Economic Systems 47 (2023) 101073

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

On illiquidity of an emerging sovereign bond market☆

Cenk C. Karahan[a,*], Emre Soykök[b]

[a] Department of Management, Bogazici University, Istanbul 34342, Turkey
[b] Naveen Jindal School of Management, The University of Texas at Dallas, Richardson, TX, 75080, USA

ARTICLE INFO

JEL Classification:
E31
E43
G12

Keywords:
Inflation uncertainty
Interest rates
Liquidity
Sentiment
Term structure

ABSTRACT

This study offers an analysis of a sovereign bond market in an emerging country, Turkey, and its illiquidity. We employ the Nelson-Siegel model to generate a term structure for interest rates directly from daily bond price quotes in the Turkish market. We take the noise measure, which is the byproduct of term structure estimation, as a proxy for market-wide illiquidity. Our results show that this noise measure can capture the illiquidity in the Turkish fixed-income market from global financial turbulence as well as local dynamics. Inflation uncertainty and sentiment are the major macro drivers of liquidity crunches. It has also become clear that liquidity in an emerging market such as Turkey in the aftermath of the 2008 crisis has been driven by global forces, however, since 2013 local factors have taken over. This apparent decoupling in liquidity between a major emerging market and global markets followed the approaching end of quantitative easing and a rise in economic turbulence in the country since then.

1. Introduction

Yields of Treasury bonds in relation to their time to maturity form the yield curve, which is also called the term structure of interest rates. As the term structure depicts expectations about the future path of an economy, it is also a source of information for investors of financial markets and economy in general. For instance, the properties of a term structure are known to anticipate future business cycle phases. The slope of the term structure was shown to be a predictor of future growth rate of the gross domestic product (GDP) (Ang et al., 2006) and a better forecaster of growth than expectation surveys (Estrella and Hardouvelis, 1991). Ang et al. (2008) demonstrate that the upward slope of a term structure in economic boom periods is mainly associated with an expected rise in inflation. Chauvet and Senyuz (2016) contend that yield-curve components have better forecasting ability of the beginnings and ends of recessions than the benchmark factors, and the slope factor has major forecasting power. As such, not only does the term structure of interest rates indicate the interest rates, but specific measures associated with the curve also help estimate other financially and economically important factors.

Recent studies document that the yield curve contains valuable information about the liquidity, or rather illiquidity, of capital markets as well. Market-wide illiquidity refers to the relationship between transaction volumes and price movements when the

☆ Emre Soykök, who coauthored this study, has unexpectedly passed away shortly after the completion of the manuscript. This paper is dedicated to his memory.

* Corresponding author.
E-mail addresses: cenk.karahan@boun.edu.tr (C.C. Karahan), emre.soykok@utdallas.edu (E. Soykök).

https://doi.org/10.1016/j.ecosys.2023.101073
Received 1 June 2022; Received in revised form 4 October 2022; Accepted 23 November 2022
Available online 23 January 2023
0939-3625/

market is in financial distress. Transactions with a relatively small volume can bring about large deviations in asset prices when investors choose to stand by in order to better react to new information later. In contrast to individual-security-based illiquidity measures, such as returns on the transaction volume (Amihud, 2002), turnover ratio (Datar et al., 1998), zero-return days (Lesmond et al., 1999), or bid-ask spread (Chung and Zhang, 2014), market-wide illiquidity measures are not suitable for explaining the cross section of asset returns in a market. Rather, they can capture a market-wide flight to a liquidity premium, which stems from investor preferences for assets, permitting a hassle-free exit from the market when necessary.

The market-wide illiquidity measure proposed by Hu et al. (2013) captures liquidity crises by relating distortions in security prices to a lack of arbitrage capital. The premise of this idea is that securities in a market are consistently priced relative to one another in normal times, preventing any major arbitrage opportunities for long periods. This is because arbitrageurs armed with ample liquidity can exploit any mispricing instantly. During liquidity crunches, however, arbitrageurs are forced to abandon their relative value trades. In bond market, this is manifested as a nonsmooth yield curve with heightened noise levels, as individual securities are relatively over- or underpriced for longer periods. This mispricing means that individual bond yields may have positive or negative deviations from an otherwise smooth yield curve that fits the term structure of interest rates. These deviations collectively become the noise measure that marks the illiquidity of the market due to a lack of arbitrage capital.

The little recent research using this particular measure of systemic liquidity suggests the applicability of market-wide illiquidity measures on developed (Hattori, 2021) and, to a limited extent, emerging markets (Dziwok and Karaś, 2021). Therefore, this study fills a gap in financial illiquidity research in international markets. We apply this measure to Turkish Treasury bond market and evaluate its performance in capturing periods of financial distress in this major emerging market. We also study the changing determinants of this illiquidity based on local and global forces in different periods. As Turkey's emerging market is relatively young, cyclical developments emerging from global events have long-lasting impacts on its capital markets through the agency of international investors. Furthermore, because the prospect of liquidating capital assets without incurring large costs is of the utmost importance for international investors, market-wide illiquidity review of this market is crucial. For these reasons, we conduct a market- wide liquidity assessment of the Turkish market using an observation period with series of liquidity crises, currency crises, and political turmoil experienced by the country.

To document the noise measure as illiquidity, this study uses the extensive bond price data available on a large and centralized emerging sovereign bond market. Subsequent empirical tests document the illiquidity measure's relation to a wide set of interest rate, liquidity, and risk metrics. Assessing the spillover of illiquidity between the US and the Turkish bond markets across different periods documents a stronger and more dynamic relation than is documented between the US and Japan, a developed market (Hattori, 2021). We further document the impact of inflation uncertainty and sentiment on market-wide illiquidity. To the best of our knowledge, this is the first study to document the relation between illiquidity and inflation uncertainty, one of a few studying its relation to sentiment in the bond market. It is our hope that this study paves the way for more international studies on the determinants and impact of illiquidity in fixed-income markets.

2. Literature review

2.1. The term structure of interest rates

To model the yield curve as a smooth function, McCulloch (1971) proposes fitting the discount function by polynomial splines and then deriving the yield curve and forward interest rates from this discount curve. Fama and Bliss (Fama and Bliss, 1987) use a bootstrap method that iteratively identifies forward rates from a discount function that is updated in each step with bonds of a longer time to maturity. This method results in a piecewise linear yield curve with the number of knots equaling the number of bonds used. Bliss (1989) implements a smoothed version of the model by fitting approximating functions to the yields that price bonds precisely.

In a pioneering study, Nelson and Siegel (1987) propose a specification for the instantaneous forward rate, which uses Laguerre functions. With the intention of keeping model parameters parsimonious, they suggest using the identical roots solution of a second-order differential equation that can generate various shapes for forward curves, depending on two parameters and a constant asymptote equal to a third parameter. Svensson (1994) argues that an extended version of the Nelson-Siegel model might offer a more flexible estimation of the yield curve that has a more accurate fit. He proposes adding a fourth component with two additional parameters to account for a second hump.

In a comparison of the Nelson-Siegel model to several spline-fitting models, Bliss (1997) states that the unsmoothed Fama-Bliss model and the Nelson-Siegel model both outperform other models. He also claims that differences in the estimates of these two models are impractical and that the flexibility of splines is useful only at the long end of a yield curve.

Gürkaynak et al. (2007) use the prices of coupon-bearing bonds to model US Treasury yield curves over a long observation period starting in 1961. They assert that the Nelson-Siegel and Svensson models both successfully capture yield characteristics, despite their parsimonious structures. Diebold and Li (2006) propound that a forecasting approach using the Nelson-Siegel model parameters results in consistent out-of-sample estimates that outperform benchmark methods. They show that the Nelson-Siegel parameters might be construed as level, slope, and curvature factors of the yield curve, which could be accurately identified thanks to the composition of factor loadings enforced by the model. In implementing the model, they suggest fixing the λ parameter in which the hump factor peaks approximately at two and a half years to attain smooth time series of model parameters by ensuring factor loadings that do not change every day. They also adjust the yield curve parameter setup in order to show that parameter estimates indicate meaningful economic explanations and that they do not intrinsically include coherence, which might create multicollinearity.

Steeley (2014) claims that the dynamic Nelson-Siegel model produces superior out-of-sample forecasts against benchmark models in the post-2008 period, when interest rates were nearly zero. Wahlstrom et al. (2021) assert, in a comparison with more flexible models, that the stablest and most intuitive parameters are generated from the Nelson-Siegel model. They endorse use of the Nelson-Siegel model over the Svensson model because of economically inexplicable interaction between two curvature parameters in the latter, regardless of the shape of the yield curve or regime phases, such as financial crises.

Alper et al. (2004) compare the performance of the McCulloch model with that of Nelson-Siegel model for Turkish Treasury bonds, which went on the secondary market in June 1991. They estimate monthly yield curves using only discount bonds traded between 1992 and 2003 and remark that the Nelson-Siegel model outperforms the McCulloch method in terms of out-of-sample forecasting. Akinci et al. (2007) estimate daily Svensson yield curves between February 2005 and October 2006, including five-year Treasury coupon bonds in the analysis. Akinci et al. argue that using coupon-bearing bonds enhances the accuracy of yield-curve estimation because they have information on the time to maturity. Cepni and Kucuksarac (2017) investigate the performance of different calibration methods for the Svensson model between January 2011 and May 2016. They find that using a price minimization algorithm produces parameters that fit in-sample data better than those generated by a yield minimization algorithm. Ertan et al. (2020) compare the dynamic Nelson-Siegel model to a heuristically fixed parameter and the Svensson model between February 2005 and December 2018. They maintain that, although monthly estimates of both models similarly capture yield-curve movements, the dynamic Nelson-Siegel model has better fit performance. They attribute the underperformance of the Svensson model to a local minima problem suffered by the nonlinear least squares algorithm.

2.2. Illiquidity

Illiquidity arises when financial transactions cannot be performed easily in large volumes without incurring high costs and triggering price changes. After earlier documentation of the economic relationship between the cost of transactions and trading activity (Demsetz, 1968), liquidity and related topics have become among the main streams in financial research, and the measures devised by researchers to mimic the exposure of financial assets to illiquidity have formed an abundant literature. But scholars are still far from reaching a consensus on an illiquidity measure that persists across financial markets. This stems from the fact that illiquidity measures endeavor to capture several facets of financial transactions, such as price impacts, trading volume, and timing (Le and Gregoriou, 2020).

Academic literature on illiquidity offers factors such as information asymmetry, volatility (Ramos and Righi, 2020), and high frequency trading (Cobandag-Guloglu and Ekinci, 2021) as potential determinants of market depth and transaction costs, which are considered aspects of liquidity. Another major aspect of liquidity is market resiliency, which refers to how quickly markets tend to digest and dissipate liquidity shocks. By capturing the impact of market resiliency, the exposure to market-wide illiquidity is found to price securities, particularly during periods of financial turbulence (Black, Stock, and Yadav, 2016). This is attributed to investor preference for securities that allow a swift exit from the market when necessary. As such, the market-wide flight to a liquidity premium and individual securities' exposure to it partly explain the cross-section of asset returns.

