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Predictability in bond returns using technical trading rules

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ABSTRACT

The predictability of future returns on bond portfolios at daily frequency is investigated using a large universe of mechanical trading rules that have been popularized in literature on equity and currency markets. The predictability in returns is inversely related to interest rate risk but positively related to default risk. The return predictability is more sensitive to fluctuations in the economic business cycle rather than changes in the Federal Reserve's monetary policy. Returns on portfolios of Treasury bonds are more predictable during the restrictive monetary policy regime, whereas returns on both Treasury bonds and corporate bonds exhibit much better predictability during the economic expansions rather than recessions. The predictability of returns in various segments of the U.S. bond market has declined over time. Findings for the predictability in the highly liquid bond exchange-traded funds are largely in line with the original results of the predictability in bond portfolio returns.

1. Introduction

The predictability of future asset returns based on historical price and return data has been a popular subject in both academic literature and practitioner circles. A myriad of active investment strategies have been designed to exploit time-series predictability of returns. In particular, technical analysis explores time-series predictability of returns and it is typically used by the financial markets participants to predict the price movement for short forecasting horizons. Technical or mechanical trading rules are based on the premise that past price trends predict future price movements and trend-chasing mechanical trading rules are designed to exploit the phenomenon of price continuation. Practitioners have been known to rely on technical indicators and pursue mechanical trading strategies that use past price and volume data to infer future price movements. In financial media journalists frequently turn to financial professionals known as "technicians" or "chartists" for their take on the market's future direction. Based on the results of a survey of 692 fund managers in five countries including the United States, Menkhoff (2010) finds that the share of fund managers that put at least some importance on technical analysis is 87% and that technical analysis becomes the most important forecasting tool in decision making for shorter-term periods.

In contrast to the views of many financial practitioners, most academics have been skeptical about the usefulness of technical analysis. Despite that, numerous research papers investigating the forecasting power of different mechanical trading strategies, charts and patterns have been published over the years. Park and Irwin (2007) review a total of 135 published articles that investigate the application of different mechanical trading rules and strategies to various markets around the world during the 1960–2004 period. Table 1 shows how the total number of such publications is split between subperiods and different markets (equities, currencies, commodities and bonds). It is worth noting several interesting observations from the table. First, the interest in research on technical analysis increased substantially since the early 1990s. During the 1990–2004 period, more than half of empirical studies on technical trading rules covered in Park and Irwin (2007) were conducted. The rise of interest in research on return predictability using mechanical trading rules during that time frame is commonly attributed to two seminal publications, Sweeney (1986) and Brock et al. (1992), which find that technical analysis is able to yield excess returns in currency markets and equity markets, respectively. Second, although a plethora of published literature on

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Table 1
Number of published articles on technical analysis applied to different markets*.

Time period	Equities, equity futures and equity options	Currency exchange rates and currency futures	Commodities and commodity futures	Bonds and bond futures
1960s	9	1	4	–
1970s	6	3	5	–
1980s	6	6	10	2
1990s	22	17	3	–
2000–2004	22	18	1	–

* Based on Park and Irwin (2007).

technical analysis focuses on whether future returns on equities, currencies, commodities or their respective futures can be predicted using past prices, the subject of short-term predictability of returns in bond markets using mechanical trading rules has been studied less closely. There are only two papers on the subject published during the 1960–2004 period that use data for bond futures and none that use data on bonds. Dale and Workman (1980) investigate profitability of 11 moving average rules applied to 90-day Treasury bill futures during the 1976–1978 sample period, and Taylor (1988) explores forecasting power of four price-trend autoregressive moving average trading rules applied to Treasury bond futures during the 1978–1987 sample period. To our knowledge, a large-scale study on time-series predictability in bond returns using mechanical trading rules has not yet been attempted.

A block of literature investigates the predictability of returns and yields in the U.S. bond market using testing techniques other than technical analysis. Ilmanen and Byrne (2003) find that bond yields tend to experience trend continuation in the run-up to major events such as a release of the U.S. non-farm payroll report, and Chua et al. (2006) show that a small number of trading strategies focusing on the mean-reversion of the yield spreads can be highly profitable. Boyd and Mercer (2010) find that successful trading strategies tied to yields on bonds with short maturities can be exclusively based on the use of past information, while Moskowitz et al. (2012) document a significant time-series momentum in the U.S. Treasury bond futures.

All aforementioned studies rely on the use of monthly return data to reach their conclusions. Meanwhile, a segment of literature suggests that the use of monthly data may fail to detect or underestimate the return predictability if timing decisions occur at a more frequent interval. Bessembinder et al. (2009) analyze the empirical power and specification of test statistics designed to detect abnormal bond returns and find that using daily data significantly increases the power of the test, relative to the monthly data, even if the available time series of daily bond returns is short. Reisman and Zohar (2004) demonstrate that using weekly data improves the degree of return predictability compared to the monthly data usage. Gebhardt et al. (2005) show that stock prices adjust to new information more quickly than bond prices which may imply that bonds are more likely than equities to experience momentum when frequent data are analyzed. A number of works assess the predictability in bond returns using daily and intraday data (Hotchkiss and Ronen, 2002; Downing et al., 2009; Goyenko et al., 2011; Hong et al., 2012) but their analyses are largely confined to the investigation of the informational efficiency of bond market relative to stock market by examining cross-dependencies and lead-lag relations between the returns on bonds and equities, restricted to a single segment of the bond market or characterized by a relatively short sample period.

We do not attempt to convince one whether technical analysis is a self-fulfilling prophecy. Looking upon a larger scale, the purpose of this paper is to expand the scope of research on the predictability of returns and market efficiency in the bond markets. Time-series predictability of returns is tested for a variety of bond portfolios at daily frequency via the utilization of mechanical trading rules that have been popularized in the literature on the short-term predictability of returns in equity and foreign exchange markets. A universe of 27,000 mechanical trading strategies is employed, and the Superior Predictive Ability (SPA) bootstrapping technique and its stepwise extension is utilized to account for data snooping bias to evaluate the degree of short-term predictability in returns on a set of bond indexes. Statistically significant predictability is found in returns on the aggregate bond index covering the entire universe of the U.S. bond market as well as in the selected segments of the market after accounting for data snooping bias and mitigating for the potential nonsynchronicity bias arising from infrequent trading of the bond index components.

Further analysis reveals that the returns on the U.S. bond portfolios with shorter maturities are more predictable than the returns on the U.S. bond portfolios with longer maturities suggesting that the predictability in bond returns is negatively related to interest rate risk. This outcome has been found valid for both Treasury bonds and corporate bonds. For corporate bonds, the short-term predictability in bond returns is also found to be positively related to default risk: the returns on bond portfolios with high-risk low-quality bonds tend to be more predictable than the returns on the portfolios of low-risk high-quality bonds.

The predictability of returns in various segments of the U.S. bond market has declined over time. Such evidence can be interpreted as a consequence of the increased competitiveness for profits among traders and arbitrageurs that resulted in the improved market liquidity. Other potential explanations of the observed phenomenon of the weakening of the predictive power of mechanical trading rules would include the expansion of computational powers and technological advances which resulted in the proliferation of algorithmic trading and the reduction in transaction costs followed by the improved liquidity conditions in the market and the introduction of new investment vehicles in the form of exchange-traded securities that allow to trade baskets of bonds at low cost.

The predictability in returns on bond portfolios has been found to be more sensitive to the fluctuations in the economic business cycle rather than the changes in the monetary policy. While the returns on Treasury bond indexes tend to be more predictable during the restrictive monetary policy regime, the examination of return predictability in corporate bond indexes under different monetary policy regimes reveals no clear evidence whether returns are significantly better predictable during one of the regimes. Meanwhile, returns on both Treasury bond indexes and corporate bond indexes exhibit much better predictability during the economic expansions rather than the recessions. The evidence of the varying degree of predictability in bond returns across business expansions and recessions offers support for the adaptive market hypothesis which suggests that changing business conditions and market environment can result in temporary market inefficiencies that open opportunities for abnormal profitability.

The impact of transaction costs on the predictability of bond returns is hard to determine as transaction costs in the bond market are difficult to measure precisely and they must have declined over time. The factor of transaction costs is incorporated into analysis by assessing the predictability of returns in the most liquid exchange traded funds that have been designed to replicate the performance of a number of popular bond indexes. The obtained findings for the bond exchange-traded funds confirm the original results showing that the bond return predictability is negatively related to the interest rate risk but positively related to the default risk and that the predictability of returns in bond portfolios has been largely eliminated since the early 2000s.

The rest of the paper is structured as follows. Section 2 discusses the data on bond returns used for the analysis of short-term predictability. Section 3 presents the universe of trading rules and trading strategies based on which the return predictability is tested and it is supplemented with an appendix that offers a detailed description of parameters of the employed trading rules. Section 4 describes the data snooping adjustment techniques utilized to assure that the obtained results do not represent spurious findings or overestimate the potential success of technical trading strategies. Section 5 reveals the empirical findings and discusses the factor of transaction costs. Section 6 concludes.

2. Data

The paper employs a set of popular Bank of America (BofA) Merrill Lynch bond indexes. The BofA Merrill Lynch bond indexes track a large number of issues of publicly placed debt and provide the most timely and comprehensive measure of bond market performance available to fixed income investors. The index constituents are capitalization-weighted based on their current amount outstanding. The amount-outstanding data are reviewed regularly to account for partial calls, sinking-fund requirements, tenders, or re-openings of issues and the indexes are rebalanced on the last calendar day of the month.

The indexes are calculated in the form of total return price series. The calculations of total return accounts for distributed cash flows such as coupon payments[1] and it assumes that they are reinvested.[2] Index total returns are based on weighted average price, weighted average accrued interest, weighted average coupon and, in the case of mortgage- and asset-backed securities, anticipated and unanticipated principal payments.

