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A COMPREHENSIVE INVESTIGATION ON THE LONG-RUN AND SHORT-RUN DETERMINANTS OF THE U.S. EQUITY MARKET

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Abstract

This study aims to investigate the key factors that drive the price fluctuation of the U.S. equity market over the period of January 1992 to February 2023. Existing literature has provided plenty evidence on the associations between equity price movement and macroeconomic variables, but few jointly considers the effects outside economic fundamentals such as investor behavior. So in this study, three dimensions of factors–economy, valuation and sentiment–are included in the model to provide a more comprehensive framework in equity pricing. Using a vector error correction model, the study reveals the long-run and short-run dynamic relationships between the three dimensions and the U.S. equity market. The results show that valuation and sentiment are two important dimensions for the U.S. equity market. Timing of how these dimensions affect equity price movement is also proven to be crucial. The findings support the notion that examining the long-run and short-run determinants of financial assets through a VECM can improve strategic and tactical asset allocation performance.

Keywords: Equity Return, Macroeconomic Variable, Valuation, Investor Sentiment, VECM

1 Introduction

The key to successful equity investment management is to identify the main drivers of the equity market and forecast the price movement based on the outlook of these drivers. However, equity pricing is complicated. The equity market is driven by factors from multiple dimensions and their impacts typically come in different durations. While the associations between equity prices and their determinants have been investigated extensively, most studies focused on only one aspect of them. Some tried to figure out the relationship between macroeconomic variables and equity prices, others put their efforts on valuation side or investor sentiment, but few combined everything together to study their effects jointly. So, this study aims to identify the key drivers of equity prices by integrating various dimensions, providing a more comprehensive framework for equity investors.

When forecasting equity price movements based on their determinants, timing also matters. Some variables are associated with equity prices in the long run while some are in shorter horizons. Focusing on the right variables at the right timing will then greatly impact equity investment returns. So this study adopts the Vector Error Correction Model approach, which allows to capture both long-run and short-run dynamics between variables. For equity investors, this will help improve their portfolio management process by optimizing their strategic asset allocation and tactical asset allocation. The former refers to a long-term portfolio strategy that builds on factors driving the long-term expected return across asset classes, while the latter actively adjusts the asset allocations based on short-term market forecasts. By examining the long-run and short-run factors, this study will provide a clearer view on the right research focuses of these two types of asset allocation.

The rest of the paper is organized as follows: Section 2 summarizes the findings of existing literature. Section 3 presents the modelling framework and the data with its source and descriptive statistics. Section 4 describes the methodology and relevant tests involved in the analysis. Section 5 reports the empirical results, including model estimation, Granger Causality, Impulse Response Function, Variance Decomposition and forecasting. Section 6 concludes the paper.

2 Literature Review

Equity prices are driven by a wide variety of factors. One important aspect is the macroeconomic condition. There exists vast literature on the association between macroeconomic variables and equity returns. Chen et al. (1986). provided evidence that inflation, industrial production, term structure and risk premium have a significant bearing on the U.S. equity returns. Mukherjee and Naka (1995) discovered that the Japanese stock market was cointegrated with a group of variables, where industrial production, money supply and exchange rate had positive effects on equity prices, while inflation and long-term government bonds were negative. Kwon and Shin (1999) found that Korean stock indices are co-integrated with a combination of production, exchange rate, trade balance and money supply. Bidarkota and McCulloch (2003) proved that the variation of consumption growth is associated with the business cycle, and it provides implications about asset returns for both short and long investment horizons. Other variables being studied include GDP, gold prices, and oil prices.

Another dimension that drives equity prices is valuation. Campbell and Shiller (1998, 2001) provided evidence that valuation ratios have been historically accurate in forecasting stock price changes. Fama and French (1992) showed that low price-to-book value stocks outperformed the market significantly. Weigand and Irons (2007)'s study supported the inverse relationship between P/E ratios and long-term stock returns. Yu et al. (2023) argued that financial valuation ratios such as dividend-price ratio can be decomposed into a slow-moving component that reflects the time-varying local mean, and a cyclical component that reflects the transitory deviations from its local mean. They are found to deliver substantially different predicting power on equity returns.

