY, and MBS factors, respectively. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

TABLE 5 | Liquidity timing in bond sectors using sector-specific liquidity.

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.08***	−1.03	0.44***	−0.02	1.44***	0.26***	−0.62***	0.94
	(−2.58)	(−1.21)	(2.94)	(−0.73)	(13.62)	(16.53)	(−4.60)	
High-Yield	−0.06***	−0.12	0.36	−0.00	−0.14	0.90***	0.14	0.98
	(−2.81)	(−0.15)	(1.44)	(−0.01)	(−1.43)	(39.84)	(1.14)	
Diversified	−0.04***	0.52**	−0.04	0.01	0.65***	0.10***	−0.07	0.95
	(−2.81)	(2.43)	(−1.02)	(0.29)	(16.01)	(11.86)	(−1.50)	
Non-survivor	−0.07***	0.25	0.16*	0.02	0.65***	0.16***	−0.13	0.90
	(−3.43)	(0.74)	(1.79)	(0.87)	(9.00)	(11.43)	(−1.52)	
Survivor	−0.02*	0.27	0.11*	−0.01	0.53***	0.30***	−0.06	0.98
	(−1.67)	(0.88)	(1.65)	(−0.45)	(11.76)	(29.63)	(−1.07)	
All fund	−0.04**	0.27	0.16**	−0.00	0.57***	0.25***	−0.08	0.96
	(−2.39)	(0.88)	(2.14)	(−0.05)	(11.71)	(22.11)	(−1.51)	

Note: This table reports the regression results of the multi-sector liquidity timing model:

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{\mathrm{ig},t} - \overline{L}_{\mathrm{ig}}\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{\mathrm{hy},t} - \overline{L}_{\mathrm{hy}}\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{\mathrm{mbs},t} - \overline{L}_{\mathrm{mbs}}\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. $\mathrm{HY_t}$ and $\mathrm{MBS_t}$ are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{ig,t}$, $L_{hy,t}$ and $L_{mbs,t}$ are the sector liquidity measures for the IG, HY, and MBS sectors in month t, respectively, and $\overline{L}_{\mathrm{ig}}$, $\overline{L}_{hy}$ and $\overline{L}_{mbs}$ are the corresponding time series means of these sector liquidity measures. We multiply sector illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. The coefficients $\theta_{ig,p}$, $\theta_{hy,p}$ and $\theta_{mbs,p}$ measure liquidity timing abilities with respect to IG, HY, and MBS factors, respectively. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

4.2.3 | Liquidity Timing: Addressing Simultaneity Concerns

We then consider the possibility that our results are driven by the impact of large funds' trading on market liquidity. To address this concern, we examine liquidity-timing ability using several subsamples of small funds, because these funds' trades are unlikely to have a material effect on market liquidity. We construct two subsamples consisting of funds with assets under management (AUM) below \$50 million and below \$150 million.

Table 6 reports the results of liquidity timing for these subsamples of small funds. Regardless of the definition of small funds, we find consistent evidence of high-yield sector liquidity timing, especially for corporate bond funds. The high-yield sector liquidity timing coefficient is more pronounced for the portfolio composed of smaller funds. For the group of corporate bond funds, the high-yield liquidity timing coefficient is 0.82 ($t = 4.47$) for funds with AUM below \$50 million, compared to 0.66 ($t = 4.25$) for funds with AUM below \$150 million. Those results suggest that our findings are not driven by large fund trading that could affect market liquidity.

In our multi-sector liquidity timing model in Equation (5), we use contemporaneous market liquidity in the liquidity timing regressions, assuming that our expectation of market liquidity is informative. However, using contemporaneous market liquidity raises potential simultaneity issues, as fund trading—particularly by large funds—may itself influence aggregate market liquidity. Moreover, observed market liquidity may partly reflect procyclical or common investor flows rather than managers' forward-looking liquidity expectations.

To mitigate concerns that contemporaneous market liquidity may cause simultaneity bias and reflect procyclical investor flows, we construct liquidity innovations conditional on the fund flows to remove the predictable components of market liquidity that may be jointly determined with fund trading, thereby mitigating the contemporaneous impact of fund trading on market liquidity. This approach ensures that our liquidity timing coefficients are

TABLE 6 | Liquidity timing in bond sectors: Small-size portfolios.

Panel A: AUM < \$50 million								
	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.07*	0.81	0.82***	−0.69	0.94***	0.25***	−0.41	0.78
	(−1.64)	(0.45)	(4.47)	(−0.36)	(8.16)	(7.70)	(−2.68)	
High-yield	−0.06**	1.58	−0.22	−1.24	−0.03	0.86***	0.05	0.98
	(−2.38)	(0.95)	(−0.94)	(−0.68)	(−0.50)	(35.51)	(0.49)	
Diversified	−0.02	1.05	0.33***	1.06	0.57***	0.17***	−0.07	0.93
	(−1.15)	(−1.31)	(4.28)	(1.23)	(11.94)	(14.24)	(−1.17)	
All fund	−0.03	−0.75	0.35***	0.90	0.53***	0.32***	−0.15	0.89
	(−1.28)	(−0.68)	(3.09)	(0.74)	(7.88)	(15.26)	(−1.61)	
Panel B: AUM < \$ 150 million								
	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.08**	−4.14***	0.66***	2.48	1.08***	0.23***	−0.45***	0.89
	(−2.43)	(−2.60)	(4.25)	(1.39)	(11.83)	(9.40)	(−3.69)	
High-yield	−0.06***	0.34	0.49*	−0.80	0.01	0.86***	−0.03	0.98
	(−2.77)	(0.17)	(1.69)	(−0.38)	(0.09)	(38.06)	(−0.28)	
Diversified	−0.02**	0.20	0.14	0.72	0.67***	0.12***	−0.12**	0.93
	(−2.54)	(−0.47)	(0.25)	(1.56)	(18.00)	(10.90)	(−2.17)	
All fund	−0.04**	0.21	0.10	0.30	0.56***	0.31***	−0.15**	0.92
	(−2.31)	(0.22)	(1.19)	(0.31)	(10.90)	(20.61)	(−2.11)	

Note: This table reports the regression results of the multi-sector liquidity timing model:

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. The coefficients $\theta_{ig,p}$, $\theta_{hy,p}$ and $\theta_{mbs,p}$ measure liquidity timing abilities with respect to IG, HY, and MBS factors, respectively. We report results for equal-weighted portfolios of corporate, high-yield, diversified, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

identified from unexpected liquidity shocks rather than the predictable component of market liquidity.

We then use these liquidity innovations in the following liquidity timing regressions.

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\tilde{L}_{m,t}IG_t + \theta_{\mathrm{hy},p}\tilde{L}_{m,t}\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\tilde{L}_{m,t}MBS_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}HY_t + \beta_{\mathrm{mbs},p}MBS_t + \varepsilon_{p,t} \tag{6}$$

where $\tilde{L}_{m,t}$ is the residual from regressing market liquidity on its own two lags and on common fund flows (including one lag of common flows), which captures the unexpected component of market liquidity.

In Table 7, we find significant high-yield sector liquidity timing ability across bond funds. The liquidity timing coefficients are positive and statistically significant for the full sample of bond funds and corporate bond funds. In addition, both surviving and non-surviving funds exhibit positive high-yield sector liquidity timing skills. Overall, our results remain significant after controlling for contemporaneous liquidity and common fund flows.

Taken together, these results suggest that large fund trading, simultaneity issue, and fund flows do not drive our findings on sector liquidity timing skill among bond funds.

4.2.4 | Dealer Capacity Constraints in the OTC Market

In OTC bond markets, fund trading is often limited by capacity constraints, particularly in less liquid sectors such as high-yield bonds and MBS. To account for these constraints in our liquidity timing analysis, we use primary dealer net positions as a proxy for trading capacity because trading in OTC markets relies heavily on dealer balance-sheet intermediation. Higher dealer net positions reflect more heavily utilized dealer balance sheets and, consequently, tighter residual intermediation capacity. This may restrict fund managers' ability to scale positions in response to anticipated changes in market liquidity. We include interactions between sector-level net position and sector factor returns to capture the impact of trading frictions and capacity constraints in the OTC bond sector. The interaction terms allow funds' exposures to IG, HY, and MBS returns to vary with trading capacity, reflecting the fact that tighter intermediation capacity may limit funds' ability to scale sector exposures in OTC markets, particularly for high-yield bonds and MBS.

$$\begin{aligned} r_{p,t} = \alpha_p &+ \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY_t} \\ &+ \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY_t} + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t \\ &+ \beta^{\mathrm{Net}}_{\mathrm{ig},p}Net_{\mathrm{ig,t-1}}\mathrm{IG_t} + \beta^{\mathrm{Net}}_{\mathrm{hy},p}Net_{\mathrm{hy,t-1}}\mathrm{HY_t} + \beta^{\mathrm{Net}}_{\mathrm{mbs},p}Net_{\mathrm{mbs,t-1}}\mathrm{MBS}_t + \varepsilon_{p,t} \end{aligned} \tag{7}$$

$\mathrm{Net}_{\mathrm{j},t-1}$ represents lagged primary dealer net positions in sector j, which proxy for dealer intermediation capacity in OTC markets. Higher values indicate tighter intermediation capacity and potentially constrain funds' ability to scale exposures. We obtain primary dealer net position data from the Federal Reserve Bank of New York. Based on liquidity timing strategy framework, factor exposures in month t are determined by fund managers based on their expectations of market/sector liquidity in month t-1. Therefore, lagged dealer net positions capture the intermediation capacity prevailing when these portfolio decisions are made.

TABLE 7 | Liquidity timing in bond sectors using liquidity innovation.

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.09**	0.45	0.59***	−1.57	1.51	0.30	−0.75***	0.92
	(−2.43)	(0.26)	(4.11)	(−0.91)	(15.51)	(10.31)	(−5.65)	
High-yield	−0.08***	1.32	0.51*	−1.51	−0.08	0.93***	0.04	0.98
	(−3.45)	(0.81)	(1.79)	(−0.93)	(−1.38)	(51.40)	(0.51)	
Diversified	−0.04***	−0.18	0.07	0.77	0.69***	0.11***	−0.12**	0.94
	(−2.62)	(−0.25)	(1.25)	(1.21)	(17.40)	(10.42)	(−2.30)	
Non-survivor	−0.09**	−0.68	0.53***	1.08	0.71***	0.23***	−0.29*	0.82
	(−2.48)	(−0.51)	(3.28)	(0.80)	(6.73)	(6.72)	(−1.97)	
Survivor	−0.03**	0.30	0.25***	−0.05	0.57***	0.33***	−0.13**	0.94
	(−1.96)	(0.36)	(2.96)	(−0.06)	(12.94)	(22.48)	(−2.12)	
All fund	−0.05**	−0.02	0.37***	0.35	0.62***	0.29***	−0.18**	0.95
	(−2.27)	(−0.02)	(3.67)	(0.39)	(11.01)	(15.65)	(−2.23)	

Note: This table reports the regression results of the multi-sector liquidity timing model using liquidity innovations:

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\tilde{L}_{m,t}IG_t + \theta_{\mathrm{hy},p}\tilde{L}_{m,t}HY_t + \theta_{\mathrm{mbs},p}\tilde{L}_{m,t}\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}HY_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. $\mathrm{HY_t}$ and $\mathrm{MBS_t}$ are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $\tilde{L}_{m,t}$ is the market liquidity innovation for month t. We multiply market illiquidity by −1 to represent market liquidity. The coefficients $\theta_{ig,p}$, $\theta_{hy,p}$ and $\theta_{mbs,p}$ measure liquidity timing abilities with respect to IG, HY, and MBS factors, respectively. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

TABLE 8 | Liquidity timing in bond sectors: Control for trading constraints.