This study focuses on a subset of domestic (U.S.) bond indexes. The major domestic index in the BofA Merrill Lynch family of bond indexes is the U.S. Broad Market Index that tracks the performance of U.S. dollar denominated investment grade government and corporate public debt including collateralized products such as mortgage pass-through and asset-backed securities. The primary sub-divisions of the U.S. Broad Market Index include: the U.S. Domestic Master Index that tracks the performance of U.S. dollar denominated investment grade government and corporate public debt including mortgage pass-through securities but excluding asset-backed securities; the U.S. Corporate & Government Master Index that tracks the performance of U.S. dollar denominated investment grade government and corporate public debt excluding collateralized products; the U.S. Treasury Index that tracks the performance of the direct sovereign debt of the U.S. government; the U.S. Corporate Master Index that tracks the performance of U.S. dollar denominated investment grade corporate public debt; and the Mortgage Backed Securities Index that tracks the performance of U.S. dollar denominated 30-year, 15-year and balloon pass-through mortgage securities. Other indexes representing various segments of the U.S. bond market and their combinations include the Municipal Securities Index that tracks the performance of the investment grade U.S. tax-exempt bond market and the U.S. High Yield Index that tracks the performance of U.S. dollar denominated below investment grade corporate debt[3] among others. The daily data spanning the period from June 30, 1994 to June 30, 2011 are obtained from Bloomberg.[4]

3. Universe of trading rules

Technical analysis encompasses a large set of mechanical trading rules designed to predict future prices using historical data on price and other related observables. Testing of return predictability using mechanical trading rules requires assembling of an appropriate universe of such rules: choosing very few rules may cause biases in statistical inference due to data mining; on the other hand, loading the sample set with too many underperforming rules may also bias the statistical inference by reducing the power of the test. We therefore look for a balance and select a sufficient yet not overwhelmingly large variety of reasonable parameters within four popular families of trading rules that have been extensively applied to equity and foreign exchange markets. The employed universe of trading rules consists of 27,000 mechanical trading strategies that represent filter, moving average, support and resistance or trading range break, and channel breakout families. A brief description of each family of rules is provided below while more details on the specific parameter values are left in the Appendix.

A standard filter rule generates a buy (sell) signal when price increases (decreases) by a fixed percentage from a subsequent low (high). The subsequent high (low) can be defined in two ways: highest (lowest) closing price achieved while holding a particular long (short) position, and highest (lowest) closing price during the most recent period of fixed length not including the current price. Filter rules can be further modified to allow a neutral position by triggering closing of a long (short) position when the price decreases (increases) from the subsequent high (low) by a smaller percentage than the percentage required to open a trading position. A moving average rule generates trading signals based on the relation between a short-term moving average of recent price levels and a longer moving average. An N-period daily moving average is computed by adding together prices for the N most recent trading days of data, then dividing the sum by N. The average is recalculated each day by dropping the oldest price in the N-day sample while adding the most recent price. Under a standard moving average rule, a buy (sell) signal is triggered when a shorter moving average moves above (below) a longer moving average. A support and resistance trading rule generates a buy (sell) signal when the price rises above (falls below) the local maximum (minimum) referred as the resistance (support) level. The local maximum (minimum) is defined as the highest (lowest) price observed during the most recent period of fixed length. Lastly, a channel breakout rule is a variation of the trading approach based on support and resistance: a buy (sell) signal is triggered when the most recent price moves above (below) a channel. The channel is defined as an occasion when the highest price over the period of fixed length is within a prespecified percentage from the lowest price over the same period, excluding the current price.

Many trading rules can be implemented using either fixed or variable-length holding periods. Under the variable-length rule, a trader keeps an open position following a buy or sell signal until the opposite trading signal emerges. Under the fixed-length rule, the holding period following a buy or sell signal has a fixed length and any other buy or sell signals occurring within the holding

[1] The omission of regular income payments such as coupons and dividends has been identified as a cause of data measurement errors that result in biased returns from trading. Marshall et al. (2006) point out that many studies on the application of technical analysis to the equity market ignore dividends due to their focus on the index data that is usually in the form of a price return instead of total return and the difficulty associated with adjusting such an index data for dividends. In particular, Day and Wang (2002) argue that the results of Brock et al. (1992) are subject to a caveat that the return series of daily closing levels of the Dow Jones Industrials Average fails to reflect the component of the portfolio's return attributed to dividends.

[2] Current rules for calculation of BofA Merrill Lynch bond indexes state that cash flows from bond payments are retained in the index as a separate line item until the end of the month in which they are distributed and then are removed as part of the rebalancing. Also, currently cash does not earn any reinvestment income while it is held in an index due to the assumption of a zero reinvestment rate.

[3] Merrill Lynch did not offer high-yield market indexes until 1992.

[4] The beginning of the sample period (June 30, 1994) has been chosen because this is the first day starting from which data for the majority of BofA Merrill Lynch indexes are available at daily frequency. Before that date the data are available at monthly frequency only.

period are ignored. By design, the fixed-length holding period permits a neutral position.

A variation of a trading rule can impose one of two commonly applied filters to mitigate the influence of volatility. One of such filters is a band: a buy (sell) signal emerges if the signal-generating indicator is above (below) the pre-specified threshold by a fixed percentage, otherwise the existing position is maintained. The second filter is a time delay: it requires the signal to remain valid for a prespecified number of days before the respective position is ultimately taken. Both filters are meant to present stronger evidence that a new trend has been initiated. Normally, only one filter is imposed at a given time.

4. Methodology

Since equity prices and returns represent one of the most readily available datasets, active search for perceived anomalous trading opportunities in historical data can give a rise to spurious findings making studies on return predictability vulnerable and susceptible to unintentional data mining or data snooping. Data snooping is a result of searching through a large number of possible trading strategies to find a few that yield a much more superior in-sample performance.

The presence of data snooping bias can be mitigated by considering the performance of the best trading rule in the context of the full universe of trading rules from which such rule is conceivably drawn. Testing of the multiple inequality hypotheses can be done via Bonferroni inequality. The conservative Bonferroni bound test, however, ignores the correlation structure among the multiple models by assuming that they are independent from each other. In practice, returns on the majority of technical trading rules are correlated with each other as many of them have been designed to exploit autocorrelation in returns. Also, the test's power is affected by the number of chosen models (trading rules) for testing and thus can be effectively manipulated.

Sullivan et al. (1999) introduce the application of White's (2000) Reality Check test to evaluate the predictive ability of a set of technical trading rules. This data snooping adjustment technique has been subsequently employed by other studies on the forecasting power of technical analysis when applied to equity and futures markets. Hansen (2005) cautions that White's Reality Check suffers from two drawbacks. First, its null distribution is obtained under the configuration least favorable to the alternative hypothesis. Under such configuration the power of the Reality Check test can be substantially eroded if the universe of trading rules contains sufficiently many poorly performing trading rules. Second, the Reality Check's test statistic is not studentized. The latter implies that trading rules are compared solely on their return performance while their risk features are ignored.

To improve on the power of White's Reality Check and to incorporate risk characteristics of trading rules into account, Hansen (2005) introduces the Superior Predictive Ability (SPA) test that is designed to avoid the least favorable configuration by adopting a studentized test statistic and a sample-dependent distribution under the null hypothesis. Several recent empirical studies (Hansen and Lunde, 2005; Hsu and Kuan, 2005; Hsu et al., 2010; Park and Irwin, 2010) confirm that the SPA test is more powerful that the Reality Check test and less sensitive to the inclusion of poor and irrelevant alternatives.[5]

The SPA test's null hypothesis is that the best trading rule from the universe of K rules performs no better than a benchmark strategy and it is based on the following statistic:

$$V = \max\left(\max_{k=1,\dots,K} \frac{\sqrt{N}\bar{R}_k}{\hat{\sigma}_k}, 0\right), \tag{1}$$

$$\text{with} \quad \bar{R}_k = \sum_{t=P}^{T} R_{k,t}/N, \tag{2}$$

where $R_{k,t}$ is the day t excess return from the kth trading rule over the benchmark, $N = T - P + 1$, P is the first day in the sample when a trading signal is generated for each trading rule in the set,[6] and $\hat{\sigma}_k$ is a consistent estimator of the standard deviation of $\sqrt{N}\bar{R}_k$.

Two measures of excess return are utilized to evaluate the predictive power of technical trading rules. The first is the excess trading return relative to buy-and-hold return while using a "double-or-out" trading strategy superimposed by Brock et al. (1992), Bessembinder and Chan (1998), and Hsu and Kuan (2005): following a buy signal, a trader borrows at a risky rate to hold a double long position in the underlying asset or the portfolio, given a neutral signal, the trader holds one long position in the underlying asset, and if a sell signal emerges, any existing long positions are liquidated and the proceeds for one long position are invested in the risk-free asset, i.e., the investor is out of the market. Such trading strategy does not require taking a short position which can be a costly proposition in the bond market. The second performance measure is the excess trading return relative to risk-free return while using a "long-or-short" trading strategy employed by Sullivan et al. (1999) and Hsu et al. (2010) which takes a long position following a buy signal, opens a short position following a sell signal, and invests in the risk-free asset following a neutral signal. Consistent with the existing literature on the application of technical trading rules to equity and currency markets, we define daily return as a natural log of the difference in price relatives.

In order to use the approach that relies on the long-or-short trading strategy, the data on lending interest rate is required, while for the double-or-out trading strategy, both lending and borrowing rates must be available.[7] The lending (risk-free) rate is set to daily continuously compounded rate converted from the annualized yield on a 3-month U.S. Treasury bill. The borrowing (risky) rate is set to the daily continuously compounded rate obtained from the annualized 3-month LIBOR on Eurodollar deposits. The historical data on both rates are taken from the Federal Reserve database at http://www.federalreserve.gov/releases/h15/data.htm.

The test's p-value is subsequently obtained by comparing the performance of the best trading rule to the approximation of the asymptotic distribution of the performance measure. To reduce the influence of rules with large negative returns, Hansen (2005) recenters the null distribution of the SPA test statistic. First, for each rule k, the average of the bootstrapped sample of the centered returns is computed:

$$\bar{Z}_{k,b} = \bar{R}_{k,b} - \bar{R}_k I_{\{\sqrt{N}\bar{R}_k/\hat{\sigma}_k \geq -A\}}, \quad b = 1, \dots, B, \tag{3}$$

where I is an indicator function taking on value one if the condition is satisfied and zero otherwise, A is a preset threshold rate

[5] Hansen (2005) argues that another attractive feature of the proposed testing technique is that two researchers, who do not fully agree on which trading rules should be included in the universe of such rules, are more likely to achieve similar results and conclusion when they rely on the SPA test rather than White's Reality Check method.

