Harvesting the yield curve mispricing: Evidence from the Indian government bond market

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Introduction

The yield curve represents the prevailing interest rates in the economy for different times to maturity and is essential for pricing a well-functioning bond market. Yield curve modeling is a crucial area of research in finance. In an efficient bond market, any arbitrage opportunity is driven away immediately by the traders. Therefore, the no-arbitrage restriction is an important consideration to model the yield curve. Affine term structure models (ATSM) are the most popular class of arbitrage-free term structure models. Notwithstanding their theoretical consistency, ATSMs suffer in terms of empirical performance (Duffee, 2002).

Nelson and Siegel (1987) proposed to fit the cross-section of the yield curve using the simple functional form:

$$y(\tau) = \beta_0 + \beta_1 \left(\frac{1 - e^{-\tau/\lambda}}{\tau/\lambda} \right) + \beta_2 \left(\frac{1 - e^{-\tau/\lambda}}{\tau/\lambda} - e^{-\tau/\lambda} \right) \quad (1)$$

Nelson-Siegel form provides a good fit of the cross-section of the yield curve and can also predict most of the observed yield curve shapes. These observed benefits of the Nelson-Siegel model are driven by the fact that the loading of the three factors (β_0, β_1, and β_2) of the Nelson-Siegel framework has loading similar to the loadings of the first three principal components of the yield curve (Diebold, 2013). Over time because of its empirical tractability, Nelson-Siegel and its extensions have emerged as a workhorse model for most central banks and practitioners.

In the last three decades, the Indian central bank has taken several reform measures such as shifting to auction-based market borrowing, reducing statutory reserve requirements and introducing an anonymous electronic order matching trading system called NDS-OM. These measures have helped improve liquidity in the Indian fixed income market (Fleming et al., 2016).

In April 2001, the Clearing Corporation of India Limited (CCIL) was set up to provide clearing and settlement for the government securities and foreign exchange markets. After February 2002, all trades in the government securities are mandated to be routed through CCIL. Since 2003, CCIL also publishes zero-coupon yield curve estimates using the Nelson-Siegel model (Nath, 2012). It uses the estimated yield curve to evaluate the securities' margin requirements and valuation. These are also used as an input in many term structure studies of the Indian government debt market (Foundation, 2011; Nath et al., 2012). With such material importance and academic relevance, CCIL estimates suffer from important inconsistencies such as unstable factor estimates and heteroscedastic error terms (Kumar and Virmani (2022) provide the details). Kumar and Virmani (2022) have analyzed the in-sample performance of the term structure estimation framework adopted by CCIL.

This study analyzes CCIL term structure estimates from the trader perspective. We evaluate the CCIL model's ability to capture the profitable mispricing in the bond market. We create duration neutral trading strategy by buying undervalued bonds and selling the overvalued ones implied by the CCIL model. Such pair trading/ statistical arbitrage strategy aims to earn almost risk-less profit by capturing the model implied mispricing. Trading returns generated through this strategy are statistically greater than zero. However, the returns are not risk-free but rather extremely risky with a standard deviation of more than 800%. This finding casts serious doubt on the utility of CCIL estimates from the statistical arbitrage perspective.

The rest of the paper is organized as follows. In the next section, I provide a brief background of the evolution of the Indian government bond market and describe the data. Section 3 details the trading strategy and results. Finally, section 4 concludes.

Background and Data

Post the recommendation of the Narasimham Committee, the Reserve Bank of India (RBI) has taken a number of reform measures to promote various segments of the financial markets. National Stock Exchange (NSE) started the Wholesale Debt Market (WDM) segment in June 1994, which introduced the screen-based trading facility in the Indian debt market. Using the trade deals reported on its electronic platform, NSE started publishing zero-coupon yield curves in 1997. In April 2001, the Clearing Corporation of India Ltd (CCIL) was set up to provide clearing and settlement for government securities, foreign exchange, and money market instruments. Post-February 2002, all trades in the government securities are mandated to route through CCIL (Nath, 2012). Because of this, CCIL has access to all the transactions of the government security markets. Using this information, CCIL also started estimating and publishing the zero-coupon yield curve from February 15, 2003.[14]

