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High frequency online inflation and term structure of interest rates: Evidence from China

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ABSTRACT

In the digital era, the information value of online prices, characterized by weak price stickiness and high sensitivity to economic shocks, deserves more attention. This paper integrates the high-frequency online inflation rate into the dynamic Nelson-Siegel (DNS) model to explore its relationship with the term structure of interest rates. The empirical results show that the weekly online inflation significantly predicts the yield curve, especially the slope factor, whereas the monthly official inflation cannot predict the yield curve and is instead predicted by the yield curve factors. The mechanism analysis reveals that, due to low price stickiness, online inflation is more sensitive to short-term economic fluctuations and better reflects money market liquidity, thereby having significant predictive power for short-term interest rates and the slope factor. Specifically, online inflation for non-durable goods and on weekdays shows stronger predictive power for the slope factor. The heterogeneity in price stickiness across these categories explains the varying impacts on the yield curve.

1. Introduction

The term structure of interest rates, represented by the yield curve, is a cornerstone in finance and economics, with significant implications for monetary policy, risk management, and investment strategies. Modeling the term structure has garnered spread attention in the literature (e.g., Nelson and Siegel, 1987; Diebold and Li, 2006; Christensen et al., 2011; Bauer and Rudebusch, 2017; Sihvonen, 2024). The relationship between the term structure and macroeconomic factors has also been extensively studied (e.g., Diebold et al., 2006; Ludvigson and Ng, 2009; Bekaert et al., 2021; Huang and Shi, 2022; Lucca and Wright, 2024). A particular focus has been on the link between the yield curve and inflation, including inflation expectations (Ang et al., 2008; Chernov and Mueller, 2012; Feunou and Fontaine, 2014) and inflation risk (Wright, 2011; Ulrich, 2013; Breach et al., 2020).

However, the rapid development of the digital economy in recent years has introduced new dynamics that may challenge traditional models and findings. The digital economy reduces various economic costs, including search costs, marginal costs, transportation costs, tracking costs, and verification costs (Goldfarb and Tucker, 2019). Research indicates that online prices are less sticky than

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offline prices (Lunnemann and Wintr, 2011; Gorodnichenko et al., 2018), and are more responsive to economic shocks (Gorodnichenko and Talavera, 2017; Cavallo et al., 2024). Consequently, high-frequency online inflation indicators[1] may offer more timely and accurate insights into economic conditions. Considering the increasing significance of online marketplaces, two important questions arise: What is the relationship between high-frequency online inflation and the term structure of interest rates? How do the mechanisms through which this new macroeconomic factor impacts the yield curve differ from those of traditional monthly offline inflation? Investigating this relationship could yield valuable insights, particularly as traditional inflation indicators might not fully capture the price dynamics in the digital era.

Over the past decade, China's online market has experienced exponential growth, with e-commerce transactions reaching 46.83 trillion yuan in 2023 and 915 million online shoppers by December 2023.[2] Today, China has the world's largest online market, characterized by increased information efficiency and reduced price stickiness (Jiang et al., 2020). The financial and informational value of high-frequency online inflation warrants greater attention. Additionally, China's treasury bond market, with a stock of 29.71 trillion yuan by the end of 2023, has become the second-largest in the world.[3] While previous studies have modeled China's yield curve and examined its determinants (e.g., Fan and Johansson, 2010; Lin and Niu, 2021; Zhang et al., 2022a; Jiang et al., 2024), the relationship between online inflation and the yield curve remains unexplored. Given China's position as the largest online market and the second-largest treasury bond market, it is particularly meaningful to use Chinese data to study the relationship between online inflation and treasury bond yields. The primary objective of this paper is to investigate how high-frequency online inflation can predict the yield curve and to explain the underlying mechanisms.

In this paper, we integrate the weekly online inflation indicator into the dynamic Nelson-Siegel (DNS) model, aiming to unveil the potential of this novel macroeconomic factor in shaping our understanding and prediction of term structures in the digital age. We uncover several pivotal findings regarding the relationship between high-frequency online inflation and the term structure of interest rates. Primarily, we find that weekly online inflation can significantly predict the slope factor of the yield curve, whereas the three term structure factors do not predict online inflation. The variance decompositions reveal that the influence of online inflation is particularly pronounced on the 6-month yield compared to the 5-year and 10-year yields, and online inflation predominantly accounts for the variance in the slope factor. This underscores the pronounced predictive power of online inflation on short-term interest rates. Additionaly, when benchmarked against the yields-only model, our refined model incorporating online inflation consistently demonstrates superior predictive performance across all maturities.

In contrast, the official inflation is predicted by yield curve factors, and online inflation has significant predictive power over official inflation. Mechanism analyses show that with weak price stickiness, high-frequency online inflation can better reflect money market liquidity movements, thereby improving the predictability of short-term interest rates and the slope factor. Besides, online inflation rates in different sectors, with varying attributes, and on weekdays versus weekends, show obvious heterogeneity in predicting the yield curve, which is closely related to the heterogeneity in price stickiness across these categories.

This paper makes three key contributions to the existing literature. First, our study adds to the body of research on the relationship between the term structure of interest rates and macroeconomic factors. Scholars have emphasized the yield curve's predictive power for real economic activity (Ang et al., 2006; Han et al., 2021) and future inflation (Mishkin, 1990; Berardi, 2009). Research has also investigated the impacts of various macro factors on the yield curve, including large datasets of macroeconomic indicators (Ludvigson and Ng, 2009; Coroneo et al., 2016; Levant and Ma, 2016; Fernandes and Vieira, 2019; Huang and Shi, 2022), macro risks (Joslin et al., 2014; Bekaert et al., 2021), monetary policy (Kaminska et al., 2021; Lucca and Wright, 2024), the debt-to-GDP ratio (Nguyen, 2022), economic policy uncertainty (Leippold and Matthys, 2022), and labor market tightness (Mitra and Xu, 2024).

Despite the extensive research in this area, the relationship between online inflation and the yield curve has not yet been explored—a significant gap in the digital age. Our research addresses this gap by pioneering the study of the relationship between high-frequency online inflation and the term structure of interest rates. We demonstrate the strong predictive power of online inflation, especially concerning the slope factor. Moreover, we uncover a novel mechanism whereby the low price stickiness of online inflation enables it to reflect the money market liquidity and effectively predict the slope factor.

Second, our study contributes to the literature on integrating high-frequency data with the term structure of interest rates. As technology advances, high-frequency data and machine learning techniques have become increasingly important for providing timely insights into yield curve movements. There are two main strands of research related to this integration. The first examines the impact of monetary policy or news announcements on the term structure using high-frequency data (e.g., Beechey and Wright, 2009; Kaminska et al., 2021). The second strand involves improving yield curve estimation and prediction with machine learning (e.g., Swanson et al., 2020; Bianchi et al., 2021; Huang and Shi, 2022; Jiang et al., 2024).

Despite these advancements, the influence of high-frequency online markets on term structure has been largely overlooked in the existing literature. Our research addresses this void by highlighting the potential advantages of using high-frequency online inflation for yield curve prediction. Specifically, we incorporate high-frequency online inflation into the DNS model, providing a more granular

[1] In this study, the term "high frequency" is employed to highlight that our data is more frequent than the monthly or quarterly data commonly used in macroeconomic research. Specifically, we use the daily and weekly online inflation data (iCPI) for analysis, which is more frequent compared to the traditional monthly CPI. This terminology aligns with the established literature that treats daily or weekly data as high-frequency in the context of macroeconomic forecasting (e.g. Aruoba et al., 2009; Andreou et al., 2013; Galvão & Owyang, 2022; Zhang et al., 2022b).

[2] Refer to https://www.stats.gov.cn/sj/zxfb/202402/t20240228_1947915.html, https://www3.cnnic.cn/NMediaFile/2024/0325/MAIN1711355296414FIQ9XKZV63.pdf (accessed 01 September 2024).

[3] Refer to https://www.nafmii.org.cn/yj/scyjyfx/yjbg/2023nyjbg/202405/t20240514_318061.html (accessed 01 September 2024).

and real-time understanding of yield curve movements.

Finally, our study contributes to the literature on online markets and prices, with a focus on the financial and informational value of high-frequency online inflation data. Previous research has mainly explored topics such as the comparison between online and offline inflation (Cavallo, 2013; Yim et al., 2022), the use of online inflation for predicting official inflation (Aparicio and Bertolotto, 2020; Macias et al., 2023), online price stickiness (Lunnemann and Wintr, 2011; Cavallo, 2017; Gorodnichenko et al., 2018; Jiang et al., 2020), online price dispersion (Chellappa et al., 2011; Xiang et al., 2024), online price discounts (Cavallo and Kryvtsov, 2024), and the sensitivity of online prices to various shocks (Ellison and Ellison, 2009; Gorodnichenko and Talavera, 2017; Jiang et al., 2022; Cavallo et al., 2024).

However, the relationship between online prices and financial markets remains underexplored, leaving the financial potential of high-frequency online inflation indicators largely untapped. Our research fills this gap by examining the informational value of online prices in relation to the yield curve, which can be extended to stock price and futures price analysis in future. By doing so, we underscore the importance of leveraging high-frequency online price data to gain deeper insights into financial dynamics in the digital era.

The rest of this paper is arranged as follows. The second part introduces the model. The third part describes the data. The fourth part and fifth parts analyze the empirical results. The last part concludes the study.

2. Model and methodology

2.1. The yields-only model

The classical approach for extracting term structure factors from a vast array of yields can be traced back to Nelson and Siegel (1987), which, in fact, represents a constrained form of a static factor model. In this framework, factor loadings for yields of various maturities are determined straightforwardly by their respective maturities (τ) and a single decay parameter (λ). This predetermined configuration enhances the identifiability and simplifies parameter estimation when contrasted with unconstrained factor models. Using y_τ to denote yields, the Nelson and Siegel equation can be expressed as follows:

$$y(\tau) = \beta_1 + \beta_2\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau}\right) + \beta_3\left(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) \tag{1}$$

Here β_1, β_2, β_3 represent static factors that need to be estimated when given a yield curve at any time point. However, given the limitations of capturing dynamic patterns within this framework, Diebold and Li (2006) introduce a dynamic factor model to illustrate the evolving behavior of latent term structure factors. These factors can be intuitively interpreted as the level, slope, and curvature of the yield curve. Following Diebold et al. (2006), and combining these characteristics, the dynamic Nelson and Siegel model can be expressed as follows:

$$\begin{bmatrix} y_t(\tau_1) \\ y_t(\tau_2) \\ \vdots \\ y_t(\tau_N) \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} - e^{-\tau_1\lambda} \\ 1 & -\frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} - e^{-\tau_2\lambda} \\ \vdots & \vdots & \vdots \\ 1 & -\frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} & \frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} - e^{-\tau_N\lambda} \end{bmatrix} \begin{bmatrix} L_t \\ S_t \\ C_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t(\tau_1) \\ \varepsilon_t(\tau_2) \\ \vdots \\ \varepsilon_t(\tau_N) \end{bmatrix} \tag{2}$$

Eq. (2) serves as the measurement equation[4], linking the observed variables y_τ to the latent factors L_t, S_t and C_t. These factors are time-varying and replace the static factors used in Nelson and Siegel (1987). The dynamic behavior of these factors is elucidated by Eq. (3), which represents the state transition equation.

$$\begin{bmatrix} L_t - \mu_L \\ S_t - \mu_S \\ C_t - \mu_C \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} L_{t-1} - \mu_L \\ S_{t-1} - \mu_S \\ C_{t-1} - \mu_C \end{bmatrix} + \begin{bmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \end{bmatrix} \tag{3}$$

To facilitate a more concise understanding and estimation of the model, we reconfigure Eqs. (2) and (3) into a standard state space system, employing vector and matrix notation as follows:

$$(f_t - \mu) = \mathrm{A}(f_{t-1} - \mu) + \eta_t \tag{4}$$

$$y_t - \Lambda\mu = \Lambda(f_t - \mu) + \varepsilon_t \tag{5}$$

$$\begin{bmatrix} \eta_t \\ \varepsilon_t \end{bmatrix} \sim WN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} Q & 0 \\ 0 & H \end{bmatrix}\right) \tag{6}$$

[4] We add a minus sign in front of the coefficients of S_t, so that the estimated slope, represented by S_t, is upward, making it more intuitive.