Research on illiquidity premiums that tries to explain the cross section of asset returns focuses mainly on security-based measures and equity markets. Nonetheless, illiquidity in the Treasury bond market contains information about the broader financial markets because investors participate in the Treasury bond market not only for investment but also for collateral and funding needs. In addition, Treasury bonds offer higher credit quality and do not contain risk factors, unlike other instruments, such as corporate bonds and equities. For these reasons, illiquidity in the Treasury bond market should be informative about economic fundamentals, and vice versa. Longstaff (2004) measures the liquidity premium in Treasury bonds through a comparison of US Treasuries with comparable agency bonds and ties the premium to the supply of bonds and partly to consumer confidence. Goyenko et al. (2011) measure illiquidity via bid-ask spreads and document its relationship with various risk measures and inflation as a major macroeconomic indicator. Söderlind (2011) studies inflation uncertainty and liquidity effects on inflation expectations and interest rates, but does not explore any potential links between them. Grishchenko and Huang (2013) explain the inflation risk premium and add a noise measure, similar to this study, to distinguish the liquidity portion. O'Sullivan and Papavassiliou (2020) build spread- and depth-based illiquidity measures for European government bonds and analyze the interactions of liquidity with returns, volatility, and credit risk across maturities in the yield curve.

In their seminal study, Hu et al. (2013) propose that discrepancies between the observed yields of bonds and fitted Nelson-Siegel yields capture market-wide liquidity information that is correlated with other liquidity proxies but extends them. Because bond prices are insensitive to yield changes at the short end of yield curve, they suggest using root mean square yield errors of bonds with times to maturity longer than one year as an illiquidity risk factor. They claim that exposure to the illiquidity factor consistently explains the cross-sectional excess returns of currency carry trades and hedge funds. The basis of this measure is the relationship between liquidity and arbitrage capital in the market. Under normal circumstances, investors provide abundant funds to the market, which ensures that fluctuations in asset prices are simply eliminated by arbitrage capital, and therefore security prices are shaped by fundamentals. But liquidity crises result in insufficient arbitrage capital, which leads to persistent positive or negative price deviations from fundamental values. This market-wide illiquidity is captured by noise in Treasury bond prices.

Using the Hu et al. (2013) measure for illiquidity, Driessen et al. (2018) investigate the effect of a change in illiquidity factors in short- and long-term bonds separately and claim that, although segmentation based on liquidity occurs, its impact is economically negligible. In particular, they profess that an increase of one basis point in the illiquidity factors of short-term bonds implies on average an increase of0.75 basis points (bps) in the illiquidity factor of long-term bonds. Hattori (2021) uses this measure to study the Japanese bond market and its liquidity commonality with the US market. Dziwok and Karaś (2021) apply a duration-adjusted version of the original method to 10 emerging European countries in order to document the time series of the illiquidity measure, but they do not go beyond interpreting the peaks and troughs of these time series via market events. As such, our study is the first to offer a detailed analysis of illiquidity for an emerging market and one of the very few that address international markets beyond the US.

3. Data

Our main input for this study consists of the historical price data of all bonds traded on the Borsa Istanbul (BIST) for all trading days between January 6, 2005, and March 31, 2021. The BIST Data Platform provides historical data on all bonds available to trade on a particular day through a daily bulletin on its website.[1] We omit corporate bonds, bonds denominated in a foreign currency, stripped from their coupons or principals, floating-rate bonds, and inflation-indexed bonds. As a result, the remainder comprise the data on all discount and fixed coupon-bearing Turkish sovereign Treasury bonds. For every trading day in the observation period, it displays weighted average prices, accrued coupons, times to maturity, and time to the next coupon payments. In the Turkish Treasury market, the day count convention is 364 days, therefore, semiannual and quarterly coupons are paid once every 182 and 91 days, respectively. We calculate cash-flow amounts and times for all bonds using these raw quotes. The observation period spans a total of 4085 trading days.

Ten-year Treasury bonds were first issued on January 27, 2010. Thus, the longest time to maturity for a bond was five years before this date. Table 1 reports summary statistics after and before the issuance of 10-year bonds, as this date acts as a break in the market in terms of the composition of instruments. The number of bonds traded each day varied between 9 and 32 over the entire period. However, as can be seen in the two separate panels in Table 1, while discount bonds were the predominant type of instrument before 2010, coupon bonds dominated the market after 2010. The introduction of 10-year bonds also changed average times to maturity of bonds traded every day. Before January 2010, the mean of this figure was approximately one year, but later it tripled to approximately three years. At the same time, the corresponding impact was slightly weaker in the average duration of bonds traded daily, with mean figures jumping from 0.87 years to 2.32 years. Although the composition of the bonds available in the market changed significantly, as discussed later, we do not observe any major structural breaks in the yield-curve estimates and noise parameters after the daily 10-year bonds are issued. This attests to the resilience of the Nelson-Siegel model in capturing the yield-curve dynamics across different sets of instruments.

Fig. 1 displays the daily highest and average years to maturity of traded bonds in our sample. The left panel shows that, on some trading days, the daily longest times to maturity oscillated between two and four years until January 27, 2010, when 10-year bonds were introduced. After January 27, 2010, the longest daily times to maturity were rarely less than eight years because of the consecutive issuance of new 10-year bonds. This figure varied between 1.5 and 10 years, with a mean of 7.62 years over the full sample period. The right panel shows that average daily times to maturity of traded bonds were mostly between two and four years after January 2010. The implication of this break for yield-curve estimation is that long-term yields must be extrapolated after the last available time to maturity. Arbitrage capital is expected to ensure that deviations between extrapolated long-term yields remain in line with long-term yields estimated on days when long-term bonds were traded. As will be apparent later on, this issue did not pose a problem for fitting the term structure and associated noise values.

4. Methodology

We use the Nelson-Siegel model to extract yield curves from prices of Treasury bonds. This choice can be traced back to reasons documented in the aforementioned literature. First, the yield curve is represented by a smooth continuous function that extrapolates reasonably well to the long end of the curve after the maximum time to maturity of bonds. Second, Laguerre functions are sufficiently flexible to approximate various shapes taken by the forward curve during the period for which they will be fitted. Finally, Nelson-Siegel results are documented to fit better than more sophisticated models when tested in most markets, including Turkey.

The postulated specifications for the instantaneous forward curve and yield curve lead to equal yields in the Nelson-Siegel and Diebold-Li models. Because the estimated parameters are more intuitive in the latter, we follow the factorization by Diebold and Li (2006). In other words, the instantaneous forward rate for maturity m is represented as:

$$f^{\mathrm{NS}}(m) = \beta_1 + \beta_2 \mathrm{e}^{-\lambda m} + \beta_3 \lambda m \mathrm{e}^{-\lambda m}, \tag{1}$$

where β_1, β_2, β_3, and λ are Nelson-Siegel parameters with λ being positive. The corresponding yield curve can be represented as:

$$y^{\mathrm{NS}}(m) = \beta_1 + \beta_2 \left(\frac{1 - \mathrm{e}^{-\lambda m}}{\lambda m} \right) + \beta_3 \left(\frac{1 - \mathrm{e}^{-\lambda m}}{\lambda m} - \mathrm{e}^{-\lambda m} \right). \tag{2}$$

This equation enables us to account for three characteristics of yields separately. First, β_1 has a constant loading. Thus, it can be interpreted as a long-term component, considering that the loadings of other components vanish for a long term to maturity. Second, β_2 has an exponential loading that monotonically decreases as the time to maturity increases. Hence, it differentiates long-term yields from short-term yields and can be construed as a slope component. Third, β_3 has another exponential loading that monotonically

[1] Borsa Istanbul Debt Securities Market Data, https://www.borsaistanbul.com. As the Turkish bond market is centralized and exchange traded, the data cover all available bond prices.

Table 1
Summary statistics of treasury bonds.

Daily Observation	Mean	St. Dev.	Min	Max
Panel A. 2812 trading days between January 27, 2010 and March 31, 2021				
Number of bonds	22.37	3.67	9	32
Number of discount bonds	5.12	3.4	0	15
Number of coupon bonds	17.25	5.78	2	27
Average years to maturity	2.97	0.75	1.05	4.41
Highest years to maturity	9.28	0.73	4.27	10
Average duration	2.32	0.53	0.97	3.38
Highest duration	6.04	0.62	3.45	7.32
Panel B. 1273 trading days between January 6, 2005 and January 26, 2010				
Number of bonds	19.62	2.53	14	26
Number of discount bonds	16.89	3.18	12	23
Number of coupon bonds	2.73	1.07	0	6
Average years to maturity	0.97	0.24	0.53	1.43
Highest years to maturity	3.97	1.05	1.49	5
Average duration	0.87	0.19	0.53	1.28
Highest duration	2.98	0.68	1.49	3.98

Notes: This table shows summary statistics for Treasury bonds traded between January 6, 2005 and March 31, 2021.

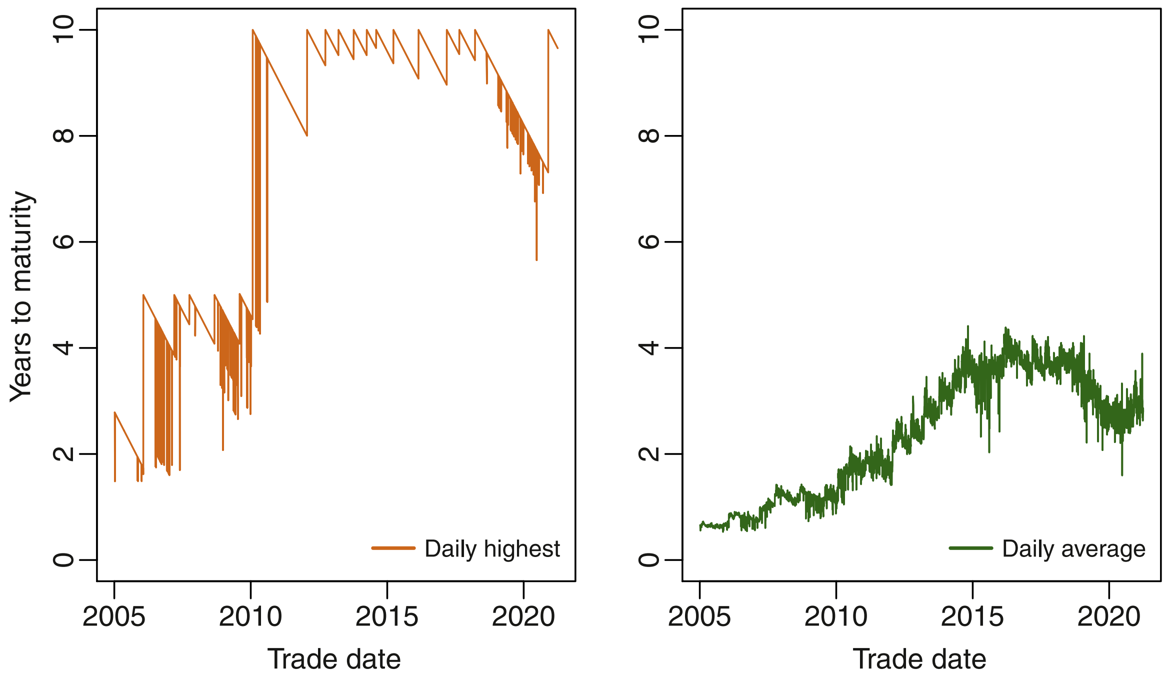

Fig. 1. Daily highest and average years to maturity of traded treasury bonds. *Notes:* This figure displays the highest and average years to maturity of traded treasury bonds for each day in sample period.

decreases after peaking at the medium term to maturity, generating a hump shape. It is deemed a curvature component because it differentiates medium-term yields from others. The location of the peak generated by the curvature factor is determined solely by the λ parameter. For a specified $\hat{\lambda}$ value, the location of this peak can be identified by equating the derivative of the curvature loading with zero in Eq. (2).

