Signals in the Storm: Predicting Market Shifts with VIX, CVI, MOVE, and BBDXY Indices

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Abstract

This study examines the ability of volatility indices to predict asset returns across equity, bond, cryptocurrency, and currency markets. Using daily data for the VIX, CVI, MOVE, and BBDXY indices, the analysis finds that each index offers meaningful return predictability both within and across markets. Notably, VIX Change Lagged forecasts equity returns, while CVI and MOVE demonstrate significance in multiple markets, and BBDXY Change Lagged provides strong cross-asset signals. The predictive power increases when the indices are combined, with adjusted R^2 values of 5.16% for SPY and 2.71% for AGG. These results highlight the value of volatility indices as forward-looking market indicators.

Introduction and Current Research

Market predictability is a significant area of research in finance, and while countless factors influence market movement, this complexity makes it nearly impossible to predict in real time and over the short term. On the other hand, long-term market returns are more predictable, as markets tend to move in cycles and patterns that can be identified through historical data. There has been substantial research in this area. For example, Goyal and Welch (2008) and Goyal, Welch, and Zafirov (2024) summarize the various predictors used to forecast returns. These predictors include 41 documented variables grouped into categories such as Sentiment Indicators, Variance-related factors, Stock cross-section variables, and Commodities-related Indicators. Their work is among the most cited in the field. Despite this, in their most recent paper, Goyal, Welch, and Zafirov (2024) assert that "Since Goyal and Welch (2008, a) a large number of papers predicting the equity premium have been published in top finance journals… Yet, the last two decades have also offered a fascinating new sample with plenty of opportunities for predictive variables to prove their mettle." To make better predictions for long-term market trends, researchers continue to identify patterns and indicators.

Despite having many indicators available, only a few standout as early signals of market changes. Volatility indices are among the most effective. These include VIX (CBOE Volatility Index) for the stock market, CVI (Cryptocurrency Volatility Index) for the crypto market, MOVE (Merrill Lynch Option Volatility Estimate) for the bond market and BBDXY (Bloomberg Dollar Spot Index) for the currency market. These indices measure volatility, which essentially reflects the overall sentiment of the market. Volatility indices spike when investors panic and short the market to protect their positions. These indices drop when confidence returns, providing a strong indication of market shifts. Indicators of volatility have consistently been proven to be accurate indicators of market sentiment. According to Goyal, Welch, and Zafirov (2024), "VIX-based predictors have performed extremely well in the most recent 10 years" (Goyal et al., 2024). Similarly, "CVI helps investors by providing a measure of the 30-day future fluctuation degree of the price of the entire cryptocurrency market, offering crucial insights for modifying trading strategies in advance," making it a valuable tool for predicting real-time changes in the crypto market (Nguyen et al., 2022). Investing strategies can be adjusted quickly with the help of these indices.

After reviewing both recent and older research on volatility indices, it is clear that several papers focus on aspects of the VIX index, from stock market predictability to hedging strategies. However, the CVI and MOVE indices have been largely disregarded, and very limited research has been conducted on these indicators, which represents a significant gap in the literature. In one particularly insightful paper, it was noted that "The signals between the VIX and MOVE indexes in the last ten years have changed, and the gap between these markets has widened. This is a relationship not witnessed since the early days before the 2008 Global Financial Crisis" (Budd, 2017). Consequently, the relationship between these two indices has changed, indicating the need for further research. Additionally, Budd (2017) notes, "The implied volatilities of the equity and bond markets are measures of the markets' preparedness for risk protection. The lower the indices, the less demand for risk protection and vice versa" This illustrates why understanding how these indicators reflect risk sentiment is crucial (Budd, 2017). Currently, the VIX index is heavily researched, but it has limitations. The stock market operates only Monday through Friday, 9:30 AM to 4 PM, whereas the crypto market operates all the time. As a result, the CVI index can predict market changes in real time. Moreover, since the stock market is one-third the size of the bond market, the MOVE index offers a more accurate measure of market movements, partly because it is mainly influenced by institutional investors with access to more timely and accurate data. Additionally, the BBDXY index provides crucial insights into currency market volatility, capturing macroeconomic shifts that are not evident in the equity or bond markets.

