To What Extent Can Risk Indicators Identify a Coming Financial Crisis? Evaluating Indicator Performance On Economic Downturns In The US.

"If shoe shine boys are giving stock tips, then it's time to get out of the market"
~ Joseph P. Kennedy Sr.

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Abstract

There are several economic variables used by investors to assess the risk of financial downturns. In this paper, we test twelve variables, divided into three categories: macroeconomic-, financial risk-, and sentiment indicators, in a logistic regression model, on in-sample data, with a binary outcome to evaluate their predictive power of economic downturns in the US, including the S&P 500, US recessions and Bitcoin. This was achieved by answering the question: “To What Extent Can Risk Indicators Identify a Coming Financial Crisis?”. We found that the most effective predictions came from the San Francisco Fed News Sentiment Index, the Chicago Board of Exchange Volatility Index, and the Consumer Confidence Index. These variables showed to be good leading indicators in combination for stock market crises and recessions. The variables evaluated on Bitcoin crises had weak predictive power.

1. Introduction

Throughout history, financial crises have been a recurring and often devastating feature of modern economies. These crises, marked by sudden economic downturns and widespread social and political repercussions, have left lasting imprints on the economic landscape of nations. Musgrove (1987) stated that worsened economic conditions had severe effects on health status through reduced income and reduced government spending. The great recession of 2008 serves as a stark reminder of the far-reaching consequences that a financial crisis can unleash. These crises have shown the need for preemptive measures to mitigate their impact. In the aftermath of such financial downturns, many individuals and institutions find themselves lamenting that they didn't see it coming. However, it is often the case that there were discernible signs leading up to these crises. The ability to identify these signals and heed their warnings can make the crucial difference between preparedness and unpreparedness, resilience and vulnerability.

In this paper, we seek to add to the academia on predicting financial crises by trying to answer the question: To What Extent Can Risk Indicators Predict a Coming Financial Crisis? We try to answer this question by identifying economic variables related to risk that behave in a certain way in the lead-up to a crisis. We also evaluate if indicators that work well for the S&P 500 have predictive power when applied to different types of crises.

Our research methodology employs both univariate and multivariate logit models. The univariate models are assessed by examining coefficients and their significance, while the multivariate models are evaluated through a prediction framework. We incorporate a twelve-month lead-up dummy variable to enhance foresight capabilities. Furthermore, the models' predictive performance is also analyzed when taking into account the 'post-crisis bias' (Bussiere & Fratzscher, 2002). Through this approach, we aim to evaluate the different categories of indicators' ability to identify financial crises within the coming 12-month period. The S&P 500 is used to represent the U.S. stock market. To illustrate a low-volatility event, we chose US recessions, and for a high-volatility event, we chose the Bitcoin to USD price.

This paper proceeds as follows. Section 2 discusses the theoretical background and previous literature. Section 5 specifies the indicators, the dependent variable, and the models used. Section 6 discusses the results of the models.

2. Background

The analysis of financial crisis indicators is rooted in various theories. In the early stages of the development of economic thought, it was economists such as Keynes (1936) and later on economists like Minsky (1992) who emphasized the change in risk behavior among economic agents in response to financial risk fluctuations. This concept of risk behavior has formed the foundation of much of the academic research on financial risk. These theories suggest that as perceptions of financial risk evolve, so do the strategies and behaviors of investors, lenders, and other financial participants. This shift in behavior is key to understanding the dynamics leading to financial crises and their subsequent management and mitigation.

Several working papers try to predict different types of financial crises using logistic regression models (Frankel & Rose, 1996; Eichengreen, Rose & Wyplosz, 1995; Berg & Pattillo, 1999). These papers only take into consideration the behavior of the indicators up until, and during the crisis period. However, other papers (Bussiere & Fratcher, 2002; Coudert & Gex, 2008) discussed the problem of a post-crisis bias when trying to predict a crisis. They argued that the results of predicting a crisis can be, in part or fully explained by the behavior of the independent variable during and after the crisis. Thus showing the importance of distinguishing between calm, crisis, and post-crisis periods as one could exist in all three scenarios.