Both CCIL and NSE publish estimates of the yield curve using Nelson-Siegel (Nelson and Siegel, 1987) and its extension, on a daily basis. These estimates are used as an input in many term structure studies of the Indian government debt market (Sowmya and Prasanna, 2018; Virmani, 2006; Rathi and Pradhan,

[14] https://www.ccilindia.com/AboutUs/Pages/MileStones1.aspx

2017). CCIL also uses the estimated yield curve for evaluating the margin requirements and valuation of the securities. Many trading firms and banks use government bonds as collateral for borrowing. With such material importance and academic relevance, it is important for the CCIL estimates to be theoretically consistent and numerically robust.

We evaluate the trading returns using daily bond prices and term structure estimates provided by CCIL from September 2009 to December 2017. The aggregated data set has 82149 observations. Following Gürkaynak et al. (2007), I exclude bills and bonds with less than three-month maturity from the sample. The final sample has a total of 52358 observations spanning over 1997 trading dates. Table 1 summarizes the in-sample fit of the CCIL estimates over the years and across the maturity bins. The first row provides the mean of the estimation error of YTM (Yield to Maturity) of the CCIL estimates. The value in parentheses below provides the standard deviation of the same.

Table 1: Summary of in-sample fit: Table summarizes the in-sample fit of the CCIL estimates over the years and across the maturity bins. First row provides mean of the estimation error of YTM of the CCIL estimates in the particular year (given in row heading) for the given maturity segment (provided in column name). The value in parentheses provides the standard deviation of the same

Year	<1Y	1Y-2Y	2Y-5Y	5Y-7Y	7Y-10Y	10Y-12Y	12Y-15Y	15Y-20Y	20Y-25Y	25Y-30Y	30Y-50Y
2009		0.020	0.030	-0.018	-0.070	-0.020	0.118	0.104	-0.017	-0.074	
		(0.111)	(0.116)	(0.100)	(0.201)	(0.103)	(0.098)	(0.043)	(0.063)	(0.057)	
2010	0.048	-0.055	-0.021	0.010	-0.100	-0.094	-0.045	0.066	0.029	0.013	0.048
	(0.167)	(0.156)	(0.125)	(0.091)	(0.111)	(0.086)	(0.120)	(0.034)	(0.065)	(0.050)	(0.018)
2011	-0.018	-0.052	0.083	0.046	-0.067	-0.064	-0.006	0.052	0.024	0.010	-0.007
	(0.103)	0.(092)	(0.124)	(0.059)	(0.075)	(0.048)	(0.041)	(0.031)	(0.030)	(0.031)	(0.012)
2012	-0.002	-0.037	0.005	0.051	-0.014	0.006	-0.032	0.026	-0.002	-0.027	-0.076
	(0.089)	(0.065)	(0.054)	(0.037)	(0.068)	(0.039)	(0.049)	(0.040)	(0.038)	(0.028)	
2013	0.081	-0.035	0.0002	0.028	-0.019	0.061	-0.021	0.016	-0.024	-0.010	-0.066
	(0.130)	(0.108)	(0.087)	(0.057)	(0.125)	(0.056)	(0.057)	(0.048)	(0.031)	(0.044)	(0.014)
2014	0.084	-0.124	-0.048	0.030	-0.016	0.018	0.002	-0.019	-0.030	-0.026	-0.038
	(0.123)	(0.098)	(0.066)	(0.060)	(0.109)	(0.056)	(0.063)	(0.026)	(0.038)	(0.029)	(0.013)
2015	-0.003	0.003	-0.012	0.029	-0.030	0.008	-0.017	0.008	-0.002	0.004	-0.090
	(0.093)	(0.058)	(0.045)	(0.030)	(0.092)	(0.055)	(0.077)	(0.049)	(0.047)	(0.043)	(0.070)
2016	0.093	0.022	-0.029	-0.016	-0.050	0.016	-0.034	0.008	-0.045	0.029	-0.074
	(0.067)	(0.059)	(0.040)	(0.095)	(0.113)	(0.093)	(0.098)	(0.063)	(0.126)	(0.055)	(0.058)
2017	0.090	0.029	-0.010	-0.067	-0.072	0.030	-0.093	-0.023	0.043	0.035	-0.088
	(0.079)	(0.061)	(0.053)	(0.073)	(0.160)	(0.065)	(0.159)	(0.109)	(0.125)	(0.083)	(0.073)