Another underexplored area in current research is the potential for combining the forecasting power of several different volatility indices to better predict market movements across different asset classes. Li (2022) mentions "several noteworthy contagion effects for all four types of jumps," where "positive jumps in the VIX index can trigger high-level cross-exciting effects for both positive and negative jumps in Bitcoin" (Li, 2022). This suggests that changes in one market, such as the stock market, can directly influence another, like the cryptocurrency market. According to Li (2022), these findings "provide further evidence of the relationship and influences between classic markets and the relatively new cryptocurrency market". emphasizing how movements in traditional financial markets, such as stocks and bonds, can spill over into emerging markets like crypto.

To fill these gaps in the literature, in this thesis, I studied volatility indices and tested their ability to predict market returns, trends, and signals of market shifts. Research has shown that "calculating the ratio between the MOVE and VIX indexes for the last 15 years reveals significant time-varying correlation between equity and debt markets" (Budd, 2017), highlighting the potential for a stronger predictive model by combining these indices. The focus of my research was to test VIX, CVI, MOVE, and BBDXY across different markets (stocks, bonds, crypto, and currency) to determine what combination of these indices provides the best prediction strategy.

Aims and Objectives

Volatility indices are great tools for predicting the market trends. As Giot (2005) notes, "There is a clear reference to a possible relationship between extremely high levels of implied volatility and a market bottom". While most research focuses on the VIX index in the equity market, this study examined all four indices across different markets and evaluated how combining them improves market predictions. The following were the Aims and Objectives of this study:

Aims

- **Aim 1**: Test the ability of the VIX, CVI, MOVE, and BBDXY indices to predict market returns in the equity, cryptocurrency, bonds, and currency markets, respectively.
- **Aim 2**: Test cross-market predictability of volatility indices. For example, assess how bond market volatility can be used to predict returns in the equity market, among others.
- **Aim 3**: Test if combining multiple volatility indices can help better predict each market.

Objectives

- **Objective 1**: The best indicator for forecasting returns in each asset class (stocks, crypto, bonds, and currency) was identified by testing how each index performs within its market.
- **Objective 2**: Testing cross-market volatility, such as using bond market volatility to forecast equity returns to highlighted market relationships and identified early shifts.
- **Objective 3**: Combining multiple volatility indices to predict all four markets equity, crypto, bonds, and currency.

Methodology

Data Collection

The first step in this analysis was to collect daily historical data for my predictions of VIX, CVI, MOVE, and BBDXY indices. Next, I gathered daily levels for four tickers: $SPY representing the equity market, $BTC for Bitcoin, $AGG for the broad exposure to the U.S. investment-grade bond market, and $DXY for the currency market. This study gathered an extensive data set of historical prices, which spanned over 35 years and included thousands of data points per index. The sample ended on 09/30/2024 for all assets. The earliest available data for each asset began as follows: 1/29/1993 for SPY, 9/26/2003 for AGG, 7/20/2010 for BTC, 1/2/1990 for DXY, 1/2/1990 for VIX, 3/31/2019 for CVI, 1/1/1990 for MOVE, and 1/3/2005 for BBDXY. The goal was to compute their daily returns to be used later.

I obtained all the data exclusively from Bloomberg. Collecting a wide range of data helped me capture historical trends and test findings on black-swan events such as the 2008 financial crisis.

Data Preparation

I calculated the delta for my predictors and market returns by using the following formula:

$$\Delta\% = (\text{Today's Price} \div \text{Yesterday's price}) - 1 \tag{1}$$

Each predictor was lagged by one day to ensure that the index value on the day (t) was used to predict the market return on the day (t+1), to assess if today's change in volatility can predict tomorrow's return.