The Nelson-Siegel parameters can be estimated using nonlinear least squares optimization. To do so, first, simplification is needed, as the prices of both discount and coupon-bearing bonds will be used. Because the intention is to estimate yields as a function of the time to maturity, before calibrating the model for bond prices, we deconstruct the cash flows pertaining to coupon-bearing bonds and represent them as a portfolio of discount bonds. This is because only when coupon payments are assumed to be priced separately can we estimate yields for their terms to maturity. One can consider any coupon bond as a portfolio of cash flows $C = (c_1, c_2, \ldots, c_T)$ that have respective times to maturity vector $M = (m_1, m_2, \ldots, m_T)$. The last element of the cash-flow vector is the coupon plus par value for a coupon-bearing bond, whereas the cash-flow and time-to-maturity vectors have only one element for discount bonds. Then, the price of a bond is defined as:

$$P_{C,M} = \sum_{i=1}^{T} c_i e^{(-m_i y_{m_i})}. \tag{3}$$

Similarly, the Nelson-Siegel price of a bond is defined as:

$$P_{C,M}^{\mathrm{NS}} = \sum_{i=1}^{T} c_i e^{(-m_i y^{\mathrm{NS}}(m_i))}. \tag{4}$$

Using the specifications for observed prices in Eq. (3) and theoretical prices in Eq. (4), the objective function can be established. The Nelson-Siegel parameters on day t minimize the t-day sum of squared price errors, defined as:

$$S_t^2 = \sum_{k=1}^{n_t} (P_{C,M,k} - P_{C,M,k}^{\mathrm{NS}})^2, \tag{5}$$

where n_t denotes the number of bonds traded on day t, $P_{C,M,k}$, and $P_{C,M,k}^{NS}$ denote, respectively, observed and Nelson-Siegel prices of bond k traded on day t. The fitting performance of the model on day t can be measured by the root mean square error, which is defined as:

$$RMSE_t = \sqrt{\frac{S_t^2}{n_t}}. \tag{6}$$

Before we continue with the daily fitting, however, we replace λ in Eq. (2) with a constant $\hat{\lambda}$. This approach goes back to Diebold and Li (2006), who fixed $\hat{\lambda}$ at 0.7308 implying that impact of curvature component on yield curve peaks at approximately 2.5 years. Subsequent researchers numerically searched for $\hat{\lambda}$ so that cumulative errors in yields or prices are minimized (Gilli et al., 2010; Ibáñez, 2016). We follow the literature by picking a parameter that minimizes the sum of squared errors in bond prices over the entire observation period which is defined as:

$$S^2 = \sum_{k=1}^{N_t} (P_{C,M,k} - P_{C,M,k}^{\mathrm{NS}})^2, \tag{7}$$

where N_t denotes the total number of bond transaction quotes over all daily observations.

Recent literature provides evidence that fitting errors in the Nelson-Siegel model have valuable information on financial markets. When a shock to bond prices cannot be absorbed by arbitrage capital in the market, fitting errors remain high for a series of days or even months. That is, insufficient trade volumes in the bond market make room for arbitrage opportunities. Following Hu et al. (2013), we define a market-wide illiquidity measure that tracks episodes of liquidity crises as a mean root square yield error of bonds with times to maturity of longer than one year. Because the yields on coupon-bearing bonds are not observed, we define the Nelson-Siegel yield to maturity of a bond as y_{ytm}^{NS}, which is a constant interest rate that results in the bond's Nelson-Siegel price:

$$P_{C,M}^{\mathrm{NS}} = \sum_{i=1}^{T} c_i e^{(-m_i y_{ytm}^{\mathrm{NS}})}. \tag{8}$$

Next, comparing the yield to maturity of bond k on day t implied by the market price $y_{ytm\ \mathrm{m},k}$ to that implied by the Nelson-Siegel model $y_{ytm,k}^{NS}$, market illiquidity on day t is defined as:

$$\text{Illiquidity}_t = \sqrt{\frac{\sum_{k=1}^{l_t} (y_{ytm,k} - y_{ytm,k}^{NS})^2}{l_t}}, \tag{9}$$

where l_t denotes the number of bonds with times to maturity longer than one year traded on day t. This daily noise measure becomes the proxy for bond market illiquidity and the subject of further empirical analysis.

5. Empirical findings

5.1. Term structure of interest rates

We follow the Nelson-Siegel specification in Eq. (2) to minimize the error function defined in Eq. (5) through a nonlinear optimization algorithm. The Nelson-Siegel components do not generate smooth time series with the specification in Eq. (2). To fix this obstacle in parameter estimation, Diebold and Li (2006) heuristically select a constant $\hat{\lambda}$ that locates the height of the curvature loading in between years 2 and 3. Gilli et al. (2010) suggest employing a grid search for the optimal $\hat{\lambda}$ in a tight range of values to avoid collinearity in factor estimates and to keep the problem tractable. Ibáñez (2016) minimizes the absolute mean error in yields in the US market with $\hat{\lambda}$ searched in the range of 0.2–1, arguing that any value too high or too close to zero yields highly correlated factor loadings for the slope and curvature. We execute a grid search between 0.5 and 1.5 to estimate a $\hat{\lambda}$ that minimizes the objective function in Eq. (7).[2]

[2] As a robustness test, we also used the specification by Svensson (1994) that makes the Nelson-Siegel model more flexible with more parameters. The results show extreme collinearity between the two curvature components. Furthermore, the beta values did not have a smooth time series. This unappealing impact of adding a fourth component is best observed on days when the number of bonds traded is relatively low or the yield curve is flat. To avoid losing the financial interpretation and smooth time series of Nelson-Siegel parameters without improving the fitting power of the model, we retained the simpler model.

Table 2
Summary statistics of estimated Nelson-Siegel yields.

	1-month	3-month	6-month	1-year	2-year	5-year	10-year
Mean	0.114	0.116	0.117	0.12	0.121	0.118	0.104
St. Dev.	0.04	0.041	0.042	0.043	0.042	0.036	0.023
Skewness	0.561	0.56	0.577	0.627	0.669	0.81	0.989
Kurtosis	− 0.507	− 0.613	− 0.66	− 0.584	− 0.423	− 0.111	0.641
Min	0.041	0.041	0.042	0.044	0.048	0.055	0.06
Max	0.24	0.242	0.244	0.243	0.259	0.238	0.189

Notes: This table shows summary statistics of daily Nelson-Siegel yields from January 6, 2005 to March 31, 2021 for times to maturity up to 5 years. Statistics for 10-year yields pertain to the observation period starting January 27, 2010.

Although the extended results are unreported for the sake of brevity, the optimization problem yields a local minimum for pricing errors, with $\hat{\lambda}$ estimated as 0.7865, which is precise up to four digits after the decimal. This figure conditions the loading of the curvature component to peak at 2.28 years for yield curves between January 6, 2005, and March 31, 2021. This method requires extra time to optimize the curvature loading. However, replacing variable λ in Eq. (2) with the constant $\hat{\lambda}$ changes the optimization problem with the objective function defined in Eq. (5) into a linear one. Doing so immensely saves time for solving 4085 optimization problems, one for each trading day in the observation period. Now, Eq. (2) becomes:

$$y_t^{\mathrm{NS}}(m) = \beta_1^t + \beta_2^t\left(\frac{1-\mathrm{e}^{-0.7865m}}{0.7865m}\right) + \beta_3^t\left(\frac{1-\mathrm{e}^{-0.7865m}}{0.7865m} - \mathrm{e}^{-0.7865m}\right). \tag{10}$$

We estimate Nelson-Siegel parameters β_1^t, β_2^t, and β_3^t, which minimize the objective function in Eq. (7). Panel C in Table 3 reports the sample statistics of the estimated parameters, and the middle panel of Fig. 7 demonstrates the time series of long-term, time-decay, and curvature components, corresponding to the beta values, respectively. The introduction of 10-year bonds on January 27, 2010, might cause a structural break in interest rate dynamics in the market. However, our comparison between the 30-day periods before and after this event did not show any statistical difference in the t-tests of interest rates and yield-curve parameters, with the exception of the slope. Any apparent stability in the yield-curve parameters around that date could be considered the reason for the government's introduction of 10-year bonds, as they would have the confidence to issue long-term bonds. The long-term yield component has an increasing trend between 2005 and 2009, when it rose as high as 0.25. Then, in 2010, it declined to 0.1, its sample mean, and remained near this point until 2018. Beginning in the summer of 2018, it became more volatile and fluctuated between 0.1 and 0.15 until March 2021, when it exceeded 0.15. As the loading of β_2 is the highest in the short term, the parameter is expected to increase when the market experiences a liquidity crisis, which is observed in the time series. β_2 jumped to extraordinarily high levels during the crises of 2007 and 2018. The curvature component β_3 differentiates medium-term yields from other yields. As expected, it peaked in the summer of 2018, when medium-term interest rates rose because of expectations of higher inflation.

Table 2 reports summary statistics for selected Nelson-Siegel yields. It is observed that both means and standard deviations of yields peak at the middle terms to maturity. Daily observed maximum yields peak at the middle terms to maturity as well, while daily observed minimum yields in the observation period increase with term to maturity.

Table 2 reports summary statistics for selected Nelson-Siegel yields. The means and standard deviation of yields both peak at medium terms to maturity around 2–5 years. Daily observed maximum yields peak at medium terms to maturity as well, while daily observed minimum yields in the observation period increase with longer terms to maturity.

The top panel of Fig. 2 displays the time series for monthly and annual yields, and the bottom panel shows time series of two- and five-year yields. Monthly yields can be deemed a short-term interest rate that is approximately explained by a weighted average of β_1 and β_2. It has a smoother series than individual parameters because it does not fluctuate when parameters move in opposite directions. The time series of one- and two-year yields show sharp spikes on trading days when the β_3 parameter jumps. Because the five-year yield is close to the long end of yield curve, related time series follow the trajectory of β_1 more closely than other yields.