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	$\beta^{Net}_{ig,p}$	$\beta^{Net}_{hy,p}$	$\beta^{Net}_{mbs,p}$	R^2
Corporate	−0.01	−18.27***	3.82*	16.65*	1.50***	0.26***	−0.80***	1.00**	−0.79**	−0.11	0.97
	(−0.19)	(−2.67)	(1.67)	(1.69)	(12.29)	(11.40)	(−4.59)	(2.10)	(−2.18)	(−0.92)	
High-Yield	−0.05***	0.81	3.34**	9.97	−0.01	0.93***	−0.06	−0.32	−0.56**	−0.17**	0.99
	(−4.02)	(0.17)	(2.25)	(1.54)	(−0.15)	(47.80)	(−0.57)	(−1.29)	(−2.05)	(−2.16)	
Diversified	0.00	−7.67*	0.41	5.95	0.68***	0.08***	−0.15	0.41	−0.15	−0.01	0.98
	(0.18)	(−1.83)	(0.52)	(1.09)	(9.01)	(7.54)	(−1.46)	(1.51)	(−1.23)	(−0.10)	
All fund	−0.01	−6.68*	2.19***	8.08	0.59***	0.31***	−0.20**	0.29	−0.46***	−0.08	0.99
	(−1.32)	(−1.68)	(2.71)	(1.59)	(8.91)	(25.36)	(−2.20)	(1.24)	(−3.76)	(−1.13)	

Note: This table reports the regression results of the multi-sector liquidity timing model:

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY_t} + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY_t} + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t$$
$$+ \beta^{\mathrm{Net}}_{\mathrm{ig},p}Net_{\mathrm{ig,t-1}}\mathrm{IG_t} + \beta^{\mathrm{Net}}_{\mathrm{hy},p}Net_{\mathrm{hy,t-1}}\mathrm{HY_t} + \beta^{\mathrm{Net}}_{\mathrm{mbs},p}Net_{\mathrm{mbs,t-1}}\mathrm{MBS}_t + \epsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. HY_t and $\mathrm{MBS_t}$ are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{\mathrm{L}}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. $\mathrm{Net}_{j,t-1}$ represents lagged primary dealer net positions in the sector j, which is a proxy for dealer intermediation capacity in OTC markets. Higher values indicate tighter intermediation capacity and potentially constrain funds' ability to scale exposures. We report results for equal-weighted portfolios of corporate, high-yield, diversified, and all bond funds for the period of March 2013–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

The coefficient on the interaction between net positions and sector returns captures how dealer intermediation capacity affects funds' exposures to sector returns. A negative coefficient indicates that funds' exposure to the factor decreases when dealer net positions are high, signalling tighter intermediation capacity.

Table 8 reports the results for the multi-sector liquidity timing model after controlling for primary dealer capacity constraints.[8] As expected, dealer intermediation capacity negatively affects funds' exposure to high-yield factor returns when dealers' net positions are high in the relatively illiquid high-yield bond market. For example, the estimated coefficient of the interaction term $\lambda_{hy,p}$ is −0.46 with a t-statistic of −3.76 for the portfolio of all funds. This negative effect also holds for corporate bond funds and high-yield bond funds, which hold a substantial proportion of high-yield bonds in their portfolios. Overall, these results suggest that capacity constraints may limit funds' ability to adjust high-yield factor exposure in response to market movements, reducing the incremental return benefit from high-yield exposure during periods of tight dealer intermediation capacity.

We find significant evidence of high-yield sector liquidity-timing ability after controlling for dealer capacity constraints, for both the full bond fund sample and corporate bond funds. Interestingly, we find that high-yield bond funds exhibit significant high-yield liquidity timing coefficients after controlling for capacity restriction. However, the negative coefficient on the interaction between high-yield sector return and lagged dealer net positions suggests that tight dealer intermediation capacity weakens the effectiveness of liquidity-timing strategies. This implies that, although high-yield bond fund managers correctly anticipate liquidity conditions, their ability to scale or adjust high-yield exposures is partially constrained when dealer intermediation capacity is limited, consistent with trading frictions in OTC bond markets.

4.3 | Liquidity Timing Performance: US Onshore vs. Offshore Funds

We next examine whether the findings about liquidity timing performance are biased by the inclusion of overseas bond mutual funds. Our sample comprises both onshore (US-domiciled) bond funds and offshore (non-US domiciled) funds, all of which invest in the US corporate bond market. Both types of funds in our sample primarily hold USD-denominated corporate bonds, and all returns are expressed in USD, therefore differences arising from currency conversion or currency hedging are unlikely to materially affect our results. However, regulatory frameworks and investor base characteristics across domiciles could influence fund trading patterns and liquidity management. To address these concerns, we conduct a subsample analysis to compare liquidity timing performance between onshore and offshore funds.

In Table 9, Panel A shows the performance of liquidity timing ability using the aggregate bond market liquidity timing model in Equation (3), while Panel B shows the sector liquidity timing performance using bond sector liquidity timing model in Equation (5). In Panel A, we only find evidence of liquidity timing for the group of all offshore funds and diversified bond funds. However, there is no evidence of market liquidity timing for offshore funds.

In Panel B, we find that both onshore and offshore funds exhibit high-yield sector liquidity timing ability. Specifically, the high-yield sector liquidity timing coefficients are positively significant for the group of all onshore funds and the group of all offshore funds. Across fund categories, both onshore and offshore corporate bond funds demonstrate significant positive high-yield sector liquidity skills. Interestingly, offshore funds show particularly strong evidence of high-yield sector liquidity timing. For

TABLE 9 | Liquidity timing performance: Onshore versus offshore.

Panel A: Aggregate market liquidity timing model

	α_p	$\theta_{m,p}$	MKT	HY	MBS	R^2
Onshore funds						
Corporate	−0.04	0.57	1.62***	0.18***	−0.70***	0.94
	(−1.42)	(0.66)	(14.02)	(7.38)	(−4.55)	
High-Yield	−0.03	0.58	0.01	0.88***	−0.02	0.98
	(−1.06)	(0.60)	(0.05)	(28.14)	(0.12)	
Diversified	−0.03***	0.56***	0.80***	0.07***	−0.18***	0.95
	(−2.63)	(3.43)	(17.90)	(8.40)	(−3.19)	
All Onshore	−0.03**	0.64**	0.71***	0.22***	−0.20***	0.97
	(−2.01)	(2.27)	(11.93)	(20.72)	(−2.68)	
Offshore funds						
Corporate	−0.05*	−0.39	1.75***	0.05*	−0.81***	0.92
	(−1.69)	(−0.40)	(13.70)	(1.94)	(−4.58)	
High-Yield	−0.08***	0.56	−0.03	0.89***	0.01	0.97
	(−2.85)	(0.55)	(−0.30)	(23.58)	(0.10)	
Diversified	−0.06***	−0.09	0.71***	0.02**	−0.12**	0.94
	(−4.96)	(−0.45)	(17.26)	(2.11)	(−2.54)	
All Offshore	−0.04*	0.35	0.81***	0.18***	−0.32**	0.90
	(−1.76)	(0.66)	(6.87)	(8.29)	(−2.10)	

Panel B: Sector liquidity timing model

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Onshore funds								
Corporate	−0.07**	0.25	0.41**	−0.54	1.47***	0.34***	−0.69***	0.92
	(−2.05)	(0.10)	(2.15)	(−0.22)	(15.41)	(12.84)	(−5.59)	
High-Yield	−0.06	1.12	0.37	−1.48	−0.03	0.92***	−0.00	0.98
	(−0.98)	(0.55)	(1.19)	(−0.69)	(−0.58)	(44.29)	(−0.03)	
Diversified	−0.03*	−0.32	0.02	1.28*	0.70***	0.12***	−0.12**	0.94
	(−1.88)	(−0.42)	(0.42)	(1.75)	(18.12)	(11.82)	(−2.33)	
All Onshore	−0.04**	−0.19	0.20**	0.82	0.61***	0.28***	−0.14**	0.95
	(−2.12)	(−0.18)	(2.25)	(0.82)	(13.47)	(19.70)	(−2.40)	
Offshore funds								
Corporate	−0.10***	−2.45	0.71***	1.14	1.57***	0.25***	−0.78***	0.90
	(−2.72)	(−0.99)	(3.36)	(0.44)	(15.36)	(8.94)	(−5.84)	
High-Yield	−0.10***	1.83	0.14	−1.93	−0.07	0.91***	0.04	0.98
	(−4.46)	(−0.85)	(0.41)	(−0.83)	(−1.06)	(33.22)	(0.45)	
Diversified	−0.06***	−0.44	−0.02	0.55	0.62***	0.07***	−0.08	0.92
	(−4.04)	(−0.49)	(−0.21)	(0.62)	(14.59)	(6.88)	(−1.46)	
All Offshore	−0.07***	−0.60	0.45***	0.36	0.68***	0.28***	−0.25**	0.89
	(−2.65)	(−0.38)	(2.75)	(0.82)	(7.12)	(7.05)	(−2.14)	

Note: This table reports the regression results of the liquidity timing models:

$$r_{p,t} = \alpha_p + \beta^0_{m,p} MKT_t + \theta_{m,p}\left(L_{m,t} - \overline{\mathrm{L}}_m\right) MKT_t + \beta_{\mathrm{hy},p} HY_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right) IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p} IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. MKT_t is the excess return on the Bloomberg US Universal Index in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{\mathrm{L}}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

example, the high-yield sector liquidity timing coefficient for offshore funds is 0.45 ($t = 2.75$), compared to 0.20 ($t = 2.25$) for onshore funds. This suggests that offshore funds may be more likely to adopt a sector-level liquidity timing strategy.

Overall, these results indicate that our main conclusions are not driven by the inclusion of offshore funds.

4.4 | Liquidity Timing: Value-Weighted Portfolio

In the previous sections, we report liquidity timing performance using equal-weighted fund portfolios. Investors may also be interested in the performance of value-weighted portfolios. For comparison purposes, we therefore report liquidity timing results for value-weighted portfolios in Table 10. Panels A and B of Table 10 present the results for aggregate and sector liquidity timing models, respectively.[9]

In Panel A, we find significant aggregate market liquidity timing ability for the value-weighted portfolio of all bond funds ($t = 2.99$), a result that is not observed when using equal-weighted portfolios. Diversified bond funds also exhibit stronger and statistically significant aggregate market liquidity timing ability at the 5% level compared with the corresponding equal-weighted portfolios.

In Panel B, using the sector liquidity timing model, we find significant high-yield sector liquidity timing ability for the value-weighted portfolio of all bond mutual funds, consistent with our earlier results using equal-weighted portfolios. Interestingly, corporate bond funds no longer exhibit significant positive high-yield sector liquidity timing ability using the value-weighted portfolio. Taken together with the results in Section 4.2.3, which show that smaller corporate bond funds display significant high-yield sector liquidity timing ability, this finding suggests that larger corporate bond funds are less effective at timing high-yield sector liquidity, because value-weighted portfolios place greater weight on larger corporate bond funds. We further confirm this idea using a subsample of large corporate bond mutual funds (results are available upon request).

4.5 | Liquidity Timing: Excluding Crisis Periods

To ensure that our results are not driven by the 2008 global financial crisis or the 2020 market crash associated with the COVID-19 pandemic, we exclude data from July to December 2008 and from January to April 2020 as a robustness test. We repeat the tests in Equations (3) and (5) and report the results in Table 11. In Panel A, compared to the results in Table 3, we still find no evidence of market liquidity timing ability for bond funds after excluding the crisis periods.