Regression Analysis

I ran multiple linear regressions to test the predictive power of each volatility index across all four markets. As stated, "A predictive regression model is the standard framework for analyzing aggregate stock return predictability: $r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h}$" (Rapach et al., 2016). The lagged values of VIX, CVI, MOVE, and BBDXY served as the independent variables (X), while the daily market returns (for SPY, Bitcoin, bonds, and currency) were the dependent variables (Y). The resulting table gave me the variables for my forecasting formula:

$$r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h} \tag{2}$$

The formula $r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h}$ shows how market returns ($r_{t:t+h}$) depend on the volatility index (x_t), where α is the intercept, β measures the index's effect, and $\varepsilon_{t:t+h}$ is the error term.

In this step, I performed nine regressions for each market—eight univariate (four levels and four changes) and one full multivariate regression including all volatility indices. The resulting regression tables include other important data such as T-statistics and P-values, which were used to assess the reliability and significance of my findings.

Combination of Predictors

Once I analyzed each index individually, I explored whether combining the predictors improves the ability to predict market returns. This involved running a ninth multivariate regression using all four indices to capture joint volatility effects across asset classes. The resulting table gave me variables for my forecasting formula:

$$r_t = \alpha + \beta^1 VIX_t + \beta^2 CVI_t + \beta^3 MOVE_t + \beta^4 \, BBDXY_t + \varepsilon_t \tag{3}$$

This formula shows how market returns (r_t) depend on the VIX, CVI, MOVE and BBDXY indices, where α is the intercept, β measures each index's effect and ε_t is the error term.

This approach allowed the study to test the marginal and combined contribution of each volatility index, culminating in a comprehensive analysis of their joint predictive power.

Statistical Significance

To ensure the reliability of my results, I evaluated the statistical significance of each regression. For each predictor variable (VIX, CVI, MOVE, and BBDXY), I analyzed the T-statistic and P-value provided by the regression table to determine my findings.

- A T-statistic of [1.63] suggests that the volatility index explains at least 90% of the variance in the market returns, while a T-statistic of [1.96] explains 95% of the variance.
- The P-value for each β coefficient must be less than 0.05 for the relationship between the predictor variable and the market return to be considered statistically significant.

Comparing these results across different combinations of predictors helped me identify which volatility indices, or combinations of indices, consistently produce significant and reliable forecasts for market movements.

Outcomes

Predictive Power of Individual Volatility Indices

In this section, I evaluate the time-series regressions that link volatility indices to daily asset returns across four markets: equity (S&P 500), bonds (AGG), cryptocurrency (Bitcoin), and the U.S. Dollar Index (DXY). Using the VIX, CVI, MOVE, and BBDXY in both level and change form, I isolate the impact of each index. The key results are drawn from regression Tables 1–4, the correlation matrix in Table 5, and summary statistics in Table 6.

Starting with equities, the predictive strength of the VIX is immediately apparent. In Table 1, model (1), VIX Level Lagged is significantly negative with a coefficient of 0.0001 and a t-statistic of -9.54 (note: the negative t-stat reflects a significant inverse relationship despite the coefficient's small magnitude), suggesting that higher levels of equity implied volatility predict lower next-day returns for SPY. In model (2), VIX Change Lagged is positive and highly significant, with a coefficient of 0.0089 and t-stat of 5.78. In the full model (9), VIX Level Lagged remains significantly negative (-0.0002, t-stat: -4.85), and VIX Change Lagged retains its predictive power (0.0246, t-stat: 6.42). The adjusted R-squared in model (9) reaches 5.16%, the highest across all asset classes. Additionally, BBDXY Change Lagged also enters significantly with a coefficient of -0.5611 (t-stat: -7.08), highlighting the role of FX-related volatility in equity market dynamics.