While equity prices are assumed to reflect their fundamental values, investor's irrational behavior may incorrectly evaluate asset values, causing asset prices to deviate from their intrinsic values (Lee et al. 1991). As a consequence, investor sentiment exhibits predictive power for equity returns. Brown and Cliff (2004) documented a contemporaneous relation between changes in investor sentiment and U.S. stock market return. According to Baker and Stein (2004), Simon and Wiggins (2001) and Lee and Song (2003), indicators measuring investor sentiment include stock return, trading volume, VIX index and option put-call ratio.

In terms of factor timing, studies showed that it is feasible to improve strategic and tactical asset allocation by capturing the long and short-run relations of asset prices and their drivers. Lucas (1997) disentangles the different effects of long-term relations on optimal asset allocation with different planning horizons: cointegration mainly affects strategic asset allocation, while error-correction affects both tactical and strategic asset allocation. Füss and Kaiser (2007) pointed that long-term (passive) investors can benefit from the knowledge of cointegrating relationships, while the built-in error correction mechanism allows active asset managers to anticipate short-run price movements.

3 Model and Data

This objective of this study is to capture the full picture of factors that drive the U.S. equity market. The base model is in the following form (1) that integrates three main dimensions of variables.

$$SPX = \beta_0 + \beta_1 Economy + \beta_2 Valuation + \beta_3 Sentiment + \varepsilon_t \quad (1)$$

where *SPX*, the target dependent variable, is the close price of the S&P 500 index; the *Economy* dimension reflects the macroeconomic condition and is divided into three subcategory – Growth, Inflation and Liquidity; the *Valuation* dimension represents the metrics used to evaluate the market price of an equity asset by comparing with its financial profile; the *Sentiment* dimension is consisted of several indicators that measure the investor sentiment. Based on existing literature, this study lists the potential independent variables that contain information about each dimension in Table 1.

Table 1. Potential Independent Variables

Dimension		Independent Variable		Data Type	Frequency
Economy	Growth	PMI	US ISM Manufacturing PMI	Index (diffusion)	Monthly
		IP	US Industrial Production	Index (2017=100)	Monthly
		RS	US Retail Sales	Billion US Dollar	Monthly
	Inflation	CPI	US Consumer Price Index	Index (1982=100)	Monthly
		EXINF	5y5y Forward Inflation Expectation Rate	Percentage	Monthly
	Liquidity	10Y%	US 10 Year Treasury Yield	Percentage	Monthly
		FFR	Effective Federal Funds Rate	Percentage	Monthly
		M2	M2 Money Supply	Billion US Dollar	Monthly
Valuation		P/E	S&P 500 Price-Earnings ratio	Multiple	Monthly
		P/B	S&P 500 Price-Book ratio	Multiple	Monthly
		P/S	S&P 500 Price-Sales ratio	Multiple	Monthly
Sentiment[1]		VIX	CBOE Volatility Index	Point (1% per annum)	Monthly
		HYS	US High Yield Bond Credit Spread[2]	Percentage	Monthly
		VOL	S&P 500 Trading Volume	US Dollar	Monthly
		CFTC	S&P 500 CFTC Speculative Positions[3]	Number (of contract)	Monthly

To mitigate multicollinearity problem, the study narrowed down the number of variables to five, where each variable represents one of the dimensions above. The main consideration in variable selection is to filter out those that are not I(1), or not suitable for VECM modeling. The remaining variables were selected based on their fitness to the model. The final model is in the form (2).

$$SPX = \beta_0 + \beta_1\, RS + \beta_2\, CPI + \beta_3\, 10Y\% + \beta_4\, P/E + \beta_5\, VOL + \varepsilon \quad (2)$$

The dataset for this study is a monthly dataset from January 1992 to February 2023 of the United States. The number of observation is 374 without any missing value. The dataset is collected from

[1] "Sentiment" dimension captures the dynamics of investor sentiment that could lead to short-run or long-run fluctuation of stock prices. For example, VIX and HYS measure how the market is pricing in risk and uncertainty, reflecting the risk attitude of investors; Volume represents the buying pressure of the market; CFTC shows the movement of speculative money flow in the market.
[2] Bloomberg US Corporate High Yield Average Option-adjusted spread, measuring the difference in yield between a bond and Treasuries
[3] Bloomberg CFTC CME E-Mini S&P 500 Net Non-Commercial Combined Positions, measuring the future position of speculative money

Bloomberg, and the original source can be located in S&P Global, Institute for Supply Management, US Census Bureau and US Department of the Treasury.