In Panel B, when we exclude the crisis periods, the evidence of high-yield sector liquidity timing becomes slightly stronger. For example, for the all-bond fund portfolio, the liquidity timing coefficient is 0.48 with a t-statistic of 2.89 when we exclude the 2008 crisis and the 2020 crash, whereas it is 0.28 with a t-statistic of 2.60 when these periods are included (see Table 4). For high-yield bond funds, we find significant positive liquidity timing skills in the absence of crisis periods. Combined with the results in Table 4, this suggests that high-yield funds fail to time market liquidity during the crisis period. This result is consistent with Section 4.2.4 that high-yield fund liquidity timing ability is constrained when dealer net positions of high-yield bonds are high, a situation that typically occurs during crisis or market-crash periods.

In contrast, we find that corporate bond funds show weaker evidence of high-yield sector liquidity timing after excluding crisis and market crash periods. The coefficient is 0.37 with a Newey-West t-statistic of 1.65, compared with 0.53 ($t = 2.71$) in Table 4 when crisis periods are included. This suggests that corporate bond funds demonstrate their liquidity timing ability more evidently during crisis periods when liquidity conditions deteriorate sharply and liquidity risk becomes most salient. These results also indicate that corporate bond fund managers are likely genuine liquidity timers who employ a high-yield sector liquidity timing strategy.

4.6 | Time-Varying Fund Categories

Our data contains the most recent bond fund category classifications. To mitigate concerns that our results are biased by fund category reclassifications over time, we employ a machine-learning approach to infer time-varying fund categories. Specifically, we train a random forest classifier to identify changes in fund classifications. We find that fund category reclassifications are relatively infrequent. Using this approach, we identify only 78 funds (9.2% of all funds) that change their category at some point during the sample period. This suggests that the vast majority of funds maintain consistent category classifications. The detailed methodology is described in Appendix S1.

To ensure that our results are not biased by category reclassifications, we exclude these 78 funds and re-estimate our two liquidity timing models. To save space, the corresponding results are reported in the Appendix S1. After excluding funds that change their category classification, our results remain unchanged. On average, diversified funds continue to exhibit positive and statistically significant aggregate market liquidity timing ability, while corporate bond funds continue to display positive and statistically significant high-yield sector liquidity timing ability.

4.7 | Moving Block Bootstrap for Standard Errors

To control for potential heteroskedasticity and autocorrelation effects, apart from the Newey-West standard errors, we also calculate bootstrap p-values using a moving block bootstrap procedure. We bootstrap the sample B times ($B = 1000$) with a block length of 6 months. For each bootstrap replication b, we estimate the liquidity timing coefficient and compute the corresponding t-statistic $t_i^{(b)} = \frac{\theta_i^{(b)} - \hat{\theta}_i}{SE\left(\theta_i^{(b)}\right)}$, ($b = 1, 2, 3, \ldots, B$), where $\theta_i^{(b)}$ denotes the bootstrap estimate of the timing coefficient and $\hat{\theta}_i$ is the estimate from the original sample. After B bootstrap draws, we get an empirical distribution of the bootstrap t-statistic, $t_i^{(b)}$, which

TABLE 10 | Liquidity timing test value-weighted portfolios.

Panel A: Aggregate market liquidity timing model

	α_p	$\theta_{m,p}$	MKT	HY	MBS	R^2
Corporate	−0.04	0.17	1.51***	0.13***	−0.50***	0.95
	(−1.59)	(0.23)	(15.13)	(6.25)	(−3.98)	
High-Yield	−0.03	0.46	0.05	0.90***	−0.11	0.98
	(−1.14)	(0.49)	(0.50)	(28.95)	(−0.82)	
Diversified	−0.02	0.58**	0.95***	0.06***	−0.10*	0.96
	(−1.45)	(2.54)	(20.79)	(5.79)	(−1.83)	
All fund	−0.01	0.58***	0.82***	0.18***	−0.10*	0.97
	(−1.12)	(2.99)	(20.21)	(21.25)	(−1.91)	

Panel B: Sector liquidity timing model

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.06**	0.07	0.24	−0.47	1.37***	0.28***	−0.49***	0.92
	(−1.96)	(0.03)	(1.21)	(−0.20)	(15.00)	(12.11)	(−4.35)	
High-Yield	−0.05**	0.54	0.29	−0.55	−0.01	0.94***	−0.05	0.98
	(−2.50)	(0.23)	(0.87)	(−0.23)	(−0.17)	(44.35)	(−0.71)	
Diversified	−0.02	−0.67	0.18**	1.33*	0.86***	0.14***	−0.09*	0.96
	(−1.47)	(−0.90)	(2.19)	(1.66)	(23.72)	(13.99)	(−1.80)	
All fund	−0.02*	−0.49	0.27***	0.89	0.75***	0.26***	−0.09**	0.98
	(−1.79)	(−0.56)	(3.93)	(1.01)	(22.11)	(28.38)	(−2.11)	

Note: This table reports the regression results of the liquidity timing models:

$$r_{p,t} = \alpha_p + \beta^0_{m,p}\mathrm{MKT}_t + \theta_{m,p}\left(L_{m,t} - \overline{\mathrm{L}}_m\right)\mathrm{MKT}_t + \beta_{\mathrm{hy},p}HY_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. MKT_t is the excess return on the Bloomberg US Universal Index in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{\mathrm{L}}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. We report results for value-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

approximates the true sampling distribution of the t-statistic under time dependence. We then use the distribution of $t_i^{(b)}$ to compute two-sided bootstrap p-values:

$$p_i = \frac{1}{B}\sum_{b=1}^{B} I\left(\left|t_i^{(b)}\right| \geq |t_i|\right) \tag{8}$$

where $I(\cdot)$ is an indicator function, and the observed t-statistic is $t_i = \frac{\hat{\theta}_{\mathrm{i}}}{SE(\hat{\theta}_{\mathrm{i}})}$.

In unreported results, we find that corporate bond funds exhibit positive and statistically significant high-yield sector liquidity timing ability based on bootstrap p-values, consistent with our earlier findings. In contrast, we do not find evidence that diversified funds display significant aggregate market liquidity timing ability when inference is based on bootstrap p-values.

4.8 | State Space Model for Liquidity Timing

In the previous sections, in order to test liquidity timing ability of mutual fund managers, we model the change in market/sector exposure as a linear function of changes in the market liquidity. In this section, we do not impose the existence of an average market exposure for mutual funds. Instead, we allow market and sector exposures to evolve over time, even in the absence of market timing ability, by modelling fund betas as following a random walk when no timing is detected. Consequently, observed dynamics in market exposure may reflect factors other than liquidity timing, such as changes in investment strategies or in the composition of underlying assets.

We estimate the state-space model, which consists of the measurement equation (Equation (1) for aggregate liquidity timing

TABLE 11 | Liquidity timing test: Excluding crisis periods.

Panel A: Aggregate market liquidity timing model

	α_p	$\theta_{m,p}$	MKT	HY	MBS	R^2
Corporate	−0.04**	0.55	1.56***	0.13***	−0.66***	0.94
	(−2.02)	(0.36)	(27.85)	(10.57)	(−9.16)	
High-Yield	−0.02	2.88*	−0.00	0.88***	−0.10	0.98
	(−0.99)	(1.92)	(−0.05)	(23.34)	(−1.18)	
Diversified	−0.02**	−0.36	0.72***	0.04***	−0.06	0.94
	(−2.42)	(−0.69)	(20.03)	(5.98)	(−1.43)	
Non-survivor	−0.04**	0.42	0.79***	0.11***	−0.27***	0.86
	(−2.13)	(0.62)	(9.65)	(6.07)	(−2.95)	
Survivor	−0.00	0.37	0.61***	0.25***	−0.11***	0.98
	(−0.82)	(0.61)	(20.99)	(27.58)	(−3.00)	
All fund	−0.02	0.45	0.68***	0.20***	−0.16***	0.96
	(−1.39)	(0.76)	(18.81)	(16.72)	(−3.76)	

Panel B: Sector liquidity timing model

	α_p	$\theta_{ig,p}$	$\theta_{hy,p}$	$\theta_{mbs,p}$	IG	HY	MBS	R^2
Corporate	−0.03	−2.77*	0.37*	4.53**	1.45***	0.25***	−0.68***	0.94
	(−1.46)	(−1.96)	(1.65)	(2.23)	(20.87)	(18.60)	(−7.55)	
High-Yield	−0.04***	0.03	1.39***	0.87	−0.05	0.90***	−0.00	0.99
	(−3.30)	(0.02)	(6.71)	(0.57)	(−1.11)	(84.94)	(−0.07)	
Diversified	−0.04*	−0.34**	0.01	1.08**	0.68***	0.11***	−0.11	0.94
	(−1.73)	(−2.00)	(0.14)	(2.27)	(18.22)	(13.95)	(−1.59)	
Non-survivor	−0.04**	−2.34***	0.55**	3.24***	0.69***	0.19***	−0.23**	0.85
	(−2.28)	(−2.94)	(2.18)	(3.06)	(9.20)	(12.06)	(−2.44)	
Survivor	−0.01	−0.95	0.36**	1.32	0.55***	0.31***	−0.09**	0.97
	(−0.87)	(−1.12)	(2.41)	(1.40)	(15.90)	(40.14)	(−2.10)	
All fund	−0.02	−1.47*	0.48***	1.99*	0.60***	0.26***	−0.14***	0.95
	(−1.55)	(−1.83)	(2.89)	(2.19)	(15.68)	(29.19)	(−2.78)	

Note: This table reports the regression results of the liquidity timing models:

$$r_{p,t} = \alpha_p + \beta^0_{m,p}\mathrm{MKT}_t + \theta_{m,p}\left(L_{m,t} - \overline{\mathrm{L}}_m\right)\mathrm{MKT}_t + \beta_{\mathrm{hy},p}HY_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

$$r_{p,t} = \alpha_p + \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{HY}_t + \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t + \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}\mathrm{HY}_t + \beta_{\mathrm{mbs},p}\mathrm{MBS}_t + \varepsilon_{p,t}$$

where $r_{p,t}$ is the excess return of fund p in month t. MKT_t is the excess return on the Bloomberg US Universal Index in month t. IG_t is the excess return on the Bloomberg US Aggregate Index in month t. HY_t and MBS_t are the excess returns of the Bloomberg US Corporate High-Yield Index and the Bloomberg US MBS Index, respectively. We use the 1-month Treasury bill rate as our proxy for the risk-free rate. $L_{m,t}$ is the market liquidity measure for month t, and $\overline{L}_m$ is the time series mean of market liquidity measures. We multiply market illiquidity by −1 to represent market liquidity. We use the average liquidity estimate over the previous 36 months as a proxy for the means of liquidity measures. We report results for equal-weighted portfolios of corporate, high-yield, diversified, non-surviving, surviving, and all bond funds for the period of July 2002–September 2021. The Newey-West t-statistics with 2 lags are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

or Equation (4) for sector liquidity timing) and the transition equation, $\beta_t = \beta_{t-1} + \upsilon_t$, using the Kalman filter.[10] The residuals are assumed to be normally distributed. We first estimate time-varying betas of equal-weighted portfolios of all funds and then regress their first differences on liquidity innovations, $\tilde{L}_t$.[11]

$$\Delta\beta_{p,t} = \alpha_p + \theta_p\tilde{L}_t + \varepsilon_{p,t} \tag{9}$$

In Table 12, we report the results of the state-space liquidity timing models. We find that high-yield sector liquidity timing ability remains positive and statistically significant. In contrast, investment-grade sector timing is statistically significant but negative, a pattern that does not appear in the previous sections. We do not find evidence of significant aggregate market liquidity timing or MBS sector liquidity timing.