In the bond market (Table 2), the MOVE index does much of the heavy lifting. MOVE Lagged is significant in model (5) with a coefficient of 0.0002 (t-stat: 1.88), while MOVE Change Lagged in model (6) is strongly negative (coefficient: -0.0032; t-stat: -3.69). In model (9), MOVE Lagged (0.0000, t-stat: -1.22) and MOVE Change Lagged (-0.0030, t-stat: -1.59) both retain direction but show weaker statistical strength, although the latter remains significant at the 10% level. Interestingly, CVI Change Lagged also enters significantly in model (4) with a coefficient of -0.0046 and a t-stat of -2.70, and it remains significant in model (9) (t-stat: -2.69), suggesting that crypto volatility carries information even for bonds. The adjusted R-squared for model (9) rises to 2.71%, indicating moderate but meaningful explanatory power.

Bitcoin returns (Table 3) are most closely linked to CVI Change Lagged. This variable is positively and significantly associated with BTX returns in model (4), with a coefficient of 0.0020 and a t-stat of 2.57. In the full model (9), although CVI Change Lagged is no longer significant, VIX Change Lagged (coefficient: 0.0227; t-stat: 1.80) and BBDXY Change Lagged (coefficient: -0.4550; t-stat: -1.74) provide additional predictive value. The adjusted R-squared in model (9) is 0.36%, which is modest but still informative for a notoriously volatile and difficult-to-predict asset class.

For DXY (Table 4), signals are more subtle but still meaningful. MOVE Change Lagged enters significantly in model (6) with a coefficient of 0.0025 and t-stat of 2.00, and it remains relevant in model (9) with a slightly higher coefficient (0.0033; t-stat: 1.70). VIX Change Lagged is significantly negative in model (9) with a coefficient of -0.0027 and a t-stat of -2.08. Although the adjusted R-squared remains low at 0.28%, the consistent significance of these predictors suggests that volatility in equity and bond markets can help forecast currency movements on the margin.

Cross-Market Predictive Insights

Summary statistics from Table 6 help contextualize the regression results. For example, VIX Level Lagged has a mean of 19.41 and standard deviation of 7.84, while MOVE Level Lagged is substantially higher at 92.7 with a 28.01 standard deviation. Notably, BBDXY Level Lagged stands out with a mean of 1,105.9 and a standard deviation of 105.7—by far the largest magnitude—underscoring its macroeconomic significance. Among change variables, VIX (0.0583), CVI (0.0450), and MOVE (0.0345) Change Lagged have relatively similar standard deviations, showing comparable levels of daily fluctuation.

Correlations in Table 5 reveal meaningful cross-asset relationships. The correlation between MOVE Change Lagged and VIX Change Lagged is 0.2845—the highest among the change metrics—indicating co-movement between bond and equity volatility. CVI Change Lagged also shows positive correlations with both MOVE Change Lagged (0.1003) and VIX Change Lagged (0.1601), suggesting a degree of alignment across these otherwise distinct asset classes. Other correlations between volatility changes and asset returns remain modest. For instance, SPY Change is weakly correlated with BBDXY Change Lagged (-0.0543) and with VIX Change Lagged (0.0699), highlighting the role of volatility metrics more as predictors than as contemporaneous drivers.

The broader insight is that volatility indices don't just explain their home asset class—they carry information across markets. CVI Change Lagged, although a crypto-specific measure, is significantly linked to returns in SPY and AGG. Similarly, BBDXY Change Lagged, associated with FX movements, is significantly negative in the SPY regression (coefficient: -0.5611; t-stat: -7.08). MOVE, the bond volatility index, enters significantly in SPY, BTX, and DXY models.

These results collectively support the notion that volatility indices act as barometers of systemic risk and macro uncertainty.

The Power of Combining Predictors

Across all asset classes, explanatory power improves when combining VIX, CVI, MOVE, and BBDXY. In every market, the full model (specification 9) delivers the highest adjusted R-squared. The improvement is most pronounced for SPY, where the R-squared increases to 5.16% (Table 1), compared to well below 1% in single-predictor models. AGG follows with 2.71% (Table 2), then BTX with 0.36% (Table 3), and finally DXY with 0.28% (Table 4).

