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An Improved Model for Long-Horizon Prediction of S&P 500 Return

The Power of TR CAPE ratio and Term Spread on Long-Term Trends

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Abstract

In this paper we contribute to the literature of long-horizon predictions by constructing an improved OLS regression model of S&P 500 return. The research of Robert Shiller has found the Total Real Cyclically Adjusted Price Earnings (TR CAPE) ratio to be the optimal predictor of the real long-term return of the S&P 500. Campbell Harvey found that the Term Spread, how investors price the long-term bonds relative to the short-term bill contains valuable information about impeding financial conditions. Due to the upside of fixed income being inherently limited by the face value, the bond market does not have the same tendency to be overly optimistic about the future. This makes the Term Spread a robust supplementation to the equity market when estimating future growth. Our model uses the logarithm of TR CAPE ratio and the Term Spread as independent variables, and the 10-year annualized Total Real Return of S&P 500 as the dependent variable. We found that adding Term Spread to the original TR CAPE model improves the model's explanatory power by 9 percentage points, from 0.295 to 0.394. Leading us to conclude that the Term Spread adds complementary information, not priced in by the equity market when predicting long-term returns. Our approach underscores the importance of long-term trends from both the equity and bond market when predicting long-term return of the S&P 500.

Acknowledgments

As relative newcomers to the financial markets, our experience has been primarily within the tranquil period following the Great Financial Crisis of 2008. This endeavor has provided a rewarding opportunity to analyze financial markets from a broader historical perspective, something that has deepened our understanding of the complex interactions of the financial system.

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1 Introduction

In this study, our aim is to delve into a comprehensive history of financial data to enhance our understanding of the ebb and flow of the financial markets. Howard Marks (2022) describes the market as behaving like a pendulum, where the market is moving back and forth. In this paper we are asserting that the prices observed in capital markets can provide insight into future returns. Our aim is to develop an OLS regression model, inspired by the work of Robert Shiller, that attempts to predict equity market returns. This model is based on the expectations reflected in equity prices and benefits from incorporating insights from the bond market. Our predictive approach is based on the hypothesis that future returns are likely to align more closely with long-standing historical trends. At its core, our model seeks to predict equity returns using stock valuation as its main component, while the Term Spread serves as a supplementary predictor. Enabling us to leverage insights from both equity and bond markets for long-term S&P 500 return prediction.

In Graham and Dodd (1940) ground-breaking work, “Security Analysis”, they stressed the significance of using price-to-earnings (PE) ratios in relation to historical averages when analyzing long-term market data. Caution was advised against overpaying for stocks with high PE ratios. They recognized how low-frequency fluctuations impact market valuations and the need to smooth out business cycles. To emphasis the fundamental attributes of the investments, they advocated for discarding short-to-medium-term market noise. Robert Shiller's research on the predictive power of valuation metrics was significantly influenced by this impactful approach.

Campbell and Shiller (1998, 2001) conducted a comprehensive investigation of the predictive potential of valuation metrics, with a specific focus on PE ratios. They examined the mean reversion characteristics of these ratios, observing that normalization could be spurred by either an increase in earnings or a decrease in price. Their findings suggested that while valuation had little predictive power for future earnings, they showed significant potential for predicting future price changes. As a result, they concluded that long-horizon OLS regressions based on the Cyclically Adjusted Price Earnings (CAPE) ratio provided the most reliable means of predicting long-term stock market behavior. The CAPE ratio, which is calculated by dividing the current price by the average earnings of the past 10 years, helps smooth out fluctuations, reducing the noise caused by short-term volatility and business cycles. This allows low-frequency trends to provide a more stable prediction of market returns. Shiller (2014) further research revealed that the predictability of asset returns, including stocks, improves over longer time horizons compared to shorter ones, highlighting the importance of low-frequency trends in forecasting long-term performance. These insights have been utilized by researchers like Weigand and Irons (2007) to predict future returns.

Siegel (2016) brings attention to potential issues with the long-term stock return forecasts provided by the CAPE ratio, suggesting they may lean towards undue pessimism due to changes in accounting standards. The standards have generally trended towards conservatism, particularly after 1990, and have had a disproportionate impact on reported earnings during economic downturns. Siegel also notes a shift since 1945 in the way companies return capital to shareholders, moving from dividends to stock repurchases. This shift has resulted in increased earnings growth per share. However, the original CAPE methodology doesn't account for these changes, potentially causing an incorrect assessment of overvaluation. Siegel (2016) suggests an alternative approach to address potential biases in the CAPE ratio by using National Income and Product Accounts (NIPA) earnings. NIPA earnings, which encompass income from both corporations and individuals, are used to track economic activity in the United States. Given these considerations, Siegel questions the accuracy of the CAPE ratio.

In a revision to the CAPE model, Bunn and Shiller (2014) proposed a CAPE ratio that accounts for a growing trend of companies returning capital via share buybacks. They achieved this by incorporating total return indices in their analysis, which addressed discrepancies associated with changes in payout ratios relative to earnings throughout their data set. However, this adjustment was specific to a study of the S&P 500's underlying sectors and may not fully respond to Siegel’s critiques. To address Siegel's criticisms, Jivray and Shiller (2017) conducted a comprehensive analysis of several models to enhance their insights. They expressed reservations about Siegel's method of mitigating bias, particularly the use of NIPA earnings in the calculation of the CAPE ratio. They argued that such a method might result in outputs that are not directly comparable with a CAPE ratio based on reported earnings, thereby potentially undermining the reliability of Siegel's approach as a market valuation tool. Moreover, they introduced a revised version of the original CAPE model that incorporates reinvested dividends, thus transforming the model into the Total Return CAPE (TR CAPE). After examining various earnings proxies, Jivray and Shiller (2017) found the TR CAPE to consistently be the most robust measure. We therefore choses to deploy the TR CAPE as an updated version of CAPE.

A number of scholars posit that the bond market holds considerable promise for improving our comprehension of future stock returns (Campbell, 1987; Campbell & Yogo, 2006; Faria & Verona, 2020) among others. Fama and French (1989) found that the Term Spread, which indicates the difference between long-term and short-term rates, has the potential to predict both stock and bond returns. This suggests that the bond market incorporates information regarding expected growth and financial conditions. This hypothesis is further supported by Campbell and Yogo (2006), who illustrated that the Term Spread can predict stock returns.

Several theories seek to explain what influences the Term Spread. The first, known as the Expectations Hypothesis, suggests that long-term rates are fundamentally determined by the expected path of short-term rates. This implies that the anticipated return stays constant regardless of the holding (Ozturk & Pereira, 2013). If this theory holds, long-term rates should act as an indicator of the future direction of short-term rates.