5.2. Noise as Illiquidity

We next proceed to compile the illiquidity measure per the definition in Eq. (9) based on errors between model-implied yields and actual yields. For example, Fig. 3 displays the fitted yield curve and yields to maturity of individual bonds on August 20, 2018, the day with the highest illiquidity in the observation period. The left panel shows the yields with respect to times to maturity, and the right panel shows them with respect to Macaulay durations. The individually observed yields do not indicate a reasonable pattern for a smoothing function to approximate, thus seemingly giving traders arbitrage opportunities. For example, six bonds with yields to maturity between 0.19 and 0.22, each with an approximate duration of 4.5 years, indicate an arbitrage opportunity. That is, selling the bond with the lowest yield to maturity and using the proceedings to buy the bond with the highest yield to maturity generates a nonnegative return that is largely hedged against interest rate risk. But low trading volumes limit profits from existing arbitrage opportunities. Thus, the illiquidity measure peaked on that day.

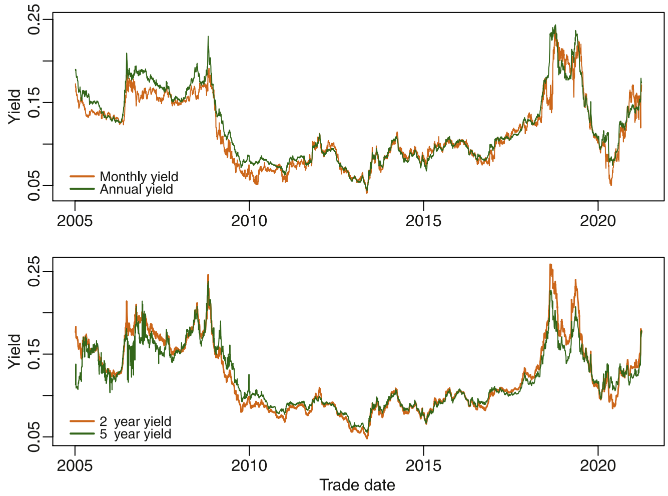

Fig. 2. Time series of Nelson-Siegel yields. *Notes:* This figure displays time-series of sample Nelson-Siegel yield estimates. The top panel displays 1-month and annual yields, while the bottom panel displays 2- and 5-year yields.

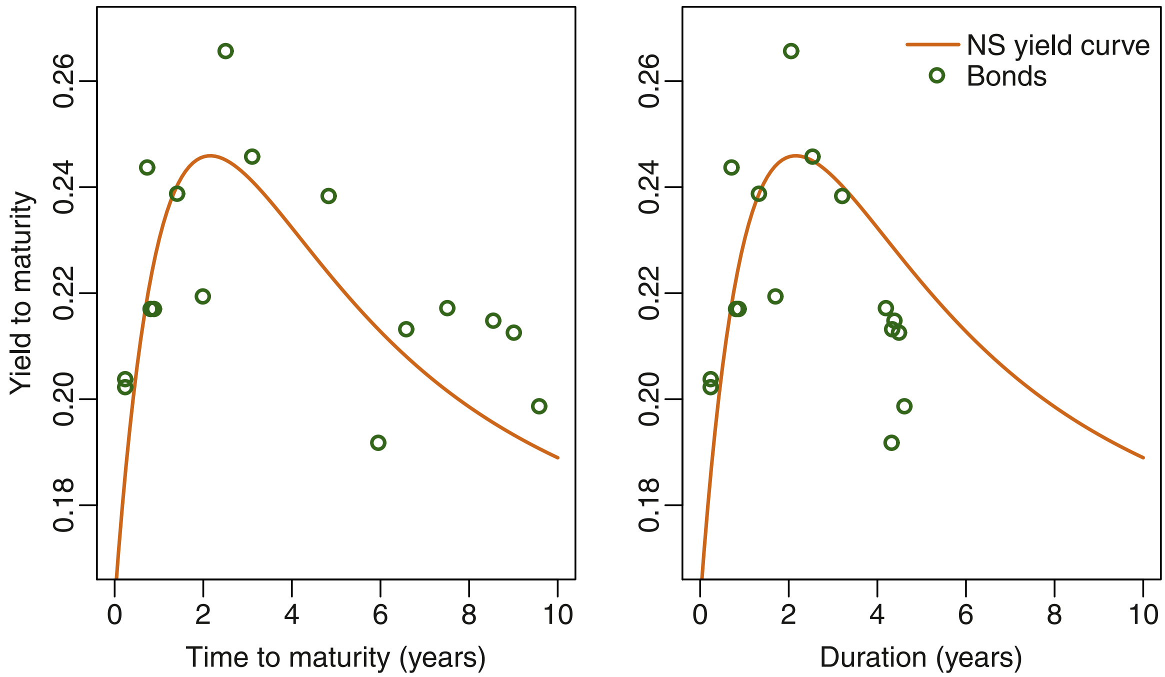

Fig. 3. Nelson-Siegel Yield curve and yields to maturity on August 20, 2018. *Notes:* This figure displays fitted Nelson-Siegel yield curves along with actual yields to maturity for the bonds traded on August 20, 2018, the day with the peak illiquidity in the sample period. The left panel maps yields to time to maturity, while the right panel has Macaulay durations on the x-axis.

Fig. 4 demonstrates the time series of the market-wide illiquidity measure of Turkish Treasury bonds on the left axis in blue and the US illiquidity measure on the right axis in red.[3] In the Turkish illiquidity series, the level jumps to exorbitant levels when new information leads to rapid changes in bond prices, and insufficient trading volumes leave room for arbitrage opportunities. As shown in Fig. 4, illiquidity measure occasionally spikes and stays high, indicating that liquidity crises continue for a period of time. The highest illiquidity in the observation period was recorded in August 2018. Later, the measure stayed abnormally high until February 2019, when it jumped again, with continuation of the effect until October 2019. The last two weeks of March 2021 also recorded abnormally high illiquidity on consecutive trading days.

[3] The US illiquidity measure is calculated by Hu et al. (2013) and obtained from Prof. Jun Pan's website en.saif.sjtu.edu.cn/junpanwith the latest available data until the end of 2020 at the time of writing.

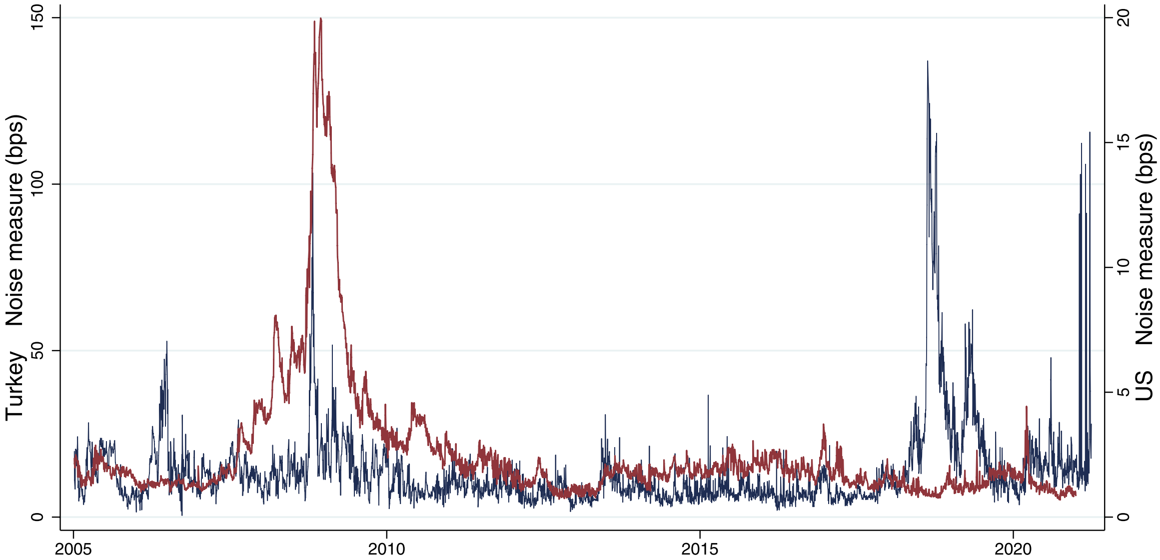

Fig. 4. Time series of noise as market-wide illiquidity proxy for Turkey and the US. *Notes:* This figure displays time series of the measure for Turkey and the US. The blue curve on the left axis is for Turkey produced by our own Nelson-Siegel fitting. The red curve on the right axis is the US data until the end of 2020 calculated by Hu et al. (Hu et al., 2013) and retrieved from Prof. Jun Pan's website.

Table 3
Summary statistics for illiquidity measures and other metrics of interest.

	Obs.	Mean	Std. Dev.	Min	Max
Panel A. Bond Market Illiquidity Measures					
Noise measure (bps)	4085	13.565	12.553	0.518	136.995
Amihud measure ($\times$ 10^{-10})	4084	1.073	2.156	0.024	37.488
Time b/w transactions (seconds)	4085	61.35	75.055	6.774	1145.455
Turnover cycle (days)	4085	1276.775	1966.153	105.89	44117.87
Bid/Ask spread (bps)	3710	61.527	27.892	11.78	158.5
Panel B. Other Market Indicators					
CDS 5Y (bps)	3137	260.3	108.887	109.818	835.01
Swap spread (bps)	4016	103.209	117.997	− 398.421	941.844
Default spread (bps)	4085	369.659	265.798	− 364.344	1491.423
Panel C. Term Structure Parameters					
Level β_1 (%)	4085	11.324	2.971	0	23.881
Slope β_2 (%)	4085	0.002	3.495	− 12.357	16.821
Curvature β_3 (%)	4085	2.69	6.413	− 10.358	45.39
Panel D. International Market Indicators					
US Noise measure (bps)	3866	2.531	2.606	0.691	19.978
TED spread (bps)	3699	40.793	34.981	− 18.95	324
MOVE index	4085	80.169	30.862	36.6	264.6
VIX index	3952	19.111	9.349	9.14	82.69
Panel E. Macro Indicators					
Exp. inflation (%)	180	7.224	1.672	4.67	12.97
St. dev. of exp. inflation (%)	180	1.025	0.432	0.57	3.05
Economic confidence index	171	95.719	16.152	29.1	124.8
Emerging markets bond sentiment	168	− 1.311	9.189	− 25.75	15.25

Notes: This table shows descriptive statistics for illiquidity measures and other metrics of interest.

We next document the relation between the noise measure, which is proposed as an illiquidity measure, and various other local and international measures. Our objective is to document the explanatory power of our noise measure, as well as shed some light on its determinants. Table 3 documents the summary statistics of Turkish bond market illiquidity measures, such as the Amihud measure, the time between transactions, the turnover cycle, and the bid-ask spread in Panel A. Panel B gives the < spell out > CDS, swap, and default spreads for Turkey. Panel C shows the term structure parameters retrieved from our Nelson-Siegel fitting. Panel D includes the US noise measure as well as other US-based measures: Treasury bill and Euro Dollar (TED) spread, Merrill Lynch Option

Volatility Estimate (MOVE) index, and Chicago Board Options Exchange's Volatility Index (VIX). Finally, Panel E documents monthly statistics for inflation expectations and uncertainty along with an economic confidence index and emerging markets bond sentiment. Descriptions of the variables are given in the following sections.