[6] In the employed universe of trading rules described in the Appendix, the first trading signal is generated for the 201th observation for all specifications because some rules require 200 days of previous data to provide a trading signal. Hence, $P = 201$, while T may vary depending on the sample size.

[7] The cost of shorting for the long-or-short trading strategy is assumed to be determined by the difference between the borrowing rate and the lending rate, whereas the double-or-out trading strategy does not require taking a short position in the underlying asset.

and B is the number of bootstrap resamples. Then, the consistent p-values of are determined by the empirical distribution of V.

The stationary bootstrap method of Politis and Romano (1994) is employed to obtain the empirical distribution of V.[8] This method resamples blocks of varying length from the original data of the observed values of $R_{k,t}$, $t = P,\ldots T$, where the block length follows a geometric distribution.[9] If the p-value of the test is smaller than a given significance level, the null hypothesis is rejected. Rejection of the null implies that the best trading rule achieves performance superior to the benchmark after adjusting for data snooping bias.

Hansen (2005) argues that the threshold rate $A = \sqrt{2 \ln \ln N}$ gives a consistent estimate of the null distribution, which in turn improves the power of the test. Other threshold rates, however, also produce valid results. Thus, effectively, a range of rates can be used for the purpose of discriminating against good and poor alternatives. Since different threshold rates may result in different p-values in finite samples, two additional estimators are used in order to determine a lower and an upper bound for the consistent p-value:

$$\overline{Z}^{L}_{k,b} = \overline{R}_{k,b} - \max(\overline{R}_k, 0), \quad b = 1, \ldots, B \tag{4}$$

$$\overline{Z}^{U}_{k,b} = \overline{R}_{k,b} - \overline{R}_k, \quad b = 1, \ldots, B \tag{5}$$

It can be seen that $\overline{Z}^{L}_{k,b} \leq \overline{Z}_{k,b} \leq \overline{Z}^{U}_{k,b}$. The lower and upper bounds for the consistent p-value are determined in a similar fashion as that of the consistent p-value. The SPA test is deemed more powerful than the Reality Check test because the bootstrapped SPA p-values are normally smaller than the corresponding Reality Check p-values.

To run the SPA routine, the number of bootstrap resamples should be sufficiently large to reduce the additional layer of randomness introduced by the resampling scheme and thus is set to 1000. The smoothing parameter for the stationary bootstrap is set to 0.1.[10] A large value of the smoothing parameter is appropriate for data with little dependence, and a smaller value is appropriate for data that exhibits more dependence.

Although Hansen's SPA test is more powerful than White's Reality Check, it only addresses the question whether the best performing trading rule beats the benchmark after adjusting for data snooping bias. To improve on the informativeness of the original SPA method, Hsu et al. (2010) introduce a stepwise extension of Hansen's SPA, a Step-SPA. Apart from the best trading rule and the statistical significance of its performance with respect to the universe of rules, the Step-SPA allows to identify the set of outperforming trading rules. If the null hypothesis of no outperformance is rejected for the top rule at the given critical level of significance, the rule is removed from the universe and the SPA test is repeated for the reduced sample of trading rules. The procedure stops when the null cannot be rejected for the remaining share of the universe of trading rules at the given critical level.

5. Empirical results

5.1. Predictability of returns in the aggregate bond market index and its segments

In many instances one can argue that claimed predictability in asset returns is an artifact of market frictions or market inefficiencies. It is well known that bonds are not as heavily traded as many of the equities or currencies. As a result, a legitimate concern is that any documented predictability in returns on bond portfolios can have spurious nature due to nonsynchronous trading of the bonds—components of the underlying indexes since bid-ask bounce and stale quotes can cause spurious serial correlation in quoted index values. The presence of nonsynchronicity bias inflates autocorrelations in the return series, particularly for shorter lags, thus overestimating the true predictability in returns and exaggerating the profitability of trend-chasing trading strategies designed to exploit the time-series momentum.

The issue of nonsynchronicity in quoted bond index values is partially mitigated by the adopted practice of determining the fair value for bonds that are infrequently traded. Since some bonds may have no recorded transactions on particular days, brokers resort to matrix pricing. If a particular bond is not traded on a specific day, the broker sets a matrix price for that bond based on recorded prices of bonds with similar characteristics that traded on that day. Although it is not a perfect solution, nonetheless, bond matrix pricing is a sensible method to determine a fair price value for bonds that trade infrequently and it allows to mitigate the nonsynchronicity bias stemming from old or stale prices.

A popular remedy to mitigate the nonsynchronicity bias while testing the predictability in asset returns has been the introduction of a lag between the time when the trading signal emerges and the time when the respective trading position is taken. The length of such lag depends on the estimated average time period during which every index component is traded at least once. In the existing literature on the application of technical analysis to equities and currencies, a 1-day delay adjustment is normally used.[11]

Table 2 shows the results of the application of the data snooping test when the trader is forced to wait 1 day until the respective trading position can be taken to eight bond indexes that represent different segments of the U.S. bond market, combinations of such segments, and the broad market index that covers the entire universe of the U.S. bond market. The hypothesis of no outperformance of trading rules is rejected for seven bond indexes. The Treasury bond index is not characterized by statistically significant predictability in its returns, however, returns on combined portfolios that include Treasurys among others are found to be predictable. The percentage of profitable trading rules varies from 50 for the municipal index to more than 93 for the high yield index. The number of outperforming trading rules after accounting for data snooping bias is quite significant for the broad market index and the combined portfolio of government and corporate bonds and mortgage securities, and it is particularly high for the high yield, mortgage and municipal indexes.

Comparison of the findings in Table 2 to the unreported results for the case when the 1-day lag is omitted reveals that the percentage of profitable trading rules as well as the number of outperforming trading rules after accounting for data snooping bias do not change significantly across all eight bond indexes after the introduction of the 1-day delay between the trading signal

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[8] The estimate $\hat{\sigma}_k$ is computed using the stationary bootstrap procedure: $\hat{\sigma}_k^2 = \hat{\gamma}_{0,k} + 2\sum_{i=1}^{N-1} \kappa(N,i)\hat{\gamma}_{i,k}$, where $\hat{\gamma}_{i,k} = \sum_{t=1}^{N-i} (R_{k,t} - \bar{R}_k)(R_{k,t+i} - \bar{R}_k), i = 0, 1, \ldots, N-1$, are the empirical covariances and the kernel weights are given by $\kappa(N,i) = \frac{N-i}{N}(1-q)^i + \frac{i}{N}(1-q)^{N-i}$, with q being the smoothing parameter.

[9] We follow Sullivan et al. (1999), Hsu and Kuan (2005) and Hsu et al. (2010) and adopt a "wrap-up" feature for resampling purposes.

[10] Marshall et al. (2008a, b), Hsu et al. (2010), and Park and Irwin (2010) also set the probability parameter to 0.1. Sullivan et al. (1999) find that their p-values are insensitive to the choice of the smoothing parameter. Similarly, Hsu and Kuan (2005) find that the smoothing parameters of 0.01, 0.1, and 0.5 in the stationary bootstrap yield similar results.

[11] A similar way to tackle possible nonsynchronicity bias has been employed in the literature on cross-section momentum in equity returns. The papers that rely on weekly data introduce a one-week gap between the formation period and the holding period, while the papers that rely on monthly data employ a one-month gap.

Table 2
Predictability of returns in the aggregate bond market and its major segments. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Broad Market	6.21	3.93	78.79	**0.009**	**0.011**	**0.011**	575	84.07	**0.012**	**0.014**	**0.014**	383
US Corporate, Government and Mortgage	6.25	3.98	79.20	**0.008**	**0.012**	**0.012**	613	84.64	**0.013**	**0.014**	**0.014**	394
US Corporate and Government	6.17	4.50	73.80	**0.077**	**0.092**	**0.096**	2	78.74	**0.052**	**0.059**	**0.059**	2
US Treasury Master	5.96	4.71	72.21	0.144	0.175	0.180	0	77.30	0.157	0.175	0.175	0
US Corporate Master	6.65	5.14	81.39	**0.032**	**0.036**	**0.036**	15	86.17	**0.039**	**0.042**	**0.042**	11
US High Yield Master II	7.50	4.38	93.50	**0.000**	**0.000**	**0.000**	2026	94.27	**0.000**	**0.000**	**0.000**	3472
Mortgage Master	6.39	3.34	87.00	**0.000**	**0.000**	**0.000**	3163	89.90	**0.001**	**0.001**	**0.001**	2747
Municipal Master	5.79	3.96	49.94	**0.000**	**0.000**	**0.000**	488	57.92	**0.000**	**0.000**	**0.000**	680

Table 3
Predictability of returns in Treasury bonds split by maturities. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	4.55	1.58	93.74	**0.000**	**0.000**	**0.000**	6252	95.52	**0.000**	**0.000**	**0.000**	7050
US Treasury 3–5 Years	5.80	3.70	86.05	**0.016**	**0.016**	**0.016**	577	88.84	**0.006**	**0.006**	**0.006**	224
US Treasury 5–7 Years	6.37	4.93	78.77	**0.065**	**0.076**	**0.078**	2	82.58	**0.091**	**0.095**	**0.095**	3
US Treasury 7–10 Years	6.66	6.39	68.42	0.109	0.139	0.145	0	75.77	0.110	0.123	0.126	0
US Treasury 10–15 Years	7.03	7.10	54.57	0.307	0.387	0.401	0	62.28	**0.090**	0.111	0.114	0
US Treasury 15+ Years	7.42	10.64	40.53	0.336	0.457	0.470	0	50.89	0.214	0.268	0.271	0

and the actual trade. The return on the best trading rule in the universe, however, is sharply reduced by the 1-day delay feature for the high-yield bond index and the municipal bond index. Such finding indicates the presence of spurious autocorrelations in the index return series validating concerns about the presence of nonsynchronicity bias. This observation is consistent with the empirical evidence that high-yield corporate bonds and municipal bonds are the least liquid segments of the U.S. bond market since nonsynchronous trading is an artifact of low liquidity. To mitigate the influence of nonsynchronous trading, the 1-day delay between the emergence of a trading signal and the time of taking the respective trading position is applied throughout the rest of the analysis. The study is proceeded to uncover the differences in the degree of predictability in bond returns across different market segments and various market conditions.

