Topological Data Analysis of Treasury Yield Curve Rates

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Abstract

We explore the use of Topological Data Analysis (TDA) to study the evolution of US Treasury Yield Curve Rates from 2015 - 2020. We particularly focus on the use of TDA to understand the shape and structure of our multidimensional rates series and whether useful inference can be derived from topological tools.

1 Introduction

Topological Data Analysis (TDA) is an emerging multidisciplinary field that uses tools from topology, statistics, and scientific computing to extract insights about complex data. Many existing papers introduce the technique to an unfamiliar reader [7, 9, 13, 18]. From a practical perspective, TDA can be used primarily to explore the structure of multidimensional data with regard to shape and connectivity.

TDA has shown significant promise in a variety of areas, including cosmology [10, 16, 17, 15], image analysis [6, 12, 8, 14, 1], finance [11], and neuroscience [2, 3, 4, 5]. Across all of its prior uses, the general theme of extracting information about the shape and structure of complex multidimensional data persists.

With this paper, I aim to demonstrate the utility of TDA for exploring economic and financial questions, with a specific focus on treasury yield curve rates. A similar exploration takes place in [11] with attention to the equity markets, and we follow their example in our study of treasury rates.

2 Background of TDA

3 Background of Treasury Curve Yield Rates

4 Methodological Description and Simulation

5 Data Description

6 Results

7 Conclusion

References

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