The dynamics of the noise measure and its relation to other measures show time-varying characteristics at first glance. We expect that the tectonic shifts in international markets and their local repercussions impact illiquidity and noise in this open emerging market. We conjecture that the end of quantitative easing in the US and later rise of local economic and political turmoil in Turkey could lead to a shift in these dynamics. We next look at the dynamics of each variable before and after 2013, roughly corresponding to the first time that the tapering of quantitative easing was publicly mentioned.[4] Table 4 documents the correlation levels between the Turkish noise measure and various variables for the full sample period as well as pre- and post-2013. To keep the analyses simple and avoid any data-mining bias that might emanate from looking for a statistical regime switch in the relations, we use a rough cut-off point.[5]

5.3. Illiquidity Spillover: Turkey vs. the US

The time series dynamics for Turkey and the US noise measures shown in Fig. 4 point to a close relationship, especially in the earlier years of the analysis period, which include the 2008 financial crisis and its aftermath. Simple correlation measures documented in Panel D of Table 4 corroborate our conjecture with a significant but moderate 0.148 correlation for the full period, which extends to the end of 2020. However, when the sample is divided into two parts, the pre-2013 correlation is a relatively high 0.441, whereas the post-2013 correlation becomes negative, at -0.363. In a univariate regression of the Turkish noise measure with that of the lagged US noise measure, the coefficient turns from a positive value pre-2013 to a significant and high negative value post-2013. Panel A of Table 5 reports the regression results documenting the relation. Because the trading day in the US begins at the end of the trading day in Turkey, we regress Turkish measures with the US measures with a one-day lag.

For further assessment of the relationship between the Turkish and the US noise measures, we look at vector autoregression (VAR) models and document Granger causality between the pair. Panel B of Table 5 documents the p-values of Granger-causality tests. The full period does not show any Granger causality between the US and the Turkish noise measure and only relatively weak Turkish causality on the US. However, the sample is divided into two subperiods, the US noise Granger causes the Turkish noise measure in both periods. Turkey's impact on the US dissipates after 2013. The impulse response function of the Turkish noise measure to that of the US, displayed in Fig. 5, shows a positive response pre-2013 but a larger negative response post-2013.

5.4. Noise measure and other illiquidity measures

In this section, we document the extent to which the noise measure captures information in other liquidity measures. We calculate or retrieve other available liquidity measures for the Turkish fixed-income market. The most important empirical measure of illiquidity is the eponymous Amihud (2002) measure, which we calculate as:

$$\text{Amihud}_t = \text{average}\left(\frac{|r_t|}{\text{Volume}_t}\right), \tag{11}$$

where r_t is the return and $Volume_t$ is the trading volume of treasury bonds in our analysis on day t. This measure captures the price impact of trading volume, in effect showing the illiquid market conditions with higher values. The time between transactions is measured by the total time in an eight-hour trading day divided by total number of trades that day. This measure, sometimes called average trade duration, directly measures the time aspect of illiquidity. The turnover cycle is measured by total Turkish government outstanding debt denominated in the Turkish lira,[6] divided by the total trading volume that day. This is a measure of trading volume relative to the available debt, inverted to capture illiquidity.

One of the most important measures of illiquidity is the bid-ask spread, which captures the cost of trading. Bid and ask prices or interest rates for the bonds in our analysis were not readily available, so instead we use the difference between bid and ask interest rates on the overnight interbank borrowing market.[7] This measure serves as a good proxy for general fixed-income market illiquidity in Turkey. Summary statistics for variables are in Panel A of Table 3, and correlations are in Table 4. Fig. 6 juxtaposes the time series of each of these variables in blue with the noise measure in gray.

The noise measure is strongly correlated with the Amihud measure and bid-ask spread across the full sample period as well as the two subperiods. The correlations are somewhat lower for the transaction-based measures, though they are still positive and significant, especially since 2013. The strong relationship with the most widely used illiquidity measures leads us to run univariate and

[4] "Key events for the Fed in 2013: the year of the 'taper tantrum'," *Reuters*, January 11, 2019, www.reuters.com/article/us-usa-fed-2013-timeline-idUSKCN1P52A8.

[5] Because the issuance of 10-year bonds on January 27, 2010, changes the composition of available instruments, it might cause a structural break in the liquidity dynamics in the market. However, our comparison between the 30-day period before and after this event did not show any statistical difference in t-tests of the noise measure. Furthermore, unreported regression results using data after January 27, 2010, have coefficients similar to those for the full sample period. Therefore, the results are robust to the introduction of long-term bonds to the market.

[6] Weekly data are retrieved from Refinitiv Datastream and assumed to be constant every day of the week.

[7] Daily data are retrieved from Refinitiv Datastream starting on July 3, 2006.

Table 4
Correlation of noise measure with other metrics of interest.

	Full sample	2005–2012	2013–2021
Panel A. Bond Market Illiquidity Measures			
Amihud measure ($\times 10^{-10}$)	0.411 * **	0.508 * **	0.440 * **
Time b/w transactions (seconds)	0.194 * **	− 0.172 * **	0.243 * **
Turnover cycle (days)	0.211 * **	− 0.029	0.244 * **
Bid/Ask spread (bps)	0.436 * **	0.306 * **	0.580 * **
Panel B. Other Market Indicators			
CDS 5Y (bps)	0.528 * **	0.690 * **	0.493 * **
Swap spread (bps)	0.368 * **	− 0.402 * **	0.564 * **
Default spread (bps)	0.091 * **	− 0.225 * **	0.248 * **
Panel C. Term Structure Parameters			
Level β_1	0.359 * **	0.488 * **	0.436 * **
Slope β_2	0.203 * **	− 0.153 * **	0.438 * **
Curvature β_3	0.531 * **	0.234 * **	0.758 * **
Panel D. International Market Indicators			
US Noise measure (bps)	0.148 * **	0.441 * **	− 0.363 * **
TED spread (bps)	0.120 * **	0.465 * **	− 0.073 * **
MOVE index	0.047 * **	0.376 * **	− 0.226 * **
VIX index	0.192 * **	0.404 * **	0.109 * **
Panel E. Macro Indicators			
Exp. inflation (%)	0.545 * **	0.107	0.709 * **
St. dev. of exp. inflation (%)	0.740 * **	0.374 * **	0.809 * **
Economic confidence index	− 0.478 * **	− 0.623 * **	− 0.537 * **
Emerging markets bond sentiment	− 0.397 * **	− 0.773 * **	− 0.287 * **

Notes: This table shows correlations of the noise measure with various metrics of interest. The time period is divided into two subperiods to document the changing relation dynamics. * ** , * *, and * 1 %, 5 %, and 10 % significance levels, respectively.

Table 5
The Relationship between Turkey's noise measure and the US noise measure.

	Full Sample	2005–2012	2013–2020
Panel A. TR Noise Measure Regressed on the US Noise Measure			
US Noise Measure	0.667 * **	1.051 * **	− 10.716 * **
	(0.096)	(0.093)	(0.928)
Obs.	3866	1933	1932
Adj. R^2	0.021	0.189	0.129
Panel B. p-values for Granger Causality Tests Between TR and US Noise Measures			
Null: The US does not Granger cause TR	0.4	0.095	0.065
Null: TR does not Granger cause the US	0.06	0	0.226

Notes: Panel A shows univariate regression results between Turkey's noise measure and the US noise measure with a one-day lag because the US trading day begins at the end of Turkey's trading hours. Panel B reports the p-values of Granger-causality tests. Robust standard errors are in parentheses. * ** , * *, and * 1 %, 5 %, and 10 % significance levels, respectively.

multivariate regressions to assess whether the information in the noise measure is explained by other popular illiquidity measures. Table 6 reports the results of regressions for the full period as well as the pre- and post-2013 subperiods.

All four illiquidity measures have significant coefficients in univariate regressions, however, the time between transactions and turnover cycles lose their significance in multivariate regressions. This is expected as the Amihud measure partly captures the impact of volume, leading to multicollinearity issues. Overall, these measures capture up to 40 % of the variation in the noise, measured by R^2. The fact that the results improve for each period, as opposed to the full time period, supports our hypothesis that the dynamics differ over time.

5.5. Noise measure and other financial indicators

We explore the relation of the noise measure to other local and international financial met- rics. For local financial metrics, we include benchmark CDS spreads for Turkey's five-year dollar-denominated government bonds. This provides a reliable and liquid

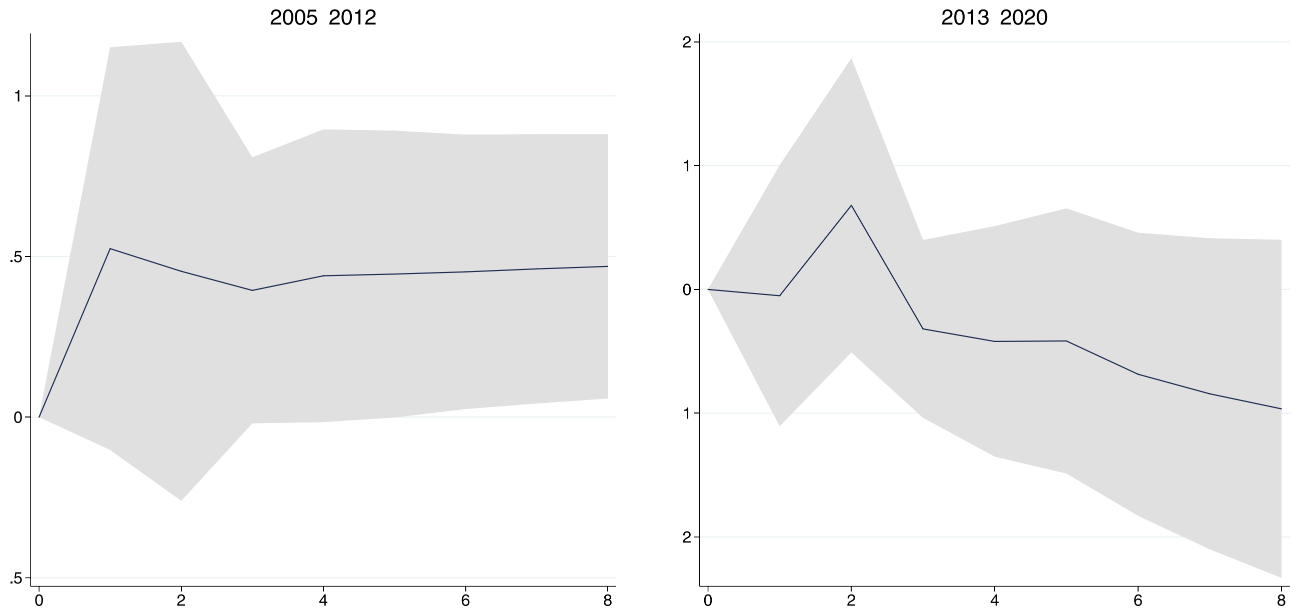

Fig. 5. Impulse response function of Turkey's noise measure to the US Noise Measure. *Notes:* This figure displays the impulse response functions of Turkey's noise measure to that of the US. The shaded areas denote ± 2 standard error bands. The left panel is before 2013, and the right panel is for 2013 and later.