In this formulation, the state transition Eq. (4) corresponds to Eq. (3), where$f_t = [L_t, S_t, C_t]'$, represents the state vector. The measurement Eq. (5) links demeaned factors to deflated yields $\widetilde{y}_t = y_t - \Lambda\mu$. Following the standard practice of assuming orthogonal measurement errors, we posit that the H matrix is diagonal, while the Q matrix is non-diagonal.

2.2. The yield curve model with online inflation

To explore the relationship between the macroeconomy and the yield curve, Diebold et al. (2006) extend the Dynamic Nelson-Siegel (DNS) model by incorporating observable macroeconomic variables, including real activity, inflation and monetary policy. This framework has been widely used in analyzing the interplay between the term structure and macroeconomic variables. For example, Levant and Ma (2016) apply this framework, also called as the Macro-Factor Augmented Dynamic Nelson-Siegel (MFA-DNS) model, to study the interconnections between yields, real economic activity and monetary policy in the UK. Similarly, Fernandes and Vieira (2019) utilize the factor-augmented dynamic Nelson-Siegel (FADNS) model to forecast the yield curve in the US, combining a large data set of macroeconomic variables. Salachas et al. (2024) examine the accuracy and predictability of different term structure models during the COVID-19 crisis, and find that the factor-augmented DNS model has better forecasting accuracy.

Following Diebold et al. (2006) and Levant and Ma (2016), we adopt the classical Macro-Factor Augmented DNS model, and incorporate the online inflation rate P_t into the model. Let $F_t = [L_t,\ S_t,\ C_t,\ P_t]'$ denote the vector combining three term structure factors and online inflation factor. Eq. (3) is extended to:

$$\begin{bmatrix} L_t - \mu_L \\ S_t - \mu_S \\ C_t - \mu_C \\ P_t - \mu_P \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} L_{t-1} - \mu_L \\ S_{t-1} - \mu_S \\ C_{t-1} - \mu_C \\ P_{t-1} - \mu_P \end{bmatrix} + \begin{bmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \\ \eta_t(P) \end{bmatrix} \tag{7}$$

The transition Eq. (8) generalizes Eq. (7). Compared to Eqs. (3) and (4), the inclusion of P_t introduces incremental information into the VAR system, verifiable through impulse response analysis. This enhancement improves the prediction of term structure factors, thereby improving yield curve forecasts in the observation Eq. (9). Notably, online inflation is exogenous and not derived from the yield curve. So in Eq. (9), loadings for P_t are fixed at zero or one, the measurement error of P_t is set to zero:

$$(F_t - \nu) = A(F_{t-1} - \nu) + \theta_t \tag{8}$$

$$\begin{bmatrix} y_t \\ P_t \end{bmatrix} - \begin{bmatrix} \Lambda & 0 \\ 0 & I \end{bmatrix} \nu = \begin{bmatrix} \Lambda & 0 \\ 0 & I \end{bmatrix} (F_t - \nu) + \begin{bmatrix} \varepsilon_t \\ 0 \end{bmatrix} \tag{9}$$

$$\begin{bmatrix} \theta_t \\ \varepsilon_t \end{bmatrix} \sim WN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Omega & 0 \\ 0 & H \end{bmatrix} \right) \tag{10}$$

In this extended formulation, θ_t represents a 4-dimensional error term corresponding to the term structure factors and online inflation factor, leading to a change in the dimension of Ω to 4 by 4. Furthermore, the dimension of the A matrix also expands to 4 by 4 to accommodate this augmented factor model. The model now captures dynamic interactions among term structure factors and online inflation while preserving parsimony.

2.3. Estimation method

The state space system (8) (9) (10) can be estimated by maximum likelihood estimation (MLE) via the Kalman filter. However, this technique is widely known to be sensitive to the initial parameter values. Therefore, we follow the two-step approach of Diebold and Li (2006) to initialize the estimation.

The two-step approach works as follows: First, we set a fixed value for λ and estimate the level, slope, and curvature parameters for the yield curve at each time point. This step generates a three-dimensional time series of estimated factors by repeatedly applying the OLS fitting process to each observed yield curve. Next, a first-order autoregressive model is applied to the time series of factors derived in the first step.

After obtaining the initial parameter values through this preliminary two-step estimation, we can accurately estimate the state space system. Our findings indicate that the maximum likelihood estimation, based on the initial values, results in only minor adjustments compared to the two-step method, confirming the accuracy and reliability of the results.

3. Data and explorative analysis

3.1. Data description

The dataset used in this study consists of two main components. The first component encompasses an online inflation indicator obtained from the iCPI (Internet-based Consumer Price Index) project at Tsinghua University.[5] The iCPI goods basket follows the latest official CPI basket in China, which consists of the main index, 8 sectors, 27 groups, and 262 classes. Both the methods for determining iCPI weights and the calculation methods for iCPI are consistent with those of the official CPI. The iCPI includes daily, weekly[6], ten-day, and monthly indices, which are generated through automatic computation procedures, including data collection, data cleaning, and final processing for online publication. Unlike official CPI data, which is released with a half-month lag, the iCPI can be updated in real-time. The iCPI data have been continuously collected and updated since January 1, 2016, providing a robust dataset that forms a solid foundation for this research.

The second component includes Chinese treasury bond yields with maturities ranging from the short to long term, specifically: 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 6 years, 7 years, 8 years, 9 years, and 10 years. This yield data is sourced from the Wind database. Both the yield and inflation data are synchronized on a weekly basis, with each data point corresponding to a Friday. If the yield data pertains to a non-trading Friday, the rate from the closest trading day is used. The dataset spans from February 19, 2016, to August 4, 2023, encompassing a total of 391 observations. Specifically, we use the weekly data for primary analysis, and the daily data for robustness check. This approach is justified as daily treasury rate fluctuations are often driven by short-term factors such as trader sentiment, and daily online inflation may contain more noise and outliers. In contrast, weekly online inflation better captures the economic fundamentals and market liquidity conditions, thus offering a clearer and more significant signal for yield curve analysis.

Table 1 presents the descriptive statistics, while Fig. 1 offers a more intuitive visualization of the Yield Curves for Chinese treasury bonds. As shown in Table 1 and Fig. 1, the bond yields tend to increase as the maturity increases, which is typical of a normal yield curve. For instance, the average of 6-month yield is 2.38%, whereas the average of 10-year yield is 3.11%. Additionally, the standard deviation of yields generally decreases as the maturity increases. Specifically, the standard deviation of the 6-month yield is 0.54%, while that for the 10-year yield is 0.36%. This suggests that longer-term bonds have more stable yields than shorter-term ones in this dataset. Meanwhile, the average weekly online inflation rate (P) is 0.01%, with a standard deviation of 0.11%, indicating some variability around the mean inflation rate.

3.2. Explorative analysis

Previous studies have explored various techniques to extract yield term structure factors. Among these, the most straightforward and intuitive method relies on empirical proxies drawn from data. Specifically, the level factor, which represents the long-term trend, can be estimated by averaging the yields of 6-month, 2-year, and 10-year bonds. The slope factor, which reflects short-term dynamics, can be measured as the difference between the 10-year and 6-month yields. Given that the standard deviation of the 6-month yield is significantly higher than that of the 10-year yield, it is evident that the fluctuations of the slope factor are primarily driven by changes in short-term interest rates. Meanwhile, the curvature factor, which captures mid-term movements, can be calculated as twice the 2-year yield minus the sum of the 6-month and 10-year yields.

Fig. 2 provides a graphical representation of the empirical proxy factors of yield curve and online inflation. It's evident that all four indicators exhibit significant fluctuations throughout the observed period. The level factor seems to show a smoother, long-term trend compared to the more volatile slope and curvature. Online inflation, while also volatile, might have certain trends or patterns that correlate with the yield curve factors. We would further conduct more in-depth econometric analyses to understand the interrelationships of the four indicators.

4. Model estimation and analysis

4.1. Main estimation results

The parameter estimates are presented in Table 2. For the estimation of the level factor (L_t), the results show that the average yield exhibits a high degree of persistence. The coefficient for online inflation (P_{t-1}) is positive (0.049) but not statistically significant. This indicates that while there's a slight upward push on average yield with an increase in online inflation from the past week, it's not strong enough to be considered a consistent or reliable predictor in the model.

For the slope factor (S_t), it tends to remain consistent over time. The coefficient for online inflation (P_{t-1}) is significantly positive (0.111) at 5% significance level, suggesting that an increase in online inflation from the past week pushes the difference between long-term and short-term rates to increase, indicative of a steepening yield curve.

[5] iCPI has been published on the website (http://www.bdecon.com) since January 1, 2016, which can be downloaded in databases, including Bloomberg, Wind and CEIC. More details are available in the paper of Liu et al. (2019) and Jiang et al. (2022).

[6] Specifically, the weekly iCPI index is not simply the average of the daily indices over seven days. Instead, it is calculated by first dividing the average price of goods for the current week's seven days by the average price for the previous week's seven days.The resulting ratios are then weighted and averaged to obtain the final weekly index. More details are available in the paper of Liu et al. (2019) and Jiang et al. (2022).

Table 1
Descriptive statistics.