On the other hand, Harvey (1989, 1993) argues that the Term Spread is shaped by the demand for bonds of different maturities. Current interest rates reflect market expectations about future economic conditions. If investors foresee an economic downturn, bond purchases can push prices higher, reducing long-term yields, while the selling of short-term assets can increase their yields. This activity can flatten or even invert the yield curve, thus providing a forecast of future economic growth and reflecting market sentiment about the economy's prospective trajectory. Hence, the analysis of the term structure is crucial for predicting future economic conditions. While the first theory is more theoretically based, outlining how investors should behave, the second is more empirical, documenting what occurs due to shifts in investor sentiment. However, both theories lead to similar market structure implications.

Within financial theory, it is understood that stock prices represent the present value of future cash flows. As such, stock prices are closely linked to economic growth and activity. Harvey (1988) concluded that expectations of real interest rates are more adept at forecasting consumption growth than real stock returns. Resnick and Shoesmith (2002) supported this view, showing that the Term Spread can be used to gauge the likelihood of an upcoming recession. Further, Ozturk and Pereira (2013) elaborated on how the yield curve can act as a predictor of future recessions. A positive (negative) Term Spread, indicating higher (lower) long-term than short-term interest rates, anticipates economic growth and inflation (decreased growth and inflation), thus predicting a decreased (increased) probability of recession. This reflects both the expectations of investors and the strategies enacted by the central bank. A restrictive monetary policy, which contracts the money supply by raising interest rates, can potentially invert the yield curve, thereby suppressing growth and heightening the risk of a recession.

Harvey (1989) argues that variations in stock prices can signal changes in expected economic growth and alterations in perceived risk tied to stock cash flows. The challenge, however, lies in deciphering this information when shifting perceptions of cash flow riskiness become entangled with economic growth forecasts. As noted by Campbell and Shiller (1991), an interesting paradox is that while the yield curve frequently mispredicts short-term interest rate changes, it reliably forecasts long-term variations. Harvey (1989) asserts that even though both the stock and bond markets provide data predictive of Gross National Product (GNP) growth, the bond market predictions tend to be more accurate, thanks to their direct ties with macroeconomic variables and central bank policy. As a result, bond market analysis can be used to anticipate stock market returns, drawing on interest rate indicators and their interconnectedness. This view is echoed by Faria and Verona (2020), who found the Term Spread to be a strong predictor of stock market trends, affected by variables such as economic growth, inflation, and interest rates. Given that treasury securities are generally considered free of credit risk, the main risks factored in are interest rate risk and duration, both closely tied to economic activities. By committing to a rate for a decade, bond investors become attuned to low-frequency movements, thus effectively isolating high-frequency shifts and the business cycle.

The concept of mean reversion forms a foundational assumption within Shiller's proposed models. Many researchers, including Campbell and Shiller (1998, 2001), posit that the PE ratio exhibits a mean reverting behavior. Becker et al. (2012) underscore the importance of statistical evidence, arguing that the PE ratio time-series must meet the conditions of stationarity for it to demonstrate mean reversion. According to their research, the PE ratio time-series appears to be stationary and mean reverting, given the presence of structural breaks, with an unconditional mean ranging around 14 to 15. Contrarily, Weigand and Irons (2008) and Irons and Wu (2013) provide counter evidence, observing that PE ratios initially appear stationary but later exhibit non-stationary characteristics, suggesting a transformation in the core economic relationship between stock prices and earnings. In a more recent study, Baek and Lee (2018) investigated the effect of structural shifts on long-term stock market returns by analyzing alterations in the market's PE ratio. Their findings suggest that the PE ratio fluctuates around a stationary point, accompanied by structural changes in the mean of the market's PE ratio.

Asness (2003) introduces the Fed Model as a framework for understanding how investors determine equity valuations. He suggests that the earnings yield on stocks is gauged against the yield on 10-year Treasury notes. While this model might not be a robust predictor of long-term stock returns, Weigand and Irons (2008) and Irons and Wu (2013), endorse the Fed Model as an effective instrument for tracking shifts in the market's PE ratio. They highlight that these ratios have progressively become cointegrated over time, transitioning from a stationary to a non-stationary state around the mid-20th century. Building on this line of research, Irons and Wu provide a more specific estimate of the timing of this shift in the market's PE ratio, identifying it to have occurred around 1950. This pattern indicates the presence of a long-term equilibrium relationship between Earnings-to-Price (E/P) ratios and the yield on 10-year Treasury notes, thus impacting how investors respond to changes in interest rates.

The appropriateness of using long-horizon overlapping variables in economic models has generated considerable debate. With the limited availability of decade-long observations, Boudoukh et al. (2019) suggest that scholars often split observations into numerous segments, thereby augmenting their sample size and enhancing the statistical significance of their models. However, the high degree of autocorrelation between observations and the existence of heteroscedasticity suggests that the primary contribution of overlapping may represent statistical inaccuracies. This viewpoint resonates with Valkanov (2003) contention that while long-horizon regressions are commonly seen as a way to separate signal from noise in economic literature, standard regression estimations and tests may be unsuitable due to their non-standard asymptotic properties. By using data generated through Monte Carlo simulations, Britten-Jones et al. (2011) underscore this issue, showing that overlapping observations in models tend to exaggerate statistical significance when compared to control simulations. Boudoukh et al. (2022) add to this argument, stating that such models often yield negative out-of-sample R^2 values.

In his Nobel Institute lecture, Shiller (2014) underscored the committee's recognition of the enhanced predictive power of his models as reflected by the coefficient of determination (R^2), all while acknowledging the ongoing debate. Challenging the random walk hypothesis, Campbell and Yogo (2006) advocate for the existence of stock market predictability. In response to the issues presented by long-horizon observations, we adopt the solution widely accepted in the literature (Catanho & Saville, 2022) by Newey and West (1987), a technique that corrects for heteroskedasticity and autocorrelation, often referred to as HAC.

In our research, we aim to contribute to the existing literature of long-horizon predictions by analyzing the relationship between equity returns and Term Spread. We deploy an OLS regression model as a method to quantify this relationship. By including Term Spread as a variable, we seek to examine its potential influence on stock returns and assess its significance as a predictor of future returns. Shiller's model offers substantial insights into the dynamics of the stock market; however, we aim to enhance its predictive capacity by incorporating additional information. We propose the inclusion of Term Spread in our model. Our underlying premise is that Term Spread, a critical measure in the bond market, holds potential for revealing more about future equity returns. We make this argument considering that Term Spread offers valuable insights into expectations of future economic conditions, thereby providing a more comprehensive perspective on the market's trajectory.

The remainder of this paper is organized as follows: Section 2 introduces the data utilized in our study. The methodology applied is outlined in Section 3. The results of our analysis are presented in Section 4. In Section 5, we explore a scenario analysis, followed by a discussion in Section 6. Finally, we draw our conclusions in Section 6.