5.2. Predictability of bond returns as a function of time to maturity

Historical evidence demonstrates significant differences in the returns generated by bonds of various maturities. In periods when interest rates rise, short-duration funds will outperform long-duration funds, and in periods when interest rates fall, long-duration funds will outperform short-duration funds. Returns on bonds of different maturities have also been shown to be driven by different factors. For example, prices of Treasury bills and short-term notes are largely affected by the Fed's monetary policy actions while prices of long-term Treasury bonds are influenced by expected inflation and, more recently, worries about sustained oversized budget deficits. Therefore, it can be argued that over a period of the term structure fluctuations, returns on portfolios consisting of bonds with substantially different levels of interest rate risk will be less predictable than returns on portfolios of bonds with same or very similar exposures to interest rate risk.

Table 3 summarizes the results for the universe of trading rules applied to the Treasury indexes of different maturities. The percentage of profitable trading rules declines monotonically with the maturity range while the SPA p-value increases for longer maturities. The no outperformance hypothesis is rejected for the indexes that hold portfolios of Treasury bonds with shorter maturities, up to 7 years. The number of outperforming trading rules after accounting for data snooping bias is fairly large for the portfolio with bonds maturing in 3–5 years and substantial for the Treasury bond portfolio holding bonds with maturities less than 3 years. The finding of the strongest predictability of returns for the portfolio of bonds with the shortest maturity, up to 3 years, can be attributed to the "pull-to-par" phenomenon: as maturity approaches, prices of bonds in good standing, that is, with no risk of default, converge to their par values. The nearer is the maturity, the greater is the influence because the bond will only pay out the stated principal amount.[12]

Table 4 provides further supporting evidence of the results obtained in Table 3. This time portfolios are composed of corporate bonds instead of Treasury securities but they are also differentiated by their respective maturity ranges. The pattern observed in Table 3 appears again: the percentage of profitable trading rules declines with maturity while the test's *p*-values rise. The null hypothesis of no outperformance of mechanical trading rules is rejected for three indexes with maturities below 7 years, and the number of outperforming trading rules after accounting for data snooping bias is substantial for all three, particularly for the index tracking bonds with the shortest maturities in the sample, providing yet another evidence of linkage between the bond return predictability and the "pull-to-par" phenomenon. The combined

[12] Plus the last coupon if it is a coupon-paying bond.

Table 4
Predictability of returns in corporate bonds split by maturities. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Corporate 1–3 Years	5.43	1.84	91.90	**0.000**	**0.000**	**0.000**	7144	91.83	**0.000**	**0.000**	**0.000**	7414
US Corporate 3–5 Years	6.24	3.46	87.67	**0.001**	**0.001**	**0.001**	2791	89.72	**0.001**	**0.001**	**0.001**	2410
US Corporate 5–7 Years	7.00	4.76	88.82	**0.011**	**0.011**	**0.011**	739	91.09	**0.007**	**0.007**	**0.007**	541
US Corporate 7–10 Years	6.78	6.00	80.85	**0.103**	0.132	0.136	0	85.27	0.115	0.131	0.134	0
US Corporate 10–15 Years	7.73	6.75	79.47	**0.096**	0.117	0.117	0	84.82	**0.093**	**0.100**	**0.100**	2
US Corporate 15+ Years	7.37	8.85	65.33	0.387	0.506	0.512	0	73.49	0.229	0.273	0.273	0

Table 5
Predictability of returns in corporate bonds split by credit ratings. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	*R* > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Corporate AAA	6.21	5.40	52.45	0.152	0.189	0.193	0	59.57	0.177	0.198	0.199	0
US Corporate AA	6.32	4.86	77.43	**0.026**	**0.029**	**0.030**	16	81.65	**0.037**	**0.037**	**0.038**	9
US Corporate A	6.36	5.32	78.98	**0.061**	**0.075**	**0.077**	3	83.87	**0.015**	**0.017**	**0.017**	11
US Corporate BBB	7.00	5.25	86.44	**0.029**	**0.030**	**0.030**	53	90.19	**0.035**	**0.036**	**0.036**	41
US High Yield BB	7.07	4.06	90.11	**0.000**	**0.000**	**0.000**	1870	91.91	**0.000**	**0.000**	**0.000**	2102
US High Yield B	5.68	5.03	86.26	**0.000**	**0.000**	**0.000**	2023	88.61	**0.000**	**0.000**	**0.000**	2256
US High Yield CCC and lower	6.93	7.56	96.18	**0.000**	**0.000**	**0.000**	4645	96.77	**0.000**	**0.000**	**0.000**	5416

findings reveals that the returns on the U.S. bond portfolios with shorter maturities are more predictable than the returns on the U.S. bond portfolios with longer maturities suggesting that the predictability in bond returns is negatively related to the interest rate risk and implying that technical trading in the U.S. bond market is more successful if applied to portfolios of bonds with shorter maturities. This result remains valid for each of the two major segments of the U.S. bond market, both Treasury bonds and corporate bonds.

5.3. Predictability of bond returns as a function of credit rating

One can argue that returns on portfolios consisting of bonds with substantially different levels of credit risk are less likely to be predictable than returns on portfolios of bonds with similar credit risk characteristics. During times of increased market stress that normally follow the start of an economic downturn, the returns on government bonds and corporate bonds can become negatively correlated due to the phenomenon of "flight to quality": investors look for safety by selling riskier assets in favor of safer assets. Returns on government and corporate bonds have also been shown to be explained by different risk factors: returns on government bonds are mainly affected by the Federal Reserve's monetary policy and inflation expectations whereas returns on corporate bonds are strongly impacted by default risk. Returns on high grade corporate bonds and low grade corporate bonds can also be influenced by different factors or by the same factors but to a different degree. Chen and Maringer (2011) find that high quality corporate bonds adjust to changes in economic conditions faster than low quality bonds. Such findings suggest that macroeconomic conditions are reflected in the prices of low quality bonds at a slower rate which, in turn, may imply the existence of price continuation.

BofA Merrill Lynch segments the US Corporate Master index into sub-portfolios by bond's credit rating where all corporate bonds are classified into seven major rating categories. The BofA Merrill Lynch index composite ratings are the simple averages of ratings from three major credit rating agencies. For the majority of the BofA Merrill Lynch index universe, the composite rating is based on the average of Moody's, S&P and Fitch. The composite rating is calculated by assigning a numeric equivalent to the ratings in each agency's scale. The average of the numeric equivalents for each agency that rates a bond is rounded to the nearest integer and then converted back to an equivalent composite rating. If only two of the designated agencies rate a bond, the composite rating is based on an average of the two. Likewise, if only one of the designated agencies rates a bond, the composite rating is based on that one rating.

Table 5 provides results of the application of the SPA data snooping testing technique to the corporate bond indexes sorted by the credit ratings assigned to the issued bonds. The percentage of profitable trading rules generally increases with a lower credit rating and the *p*-value declines. The no outperformance hypothesis cannot be rejected for the index with the highest credit rating but it is rejected for the remaining three portfolios with investment grades (BBB or higher) as well as for all three high yield indexes (BB or lower). The number of outperforming trading rules after accounting for data snooping bias is substantial for all three high yield indexes. One can conclude that the returns on portfolios of lower-quality bonds tend to be more predictable than the returns on portfolios of higher-quality bonds implying that portfolios of higher-risk bonds are more suitable for mechanical trading strategies than portfolios of lower-risk bonds.

To check robustness of the findings presented in Tables 4 and 5, Table 6 summarizes the results of the application of the data snooping bias adjustment technique to the portfolios of corporate bonds split by both maturity range and credit rating. The percentage of profitable trading rules declines with the maturity range holding the credit rating constant but it increases for indexes

Table 6
Predictability of returns in corporate bonds split by maturities and credit ratings. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Corporate AAA 1–5 Years	5.70	3.15	66.50	**0.002**	**0.002**	**0.002**	673	67.70	**0.002**	**0.002**	**0.002**	550
US Corporate AA 1–5 Years	5.69	2.70	86.21	**0.000**	**0.000**	**0.000**	4641	88.10	**0.000**	**0.000**	**0.000**	4406
US Corporate A 1–5 Years	5.58	2.88	85.14	**0.000**	**0.000**	**0.000**	4435	86.78	**0.001**	**0.001**	**0.001**	4140
US Corporate BBB 1–5 Years	6.14	2.72	94.54	**0.000**	**0.000**	**0.000**	5183	95.45	**0.000**	**0.000**	**0.000**	5502
US Corporate AAA 5–10 Years	6.49	6.36	47.57	0.258	0.331	0.337	0	54.52	0.241	0.286	0.288	0
US Corporate AA 5–10 Years	6.55	5.82	74.35	**0.094**	0.112	0.114	0	78.16	**0.049**	**0.053**	**0.056**	4
US Corporate A 5–10 Years	6.59	7.90	65.86	0.232	0.260	0.266	0	72.16	0.100	0.107	0.108	0
US Corporate BBB 5–10 Years	7.13	5.50	88.68	**0.010**	**0.011**	**0.011**	132	91.47	**0.013**	**0.014**	**0.014**	79
US Corporate AAA 10–15 Years	7.09	8.24	37.95	0.330	0.403	0.412	0	47.79	0.142	0.173	0.174	0
US Corporate AA 10–15 Years	7.62	7.50	65.26	0.444	0.560	0.573	0	74.26	0.557	0.627	0.634	0
US Corporate A 10–15 Years	7.32	7.20	72.89	0.243	0.300	0.307	0	79.52	0.180	0.199	0.200	0
US Corporate BBB 10–15 Years	8.07	6.48	85.02	**0.055**	**0.066**	**0.067**	4	88.67	**0.028**	**0.029**	**0.029**	16
US Corporate AAA 15+ Years	6.16	9.87	27.26	0.698	0.844	0.856	0	36.89	0.212	0.281	0.282	0
US Corporate AA 15+ Years	7.36	9.31	49.45	0.584	0.719	0.727	0	61.57	0.200	0.241	0.241	0
US Corporate A 15+ Years	7.18	9.16	63.47	0.335	0.458	0.466	0	71.11	0.259	0.313	0.315	0
US Corporate BBB 15+ Years	7.68	8.56	76.93	0.337	0.440	0.447	0	83.49	**0.066**	**0.072**	**0.073**	22

Table 7
Predictability of returns in Treasury bonds in subsample periods. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine. "O/S" is the measure of out-of-sample performance denoting the percentage of profitable trading rules in the first subsample period that remain profitable in the second subsample period.