Empirical studies in financial markets have investigated various aspects of market dynamics and crisis prediction. Danielsson, Valenzuela, and Zer (2016) found that volatility by itself was not a significant predictor of a crisis, but unusually low and high volatility are, and increases the probability of a crisis. Using the credit-to-GDP gap as a proxy for risk-taking, they found that low volatility significantly increased risk-taking. These findings are in line with Minsky's (1992) instability hypothesis which states that a low volatility environment will encourage economic agents to engage in excess risk-taking behavior moving from an equilibrium environment, which in turn may lead to a crisis environment. These findings build on Sharpe's (1964) Capital Asset Pricing Model (CAPM), which provides a framework to determine the expected return of an asset given its risk. where he assumed that all individuals are rational and risk-averse and thus generally want to avoid risk, an individual who takes on a risk through the acquisition of an asset will want to be compensated for the downside potential of the asset, the risk premium.

A basic idea in the theory of finance is that asset prices change as they incorporate fundamental information. Kendall and Hill (1953) examined stock market prices at the beginning of the 1950s and observed no identifiable pattern in financial time series, but instead that the patterns in stock prices followed a random walk, that they had an equal probability of going up as going down on a particular day independent of previous price changes. These findings suggest some form of market efficiency. Which is that the market prices incorporate currently available information (Bodie & Kane, 2021). This became known as The Efficient Market Hypothesis (EMH).

The literature regarding how movement in stock prices relates to information sources such as news has in previous years seen limited success in proving the relationship, especially since Roll's (1988) paper, where he found little to no relation between stock prices and news. In later years, with the improvement in textual processing, a larger number of news articles have been able to be analyzed and taken into account by researchers. Huang, Simpson, Ulybina, and Roitman (2019) constructed 10 news sentiment indices for 20 countries using the Financial Times's news articles and found that sentiment spiked or had an upward trend ahead of financial crises. Boudoukh, Feldman, Kogan, and Richardsson (2012) found that where news information can be identified with a tone (positive or negative) there is a link between the movement in stock prices and the information indicating a relationship. Chakravarty (2001) argued that institutional investors hold more information than retail investors and thus can make more informed investment decisions.

Several papers have evaluated consumer confidence and its relationship with other factors. Among them is a study where Fisher and Statman (2002) found that variations in consumer confidence have predictive power in stock return fluctuations. Showing its potential as a leading economic indicator. Lemmon and Portniaguina (2006) also found a relationship between consumer confidence and stock performance. However, they saw that the relationship was more significant when looking at small-cap stocks and other stocks with a small institutional ownership. These papers argue that consumer confidence significantly reflects overall economic health. However, there is still uncertainty around its relationship to stock performance and whether it's endogenous or exogenous. Consumer confidence indicates future households' consumption and savings which is why it's important to understand how consumption possibilities affect investors' willingness to take on more risk (OECD n.d). The Consumption Capital Asset Pricing Model (CCAPM) builds on the previously stated CAPM but also considers the investor's consumption possibilities. An investor has to balance current consumption, against investments that will yield increased future consumption. By optimizing these allocations, the consumer will find an equilibrium where the utility of consumption today, equals the utility value of the expected future consumption of the same amount. The asset's perceived risk is dependent on the investor's consumption possibilities of the investor. In a scenario where consumption possibilities are lower, investors will value additional income higher than in situations where the consumption possibilities are higher, in other words, the marginal return for additional income is diminishing for higher consumption possibilities. The CCAPM takes this into account. The expected return is thus dependent on the covariance between the consumption growth of the individual and the variance of the asset. Equilibrium risk premiums will thus be higher for assets that exhibit a positive covariance with consumption growth (Bodie et al., 2021).

Schwert (1989) discussed a theory that the stock market discounts expected future events into the current stock market prices. As a result, fluctuations that are seen in stock market returns can be interpreted as uncertainties revolving around future cash flows and the rates at which these cash flows are discounted. Furthermore, this uncertainty could extend into the factors that generate these future cash flows and discount rates. This outlook could therefore be interpreted as movements in stock prices act as an indicator of growing uncertainty about the future trajectory of the economy (Schwert, 1989). This perceived risk spills over into the real economy which can be seen in macroeconomic variables such as the money supply, consumer spending, and investments. In the context of rational expectations and efficient markets, this implies that changes in stock market volatility over time provide valuable insight into future macroeconomic trends (Schwert, 1989).