TABLE 12 | State space liquidity timing model.

	α_p	θ_p	R^2
MKT timing	−0.001	0.090	0.02
	(−0.009)	(1.362)	
IG timing	0.001	−0.158**	0.03
	(0.017)	(−2.405)	
HY timing	−0.001	0.187***	0.01
	(−0.020)	(2.869)	
MBS timing	−0.001	0.083	0.01
	(−0.009)	(1.261)	

Note: This table reports results from the state-space liquidity timing models estimated using the Kalman filter. We first estimate time-varying betas for equal-weighted portfolios of all funds and then regress their first differences on liquidity innovations, $\tilde{L}_t$. The reported standardized coefficient θ captures the sensitivity of changes in fund exposure to unexpected changes in market liquidity. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

5 | Individual Fund Level Analysis

5.1 | Cross-Section Distribution of t-Statistics for Liquidity Timing

In this section, we evaluate liquidity timing skills using regression Equations (3) and (5) for individual bond funds. To ensure reliable regression estimates, we require each fund to have at least 36 monthly observations.

Table 13 reports the cross-sectional distribution of t-statistics for liquidity timing coefficients across individual funds. In particular, the table shows the percentage of t-statistics exceeding the indicated cutoff values.

Panel A of Table 13 estimates the liquidity timing coefficients and t-statistics for the overall bond market using Equation (3). We find that about 18.21% of funds have t-statistics greater than 1.96, which indicates that some funds have significantly positive liquidity timing at the individual fund level. For the overall sample, the distribution is right-skewed with the proportion of positive t-statistics greater than the negative proportion. In terms of subgroups of bond funds, about 23.21% of diversified bond funds demonstrate significant positive liquidity timing skills at the 5% level. For diversified bond funds, the proportion of positive liquidity timing is also greater than negative liquidity timing. This may explain why diversified funds show significant positive liquidity timing at the portfolio level in Table 3. We also confirm previous findings that non-surviving funds may disappear because of other factors rather than liquidity timing, since non-surviving funds have a higher percentage of positive t-statistics than surviving funds at the 5% level.

In Table 13, Panels B–D report the t-statistics of timing coefficients with respect to investment grade (IG), high-yield (HY), and MBS risk factors, respectively, using Equation (5). In Panel B, we find some evidence of investment grade liquidity timing at the individual fund level, although we don't find evidence of significant investment grade liquidity timing at the portfolio level in Table 4. The distribution of t-statistics for the IG sector liquidity timing coefficient is right-skewed. The proportion of positive IG sector liquidity timing coefficients exceeds the proportion of negative ones, and around 12.22% of funds exhibit significant liquidity timing skills at the 5% level. We also find that around 12.03% of high-yield bond funds demonstrate positive IG sector liquidity timing at the 5% level, which is not revealed at the portfolio level.

In Table 13 Panel C, the results show strong evidence that fund managers possess high-yield liquidity timing skills at the individual fund level. For the overall sample, the right tail of the t-statistics appears thicker than the left tail. Around 20.09% of bond funds demonstrate positive high-yield liquidity timing coefficients with t-statistics greater than 1.96. The result is more significant for corporate bond funds with 31.25% of funds having significant and positive HY sector liquidity timing at the 5% level. Taken together, these results support the evidence in Table 4 that bond funds have significant high-yield liquidity timing skills at the portfolio level.

For the MBS sector liquidity timing skills in Panel D, we focus on their negative MBS sector timing skills. That is, we expect the bond fund managers to hold less MBS when the corporate bond market liquidity increases. A small number of funds have significant negative MBS sector liquidity timing skills. The proportion of significantly negative MBS timing coefficients is around 8.81% at the 5% level.

Overall, the distributions of t-statistics suggest the presence of liquidity timing skills at the individual fund level based on the conventional significance values under the normality assumption.

5.2 | False Discovery Rate (FDR)

In Section 5.1, we use the standard procedure of examining each fund's liquidity timing coefficient independently and identifying how many funds have significantly positive or negative coefficients, implicitly assuming that the false discoveries are zero. In a multiple hypothesis testing framework, however, this approach increases the probability of false discoveries (Type I errors). Therefore, it is essential to control the proportion of false discoveries to avoid incorrectly rejecting the null hypothesis. In this section, we examine the liquidity timing of bond mutual funds by controlling the false discovery rate (FDR) to find out how many funds are truly liquidity timers. We use the standard Benjamini and Hochberg (1995) method to control false discoveries and get adjusted p-values for each timing coefficient.[12]

In Table 14, we report the percentage of funds exhibiting significant liquidity timing ability after controlling for the FDR. We still find a substantial proportion of significant positive liquidity timers, particularly for aggregate market liquidity timing and high-yield sector timing (9.64% and 13.98%, respectively, at the

TABLE 13 | Cross-sectional distributions of t-statistics for liquidity timing coefficients across individual funds.

Group	$t < -2.326$	$t < -1.960$	$t < -1.645$	$t < -1.282$	$t > 1.282$	$t > 1.645$	$t > 1.960$	$t > 2.326$
Panel A: Overall MKT timing								
Corporate	25.00	28.12	29.69	39.06	15.62	10.94	6.25	4.69
High-Yield	5.70	6.33	7.59	12.66	12.03	5.06	3.16	1.90
Diversified	6.68	8.11	9.86	15.58	37.04	28.62	23.21	16.69
Non-survivor	2.86	3.81	6.03	13.33	36.83	28.89	23.81	18.10
Survivor	10.82	12.50	13.81	18.84	27.24	19.40	14.93	10.07
All fund	7.87	9.28	10.93	16.80	30.79	22.91	18.21	13.04
Panel B: IG sector timing								
Group	$t < -2.326$	$t < -1.960$	$t < -1.645$	$t < -1.282$	$t > 1.282$	$t > 1.645$	$t > 1.960$	$t > 2.326$
Corporate	7.81	14.06	15.62	25.00	6.25	4.69	4.69	3.12
High-Yield	4.43	5.70	8.23	10.13	27.22	15.82	12.03	6.96
Diversified	5.72	8.43	11.92	16.69	22.10	16.85	13.04	9.06
Non-survivor	4.13	6.35	8.25	12.38	22.86	18.10	13.65	8.89
Survivor	6.53	9.51	13.43	18.28	21.27	14.37	11.38	7.84
All fund	5.64	8.34	11.52	16.10	21.86	15.75	12.22	8.23
Panel C: HY sector timing								
Group	$t < -2.326$	$t < -1.960$	$t < -1.645$	$t < -1.282$	$t > 1.282$	$t > 1.645$	$t > 1.960$	$t > 2.326$
Corporate	0.00	3.12	4.69	7.81	39.06	34.38	31.25	23.44
High-Yield	3.16	3.80	8.23	12.66	31.65	25.95	18.99	15.19
Diversified	14.63	20.19	25.60	31.32	27.34	21.78	19.24	14.63
Non-survivor	13.02	18.73	24.44	30.79	24.13	17.78	15.87	13.02
Survivor	10.45	14.18	18.66	23.32	31.90	26.87	22.57	16.79
All fund	11.40	15.86	20.80	26.09	29.02	23.50	20.09	15.39
Panel D: MBS sector timing								
Group	$t < -2.326$	$t < -1.960$	$t < -1.645$	$t < -1.282$	$t > 1.282$	$t > 1.645$	$t > 1.960$	$t > 2.326$
Corporate	1.56	3.12	9.38	10.94	17.19	14.06	7.81	6.25
High-Yield	6.33	10.76	19.62	31.65	12.66	6.96	4.43	4.43
Diversified	6.84	8.90	11.61	16.22	21.30	15.26	11.76	8.90
Non-survivor	7.62	10.79	15.87	20.00	17.46	12.70	9.21	6.67
Survivor	5.60	7.65	11.19	17.91	20.52	14.18	10.63	8.58
All fund	6.35	8.81	12.93	18.68	19.39	13.63	10.11	7.87

Note: The table summarizes the distribution of t-statistics for the liquidity timing coefficients using Equations (3) and (5). We require funds to have at least 36 monthly observations to be included in the analysis. The Newey-West t-statistics are reported. Results are presented for corporate, high-yield, diversified, non-surviving, surviving, and all bond funds. This table shows the percentage of funds with t-statistics that are greater than or less than the indicated *t*-values.

5% significance level). These results are consistent with results obtained from the standard approach, which simply counts the number of significant positive timing coefficients.

5.3 | Bootstrap Analysis

We conduct a bootstrap analysis in this subsection based on the key findings described in Section 5.1. Our goal is to test whether the actual bond funds with liquidity timing skills are statistically significantly different from those bootstrapped bond funds without liquidity timing skills. The bootstrap approach ensures that regression results are valid for funds with highly non-normal returns.

Our procedure is very similar to the bootstrap approaches of Cao, Chen, et al. (2013) and Cao, Simin, and Wang (2013). We first estimate the liquidity timing model in Equation (3) for each fund p and retain the parameter estimates and time series of residuals, that is,$\{\hat{\alpha}_p, \hat{\theta}_{m,p}, \hat{\beta}_{m,p}, \hat{\beta}_{hy,p}, \hat{\beta}_{mbs,p}\}$ and $\{\hat{\varepsilon}_{p,t}, t = 0, \ldots, T_p\}$, where T_p is the number of monthly observations for fund p. We then resample the residuals with replacement and obtain a randomly

TABLE 14 | False discovery rate.

	$\theta < 0$			$\theta > 0$		
	$p < 0.01$	$p < 0.05$	$p < 0.10$	$p < 0.10$	$p < 0.05$	$p < 0.01$
MKT timing	3.64	6.23	7.76	12.93	9.64	5.99
IG timing	1.65	3.17	4.11	6.35	4.47	2.47
HY timing	6.46	9.05	12.69	16.33	13.98	9.4
MBS timing	0.94	2.70	4.70	5.64	4.35	1.76

Note: This table reports the percentage of funds with *p*-values (2-sided) below the indicated thresholds after controlling for the false discovery rate. $\theta < 0$ and $\theta > 0$ denote negative and positive liquidity timing ability, respectively.

resampled time series of residuals $\{\hat{\varepsilon}^b_{p,t}, b = 1, 2, \ldots, B\}$, where B is the total number of bootstrap iterations.

We construct a time series of bootstrapped returns for fund p that has no liquidity timing skills, that is, we set the coefficient on the liquidity timing term, $\hat{\theta}_{m,p}$,to be zero, as follows:

$$r^b_{p,t} = \hat{\alpha}_p + \hat{\beta}_{m,p} MKT_t + \hat{\beta}_{hy,p,} \; HY_t + \hat{\beta}_{mbs,p} MBS_t + \hat{\varepsilon}^b_{p,t} \qquad (10)$$

We then estimate the bootstrapped liquidity timing coefficient, $\hat{\theta}^b_{m,p}$, for fund p and its Newey-West t-statistic, $\hat{t}^b_{\hat{\theta}_{m,p}}$, using the liquidity timing model in Equation (3). By construction, the bootstrapped liquidity-timing ability is equal to zero, and any non-zero timing coefficients and their t-statistics are purely due to sample variation or luck.