Statistic	N	Mean(%)	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
P	391	0.01	0.11	-0.49	-0.05	0.07	0.50
6M	391	2.38	0.54	1.00	2.05	2.63	3.96
1Y	391	2.50	0.52	1.13	2.15	2.73	3.80
2Y	391	2.67	0.46	1.37	2.34	2.90	3.80
3Y	391	2.77	0.45	1.41	2.44	2.99	3.80
4Y	391	2.85	0.43	1.59	2.53	3.05	3.83
5Y	391	2.93	0.41	1.79	2.61	3.12	3.90
6Y	391	3.04	0.38	2.10	2.75	3.25	3.95
7Y	391	3.11	0.37	2.33	2.82	3.30	3.97
8Y	391	3.11	0.36	2.42	2.82	3.30	3.96
9Y	391	3.11	0.36	2.45	2.83	3.31	3.95
10Y	391	3.11	0.36	2.51	2.83	3.31	3.98

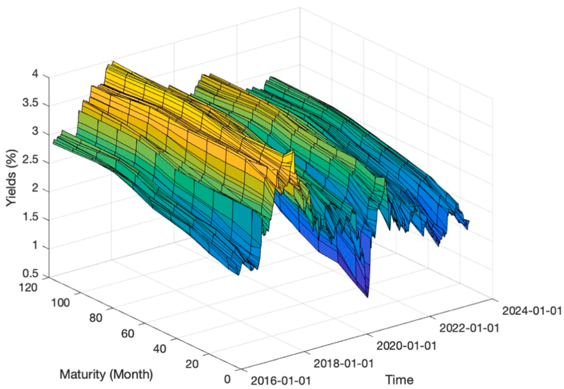

Fig. 1. Yield curves of Chinese treasury bond yields.

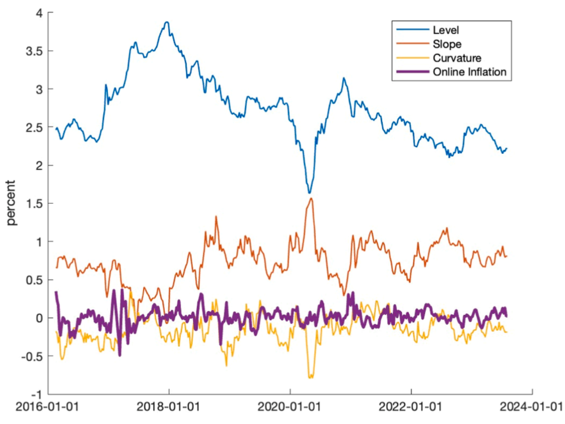

Fig. 2. Weekly online inflation and empirical proxy factors.

For the curvature factor (C_t), it still shows substantial persistence. The coefficient for online inflation (P_{t-1}) is negative (-0.032) but not statistically significant. This suggests that an increase in the online inflation from the prior week might be associated with a slight downward adjustment in the curvature of the yield curve, but this effect is neither robust nor consistently detectable in the model.

For the online inflation (P_t), it still shows significant persistence, but the factors of yield curve cannot predict it. The coefficients associated with the level (L_{t-1}), slope (S_{t-1}), and curvature (C_{t-1}) of the yield curve are not statistically significant, suggesting that the traditional term structure factors-level, slope, and curvature-do not robustly predict movements in online inflation.

In conclusion,our analysis reveals that the weekly online inflation rate effectively predicts the slope factor of the yield curve, whereas the three term structure factors-level, slope, and curvature-do not exhibit predictive power over the online inflation rate.

Besides, we provide a theoretical mechanism analysis of the findings discussed above, with further empirical verification to be presented in Section 4.5. The slope factor is primarily driven by short-end interest rates (Diebold and Li, 2006; Diebold et al., 2006),

Table 2
Parameter estimation results with weekly online inflation.

Estimated A matrix and μ vector					
	L_{t-1}	S_{t-1}	C_{t-1}	P_{t-1}	μ
L_t	0.962***	-0.026*	-0.001	0.049	3.294***
	(0.016)	(0.015)	(0.008)	(0.039)	(0.250)
S_t	-0.039*	0.948***	-0.001	0.111**	1.142***
	(0.023)	(0.019)	(0.012)	(0.054)	(0.264)
C_t	0.068	-0.015	0.903***	-0.032	-0.354*
	(0.063)	(0.057)	(0.031)	(0.166)	(0.187)
P_t	-0.014	-0.018	-0.003	0.651***	0.010
	(0.017)	(0.016)	(0.008)	(0.030)	(0.014)
λ			0.048***		
			(0.002)		
Estimated Ω matrix					
	L_t	S_t	C_t	P_t	
L_t	0.005***	0.003***	-0.012***	0.000	
	(0.001)	(0.001)	(0.002)	(0.000)	
S_t		0.009***	-0.004*	0.001	
		(0.001)	(0.002)	(0.001)	
C_t			0.068***	0.000	
			(0.008)	(0.001)	
P_t				0.007***	
				(0.000)	

Notes: (1) The first panel includes the estimates of the A matrix and the μ vector. In the top-left 4-by-4 matrix, each row represents the coefficients from the transition equation for the corresponding state variable. (2)The second panel displays the covariance matrix of the transition error term, with standard errors indicated in parentheses. (3) Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

and the lack of predictive power of P_{t-1} on L_t also indicates that the predictive role of P_{t-1} on S_t is mainly manifested at the short end. According to the liquidity premium theory of the term structure, short-term treasury bonds exhibit excellent liquidity and strong substitutability with cash (Culbertson, 1957). Empirical results demonstrate that the funding liquidity conditions significantly impact bond price movements (Fontaine and Garcia, 2012). Thus, while long-term rates are influenced by complex factors such as inflation expectations and liquidity premiums, short-term rates are primarily influenced by funding liquidity conditions. In fact, interest rate changes reflect the impact of general funding liquidity condition, which are affected by business conditions and monetary policy alterations on various credit markets (Culbertson, 1957).

Therefore, the predictive capacity of online inflation for the slope factor and short-end rates demonstrates the online market's sensitive reflection of general funding liquidity fluctuations. This finding aligns with the theory of price stickiness, as the low cost of price adjustments in online markets results in lower price stickiness, enabling online prices to quickly respond to liquidity changes, thereby facilitating the price discovery of online inflation on short-term interest rates and slope factor.

4.2. Impulse responses analysis

In this section, we examine the impulse response relationships implied by the state space model. Fig. 3 illustrates the impulse responses between latent factors and online inflation, as derived from the state space model. It's evident that these factors exhibit pronounced autoregressive dynamics along the diagonal direction. This means that when any of these factors experience a shock, the effects tend to persist over time.

We focus on the responses of three factors of yield curve to a shock in weekly online inflation. First, a moderate positive response in the level factor can be seen due to a shock in online inflation, suggesting that increases in online inflation may lead to a rise in the average yield. Second, the slope factor experiences a significant and prolonged positive response to an online inflation shock, which gradually diminishes over time. Third, the response of the curvature factor to an online inflation shock is minimal, with only slight fluctuations.

We further analyze the responses of online inflation to the three factors of the yield curve. First, a shock in the level factor appears to have a minor positive effect on online inflation initially, which diminishes to zero over time. Second, a shock in the slope factor has a positive effect on online inflation. After an initial increase, the inflation slightly decreases. Third, a shock in the curvature factor has almost no impact on online inflation.

In summary, Fig. 3 provides a comprehensive view of the dynamic interrelationships among the yield curve factors and online inflation. It underscores the persistent nature of each factor, the intricate interplay among them, and highlights the predictive power of online inflation on the slope of the yield curve. These findings are consistent with those presented in Table 2, which show that the online inflation rate serves as a robust predictor of the yield curve's slope factor.

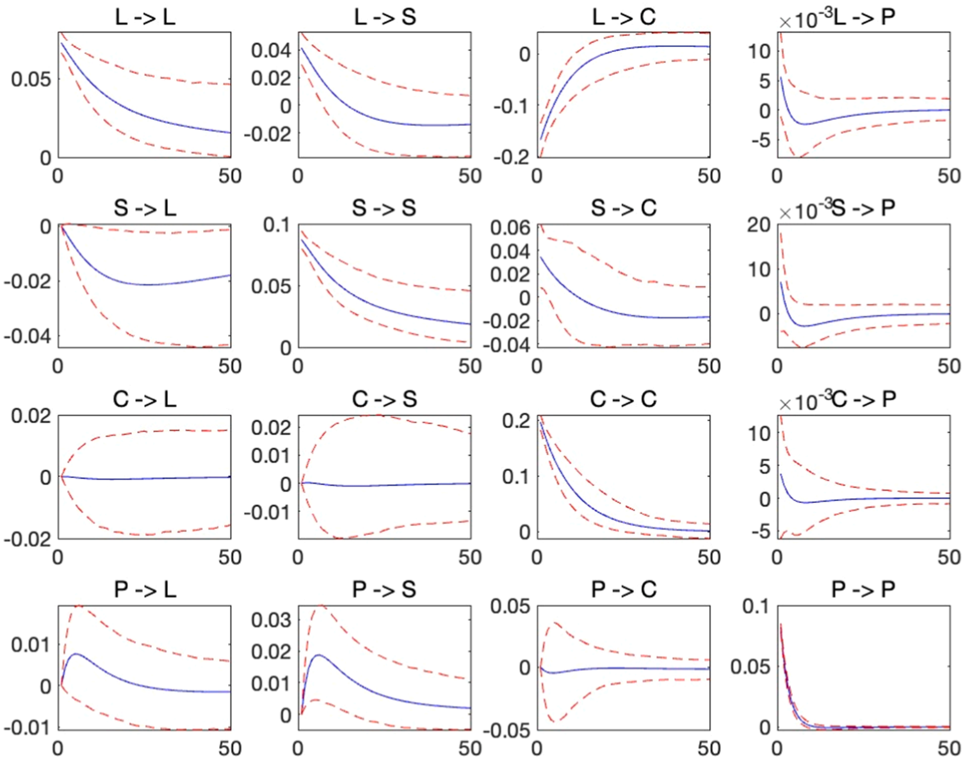

Fig. 3. Impulse responses between latent factors and online inflation based on State Space model
Notes: The graph illustrates various impulse responses resulting from a one-standard-deviation shock, accompanied by a 90% confidence interval.

4.3. Variance decompositions

4.3.1. Variance decompositions of yields

As shown in Table 3, the variance decomposition results indicate the relative contributions of different factors of yield curve and high frequency online inflation in explaining the forecast error variances of yields at various maturities across different forecast horizons.

For the 6-month yield with a 1-week forecast horizon (h=1), the slope (S) is the predominant factor, accounting for 85.93% of the forecast variance. The level (L) contributes 5.69%, and the curvature (C) contributes 8.24%. As the forecast horizon increases to 48 weeks, the influence of the slope decreases to 69.27%, while the contribution of the level increases to 28.38%, suggesting the changing dynamics over time. Notably, at a 1-week forecast horizon, the contribution of online inflation (P) is minimal at 0.15%. This

Table 3
Variance decompositions of different yields.