Fama (1986) showed the relationship between term- and default premiums, and business cycles where default premiums decrease with maturity and rise during recession, and term premiums rise during stable economic conditions and exhibit 'humps' during recessions.

Gilchrist and Zakrajsek (2011) explored the relationship between credit spreads and economic activity. They did this partly through a new index called the Excess Bond Premium (EBP). Gilchrist, Wei, Yue, and Zakrajsek (2021) argued that the EBP is crucial in understanding when crises occur. It was observed that during the 2007-2009 financial crisis as well as the COVID-19 pandemic, the alternative short-term EBP measure increased dramatically. Gilchrist and Zakrajsek (2011) observed that in various crises, there is an early rise in the EBP, suggesting it is a reflection of increased perceived risk in the corporate bond market. They demonstrated a connection between the EBP and the risk-bearing capacity of the financial sector. This relationship implies that fluctuations in the EBP indicate changes in credit supply, which subsequently has an impact on the macroeconomy.

The negative correlation between inflation and stock returns has been discussed extensively in research (Lintner, 1975; Bodie, 1976; Fama & Schwert, 1977; Jaffe & Mandelker, 1976; Nelson, 1976; Fama, 1981; Pindyck, 1984) as it contradicts Fisher's (1930) hypothesis. Which states that nominal asset returns should move with expected inflation, for real stock returns to be determined by real factors independently of the rate of inflation. Boucher's (2006) findings revealed the expected inflation's role in predicting stock market fluctuations and that it is a key factor in financial forecasting and risk assessment.

3. Method

3.1 Indicators

12 variables have been chosen for three categories based on previous literature and theory, with a monthly time-series data sample over the period 1990M1 to 2022M12 (Table 1). Additionally, a shorter time period with daily frequency is used for the estimation of Bitcoin to USD crises due to data availability, here only four indicators have data on a daily frequency (Table 1). Furthermore, as noted in Table 1, two indicators – the Twitter-derived uncertainty index, and the State Street investor confidence index –have shorter periods.

For the financial indicators, we evaluated the CBOE Volatility Index VIX, the Excess Bond Premium (Gilchrist & Zakrajsek, 2011), and the Risk Aversion Index (Bekaert, Engstrom, & Xu, 2021). Concerning sentiment indicators, we analyse the Twitter-based Uncertainty Index (Baker, Bloom, Davis & Renault, 2021), the Consumer Confidence Index, and the State Street Investor Confidence Index. For macroeconomic indicators, we focus on changes in the monetary base, the spread between ten-year and three-month as well as ten-year and two-year bonds, and inflation expectations at one- and ten-year horizons. This paper uses a data sample over the period 1990M1 to 2022M12, tho the data availability over the period differs between the indicators. The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is a risk indicator derived from the option prices of the S&P 500, that measures the market's expectations for volatility over the next 30 days, or in simpler terms, the indicator looks at implied volatility. A high volatility in option prices for the underlying security indicates that the agents are uncertain of what the present value of future cash flow is, thus indicating an uncertainty of the future (Schwert, 1989). The VIX can therefore act as a proxy for expected future risks.

The Risk Aversion Index (BEX) developed by Bekaert, Engstrom, and Xu (2021) is constructed using a dynamic no-arbitrage asset pricing model. This model accounts for time variation in risk aversion as well as economic uncertainty. The Risk Aversion Index also includes a detrended earnings yield, corporate return spread (Baa-Aaa), term spread (10yr-3mth), equity return realized variance, corporate bond return realized variance, and equity risk-neutral variance. It uses a utility function that is defined over both consumption and a potential "non-fundamental" factor. As the Risk Aversion Index integrates several different economic factors into the model, it creates a dynamic measure of risk aversion, which gives a better understanding of market sentiment and behavior.