First subsample period: 6/30/1994–6/30/2003

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	5.97	1.56	95.15	**0.000**	**0.000**	**0.000**	6880	96.14	**0.000**	**0.000**	**0.000**	7615
US Treasury 3–5 Years	7.29	3.46	87.32	**0.015**	**0.018**	**0.018**	779	90.72	**0.011**	**0.011**	**0.011**	257
US Treasury 5–7 Years	7.87	4.59	83.51	**0.081**	**0.089**	**0.091**	4	88.47	**0.068**	**0.075**	**0.075**	6
US Treasury 7–10 Years	8.32	5.85	76.33	**0.016**	**0.019**	**0.020**	7	82.75	**0.017**	**0.020**	**0.020**	10
US Treasury 10–15 Years	8.72	5.90	78.77	**0.070**	**0.082**	**0.086**	2	84.69	**0.076**	**0.083**	**0.085**	2
US Treasury 15+ Years	9.75	9.24	60.72	**0.059**	**0.089**	**0.091**	2	68.61	**0.045**	**0.055**	**0.055**	2

Second subsample period: 7/01/2003–6/30/2011

Index			Benchmark: riskless return						Benchmark: buy-and-hold					
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	O/S	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	O/S
US Treasury 1–3 Years	2.96	1.60	87.85	**0.044**	**0.049**	**0.051**	4	87.64	90.83	0.134	0.152	0.156	0	89.92
US Treasury 3–5 Years	4.14	3.95	72.58	0.289	0.353	0.365	0	75.39	74.55	0.106	0.121	0.122	0	76.83
US Treasury 5–7 Years	4.69	5.29	58.04	0.346	0.438	0.452	0	61.09	58.41	0.205	0.244	0.246	0	60.98
US Treasury 7–10 Years	4.82	6.95	41.76	0.472	0.614	0.633	0	35.92	44.09	0.254	0.327	0.332	0	40.60
US Treasury 10–15 Years	5.14	8.23	30.22	0.700	0.859	0.864	0	23.08	32.52	0.472	0.589	0.598	0	28.01
US Treasury 15+ Years	4.81	12.02	31.82	0.739	0.896	0.909	0	20.47	35.30	0.682	0.806	0.817	0	27.20

reflecting lower credit rating holding the maturity range constant. The no outperformance hypothesis is soundly rejected for all four indexes with short maturities up to 5 years but it cannot be rejected for all other but four indexes, where three of those four are characterized by the lowest investment grade credit rating in the sample (BBB). Such results further strengthen the findings that the predictability of returns in the U.S. corporate bond market is negatively related to both maturity and credit rating. It should be noted that the percentages of profitable trading rules will certainly decline while the reported SPA *p*-values are bound to rise if transaction costs are imposed. The factor of transaction costs is considered later in the paper.

5.4. Predictability of bond returns: a subsample analysis

Table 7 presents the evidence that the predictability of returns in the Treasury bond market has declined over time. The results reveal that during the first subsample period all six Treasury indexes sorted by maturity exhibit statistically significant predictability in returns, whereas only the index with the lowest maturity range, if compared versus the riskless benchmark, possesses this feature in the second subsample period. The percentage of profitable rules is uniformly lower across all Treasury indexes in the second subsample period compared to the first subsample period. The out-of-sample performance represented by the percentage of trading rules

Table 8
Predictability of returns in corporate bonds in subsample periods. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine. "O/S" is the measure of out-of-sample performance denoting the percentage of profitable trading rules in the first subsample period that remain profitable in the second subsample period.

First subsample period: 6/30/1994–6/30/2003

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Corporate AAA 1–5 Years	7.14	2.42	92.24	**0.001**	**0.001**	**0.001**	5287	94.28	**0.001**	**0.001**	**0.001**	5359
US Corporate AA 1–5 Years	7.38	2.52	93.19	**0.000**	**0.000**	**0.000**	5771	94.60	**0.000**	**0.000**	**0.000**	5963
US Corporate A 1–5 Years	7.37	2.57	90.49	**0.000**	**0.000**	**0.000**	5499	92.87	**0.000**	**0.000**	**0.000**	5404
US Corporate BBB 1–5 Years	7.05	2.63	90.26	**0.004**	**0.004**	**0.004**	2668	92.47	**0.005**	**0.005**	**0.005**	1851
US Corporate AAA 5–10 Years	8.66	5.62	78.02	**0.077**	**0.089**	**0.090**	2	84.17	**0.024**	**0.026**	**0.026**	11
US Corporate AA 5–10 Years	8.82	5.30	79.21	**0.035**	**0.038**	**0.039**	27	84.34	**0.013**	**0.014**	**0.014**	53
US Corporate A 5–10 Years	8.66	9.12	50.68	0.255	0.320	0.322	0	56.79	0.135	0.151	0.152	0
US Corporate BBB 5–10 Years	8.23	5.37	66.89	**0.062**	**0.083**	**0.089**	2	76.68	**0.079**	0.104	0.105	0
US Corporate AAA 10–15 Years	9.02	7.52	59.17	**0.067**	**0.096**	0.102	2	66.20	**0.066**	**0.084**	**0.087**	2
US Corporate AA 10–15 Years	9.29	6.86	67.68	0.159	0.227	0.230	0	76.27	**0.066**	**0.084**	**0.084**	4
US Corporate A 10–15 Years	9.41	6.93	67.82	0.107	0.160	0.164	0	75.50	**0.059**	**0.074**	**0.074**	2
US Corporate BBB 10–15 Years	9.30	6.48	65.59	0.108	0.138	0.141	0	75.21	**0.057**	**0.066**	**0.066**	6
US Corporate AAA 15+ Years	9.16	7.60	53.63	0.195	0.307	0.314	0	59.84	**0.089**	0.124	0.126	0
US Corporate AA 15+ Years	9.41	7.88	58.90	0.289	0.431	0.439	0	66.45	0.156	0.211	0.213	0
US Corporate A 15+ Years	9.29	7.88	53.66	0.305	0.490	0.516	0	59.79	0.304	0.419	0.422	0
US Corporate BBB 15+ Years	8.88	7.34	55.06	0.339	0.492	0.500	0	66.62	0.449	0.539	0.539	0

Second subsample period: 7/01/2003–6/30/2011

Index			Benchmark: riskless return						Benchmark: buy-and-hold					
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	O/S	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	O/S
US Corporate AAA 1–5 Years	4.09	3.80	45.40	0.132	0.146	0.146	0	56.72	43.83	**0.088**	**0.095**	**0.095**	2	54.76
US Corporate AA 1–5 Years	3.81	2.88	76.52	**0.011**	**0.011**	**0.011**	6	81.69	78.33	**0.010**	**0.010**	**0.010**	6	83.05
US Corporate A 1–5 Years	3.59	3.19	80.23	**0.033**	**0.034**	**0.034**	133	88.48	81.35	**0.026**	**0.026**	**0.027**	115	89.85
US Corporate BBB 1–5 Years	5.12	2.81	94.14	**0.007**	**0.009**	**0.009**	1206	97.75	94.60	**0.004**	**0.004**	**0.004**	1356	98.30
US Corporate AAA 5–10 Years	4.08	7.09	23.88	0.446	0.590	0.608	0	19.79	26.83	0.497	0.619	0.625	0	26.79
US Corporate AA 5–10 Years	4.01	6.35	53.16	0.100	0.116	0.118	0	50.30	57.51	**0.063**	**0.068**	**0.068**	2	57.41
US Corporate A 5–10 Years	4.28	6.27	78.36	**0.095**	0.110	0.111	0	77.70	81.07	0.124	0.142	0.144	0	80.96
US Corporate BBB 5–10 Years	5.90	5.64	91.56	**0.016**	**0.016**	**0.016**	161	97.52	92.41	**0.011**	**0.011**	**0.011**	223	97.28
US Corporate AAA 10–15 Years	4.94	8.99	31.27	0.411	0.512	0.518	0	16.97	33.06	0.250	0.300	0.300	0	23.86
US Corporate AA 10–15 Years	5.77	8.15	40.23	0.325	0.417	0.423	0	31.21	45.52	0.363	0.436	0.440	0	40.64
US Corporate A 10–15 Years	4.99	7.47	66.16	0.186	0.229	0.234	0	69.20	71.21	**0.081**	**0.090**	**0.091**	2	75.38
US Corporate BBB 10–15 Years	6.70	6.48	87.83	**0.026**	**0.026**	**0.026**	33	95.76	88.68	**0.021**	**0.021**	**0.021**	110	96.17
US Corporate AAA 15+ Years	2.80	11.90	25.71	0.444	0.622	0.633	0	8.84	28.62	0.297	0.390	0.395	0	14.85
US Corporate AA 15+ Years	5.08	10.67	36.62	0.428	0.554	0.560	0	19.71	40.10	0.260	0.316	0.317	0	27.78
US Corporate A 15+ Years	4.82	10.40	50.12	0.177	0.220	0.222	0	31.96	54.56	0.118	0.144	0.144	0	42.52
US Corporate BBB 15+ Years	6.35	9.74	77.46	0.112	0.127	0.128	0	80.69	80.45	**0.079**	**0.084**	**0.085**	4	84.41

profitable in the first subsample period that are also profitable in the second subsample period deteriorates with the maturity range confirming previous findings about better return predictability for Treasury bond portfolios with shorter maturities.

Table 8 documents that the property of diminishing predictability over time is not confined to returns on Treasury bonds but that it has also been observed in the U.S. corporate bond market. The SPA data snooping test applied to trading returns on corporate bond indexes split by both the maturity range and the credit rating results in higher *p*-values in the second subsample period for 10 indexes and lower percentage of profitable trading rules for 11 indexes. The indexes that demonstrate predictability in their returns during the second subsample period are generally characterized by the lowest maturity range (1–5 years) or the lowest credit rating (BBB) in the sample, or both. This observation combined with the results of the out-of-sample performance confirm previous findings, specifically, that the predictability of returns in corporate bond portfolios declines with maturity given the credit rating and is negatively related to the credit rating holding the maturity range constant.

