Technical Requirements for RDD Analysis of Treasury Inflation Risk Premia

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Abstract

This paper synthesizes technical requirements for conducting Regression Discontinuity Design analysis of Treasury inflation risk premia using Federal Reserve Economic Data. The methodology combines causal inference techniques with financial econometrics to address the limited application of RDD frameworks to Treasury markets. Key contributions include coverage error-optimal bandwidth selection protocols, FRED data preprocessing standards, contemporary inflation risk premia modeling approaches, and econometric considerations for financial time series RDD applications. The framework addresses significant methodological gaps at the intersection of causal inference and Treasury market analysis, providing empirical researchers with comprehensive guidance for rigorous academic implementation.

The paper ends with "The End"

1 Introduction

The application of Regression Discontinuity Design to Treasury market analysis represents a significant methodological opportunity at the intersection of causal inference and financial econometrics. While RDD has gained widespread acceptance across economics disciplines, its application to Treasury inflation risk premia remains underdeveloped despite clear potential for identifying causal effects around policy thresholds and market structure discontinuities.

This paper provides comprehensive technical guidance for conducting RDD analysis of Treasury inflation risk premia using Federal Reserve Economic Data. The methodology addresses critical gaps in existing literature while incorporating recent advances in RDD estimation techniques, state-space modeling of inflation expectations, and financial time series econometrics.

The research framework synthesizes four essential technical domains: modern RDD methodology incorporating coverage error-optimal bandwidth selection and robust bias-corrected inference; FRED data analysis standards for Treasury research including data preprocessing protocols and stationarity considerations; contemporary inflation risk premia modeling approaches utilizing affine term structure models and dynamic Nelson-Siegel specifications; and econometric considerations specific to financial time series RDD applications addressing serial correlation, heteroskedasticity, and structural breaks.

2 Current RDD Methodology for Financial Research

2.1 Coverage Error-Optimal Bandwidth Selection

Recent methodological advances have moved beyond mean squared error optimal bandwidth selection toward coverage error-optimal approaches developed by [1]. For Treasury market applications with potentially high-frequency data, this innovation proves crucial for reliable statistical inference.

The coverage error-optimal bandwidth formula follows:

$$h_{RBC} = H \times n^{-1/(3+p)} \tag{1}$$

where H minimizes the absolute value of coverage error components. In practice, this typically requires shrinking the MSE-optimal bandwidth by approximately 27% for local linear specifications ($p = 1$), leading to more reliable confidence intervals for treatment effects.

Robust bias-corrected inference represents another critical advancement. The RBC estimator provides:

$$\hat{\tau}_{\nu,BC}(h) = \hat{\tau}_{\nu}(h) - h^{1+p-\nu} \times \hat{B}(b) \tag{2}$$

This specification achieves valid inference with MSE-optimal bandwidths while obtaining faster coverage error decay rates of $O(n^{-2+p}/(3+p))$ compared to traditional undersmoothing approaches.

2.2 Local Polynomial Regression Specifications

For Treasury market analysis, local linear regression ($p = 1$) with triangular kernels provides optimal boundary properties essential when cutoff points lie near data boundaries. The triangular kernel specification:

$$K(u) = (1 - |u|) \times \mathbf{1}(|u| \leq 1) \tag{3}$$

offers MSE-optimality while the local linear specification automatically corrects boundary bias, making it superior to local constant approaches for financial applications.

Higher-order polynomials ($p \geq 2$) should be avoided due to poor boundary behavior and overfitting concerns, particularly problematic in Treasury yield curve analysis where relationships may be nonlinear but relatively smooth.

2.3 Comprehensive Robustness Framework

Modern RDD applications require extensive validation beyond basic estimation. McCrary density tests using updated `rddensity` package implementations test for manipulation around cutoffs. Covariate balance tests examine whether predetermined variables exhibit discontinuities at the threshold, while placebo tests at alternative cutoff points verify the absence of spurious treatment effects.