Table 1 shows that CCIL estimates have around 10 basis points of the standard deviation of the error term, which is comparable to most of the emerging market term structure estimates. However, Kumar and Virmani (2022) have highlighted four important limitations of the existing term structure estimation framework adopted by CCIL:

1. CCIL includes liquid and illiquid securities in the term structure estimation without considering the possible liquidity-induced heterogeneity. Subramanian (2001) argued that liquid and illiquid securities are a heterogeneous class, and one should incorporate that in the term structure estimation. Further, CCIL includes T-bills along with the coupon bonds in the estimation without considering the possible segmentation of these two markets, as highlighted by Gürkaynak et al. (2007).

2. Nelson-Siegel and Nelson-Siegel-Svenson (NSS), both the methods used by CCIL, are not arbitrage-free (Bjork and Christensen, 1999; Filipovic, 1999). No-arbitrage is an important theoretical consistency restriction for the term structure estimation.

3. De Pooter (2007) highlights that independent cross-sectional estimates of betas in the Nelson-Siegel specification display strong variation in the time series. CCIL cross-sectional estimates also show strong variation in their factor estimates. This seems unreasonable considering the slowmoving nature of interest rates.

4. Nelson-Siegel estimation procedure assumes constant variance (homoscedasticity) of the yield error (observed yield- predicted yield). However, there is a large variation in the yield error for the less traded securities. Further, the homoscedastic yield error assumption with respect to the duration also seems to be violated.

This study further evaluates whether CCIL is still doing a reasonable job of fitting the yield curve with all the above-mentioned limitations. In particular, I explore the utility of CCIL model from the statistical arbitrage perspective, where traders try to earn almost risk less profit by buying undervalued securities and selling overvalued securities implied by the model. I discuss the details of the trading strategy and the results in the next section.

Trading Strategy and Results

Every day, I sort all the observations in 5 quintiles in terms of yield error calculated as the difference between observed yield and yield predicted by the CCIL estimates. Indian government bonds also suffer from infrequent trading. To address this issue,I consider only those observations that trade at least one more day after the trading date. This allows me to close the position in the future.

Everyday, I buy bottom quintile bonds and sell top quintile bonds to create duration neutral portfolio of bonds. Since duration is the most important systematic risk factor for the government bond, such construction allows us to control for the return attributed to the duration exposure. We re-balance the portfolio daily with the exception of non-traded bonds.

First, I summarize returns across different maturity buckets in table 2. Most of the profitability comes from the 7-15 year maturity bucket, where strategy is usually short. These segments of bonds are usually overpriced, with the maximum demand around the 10 year maturity. On the other hand, the strategy is not profitable at the short end of the yield curve, with net long in that segment. It is important to note that while trading portfolios are duration neutral, they are not convexity neutral. Convexity captures the second order risk of the bond price. However, there is no correlation between the portfolio convexity and returns (correlation is 0.02).