2 Data

Our analysis primarily relies on data from the dataset methodically assembled and graciously shared by Robert Shiller[1], as illustrated in table 1. The dataset's construction employed the subsequent procedure. Variables such as price, dividend and earnings were extracted from Standard & Poor's (S&P 500) quarterly data and converted into monthly observations through the application of linear interpolation. The stock price is the monthly average closing price. The Consumer Price Index for All Urban Consumers (CPI) was acquired from the U.S. Bureau of Labor. Additionally, we incorporated data on 3-month U.S. Government Bills, which was obtained from FRED. While Shiller's initial dataset features observations extending back to 1871, our dataset, limited by the availability of 3-month rates, encompasses a range from January 1960 to January 2023.

***Table 1**: Overview of raw data variables*

Variables	Variable description	Source
P	Price of S&P 500	Shiller Dataset
D	Dividend of S&P 500	Shiller Dataset
E	Earnings of S&P 500	Shiller Dataset
CPI	Consumer Price Index basket of the U.S.	Shiller Dataset*
RLong	10-year U.S. government bonds	Shiller Dataset*
RShort	3-month U.S. government bills	FRED

*Notes: * Collected by Shiller from Bloomberg, who used FRED.*

Table 2 below depicts how Robert Shiller made variables from the raw data.

In equation (1-3), by multiplying the data with the corresponding fraction of CPI at the time of the observation, the variables have been corrected for inflation and is presented in real term. Equation (4) takes into account the total return based on price changes and dividends, where the current price and the previous period's price are weighted. Equation (5) is the total return based on earnings, where the current earnings are weighted relative to the current price. Equation (6) exhibit the conventional price to earnings ratio, with current price and the latest year of earnings. The stock market is known to demonstrate cyclical fluctuations in earnings over time. The concept of CAPE ratios is introduced in equation (7), which aim to mitigate the impact of cyclicality. By averaging the earnings of the past ten years, a more stable and dependable estimate of earnings is obtained. In equation (8) the CAPE ratio is also calculated with the use of total return variables as well, to produce the TR CAPE. Now that we have

[1] Some of the variables used in our study have been collected [2023] from Robert Shiller's dataset, which is available for download at his website; http://www.econ.yale.edu/~shiller/data.htm

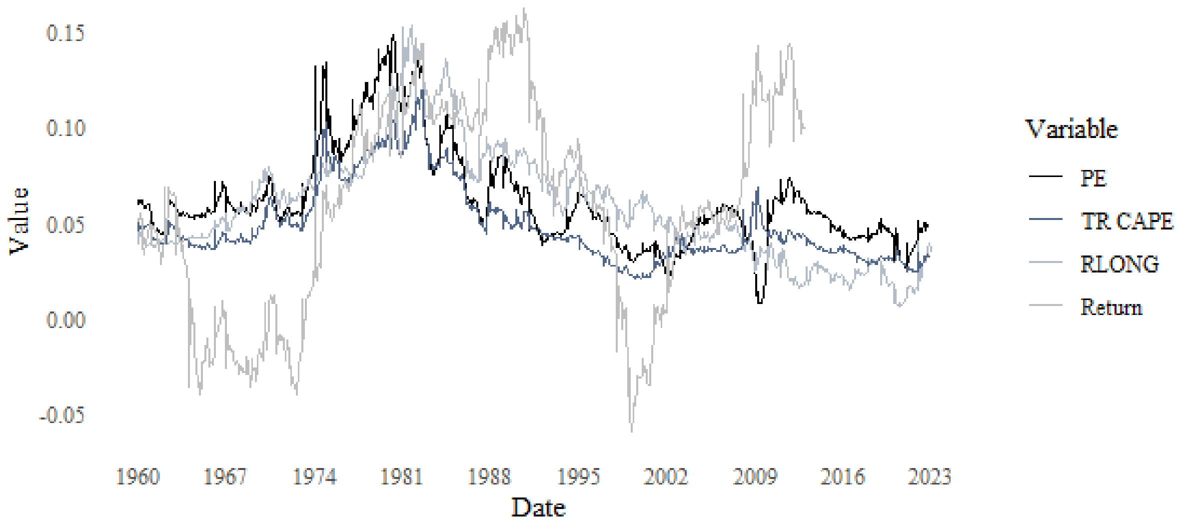
established how the price of the S&P 500 is determined both on a regular basis as well as with reinvestments of dividends, the next step is to calculate the return. Both equation (9-10) represents the compounded annual growth rate of the total return price over the 10-year period, expressed as a percentage. Different from equation (9), equation (10) includes dividend payments. Since this is a study of long-horizon return, return is calculated on an annualized basis of a decade, calculated with the use of geometrical average.

***Table 2**: Overview of equations used in the analysis of Shiller*

Variable	Equation
(1) Real Price$_t$	$P_t * \frac{CPI_p}{CPI_t}$
(2) Real Earnings$_t$	$E_t * \frac{CPI_p}{CPI_t}$
(3) Real Dividend$_t$	$D_t * \frac{CPI_p}{CPI_t}$
(4) Total Return Price$_t$	$\text{Total Return Price}_{t-1} * \frac{\text{Real Price}_t + \frac{\text{Real Dividend}_t^*}{12}}{\text{Real Price}_{t-1}}$
(5) Total Return Earnings$_t$	$\text{Real Earnings}_t * \frac{\text{Total Return Price}_t}{\text{Real Price}_t}$
(6) Price Earnings$_t$	$\frac{\text{Real Price}_t}{\text{Real Earnings}_t}$
(7) CAPE Ratio$_t$	$\frac{\text{Real Price}_1}{\frac{\text{Real Earnings}_t + \text{Real Earnings}_{t-12} + \ldots + \text{Real Earnings}_{t-120}}{10}}$
(8) Total Return CAPE$_t$	$\frac{\text{Total Return Price}_1}{\frac{\text{Total Return Earnings}_t + \text{Total Return Earnings}_{t-10} + \ldots + \text{Total Return Earnings}_{t-120}}{10}}$
(9) Real Return$_t$	$\frac{\text{Real Price}_{t+120}}{\text{Real Price}_t}^{\frac{1}{10}} -1$
(10) Total Real Return$_t$	$\frac{\text{Total Return Price}_{t+120}}{\text{Total Return Price}_t}^{\frac{1}{10}} -1$

*Notes: * It is important to note that the initial observation of the "Total Return Price" is equal to the "Real Price".*

***Figure 1**: Historical Comparison of PE, TR CAPE, Real Long Rate and Total Real Return*



Notes: This figure shows the plot of implied yield of different versions of Price-to-Earnings ratios (PE and TR CAPE) and the yield of 10-year U.S. Treasuries, aligned with the annualized real total return for the corresponding decade (Return). The theory of mean reversion in financial markets, proposes that over time, valuations and returns are inclined to revert to their long-term averages. The implication is that periods marked by comparatively low valuations, as indicated by higher earnings yields, often signal more favorable investment returns.