We repeat this process for each fund p and obtain the cross-sectional distribution of liquidity-timing coefficients and their t-statistics across all sample funds. We save these values at various percentile points in the cross-section, that is, 1st, 5th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles.

Repeating this procedure for B-time iterations, we obtain hypothetical distributions of cross-sectional timing coefficients and their t-statistics for each percentile. The bootstrapped *p*-value is calculated as follows:

$$p = \frac{1}{B} \sum_{b=1}^{B} I_{|\pi^b| > |\pi|} \qquad (11)$$

$$I_{|\pi^b| > |\pi|} = \begin{cases} 1 & |\pi^b| > |\pi| \\ 0 & \text{otherwise} \end{cases} \qquad (12)$$

where B is the number of iterations and I is an indicator function. π^b and π are the cross-sectional statistics of the bootstrapped and actual liquidity timing coefficients or their t-statistics, respectively. We run our bootstrap tests mainly for the t-statistics of the liquidity timing coefficients because of their superior statistical properties in bootstrap analysis (Kosowski et al. 2006; Jiang et al. 2007; Cao, Chen, et al. 2013; Cao, Simin, and Wang 2013).

We then perform other bootstrap tests in which the t-statistics are sorted by liquidity timing coefficients with respect to investment grade, high-yield, and MBS factors. For each bond sector, using our multifactor liquidity timing model in Equation (5), we first generate time series returns of bootstrapped funds that have no liquidity timing skills. Then, we estimate the t-statistics of these liquidity coefficients for actual funds as well as bootstrapped funds. After that, for liquidity timing skills with respect to bond sectors, we draw inferences about the existence of skilled managers by comparing the actual t-statistics to the bootstrapped t-statistics for individual funds at various percentile points in the cross-sectional distribution. *p*-values are calculated using Equation (11).

If the bootstrapped *p*-value for a positive t-statistic is close to zero (i.e., the t-statistic of actual positive liquidity coefficient is consistently higher than the corresponding bootstrapped values), this fund is said to exhibit positive liquidity timing ability that is not purely due to luck. Similarly, if the bootstrapped *p*-value for a negative t-statistic of the liquidity timing coefficient is close to zero, we infer that this fund has negative liquidity timing skill that is not due to bad luck.

Panel A of Table 15 reports the cross-sectional distribution of t-statistics of liquidity timing coefficients for the overall bond market and corresponding *p*-values at different percentiles from the bootstrap analysis. For the all-bond fund group, the evidence suggests that the top-liquidity timing funds (e.g., 90th to 99th) are unlikely to be attributed to random chance. Specifically, for the sample of all bond funds, the t-statistics of liquidity timing coefficients at the 90th, 95th, and 99th percentiles are 2.69, 3.69, and 5.54, respectively, with empirical *p*-values all close to zero. In terms of subgroups of bond funds, the significant liquidity timing coefficients produced by the top percentile funds from 90th to 99th are not purely due to luck for the sample of diversified fund, surviving, and non-surviving fund groups. However, the top percentiles of corporate bonds and high-yield bonds show liquidity timing ability that is attributed to random sampling variation, as the *p*-values associated with t-statistics of timing coefficients are greater than 10% (with only the exception of the top 1% fund).

In Table 15, Panels B–D report the t-statistics and associated *p*-values for the liquidity timing coefficients with respect to investment grade, high-yield, and MBS factors, respectively. Our bootstrap tests reveal three main features related to investment grade, high-yield, and MBS sectors.

First, in terms of IG sector liquidity timing, the result provides strong evidence that fund managers have positive liquidity timing skills for the investment grade factor that is not due to luck. For all bond funds, top percentiles (90th, 95th, and 99th) show consistent and significant timing skills for investment grade factor as t-statistics of their timing coefficients are significant at 5% level

TABLE 15 | Bootstrap analysis of liquidity timing.

Group	Percentile	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Overall MKT timing										
Corporate	t-statistic	−8.01	−5.55	−4.12	−2.40	−0.79	0.53	1.64	2.11	3.96
	p	0.00	0.00	0.00	0.00	0.00	0.92	0.50	0.49	0.04
High-Yield	t-statistic	0.00	−2.60	−1.44	−0.31	0.33	0.86	1.32	1.61	4.75
	p	0.93	0.05	0.93	1.00	0.02	0.53	0.98	1.00	0.00
Diversified	t-statistic	−6.84	−2.80	−1.63	−0.53	0.68	1.87	3.00	3.80	5.58
	p	0.00	0.00	0.78	1.00	0.00	0.00	0.00	0.00	0.00
Non-survivor	t-statistic	−3.43	−1.72	−1.39	−0.54	0.62	1.88	3.20	3.92	5.59
	p	0.37	1.00	0.99	1.00	0.00	0.00	0.00	0.00	0.00
Survivor	t-statistic	−7.47	−3.76	−2.52	−0.72	0.44	1.38	2.33	3.16	5.27
	p	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00
All fund	t-statistic	−6.93	−3.07	−1.77	−0.57	0.51	1.55	2.69	3.69	5.54
	p	0.00	0.00	0.15	1.00	0.00	0.00	0.00	0.00	0.00
Panel B: IG sector timing										
Group	**Percentile**	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
Corporate	t-statistic	−4.41	−3.16	−2.17	−1.30	−0.43	0.42	1.10	1.50	2.71
	p	0.07	0.01	0.03	0.03	0.04	0.98	0.97	0.94	0.55
High-Yield	t-statistic	−4.29	−2.22	−1.36	−0.47	0.37	1.36	2.08	2.55	3.88
	p	0.04	0.22	0.91	1.00	0.00	0.00	0.01	0.02	0.02
Diversified	t-statistic	−4.21	−2.47	−1.78	−0.89	0.16	1.16	2.20	2.99	4.20
	p	0.00	0.00	0.06	0.36	0.02	0.00	0.00	0.00	0.00
Non-survivor	t-statistic	−3.72	−2.14	−1.46	−0.66	0.30	1.21	2.21	2.99	4.10
	p	0.12	0.51	0.93	0.98	0.00	0.00	0.00	0.00	0.00
Survivor	t-statistic	−4.48	−2.54	−1.93	−0.94	0.06	1.04	2.05	2.64	4.08
	p	0.00	0.00	0.00	0.11	0.43	0.01	0.00	0.00	0.00
All fund	t-statistic	−4.19	−2.47	−1.74	−0.87	0.16	1.16	2.17	2.82	4.09
	p	0.00	0.00	0.07	0.43	0.01	0.00	0.00	0.00	0.00
Panel C: HY sector timing										
Group	**Percentile**	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
Corporate	t-statistic	−2.13	−1.66	−1.20	−0.26	1.05	2.30	3.91	4.68	7.14
	p	0.96	0.95	0.97	1.00	0.00	0.00	0.00	0.00	0.00
High-Yield	t-statistic	−2.92	−1.93	−1.57	−0.69	0.53	1.70	3.16	4.25	7.05
	p	0.90	0.90	0.72	0.87	0.00	0.00	0.00	0.00	0.00
Diversified	t-statistic	−6.73	−4.08	−3.03	−1.67	−0.15	1.42	2.92	4.03	6.40
	p	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Non-survivor	t-statistic	−5.85	−3.62	−2.65	−1.63	−0.15	1.19	2.70	3.70	6.18
	p	0.00	0.00	0.00	0.00	0.11	0.01	0.00	0.00	0.00
Survivor	t-statistic	−6.18	−3.66	−2.34	−1.14	0.24	1.74	3.37	4.28	7.23
	p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
All fund	t-statistic	−5.93	−3.62	−2.50	−1.35	0.07	1.54	3.14	4.14	6.98
	p	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00
Panel D: MBS sector timing										
Group	**Percentile**	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
Corporate	t-statistic	−2.70	−1.83	−1.60	−0.70	0.07	0.77	1.78	2.44	3.07
	p	0.72	0.85	0.59	0.81	0.73	0.57	0.18	0.09	0.25
High-Yield	t-statistic	−4.31	−2.67	−2.04	−1.41	−0.54	0.42	1.39	1.81	3.51
	p	0.03	0.01	0.02	0.00	0.00	1.00	0.85	0.81	0.05
Diversified	t-statistic	−3.91	−2.60	−1.85	−0.83	0.06	1.09	2.16	2.98	4.26
	p	0.00	0.00	0.01	0.74	0.41	0.00	0.00	0.00	0.00
Non-survivor	t-statistic	−3.97	−2.85	−2.06	−0.97	−0.16	0.83	1.87	2.54	3.76
	p	0.03	0.00	0.00	0.18	0.08	0.60	0.02	0.01	0.02
Survivor	t-statistic	−4.00	−2.41	−1.77	−0.92	−0.01	1.07	2.11	3.01	4.17
	p	0.00	0.01	0.08	0.26	0.91	0.00	0.00	0.00	0.00
All fund	t-statistic	−3.81	−2.55	−1.87	−0.93	−0.06	1.00	1.99	2.74	4.17
	p	0.00	0.00	0.00	0.16	0.32	0.00	0.00	0.00	0.00

Note: This table presents the results of the bootstrap analysis using the liquidity timing models in Equations (3) and (5). We require funds to have at least 36 monthly observations to be included in the analysis. Results are provided for corporate, high-yield, diversified, non-surviving, surviving, and all bond funds. For each fund group, the first row reports the sorted Newey-West t-statistics of the liquidity-timing coefficients, and the second row shows the corresponding bootstrapped *p*-values.

and associated bootstrap p-values are all less than 1%. This finding holds for subgroups of non-surviving and surviving, diversified funds, and high-yield funds. For example, diversified funds in the 90th, 95th, and 99th percentiles of the distribution of timing coefficients exhibit significant and positive t-statistics with associated p-values close to zero. Top-ranked corporate funds do not show liquidity timing ability due to skills, as the p-values associated with the t-statistics of timing coefficients are greater than 10%.

Second, for the HY sector liquidity timing, we find that top percentile funds (from 90th to 99th percentile) in the group of all bond funds show positive and significant liquidity timing abilities that are not purely due to luck. This pattern holds for subgroups of corporate, high-yield, diversified, surviving, and non-surviving bond funds. The evidence is stronger for corporate bond funds, where the fund ranked at the 75th percentile still has significant t-statistics of 2.30 with bootstrapped p-values close to zero. These findings are consistent with those documented at the portfolio level in Section 4.2 and confirm that fund managers successfully time market liquidity by overweighting the high-yield bond as corporate market liquidity increases.

For the MBS sector, we are interested in the bottom percentile of MBS sector liquidity timing coefficients, as we expect funds to reduce their sensitivity to the MBS sector when corporate bond market liquidity improves. There is evidence of significant negative MBS sector liquidity timing ability due to skills rather than pure luck for the bottom percentiles from 1st to 10th. For all bond funds, the bottom 1st–10th percentile funds have significant and negative liquidity timing coefficients for the MBS factor. The associated p-values for the t-statistics of MBS timing coefficients are close to zero. This negative MBS timing pattern is observed across all bond fund categories, except in the case of corporate bond funds.

To address serial dependence in liquidity and returns, we implement a time-series block bootstrap with a block length of 6 months. Each block contains all funds observed over six consecutive months, ensuring that both serial correlation within funds and cross-sectional dependence across funds are preserved. In untabulated results, our findings remain unchanged.

Overall, our bootstrap analysis confirms the findings in Section 5.1 that the top-ranked fund shows significant liquidity timing skills at the individual fund level. The bootstrap test shows strong evidence of significant market and sector liquidity timing skills that are not due to sampling variation.