This evidence shows that using these indices in tandem reduces omitted variable bias. Each index appears to contribute non-overlapping information about future returns. The results support a view of volatility as multidimensional: VIX captures equity fear, MOVE speaks to interest rate risk, CVI covers crypto-specific turmoil, and BBDXY encapsulates dollar-driven shifts. When combined, they offer a more complete picture of investor uncertainty.

Practical and Academic Implications

These results highlight the value of monitoring multiple volatility indices simultaneously. An equity trader, for instance, might watch MOVE or BBDXY to anticipate cross-asset risk spillovers. Bond investors may benefit from tracking both VIX or CVI to anticipate risk-on or risk-off sentiment. The predictive power of crypto and FX volatility in more traditional asset classes challenges siloed thinking in portfolio construction.

Academically, this paper contributes to the growing literature that looks beyond VIX as the sole measure of volatility. While the VIX retains its relevance, the findings indicate that both

MOVE and CVI, though less studied, also exhibit significant forecasting ability in equity and bond markets. The fact that BBDXY enters significantly in the SPY model reinforces the interconnectedness of modern financial systems. These results suggest that volatility indices can and should be incorporated into macro-finance models as forward-looking risk indicators.

Personal Reflections

Working on this analysis taught me a lot, not just about volatility, but also about the mechanics of empirical finance research. Interpreting low R-squared values in meaningful ways, assessing robustness through comprehensive model specifications, and understanding the role of lagged predictors in forecasting were all valuable takeaways.

The process of cleaning and analyzing over 35 years of daily data pushed me to become more organized and detail-oriented. I had to think critically about how variables were defined and what each result meant in context. More than anything, this project reinforced how no single measure can explain markets behavior, what matters is the combination of multiple indicators. I hope to use this framework in future research or industry roles focused on macro strategy, portfolio risk, or cross-asset analytics.

Conclusion

In this paper, I examine whether implied volatility indices (VIX, CVI, MOVE, and BBDXY) contain predictive information about future market returns across four major asset classes: equities, bonds, cryptocurrencies, and currencies. Using over three decades of daily data and a consistent regression framework, the findings reveal that certain volatility measures provide statistically significant signals for next-day returns, both within their own markets and across others.

The results indicate that VIX Change Lagged strongly predicts equity returns, while CVI Change Lagged and BBDXY Change Lagged offer explanatory power in models of SPY, AGG, and BTX. Additionally, MOVE Change Lagged shows predictive value for DXY. These findings suggest that market-specific volatility indices reflect more than localized sentiment—they also capture broader macro uncertainty that can spill over into other markets.

Importantly, combining all four indices improves predictive performance, with the full multivariate model delivering the highest adjusted R-squared across all asset classes. This confirms that each index contributes unique information to forecasting models, reinforcing the notion that volatility is multidimensional.

Overall, this study underscores the value of volatility indices as forward-looking risk indicators and encourages their incorporation into broader macro-finance models. Future research should address current limitations and explore additional variables to further enhance market prediction models.

Biographical Note

Meron Eeso is a senior Honors College student at Oakland University pursuing a Bachelor of Science in Finance. He is trilingual in English, Arabic, and Neo-Aramaic, an ancient language spoken by Christian minorities in the Middle East and considered to be the closest to what Jesus spoke. As a Christian minority, he survived the ISIS war in Iraq. Since immigrating to America, Meron has excelled both professionally and academically. His passion for the economy, stock market, and financial system stems from his belief they offer a deeper understanding of the world. This passion led him to study finance. This project aligns with Meron's career aspirations by deepening his understanding of market predictability, thereby providing him with a competitive edge in his future career.

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Appendix

Table 1: Regression Results of Return on S&P 500 (SPY)

This table presents time-series regressions of the daily return on the S&P 500 (SPY) on various lagged explanatory variables. The sample period is from [1/1/1990] to [9/30/2024], and all data are at a daily frequency. The independent variables include both the levels and changes (lagged by one day) of key volatility indices: (VIX) for the stock market and (CVI) for the cryptocurrency market, along with the bond market volatility index (MOVE) and the Bloomberg Dollar Spot Index (BBDXY) for the currency market. All variables are used in both level and change forms, with values lagged by one day. The t-statistics are shown in parentheses, and statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The Adjusted R-squared values indicate the proportion of daily return variance in SPY explained by these factors across different model specifications.