To supplement the variables and data supplied by Robert Shiller, we have incorporated several additional variables.

The Term Spread serves as an indicator of credit-market expectations of future interest rates. As interest rates are influenced by economic growth and inflation, this permits investors to discern anticipated trends. One signal is the yield curve inversion, as documented by Campbell Harvey, a well-known predictor of impending economic and financial challenges. Harvey (1989) have found that the Term Spread contains information about expectations of the future economic conditions. Given the time premium, it is expected that long-term loans would necessitate a higher premium than short-term loans (Wright, 2006). However, the credit market also incorporates future expectations. Consequently, if the market anticipates lower interest rates in the future, an inverted yield curve may be rational. It is essential to consider the reasons behind the projected decline in interest rates. Decreased interest rates typically coincide with a recession, as monetary policy aims to bolster the economy (Estrella & Mishkin, 1996). It is crucial to recognize that the credit market is both larger and more professional than the equity market, potentially rendering credit market signals more dependable.

(11) $$\text{Term Spread}_t = \text{RLong}_t - \text{RShort}_t$$

Where: $RLong_t$= The rates of the 10- year U.S government bond, $RShort_t$= The rates of 3-month U.S Government Bill

In essence, inflation's influence on the economy is such that an increase in inflation is often a precursor to a decrease in future economic growth. The main tool of central banks to curb inflation is to stagnant growth. Scholarly research affirms the relationship between inflation and growth (Bruno & Easterly, 1998; Fischer, 1993), signifying that elevated inflation rates invariably correspond with diminished asset valuations.

$$(12) \qquad \text{Inflation}_t = \frac{\text{CPI}_t}{\text{CPI}_{t-12}} - 1$$

Where: CPI_t = CPI at the time of current observation, CPI_{t-12} = CPI one year prior.

In conjunction with inflation, we integrated Long Term Real Interest Rates (Real Rates) into our analysis, where inflation is subtracted from long rates to isolate the effects of interest rates. Predominantly, elevated Real Rates increased funding costs for businesses, intensifying the costs linked to debt servicing. Furthermore, the escalation in funding costs also impacts the equity component of financing, consequently heightening the returns demanded by investors, which results in a depreciation of valuation.

$$(13) \qquad \text{Real Rates}_t = \text{Long Rates}_t - \text{Inflation}_t$$

Where Long $Rates_t$: = 10-year U.S Government Bonds, $Inflation_t$= Yearly inflation in the U. S

In table 3 below, we have collected all the variables in one table and made a summary.

***Table 3**: Summary of all variables used in the statistical models*

Variable	Min	1 st Qu	Median	Mean	3rd Qu	Max	NA
RLong	0,62 %	3,86 %	5,54 %	5,84 %	7,56 %	15,32 %	-
RShort	0,01 %	1,86 %	4,44 %	4,36 %	6,04 %	16,30 %	-
Term Spread	-2,65 %	0,57 %	1,52 %	1,48 %	2,48 %	4,42 %	-
Inflation	-2,10 %	1,84 %	3,02 %	3,81 %	4,73 %	14,76 %	12
Real Rates	-6,41 %	0,72 %	2,12 %	2,06 %	3,44 %	9,34 %	12
PE	6,736	14,664	18,12	19,649	22,319	127,519	3
TR CAPE	8,4	18,15	24,02	23,82	28,49	48,11	-
Real S&P 500 Return	-8,20 %	-1,66 %	3,48 %	2,91 %	7,11 %	13,53 %	121
Real TR Return	-5,92 %	1,15 %	6,00 %	5,97 %	1,06 %	16,13 %	121

Note that RShort have a higher max than RLong. Also note that both the Term Spread and Real Rates are usually positive in terms of both the mean and 1st quarter, however, both have instances of negative observations. The valuation metrics are consistently rising with TR CAPE having the highest average; however, PE has the highest max by quite a margin. Lastly it is important to note the significantly higher TR return compared to S&P 500 Return.

3 Methodology

The present study is based on the datasets and methodologies outlined in previous works by Campbell and Shiller (1998, 2001) and Harvey (1988). To predict long-term returns in the stock markets, ordinary least squares (OLS) regression models were constructed. and Harvey (1988). To predict long-term returns in the S&P 500, ordinary least squares (OLS) regression models were constructed.

As the literature has found, the valuation of stock markets, such as the TR CAPE ratio, can be used to gauge future price development and return. Thereby, if we can predict the future valuation of the market, then we could also use the same variables to improve the CAPE model and predict future return. In this section we will try to uncover which macro variables which has the greatest ability to predict the valuation of the S&P 500 one year ahead.

Valuation predictive models:

$$PE_t = \beta_0 + \beta_1 * Inflation_{t-1} + \beta_2 * Real\ Rates_{t-1} + \beta_3 * Term\ Spread_{t-1} + \varepsilon_t \tag{15}$$

$$TR\ CAPE_t = \beta_0 + \beta_1 * Inflation_{t-1} + \beta_2 * Real\ Rates_{t-1} + \beta_3 * Term\ Spread_{t-1} + \varepsilon_t \tag{16}$$

Where:
PE is the price to earnings ratio of S&P 500
TR CAPE is the Total Return Cyclically Adjusted Price to Earnings ratio of the S&P 500.
Inflation is the yearly inflation rate based on the change in the CPI.
Real Rates is the 10-U.S. Bond subtracted for inflation.
Term Spread is the difference between the 10-U.S. Bond and the 3-month U.S. Bill

In the subsequent section of our paper, we aim to utilize the knowledge acquired from predicting S&P 500 valuation to forecast 10-year annualized total real return. Our underlying assumption posits that if valuation is correlated with long-term returns, variables correlated to valuation may provide additional explanatory power in our model of predicting the return. It is essential to highlight that since returns are presented in real terms, the inflation variable has been excluded from the models where we are predicting return. The original model, as proposed by Robert Shiller, featured Total Real Return (TR Return) as the dependent variable and the logarithm of TR CAPE as the independent variable. Since the other variables have instances of negative observations, they were not converted to the logarithm. Our research indicates that integrating Term Spread analysis into the methodology proves beneficial in enhancing the predictive power of long-term financial returns.

(17) $\text{Real TR Return}_t = \beta_0 + \beta_1 * \text{Log}(\text{PE}_{t)} + \beta_2 * \text{Term Spread}_t + \varepsilon_t$

(18) $\text{Real TR Return}_t = \beta_0 + \beta_1 * \text{Log}(\text{TR CAPE}_t) + \beta_2 * \text{Term Spread}_t + \varepsilon_t$

Where:
Real TR Return, is the 10-year annualized total real return of the S&P 500
PE is the price earnings ratio of the S&P 500
TR CAPE is the total return cyclically adjusted price earnings ratio of the S&P 500.
Term Spread is the difference between the 10-U.S. Bond and the 3-month U.S. Bill

In light of the inherent properties of long-horizon data, addressing the statistical complications arising from overlapping observations is essential. To this end, we utilize the Newey-West method to rectify autocorrelations present in the residuals (Newey & West, 1987).