Our results thus give us strong support to claim that sector liquidity timing skills are likely to be misidentified as market liquidity timing skills in models that account only for the overall bond market risk factor. This misidentification problem turns out to be important but is ignored in previous studies (e.g., Chen et al. 2010; Li et al. 2017).

6 | Persistence and Performance

6.1 | Persistence in Liquidity Timing Skills

In this section, we study the persistence of liquidity timing skills, as true timing skills due to managerial skills should persist over time (Chen et al. 2013). We examine whether fund managers who have demonstrated substantial liquidity timing skills over the past 3 years continue to exhibit such skills in the subsequent periods. In order to accomplish this goal, we proceed in four steps.

First, for each fund, we estimate its past liquidity timing coefficients by running the liquidity timing models in Equation (3) using the most recent 36-month returns. Second, we sort funds by their past liquidity timing coefficients, assign them to decile portfolios, and hold these portfolios for 12 months. The time series of portfolio returns during the holding period is obtained. We also calculate the return of the spread portfolio, which is the difference in returns between the top and bottom decile portfolios. Third, after holding the portfolio for 12 months, we reform decile portfolios based on the most recent 3-year liquidity timing coefficients and calculate the holding period returns of these decile portfolios. Finally, for each portfolio, the post-ranking liquidity timing coefficient is estimated by running the corresponding liquidity timing model over the full sample period. To check the robustness of our results, we also form portfolios using alternative holding periods, that is, 6-, 24-, and 36-month. We follow the same procedure to estimate the post-ranking liquidity timing coefficients with respect to investment grade, high-yield, and MBS factors, using the liquidity timing model in Equation (5).

Table 16 reports the results. As shown in the table, fund managers exhibit strong persistence of HY sector liquidity timing skills in Panel C, while they show no persistence of liquidity timing for the MKT factor in Panel A. For example, when funds are ranked based on their HY timing coefficients, the post-ranking liquidity timing coefficient is increasing in magnitude from the bottom decile to the top decile portfolios. For all holding periods, the HY liquidity timing coefficients for all top portfolio and spread portfolios are statistically significant at the 1% level.

In Panels B and D, there is some evidence of liquidity timing persistence with respect to IG and MBS factors. When funds are ranked based on their liquidity timing coefficients for the IG (MBS) factor, the post-ranking timing coefficients show an increasing (decreasing) pattern from the bottom decile to the top decile. However, we only find significant IG and MBS liquidity timing coefficients at the 5% level for a short holding period (i.e., 6 months).

Based on these persistence tests, we conclude that liquidity timing in the high-yield sector is more evident than in the investment grade and MBS sectors. We do not find persistence of liquidity

TABLE 16 | Persistence in liquidity timing skills.

	6 months		12 months		24 months		36 months	
	Panel A: overall MKT timing							
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Top	−0.36	(−0.42)	−0.26	(−0.32)	−0.08	(−0.10)	0.01	(0.01)
Bottom	0.19	(0.30)	−0.14	(−0.25)	−0.03	(−0.06)	0.12	(0.30)
T-B	−0.55	(−0.38)	−0.13	(−0.10)	−0.05	(−0.04)	−0.11	(−0.10)
	Panel B: IG sector timing							
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Top	3.85***	(3.65)	0.45	(0.33)	1.76*	(1.77)	1.36	(1.07)
Bottom	−1.33	(−0.56)	−0.55	(−0.28)	−1.20	(−0.59)	−1.56	(−0.80)
T-B	5.18**	(2.24)	1.00	(0.53)	2.96*	(1.67)	2.93	(1.59)
	Panel C: HY sector timing							
	Coefficient	**t-statistic**	**coefficient**	**t-statistic**	**coefficient**	**t-statistic**	**coefficient**	**t-statistic**
Top	1.39***	(8.33)	1.44***	(7.18)	1.25***	(5.75)	1.22***	(4.71)
Bottom	−0.05	(−0.32)	−0.07	(−0.70)	0.24***	(2.68)	0.12	(0.86)
T-B	1.44***	(8.16)	1.52***	(6.27)	1.02***	(4.51)	1.10***	(3.95)
	Panel D: MBS sector timing							
	Coefficient	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Top	2.08	(0.78)	1.10	(0.50)	1.86	(0.78)	2.30	(0.96)
Bottom	−4.60***	(−2.74)	0.77	(0.47)	−1.12	(−0.82)	−0.64	(−0.42)
T-B	6.69**	(2.07)	0.34	(0.14)	2.99	(1.25)	2.94	(1.23)

Note: For each fund, we estimate its past liquidity timing coefficient by running the liquidity timing model in Equation (3) using the most recent 36-month returns. We sort funds by their past liquidity timing coefficients, assign them to decile portfolios, and hold these portfolios for 12 months. The time series of portfolio returns during the holding period is obtained. We also calculate the return of the spread portfolio, which is the difference in returns between the top and bottom decile portfolios. After holding the portfolios for 12 months, we reform decile portfolios based on the most recent 3-year liquidity timing coefficients and recalculate the holding period returns of these decile portfolios. We repeat this process over the full sample period. Finally, for each portfolio, the post-ranking liquidity timing coefficient is estimated by running the corresponding liquidity timing models over the whole sample period. To check the robustness of our results, we also form portfolios using alternative holding periods, that is, 6-, 24-, and 36-month. We follow the same procedure to estimate the post-ranking liquidity timing coefficients with respect to investment grade, high-yield, and MBS factors, using the liquidity timing model in Equation (5). ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

timing skills for the overall bond market. Overall, the persistence evidence supports our main finding that sector-level liquidity timing—especially in the high-yield sector—reflects genuine managerial skill.

6.2 | Liquidity Timing Ability and Future Fund Performance

It is natural to ask whether liquidity timing ability transfers into superior performance. In this section, we examine whether liquidity timing predicts the future risk-adjusted performance of bond mutual funds. Using the decile portfolio returns from Section 6.1, we are able to evaluate the out-of-sample performance of bond funds sorted by their liquidity timing coefficients. For each portfolio, we estimate its raw return and post-ranking alpha by running the corresponding performance models in Equations (1) and (4).

In Table 17, panels A–D report the raw returns and post-ranking alphas for the decile portfolios based on the liquidity timing coefficients with respect to the MKT, IG, HY, and MBS sectors, respectively. We find little evidence of superior performance from decile portfolios ranked by the MKT timing coefficient. However, there is some evidence of significant alphas for funds ranked by liquidity timing coefficient for bond sectors in the short to medium term, although not all holding periods generate statistically significant results.

First, we find some evidence of positive and significant alphas for portfolios sorted by IG liquidity timing coefficients. For a 6-month holding period, the alpha of the-top-minus bottom spread portfolio is 0.16% per month (1.92% annually), which is statistically significant at the 5% level. The top deciles have positive alpha (though not significant), while the bottom deciles show negative alphas. Second, the funds with positive HY liquidity timing ability outperform those with negative liquidity HY timing ability. The alpha is statistically significant for the difference between the top and bottom decile (T-B) with a magnitude of 0.11% per month (or 1.31% annually) and a t-statistic of 1.86 when the holding period is 24 months. Finally, we also find positive abnormal performance for decile portfolios ranked

TABLE 17 | Liquidity timing and fund performance.

	6 months		12 months		24 months		36 months	
	Panel A: MKT timing							
	Raw return	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**
Top	0.39	−0.03	0.37	−0.05	0.33	−0.05	0.30	−0.08*
Bottom	0.37	0.03	0.37	0.04	0.33	0.00	0.31	−0.02
T-B	0.02	−0.06	0.00	−0.10	0.00	−0.06	−0.01	−0.06
		(0.53)		(−1.01)		(−0.74)		(−0.83)
	Panel B: IG sector timing							
	Raw return	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**
Top	0.49	0.08	0.43	0.04	0.35	−0.04	0.39	0.00
Bottom	0.27	−0.07	0.26	−0.04	0.26	−0.03	0.21	−0.10**
T-B	0.23	0.16**	0.17	0.08	0.09	−0.01	0.19	0.10
		(2.57)		(1.40)		(−0.12)		(1.40)
	Panel C: HY sector timing							
	Raw return	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**	**Raw return**	**Alpha**
Top	0.39	0.09	0.41	0.06	0.36	0.04	0.33	−0.05
Bottom	0.38	−0.02	0.32	−0.02	0.28	−0.08	0.28	−0.06
T-B	0.01	0.11	0.09	0.09	0.07	0.11*	0.05	0.01
		(1.57)		(1.18)		(1.86)		(0.19)
	Panel D: MBS sector timing							
	Raw return	**Alpha**	**Raw return**	**Alpha**	**Raw Return**	**Alpha**	**Raw return**	**Alpha**
Top	0.31	−0.07	0.30	−0.05	0.29	−0.04	0.20	−0.10**
Bottom	0.49	0.1	0.43	0.08	0.36	0.01	0.41	0.03
B-T	0.17	0.17**	−0.13	0.13*	0.07	0.06	0.21	0.13
		(2.12)		(1.79)		(0.71)		(1.63)

Note: For each fund, we estimate its past liquidity timing coefficient by running the liquidity timing models in Equation (3) using the most recent 36-month returns. We sort funds by their past liquidity timing coefficients, assign them to decile portfolios, and hold these portfolios for 12 months. The time series of portfolio returns during the holding period is obtained. We also calculate the return of the spread portfolio, which is the difference in returns between the top and bottom decile portfolios. After holding the portfolios for 12 months, we reform the decile portfolios based on the most recent 3-year liquidity timing coefficients and recalculate the holding period returns of these decile portfolios. We repeat this process over the full sample period. To check the robustness of our results, we also form portfolios using alternative holding periods, that is, 6-, 24-, and 36-month. We follow the same procedure to construct decile portfolios based on the liquidity timing coefficients with respect to investment grade, high-yield, and MBS factors, using the liquidity timing model in Equation (5). Finally, for each portfolio and liquidity timing type, we estimate the post-ranking alpha by running the corresponding liquidity timing models in Equations (1) and (4). ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

by MBS liquidity timing coefficients. Recall that we expect negative MBS liquidity ability. Funds with the negative liquidity MBS timing ability outperform those with positive liquidity MBS timing coefficients. The spread portfolio (B-T) generates significant alphas of 0.17% per month (2.04% annually) and 0.13% per month (1.56% annually) for a 6-month and 12-month holding period, respectively.

Collectively, the evidence suggests that funds with more significant IG, HY, and MBS sector liquidity timing abilities generate higher future risk-adjusted performance at least to some extent. These results are both economically and statistically significant.

6.3 | Liquidity Timing Ability and Fund Characteristics

While we document positive liquidity timing ability at the individual fund level, it remains unclear what kind of funds are more likely to possess liquidity timing ability. In this section, we examine whether liquidity timing is associated with fund characteristics. Answering this question would help investors identify successful liquidity timers. To answer this question, we examine the cross-sectional relationship between liquidity timing and the following characteristics: age, size, net expense ratio, turnover ratio, and flow. We first estimate the liquidity timing models in Equations (3) and (5) and obtain the liquidity timing coefficient, θ, for all bond funds with a minimum of 36 monthly return observations. We then estimate the following cross-sectional regression model using funds within each category:

$$\phi_{k,p} = \alpha + b_1 \text{Age}_p + b_2 \text{Size}_p + b_3 \text{Expense}_p + b_4 \text{Turnover}_p + b_5 \text{Flow}_p + \varepsilon_p \tag{13}$$

where $\phi_{k,p}$ is the liquidity timing coefficient for fund p under timing strategy k, which includes aggregate market timing, investment grade sector timing, high-yield sector timing, and MBS sector timing. We define ϕ as the estimated timing coefficient multiplied by a statistical significance indicator. Specifically, $\phi = \hat{\theta} \cdot D$, where D equals one if the corresponding coefficient is statistically significant at the 10% level (t = 1.645) and zero otherwise. This construction ensures that only statistically reliable effects contribute to ϕ. Age_p represents the age of fund p, and Size_p, Expence_p, Turnover_p, and Flow_p denote the time-series averages of total net assets (TNA), net expense ratio, turnover ratio, and fund flows for fund p, respectively. All variables have been standardized to account for differences in scale.