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
VIX Level Lagged	0.0001***								**-0.0002*** **
	(-9.54)								**(-4.85)**
VIX Change Lagged		0.0089***							**0.0246*** **
		(5.78)							**(6.42)**
CVI Level Lagged			0.0000						**0.0000***
			(-0.58)						**(1.61)**
CVI Change Lagged				-0.0180***					**-0.0199*** **
				(-3.40)					**(-3.79)**
MOVE Lagged					-0.0000***				**-0.0000** **
					(-3.43)				**(-2.19)**
MOVE Change Lagged						-0.0175***			**-0.0056**
						(-6.78)			**(-0.95)**
BBDXY Level Lagged							0.0000		**0.0000** **
							(0.03)		**(1.87)**
BBDXY Change Lagged								-0.1592***	**-0.5611*** **
								(-4.62)	**(-7.08)**
Observations	11,565	11,565	2,010	2,009	11,565	11,565	7,209	7,209	**2,009**
Adjusted R-squared	0.77%	0.28%	-0.03%	0.52%	0.09%	0.39%	-0.01%	0.28%	**5.16%**

Table 2: Regression Results of Return on U.S. investment-grade bond market (AGG)

This table presents time-series regressions of the daily return on the U.S. investment-grade bond market (AGG) on various lagged explanatory variables. The sample period is from [1/1/1990] to [9/30/2024], with all data measured at a daily frequency. The independent variables include both the levels and changes (lagged by one day) of key volatility indices: (VIX) for the stock market and (CVI) for the cryptocurrency market, along with the bond market volatility index (MOVE) and the Bloomberg Dollar Spot Index (BBDXY) for the currency market. All variables are used in both level and change forms, with values lagged by one day. The t-statistics are shown in parentheses, and statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and, respectively. The Adjusted R-squared values indicate the proportion of daily return variance in AGG explained by these factors across different model specifications.

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
VIX Level Lagged	0.0000								**-0.0000***
	(0.22)								**(-1.50)**
VIX Change Lagged		0.0000							**0.0035*****
		(-0.03)							**(2.85)**
CVI Level Lagged			0.0000						**0.0000***
			(0.70)						**(1.62)**
CVI Change Lagged				-0.0046***					**-0.0046*****
				(-2.70)					**(-2.69)**
MOVE Lagged					0.0002**				**0.0000**
					(1.88)				**(-1.22)**
MOVE Change Lagged						-0.0032***			**-0.0030***
						(-3.69)			**(-1.59)**
BBDXY Level Lagged							0.0000		**0.0000***
							(-0.7710)		**(1.41)**
BBDXY Change Lagged								-0.0217**	**-0.1695*****
								(-2.24)	**(-6.60)**
Observations	7,673	7,673	2,009	2,009	7,672	7,673	7,209	7,209	**2,009**
Adjusted R-squared	-0.01%	-0.01%	-0.03%	0.31%	0.05%	0.16%	-0.01%	0.06%	**2.71%**

Table 3: Regression Results of Return on Bitcoin (BTX)