4 Results

We commence our analysis by building an OLS regression model to forecast PE and TR CAPE in 1 year. When comparing our results of the PE model (table 4) and the TR CAPE model (table 5), our findings reveal a considerably enhanced capability to predict TR CAPE, evidenced by the higher explanatory power of the model. Moreover, the coefficients generally exhibit greater significance for the TR CAPE model. The result lends support to the assertion that PE is volatile and predominantly influenced by high frequency noise which are transitory in nature.

***Table 4**: Model to predict PE in 1 year*

PE in 1 year

	Model 1	Model 2	Model 3
Inflation_{t-1}	-2.034***	-2.330***	-2.476***
	(0.588)	*(0.522)*	*(0.574)*
Real Rates_{t-1}		-0.809*	-0.727*
		(0.459)	*(0.433)*
Term Spread_{t-1}			-1.175
			(0.824)
Constant	27.417***	30.222***	32.366***
	(3.346)	*(3.034)*	*(3.853)*
Observations	742	742	742
R^2	0.237	0.262	0.274
Adjusted R^2	0.236	0.26	0.271

*Notes: The figures presented in each model correspond to the regression results for the associated independent variable, as detailed in the respective row. Across all three models, the dependent variable is the PE at a 1-year horizon. Parenthetical values indicate Standard Errors. Note that all independent variables have been lagged and adjusted according to HAC. The notation of stars (*) represent significanse level of ***>1%, **>5%, * >10%.*

All three independent variables in table 4 exhibit negative coefficients across all model iterations, indicating an inverse relationship between the independent variables and dependent variable, the future PE ratio. Among these, only inflation is statistically significant at a 1% level, while the Real Rates is significant at a 10% level. The Term Spread coefficient shows no statistical significance. Incorporating these additional independent variables, Real Rates and Term Spread, into model 1 results in an increase in the adjusted R^2 from 0.236 to 0.271. This demonstrates a modest improvement in the model's explanatory power.

Our analysis yields compelling evidence of a robust and inverse relationship between inflation and subsequent valuation of the S&P 500. This finding, which resonates with previous studies (Bruno & Easterly, 1998; Fischer, 1993) asserts that stock market values tend to dwindle in the face of escalating inflation. This association is consistent across the two models utilized in our investigation. It's understood that higher rates of inflation typically decelerate economic growth, leading to depreciated stock market valuations.

Table 5*: Model to predict TR CAPE in 1 year*

TR CAPE in 1 year

	Model 1	Model 2	Model 3
$Inflation_{t-1}$	-1.580***	-2.158***	-2.347***
	(0.269)	*(0.367)*	*(0.411)*
$Real\ Rates_{t-1}$		-1.563***	-1.460***
		(0.382)	*(0.415)*
$Term\ Spread_{t-1}$			-1.514**
			(0.704)
Constant	29.879***	35.304***	38.074***
	(1.512)	*(2.470)*	*(3.486)*
Observations	745	745	745
R^2	0.279	0.467	0.506
Adjusted R^2	0.278	0.466	0.504

*Notes: The figures presented in each model correspond to the regression results for the associated independent variable, as detailed in the respective row. Across all three models, the dependent variable is the TR CAPE at a 1-year horizon. Parenthetical values indicate Standard Errors. Note that all independent variables have been lagged and adjusted according to HAC. The notation of stars (*) represent significanse level of ***>1%, **>5%, * >10%.*

In table 5, as with table 4, all independent variables exhibit negative coefficients across all three models. This implies that an increase in these variables inversely impacts the projected TR CAPE ratio (the dependent variable). By adding Real Rates and Term Spread as additional independent variables to model 1, the adjusted R^2 increases significantly from 0.278 to 0.504, indicating a substantial improvement in the model's explanatory power. All coefficients are statistically significant at a 1% level, except for Term Spread, which shows statistical significance at the 5% level.

Our models demonstrate a negative correlation between Real Rates and equity valuations, a relationship that is consistent with theoretical predictions. The negative coefficient in our model indicates that an increase in Real Rates leads to a decline in stock valuations. This happens because future earnings are discounted at a higher rate when Real Rates rise. In turn, this increases the opportunity cost of investing in equities, leading investors to demand higher returns from stocks to compensate for this increased cost. Furthermore, a rise in Real Rates results in higher borrowing costs for businesses. This makes it more expensive for businesses to service their debts and finance new projects, which can negatively affect their profitability and growth prospects. As a result, investors may lower their expectations for future earnings, leading to further declines in stock valuations.

The negative coefficient for Term Spread in our model appears counterintuitive. Typically, a positive Term Spread suggests that the bond market anticipates future economic growth. However, our model implies a decrease in valuation of the S&P 500 under these conditions. One possible explanation for this could be the phenomenon of “Irrational Exuberance” in the stock market, a term popularized by Alan Greenspan and Robert Shiller. This concept suggests that when returns have been exceptionally high, investors often overvalue stocks, anticipating the continuation of these elevated returns. Conversely, if the fixed income market anticipates strong growth in the future, short-term bill rates tend not to decrease, while long-term bond rates increase, thereby, steepening the yield curve. Furthermore, since the bond market have their upside limited by the face value, the bond investor is primarily focused on the downside potential. Consequently, the Term Spread does not mirror the same level of over-optimism that can be observed in the stock market. As a result, the more optimistic the stock market becomes, the larger the discrepancy between the bond and stock markets' expectations.

An additional factor contributing to this negative relationship could be the influence of economic downturns on the yield curve. When the Term Spread is negative, it often signals an increased probability of a recession. In this scenario, our model predicts that the valuation would be higher in one year. During a recession, earnings typically decline more rapidly than stock prices. This discrepancy can lead to an apparent increase in valuation measures, despite an overall negative return. Policymakers often respond to such scenarios by lowering short-term rates to stimulate the economy. However, when we consider earnings over a more extended period, as with the TR CAPE, the effects of the downturn get averaged out, potentially lessening its impact compered to PE ratios.

Taking these factors into account, our analysis provides a more comprehensive perspective. Unlike PE ratios, TR CAPE mitigate the impact of downturns by consider earnings over an extended period. As a result, our model estimates that the TR CAPE will reach 29.9 on January 2024:

$$TR\ CAPE_{t+1} = 38 + (-2.347)*5.4 + (-1.46)*(-2) + (-1.514)*(-1.1) = 29.9$$

The TR CAPE of January 2023, was 31.5, implying a fall of 5%. The high inflation is acting as a drag on valuation. However, this is being somewhat counteracted by the stimulating effect of negative Real Rates and the negative Term Spread. It is important to note the 5% drop is only in valuation, and given the deeply negative Term Spread, a recession seem possible. Thereby, if earnings fall and valuations follow, the effect on return is amplified.