Table 2 presents the descriptive statistics of the variables. The most variation can be noticed in VOL series, followed by SPX series, while the least variation can be seen in 10Y% series. The mean values across variables differ greatly due to different units and different data types, especially for VOL. The log-transformation is conducted to address skewness towards large values and to better fit the model.

Table 2. Descriptive Statistics

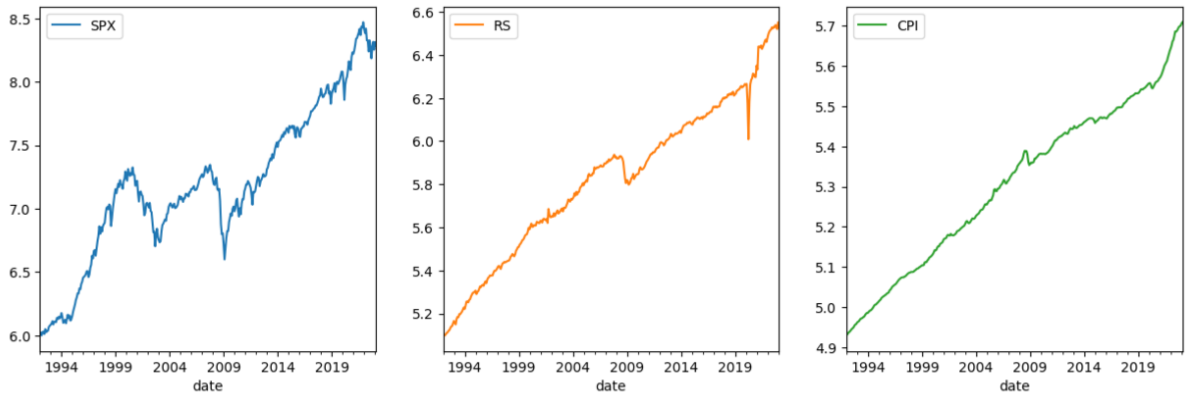
	SPX	RS	CPI	10Y%	P/E	VOL
count	374	374	374	374	374	374
mean	1593.02	360.64	205.74	3.97	20.04	1.67E+10
std	998.64	128.17	41.28	1.81	4.58	9.26E+09
min	403.69	163.72	138.30	0.53	10.65	2.56E+09
25%	975.95	262.60	168.18	2.39	16.70	1.08E+10
50%	1284.48	354.31	207.64	3.93	19.04	1.39E+10
75%	2055.16	442.87	237.47	5.46	22.19	2.45E+10
max	4766.18	700.68	301.65	7.91	34.36	4.68E+10

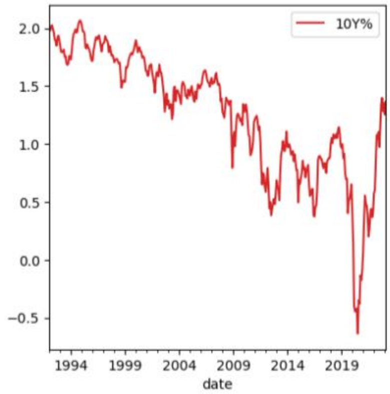
Table 3 shows the correlations between variables. The target independent variable SPX exhibits generally high correlations with the dependent variables. However, some dependent variable pairs, such as RS-CPI, RS-10Y% and CPI-10Y%, are strongly correlated. This may cause multicollinearity problem, leading to the insignificance of estimated coefficients from the model.