As shown in Table 18, first, we find a consistently positive and statistically significant relationship between net expense ratios and liquidity timing ability across all timing strategies, suggesting that higher expense bond funds tend to exhibit stronger timing behaviour. This may reflect the greater costs associated with active liquidity management. Second, fund flows and fund age are negatively related to high-yield sector liquidity timing ability, indicating that liquidity timing skill may decline with larger investor inflows or longer fund histories. Third, the evidence on turnover is mixed: aggregate market liquidity timing ability increases with fund turnover, whereas investment grade sector liquidity timing ability decreases with turnover. Finally, we find no significant relationship between fund size and liquidity timing ability across any of the strategies.

7 | Further Robustness Tests

We further conduct additional analyses to ensure the robustness of our results. In the following tests, we control for alternative liquidity measures, additional risk factors, and alternative liquidity timing specifications. To conserve space, these results are reported in the Appendix S1.

7.1 | Alternative Liquidity Measures

Liquidity is difficult to observe, so our findings of liquidity timing using the latent market liquidity factor may differ from a specific liquidity measure. We examine this question using alternative liquidity measures described in Section 3.2. We find broadly similar evidence of liquidity timing across all alternative liquidity measures. For example, for all liquidity measures (except for Amihud liquidity measures), the liquidity timing coefficients for portfolios of all bond funds are insignificant at the 5% level. Among funds with different investment objectives, diversified funds display the most significant liquidity-timing ability with t-statistics greater than 2 for all liquidity measures. These results are consistent with the results in Table 3 using the PCA to measure market liquidity. Therefore, our results of liquidity timing are not influenced by the use of a particular liquidity measure.

7.2 | Control for Liquidity Risk Factor

Lin et al. (2011) show that liquidity risk plays a vital role in describing bond returns. Our findings may be biased by omitting a liquidity risk factor. To address this concern, we construct the traded liquidity risk factor of Pástor and Stambaugh (2003), measured as the return spread between the top and bottom equally-weighted decile portfolios of bonds sorted on historical liquidity betas. Specifically, at the end of each month t, we estimate a bond's sensitivity to innovations in aggregate liquidity, that is, liquidity beta, by running the following regression using the most recent 3 years of data.

$$r_{i,t} = \alpha_i + \beta_{l,i} \tilde{L}_{m,t} + \beta_{m,i} \text{MKT}_t + \beta_{\text{hy},i} HY_t + \beta_{\text{mbs},i} \text{MBS}_t + \varepsilon_{p,t} \tag{14}$$

where $r_{i,t}$ denotes bond's excess return, $\tilde{L}_{m,t}$ is the innovation in aggregate liquidity. We rank bonds according to estimated liquidity betas, $\beta_{l,i}$, across bonds and form equally weighted decile portfolios based on rank. The monthly excess returns of these portfolios over the next month are computed, after which we roll the process by 1 month. To form the tradable portfolio, LIQ, we long the top decile with high liquidity betas and short the bottom decile with low liquidity betas.

We then employ the liquidity timing model of Equation (3) augmented by a traded liquidity risk factor:

$$\begin{aligned} r_{p,t} = \alpha_p + \beta^0_{m,p} \text{MKT}_t + \theta_{m,p} \left(L_{m,t} - \overline{\text{L}}_m \right) \text{MKT}_t + \beta_{\text{hy},p} HY_t \\ + \beta_{\text{mbs},p} \text{MBS}_t + \beta_{l,p} LIQ_t + \varepsilon_{p,t} \end{aligned} \tag{15}$$

Comparing the results with those in Table 3, we find that liquidity timing results remain materially unchanged when the liquidity risk factor is considered to explain bond mutual fund returns. The liquidity timing coefficient of all bond funds remains insignificant after controlling for the liquidity risk factor. Besides, there are no significant beta estimates on the liquidity risk factor in explaining bond mutual fund returns. This finding is similar to Cao, Simin, and Wang (2013), who find that the liquidity risk factor is insignificant in explaining equity fund returns. The results indicate that adding liquidity risk is unlikely to substantially affect the significance of liquidity timing coefficients.

7.3 | Alternative Timing Model

A particular timing specification might affect the results of liquidity timing skills. As a further robustness test, we use alternative

TABLE 18 | Cross-sectional regression of liquidity-timing coefficients on fund characteristics.

	Intercept	Age	Size	Expense	Turnover	Flow	R^2
ϕ_{mkt}	0.22***	0.02	0.01	0.03**	0.03**	−0.03*	0.03
	(14.31)	(1.17)	(0.65)	(2.08)	(2.29)	(−1.65)	
ϕ_{ig}	0.17***	0.02	−0.01	0.04***	−0.03**	−0.01	0.03
	(10.48)	(1.12)	(−0.09)	(2.82)	(−2.00)	(−0.81)	
ϕ_{hy}	0.21***	−0.10***	0.01	0.11***	0.04*	−0.08***	0.05
	(8.50)	(−3.54)	(0.50)	(4.45)	(1.75)	(−2.64)	
ϕ_{mbs}	0.14***	0.00	0.00	0.05***	−0.00	0.01	0.02
	(9.56)	(0.17)	(0.18)	(3.48)	(−0.51)	(0.39)	

Note: This table reports the regression results of liquidity-timing coefficients on fund characteristics:

$$\phi_{k,p} = \alpha + b_1\text{Age}_p + b_2\text{Size}_p + b_3\text{Expense}_p + b_4\text{Turnover}_p + b_5\text{Flow}_p + \varepsilon_p$$

where $\phi_{k,p}$ is the liquidity timing coefficient for fund p under timing strategy k, which includes aggregate market timing, investment-grade sector timing, high-yield sector timing, and MBS sector timing. We define ϕ as the estimated timing coefficient multiplied by a statistical significance indicator. Specifically, $\phi = \hat{\theta} \cdot D$, where D equals one if the corresponding coefficient is statistically significant at the 10% level ($t = 1.645$) and zero otherwise. This construction ensures that only statistically reliable effects contribute to ϕ. Age_p represents the age of fund p, and Size_p, Expense_p, Turnover_p, and Flow_p denote the time-series averages of total net assets (TNA), net expense ratio, turnover ratio, and fund flows for fund p, respectively. All variables have been standardized to account for differences in scale. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

timing specifications to test the liquidity timing skill:

$$r_{p,t} = \alpha_p + \beta^0_{m,p}\text{MKT}_t + \theta_{m,p}\max\left(L_{m,t} - \overline{L}_m, 0\right)\text{MKT}_t + \beta_{\text{hy},p}HY_t + \beta_{\text{mbs},p}\text{MBS}_t + \varepsilon_{p,t} \tag{16}$$

where *max* denotes the maximum operator. This timing specification is based on the market timing model developed by Henriksson and Merton (1981), which provides an alternative way to measure liquidity timing ability.

The result shows little evidence of liquidity timing for all groups of bond mutual funds. Compared with the result in Table 3, the significance of the liquidity timing coefficient for diversified bond funds disappears. Overall, our result is highly consistent with the results reported in Table 3.

7.4 | Robustness Tests for the Multi-Sector Liquidity Timing Model

In unreported tables, we conduct all the robustness tests from Sections 7.1 to 7.3 using the multi-sector liquidity timing model in Equation (5). Overall, the result suggests that controlling for alternative liquidity measures, alternative timing specifications, and the liquidity risk factor does not materially affect the significance of liquidity timing coefficients with respect to IG, HY, and MBS factors. For brevity, these results are not reported but are available upon request.

7.5 | Control for Additional Risk Factors

Bond funds' returns are highly driven by interest rate risk (duration) and credit risk exposure. To control for potential omitted variable bias, we augment the bond fund model in Equation (5) with those two factors, including fund interest risk and credit risk.

$$r_{p,t} = \alpha_p + \theta_{\text{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\text{hy},p}\left(L_{m,t} - \overline{L}_m\right)\text{HY}_t + \theta_{\text{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\text{MBS}_t + \beta_{\text{ig},p}IG_t + \beta_{\text{hy},p}\text{HY}_\text{t} + \beta_{\text{mbs},p}\text{MBS}_t + \beta_{\text{ir},p}IR_t + \beta_{\text{cr},p}CR_t + \varepsilon_{p,t} \tag{17}$$

where *IR* is the interest risk, which is calculated as the term spread between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity, and the CR is credit risk, which is the ICE BofA US Corporate Index Option-Adjusted Spread (OAS). All related data are obtained from the Federal Reserve Bank of St. Louis.

After adding interest rate risk and credit risk factors into the model, we still find positive and significant HY sector liquidity timing for the portfolio of all bond funds and corporate bond funds after controlling for interest risk and OAS spread. Therefore, adding those two factors does not materially change our conclusions.

7.6 | Control for Government Bond Market Liquidity Timing

The purpose of this section is to examine whether bond funds can jointly time movements in corporate and government bond market liquidity. Our assumption is that bond fund managers may monitor the movement of liquidity in these two markets and use this information to adjust the underlying portfolio's exposure in their focused market, especially for diversified bond funds that hold substantial amounts of both government and corporate bonds.

To investigate whether bond funds jointly exploit the movements in corporate and government bond market liquidity, we extend the liquidity timing model in Equation (3) to test bond fund managers' joint timing ability regarding the corporate bond market and the government bond market. We hypothesize that bond fund managers forecast the fixed-income market betas using information on both corporate and government market liquidity as follows:

$$\beta_{m,p} = \beta^{0}_{m,p} + \theta^{c}_{m,p}\left(L^{c}{}_{m,t} - \overline{L}^{c}_{m}\right) + \theta^{g}_{m,p}\left(L^{g}{}_{m,t} - \overline{L}^{g}_{m}\right) \tag{18}$$

where $L^{c}{}_{m,t}$ and $L^{g}{}_{m,t}$ are measures of the corporate bond market liquidity and government bond market liquidity in month t, respectively. The manager's signal is de-meaned by subtracting the corresponding means, $\overline{\mathrm{L}}^{c}_{m}$ and $\overline{\mathrm{L}}^{g}_{m}$, over the previous 36 months for ease of interpretation. The $L^{g}{}_{m,t}$ is measured as the high-low spread for the on-the-run benchmark 10-year US Treasury bond.

We substitute Equations (18) into (1) to time both corporate and government bond liquidity:

$$\begin{aligned}\mathrm{r}_{\mathrm{p,t}} = \alpha_{\mathrm{p}} &+ \beta^{0}_{\mathrm{m,p}}\mathrm{MKT}_{\mathrm{t}} + \theta^{\mathrm{c}}_{\mathrm{m,p}}\left(\mathrm{L}^{\mathrm{c}}_{\mathrm{m,t}} - \overline{\mathrm{L}}^{\mathrm{c}}_{\mathrm{m}}\right)\mathrm{MKT}_{\mathrm{t}} \\ &+ \theta^{\mathrm{g}}_{\mathrm{m,p}}\left(\mathrm{L}^{\mathrm{g}}_{\mathrm{m,t}} - \overline{\mathrm{L}}^{\mathrm{g}}_{\mathrm{m}}\right)\mathrm{MKT}_{\mathrm{t}} + \beta_{\mathrm{hy,p}}\mathrm{HY}_{\mathrm{t}} + \beta_{\mathrm{mbs,p}}\mathrm{MBS}_{\mathrm{t}} + \varepsilon_{\mathrm{p,t}}\end{aligned} \tag{19}$$

The coefficient $\theta^{\mathrm{c}}_{m,p}$ and $\theta^{\mathrm{g}}_{m,p}$ measure the liquidity timing ability for the corporate bond market and government bond market, respectively. If the fund managers have joint timing skills, both parameters $\theta^{\mathrm{c}}_{m,p}$ and $\theta^{\mathrm{g}}_{m,p}$ are expected to be positive and significant.