Table 2: Maturity-wise return profile: Table provides distribution of return distribution across different maturity buckets

Maturity	position	return
<1Y	16.60	-206.12
1-2Y	-0.60	-17.06
2-5Y	3.60	1.01
5-7Y	7.10	15.77
7-10Y	-6.80	16.31
10-12Y	-4.40	19.38
12-15Y	-6.60	24.95
15-20Y	5.90	81.46
20-25Y	1.00	25.33
25-30Y	-1.40	18.52
30-50Y	-10.80	50.12

Figure **1** plots the histogram of the annualized trading returns generated with this strategy. With the median annualized return of 8.68%, CCIL estimates seem to capture some profitable mispricing. Wilcox rank test of the trading return also confirms this assertion with p-value < 0.0001. However, this profit is not statistically risk- free, but rather extremely risky, with a standard deviation of more than 868%. From the trading point of view, it would require large capital in terms of VAR (Value at risk). Under the assumption of a risk-free rate of 6%, it would result in a meager Sharpe ratio of less than 0.0025. This should be seen as a serious red flag for using CCIL estimates for the purpose of statistical arbitrage.

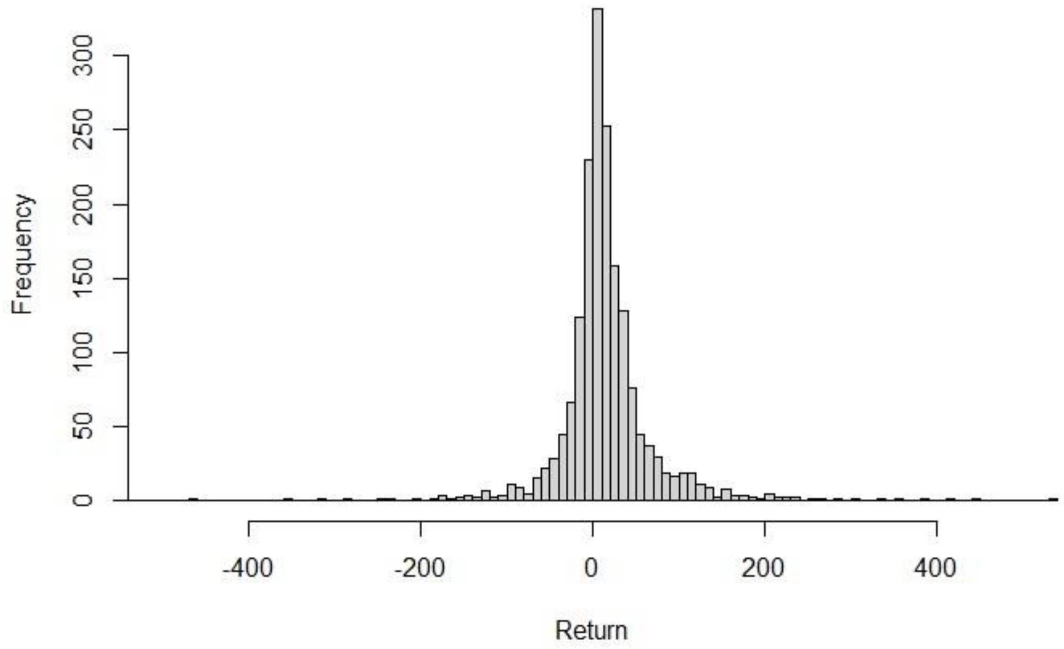

Figure 1: Histogram of the return: This represents histogram of the returns generated through the trading strategy

Conclusion

CCIL term structure estimates are important for the bond market participants, regulators and researchers. Fiven the importance, the estimates should be theoretically consistent and capture mispricing in the government market. Term structure estimation literature has evolved considerably in recent decades. Christensen et al. (2011) combined the theoretical appeal of the no-arbitrage term structure model with the empirical tractability of Nelson Siegel models. Andreasen et al. (2019) extended the same in the big data settings, where they fit the yield curve directly from the bond prices. Kumar and Virmani (2022) used a similar approach in the Indian setting, while incorporating liquidity heterogeneity across bonds.

In his book, *An engine, not a camera*, MacKenzie (2008) argues 'financial models do more than analyze markets; it alters them. It is an "engine" an active force transforming its environment, not a camera passively recording it.'. As regulators are trying to increase participation in the secondary bond market by opening up direct retail participation and other initiatives. They must also upgrade CCIL's existing methodology, which is dated and does not seem to capture mispricing in the bond market consistently.

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