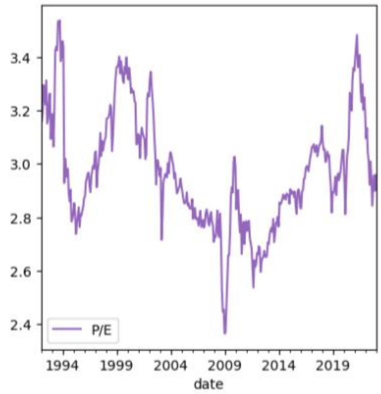
Table 3. Correlation Matrix

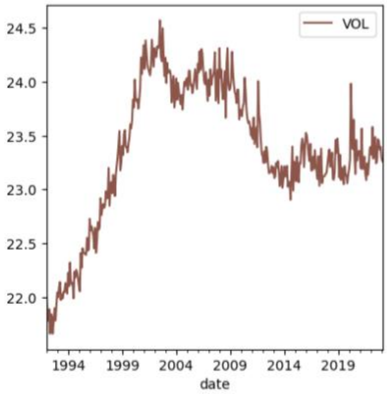
	SPX	RS	CPI	10Y%	P/E	VOL
SPX	1.0000					
RS	0.9445	1.0000				
CPI	0.9094	0.9896	1.0000			
10Y%	-0.7465	-0.8050	-0.8334	1.0000		
P/E	0.0242	-0.2250	-0.2892	0.1860	1.0000	
VOL	0.3671	0.4015	0.3550	-0.1877	-0.2543	1.0000

Figure 1. Time Series Plot of Variables (in log term)









4 Methodology

To investigate the long-run and short-run determinants of the U.S. equity market, this study adopts Johansen and Juselius (1990)'s cointegration framework and constructs a Vector Error Correction Model. This model describes a short-run dynamics by vector autoregression terms as well as a long-run equilibrium by error correcting terms, allowing to establish dynamic relationships between variables more accurately. The model specification takes the following form (3) :

$$\Delta X_t \; = \; \prod X_{t-1} \; + \; \sum_{i=1}^{p-1} \Gamma_i \, \Delta X_{t-i} \; + \; C\, D_t \; + \; \varepsilon_t \;\; (3)$$

Before modeling, Augmented Dickey-Fuller (1979) unit root test is performed to make sure all variables are integrated of order 1. Second, cointegration relationships among variables is tested through Johansen's approach. Third, a Vector Error Correction Model is estimated and Jarque-Bera normality test (1987) and Ljung–Box serial correlation test (1978) are examined for model diagnosis. After the model is constructed, the results from the VECM estimation are reported, including the long-run and short-run VECM coefficients, Granger-causality relationships, impulse response function and variance decomposition. Finally, an out-of-sample forecasting is represented.

First, Augmented Dickey-Fuller Unit Root Test shows that are all series are non-stationary at level, and all become stationary at 1% significance level after taking first differences. Thus, all variables are confirmed to be integrated of order 1. This allows to proceed towards cointegration test.

Table 4. Augmented Dickey-Fuller Unit Root Test

Variables	Order of Integration	t-statistics			
		Level		First Difference	
		Constant	Trend	Constant	Trend
SPX	I(1)	1.8562	-0.4467	-5.3479***	-6.0383***
RS	I(1)	1.4292	-0.5171	-4.3177***	-4.6348***
CPI	I(1)	1.4289	-1.4574	-3.5757***	-3.8758**
10Y%	I(1)	-1.9195	-1.9680	-13.0328***	-13.0924***
P/E	I(1)	-2.4530	-2.4168	-7.7381***	-7.7357***
VOL	I(1)	-1.6293	-3.2659*	-3.7305***	-3.7691***

Note: *, ** and *** indicate significance at 10%, 5% and 1% level.

Second, Johansen cointegration test is applied to investigate the long-run associations between the variables. For the parameter inputs, the optimal VAR lag order is found to be 3 (Table 5), and the regression method is identified as "constant and trend" according to the time series plots in Figure 1. Results of the Johansen cointegration test are reported in Table 6. For both trace test and maximum eigenvalue test, the null hypothesis can be rejected at r = 0 and r ≤ 1, concluding there are at least 2 co-integrating relationships between the variables. Therefore, rank = 2 will be used in the VECM.