Horizons\Factors	L	S	C	P
Panel A: 6-month Yield				
h=1	0.0569	0.8593	0.0824	0.0015
h=12	0.1558	0.7951	0.0375	0.0116
h=24	0.2262	0.7403	0.0229	0.0106
h=48	0.2838	0.6927	0.0146	0.0089
Panel B: 5-year Yield				
h=1	0.0755	0.1275	0.7970	0.0000
h=12	0.2822	0.3080	0.4097	0.0001
h=24	0.3653	0.4011	0.2329	0.0007
h=48	0.3934	0.4680	0.1367	0.0019
Panel C: 10-year Yield				
h=1	0.5583	0.0424	0.3986	0.0008
h=12	0.6343	0.1772	0.1854	0.0031
h=24	0.6024	0.2864	0.1093	0.0019
h=48	0.5461	0.3842	0.0675	0.0023

contribution slightly increases over time, reaching 1.16% at the 12-week forecast horizon and 0.89% by the 48-week forecast horizon.

For the 5-year yield with a 1-week forecast horizon, the curvature is the dominant factor, explaining 79.70% of the forecast variance. The level contributes 7.55%, and the slope accounts for 12.75%. However, by the 48-week forecast horizon, the prominence of the curvature drops dramatically to 13.67%. In contrast, the roles of the level and slope become more pronounced. Furthermore, the impact of online inflation is virtually non-existent at the 1-week forecast horizon, contributing 0.00%, but it slightly increases to 0.19% by the 48-week forecast horizon.

For the 10-year yield with a 1-week forecast horizon, the level emerges as the central factor, explaining 55.83% of the forecast variance. The slope contributes 4.24%, while the curvature represents 39.86%. As the forecast horizon extends, the influence of the level decreases, while the contribution of slope increases, especially by the 48-week horizon. Additionally, the contribution of online inflation at the 1-week forecast horizon is minimal at 0.08%, slightly increasing to 0.23% by the 48-week forecast horizon.

Overall, the 6-month yield exhibits a more pronounced contribution from online inflation compared to the 5-year and 10-year yields, especially as the forecast horizon lengthens. This suggests that online inflation has significantly stronger predictive power for short-term interest rates, yet its predictive ability is notably weaker for medium- and long-term yields.

4.3.2. Variance decompositions of factors

The results of variance decompositions of three term structure factors and online inflation are shown in Table 4. For the level factor, 99.8% of the variance at a 1-week forecast horizon is attributed to shocks in the level itself. This percentage reduces slightly as the forecast horizon increases, but even at 48 weeks, the level itself contributes approximately 78.67% to its own variance. Moreover, the online inflation contributes only 0.16% to the variance of the level at a 1-week forecast horizon. This contribution marginally increases over time, reaching 1.03% at 12 weeks, but drops slightly to 0.64% by 48 weeks.

For the slope factor, 82.05% of the variance is explained by its own shocks, while the level contributes 17.49% at the 1-week forecast horizon. As the forecast horizon expands, the contribution of the level to the slope's variance decreases, with the slope's own shocks accounting for a higher proportion. Notably, online inflation's impact on the slope is more significant. It starts at a mere 0.46% at the 1-week horizon, peaks at 4.6% by 24 weeks, and slightly decreases to 4.06% by 48 weeks.

For the curvature factor, a significant part of the variance is explained by its own shocks, especially in the short term. The contribution of the level to the curvature's variance is notable initially but decreases over time. Furthermore, online inflation contributes a minimal 0.01% to the curvature's variance at a 1-week horizon. This contribution remains consistently low across all horizons, reaching a maximum of 0.05% by the 48-week forecast horizon.

For the online inflation, the variance is almost exclusively determined by its own shocks across all forecast horizons. This suggests that online inflation is mostly self-driven and not significantly influenced by the three factors of yield curve.

The above results clearly indicate that online inflation has a stronger explanatory power over the variance of the slope factor during the periods considered, compared to the level and curvature factors. These findings are consistent with the results presented in Table 2 and Fig. 3.

4.4. Prediction of yield curve

In this section, we further investigate the prediction power of the high frequency online inflation rate for the yield curve. Table 5 reports the relative RMSFE (Root Mean Square Forecasting Error) of the yield curve model with online inflation compared to the yields-only model for various maturities over different forecasting horizons. A value less than 1 suggests that the new model is outperforming the yields-only model.

The sample begins on February 19, 2016, and the evaluation period spans from January 19, 2018, to August 4, 2023. With the out-of-sample evaluation encompassing 75% of the total sample, the results are compelling. Predictions are generated using a cumulative window approach, which involves incrementally expanding the training dataset over time.

The out-of-sample forecasts generated by the model have yielded highly positive outcomes. Compared to the yields-only model used as a baseline, the new model has consistently outperformed it across all maturities and forecast horizons. Notably, the medium-term forecast horizons, particularly at 12 and 24 weeks, have shown the most significant improvements, with all results achieving statistical significance.

When examining the performance across different maturities, it is evident that the new model exhibits stronger predictive capabilities for short-term yields. The most substantial enhancements are observed in the forecasting of 6-month yields across various forecast horizons. This is consistent with the findings that online inflation is effective at predicting the slope factor, which is sensitive to changes in short-term interest rates.

4.5. Online inflation and money market liquidity

As discussed earlier, due to the lower price stickiness in online markets, online inflation can more effectively reflect liquidity conditions in the money market and, therefore, predict changes in short-term interest rates and the slope factor. The theoretical foundation of this view lies in the higher informational efficiency and price discovery function of online markets.

Table 4
Variance decompositions of different factors.

Horizons\Factors	L	S	C	P
Panel A: The Level Factor				
h=1	0.9980	0.0004	0.0000	0.0016
h=12	0.9490	0.0406	0.0001	0.0103
h=24	0.8803	0.1117	0.0002	0.0078
h=48	0.7867	0.2067	0.0002	0.0064
Panel B: The Slope Factor				
h=1	0.1749	0.8205	0.0000	0.0046
h=12	0.1014	0.8536	0.0000	0.0449
h=24	0.0875	0.8664	0.0001	0.0460
h=48	0.1167	0.8425	0.0001	0.0406
Panel C: The Curvature Factor				
h=1	0.4097	0.0173	0.5730	0.0001
h=12	0.3631	0.0130	0.6235	0.0004
h=24	0.3489	0.0165	0.6341	0.0005
h=48	0.3505	0.0365	0.6125	0.0005
Panel D: The Online Inflation				
h=1	0.0038	0.0060	0.0018	0.9883
h=12	0.0070	0.0102	0.0018	0.9809
h=24	0.0086	0.0122	0.0019	0.9773
h=48	0.0088	0.0125	0.0019	0.9768

Table 5
Out-of-sample relative performance for yields prediction.

Maturities\Horizons	h=1	h=4	h=12	h=24	h=48
6M	0.954***	0.960*	0.947***	0.954*	0.954***
1Y	0.993	0.973**	0.953**	0.959*	0.993
2Y	0.991	0.986	0.964**	0.960*	0.991
3Y	0.985*	0.984	0.965**	0.960*	0.985*
4Y	0.994	0.975	0.958**	0.956**	0.994
5Y	0.982	0.962*	0.947**	0.950**	0.982
6Y	0.969**	0.963*	0.948*	0.940**	0.969**
7Y	0.983*	0.973	0.954*	0.936**	0.983*
8Y	0.986	0.971	0.951**	0.934**	0.986
9Y	0.990	0.967**	0.950**	0.935**	0.990
10Y	0.981*	0.966**	0.951**	0.937**	0.981*

Notes: *, **, and *** denote significant outperformance at 10%, 5% and 1% level according to Diebold–Mariano forecast accuracy comparison tests.

First, online markets benefit from a large user base and high market activity, ensuring the rapid flow of information and goods. Online markets overcome geographic barriers, allowing consumers and traders from across the country to participate easily, thereby aggregating more information and diverse perspectives. This enhances the comprehensiveness and accuracy of market information. As of December 2023, the number of online shopping users in China reached 915 million, accounting for 83.8% of all internet users.[7] This large user base and frequent trading activity enable online markets to react more quickly to market changes than traditional offline markets.

Second, online markets have lower transaction costs and entry barriers, improving the efficiency of information transmission. In traditional financial markets, participants must open accounts, pay commissions, or access specialized platforms, whereas online trading bypasses these restrictions, significantly reducing transaction costs. By lowering searching and matching costs (Goldfarb and Tucker, 2019), online markets are more efficient information markets, facilitating faster and more efficient price discovery.

Moreover, a key difference between online markets and traditional financial markets is that online markets operate 24/7. While traditional offline markets are constrained by working days and holidays, online markets allow trading at any time, with weekends and public holidays often seeing increased activity. This round-the-clock trading feature enables online markets to facilitate quicker information flow, providing a unique advantage in reflecting economic conditions, particularly liquidity in the money market.

To empirically test this theoretical mechanism, we construct a VAR model that includes the online inflation rate, money market interest rates, and short-term government bond yields. Specifically, we use the 1-month pledged repo rate (R1M) to represent the money market interest rate, which is a crucial indicator of money market liquidity conditions and is widely used by financial

[7] Refer to https://www3.cnnic.cn/NMediaFile/2024/0325/MAIN1711355296414FIQ9XKZV63.pdf (accessed 01 September 2024).

institutions for liquidity management. Additionally, the weekly iCPI index is used to represent online inflation, while the 6-month government bond yield (6M yield) is employed to represent short-term bond rates. It is important to note that short-term bond yields and money market rates are not identical. While both reflect market conditions, short-term bond yields are influenced not only by liquidity changes in the money market but also by other factors, such as institutional trading and allocation behaviors in the bond market. Therefore, we include both R1M and the 6M yield in the model to capture their dynamics.

As shown in Fig. 4, the last two charts in the first row indicate that iCPI significantly negatively predicts R1M and 6M yield. Conversely, the last two charts in the first column show that neither R1M nor the 6M yield significantly predicts iCPI. Additionally, the third chart in the second row reveals a positive correlation between R1M and the 6M yield in the same period. The impulse response diagrams of the VAR model together depict the whole story of the mechanism. When online inflation increases, it reflects easing liquidity conditions, which effectively predict a subsequent decline in money market rates and short-term bond yields, with the slope factor also becoming steeper.

In summary, the empirical results support the hypothesis that online inflation is an efficient predictor of liquidity conditions in the money market, influencing short-term interest rates and the slope factor. The unique characteristics of online markets, such as lower price stickiness, higher market activity, and 24/7 operation, enable them to provide timely insights into economic conditions and respond quickly to changes in liquidity. This enhances the ability of high-frequency online inflation to reflect and predict changes in short-term interest rates and the slope of the yield curve.

5. Further analysis

5.1. Robustness checks

In this section, we employ four methods to show the robustness of the main estimation results.

5.1.1. Comparison of the model-based factors with their empirical proxies

We first compare the model-based factors with their empirical proxies, as shown in Fig. 5. For the level factor, both series tend to move in tandem, suggesting a strong correlation between the empirical proxy and the model-based factor for the long-term trend. While there are periods where the two lines diverge slightly, they generally follow the same trajectory. This indicates that the Level Estimator captures the overall long-term movement in the data well.