For Treasury market applications, particular attention should focus on donut hole specifications that exclude observations immediately around the cutoff to test for precise manipulation, and bandwidth sensitivity analysis testing effects at $h_{opt}/4$, $h_{opt}/2$, h_{opt}, $2 \times h_{opt}$, and $4 \times h_{opt}$ to ensure stability.

3 FRED Data Analysis Standards for Treasury Research

3.1 Essential Treasury Data Series

Treasury inflation risk premia research should utilize specific FRED series codes with established academic precedent. Primary nominal Treasury yields include DGS10 (10-year constant maturity), DGS5 (5-year), DGS2 (2-year), and DGS3MO (3-month) for yield curve construction. Treasury Inflation-Protected Securities data include DFII10 (10-year TIPS), DFII5 (5-year TIPS), and DFII30 (30-year TIPS).

Breakeven inflation rates are directly available as T10YIE (10-year breakeven), T5YIE (5-year breakeven), and the critical T5YIFR (5-year, 5-year forward inflation expectation rate) that captures longer-term inflation expectations. The T5YIFR calculation involves complex compounding reflecting market-based inflation expectations over specific forward periods.

3.2 Data Preprocessing Protocols

Missing data handling requires careful attention since Treasury data are not reported on weekends and holidays. Standard practice involves forward-filling the last available value for short gaps, while longer gaps may require interpolation methods or explicit modeling of missing data patterns.

Stationarity testing follows established protocols: visual inspection, Augmented Dickey-Fuller tests, Elliott-Rothenberg-Stock tests, and KPSS tests for stationarity confirmation. Treasury yields typically exhibit $I(1)$ behavior, requiring first differencing for stationarity, though breakeven inflation measures may have different integration properties.

For cointegration analysis, test yield spreads directly using ADF tests when the cointegrating vector is known ($\theta = 1$), or apply Engle-Granger procedures for unknown relationships. The Johansen procedure handles multiple cointegrating relationships common in term structure models with multiple maturities.

3.3 Frequency and Seasonal Considerations

Daily data capture high-frequency market movements crucial for identifying Treasury market discontinuities, though weekend and holiday gaps require careful handling. Monthly data eliminate missing values and facilitate integration with macroeconomic variables, while quarterly data match standard macroeconomic modeling frequencies.

Treasury yields typically require no seasonal adjustment since they reflect market expectations rather than seasonal economic patterns, though some derived series may exhibit mild seasonal behavior requiring X-13ARIMA-SEATS treatment.

4 Contemporary Inflation Risk Premia Modeling

4.1 Theoretical Frameworks and Empirical Methods

Affine term structure models provide the dominant theoretical framework, with yields specified as affine functions of state variables:

$$y_n(\tau) = \frac{A_n(\tau)}{\tau} + \frac{B_n(\tau)'\mathbf{X}_t}{\tau} \quad \text{(nominal yields)} \tag{4}$$

$$y_r(\tau) = \frac{A_r(\tau)}{\tau} + \frac{B_r(\tau)'\mathbf{X}_t}{\tau} \quad \text{(real yields)} \tag{5}$$

where state variables $\mathbf{X}_t$ typically include level, slope, and curvature factors, potentially augmented with a liquidity factor.

TIPS breakeven decomposition forms the empirical foundation, separating breakeven rates into expected inflation, inflation risk premium, and liquidity premium components. Critical methodological refinements include indexation lag corrections ranging from 0.03 basis points for 1-year to 4.2 basis points for 10-year maturities.

4.2 Dynamic Nelson-Siegel Applications

Factor-Augmented DNS models incorporate macroeconomic principal components, improving forecasts by up to 18% quarterly and 40% at higher frequencies. Shadow-Rate DNS extensions accommodate zero lower bound constraints through smooth transition modeling while maintaining tractability with negative shadow rates.