Table 5. VAR Lag Order Selection

lag	AIC	BIC	FPE	HQIC
0	-25.8800	-25.7500	0.0000	-25.8300
1	-41.1600	-40.6400	0.0000	-40.9500
2	-41.6500	-40.75*	0.0000	-41.29*
3	-41.80*	-40.5100	7.008e-19*	-41.2900
4	-41.7500	-40.0700	0.0000	-41.0800
5	-41.73	-39.67	7.56E-19	-40.91
6	-41.73	-39.28	7.59E-19	-40.75
7	-41.67	-38.84	8.03E-19	-40.55
8	-41.59	-38.37	8.74E-19	-40.31
9	-41.52	-37.91	9.40E-19	-40.09
10	-41.42	-37.42	1.05E-18	-39.83

Note: (1)* highlights the minimums; (2)lag 2 and 3 both have two minimums, this study selects lag 3 for modeling

Table 6. Johansen cointegration test

	Trace Test				Maximum Eigenvalue Test			
	t-stats	**10% cv**	**5% cv**	**1% cv**	**t-stats**	**10% cv**	**5% cv**	**1% cv**
r ≤ 2	43.33	44.49	47.85		18.88	25.12	27.59	
r ≤ 1	77.51**	65.82	69.82	77.82	34.18**	31.24	33.88	39.37
r = 0	129.4***	91.11	95.75	105.5	51.90***	37.28	40.08	45.87

Note: (1)*, ** and *** indicate significance at 10%, 5% and 1% level; (2)regression type = "constant"; (3)lag order = 2

Third, Jarque-Bera test and Ljung–Box test are performed for diagnosis before estimating the VECM. According to Table 7, the VECM, unfortunately, reject both test, indicating that the residuals does not follow a normal distribution and serial correlation is found to be significant. Further investigations on the data distribution, variable relationships and more need to be conducted to fix this problem.

Table 7. Residual Diagnosis Test

lag	t-statistics	5% Critical Value	p-value
Jarque-Bera normality test	2.08E+4	21.03	0.000
Ljung–Box serial correlation test	489.1	392.5	0.000

Note: (1)Jarque–Bera test H0: Residuals are normally distributed. (b) Ljung–Box test H0: No serial correlation.

5 Results

Based on Johansen cointegration test, a VECM is estimated to examines the long-run and short-run determinants of the S&P 500 Index. Results in Table 8 shows that there are two cointegrating equations and the coefficients are reported. For the concern of this study, only ECM1 will be under further analysis next. It is found that there is a long-run equilibrium relationship between SPX, CPI, 10Y%, P/E and VOL. The equation can be rewritten as form (4) to highlight the dependent variable: CPI, P/E and VOL are significant and positively related to SPX. In the long run, 1% increase in these three variables would lead to 3.25%, 0.42% and 0.30% increase in SPX.

$$ECM_1\text{:}\;\; SPX_{t-1} = 3.2548\; CPI_{t-1}^{***} + 0.0833\; 10Y\%_{t-1} + 0.4223\; P/E_{t-1}^{***} + 0.2991\; VOL_{t-1}^{***} \quad (4)$$

Table 8. Long-Run Relationship: Coefficients of Cointegrating Equations

	ECM_1			ECM_2	
	coefficient	std error		coefficient	std error
SPX	1.0000		SPX		
RS			RS	1.0000	
CPI	-3.2548***	0.466	CPI	-1.6630***	0.218
10Y%	-0.0833	0.102	10Y%	0.0339	0.047
P/E	-0.4223***	0.163	P/E	0.0402	0.594
VOL	-0.2991***	0.036	VOL	-0.0825***	0.016

Note: *, ** and *** indicate significance at 10%, 5% and 1% level

Table 9 presents the short run coefficients of the VECM. The result indicates that at 10% significance level, RS_{t-1} has positive influence on SPX and P/E_{t-2} is negative associated with SPX in the short run. The coefficient of error correction term 2 is -0.1463 significant at 1%, implying that 14.63% of the deviation from the long-run equilibrium path is corrected within one month.