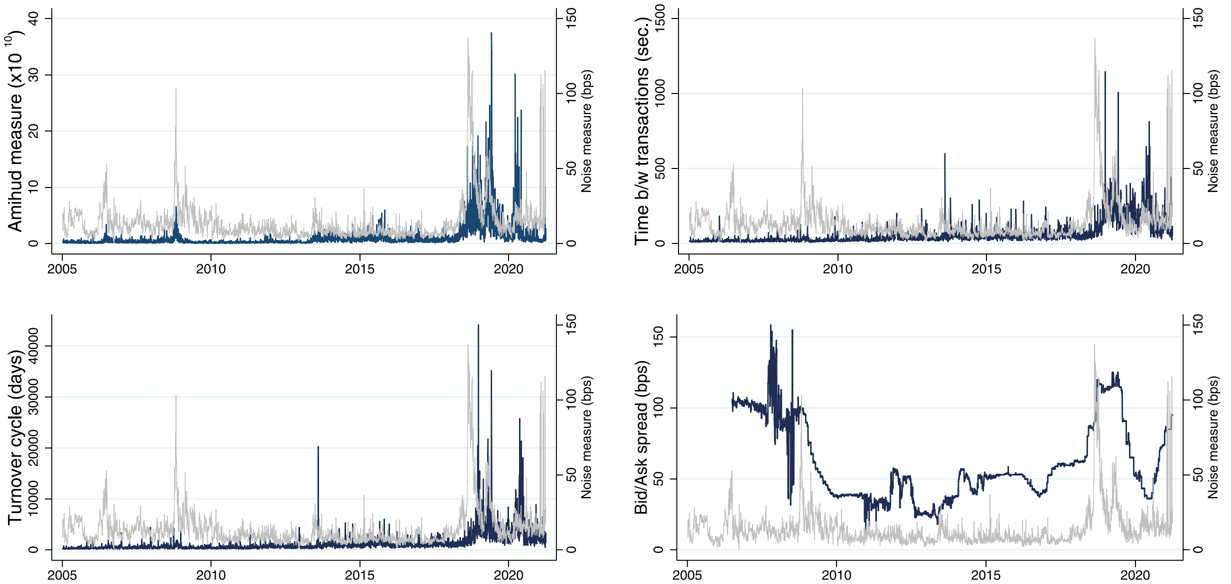

Fig. 6. Daily noise measure vs. fixed-income market illiquidity measures. *Notes:* This figure displays the time series of fixed-income illiquidity measures along with the noise measure. The noise measure is denoted with gray data points on the right axis, and other illiquidity measures denoted with blue data points on the left axis.

proxy for the country's credit risk with the longest coverage. Another creditworthiness proxy is the swap spread, which we calculate by subtracting the two-year government yield from the two-year swap rate quotes in the market. We then include the default spread in the economy as the difference between two-year commercial loan rates and the government yields calculated earlier.[8] Panel B of Table 3 shows the descriptive statistics with correlations in Table 4. CDS is always highly correlated with the noise measure. Swap and default spreads, however, have changing signs in correlations, such that those before 2013 are negative and those after 2013 are positive. This shows that the local credit market is not in line with liquidity levels pre-2013, leading us to think that liquidity might be artificially improved before 2013 by quantitative easing on a global scale. Fig. 7 shows the time series of relevant measures along with the noise measure.

We also assess the relation between noise and the term structure parameters, level (β_1), slope (β_2), and curvature (β_3). The level is consistently positively correlated, as illiquidity in an emerging market is coupled with higher borrowing costs, a reality in stark contrast to the US results. The slope is negatively correlated with illiquidity before 2013, confirming that the fundamental realities are not reflected in a world awash in excess liquidity. Post-2013, the relationship turns positive, as expected, whereas, the curvature is especially highly correlated with noise since 2013. However, one should not read too much into this, as it might be due to especially high fitting errors, which causes elevated noise levels when the curvature of the term structure is high. This may not be necessarily related to the numerical issues but, rather, about the excess arbitrage opportunities available with relatively limited arbitrage capital.

Financial indicators in the US market play a significant role in international markets, which leads us to explore how the noise measure is impacted by international indicators. The TED spread is the difference between the three-month Treasury bill and the three-month Eurodollars contract as represented by the three-month London Interbank Offered Rate (LIBOR) denominated in US dollars. This spread is said to proxy the perceived default risk in financial institutions as well as the funding liquidity risk. The MOVE index is a measure of the US interest rate volatility implied by prices of options on Treasuries. As such, it is a risk measure for the US interest rates. The VIX index tracks the implied volatility in S&P 500 options. Although it is derived from stock market options, it is now accepted as the fear index for the entire financial market.[9] The descriptive statistics and correlations with the noise measure are reported in Panel D in Tables 3 and 4, respectively. The correlations, although significant, turn negative after 2013.

Univariate and multivariate regressions to explain the noise measure with various indicators are reported in Table 7. Local market indicators explain 34–64 % of the noise variation, with the most significant contribution coming from CDS levels. Swap and default spreads have a negative impact on the noise measure before 2013. The swap spread has higher explanatory power after 2013. The term structure parameters have higher R^2 levels, but once again the impact of curvature is very likely due to the relative lack of arbitrage capital affecting both variables at the same time. The consistent relations with other variables confirm that this is not due to the numerical issues related to fitting Nelson-Siegel curves. The negative relation of the slope level before 2013 points to an imminent

[8] Daily data are retrieved from Refinitiv Datastream. CDS data are available since October 8, 2008. Swap rates are available since April 18, 2005. Commercial loan rates are available for the period beginning January 6, 2005.

[9] Daily data are retrieved from Refinitiv Datastream. The TED spread is available since July 18, 2006. The MOVE one-month bond volatility index and the baseline VIX index are available for the full period beginning in January 6, 2005. Some days are omitted from analysis because some public holidays in Turkey and the US do not overlap.

Table 6
Daily noise measure regressed on other bond market illiquidity measures.

	Full Sample					2005–2012					2013–2021				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Amihud	2.393 * **				2.033 * **	9.445 * **				10.513 * **	2.438 * **				1.279 * **
	(0.255)				(0.263)	(0.860)				(0.970)	(0.280)				(0.214)
Time b/w transactions		0.032 * **			− 0.000		− 0.078 * **			− 0.048 * **		0.041 * **			− 0.018 * *
		(0.003)			(0.007)		(0.008)			(0.018)		(0.004)			(0.008)
Turnover cycle			0.001 * **		− 0.000			− 0.001		− 0.004 * **			0.002 * **		0.000
			(0.000)		(0.000)			(0.001)		(0.001)			(0.000)		(0.000)
Bid/Ask spread				0.200 * **	0.154 * **				0.076 * **	0.026 * **				0.370 * **	0.317 * **
				(0.010)	(0.009)				(0.006)	(0.005)				(0.018)	(0.022)
Obs.	4084	4085	4085	3710	3710	2011	2012	2012	1637	1637	2073	2073	2073	2073	2073
Adj. R^2	0.169	0.037	0.044	0.190	0.285	0.258	0.029	0.000	0.093	0.404	0.193	0.059	0.059	0.336	0.370

Notes: This table shows robust regression results between the daily noise measure and other illiquidity measures across the full time period and two subperiods. Robust standard errors are in parentheses. * ** , * *, and * 1 %, 5 %, and 10 % significance levels, respectively.

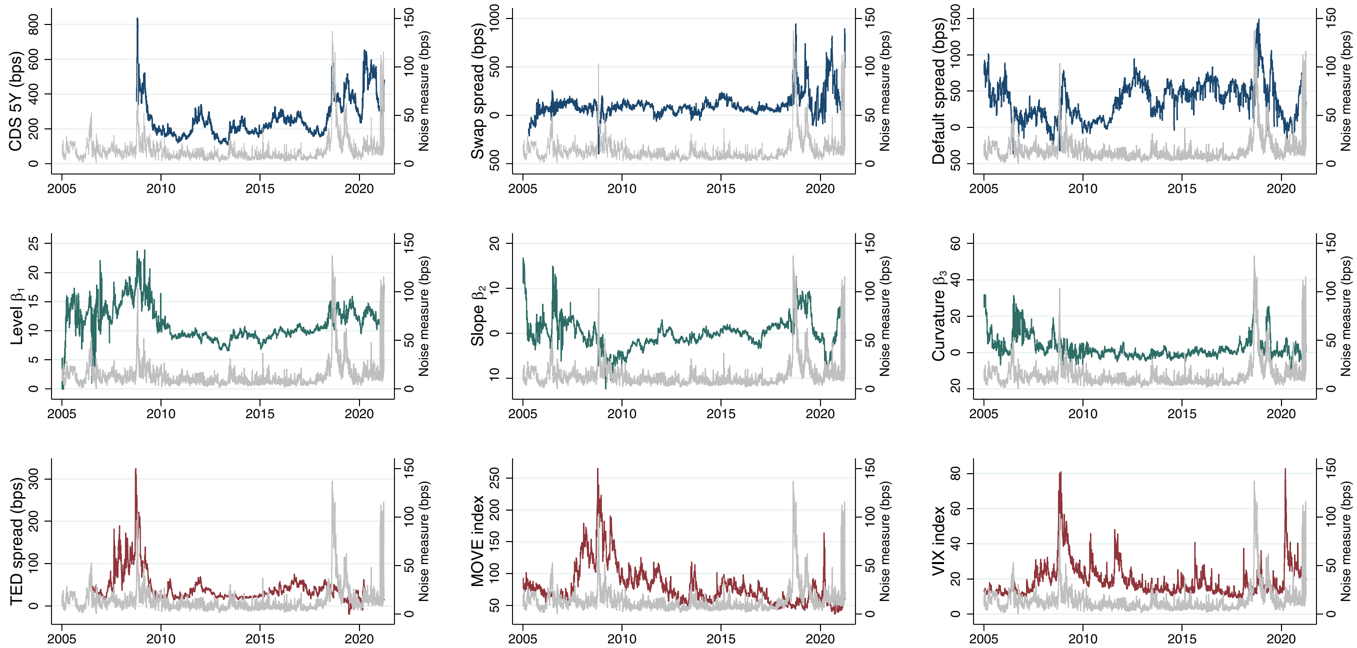

Fig. 7. Daily noise measure vs. other market measures. *Notes:* This figure displays the time series of financial variables of interest along with the noise measure. Noise measure is denoted with grey data points on the right axis with other metrics denoted in colored data points on the left axis.