Having successfully determined the predictability of market valuation and identified a set of predictive variables from our results in table 4 and 5, our subsequent task is to incorporate the meaningful variables into a new model. The new predictive models are built on an OLS regression model to project annualized total real returns for the forthcoming decade by utilizing PE and TR CAPE, along with other independent variables.

Table 6: *Model of PE to predict 10-year annualized Total Real Return of S&P500*

10-year annualized Total Real Return of S&P 500

	Model 1	Model 2	Model 3
Log (PE_t)	-0.042**	-0.057***	-0.057***
	(0.018)	*(0.019)*	*(0.020)*
Term $Spread_t$		0.021***	0.019**
		(0.006)	*(0.008)*
Real $Rates_t$			0.002
			(0.003)
Constant	0.178***	0.189***	0.188***
	(0.047)	*(0.057)*	*(0.054)*
Observations	636	636	624
R^2	0.113	0.319	0.326
Adjusted R^2	0.111	0.317	0.323

*Notes: The figures presented in each model correspond to the regression results for the associated independent variable, as detailed in the respective row. Across all three models, the dependent variable is the 10-year annualized Total Real Return of S&P 500. Parenthetical values indicate Standard Errors. Note that all independent variables have been lagged and adjusted according to HAC. The notation of stars (*) represent significanse level of ***>1%, **>5%, * >10%.*

The logarithm of the PE ratio exhibits a negative coefficient, indicating that an increase in the PE ratio correlates with a decrease in return. Conversely, the other independent variables display positive coefficients, suggesting that higher Term Spreads and Real Rates correspond to increased returns. The PE yield a statistical significance level of 1%, except for in model 1. Term Spread yield a significance level of both 1% and 5%, while Real Rates show statistical insignificance. Model 1, the Original Shiller model, has the least explanatory power among all three models. Model 3 significantly improves the model's explanatory power, yielding an adjusted R^2 value of 0.323, a result primarily driven by Term Spread.

It is also important to mention that our models have in general lower explanatory power than original papers, even when reconstructing the original model. The drop is primarily driven by the reduction in observations when adding short-term rates.

Table 7*: Model of TR CAPE to predict 10-year annualized Total Real Return of S&P500*

10-year annualized Total Real Return of S&P 500

	Model 1	Model 2	Model 3
Log (TR CAPE$_t$)	-0.078***	-0.075***	-0.076***
	(0.002)	*(0.004)*	*(0.004)*
Term Spread$_t$		0.014***	0.012**
		(0.004)	*(0.001)*
Real Rates$_t$			0.002
			(0.003)
Constant	0.297***	0.266***	0.266***
	(0.008)	*(0.025)*	*(0.020)*
Observations	636	636	624
R^2	0.296	0.396	0.402
Adjusted R^2	0.295	0.394	0.399

*Notes: The figures presented in each model correspond to the regression results for the associated independent variable, as detailed in the respective row. Across all three models, the dependent variable is the 10-year annualized Total Real Return of S&P 500. Parenthetical values indicate Standard Errors. Note that all independent variables have been lagged and adjusted according to HAC. The notation of stars (*) represent significanse level of ***>1%, **>5%, * >10%.*

Table 7's results indicate that the logarithm of the TR CAPE ratio has a negative coefficient. This suggests that an increase in the independent variable, TR CAPE ratio, correlates with a decline in return, and yield a steady statistical significance level at 1%. The other explanatory variables yield similar results as those in table 6, both in terms of statistical significance levels and positive coefficients. By integrating the additional independent variables, the adjusted R^2 shows an increase, with model 3 displaying an adjusted R^2 of 0.399, a result mainly driven by Term Spread.

In agreement with the previous literature (Jivray & Shiller, 2017), we find that by cyclically adjusting the earnings, the TR CAPE becomes substantially better than the PE ratio at predicting long-term return. This finding is substantially supported by a higher explanatory power. There is also a noticeably difference between the models. The TR CAPE is much more sensitive to changes in valuation, giving rise to the notion that short-term fluctuations in price and earnings and the effect of the business cycle produces mainly noise. In Model 1 at both table 6 and 7, we observe negative coefficients. This suggests an inverse relationship between price and expected return - the greater the price an investor is prepared to pay, in terms of valuation, the lower the anticipated return. This observation is also in line with Shiller's original research, which suggests that it is predominantly the price that experiences reversion, not future earnings.

Our key finding is the integration of the predictive power of the bond market, specifically the Term Spread, into the model of S&P 500 returns. The inclusion of the Term Spread increases the model's explanatory power and maintains statistical significance across the iterations of the model, suggesting that the bond market incorporates supplementary information about the market and the financial conditions. The positive coefficient for the Term Spread variable suggests that a steeper yield curve, which reflects more optimistic growth expectations, can indeed reliably forecast growth. Fixed-income investors are not exposed to the same increase in return when equities get too carried away with stories of increased growth. Making them less likely to be influence by “Irrational Exuberance” and thereby enabling the Term Spread to be a reliable predictor for long-term forecasts. Consequently, our model bridges the gap between the predictions of the equity and fixed-income markets, creating a more comprehensive forecasting tool. To control for the effect of interest rate we included Real Rates into our model. Since returns are adjusted for inflation, comparing them with nominal rates might not be correct. We therefore use Real Rates of return for a more equal comparison. The finding runs contrary to our model of valuation, where the Real Rates have a significant effect. It has a different time horizon implying that Real Rates is mostly noise in the long term.

Upon finalizing our model construction, we proceeded to employ it to derive an out-of-sample prediction of the total real return of the S&P 500 in forthcoming periods. The computation applied to this model is represented by the formula below.

This base scenario forecasts a potential return on the S&P 500, computed as follows:

$$\text{TR Return} = 0.266 + (-0.075)*3.452 + 0.014*(-1.11) = -0.84\%.$$

Subsequently, we further refine our predictions by establishing bear and bull cases, where we account for one Standard Error (SE) in the negative and positive directions, respectively.

For the bear case, reflecting a 1 SE negative shift, we estimate:

$$\text{TR Return} = 0.241 + (-0.079)*3.452 + 0.01*(-1.11) = -4.28\%$$

For the bull case, reflecting a 1 SE positive shift, we estimate:

$$\text{TR Return} = 0.291 + (-0.071)*3.452 + 0.018*(-1.11) = 2.60\%$$

What remains a salient point from our models' output is that the average real return in the S&P 500 in the upcoming decade could be as low as negative 0.84%. This indication serves as a caveat for investors to reassess their projections of risks and rewards when contemplating stock market investments. While the stock market traditionally has the potential to generate superior returns, this promise comes with much uncertainty, especially during phases of heightened valuations.