Table 9. Short-Run Relationship: Coefficients of the VECM

	coefficient	std error		coefficient	std error
ΔSPX_{t-1}	0.0301	0.073	ΔSPX_{t-2}	0.0193	0.075
ΔRS_{t-1}	0.2622*	0.145	ΔRS_{t-2}	0.1090	0.136
ΔCPI_{t-1}	-0.5520	1.011	ΔCPI_{t-2}	0.8501	0.979
$\Delta 10Y\%_{t-1}$	-0.0168	0.026	$\Delta 10Y\%_{t-2}$	0.0273	0.028
$\Delta P/E_{t-1}$	-0.0467	0.047	$\Delta P/E_{t-2}$	-0.0837*	0.047
ΔVOL_{t-1}	0.0003	0.016	ΔVOL_{t-2}	0.0189	0.016
$ECM1_{t-1}^{1}$	0.0365***	0.015	$Intercept$	-0.0216	0.182
$ECM1_{t-1}^{2}$	-0.1463***	0.066			

Note: *, ** and *** indicate significance at 10%, 5% and 1% level

The association between S&P 500 and other variables is proven by Johansen cointegration test and the VECM estimation. Next step is to examine the direction of improvement in predicting power through Granger Causality Test. The result in Table 10 shows five unidirectional relationships in the short run. None of the independent variable is able to improve the prediction of S&P 500, while on the other hand, S&P 500 granger-causes all of the five independent variables.

Table 10. Granger Causality F-test

	RS	CPI	10Y%	P/E	VOL
Variables → SPX	0.7215	0.6045	0.9357	2.069	0.8228
Variables ← SPX	6.999***	2.806**	3.393**	2.644**	6.670***

Note: *, ** and *** indicate significance at 10%, 5% and 1% level

To further analyze the dynamic relationships between the variables, impulse response functions are derived from the VAR estimates. Figure 2 presents the cumulative impulse responses of SPX to one standard deviation innovations in all the other independent variables. The result suggest that SPX itself, RS and VOL exert a positive influence in explaining SPX, while CPI, 10Y% and P/E tend to have a negative impact on SPX, which are generally in line with classic economic and finance theories. In terms of timing, the plots show that the impact of SPX itself, RS, CPI on SPX last for four months. The shock from P/E ends at around the second months. 10Y% and VOL exhibit a longer-lasting effect, around six months.

Figure 2. Cumulative Impulse Response of SPX (generalized)