Table 7
Daily noise measure regressed on other metrics of interest.

	Full Sample				2005–2012				2013–2021			
Panel A. Other Market Indicators												
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
CDS 5Y	0.067 * **			0.055 * **	0.064 * **			0.049 * **	0.070 * **			0.046 * **
	(0.003)			(0.004)	(0.005)			(0.003)	(0.004)			(0.004)
Swap spread		0.039 * **		0.025 * **		− 0.048 * **		− 0.044 * **		0.063 * **		0.041 * **
		(0.004)		(0.005)		(0.006)		(0.006)		(0.004)		(0.004)
Default spread			0.004 * **	0.007 * **			− 0.007 * **	− 0.014 * **			0.016 * **	0.021 * **
			(0.001)	(0.001)			(0.001)	(0.001)			(0.002)	(0.002)
Obs.	3137	4016	4085	3137	1064	1943	2012	1064	2073	2073	2073	2073
Adj. R^2	0.278	0.135	0.008	0.345	0.475	0.161	0.050	0.638	0.243	0.318	0.061	0.448
Panel B. Term Structure Parameters												
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Level (β_1)	1.516 * **			1.341 * **	1.127 * **			0.913 * **	3.507 * **			1.545 * **
	(0.066)			(0.070)	(0.078)			(0.062)	(0.174)			(0.122)
Slope (β_2)		0.730 * **		0.144		− 0.339 * **		− 0.689 * **		2.198 * **		0.645 * **
		(0.088)		(0.094)		(0.058)		(0.070)		(0.156)		(0.108)
Curvature (β_3)			1.039 * **	0.933 * **			0.296 * **	0.598 * **			1.918 * **	1.622 * **
			(0.068)	(0.080)			(0.038)	(0.052)			(0.077)	(0.089)
Obs.	4085	4085	4085	4085	2012	2012	2012	2012	2073	2073	2073	2073
Adj. R^2	0.129	0.041	0.282	0.375	0.238	0.023	0.054	0.350	0.190	0.192	0.574	0.625
Panel C. International Market Indicators												
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
TED spread	0.044 * **			0.050 * **	0.079 * **			0.026 * **	− 0.078 * **			− 0.027
	(0.007)			(0.007)	(0.008)			(0.005)	(0.021)			(0.021)
MOVE index		0.019 * *		− 0.096 * **		0.089 * **		0.033 * **		− 0.238 * **		− 0.281 * **
		(0.009)		(0.011)		(0.010)		(0.007)		(0.023)		(0.023)
VIX index			0.258 * **	0.404 * **			0.319 * **	0.258 * **			0.230 * **	0.364 * **
			(0.028)	(0.030)			(0.036)	(0.044)			(0.035)	(0.034)
Obs.	3699	4085	3952	3580	1626	2012	1945	1573	2073	2073	2007	2007
Adj. R^2	0.014	0.002	0.037	0.064	0.216	0.141	0.163	0.346	0.005	0.051	0.011	0.079

Notes: This table shows robust regression results between the daily noise measure and other financial measures of interest across the full time period and two subperiods. Robust standard errors are in parentheses. * ** , * *, and * 1 %, 5 %, and 10 % significance levels, respectively.

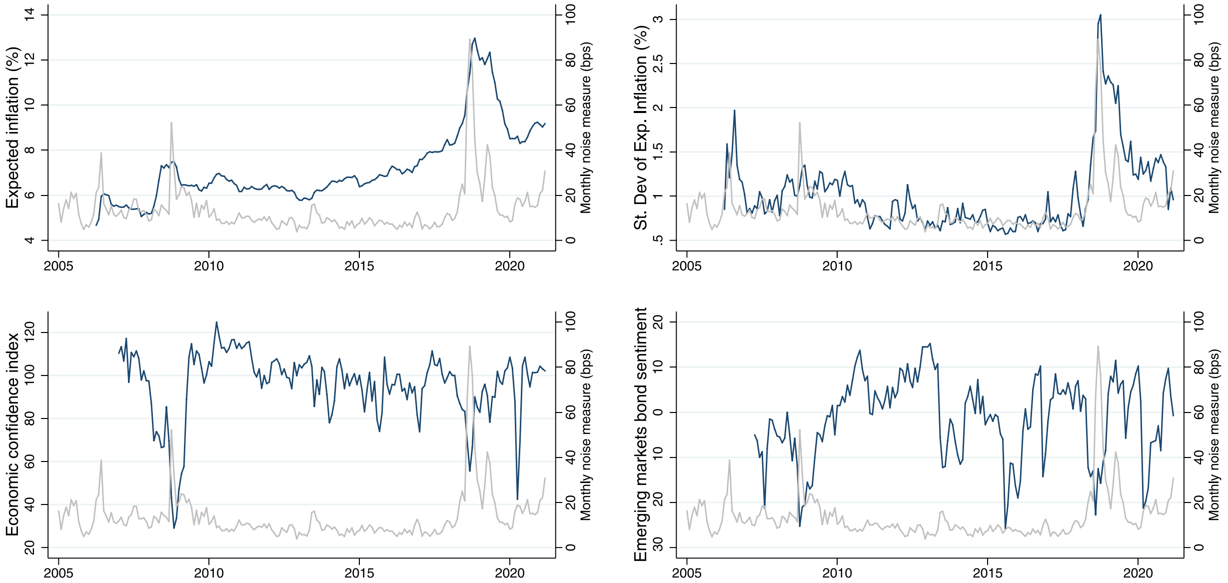

Fig. 8. Monthly average noise measure vs. macro indicators. *Notes:* This figure displays the time series of selected macro indicators along with the monthly average noise measure. The noise measure is denoted with gray data points on the right axis, and other metrics are denoted in blue data points on the left axis.

economic crisis yet improved liquidity, most likely due to the impact of quantitative easing. US-based measures all have considerable explanatory power, with an aggregate R^2 of 35 % before 2013, yet they lose that explanatory power after 2013, when two of the measures have negative coefficients.

5.6. *Noise measure and macro indicators*

We next turn our attention to the possible channels of influence between the macroeconomic variables, relevant to the entire economy or market, and the illiquidity of the sovereign bond market. The literature lacks clear guidance on the confluence of the two of them, especially the bond market. Therefore, this analysis makes a particularly novel contribution to the literature.

Because the macro variables are reported less frequently, we average the daily noise measure each month to obtain a monthly time series of illiquidity. Inflation expectations, one of the most important factors in bond markets and interest rates, are compiled by the Central Bank of the Republic of Turkey based on a survey of market participants. Furthermore, they report the standard deviation of survey answers, which we use as a proxy for inflation uncertainty.[10] We use two-year expectations to avoid excessive volatility in the short-term estimates and match the average duration of bonds traded more closely.

As a measure of international investor sentiment, we use the monthly Emerging Markets Bonds Sentiment Index published by Sentix.[11] The Turkish bond market does not have a direct local counterpart to a market sentiment index. As a robustness check, we use the monthly values of Economic Confidence Index published by the Turkish Statistical Institute, specifically the subindex compiled from answers about the general business situation, which is the closest to a local sentiment measure.[12] Panel E of Table 3 reports summary statistics, with noise measure correlations in Table 4. Fig. 8 displays the monthly time series of each measure along with the noise measure. Inflation uncertainty is positively correlated with the noise measure, with a particularly strong relationship since 2013. Sentiment measures are negatively correlated with illiquidity as expected, and the international sentiment's relation weakens after 2013.

The monthly regression results between the noise measure and macro indicators are reported in Table 8. The coefficients are all significant in univariate regressions, with the exception of inflation expectations between 2006 and 2012, with positive coefficients for inflation variables and negative ones for sentiment. However, some of the influence is subsumed by other variables in multivariate regressions, as these four variables are highly correlated at times. Looking at the two subperiods, the emerging markets bond sentiment remains the only significant factor prior to 2013 with a negative coefficient. Inflation uncertainty has relatively low explanatory power, whereas the local confidence index has a high R^2, almost 38 %. The impact of both is subsumed by the emerging markets bond sentiment. Since 2013, however, local inflation uncertainty is the most important factor, with an R^2 of 65 %. The local confidence index is relatively strong after 2013, but the significance of the sentiment indexes is weakened in multivariate regressions,

[10] Monthly data for the modified mean and standard deviation of the Expectation of 24 Months Ahead Annual CPI are retrieved from the Central Bank of the Republic of Turkey Electronic Data Delivery System, https://evds2.tcmb.gov.tr. The data are available since April 2006.

[11] Monthly data are retrieved from Refinitiv Datastream, available since April 2007.

[12] Monthly data for the Economic Confidence Index and Subindexes are retrieved from the Turkish Statistical Institute, https://data.tuik.gov.tr. The data for the General Business Situation subindex are available since January 2007.

Table 8
Monthly average noise measure regressed on macro indicators.

	Full Sample					2006–2012					2013–2021				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Exp. inflation	3.697 * **				0.162	1.260				2.481	5.441 * **				− 0.243
	(0.818)				(0.655)	(1.996)				(1.718)	(0.972)				(1.650)
St. dev. of exp. inflation		19.410 * **			17.704 * **		11.562 * **			− 0.719		20.606 * **			19.403 * **
		(3.081)			(3.777)		(3.371)			(3.818)		(3.317)			(6.580)
Economic confi- dence index			− 0.338 * **		− 0.097 *			− 0.205 * **		− 0.027			− 0.638 * **		− 0.185 *
			(0.085)		(0.049)			(0.058)		(0.030)			(0.230)		(0.111)
Emerging markets bond senti- ment				− 0.497 * **	− 0.269 * **				− 0.589 * **	− 0.546 * **				− 0.429 * *	− 0.194 *
				(0.133)	(0.080)				(0.122)	(0.130)				(0.205)	(0.104)
Obs.	180	180	171	168	168	81	81	72	69	69	99	99	99	99	99
Adj. R^2	0.294	0.545	0.224	0.152	0.665	−0.001	0.129	0.379	0.592	0.628	0.498	0.651	0.281	0.073	0.702

Notes: This table shows robust regression results between the monthly average noise measure and selected macro indicators across the full time period and two subperiods. Robust standard errors are in parentheses. * ** , * *, and * 1 %, 5 %, and 10 % significance levels, respectively.

subsumed by inflation uncertainty. Inflation expectations, although somewhat significant in univariate regressions, remain insignificant in multivariate regressions. Because the level and standard deviation of inflation expectations are highly correlated, it is natural that the impact of level is subsumed by inflation uncertainty, which may be more relevant for liquidity.

6. Conclusion

This study constructs the term structure for Turkey with the widest possible data set, from the raw daily bond prices. The extensive methodology employed here yields results that are new to the literature on the local yield curve. For example, a grid search to identify the optimal $\hat{\lambda}$ parameter indicates that a factor that affects Treasury yields culminates at 27 months. Therefore, the sample statistics of estimated yields should be meaningful for describing their characteristics. The results can be useful for macrofinance researchers as well as those exploring term premiums.