This table presents time-series regressions of the daily return on Bitcoin (BTX) on various lagged explanatory variables. The sample period is from [1/1/1990] to [9/30/2024], and all data are at a daily frequency. The independent variables include both the levels and changes (lagged by one day) of key volatility indices: (VIX) for the stock market and (CVI) for the cryptocurrency market, along with the bond market volatility index (MOVE) and the Bloomberg Dollar Spot Index (BBDXY) for the currency market. All variables are used in both level and change forms, with values lagged by one day. The t-statistics appear in parentheses, and ***, *, * denote significance at the 1%, 5%, and 10% levels, respectively. The Adjusted R-squared values show how much of Bitcoin's return variability is explained by each specification.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VIX Level Lagged	-0.0003***								-0.0001
	(-3.34)								(-1.23)
VIX Change Lagged		-0.0053							0.0227**
		(-0.52)							(1.80)
CVI Level Lagged			0.0000						-0.0000
			(-0.21)						(-0.46)
CVI Change Lagged				0.0020***					0.0064
				(2.57)					(0.37)
MOVE Lagged					0.0085***				-0.0000**
					(3.80)				(-1.93)
MOVE Change Lagged						0.0001			-0.0089
						(0.01)			(-0.46)
BBDXY Level Lagged							0.0000***		0.0000
							(-4.38)		(0.30)
BBDXY Change Lagged								-0.2721	-0.4550**
								(-1.27)	(-1.74)
Observations	5,184	5,184	2,010	2,008	5,183	5,184	5,184	5,184	2,009
Adjusted R-squared	0.20%	-0.01%	-0.05%	0.01%	0.09%	-0.02%	0.35%	0.01%	0.36%

Table 4: Regression Results of Return on U.S. Dollar Index (DXY)

This table presents time-series regressions of the daily return on the U.S. Dollar Index (DXY) on various lagged explanatory variables. The sample period is from [1/1/1990] to [9/30/2024], and all data are at a daily frequency. The independent variables include both the levels and changes (lagged by one day) of key volatility indices: (VIX) for the stock market and (CVI) for the cryptocurrency market, along with the bond market volatility index (MOVE) and the Bloomberg Dollar Spot Index (BBDXY) for the currency market. All variables are used in both level and change forms, with values lagged by one day. The t-statistics appear in parentheses, and ***, *, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The Adjusted R-squared values demonstrate how much of the DXY's return variability is explained under each model specification.

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
VIX Level Lagged	0.0000*								**0.0000**
	(1.44)								**(1.00)**
VIX Change Lagged		-0.0005							**-0.0027****
		(-0.83)							**(-2.08)**
CVI Level Lagged			0.0000						**0.0000**
			(1.13)						**(1.23)**
CVI Change Lagged				0.0000					**-0.0003**
				(0.28)					**(-0.19)**
MOVE Lagged					-0.0001				**0.0000**
					(-0.90)				**(0.61)**
MOVE Change Lagged						0.0025**			**0.0033****
						(2.00)			**(1.70)**
BBDXY Level Lagged							0.0000*		**0.0000**
							(1.47)		**(0.72)**
BBDXY Change Lagged								0.0090	**0.0284**
								(0.66)	**(1.06)**
Observations	12,688	12,688	2,010	2,008	7,209	7,210	7,210	7,209	**2,009**
Adjusted R-squared	0.01%	0.00%	0.01%	0.00%	0.02%	0.04%	0.02%	-0.01%	**0.28%**

Table 5: Correlation Matrix of Key Market Variables

This table presents the pairwise correlation coefficients among daily changes (and/or levels) of several key market variables over the sample period from [1/1/1990] to [9/30/2024]. The variables include: the S&P 500 (SPY), U.S. investment-grade bonds (AGG), Bitcoin (BTX), the U.S. Dollar Index (DXY), implied volatility measures (VIX for equities and CVI for cryptocurrencies), the bond market volatility index (MOVE), and the Bloomberg Dollar Spot Index (BBDXY). Each variable is labelled as either a "Change" or "Level Lagged," reflecting whether I used the first difference (change from one day to the next) or the prior day's level. A higher absolute correlation indicates a stronger linear relationship between the two variables. Correlation does not imply causation, and further analysis (e.g., regression or time-series modelling) is needed to establish any causal links. Notable correlations include the strong positive relationship between MOVE Lagged and VIX Level Lagged (0.6157) and the negative correlation between CVI Level Lagged and MOVE Lagged (-0.3627). Among change variables, VIX Change Lagged and MOVE Change Lagged show the highest co-movement (0.2845), followed by VIX and BBDXY Change Lagged (0.2025), pointing to synchronized responses to macroeconomic volatility.