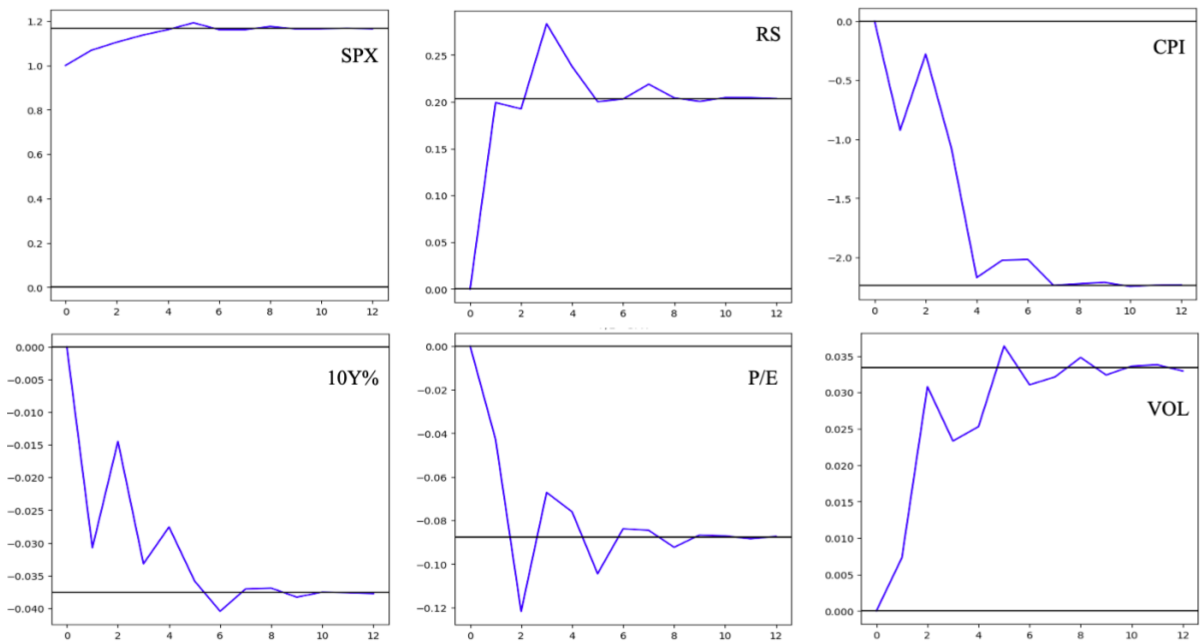


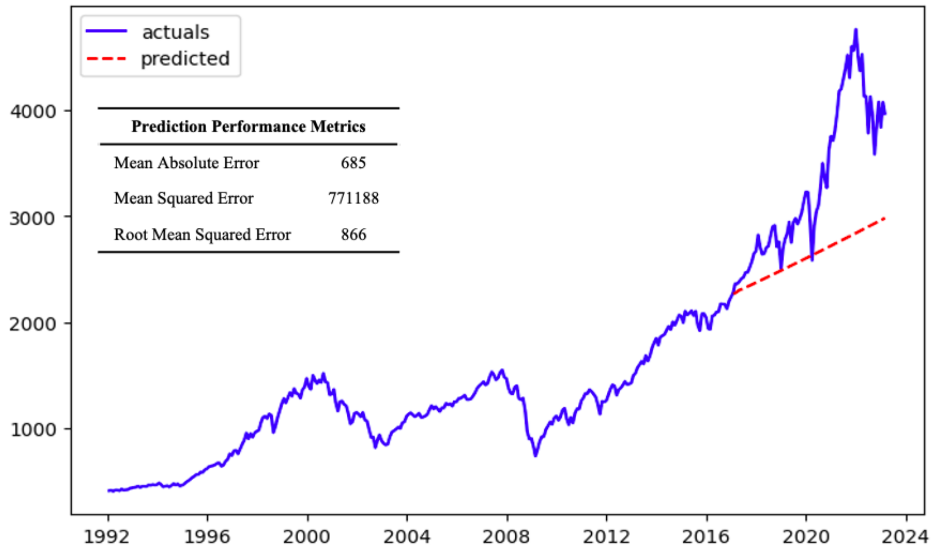
Table 11 provides Cholesky variance decompositions of SPX in respect of the independent variables. The results show that the variance of SPX is over 95% explained by its past prices, and the other five factors explain less than 5% of variation. Among the independent variables, P/E has the strongest explanatory power in contributing to the forecast variance of the SPX, while RS has the least. Another observation is that the explanatory power of P/E and VOL goes up substantially at the second month.

Table 11. Variance Decomposition of SPX

	SPX	RS	CPI	10Y%	P/E	VOL
0	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
1	98.71%	0.24%	0.40%	0.39%	0.22%	0.05%
2	97.33%	0.25%	0.49%	0.45%	0.95%	0.53%
3	96.65%	0.27%	0.68%	0.56%	1.27%	0.57%
4	96.26%	0.36%	0.96%	0.57%	1.27%	0.57%
5	96.02%	0.38%	0.96%	0.60%	1.36%	0.67%
6	95.94%	0.38%	0.96%	0.61%	1.41%	0.70%
7	95.93%	0.38%	0.97%	0.61%	1.41%	0.70%
8	95.91%	0.38%	0.97%	0.61%	1.42%	0.70%

Finally, an out-of-sample forecast on SPX using the VECM is carried out. The original dataset is broken into a training set from January 1992 to December 2016 (80%), and a test set from January 2017 to February 2023 (20%). The forecasting result is presented in Figure 3. While the model does not deliver a decent prediction performance score, it can actually be used as a bottom valuation tool. The predicted series capture the bottom of SPX quiet accurately such that a “buy the dip” strategy can be implemented whenever the SPX price hits the predicted fair value. The divergence between the predicted and actual values starts in the second half of 2020. This could be resulted from the unprecedented policy stimulus after the COVID recession, causing a structural change in the financial system that past data is not able to make good predictions.