5 Scenarios

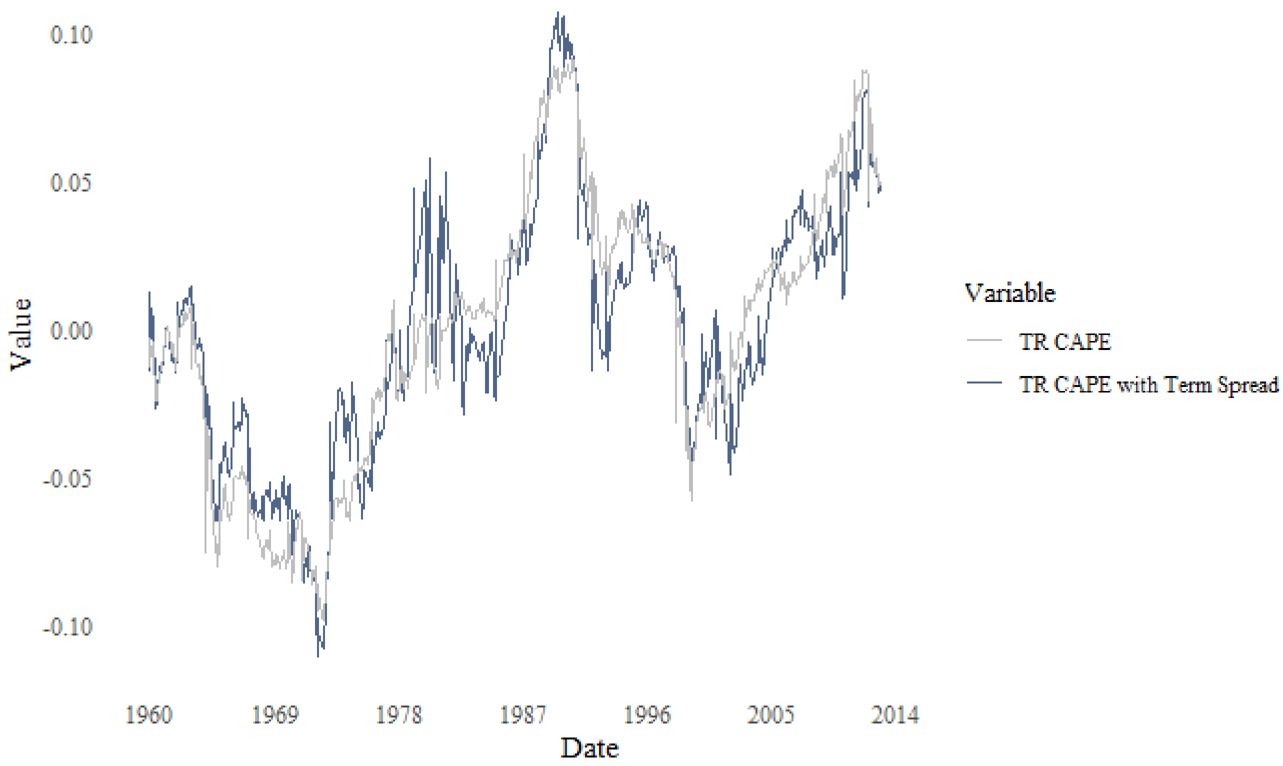
The complexity of financial markets inevitably leads to omitted and hidden variables in any model. Understanding the residuals in their historical context can enhance the insights provided by the model. Hence, while the model may forecast an average real return of -0.84%, the prevailing economic climate must be considered when adjusting predictions.

Upon analyzing the residuals from the 1960s and 1970s, it is evident that the models consistently overestimated the outcomes. This overestimation was particularly notable during the mid-1970s to early-1980s, a period that was notoriously troubled by high inflation[2], which subsequently eroded the return in real terms. Interestingly, the model based solely on the stock market function better at predicting return, coming out of the inflationary period. If the forthcoming decade mirrors the macroeconomic environment of the 1970s, there is a possibility that the model's predictions might be overly optimistic. Consequently, the actual real return could be lower than anticipated. This comparison is particularly relevant given the current economic uncertainties, such as the shift in the energy mix and the re-shoring of production.

[2] A graph of historical inflation can be found at FREDs website; https://fred.stlouisfed.org/graph/ConsumerPriceIndexforAllUrbanConsumers

Along with the resurgence of inflation, the current conditions paint a potentially volatile picture of the future.

Figure 2: Residuals of TR CAPE and TR CAPE with Term Spread



Notes: This figure illustrates the residuals of TR CAPE ratio and TR CAPE ratio with Term Spread. Residuals, defined as the difference between observed and predicted values, serve as crucial indicators of a model's accuracy. A detailed examination of the residuals' distribution and patterns can expose potential deficiencies in the models, thereby highlighting possible avenues for enhancement. It is worth noting that these models are designed to predict the real return, annualized over a 10-year forecast horizon.

Contrastingly, the late 1980s and early 1990s experienced underestimations in the predictive models. The actual return at the turn of the century surpassed expectations significantly, primarily due to the dot.com boom that caused earnings multiples to skyrocket. Interestingly, parallels can be drawn between this period and the current economic climate. Dominant tech companies, often referred to as FAANG stocks, constitute an ever-increasing proportion of the S&P 500. The prevailing belief in their superiority has not waned, leading to an expansion in the earnings multiple and as a result, outperformance relative to the model's predictions. Consequently, if the interest rates decrease back towards zero in the forthcoming decade, the current models may again be overly pessimistic.

If the true source of explanatory power was a product of simply mean reversion, then a model where the valuation is substituted with previous return should be superior or at least comparable to the model proposed by Robert Shiller. We therefore set out to test the ability of past return to project return in the future.

***Table 8**: Model of Past Return's ability to predict future return*

10-year annualized Real Total Return of S&P 500

	Model 1	Model 2	Model 3
$Return_{t-120}$	-0.325**	-0.324	-0.413**
	(0.157)	*(0.218)*	*(0.162)*
$Term\ Spread_t$		0.009***	0.004
		(0.003)	*(0.004)*
$Real\ Rates_t$			0.006***
			(0.002)
Constant	0.089***	0.075***	0.072***
	(0.012)	*(0.017)*	*(0.013)*
Observations	516	516	516
R^2	0.131	0.179	0.240
Adjusted R^2	0.129	0.176	0.236

*Notes: The figures presented in each model correspond to the regression results for the associated independent variable, as detailed in the respective row. Across all three models, the dependent variable is the 10-year annualized Total Real Return of S&P 500. Parenthetical values indicate Standard Errors. Note that all independent variables have been lagged and adjusted according to HAC. The notation of stars (*) represent significanse level of ***>1%, **>5%, * >10%.*

In table 8, by using return from the preceding decade, Term Spread, and Real Rates as independent variables, we wanted to look at past return's ability to predict annualized total real returns for the forthcoming decade. Historic return demonstrates negative coefficients, which implies that it exhibits mean reversion. It yields a 5% significance level except for in model 2. Both Term Spread and Real Rates shows a positive coefficient and implies that an increase in the variable predicts higher returns. The Term Spread is both highly statistically significant, at a 1% level, and statistically insignificant. Real Rates is statistically significant at a 1% level. Model 3 shows the highest adjusted R^2 of 0.236, marking an improvement in the model's explanatory power over model 1 and 2.