The Excess Bond Premium (EBP) is a component of a corporate bond credit spread that is not directly associated with the default risk of the company and thus shows the effective measure of investors' sentiment and risk appetite (Gilchrist & Zakrajsek, 2011). The EBP could be an important financial indicator to predict the probability that the US economy will enter a recession in the next 12 months, as stated by Favara, Gilchrist, Lewis, and Zakrajsek (2016). Gilchrist and Zakrajsek (2011) found that an increase in the EBP of 100 basis points in a quarter, led to a drop in real GDP growth by more than 1.5% over the next four quarters.

The Federal Reserve of San Francisco Daily News Sentiment Index (SANFRAN) is a high-frequency measure of economic sentiment based on a lexical analysis of economics-related news articles developed by Shapiro, Sudhof, and Wilson (2020). It constructs a sentiment score from 24 major U.S. newspapers, identifying article topics. It aggregates the individual article scores into a time-series measure of news sentiment.

The Twitter Economic Uncertainty Index (TWITTER) was developed by Baker et al. (2021) and also uses lexical analysis on tweets that contain keywords related to uncertainty and the economy isolated to those that originate from users in the United States. Furthermore, each tweet is weighted by:

$$1 + log(1 + n\, of\, retweets) \tag{1}$$

The Investor Confidence Index (ICI) developed by State Street is a sentiment index that measures confidence directly and quantitatively by assessing the changes in investor holdings of equities. It can be seen that institutional investors are willing to devote more of their portfolio toward equities, the greater their risk appetite or confidence is.

The Consumer Confidence Index (CCI) is a statistical measure that considers the underlying economic health as well as the sentiment of optimism or pessimism that consumers exhibit through their level of spending and saving. Fisher et al. (2002) found that consumer confidence is significant in understanding economic behavior and consumers' influence on stock market trends. Research using survey-based indices of consumer sentiment from the Conference Board and the University of Michigan has previously been shown to have predictive power to forecast macroeconomic outcomes (Souleles 2004; Carrol, Fuhrer, & Wilcox 1994; Bram & Ludvigson 1998).

The Monetary Base (M0) is a measure of the money supply, defined by the Federal Reserve (FED, 2015) as the total currency in circulation as well as reserves held by banks in their accounts at the central bank (FED). Friedman and Schwartz (1963) argued that the money supply provides significant information about the short-term trend of the economy and helps dictate the price levels and inflation in the long run. There are arguments suggesting that the effectiveness of the monetary base (M0) as an economic indicator has diminished over time, leading to a decrease in its statistical significance. However, it remains a relevant variable, particularly when used in conjunction with other variables in economic analyses (FED, 2015).

10-year-3-month and the 10–year-2-year Treasury spread is the difference between the ten-year treasury constant maturity bond and the three-month or two-year treasury constant maturity bond. The short-term bond spread has shown to be a good indicator for recessions, where the long-term rates have fallen beneath short-term rates before recessions (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Harvey, 1988).

Inflation expectation is an important macroeconomic indicator that represents the expected rate of inflation over a certain period in the future. Its relevance stems from the fact that it can influence investor behavior as well as the market’s dynamics. Boucher (2006) found that expected inflation is linked to stock returns, which had a negative relationship with each other in general. We decided to use both the 1-year and 10-year expected inflation. The 1-year expected inflation was chosen to catch short-term fluctuations of expectations, such as policy changes, shocks, and other short-term events in the economy. The 10-year expected inflation is important to understand the long-term trend of the economy’s expectations. Changes in the 10-year expected inflation might suggest that the market’s confidence in the central bank’s ability to maintain price stability is shifting.