The sharp decline in the degree of short-term predictability in returns on bond portfolios by technical trading rules over time documented in Tables 7 and 8 poses a question of what causes might have contributed to such a phenomenon. The weakening of the predictive power by trading strategies relying on historical price patterns is commonly interpreted as a sign of improved market efficiency. Therefore, the likely reasons behind the futility of mechanical trading rules in the domestic bond market during the 2000s must have had far broader implications for the market efficiency in general. The existence of abnormal returns causes the influx of more arbitrageurs and traders which increases competitiveness for profits followed by the improved market liquidity. As a result, the excess returns would eventually disappear as the growing number of traders adopts trading strategies that were profitable in the past in the attempt to yield positive abnormal returns. Such outcome is particularly relevant to the developments in the U.S. bond market that took place since the early 2000s when the computational powers have expanded[13] substantially, new investment

[13] In a Wall Street Journal article, Lin (2011) mentions that although it is not clear exactly how much of the market is comprised of algorithmic trading, a number of signs point to prices being increasingly driven by technical factors, which is an indication that program trading has been playing a significant role in the U.S. Treasury bond market.

Table 9
Predictability of returns in Treasury bonds during business cycle phases. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Economics recessions

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	5.28	2.39	94.47	**0.015**	**0.015**	**0.015**	91	93.80	**0.033**	**0.034**	**0.034**	27
US Treasury 3–5 Years	6.84	5.43	87.50	**0.088**	**0.092**	**0.092**	3	85.92	**0.097**	0.104	0.104	0
US Treasury 5–7 Years	6.83	7.14	79.78	0.294	0.345	0.349	0	77.36	0.264	0.319	0.322	0
US Treasury 7–10 Years	6.98	9.14	68.97	0.598	0.708	0.715	0	66.70	0.585	0.693	0.697	0
US Treasury 10–15 Years	6.57	10.58	43.46	0.715	0.829	0.835	0	40.53	0.633	0.740	0.747	0
US Treasury 15+ Years	5.61	15.22	56.32	0.279	0.372	0.379	0	55.40	0.263	0.342	0.347	0

Economic expansions

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	4.44	1.43	91.69	**0.000**	**0.000**	**0.000**	5577	94.08	**0.000**	**0.000**	**0.000**	5799
US Treasury 3–5 Years	5.65	3.38	82.01	**0.035**	**0.042**	**0.044**	236	89.02	**0.008**	**0.009**	**0.009**	9
US Treasury 5–7 Years	6.30	4.52	76.91	0.136	0.172	0.182	0	86.15	0.138	0.149	0.151	0
US Treasury 7–10 Years	6.61	5.89	64.36	0.172	0.211	0.222	0	78.70	**0.090**	0.101	0.101	0
US Treasury 10–15 Years	7.10	6.43	60.99	0.326	0.398	0.421	0	72.10	0.170	0.190	0.191	0
US Treasury 15+ Years	7.68	9.80	34.44	0.249	0.372	0.380	0	49.10	0.163	0.209	0.210	0

vehicles in the form of exchange-traded securities that hold baskets of bonds have been introduced to public, overall liquidity conditions have improved and transaction costs have diminished.[14] In light of the combination of significantly expanded computational powers, adoption of fully automated electronic trading systems and sharply reduced transaction costs that has allowed to trade based on complex algorithms at lightning speeds in the 21 century, as the proliferation of high-frequency trading demonstrates, the time window of any temporary market inefficiencies allowing traders to earn abnormal returns must have been dramatically narrowed over the last decade.

5.5. Predictability of bond returns across business cycle phases

Apart from maturity or duration and the level of credit risk that can serve as the determinants of the degree of short-term predictability of bond portfolios, it is conceivable to suggest that the forecasting power of mechanical trading rules can also change over time since the investors' attitude toward risk varies with the state of the economy. The existing literature shows that bond returns tend to differ across different economic conditions (Fama and French, 1989; Chan and Wu, 1993; Boyd and Mercer, 2010; Chen and Maringer, 2011). Given the rich literature that links performance of bonds and bond portfolios to business cycles, we next examine whether the degree of short-term predictability of bond returns proxied by the success of technical trading rules differs substantially across different phases of the economic cycle.

To split the sample period in two subsample periods by the business cycle phase, we use the data on the timing of economic expansions (trough to peak) and economic contractions or recessions (peak to trough) from the National Bureau of Economic Research (NBER). Table 9 shows that portfolios of Treasury bonds exhibit better predictability in their returns during economic expansion rather than recessions. The SPA *p*-values are lower during the expansions across all six Treasury indexes. The number of outperforming trading rules after adjusting for data snooping bias is substantial for the Treasury bond index with the shortest maturity range in the sample during the expansions but it is fairly low during the recessions.

Table 10 reveals that portfolios of corporate bonds also demonstrate better predictability in their returns during the economic expansions. The *p*-values are lower during the expansions for 15 corporate indexes sorted by both the maturity range and the credit rating out of 16 for each benchmark. The hypothesis of no outperformance of mechanical trading rules is rejected for eight corporate bond indexes, mostly those reflecting the shortest maturity and/or the lowest credit rating, during the expansions but only for three such indexes during the recessions. The percentage of profitable trading rules is higher during the economic expansions for all but one corporate bond portfolio, while the number of outperforming trading rules after accounting for data snooping bias during economic expansions is quite large for indexes with the maturity range from 1 to 5 years and moderate for indexes with longer maturity ranges characterized by the lowest credit rating in the sample if measured against the riskless return benchmark. The findings in Tables 9 and 10 suggest that the algorithmic trading strategies would do better if applied to bond portfolios during the expansionary economic cycles characterized by lower volatility and bullish investor sentiment. While empirical evidence shows that changes in yields on Treasury bonds and corporate bonds tend to be negatively correlated during the economic expansions as such times are characterized by diminished risk aversion and higher returns on risky assets, Tables 9 and 10 demonstrate that the predictability in returns improves during the expansions for bond portfolios representing a wide spectrum of riskiness, from the safest Treasury bonds with short maturities to riskier corporate bonds with lower credit rating and longer maturities.

What is the likely explanation for bond returns to be more predictable during economic expansions compared to economic recessions? Tables 9 and 10 also show that returns on bond

[14] The U.S. corporate bond market underwent a fundamental change with the introduction of trade reporting and compliance engine (TRACE) in July 2002. Edwards et al. (2007), and Goldstein et al. (2007) use different samples and research designs but both conclude that the introduction of TRACE led to the increased transparency of the corporate bond market and substantial decline in investors' trading costs.

Table 10
Predictability of returns in corporate bonds during business cycle phases. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
Economics recessions												
US Corporate AAA 1–5 Years	5.37	6.23	29.58	0.293	0.317	0.318	0	27.02	0.251	0.274	0.274	0
US Corporate AA 1–5 Years	5.25	4.33	70.18	**0.079**	**0.082**	**0.082**	2	68.17	**0.068**	**0.070**	**0.070**	2
US Corporate A 1–5 Years	2.88	5.05	67.58	**0.034**	**0.034**	**0.034**	5	67.15	**0.043**	**0.043**	**0.043**	5
US Corporate BBB 1–5 Years	5.98	4.18	78.12	**0.075**	**0.077**	**0.077**	2	77.52	**0.074**	**0.074**	**0.074**	2
US Corporate AAA 5–10 Years	2.24	10.33	24.81	0.450	0.539	0.545	0	24.63	0.417	0.503	0.507	0
US Corporate AA 5–10 Years	1.81	8.87	50.51	0.419	0.518	0.523	0	50.66	0.349	0.432	0.439	0
US Corporate A 5–10 Years	1.73	8.92	67.72	0.151	0.170	0.174	0	67.43	**0.098**	0.105	0.106	0
US Corporate BBB 5–10 Years	3.35	7.76	77.98	0.317	0.401	0.406	0	78.11	0.335	0.416	0.419	0
US Corporate AAA 10–15 Years	-0.35	12.37	27.15	0.389	0.489	0.495	0	27.24	0.365	0.445	0.447	0
US Corporate AA 10–15 Years	4.22	10.53	21.96	0.727	0.903	0.912	0	22.59	0.746	0.909	0.912	0
US Corporate A 10–15 Years	2.54	9.48	60.66	0.503	0.650	0.657	0	61.09	0.433	0.564	0.572	0
US Corporate BBB 10–15 Years	3.32	8.17	70.97	0.204	0.269	0.270	0	71.08	0.158	0.199	0.199	0
US Corporate AAA 15+ Years	-5.62	16.43	27.28	0.609	0.788	0.809	0	28.18	0.610	0.776	0.791	0
US Corporate AA 15+ Years	4.46	13.06	32.83	0.646	0.773	0.787	0	33.64	0.595	0.727	0.739	0
US Corporate A 15+ Years	2.12	13.06	49.87	0.437	0.584	0.595	0	50.64	0.443	0.584	0.597	0
US Corporate BBB 15+ Years	3.07	12.04	66.38	0.217	0.270	0.274	0	66.65	0.182	0.217	0.219	0

Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
Economic expansions												
US Corporate AAA 1–5 Years	5.74	2.39	91.17	**0.000**	**0.000**	**0.000**	4652	93.65	**0.000**	**0.000**	**0.000**	4649
US Corporate AA 1–5 Years	5.75	2.36	91.90	**0.000**	**0.000**	**0.000**	5178	94.61	**0.000**	**0.000**	**0.000**	5305
US Corporate A 1–5 Years	5.98	2.40	93.04	**0.000**	**0.000**	**0.000**	5806	94.38	**0.000**	**0.000**	**0.000**	6247
US Corporate BBB 1–5 Years	6.16	2.43	95.56	**0.000**	**0.000**	**0.000**	6600	97.00	**0.000**	**0.000**	**0.000**	6835
US Corporate AAA 5–10 Years	7.11	5.54	74.07	0.144	0.178	0.184	0	80.36	**0.072**	**0.082**	**0.082**	3
US Corporate AA 5–10 Years	7.24	5.22	84.95	**0.069**	**0.083**	**0.085**	9	89.83	**0.042**	**0.044**	**0.044**	9
US Corporate A 5–10 Years	7.30	7.75	60.71	0.093	0.116	0.117	0	68.57	0.155	0.167	0.168	0
US Corporate BBB 5–10 Years	7.68	5.08	87.50	**0.042**	**0.044**	**0.046**	359	91.69	**0.014**	**0.014**	**0.014**	32
US Corporate AAA 10–15 Years	8.18	7.45	59.20	0.211	0.285	0.297	0	68.06	0.181	0.223	0.227	0
US Corporate AA 10–15 Years	8.12	6.95	78.43	0.281	0.328	0.333	0	86.09	0.170	0.194	0.194	0
US Corporate A 10–15 Years	8.02	6.80	78.12	0.253	0.297	0.303	0	84.78	0.142	0.151	0.152	0
US Corporate BBB 10–15 Years	8.76	6.19	85.24	**0.068**	**0.082**	**0.083**	192	90.63	**0.028**	**0.029**	**0.029**	4
US Corporate AAA 15+ Years	7.88	8.49	48.30	0.307	0.434	0.453	0	59.71	**0.092**	0.130	0.132	0
US Corporate AA 15+ Years	7.79	8.62	69.13	0.537	0.661	0.674	0	79.05	0.349	0.409	0.414	0
US Corporate A 15+ Years	7.92	8.44	67.42	0.290	0.406	0.411	0	78.13	0.173	0.199	0.200	0
US Corporate BBB 15+ Years	8.36	7.92	76.29	0.336	0.423	0.428	0	88.10	0.179	0.203	0.204	0

portfolios are characterized by lower volatilities during the expansions and higher volatilities during the recessions. Chaotic price movements caused by elevated volatility prevalent during a period of financial turmoil or crisis that economic recessions are commonly associated with are likely to have an adverse effect on the performance of mechanical trading strategies designed to exploit the phenomenon of price continuation. If the market is excessively volatile, as it is usually the case during a financial or economic turmoil, that is likely to result in a lot of forced buys and sells, i.e., false trading signals, which will more likely lead to losses rather than profits. As a consequence, the predictability of returns is harder to achieve for trading strategies designed to chase trends during volatile times characteristic for periods of economic recessions. Tables 7 and 8 reveal that higher volatility of bond returns is also observed during the second subsample period, which is characterized by a much lower degree of predictability in returns on bond portfolios compared to the first subsample period, when lower volatilities of returns are documented for all but one bond portfolio. Meanwhile, Table 5 shows that, when split by credit ratings, returns on the most volatile bond portfolio exhibit the highest degree of predictability. How can these findings about volatility as a factor of bond return predictability be reconciled? It is the volatility caused by negative serial correlation in returns and mean reversion common to an economic slowdown that negatively affects the predictability of returns rather that the volatility caused by positive serial correlation and mean aversion present in returns on portfolios of assets characterized by low liquidity.

5.6. Predictability of bond returns across monetary policy regimes

Some researchers suggest that interventions by monetary authorities may create predictable moves in currency exchange rates that technical traders would be able to exploit (Friedman, 1953; Sweeney, 1986; Kritzman, 1989; LeBaron, 1999). Along these lines of arguing, changes in monetary policy with regard to interest rates may create predictable moves in the values of interest-rate sensitive assets such as bonds by opening profitable opportunities for technical trading and other trend-chasing trading strategies since monetary policy can also be linked with current business conditions and investors' expectations about future business conditions and investment opportunities. Since interest rates for short maturities have been known to be particularly sensitive to the changes in monetary policy, the superior predictability in returns on bond portfolios with short maturity ranges documented earlier in this

Table 11
Predictability of returns in Treasury bonds during monetary policy regimes. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique and the Step-SPA routine that account for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper p-values, respectively. Statistically significant results are in bold. N(sig) denotes the number of trading rules that outperform the benchmark at 10% level of significance as determined by the Step-SPA routine.

Restrictive monetary policy												
Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	4.51	1.27	91.30	**0.001**	**0.001**	**0.001**	2543	95.12	**0.007**	**0.008**	**0.008**	1041
US Treasury 3–5 Years	6.00	2.98	83.10	0.114	0.133	0.139	0	91.14	**0.031**	**0.031**	**0.031**	16
US Treasury 5–7 Years	7.08	4.08	81.57	0.113	0.131	0.132	0	89.32	**0.081**	**0.087**	**0.087**	3
US Treasury 7–10 Years	7.97	5.36	76.57	0.261	0.306	0.312	0	85.91	0.101	0.107	0.107	0
US Treasury 10–15 Years	8.48	6.03	80.39	0.207	0.229	0.234	0	86.96	0.110	0.120	0.120	0
US Treasury 15+ Years	10.15	9.28	69.79	0.611	0.687	0.699	0	78.56	0.230	0.261	0.263	0
Expansive monetary policy												
Index			Benchmark: riskless return					Benchmark: buy-and-hold				
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)	R > 0, %	SPA(L)	SPA(C)	SPA(U)	N(sig)
US Treasury 1–3 Years	4.58	1.79	94.93	**0.000**	**0.000**	**0.000**	4682	96.56	**0.001**	**0.001**	**0.001**	3835
US Treasury 3–5 Years	5.65	4.18	84.97	**0.062**	**0.070**	**0.072**	4	85.66	**0.081**	**0.088**	**0.088**	4
US Treasury 5–7 Years	5.81	5.51	72.14	0.189	0.233	0.243	0	74.22	0.137	0.157	0.160	0
US Treasury 7–10 Years	5.64	7.09	51.34	0.116	0.146	0.150	0	55.91	0.100	0.124	0.125	0
US Treasury 10–15 Years	5.90	7.83	35.92	0.462	0.605	0.630	0	40.19	0.337	0.453	0.458	0
US Treasury 15+ Years	5.28	11.59	31.53	0.381	0.562	0.577	0	37.18	0.308	0.417	0.424	0

paper may be potentially explained by the policy changes in the interest rate regime adopted by the Federal Reserve.

To split the sample period in two subsample periods by the monetary policy stance, we follow the classification of monetary environments as restrictive or expansive based on changes in the Federal Reserve discount rate introduced by Jensen and Johnson (1995). This classification scheme relies on directional changes in the Fed discount rate to define turning points in the monetary cycle. Jensen et al. (1996) find that relatively long stretches of time between opposite-direction changes in the bank discount rate by the Federal Reserve's FOMC coincide with the cyclicality of changes in money market yields thus providing a useful gauge of whether the economy is generally experiencing an increasing or decreasing interest rate environment.

The federal fund discount rate is the rate charged to financial institutions on loans they receive from the Federal Reserve discount window. The direction of a discount rate change determines the current monetary policy environment. A decrease in the discount rate following a string of rate increases initiates a period of expansive monetary policy (falling rate phase), whereas an increase in the discount rate following a sequence of rate cuts initiates a period of restrictive monetary policy (rising rate phase). A discount rate change in the opposite direction from the previous change initiates a new monetary policy and consecutive changes in the same direction are interpreted as a continuation of the existing monetary stance. Following Jensen and Mercer (2002), we classify months in which the monetary policy changes as the final month of the previous monetary environment.

Table 11 shows that the returns on portfolios of Treasury bonds of different maturities tend to be more predictable during the restrictive monetary policy regime: p-values tend to be lower while the percentages of profitable rules are higher, except for the index with the shortest maturity. Changes in the monetary policy, however, are unable to explain the superior predictability in returns on the portfolio of Treasury bonds with maturities 1–3 years documented earlier: the index with the shortest maturity exhibits statistically significant predictability in its returns under both monetary policy regimes as the hypothesis of no outperformance of trading rules is rejected at 1% level in each case.

The results for return predictability in corporate bond portfolios under different monetary policy stances are left unreported since their examination reveals no clear evidence that returns on corporate bonds are significantly better predictable during one monetary policy than during the other. Based on the previous evidence obtained from Table 10, one may conclude that the predictability of returns on corporate bond portfolios is more sensitive to the economic cycles rather than to the changes in monetary policy.

The muted evidence on the differences in the degree of predictability in bond returns during the opposite monetary policy regimes could be at least partially attributed to the empirical fact that market interest rates and, respectively, bond prices often react to the anticipated changes in the discount rate before the actual change takes place. The Federal Reserve has been quite successful in signaling its intentions in advance and providing few surprises on regularly scheduled Federal Reserve Open Market Committee meetings. Historically, the market has been able to predict anticipated changes in the discount rate with a good accuracy and bond yield volatility on the meeting days has been found to be largely comparable to volatility on other days. The combined evidence documented in Tables 9–11 provides an argument in favor of the business cycle split of the timeline as a better determinant of the degree of predictability of returns on bond portfolios. However, it is not easy to perfectly time a beginning or an end of recession or expansion for trading purposes since NBER sets the timing of contraction and expansion ex-post, i.e., with a lag of at least several months after the economy actually turns around.

5.7. Transaction costs

The question of whether the superior predictive ability of technical analysis can be translated into significant trading profits must be approached by incorporating transaction costs into the analysis. Since trading position can be changed relatively frequently, in practice such portfolio turnover would result in the accumulation of certain transaction costs over the course of trading and any profits from trading could be absorbed by such transaction costs.

Transaction costs are commonly decomposed into the direct costs of trading such as commissions and the indirect costs

Table 12
Predictability of returns in bond exchange-traded funds. Table shows results of the application of Hansen's Superior Predictive Ability (SPA) technique that accounts for data snooping bias while testing the hypothesis of no outperformance of trading rules over the benchmark. A one-way transaction cost of five basis points is imposed on all mechanical trading rules. The sample period for SHY, IEF, TLT and LQD is from 7/31/2002 to 6/30/2011, for AGG—from 9/29/2003 to 6/30/2011, for HYG—from 4/11/2007 to 6/30/2011. "Mean" denotes annualized average percentage return on the respective index, "stdev" is the annualized standard deviation of daily returns on the respective index. "R > 0, %" denotes the percentage of profitable trading rules out of all rules in the universe that generated at least one buy or sell signal during the sample period. Values of SPA(L), SPA(C), and SPA(U) denote Hansen's SPA lower, consistent, and upper *p*-values, respectively. Statistically significant results are in bold.