Figure 3. SPX Out-of-Sample Forecast



6 Conclusion and Discussions

This study investigates the long-run and short-run determinants of the S&P 500 Index using VAR/VEC models. The empirical results show that there is a long-run equilibrium relationship between S&P 500 and the factors driving the price fluctuation. Inflation, P/E ratio and trading volume have a positive impact on S&P 500 in the long run. While there is no direct long-term association between growth factor and S&P 500, the positive cointegration relationship between retail sales and inflation suggests that growth also contributes to the long-term pricing of S&P 500. Furthermore, the short-run coefficients indicate that lag one month of retail sales is positively correlated with S&P 500, and lag two months of P/E ratio presents a negative influence. The impulse responses of S&P 500 to the innovations of its drivers generally supports the VECM’s short-run estimations, where the direction(±) and duration(month) of each variable is as follows: S&P500(+,4); retail sales(+,4); inflation(-,4); 10-year treasury yield(-,6); P/E ratio(-,2); trading volume(+,6). In the variance decomposition analysis, while the variation of S&P 500 is mainly driven by its past prices, it is found that P/E ratio has the strongest explanatory power among all independent variables. Finally, an out-of-sample forecast on S&P 500 is carried out based on the VECM. Despite a high mean squared forecast error, the predicted series can serve decently as the bottom fair-value of S&P 500.

The findings of this study have three implications for investment research and portfolio management.

1. Valuation and sentiment are two important dimensions for equity pricing, while most existing literature on examining the determinants of equity prices solely focuses on the macroeconomic side. A long-run cointegration between S&P 500 and P/E ratio as well as trading volume is observed in this study, and it is also found that these two variables have significant effects on S&P 500 in the short run. The result from variance decomposition also supports that valuation and sentiment should be properly monitored for equity pricing.
2. The timing of the determinants of equity prices matters. The results show that P/E ratio is positively associated with S&P 500 in the long run but the influence is negative within a two-month timeframe. The interpretation could be that a spike in P/E ratio may lead to overoptimistic surges in equity prices in the short run, thus resulting a mean-reversion price correction. But in the long run, an increase in P/E ratio reflects a positive growth in future earnings that pushes up the price. Another example is inflation. The model indicates that CPI has a negative effect in the short run but positive in the long run for S&P 500. It is widely-accepted that inflation can reduce aggregate demand and increase discount rate, weighting on equity returns. However, they exhibit a weakly positive long-term correlation. In fact, empirical evidence suggests that the relationship between equity prices and inflation lies in the threshold of inflation rate rather than the direction.
3. Following the above finding, it is possible to improve strategic and tactical asset allocation performance by examining the long-run and short-run determinants of financial assets through a vector error correction model. This study confirms the fact that the impacts of the factors driving S&P 500 come in different durations, allowing investment managers to optimize their allocations of research focuses. This is supported by Lucas (1997) that VECM is able to optimize asset allocation with different planning horizons, where cointegration mainly affects strategic asset allocation, while error-correction affects both tactical and strategic asset allocation.

There are some limitations of this study. First, more than half of the estimated coefficients of the VECM are not significant at any level. This could be a result of multicollinearity since some of the independent variable pairs exhibit high correlations in Table 3. Second, the estimated VECM fails both the Jarque-Bera normality test and the Ljung–Box serial correlation test. While failing tests for normality at least asymptotically has no implications to the results, further investigations on serial correlations need to be conducted. Finally, none of the independent variable is able to granger cause S&P 500, while S&P 500 granger causes all the of independent variables. The explanation could be that equity prices reflect the expectation of future earnings rather than past economic data. This could be the reason why Chaudhuri and Smiles (2004) includes future GDP growth and Kishor (2009) uses high-frequency data, rather than past data, in order to improve explanatory power.

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