Time-varying parameter specifications include stochastic volatility extensions, random level shift parameters for structural break accommodation, and quantile regression variants for tail risk assessment particularly relevant for inflation risk analysis.

4.3 State-Space Model Implementations

Kalman filter applications use state-space formulations for joint nominal-real yield modeling. Measurement equations couple observable yields with latent factors:

$$\begin{bmatrix} \mathbf{y}_{nom} \\ \mathbf{y}_{real} \end{bmatrix} = \mathbf{C} + \mathbf{D}\mathbf{X}_t + \boldsymbol{\varepsilon}_t \tag{6}$$

through transition equations:

$$\mathbf{X}_{t+1} = \boldsymbol{\mu} + \boldsymbol{\Phi}\mathbf{X}_t + \boldsymbol{\eta}_t \tag{7}$$

Recent innovations include Unscented Kalman Filters for nonlinear measurement equations, Extended Kalman Filters for CIR-type specifications, and variational Bayesian estimation techniques for improved computational efficiency and uncertainty quantification.

5 Recent Methodological Literature and Research Gaps

5.1 Limited Direct RDD Applications to Treasury Markets

Comprehensive literature review reveals significant research opportunities combining RDD with Treasury analysis. Recent applications focus primarily on central bank policy thresholds, with Bank of Italy and BIS working papers examining ECB corporate bond purchase eligibility using RDD, while temporal RDD frameworks address monetary policy timing effects.

Key research gaps include Federal Reserve Treasury purchase programs with threshold-based rules, primary dealer status effects, auction participation requirements, and TIPS versus nominal Treasury effects around inflation benchmarks. The proposed research framework addresses this methodological gap directly.

5.2 Relevant Methodological Advances

Recent advances in RDD methodology include local polynomial order optimization and power asymmetry considerations in fuzzy designs that provide guidance on bandwidth selection and polynomial order choice directly applicable to Treasury market analysis.

Temporal RDD extensions particularly relevant for Treasury research include regime-switching models for structural breaks, dynamic treatment effects allowing time-varying responses, and augmented local linear approaches controlling for time-varying confounders.

6 Econometric Considerations for Financial Time Series RDD

6.1 Serial Correlation and Heteroskedasticity Corrections

Newey-West HAC standard errors address both serial correlation and heteroskedasticity violations common in financial time series. Block bootstrap methods preserve temporal dependence structure through Moving Block Bootstrap with overlapping blocks, Circular Block Bootstrap handling edge effects, and Stationary Bootstrap with random block lengths for improved stationarity properties.

Optimal block lengths should be chosen at 10-20% of sample size based on data persistence, using 500-1000 bootstrap replications, and implementing bias-corrected accelerated intervals when possible.

6.2 Structural Break Detection and Time-Varying Effects

Bai-Perron tests identify multiple unknown structural breaks, while CUSUM and CUSUM-SQ tests assess parameter stability. Donut RDD specifications drop observations around suspected break points, while time-varying coefficient models allow parameters to evolve over time.

Dynamic RDD approaches estimate treatment effects varying by exposure length, particularly important for Treasury market interventions with potentially evolving impacts.

6.3 Bandwidth Selection with Temporal Dependence

Modified selection criteria adjust standard bandwidth selectors for autocorrelation. This requires using wider bandwidths than cross-sectional settings to maintain adequate power, testing robustness across multiple choices, and considering effective sample size adjustments due to serial correlation.

Integration and unit root considerations require ADF and PP tests for unit roots in outcome and running variables, KPSS tests for stationarity confirmation, and careful attention to cointegration possibilities, though binary treatment variables cannot be cointegrated by construction.

7 Implementation Recommendations

The methodological approach should implement local linear regression with triangular kernels and coverage error-optimal bandwidth selection, use robust HAC standard errors or appropriate clustering, conduct comprehensive robustness checks including McCrary density tests and covariate balance verification, and carefully document sensitivity analysis across bandwidth and specification choices.