For the slope factor, the two series also move closely together, indicating that the Slope Estimator effectively represents the short-term fluctuations in the market. The alignment of these two series reiterates the efficacy of the model in capturing the short-term

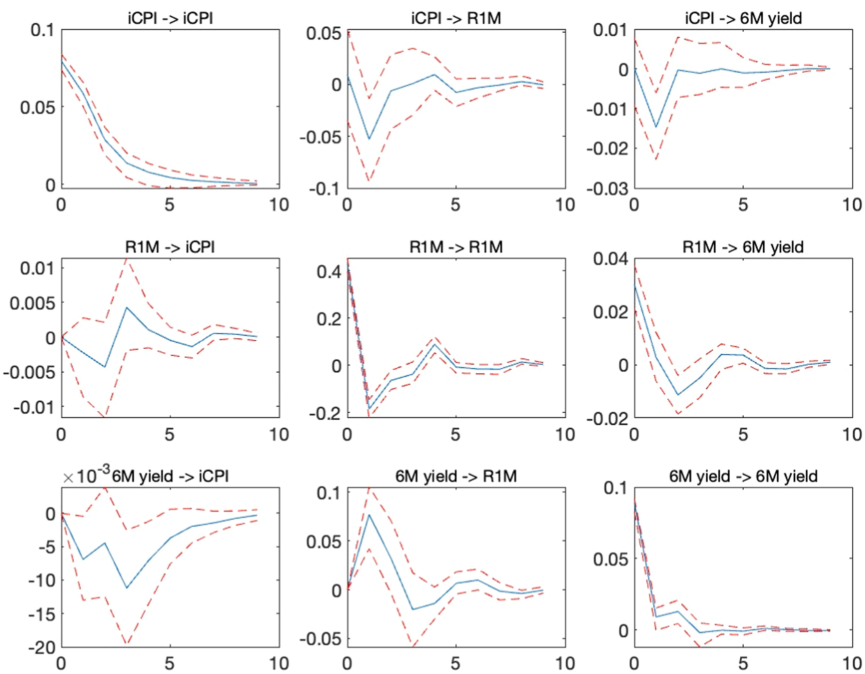

Fig. 4. Impulse response between online inflation, money market interest rates, and short-term government bond yields
Notes: This figure presents impulse responses from a VAR(3) model, with the lag order selected based on AIC. The depicted responses are generated by orthogonalized shocks, each with a magnitude of one standard deviation, and are accompanied by 90% confidence intervals. While the specific orthogonalized impulse response functions may vary depending on the arrangement of variables in the VAR model, the primary findings remain robust across different variable orderings.

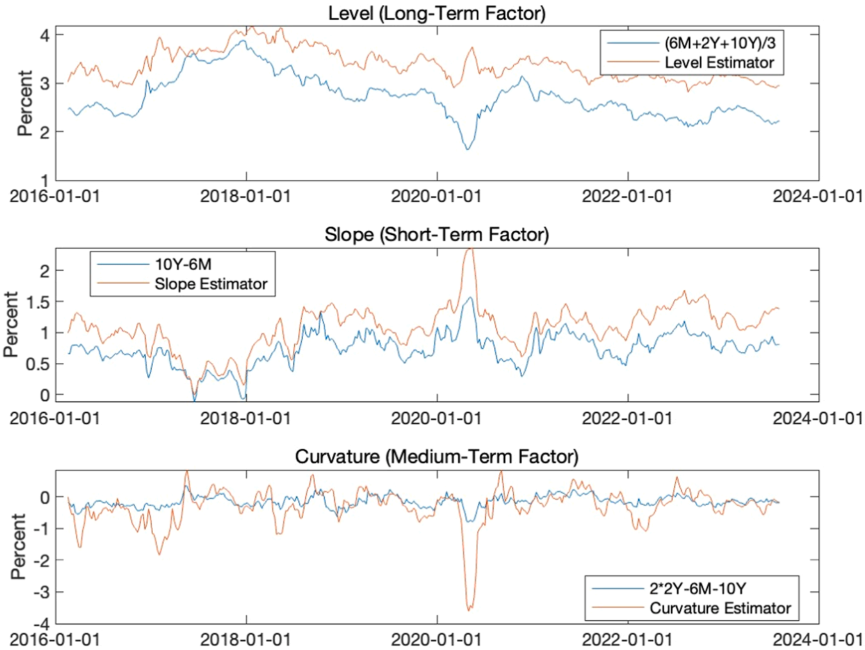

Fig. 5. Model-based factors V.S. Empirical proxies
Notes: Model-based factors are extracted using Kalman smoothing based on our yield curve model with online inflation. Empirical proxies are calculated directly from yield value.

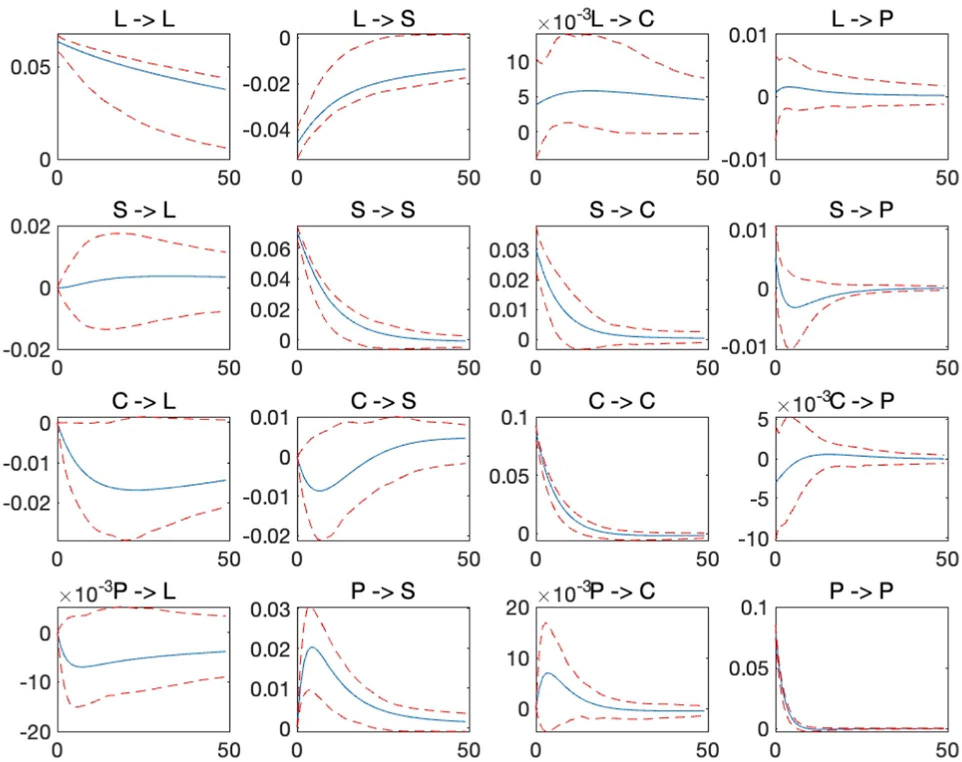

Fig. 6. Impulse response between weekly empirical proxy factors and online inflation based on VAR model
Notes: The chart depicts various impulse responses generated by orthogonalized shocks, each with a magnitude of one standard deviation and accompanied by a 90% confidence interval. While the specific orthogonalized impulse response functions may vary depending on the arrangement of variables in the VAR model, it is noteworthy that the primary findings remain robust even when the order of the variables is adjusted.

changes.

For the curvature factor, the patterns of these series consistently overlap, demonstrating that the medium-term variations in the data are effectively captured by the Curvature Estimator. The slight differences between the two series might be due to model-specific nuances.

In conclusion, across all three factors of the yield curve, the model-based estimators closely track their corresponding empirical proxies. This suggests that the model is robust and accurately captures the underlying dynamics of the data.

5.1.2. Comparison of the impulse responses based on latent factors and empirical proxy factors

We further compare the impulse responses based on the state space VAR and empirical proxies' VAR. Fundamentally, the model's structure is analogous to Eq. (7), with the only difference being the substitution of the latent term structure factors with empirical proxies. The impulse response relationships between these empirical proxy factors are depicted in Fig. 6.

We compare the responses of three factors to an online inflation shock in Figs. 3 and 6. For the level factor, Fig. 6 shows a slight positive response, but the magnitude is much smaller compared to Fig. 3. For the slope factor, Fig. 6 shows a positive response, consistent with Fig. 3. For the curvature factor, the response in Fig. 6 shows a slight negative decline, whereas Fig. 3 remains nearly consistent around the zero mark. Overall, the primary patterns and directions of the impulse responses between Figs. 3 and 6 are aligned, although there are differences in the magnitude and rate of change.

5.1.3. Different model settings and time spans

To further examine the predictive ability of online inflation and its positive influence on the slope factor, we conduct a robustness test by taking different model settings and time spans. Specifically, we adopt a recursive expansion approach for our sample range. Our complete dataset spans from February 19, 2016, to August 4, 2023. For the robustness check, we begin with a sample ranging from February 19, 2016, to September 20, 2019. Subsequently, we expand this sample, incorporating one additional week at a time until we cover the entire span up to August 4, 2023. This analysis starts before the emergence of the Covid-19 pandemic and culminates at the most recent data point within our dataset.

Considering that certain parameters exhibits only marginal economic and statistical relevance, we impose constraints in model specifications to prevent potential overfitting. The results are illustrated in Fig. 7.

For Model Setting 1, which represents the standard yield curve model with online inflation, we observe that the coefficient a_{24} fluctuates around a central value but consistently remains above zero. The 90% confidence interval remains relatively tight, suggesting a high level of certainty about the parameter's value.

For Model Setting 2, where the parameters a_{41}, a_{42}, and a_{43} are constrained to zero, the parameter a_{24} still remains significantly above zero. The confidence interval is slightly broader compared to Model Setting 1 but still indicates a significant positive relationship.