An important consideration when thinking about returns is their sources. Returns come from two sources: the earnings of the stocks, and the change in the price investors are willing to pay for the earnings. Research conducted by Campbell and Shiller (1998, 2001) asserts that price holds limited predictive power over earnings. This implies that as the earnings multiple increases (decreases), the return the investors can expect from the reinvestment of dividends decreases (increases), causing Total Return to have a more inherent tendency to mean-revert.

The mean-reversion model has an explanatory power comparable to the model of PE. However, the R^2 of the mean-reversion model falls short of the R^2 of the TR CAPE model, solidifying the benefits of smoothed earnings for cyclicality when predicting long-term returns. If the source of above-average return is due to earnings growth, then a reversion in the return can be primarily due to normalization of growth, and not a valuation compression. By being valuation based, the TR CAPE model incorporates such nuances regarding the sources of return. The return influenced by changes in valuation can be driven by human emotion, a factor that, while unpredictable in the short-term, has been shown to revert to the mean over the long run.

6 Discussion

According to our iteration of the model (figure 2) proposed by Campbell and Shiller (2001), at the time of their writing, the residuals were indeed around 0 , making the TR CAPE model accurate. However, our version of the model has altered the timespan of the observations to 1960-2023 instead of 1870-2000, and the feat is done in-sample. Furthermore, while Shiller's model was in-sample accurate, the accuracy was temporary. In the period after 2006 the model turned overly pessimistic. In Campbell and Shiller (2001), they contended that the equity market might be transitioning into a new era of valuation, making their prognosis overly pessimistic. Following their publication, Asness (2003) proposed that investors have changed how they value equities. Implying that equity valuations may have transitioned from being mean-reverting to being cointegrated with 10-year government bonds. An additional explanation of why we might have been transitioning to a new era is the shifts in corporate governance and account rules observed by Siegel (2016). Over time, the changes in investor and corporate sentiment could decrease the market premium and increase valuations, ushering in a new era and making the models overly pessimistic. An inherent attribute of long-horizon models is the slow response rate to changes, making the models less responsive to the possibility of an era in valuation.

On the other hand, the strength of the models is the ability to ignore high-frequency fluctuation and sources of noise. Campbell and Shiller (1991) found that Term Spread predicts long-term variations but frequently mispredicts short-term interest rate changes. The variables added to the Shiller model have to be carefully crafted to take advantage of this capability. Therefore, when selecting maturities to constructing the Term Spread, we align the timespan of to match the adjustment of cyclicality. In effect, when considering the usefulness of long-horizon models, it is important to balance between the flexibility of the models against the length of the trend being analyzed.

Lastly, one common critic of the rationality of long-horizon models is predicated on the test performed on Monte Carlo simulations. The simulation predicates on the market behaving as a random walk, with predetermined parameter. However, the entire premise of long-horizon modeling is that even though the market acts like a random walk in the short term, trends can be disseminated on a longer time horizon. Thereby, the entire discussion could be seen as about the nature of financial markets, and not statistical inference. Which is making us contend that Monte Carlo simulations might not provide a comprehensive assessment of long-horizon models' efficacy.

7 Conclusion

In our research we found that the construction of a long-horizon OLS regression model requires the application of variables grounded in long-term trends. The two variables best supporting this notion were TR CAPE and Term Spread. TR CAPE adjusts the earnings of the stock market for cyclicality, the business cycle, and other short-term fluctuations, while Term Spread inherently incorporates long-term effects due to the differing maturities of the underlying securities. Hence, when investors choose between short- or long-fixed income securities, they inadvertently form an opinion about future interest rate. Furthermore, the bond market is thought to not be as exposed to "Irrational Exuberance" due to the upside of bond investments being caped at face value.

Our findings lends further credence to the model proposed by Campbell and Shiller (1998, 2001). Adjusting earnings for cyclicality and the business cycle removes high-frequency fluctuations and noise, resulting in a more robust model of return. We have built on the literature by integrating Harvey's (1988, 1989) research into the bond market and the Term Spread, which considerably enhancing the explanatory power of the original model. While our model indicates a high-valued stock market and relatively modest expectations for future returns, it's essential to acknowledge that nothing is certain. Despite our tempered expectations, the actual outcomes are fundamentally dependent on broader macroeconomic trends and regimes. The future remains unknown, and our model primarily serves to provide an indication or guidepost of what might come. Our analysis of the residuals uncovered distinct periods of both overperformance and underperformance relative to our model's predictions. This observation leaves us with a degree of confidence in our out-of-sample predictions, but we are far from absolute certainty. Ultimately, our model provides a useful framework for anticipating future trends but should not be mistaken for a guaranteed forecast.

While content by the research in this paper, there are some limitations worth mentioning. When constructing models, one always must keep in mind the kind of relationship between the variables. It may not be a linear relationship especially in the extremes of the dataset. While we make several comparisons towards Shiller’s work, our dataset is substantially shorter. Even though we found that the inclusion of Term Spread was a worthy contender for the lack of observations, the models are still not directly comparable. When it comes to the dataset, our model is made from the S&P 500, making the models unable to be transnational. Lastly, our models are in-sample predictions, thereby, increasing the uncertainty for their out of sample validity.

Our study contributes to the existing body of literature on financial markets, though we acknowledge that there is much yet to uncover about these complex systems. Consequently, we propose the following areas for further research, aimed at advancing our collective understanding. An interesting avenue for research would be to investigate the applicability of our model to other international markets and to evaluate the robustness of its predictive capabilities in these new contexts. The challenge lies in gathering long-term data for these markets; during our research, we encountered difficulties in sourcing data that spanned a sufficient time frame. This experience underscored the immense value and scope of Shiller's research into the valuation of the S&P 500. Robert Shiller's (2005) book "Irrational Exuberance" emphasized the importance of behavioral economics in explaining market movements. A deeper understanding of investor sentiment and behavior could enrich our model by providing a more nuanced perspective. Future research could aim to incorporate measures of investor sentiment and other behavioral aspects to potentially enhance prediction accuracy.

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