Software implementation utilizes R packages `rdrobust`, `rddensity`, and `rdmulti` for RDD estimation, combined with `sandwich`, `lmtest`, and `vars` packages for time series diagnostics. Stata equivalents include `rdrobust`, `rdbwselect`, and `ivreg2` with HAC options.

8 Conclusion

This comprehensive framework provides the methodological foundation for rigorous RDD analysis of Treasury inflation risk premia using FRED data. The intersection of causal inference methods with Treasury market analysis represents a significant methodological contribution, particularly given limited existing applications of RDD to Treasury markets.

The research approach emphasizes transparent methodology, comprehensive robustness testing, and careful attention to the unique challenges of applying RDD to financial time series data while leveraging recent advances in both RDD techniques and inflation risk premia modeling. Future research should explore dynamic treatment effects, threshold heterogeneity, and machine learning approaches to bandwidth selection in Treasury market applications.

References

[1] Calonico, Sebastian, Matias D. Cattaneo, and Max H. Farrell. 2020. "Optimal Bandwidth Choice for Robust Bias-Corrected Inference in Regression Discontinuity Designs." *The Econometrics Journal* 23(2): 192–210.

[2] Calonico, Sebastian, Matias D. Cattaneo, and Rocío Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica* 82(6): 2295–2326.

[3] Imbens, Guido W., and Karthik Kalyanaraman. 2012. "Optimal Bandwidth Choice for the Regression Discontinuity Estimator." *The Review of Economic Studies* 79(3): 933–959.

[4] Lee, David S., and Thomas Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48(2): 281–355.

[5] Hausman, Catherine, and David S. Rapson. 2018. "Regression Discontinuity in Time: Considerations for Empirical Applications." *Annual Review of Resource Economics* 10: 533–552.

[6] Pflueger, Carolin E., and Luis M. Viceira. 2016. "Decomposing Real and Nominal Yield Curves." *Journal of Monetary Economics* 84: 182–200.

[7] Grishchenko, Olesya V., and Jing-zhi Huang. 2013. "The Inflation Risk Premium: Evidence from the TIPS Market." *Journal of Fixed Income* 22(4): 5–30.

[8] Chen, Ren-Raw, Bo Liu, and Xiaolin Cheng. 2010. "Inflation, Fisher Equation, and the Term Structure of Inflation Risk Premia: Theory and Evidence from TIPS." *Journal of Empirical Finance* 17(4): 702–721.

[9] Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright. 2010. "The TIPS Yield Curve and Inflation Compensation." *American Economic Journal: Macroeconomics* 2(1): 70–92.

[10] Kim, Don H., and Athanasios Orphanides. 2012. "Term Structure Estimation with Survey Data on Interest Rate Forecasts." *Journal of Financial and Quantitative Analysis* 47(1): 241–272.

[11] Christensen, Jens H.E., and Glenn D. Rudebusch. 2019. "A New Normal for Interest Rates? Evidence from Inflation-Indexed Debt." *Review of Economics and Statistics* 101(5): 933–949.

[12] Diebold, Francis X., and Canlin Li. 2006. "Forecasting the Term Structure of Government Bond Yields." *Journal of Econometrics* 130(2): 337–364.

[13] Nelson, Charles R., and Andrew F. Siegel. 1987. "Parsimonious Modeling of Yield Curves." *Journal of Business* 60(4): 473–489.

[14] Koopman, Siem Jan, Max I.P. Mallee, and Michel van der Wel. 2010. "Analyzing the Term Structure of Interest Rates Using the Dynamic Nelson-Siegel Model with Time-Varying Parameters." *Journal of Business & Economic Statistics* 28(3): 329–343.

[15] Bianchi, Francesco, Sydney C. Ludvigson, and Sai Ma. 2021. "A Smooth Shadow-Rate Dynamic Nelson-Siegel Model for Yields at the Zero Lower Bound." *Journal of Business & Economic Statistics* 42(2): 651–668.