For Model Setting 3, the most constrained model, with a_{41}, a_{42}, a_{43}, a_{14} and a_{34} set to zero, the parameter a_{24} remains consistently

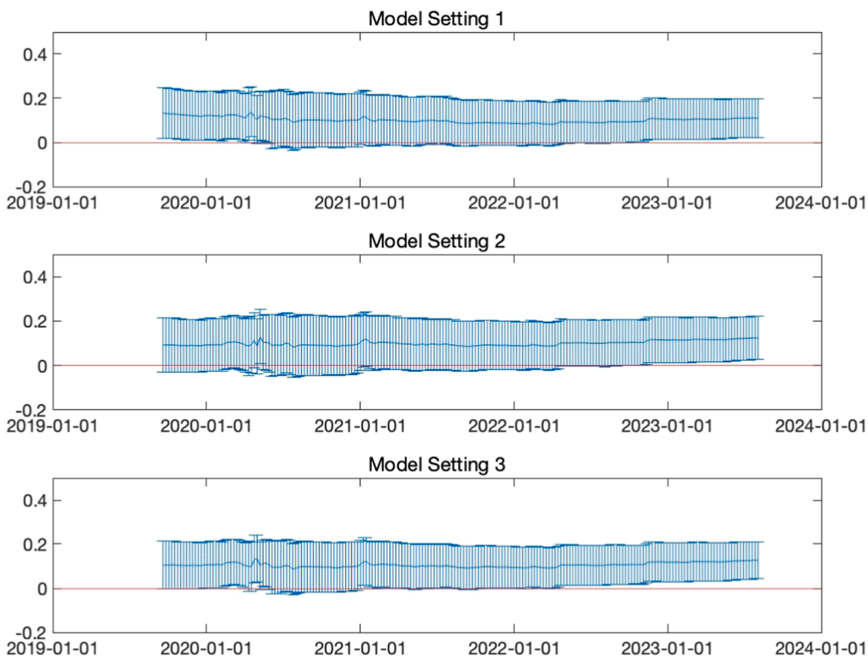

Fig. 7. Robustness test with different model settings and time spans.
Notes: The vertical axes represent the coefficient a_{24} in Eq. (7), with a 90% confidence interval.

above zero. The confidence interval remains tight, suggesting the parameter estimate is robust even when several parameters are constrained to zero.

The robustness of the results is evident in two dimensions. First, the consistent positive value of a_{24} across all three model settings suggests that online inflation indeed has strong predictive power over the slope factor. This aligns with the main findings about the significant positive value of a_{24} in Table 2. Second, the stability of a_{24} as a positive predictor across various time periods, even during significant global events like the COVID-19 pandemic, highlights its resilience.

In summary, the results in Fig. 6 reinforce the main findings: the online inflation consistently and significantly predicts the slope factor of the yield curve across various model settings and time periods. These findings are robust and hold true irrespective of the constraints placed on other parameters, highlighting the importance of a_{24} in the relationship between online inflation and the term structure of interest rates.

5.1.4. Daily data

In this section, we use daily data as a robustness check. The dataset contains 2,724 observations from February 19, 2016, to August 4, 2023. The daily indicators are displayed in Appendix Fig. A1, and the daily impulse responses are shown in Appendix Fig. A2. The parameter estimation results for the daily data are presented in Appendix Table A1.

As shown in Fig. A1, the overall trends of the daily indicators are consistent with those of the weekly indicators (depicted in Fig. 2). However, the daily online inflation exhibits greater volatility, whereas the weekly online inflation is more stable by smoothing out short-term fluctuations and noise.

According to Fig. A2, the effect of daily online inflation (P) on the slope factor (S) is significantly positive, which is consistent with the results from the weekly data (as shown in Fig. 5), albeit with a smaller magnitude. The peak of the daily impulse response reaches 0.0027, approximately 1/10th of the magnitude observed in the weekly model.

In Table A1, the coefficient for daily online inflation (P_{t-1}) on the slope factor (S_t) is significantly positive (0.016) at the 10% significance level. In contrast, Table 2 shows that the coefficient for weekly online inflation (P_{t-1}) on the slope factor (S_t) is significantly positive (0.111) at the 5% significance level. These results suggest that daily online inflation has a positive effect on the slope of the yield curve, but this effect is weaker and less statistically significant compared to the weekly data.

In conclusion, the results confirm that the relationships between online inflation and the term structure of interest rates are consistent across different data frequencies. However, daily online inflation captures more short-term fluctuations and noise, resulting in a weaker impact on the slope of the yield curve. In contrast, weekly online inflation smooths out these short-term fluctuations, reducing the influence of noise and outliers. As a result, the weekly data provides a more stable, statistically significant, and economically interpretable relationship between online inflation and the slope of the yield curve.

5.2. Comparison between online inflation and official CPI

In this section, we first investigate the relationship of the official monthly CPI and the yield curve, aiming to compare with the prior findings derived from online inflation. The dataset encompasses monthly observations from January 2002 to September 2023, totaling 261 data points. By starting the dataset in January 2002, we ensure a more comprehensive estimation with a larger number of samples, due to utilizing low-frequency monthly rather than high-frequency weekly data.

As shown in Table 6, the coefficients for official monthly CPI (P_{t-1}) on the yield curve factors (L_t, S_t, C_t) are statistically insignificant. This suggests that the official monthly inflation lacks predictive power on the yield curve factors, unlike the weekly online inflation. However, the coefficient for curvature (C_{t-1}) on official inflation (P_t) is positive and statistically significant at the 5% level. This indicates that an increase in the curvature of the yield curve in the previous period predicts an increase in official inflation in the following period.

The above findings indicate that online inflation can predict the yield curve, while the yield curve predicts official inflation. As discussed in Section 4.5, we propose that the predictive power of online inflation (iCPI) stems from its lower price stickiness, which allows it to better capture changes in money market liquidity. If this mechanism holds, then the official CPI–with its higher price

Table 6
Parameter estimation with monthly official CPI.

	L_{t-1}	S_{t-1}	C_{t-1}	P_{t-1}	μ
L_t	0.874***	-0.011	-0.004	0.024	3.963***
	(0.062)	(0.049)	(0.031)	(0.017)	(0.348)
S_t	-0.072	0.867***	-0.044	0.008	1.784***
	(0.090)	(0.070)	(0.043)	(0.025)	(0.316)
C_t	0.131	-0.075	0.838***	-0.051	-0.533*
	(0.109)	(0.074)	(0.056)	(0.032)	(0.315)
P_t	0.123	0.014	0.123**	0.936***	1.916**
	(0.094)	(0.073)	(0.048)	(0.025)	(0.959)
λ	0.031***				
	(0.002)				

Notes: The table shows the estimates of the A matrix and the μ vector. Standard errors are indicated in parentheses. Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

stickiness–should exhibit the opposite pattern, failing to predict money market liquidity. To examine this, we conduct a mechanism analysis parallel to that in Section 4.5. In this analysis, we replace online inflation (iCPI) with the official CPI, and accordingly, the data frequency is adjusted from weekly to monthly. The results are presented in Fig. 8.

Fig. 8 shows that CPI fails to significantly predict the R1M and 6M yield, whereas iCPI does as demonstrated in Fig. 4. In contrast, the last chart in the first column of Fig. 8 indicates that the 6M yield significantly predicts CPI, which confirms the predictive power of the yield curve for CPI, consistent with Table 6. These results suggest that the official CPI, due to its higher price stickiness and relatively sluggish response to market liquidity, has weaker price discovery capability compared to online inflation. This leads to contrasting outcomes, while online inflation can predict the yield curve, the official CPI is instead predicted by the yield curve.

To further explain these differences of prediction, we test the Granger causality between monthly online inflation (iCPI) and official inflation (CPI). As shown in Table 7, the results indicate that online inflation (iCPI) has significant predictive power over official inflation (CPI), whereas official inflation does not predict online inflation. This finding is consistent with Jiang et al. (2022), which show that online inflation (iCPI) at different frequencies improves the accuracy of official inflation prediction across various models, especially for the high-frequency weekly iCPI.

Online inflation is more responsive to immediate market conditions and features flexible price changes, making it a potentially leading indicator for predicting official inflation. Its real-time data collection and dynamic pricing adjustments enable online inflation to serve as a leading indicator for short-term economic conditions and money market liquidity, thus allowing it to predict the yield curve. In contrast, the more stable nature of official inflation measures means they are influenced by long-term economic trends reflected in the yield curve. This stability is due to less frequent price updates and higher price stickiness. Consequently, online inflation can predict the yield curve, while official inflation is predicted by the yield curve.

5.3. Online inflation of eight sectors and the yield curve

Given the differences in online inflation across eight sectors, we further investigate the impacts of sectoral online inflation on the yield curve. Tables 8 and 9 show the parameter estimation results. These results indicate that online inflation in different sectors has varied impacts on the yield curve's level, slope, and curvature factors. Notably, the Health Care sector significantly affects all three factors, while the Clothing sector shows a significant positive impact on the slope factor. Additionally, the Household Articles and Services and Transportation and Communication sectors exhibit significant impacts on the curvature factor.

The varied impacts of online inflation across different sectors on the yield curve reflect the complex interplay of the nature of goods

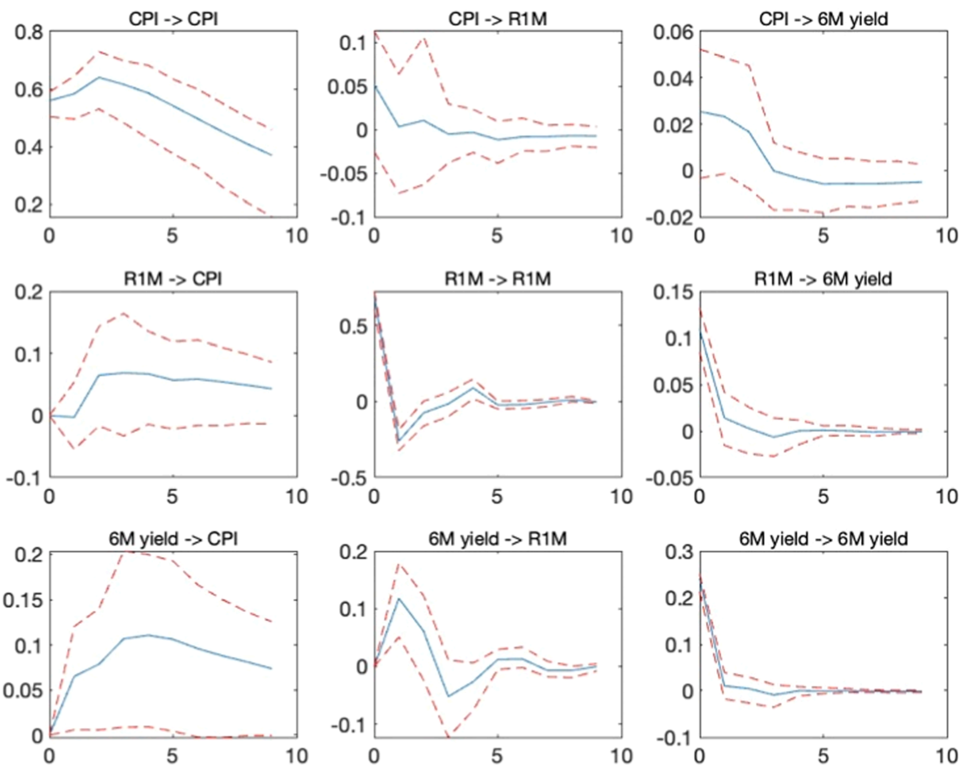

Fig. 8. Impulse response between official CPI, money market interest rates, and short-term government bond yields
Notes: This figure presents impulse responses from a VAR(3) model, parallel to Fig. 4, with iCPI replaced by the official CPI. The dataset consists of monthly observations from January 2002 to September 2023.