More important, this study uses yield-curve fitting errors in an enterprising way, as a proxy for market-wide illiquidity factors in a large emerging market. As analyzed by Hu et al. (2013), we test whether this noise measure, like other popular liquidity measures, carries information. Popular illiquidity measures, such as the Amihud measure and bid-ask spread, explain less than half the noise measure. That means that the noise measure has information about the fixed-income market that other existing measures do not provide.

By exploring the commonality between US-based measures and the Turkish noise measure, we make an important contribution to the emerging markets literature. The results are striking, as 2013 becomes a natural breakpoint, as conjectured. The liquidity is driven and dictated by the US market prior to 2013, but the dynamics shifted afterward. The impact of US measures dissipates and is even negated, as local forces take over in explaining the noise measure. We expect the results to be due to the extraordinary conditions in the aftermath of the 2008 financial crisis, with quantitative easing. The crisis caused a global liquidity crunch, and the extensive amount of cash pumped into the global markets in the aftermath improved conditions everywhere with no regard to fundamentals. However, after the announcement of tapering and the eventual end of quantitative easing, the local fundamentals gradually took over. Furthermore, any monetary tightening by the Federal Reserve attracted the excess liquidity to return to the US, essentially reversing the previous liquidity flow to emerging markets. The results have been particularly evident in Turkey, as local economic troubles since then have caused occasional illiquidity crises.

The results show us that the illiquidity in the bond market becomes stronger in periods with low sentiment, that is, a bearish outlook. This inverse relation between sentiment and illiquidity is well documented in the stock market.[13] However, bond market sentiment and liquidity have not received a similar level of attention.[14] This study contributes to the empirical canon on the relationship between bond market liquidity and sentiment, augmenting ample findings on international stock markets.

Furthermore, our empirical observations tell us that the standard deviation of inflation expectations has significant explanatory power over the noise measure. This finding is a particularly novel contribution to the literature. The theoretical literature says that uncertainty or ambiguity in available information leads to reduced market participation by ambiguity-averse investors.[15] The reduced participation leads to liquidity crunches when the future outlook becomes particularly murky. A very strong relationship between inflation uncertainty and the noise level attests to the ambiguity-aversion of bond investors. In particular, arbitrage traders refrain from taking positions in ambiguity-ridden markets with unreliable information, which act as a limit to arbitrage—hence, the elevated bond market illiquidity. The differences in dynamics between the two subperiods further support our previous finding that international indicators are dominant prior to 2013, but local dynamics take over afterward. It is our hope that this study paves the way for further studies on the relation between illiquidity and other financial and economic variables, as well as liquidity spillovers between developed and emerging markets.

References

Akinci, O., Gurcihan, B., Gurkaynak, R., Ozel, O., 2007. An estimated yield curve for Turkish treasury securities. Iktisat Islet. ve Finans 22 (252), 5–25. https://doi.org/10.3848/iif.2007.252.8676

Alper, C.E., Akdemir, A., Kazimov, K., 2004. Estimating yield curves in turkey: factor analysis approach. SSRN Electron. J. https://doi.org/10.2139/ssrn.578921

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Ang, A., Piazzesi, M., Wei, M., 2006. What does the yield curve tell us about GDP growth? J. Econ. 131 (1–2), 359–403. https://doi.org/10.1016/j.jeconom.2005.01.032

Ang, A., Bekaert, G., Wei, M., 2008. The term structure of real rates and expected inflation. J. Financ. 63 (2), 797–849. https://doi.org/10.1111/j.1540-6261.2008.01332.x

Baker, M., Stein, J.C., 2004. Market liquidity as a sentiment indicator. J. Financ. Mark. 7 (3), 271–299. https://doi.org/10.1016/j.finmar.2003.11.005

Bliss, R.R., 1989. Fitting Term Structures to Bond Prices (Unpublished manuscript). University of Chicago, Chicago, IL Retrieved from. 〈https://www.researchgate.net/〉.

Bliss, R.R., 1997. Testing term structure estimation methods. Adv. Futures Options Res. 9, 197–232. Retrieved from. 〈https://www.econstor.eu/〉.

Cepni, O., Kucuksarac, D., 2017. Optimal mix of the extended Nelson Siegel model for turkish sovereign yield curve. Econ. Bull. 37 (2), 1133–1142. Retrieved from. 〈https://www.ideas.repec.org/〉.

Chauvet, M., Senyuz, Z., 2016. A dynamic factor model of the yield curve components as a predictor of the economy. Int. J. Forecast. 32 (2), 324–343. https://doi.org/10.1016/j.ijforecast.2015.05.007

Chung, K., Zhang, H., 2014. A simple approximation of intraday spreads using daily data. J. Financ. Mark. 17 (C), 94–120. https://doi.org/10.1016/j.finmar.2013.02.004

[13] There is extensive literature, starting with Baker and Stein (2004).

[14] A recent study by Mullings (2022) studies text-based central bank sentiment and its impact on market liquidity in the euro area.

[15] See, e.g., Ozsoylev and Werner (2009).

Cobandag-Guloglu, Z., Ekinci, C., 2021. Liquidity measurement: a comparative review of the literature with a focus on high frequency (Advance online publication). J. Econ. Surv. https://doi.org/10.1111/joes.12440

Datar, Y., Naik, N., Radcliffe, R., 1998. Liquidity and stock returns: an alternative test. J. Financ. Mark. 1 (2), 203–219. https://doi.org/10.1016/S1386-4181(97)00004-9

Demsetz, H., 1968. The cost of transacting. Q. J. Econ. 82 (1), 33–53. https://doi.org/10.2307/1882244

Diebold, F.X., Li, C., 2006. Forecasting the term structure of government bond yields. J. Econ. 130 (2), 337–364. https://doi.org/10.1016/j.jeconom.2005.03.005

Driessen, J., Nijman, T.E., Simon, Z., 2018. Much ado about nothing: a study of differential pricing and liquidity of short and long term bonds (Working Paper No. 238). Leibniz Inst. Financ. Res. https://doi.org/10.2139/ssrn.3296959

Dziwok, E., Karaś, M.A., 2021. Systemic illiquidity noise-based measure—a solution for systemic liquidity monitoring in frontier and emerging markets. Risks 9 (7), 124. https://doi.org/10.3390/risks9070124

Ertan, A.S., Karahan, C.C., Temucin, T.S., 2020. Estimating the yield curve for sovereign bonds: the case of Turkey. Finans Polit. Ekon. Yorumlar 653, 137–159. Retrieved from. ⟨http://www.ekonomikyorumlar.com.tr/⟩.

Estrella, A., Hardouvelis, G.A., 1991. The term structure as a predictor of real economic activity. J. Financ. 46 (2), 555–576. https://doi.org/10.1111/j.1540-6261.1991.tb02674.x

Fama, E., Bliss, R., 1987. The information in long-maturity forward rates. Am. Econ. Rev. 77 (4), 680–692. https://doi.org/10.7208/9780226426983-025

Gilli, M., Große, S., and Schumann, E. Calibrating the Nelson-Siegel Svensson model. COMISEF Working Paper Series No.31, 2010.10.2139/ssrn.1676747.

Goyenko, R., Subrahmanyam, A., Ukhov, A., 2011. The term structure of bond market liquidity and its implications for expected bond returns. J. Financ. Quant. Anal. 46 (1), 111–139. https://doi.org/10.1017/S0022109010000700

Grishchenko, O.V., Huang, J.Z., 2013. The inflation risk premium: evidence from the TIPS market. J. Fixed Income 22 (4), 5–30. https://doi.org/10.3905/jfi.2013.22.4.005

Gürkaynak, R., Sack, B., Wright, J., 2007. The U.S. treasury yield curve: 1961 to the present. J. Monet. Econ. 54 (8), 2291–2304. https://doi.org/10.1016/j.jmoneco.2007.06.029

Hattori, T., 2021. Noise as a liquidity measure: evidence from the JGB market. Pac. - Basin Financ. J. 67 (C), 101515. https://doi.org/10.1016/j.pacfin.2021.101515

Hu, G.X., Pan, J., Wang, J., 2013. Noise as information for illiquidity. J. Financ. 68 (6), 2341–2382. https://doi.org/10.1111/jofi.12083

Ibáñez, F. (2016). Calibrating the Dynamic Nelson-Siegel Model: A Practitioner Approach Working Paper No. 774. Central Bank of Chile.

Le, H., Gregoriou, A., 2020. How do you capture liquidity? A review of the literature on low-frequency stock liquidity. J. Econ. Surv. 34 (5), 1170–1186. https://doi.org/10.1111/joes.12385

Lesmond, D.A., Ogden, J.P., Trzcinka, C.A., 1999. A new estimate of transaction costs. Rev. Financ. Stud. 12 (5), 1113–1141. https://doi.org/10.1093/rfs/12.5.1113

Longstaff, F.A., 2004. The flight-to-liquidity premium in US treasury bond prices. J. Bus. 77 (3). https://doi.org/10.1086/386528

McCulloch, J.H., 1971. Measuring the term structure of interest rates. J. Bus. 44 (1), 19–31. https://doi.org/10.1086/295329

Mullings, R., 2022. Do central bank sentiment shocks affect liquidity within the European Monetary Union? A computational linguistics approach. Eur. J. Financ. 1–27. https://doi.org/10.1080/1351847X.2022.2124530

Nelson, C., Siegel, A., 1987. Parsimonious modeling of yield curves. J. Bus. 60 (4), 473–489. https://doi.org/10.3386/w1594

O'Sullivan, C., Papavassiliou, V.G., 2020. On the term structure of liquidity in the European sovereign bond market. J. Bank. Financ. 114, 105777. https://doi.org/10.1016/j.jbankfin.2020.105777

Ozsoylev, H., Werner, J., 2009. Liquidity and asset prices in rational expectations equilibrium with ambiguous information. J. Econ. Theory 48 (2), 469–491. https://doi.org/10.1007/s00199-011-0648-0

Ramos, H.P., Righi, M.B., 2020. Liquidity, implied volatility and tail risk: A comparison of liquidity measures. Int. Rev. Financ. Anal. 69 (C), 101463. https://doi.org/10.1016/j.irfa.2020.101463

Söderlind, P., 2011. Inflation risk premia and survey evidence on macroeconomic uncertainty. Int. J. Cent. Bank. 7, 113–133. https://doi.org/10.2139/ssrn.1147638

Steeley, J.M., 2014. Forecasting the term structure when short-term rates are near zero. J. Forecast. 33 (5), 350–363. https://doi.org/10.1002/for.2292

Svensson, L. (1994). Estimating and interpreting forward interest rates: Sweden 1992–1994 (Working Paper No. 4871). National Bureau of Economic Research. Retrieved from ⟨https://www.nber.org/⟩.

Wahlstrom, R.R., Paraschiv, F., Schurle, M., 2021. A comparative analysis of parsimonious yield curve models with focus on the Nelson-Siegel, Svensson and Bliss versions. Comput. Econ. 57 (4). https://doi.org/10.1007/s10614-021-10113-w