Exchange-traded fund			Benchmark: riskless return				Benchmark: buy-and-hold			
	Mean	Stdev	R > 0, %	SPA(L)	SPA(C)	SPA(U)	R > 0, %	SPA(L)	SPA(C)	SPA(U)
iShares Barclays Aggregate Bond Fund (AGG)	4.62	5.81	27.49	0.337	0.493	0.526	27.13	0.419	0.567	0.594
iShares Barclays 1–3 Year Treasury Bond Fund (SHY)	2.86	1.76	58.11	**0.047**	**0.072**	**0.095**	50.15	0.245	0.382	0.469
iShares Barclays 7–10 Year Treasury Bond Fund (IEF)	5.57	7.24	32.55	0.662	0.850	0.867	33.24	0.521	0.703	0.713
iShares Barclays 20+ Year Treasury Bond Fund (TLT)	5.69	13.07	29.16	0.647	0.814	0.834	30.23	0.530	0.680	0.697
iShares iBoxx $ Invest Grade Corporate Bond Fund (LQD)	6.01	9.21	33.44	0.192	0.272	0.275	34.62	0.230	0.306	0.312
iShares iBoxx $ High Yield Corporate Bond Fund (HYG)	5.38	17.15	69.96	0.206	0.231	0.233	69.39	0.205	0.234	0.236

stemming from the existence of bid-ask spread. A one-way transaction cost is normally estimated as the commission plus one half of the bid-ask spread.[15] The U.S. Treasury bond market is centrally organized where quotes and trades are reported and it has been accepted that the U.S. Treasury market is the most transparent bond market in the world. Khang and King (2004) document that the average bid-ask spread on the on-the-run 10-year Treasury note was 13 cents per $100 of par value over the 1978–1987 period and 7 cents over the 1988–1998 period. Chua et al. (2006) use a more conservative set of assumptions about bid-ask spreads for U.S. Treasury bonds: three basis points from 1973 to 1980, two basis points from 1981 to 1990, and one basis point from 1991 to 2004.

Corporate bonds trade less frequently compared to U.S. Treasury bonds. The lower trading frequency of corporate bonds will, therefore, reflect their relatively large trading costs. The issue of trading costs for corporate bonds is exacerbated by the fact that until 2002 no transaction reporting system existed for the corporate bond market where most transactions take place in over-the-counter dealer markets. The National Association of Securities Dealers (NASD) began to publicly report transactions in approximately 500 corporate bond issues through TRACE which was first introduced on July 1, 2002 and then subsequently expanded in stages until full implementation in February 2005 when it began to cover essentially all publicly traded corporate bonds. Bessembinder et al. (2006) report that after the introduction of NASD's TRACE, one-way trading costs for corporate bonds decreased averaging 40% to 60% of pre-TRACE trading cost estimates, whereas transaction costs for corporate bonds ineligible for TRACE transaction reporting also fell by about 20%.

Trading costs for some bonds and bond portfolios can actually be lower than those reported above. Dynkin et al. (2006) demonstrate several approaches on how to replicate a performance of a series of bond indexes using liquid derivative products that can be traded at a low transaction cost. Ironically, a part of the replication strategy would have involved total return swaps offered by now defunct Lehman Brothers. Chua et al. (2006) also argue that transaction costs can be significantly reduced by structuring derivatives trades on a notional basis without actually funding and holding the bonds.

In general, however, one could argue that until the early 2000s it was impossible to have actually traded large portfolios of bonds on frequent basis without incurring significant transaction costs. With the introduction of the exchange-traded funds and index futures that represent low-cost and high-liquidity trading vehicles, it has become possible to bridge the gap between the predictability of returns and actual profitability of trading strategies while accounting for transaction costs and avoiding the pitfalls of nonsynchronous trading bias.

The best way to account for the influence of transaction costs is to assess the predictability of returns in highly liquid exchange-traded securities that are designed to replicate the performance of the underlying indexes. Table 12 shows the results of the application of the SPA data snooping test to a set of the most liquid bond exchange-traded funds (ETFs) that belong to the family of the iShares bond ETFs. The set of such ETFs includes a fund that tracks the performance of the aggregate bond market index, three funds that invest in U.S. Treasury bonds of different maturities (short, medium and long), and two funds that invest in corporate bonds with different credit ratings (investment grade and non-investment grade). The sample period for each ETF covers the period from the fund's respective inception date to June 30, 2011. The ETFs' daily closing prices have been converted to total return prices to reflect the reinvestment of the funds' distributions to the investors. The one-way transaction cost of five basis points is assumed. The hypothesis of no outperformance of mechanical trading rules cannot be rejected for all but one bond ETF in the set. Significant return predictability is found only for the ETF investing in short-term Treasury bonds for the case of the riskless return benchmark. The short-term Treasury bond ETF has a lower *p*-value and a higher percentage of profitable trading rules than the two funds that invest in Treasury bonds with longer maturities. Respectively, the ETF representing a portfolio of high yield bonds exhibits a lower SPA *p*-value and a higher percentage of profitable trading rules than the fund investing in less risky bonds. Both results are in line with the previous findings that the bond return predictability is negatively related to the interest rate risk but positively related to the default risk. They also confirm the previous finding obtained from the subsample analysis that the predictability in bond returns has largely been eliminated since the early 2000s after data snooping bias has been accounted for.

6. Conclusions

A plethora of finance literature focuses on whether future equity returns or currency exchange rates can be predicted via technical analysis but the subject of predictability in bond returns by applying such tools has been ignored. This study is the first to investigate whether returns in the U.S. bond market and its segments exhibit predictability over short-term investment horizons using technical trading strategies. A large set of mechanical trading rules is utilized and the established bootstrapping methods are relied on to account for the possible data snooping bias in order to explore the differences in the degree of predictability in returns on bond portfolios across different market segments and varying market conditions.

[15] In the case of the long-or-short trading strategy, the cost of shorting adds an extra layer of transaction costs: an asset can be borrowed for a fee.

The predictability in returns on bond portfolios has been found to be inversely related to interest rate risk but positively related to default risk: both Treasury bonds and corporate bonds with shorter maturities tend to exhibit better predictability in their returns given the credit rating, while the returns on corporate bonds with lower credit ratings tend to be more predictable holding the maturity range constant. The predictability in returns on bond portfolios is more sensitive to the fluctuations in the economic business cycle rather than changes in the monetary policy defined by the directional changes in the Fed discount rate. Returns on both Treasury bonds and corporate bonds demonstrate much better predictability during economic expansions rather than recessions. The returns on Treasury bonds tend to be more predictable during the restrictive monetary policy regime whereas monetary policy appears to have no clear effect on the degree of predictability in corporate bond returns. Returns on the Treasury bond portfolios as well as on the majority of the corporate bond portfolios have become less predictable over time. A number of mutually non-exclusive arguments combined together allow to explain such observation: the technological advancements resulting in wide adoption of electronic trading followed by the implementation of computer program trading, the inherently self-destructive nature of trading arbitrage when the excess returns eventually disappear as the growing number of traders adopts trading strategies that were profitable in the past, the general trend toward the reduction of transaction costs, and the improved liquidity in the bond markets.

One can argue that until the early 2000s it was hardly possible to actually have traded large portfolios of bonds on frequent basis without incurring significant transaction costs. Transaction costs in the bond market are difficult to measure precisely as they can vary from one trade to another as well as over time. With the introduction of the exchange-traded funds that have become low-cost and high-liquidity trading vehicles, it has become possible to bridge the gap between the predictability of returns and actual profitability of trading strategies while accounting for transaction costs and avoiding the pitfalls of nonsynchronous trading bias. The application of data snooping techniques to a set of the most liquid bond exchange-traded funds on the market reveals lack of predictability in returns on all but one bond fund in the second half of the 2000s suggesting the improved market efficiency in the U.S. bond market following the introduction of ETFs.

Appendix. Universe of trading rules

Filter rules (FL)

x: percentage change in price to initiate a position
y: percentage change in price to liquidate a position
z: number of x–y combinations where y is strictly less than x
k: number of days to define a local high (low)
c: number of days a position is held, ignoring all other signals during that time
x = 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, 0.28, 0.3 (24 values)
y = the same 24 values as x
$z = x \times (y - 1)/2 = 24 \times 23/2 = 276$
k = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
Number of rules in FL class $= x \times (1 + k + k \times c) + z \times (1 + k) = 24 \times (1 + 11 + 11 \times 11) + 253 \times (1 + 11) = 6504$

Moving average rules (MA)

n: number of days in a moving average
m: number of long-short combinations of n
b: fixed band multiplicative value
d: number of days for the time delay filter
c: number of days a position is held, ignoring all other signals during that time
n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)
$m = n \times (n - 1)/2 = 14 \times 13/2 = 91$
b = 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05 (10 values)
d = 2, 3, 4, 5 (4 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
Number of rules in MA class $= (n + m) \times (1 + b + d + c + b \times c) = 105 \times (1 + 10 + 4 + 11 + 10 \times 11) = 14{,}280$

Support and resistance rules (SR)

n: number of days in the support and resistance range
b: fixed band multiplicative value
d: number of days for the time delay filter
c: number of days a position is held, ignoring all other signals during that time
n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)
b = 0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05 (10 values)
d = 2, 3, 4, 5 (4 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
Number of rules in SR class $= n \times (1 + b + d + c + b \times c + d \times c) = 14 \times (1 + 10 + 4 + 11 + 10 \times 11 + 4 \times 11) = 2520$

Channel breakout rules (CB)

n: number of days for a channel
x: difference between the high price and the low price as a percentage of the low price required to form a channel
c: number of days a position is held, ignoring all other signals during that time
n = 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 175, 200 (14 values)
x = 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.22, 0.24, 0.26, 0.28, 0.3 (24 values)
c = 3, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 (11 values)
Number of rules in CB class $= n \times x \times c = 14 \times 24 \times 11 = 3696$
Total number of rules = 6504 (24.1%) + 14,280 (52.9%) + 2520 (9.3%) + 3696 (13.7%) = 27,000

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