Table 7
Granger causality between monthly online inflation and official inflation.

Hypothesis	F_statistic	P_value
H_0: The online inflation (iCPI) does not Granger-cause the official inflation (CPI).	3.352*	0.071
H_0: The official inflation (CPI) does not Granger-cause the online inflation (iCPI).	0.274	0.602

Notes: Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively. The optimal lag order of Granger causality test is decided by AIC.

Table 8
Parameter estimation with weekly online inflation of the first four sectors.

Coefficient		iCPI: Food, Tobacco and Liquor	iCPI: Clothing	iCPI: Residence	iCPI: Household Articles and Service
L->L	a11	0.963***	0.961***	0.961***	0.963***
		(0.016)	(0.016)	(0.016)	(0.016)
L->S	a21	-0.037	-0.037	-0.038	-0.037
		(0.023)	(0.024)	(0.024)	(0.024)
L->C	a31	0.066	0.069	0.069	0.062
		(0.063)	(0.064)	(0.068)	(0.063)
L->P	a41	-0.033	-0.041	-0.002	-0.032
		(0.034)	(0.046)	(0.003)	(0.027)
S->L	a12	-0.026*	-0.027*	-0.027*	-0.023
		(0.015)	(0.015)	(0.014)	(0.015)
S->S	a22	0.947***	0.945***	0.947***	0.951***
		(0.019)	(0.019)	(0.019)	(0.019)
S->C	a32	-0.017	-0.014	-0.015	-0.030
		(0.057)	(0.058)	(0.056)	(0.058)
S->P	a42	-0.027	-0.021	-0.002	-0.044**
		(0.037)	(0.047)	(0.003)	(0.022)
C->L	a13	-0.001	-0.001	-0.001	0.003
		(0.008)	(0.008)	(0.008)	(0.008)
C->S	a23	-0.002	-0.002	-0.003	0.004
		(0.012)	(0.012)	(0.012)	(0.013)
C->C	a33	0.902***	0.902***	0.901***	0.886***
		(0.032)	(0.031)	(0.030)	(0.031)
C->P	a43	0.001	-0.002	0.001	-0.024 *
		(0.018)	(0.024)	(0.002)	(0.013)
P->L	a14	0.017	0.005	-0.003	0.048
		(0.019)	(0.009)	(0.152)	(0.030)
P->S	a24	0.036	0.031*	0.322	0.059
		(0.029)	(0.018)	(0.246)	(0.041)
P->C	a34	-0.006	-0.003	-0.058	-0.225*
		(0.077)	(0.051)	(0.634)	(0.125)
P->P	a44	0.713***	0.715***	0.739***	0.587***
		(0.025)	(0.022)	(0.031)	(0.034)

Notes: The table shows the estimates of the A matrix in the Eq. (7). Standard errors are indicated in parentheses. Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

and services, supply and demand elasticity, and cyclical sensitivity. Each sector has unique characteristics that determine how price changes affect overall inflation and, consequently, the term structure of interest rates. These findings underscore the importance of monitoring online inflation trends in these sectors to understand and predict changes in the yield curve, reflecting broader economic conditions and liquidity in the money market.

5.4. *Online inflation with different attributes and the yield curve*

To further explore the reasons for the above heterogeneity, we categorize the index according to different economic attributes. Similar to the official core CPI, we calculate core online inflation by excluding food and energy prices to better reflect the general and persistent inflationary trend in the economy. Based on the attributes of goods and services, we divide the core online iCPI baskets into different categories: durable goods, non-durable goods, cyclical services, and non-cyclical services. Specifically, durable goods are items with a long lifespan that are not purchased frequently, such as cars, refrigerators, and computers. Non-durable goods are items that are consumed quickly and need to be purchased regularly, including clothing, medicine, shampoo, and beverages. Cyclical services are services whose demand tends to fluctuate with the economic cycle, such as rent, entertainment, travel, and tourism. Non-cyclical services are essential services that consumers need regardless of the economic cycle, such as healthcare services, education, and telecommunication services.

To calculate the online inflation rates of the four categories, we combine the online inflation rates of 262 classes, which make up the entire iCPI basket. First, we categorize these classes into the four aforementioned categories based on their economic attributes.

Table 9
Parameter estimation with weekly online inflation of last four sectors.

Coefficient		iCPI: Transportation and Communication	iCPI: Education, Culture and Recreation	iCPI: Health Care	iCPI: Other Articles and Services
L->L	a11	0.961***	0.961***	0.965***	0.962***
		(0.016)	(0.016)	(0.016)	(0.016)
L->S	a21	-0.040	-0.040	-0.036	-0.042*
		(0.024)	(0.025)	(0.023)	(0.024)
L->C	a31	0.055	0.070	0.056	0.067
		(0.062)	(0.064)	(0.063)	(0.064)
L->P	a41	0.006	0.008	-0.051	-0.019
		(0.018)	(0.041)	(0.039)	(0.029)
S->L	a12	-0.027*	-0.027*	-0.023	-0.026*
		(0.014)	(0.015)	(0.015)	(0.014)
S->S	a22	0.946***	0.947***	0.950***	0.945***
		(0.019)	(0.019)	(0.018)	(0.019)
S->C	a32	-0.018	-0.016	-0.027	-0.017
		(0.054)	(0.058)	(0.057)	(0.056)
S->P	a42	-0.006	-0.023	-0.048	0.006
		(0.020)	(0.044)	(0.033)	(0.029)
C->L	a13	-0.001	-0.001	-0.000	-0.000
		(0.008)	(0.008)	(0.008)	(0.008)
C->S	a23	-0.002	-0.001	-0.001	-0.003
		(0.012)	(0.012)	(0.012)	(0.013)
C->C	a33	0.898***	0.901***	0.900***	0.900***
		(0.030)	(0.030)	(0.031)	(0.031)
C->P	a43	-0.008	-0.015	0.009	-0.003
		(0.012)	(0.025)	(0.020)	(0.015)
P->L	a14	0.003	-0.001	0.045 **	0.005
		(0.031)	(0.015)	(0.021)	(0.023)
P->S	a24	0.014	0.006	0.045 **	-0.038
		(0.037)	(0.023)	(0.023)	(0.036)
P->C	a34	0.216*	-0.011	-0.154*	-0.017
		(0.115)	(0.045)	(0.085)	(0.089)
P->P	a44	0.797***	0.780***	0.600***	0.683***
		(0.029)	(0.024)	(0.026)	(0.036)

Notes: The table shows the estimates of the A matrix in the Eq. (7). Standard errors are indicated in parentheses. Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Second, we perform weighted calculations and synthesis according to the weights of the classes within the entire iCPI basket.

As shown in Table 10, online inflation of non-durable goods significantly impacts the yield curve's level factor positively and the slope factor positively. This suggests that increased online inflation in non-durable goods tends to raise the overall level of the yield curve and steepen its slope. However, online inflation rates of durable goods, cyclical services, and non-cyclical services do not significantly impact the yield curve factors.

The differences in price stickiness across these categories explain the varying impacts on the yield curve. For non-durable goods, prices adjust more frequently due to high competition, perishability, and regular purchase cycles. Retailers often change prices in response to shifts in supply and demand. Consequently, the frequent price changes in non-durable goods directly influence overall inflation levels, which in turn affect the yield curve's level factor. Additionally, these frequent price changes reflect real-time liquidity conditions, thus affecting the slope of the yield curve. This is consistent with the empirical results in Section 5.3. Clothing and Health Care are important commodities in non-durable goods and are also the most actively traded necessities on e-commerce platforms, which explains their superior ability to predict the yield curve among the eight sectors.

In contrast, prices for durable goods tend to be stickier due to long-term financing and warranty contracts, and firms may prefer stable pricing to avoid confusing customers or triggering perceptions of poor quality. Prices for cyclical services have some flexibility through promotions but are constrained by labor costs and menu costs, making these changes less frequent and impactful compared to non-durable goods. Prices for non-cyclical services tend to be sticky due to regulation, long-term contracts, and the essential nature of these services. Therefore, durable goods, cyclical services, and non-cyclical services exhibit higher price stickiness, leading to less frequent price changes and consequently less influence on the yield curve.

5.5. Online inflation on weekdays and weekends and the yield curve

Online price changes, or price stickiness, can exhibit *calendar effects* similar to those observed in traditional financial markets (Jiang et al., 2020). The differences between online inflation on weekdays and weekends can be significant due to various factors related to consumer behavior, retailer strategies, and market dynamics. Considering the *calendar effects* of online pricing, we further study the impacts of online inflation on weekends and weekdays on the yield curve.

To split the weekly iCPI index into weekdays and weekends, we use the following algorithm. Since the weekly iCPI is presented as a

Table 10
Parameter estimation for weekly online inflation with different attributes.

Coefficients		iCPI: Durable Goods	iCPI: Non-durable Goods	iCPI: Cyclical Services	iCPI: Non-cyclical Services
L->L	a11	0.964***	0.965***	0.961***	0.962***
		(0.017)	(0.016)	(0.016)	(0.016)
L->S	a21	-0.045*	-0.033	-0.040	-0.040
		(0.025)	(0.024)	(0.025)	(0.025)
L->C	a31	0.056	0.058	0.067	0.066
		(0.065)	(0.064)	(0.064)	(0.064)
L->P	a41	-0.051	-0.071*	-0.007	0.018
		(0.031)	(0.038)	(0.050)	(0.035)
S->L	a12	-0.022	-0.026*	-0.026*	-0.027*
		(0.016)	(0.015)	(0.015)	(0.015)
S->S	a22	0.939***	0.949***	0.947***	0.948***
		(0.020)	(0.019)	(0.019)	(0.019)
S->C	a32	-0.033	-0.016	-0.014	-0.014
		(0.060)	(0.056)	(0.057)	(0.059)
S->P	a42	-0.054*	-0.052	-0.013	-0.027
		(0.029)	(0.032)	(0.059)	(0.029)
C->L	a13	0.001	-0.001	-0.001	-0.001
		(0.008)	(0.008)	(0.008)	(0.008)
C->S	a23	-0.005	-0.000	-0.002	-0.001
		(0.013)	(0.012)	(0.013)	(0.012)
C->C	a33	0.894***	0.902***	0.902***	0.903***
		(0.032)	(0.031)	(0.030)	(0.032)
C->P	a43	-0.017	-0.005	-0.002	-0.020
		(0.020)	(0.018)	(0.030)	(0.017)
P->L	a14	0.019	0.027*	0.003	-0.018
		(0.020)	(0.015)	(0.013)	(0.019)
P->S	a24	-0.038	0.048*	-0.002	0.011
		(0.032)	(0.027)	(0.021)	(0.028)
P->C	a34	-0.086	-0.083	0.014	0.020
		(0.090)	(0.070)	(0.053)	(0.086)
P->P	a44	0.756***	0.723***	0.753***	0.671***
		(0.026)	(0.028)	(0.028)	(0.028)

Notes: The table shows the estimates of the A matrix in the Eq. (7). Standard errors are indicated in parentheses. Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

week-over-week percentage change, we transform it into a level value by cumulative multiplication. The iCPI for weekdays is calculated based on the percentage change from Monday to Friday, while the iCPI for weekends is calculated based on the percentage change from Friday to Sunday.