From the results of Equation (19), we do not find evidence of joint liquidity timing for all groups of bond funds. At the subgroup level, our results suggest that only diversified bond funds have significant positive liquidity timing for the corporate bond market at the portfolio level. Interestingly, diversified bond funds do not show government bond market liquidity timing skills, although those funds hold a proportion of government bonds in their portfolio. We also find that high-yield funds show positive and significant liquidity timing coefficients for the government bond market, suggesting high-yield funds use market liquidity fluctuations in government markets as input to adjust their exposure to the overall bond market.

7.7 | Control for Market Return and Market Volatility Timing

Bond mutual fund managers may also use other market information for timing purposes, such as market return or market volatility. It might be the case that funds successfully time market returns or volatility, but such timing is reflected in the liquidity timing coefficients. Therefore, market timing or volatility timing strategies may influence the significance of sector liquidity timing coefficients. To explore this possibility, we examine liquidity timing ability in the presence of market timing and volatility and express the market beta as a linear function of market excess return, market volatility, and market liquidity. This leads to the extension of the multi-sector liquidity timing model in Equation (5) to the following model:

$$\begin{aligned}r_{p,t} = \alpha_p &+ \beta^{0}_{\mathrm{ig},p}IG_t + \beta^{0}_{\mathrm{hy},p}HY_t + \beta^{0}_{\mathrm{mbs},p}MBS_t \\ &+ \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \lambda_{\mathrm{ig},p}IG^2_t + \gamma_{\mathrm{ig},p}\left(\mathrm{Vol}_{m,t} - \overline{Vol}_m\right)IG_t \\ &+ \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)HY_t + \lambda_{\mathrm{hy},p}HY^2_t + \gamma_{\mathrm{hy},p}\left(\mathrm{Vol}_{m,t} - \overline{Vol}_m\right)HY_t \\ &+ \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)MBS_t + \lambda_{\mathrm{mbs},p}MBS^2_t \\ &+ \gamma_{\mathrm{mbs},p}\left(\mathrm{Vol}_{m,t} - \overline{Vol}_m\right)MBS_t + \varepsilon_{p,t}\end{aligned} \tag{20}$$

where $Vol_{m,t}$ and $\overline{Vol}_m$ are the market volatility measure and its time series mean, respectively. We calculate time-varying market volatility as the realized market volatility following Busse (1999), which is the standard deviation of daily de-meaned excess market returns within month t. To keep consistent, we use the average volatility estimate over the previous 36 months as a proxy for the mean of volatility. The coefficients λ and γ measure market timing and volatility timing, respectively.

We find several interesting patterns after controlling for market return and market volatility timing. First, consistent with traditional timing literature, the market timing coefficients are either insignificant or significantly negative, suggesting no evidence of market timing at the portfolio level. Second, we find evidence of volatility timing for the diversified bond funds, where the volatility-timing coefficient for the investment grade sector, $\gamma_{ig,p}$, are significant at the 1% level. Lastly, we find that including market timing and volatility timing does not materially affect the significance of the liquidity timing coefficients. Comparing the results reported in Table 4, we can see that after controlling for market timing and volatility timing, the HY liquidity timing coefficients, $\theta_{hy,p}$, are still significant for the groups of all bond funds and corporate bond funds, although their t-statistics are smaller. We also find that high-yield bond funds demonstrate liquidity timing for the high-yield sector at the 1% level after controlling for return and volatility timing, which is not observed in Table 4.

These results indicate that the significance of liquidity timing is not due to the correlation between market returns (or volatility) and liquidity. Liquidity timing is therefore an important component of strategies of actively managed bond mutual fund strategies.

7.8 | Control for Coskewness Risk Factor

Bond return distributions are non-normal. Therefore, a mean–variance framework is not sufficient to fully characterize bond returns and their associated risks, and a higher-moment framework should be considered. Moreover, Chiang (2016) shows that coskewness is priced and plays an important role in bond asset allocation. To avoid potential omitted variable bias, we introduce a sector-level liquidity timing model that incorporates a coskewness risk factor.

$$\begin{aligned}r_{p,t} = \alpha_p &+ \theta_{\mathrm{ig},p}\left(L_{m,t} - \overline{L}_m\right)IG_t + \theta_{\mathrm{hy},p}\left(L_{m,t} - \overline{L}_m\right)HY_t \\ &+ \theta_{\mathrm{mbs},p}\left(L_{m,t} - \overline{L}_m\right)\mathrm{MBS}_t \\ &+ \beta_{\mathrm{ig},p}IG_t + \beta_{\mathrm{hy},p}HY_t + \beta_{\mathrm{mbs},p}MBS_t + \beta_{\mathrm{csw},p}CSW_t + \varepsilon_{p,t}\end{aligned} \tag{21}$$

where CSW_t is the coskewness risk factor. To construct the coskewness risk factor, we follow Adesi et al. (2004) and Chiang (2016) by running a regression of asset excess returns on the market excess return and its squared term. The slope coefficients from this regression are interpreted as the asset's market beta and coskewness, respectively. This coskewness measure is easy to estimate and straightforward to interpret: when market skewness increases, assets with positive coskewness become more attractive because they provide a hedge against adverse movements in the market index. To obtain time-varying coskewness for each bond, we estimate the regression recursively using a rolling window of 60 months. Bonds are ranked according to their estimated coskewness, and equally weighted quintile portfolios are formed based on these rankings. The monthly excess return of the portfolios over the next month is computed, after which we roll forward the process by 1 month. To construct the coskewness risk portfolio (CSW), we take a long position in the highest-coskewness quintile (Quintile 1) and a short position in the lowest-coskewness quintile (Quintile 5).

After adding the coskewness risk factor, we find that high-yield sector liquidity timing ability remains statistically significant for portfolios of all bond funds. At the fund-category level, corporate bond funds and high-yield bond funds exhibit stronger high-yield sector liquidity timing ability. Overall, our results remain robust after controlling for coskewness risk.

8 | Conclusion

In this paper, we examine the liquidity timing ability of bond mutual funds. This study is the first to investigate the bond fund market liquidity timing performance using intraday data from the TRACE database to measure corporate bond market liquidity. We use four common liquidity proxies that have been shown to be accurate estimators of corporate bond liquidity and apply the PCA to extract the latent liquidity factor from these liquidity proxies to represent the market-wide liquidity.

Our portfolio-level analysis reveals that US bond mutual fund managers as a group demonstrate sector-level liquidity timing skills. This sector liquidity timing strategy is achieved by tilting their portfolio towards high-yield bonds prior to periods of high (low) liquidity in the corporate bond market. These findings highlight sector liquidity timing as an important channel through which bond fund managers add value, complementing the evidence in Huang et al. (2025), which documents that a subset of U.S. bond mutual fund managers exhibits managerial skill. Our paper demonstrates that ignoring the sector-level liquidity timing may lead to incomplete or misleading inferences. Hence, we emphasize the importance of integrated liquidity timing models that incorporate sector-specific liquidity timing abilities.

We also analyse the liquidity timing performance of bond mutual funds at the individual fund level. Apart from high-yield liquidity timing skills, the results suggest that a subset of bond funds demonstrates liquidity timing skills with respect to the overall market, investment-grade, and MBS factors. Moreover, the bootstrap test shows that these liquidity timing skills are not purely due to luck. We also find that funds with high net expense ratios are more likely to exhibit these liquidity timing skills.

Finally, we examine whether the liquidity timing skills persist over time. Our results reveal persistence in liquidity timing skills for all risk factors, which motivates a further exploration of the out-of-sample performance of portfolios sorted by liquidity timing coefficients. We find partial evidence that past fund liquidity timing performance predicts future performance. Funds that report strong (weak) liquidity timing performance tend to earn positive (negative) abnormal returns subsequently, although these effects are not uniformly statistically significant.

To sum up, our findings highlight the value of active fund management for both academics and practitioners. For the former, our results add to the liquidity timing literature by providing new evidence of the sector liquidity timing ability of bond mutual funds. For the latter, we show that bond funds consistently time the market liquidity and adjust exposure to high-yield bonds, and this strategy helps predict future fund performance, which provides new insights into active bond fund management.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

Endnotes

[1] As of year-end 2024, the total net assets of taxable bond funds were around 4.27 trillion dollars, while municipal bond funds were about 0.80 trillion.

[2] Morningstar reports a fund's base currency in which it holds assets, calculates performance, and prepares financial reports. A fund may have multiple share classes offering exposure in different currencies; accordingly, Morningstar reports net asset values and returns for each share class in its respective base currency.

[3] Wharton Research Data Services (WRDS) was used in accessing the TRACE data. This service and the data available thereon constitute

valuable intellectual property and trade secrets of WRDS and/or its third-party suppliers.

[4]Dick-Nielsen (2009) suggests that the Amihud (2002) measure will be biased downwards if the agency trades are not removed.

[5]The monthly high-low spread is calculated directly using daily high and low prices. See Appendix S1 for details.

[6]We omit the time subscript t on β for notational simplicity in the paper.

[7]We keep using Newey and West (1987) t-statistic with 2 lags in the following liquidity timing analysis.

[8]Because dealers began reporting net positions in investment-grade and high-yield bonds only in March 2013, our regressions are based on data from March 2013 to September 2021. Given the relatively short sample period, we do not report equal-weighted portfolios of surviving and non-surviving funds.

[9]Due to the lack of net asset value data for non-surviving funds, we do not report the result for value-weighted portfolios of surviving and non-surviving funds.

[10]In detail, for the sector timing model, $\beta_{ig,t} = \beta_{ig,t-1} + \nu_{ig,t}$, $\beta_{hy,t} = \beta_{hy,t-1} + \nu_{hy,t}$, $\beta_{\mathrm{mbs},t} = \beta_{\mathrm{mbs},t-1} + \nu_{\mathrm{mbs},t}$.

[11]We measure liquidity innovations as the residuals from regressing market liquidity on its own two lags, changes in OAS, the bond market return, and the VIX index.

[12]We only control the false positive using the Benjamini and Hochberg (1995) method. To avoid the complexity, we do not use bootstrap p-values to control for the role of luck in the false discovery rate setting, such as Barras et al. (2010).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure A1.** Factor exposure space by fund categories. **Table A1**. Summary of bond fund features. **Table A2**. TRACE variables. **Table A3**. Liquidity timing test controlling for time-varying fund categories. **Table A4**. Liquidity timing test for alternative liquidity measures. **Table A5**. Liquidity timing test after controlling for liquidity risk factor. **Table A6**. Liquidity timing test after controlling for alternative timing model. **Table A7**. Liquidity timing test after controlling for additional risk factors. **Table A8**. Liquidity timing test after controlling for government bond market liquidity. **Table A9**. Liquidity timing test after controlling for market timing and volatility timing. **Table A10**. Liquidity timing test after controlling for coskewness risk.