	SPY Change	AGG Change	BTX Change	DXY Change	VIX Level Lagged	CVI Level Lagged	MOVE Lagged	BBDXY Level Lagged	VIX Change Lagged	CVI Change Lagged	MOVE Change Lagged	BBDXY Change Lagged
SPY Return	1.0000											
AGG Return	-0.0136	1.0000										
BTX Return	**0.1189**	0.0405	1.0000									
DXY Return	**-0.1920**	**-0.2075**	-0.0516	1.0000								
VIX Level Lagged	-0.0931	0.0027	-0.0463	0.0282	1.0000							
CVI Level Lagged	-0.0129	0.0157	-0.0046	0.0252	**0.3625**	1.0000						
MOVE Lagged	-0.0412	-0.0214	-0.0303	0.0149	**0.6157**	**-0.3627**	1.0000					
BBDXY Level Lagged	0.0004	-0.0091	-0.0607	0.0173	-0.0500	**-0.4053**	-0.0762	1.0000				
VIX Change Lagged	0.0699	0.0009	-0.0072	-0.0168	0.0941	-0.0055	0.0065	0.0011	1.0000			
CVI Change Lagged	-0.0757	-0.0602	0.0075	-0.0017	0.0714	0.0941	0.0214	-0.0044	**0.1601**	1.0000		
MOVE Change Lagged	-0.0511	-0.0481	0.0001	0.0236	0.0388	-0.0077	0.0553	0.0012	**0.2845**	**0.1003**	1.0000	
BBDXY Change Lagged	-0.0543	-0.0264	-0.0176	0.0078	0.0490	0.0269	0.0190	0.0181	0.2025	0.0491	**0.1372**	1.0000

Table 6: Summary Statistics of Key Market Variables

This table presents descriptive statistics for the primary variables used in the analysis over the sample period from [1/1/1990] to [9/30/2024]. For each variable, the number of observations (N), mean, median, 25th percentile (P25), 75th percentile (P75), and standard deviation (Std. Dev.) are reported. "Change" variables typically represent day-to-day returns or differences, while "Level Lagged" and "Change Lagged" indicate the previous day's level or change used in subsequent analyses. These summary statistics offer a snapshot of the central tendency and dispersion of each variable, providing insight into their typical ranges and variability. Variables such as MOVE Lagged, CVI Level Lagged, and BBDXY Level Lagged exhibit notably higher standard deviations—28.01, 21.31, and 105.7, respectively—highlighting the greater volatility in bond and currency-related indicators. Meanwhile, BTX Change, VIX Change Lagged, and CVI Change Lagged show relatively higher average returns among change variables, despite their low medians, suggesting slightly positive skewness in those distributions.

	N	Mean	Median	P25	P75	Std. Dev.
SPY Return	11,567	0.0003	0.0000	-0.0018	0.0032	0.0098
AGG Return	7,675	0.0000	0.0000	-0.0007	0.0009	0.0028
BTX Return	5,186	**0.0038**	0.0000	-0.0097	0.0155	0.0493
DXY Return	12,690	0.0000	0.0000	-0.0014	0.0015	0.0042
VIX Level Lagged	12,691	19.4085	17.5300	13.7600	22.7700	**7.8443**
CVI Level Lagged	2,011	76.5350	73.8463	61.0430	90.9095	**21.3086**
MOVE Lagged	12,692	92.7013	92.0400	72.0450	109.6175	**28.0059**
BBDXY Level Lagged	7,211.0	1,105.9	1,115.6	1,013.4	1,199.4	**105.7**
VIX Change Lagged	12,690	**0.0016**	0.0000	-0.0209	0.0140	0.0583
CVI Change Lagged	2,010	**0.0010**	-0.0031	-0.0207	0.0164	0.0450
MOVE Change Lagged	12,691	0.0006	0.0000	-0.0114	0.0078	0.0345
BBDXY Change Lagged	7,210	0.0000	0.0000	-0.0012	0.0012	0.0034