As shown in Table 11, weekday online inflation has a significant positive impact on the slope factor of the yield curve, indicating that increased online inflation on weekdays tends to steepen the slope of the yield curve. In contrast, weekend online inflation does not significantly impact the yield curve factors. This difference can be explained by the variations in price changes on weekdays and weekends.

To address this issue, we construct a daily online price adjustment frequency index, defined as the proportion of items with price changes each day relative to the total number of items. Following methods from existing literature (e.g. Cavallo, 2017; Gorodnichenko et al., 2018), we identify and exclude price changes of 7-day discounts. This ensures that our index mainly captures regular price adjustments, offering a more accurate reflection of economic conditions rather than promotional strategies. We then divide the data into weekday and weekend samples, calculating the sample size, mean value, and standard deviation of the price adjustment ratio for each sub-sample. Finally, we conduct a t-test to determine whether there is a significant difference in price adjustment frequency between weekdays and weekends.

As shown in Table 12, the mean frequency of price adjustments on weekdays (2.00) is higher than on weekends (1.58), which indicates that prices are adjusted more frequently on weekdays than on weekends. Besides, the T-test value of 8.003, which is significant at the 1% level, indicates a statistically significant difference between the frequency of price adjustments on weekdays and weekends.

Prices on weekdays are adjusted based on real supply and demand dynamics, reflecting ongoing economic conditions. Retailers make these adjustments considering factors such as production costs, inventory levels, and competitive pricing. Since weekday price changes are not heavily influenced by promotional strategies, they provide a clearer picture of market liquidity. Therefore, weekday online inflation gives real-time signals about economic conditions, leading to adjustments in expectations about future interest rates.

Table 11
Parameter estimation with weekly online inflation on weekday and weekend.

Coefficient		iCPI: weekday	iCPI: weekend
L->L	a11	0.959 ***	0.962 ***
		(0.016)	(0.016)
L->S	a21	-0.033	-0.039
		(0.024)	(0.025)
L->C	a31	0.077	0.073
		(0.064)	(0.066)
L->P	a41	-0.024	-0.020
		(0.030)	(0.022)
S->L	a12	-0.028 *	-0.029 *
		(0.014)	(0.015)
S->S	a22	0.950 ***	0.949 ***
		(0.019)	(0.019)
S->C	a32	-0.009	-0.018
		(0.056)	(0.057)
S->P	a42	-0.016	0.004
		(0.030)	(0.020)
C->L	a13	-0.002	-0.002
		(0.008)	(0.008)
C->S	a23	0.001	0.000
		(0.012)	(0.013)
C->C	a33	0.906 ***	0.901 ***
		(0.030)	(0.032)
C->P	a43	-0.010	0.002
		(0.019)	(0.011)
P->L	a14	-0.020	0.017
		(0.020)	(0.029)
P->S	a24	0.054 **	-0.008
		(0.027)	(0.040)
P->C	a34	0.072	0.056
		(0.081)	(0.118)
P->P	a44	0.781 ***	0.804 ***
		(0.030)	(0.030)

Notes: The table shows the estimates of the A matrix in the Eq. (7). Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12
Comparison of price adjustment frequency between weekend and weekday.

	Sample Size	Mean Frequency(%)	Standard Deviation(%)
Weekday Samples	1944	2.00	1.51
Weekend Samples	775	1.58	1.08
T test of price adjustment frequency	8.003***		

Notes: Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In contrast, prices on weekends are often changed due to sales and promotions aimed at boosting short-term sales. These changes are strategic rather than reflective of underlying economic conditions. Since weekend price changes are driven by marketing strategies and are temporary, they do not provide a reliable indicator of market liquidity or economic fundamentals. Therefore, weekend online inflation fails to significantly impact the yield curve factors due to its temporary nature and limited reflection of liquidity.

In summary, the online price adjustments exhibit notable calendar effects in China, where weekday price changes tend to be more flexible than those on weekends. This results in online inflation on weekdays and weekends influencing the yield curve differently. Weekday online inflation, being more reflective of real-time economic conditions and market liquidity, can offer stronger predictive power for the slope factor of the yield curve.

6. Conclusions

This study enhances our understanding of the relationship between online inflation and the term structure of interest rates in the digital age. By incorporating the high-frequency iCPI indicator into the DNS model, our study reveals that weekly online inflation can effectively predict the slope factor of the yield curve. The pronounced effect of online inflation on short-term yields, such as the 6-month yield, highlights its strong predictive power for short-term interest rates. Moreover, our mechanism analyses indicate that online prices, marked by low price stickiness, more timely reflect the economic conditions and liquidity movements, thereby improving the predictability for short-term interest rates and the slope factor. This study also reveals heterogeneity in the predictive power of online inflation across different sectors and between weekdays and weekends, which can be attributed to varying levels of price stickiness.

These insights underscore the value of integrating high-frequency data into yield curve models, offering a more immediate and nuanced understanding of economic dynamics. Our research suggests that incorporating high-frequency big data into economic modeling can improve the accuracy and responsiveness of predictive models for policymakers and financial analysts. Furthermore, the informational value of online markets should be further explored to fully leverage their potential in economic analysis and forecasting.

Data availability statement

The data and code that have been used in this study are available from the corresponding author upon request.

CRediT authorship contribution statement

Tao Zhang: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Ke Tang:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Taoxiong Liu:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Data curation. **Tingfeng Jiang:** Writing – review & editing, Writing – original draft, Validation, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

There are no potential conflicts of interest.

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Appendix

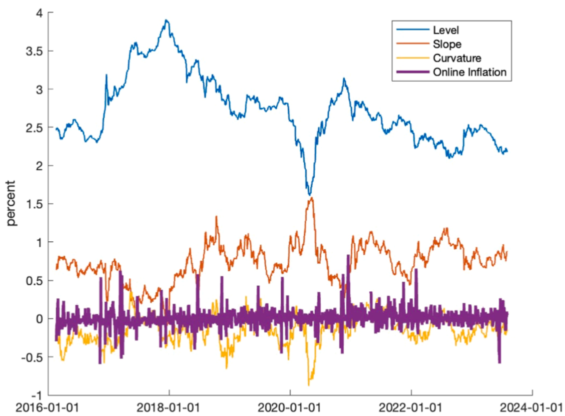

Fig. A1. Daily online inflation and empirical proxy factors.

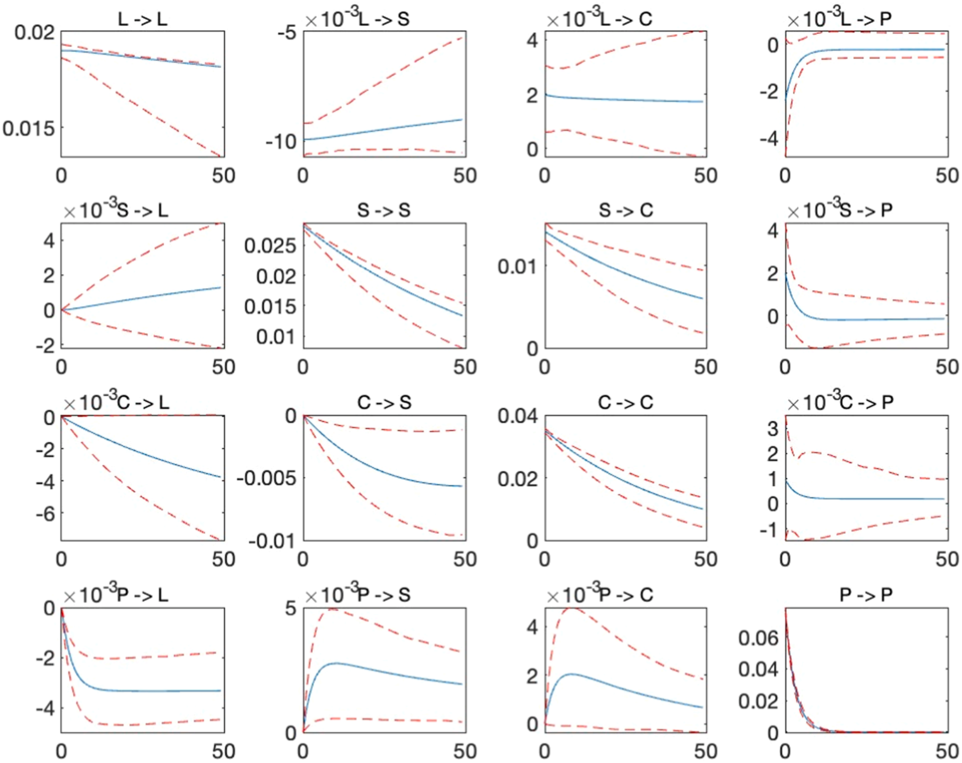

Fig. A2. Impulse response between daily empirical proxy factors and online inflation based on VAR model
Notes: The chart depicts various impulse responses generated by orthogonalized shocks, each with a magnitude of one standard deviation and accompanied by a 90% confidence interval. While the specific orthogonalized impulse response functions may vary depending on the arrangement of variables in the VAR model, it is noteworthy that the primary findings remain robust even when the order of the variables is adjusted.

Table A1
Parameter estimation results with daily online inflation.

Estimated A matrix and μ vector					
	L_{t-1}	S_{t-1}	C_{t-1}	P_{t-1}	μ
L_t	0.996 ***	-0.003 **	0.001	-0.012 ***	4.853 **
	(0.001)	(0.001)	(0.001)	(0.004)	(1.957)
S_t	-0.006 **	0.991 ***	-0.003 *	**0.016 ***	-0.462
	(0.003)	(0.002)	(0.001)	**(0.009)**	(1.953)
C_t	0.014 *	-0.000	0.983 ***	0.038 **	0.694
	(0.007)	(0.006)	(0.003)	(0.019)	(1.637)
P_t	-0.005	0.001	-0.002	0.718 ***	-0.033
	(0.006)	(0.005)	(0.003)	(0.007)	(0.061)
λ			0.062 ***		
			(0.001)		
Estimated Ω matrix					
	L_t	S_t	C_t	P_t	
L_t	0.001***	0.000***	-0.002***	-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	
S_t		0.002***	0.001***	0.000*	
		(0.000)	(0.000)	(0.000)	
C_t			0.011***	0.000	
			(0.000)	(0.000)	
P_t				0.006***	
				(0.000)	

Notes: (1) The first panel includes the estimates of the A matrix and the μ vector. In the top-left 4-by-4 matrix, each row represents the coefficients from the transition equation for the corresponding state variable. (2)The second panel displays the covariance matrix of the transition error term, with standard errors indicated in parentheses. (3) Symbols *, **, and *** are used to denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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