[16] Exterkate, Peter, Lennart Hoogerheide, and Herman K. van Dijk. 2020. "Forecasting U.S. Yield Curve Using the Dynamic Nelson-Siegel Model with Random Level Shift Parameters." *Economic Modelling* 93: 378–391.

[17] Bauer, Michael D., and James D. Hamilton. 2018. "Robust Bond Risk Premia." *Review of Financial Studies* 31(2): 399–448.

[18] Joslin, Scott, Marcel Priebsch, and Kenneth J. Singleton. 2014. "Risk Premiums in Dynamic Term Structure Models with Unspanned Macro Risks." *Journal of Finance* 69(3): 1197–1233.

[19] Wright, Jonathan H. 2011. "Term Premia and Inflation Uncertainty: Empirical Evidence from an International Panel Dataset." *American Economic Review* 101(4): 1514–1534.

[20] D'Amico, Stefania, Don H. Kim, and Min Wei. 2018. "Tips from TIPS: The Informational Content of Treasury Inflation-Protected Security Prices." *Journal of Financial and Quantitative Analysis* 53(1): 395–436.

[21] Newey, Whitney K., and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55(3): 703–708.

[22] Andrews, Donald W.K. 1991. "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation." *Econometrica* 59(3): 817–858.

[23] Bai, Jushan, and Pierre Perron. 2003. "Computation and Analysis of Multiple Structural Change Models." *Journal of Applied Econometrics* 18(1): 1–22.

[24] Engle, Robert F., and C.W.J. Granger. 1987. "Co-integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55(2): 251–276.

[25] Johansen, Søren. 1988. "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control* 12(2-3): 231–254.

[26] Dickey, David A., and Wayne A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74(366): 427–431.

[27] Elliott, Graham, Thomas J. Rothenberg, and James H. Stock. 1996. "Efficient Tests for an Autoregressive Unit Root." *Econometrica* 64(4): 813–836.

[28] Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. 1992. "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root." *Journal of Econometrics* 54(1-3): 159–178.

[29] McCrary, Justin. 2008. "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test." *Journal of Econometrics* 142(2): 698–714.

[30] Cattaneo, Matias D., Michael Jansson, and Xinwei Ma. 2019. "Simple Local Polynomial Density Estimators." *Journal of the American Statistical Association* 115(531): 1449–1455.

[31] Xu, Ke-Li. 2017. "Local Polynomial Order in Regression Discontinuity Designs." *Journal of Business & Economic Statistics* 39(3): 795–816.

[32] Gelman, Andrew, and Guido Imbens. 2019. "Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs." *Journal of Business & Economic Statistics* 37(3): 447–456.

[33] Kim, Don H., Marcelo Ochoa, and Oleksiy Kryvtsov. 2021. "Term Structure Models and the Zero Lower Bound: An Empirical Investigation of Japanese, German, and U.S. Yields." *Journal of Applied Econometrics* 36(4): 402–423.

[34] Federal Reserve Board. 2022. "Three-Factor Nominal Term Structure Model." `https://www.federalreserve.gov/data/three-factor-nominal-term-structure-model.htm`. Accessed September 2025.

[35] Federal Reserve Economic Data (FRED). 2025. "10-Year Treasury Constant Maturity Rate [DGS10]." Federal Reserve Bank of St. Louis. `https://fred.stlouisfed.org/series/DGS10`. Accessed September 2025.

[36] Federal Reserve Economic Data (FRED). 2025. "10-Year Treasury Inflation-Indexed Security, Constant Maturity [DFII10]." Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/DFII10. Accessed September 2025.

[37] Federal Reserve Economic Data (FRED). 2025. "10-Year Breakeven Inflation Rate [T10YIE]." Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/T10YIE. Accessed September 2025.

[38] Federal Reserve Bank of Cleveland. 2025. "Inflation Expectations." https://www.clevelandfed.org/indicators-and-data/inflation-expectations. Accessed September 2025.

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