Table 1: Indicators

Series	Description	Frequency
	Financial Indicators	
VIX	CBOE Volatility Index	Monthly / Daily
BEX	Bekaert, Engstrom and Xu Risk Aversion Index (2021)	Monthly / Daily
EBP	Excess Bond Premium	Monthly
	Sentiment Indicators	
SANFRAN	San Francisco Federal Reserve News Sentiment Index	Monthly / Daily
TWITTER	Twitter Uncertainty index** (2021)	Monthly / Daily
ICI	State Street Investor Confidence Index*	Monthly
CCI	Consumer Confidence Index	Monthly
	Macroeconomic Indicators	
M0	Monetary Base	Monthly
T10Y3M	10-year-3-month Treasury spread	Monthly
T10Y2Y	10-year-2-year Treasury spread	Monthly
IE1	Inflation Expectations 1-year	Monthly
IE10	Inflation Expectations 10-year	Monthly

* Data available from 1998M10 ** Data available from 2011M1. Data sources: see Appendix 1

3.2 Data Transformation and Cross-Correlation

As previously noted, two indicators, the Twitter-derived uncertainty index, and the State Street investor confidence index have shorter periods. For these indicators, the testing period is shortened to their respective time periods, which results in a smaller data sample. This could create limitations in the analysis of these indicators as potential biases could arise. Such as non-representative sample bias, where these two indicators could miss out on significant economic events, leading to the resulting analysis not being representative of how these indicators usually behave. The monetary base indicator is calculated as the percentage change in the monetary base from the previous month. The models constructed all use monthly data except the Bitcoin model, where instead daily data is used. This results in the Bitcoin model only containing four indicators which has data on a daily frequency (Table 1)

In the cross-correlation matrix (Table 2), 6 out of 45 correlations were found to be non-significant. The T10Y2Y and T10Y3M, as well as the ONEYIE and TENYIE variables, exhibit a strong positive correlation. This is most likely due to overlapping market factors. This is also seen between variables within the sentiment and financial indicator category (Table 1). A notably strong negative correlation exists between TENYEI and MB. CCI and SANFRAN show a moderately strong positive correlation, possibly indicating similar market sentiment. Interestingly, both sets of bond spreads and inflation expectations appear relatively uncorrelated with each other and with the rest of the variables, implying they capture unique economic factors. The correlation between VIX and EBP is moderate. However, the VIX and the BEX have a very strong positive relationship along with the EBP and the BEX being strongly correlated with each other. This could indicate that they contain similar economic factors. We have to consider that high correlation coefficients, especially strong positive correlations, could be signs of multicollinearity, which would need to be considered in multivariate analysis.

Table 2: Cross-correlations of indicators

	SANFRAN	T10Y3M	T10Y2Y	EBP	ONEYEI	TENYEI	VIX	MB	CCI	BEX
SANFRAN	1	-0.18***	-0.29***	-0.45***	0.30***	0.34***	-0.52***	-0.28***	0.68***	-0.54***
T10Y3M		1	0.92***	0.11**	-0.15***	-0.015	0.0088	-0.10**	-0.36***	0.10***
T10Y2Y			1	0.14***	-0.36***	-0.25***	0.047	0.0044	-0.44***	0.16***
EBP				1	-0.14***	-0.018	0.61***	-0.15***	-0.27***	0.71***
ONEYEI					1	0.88***	-0.16***	-0.51***	0.21***	-0.33***
TENYEI						1	-0.13***	-0.74***	0.34***	-0.26***
VIX							1	0.016	-0.30***	0.91***
MB								1	-0.33***	0.060*
CCI									1	-0.40***
BEX										1

Significantly different from zero at the * 90%, ** 95%, ***99% confidence levels.
n.b.: The cross-correlation matrix focuses on the variables within the same time frame. Two indicators (TWITTER and ICI) are not displayed in the matrix.

3.3 Definition of a Crises

In our study, we categorize three distinct types of crises: stock market crashes, Bitcoin crashes, and recessions. Each type of crisis corresponds to one of our selected dependent variables: the S&P 500 index, Bitcoin, and recessions. Recognizing that each of these variables possesses unique characteristics and behaviors. We employ two specialized methods for identifying their respective crisis periods. The first approach employs a generalized identification for the S&P 500 and Bitcoin, which both represent volatile financial markets. The second approach is tailored for identifying recessions.

There are a plethora of definitions regarding crisis definitions in previous literature. However, the overarching idea when identifying crashes is to take into account the three parameters as identified by Mishkin and White (2002): (1) the speed of the decline; (2) the duration and; (3) the depth. Often the depth of the crises is the parameter given the most weight in definitions, like Miskin and White (2002) who identify market crises as a broad drop in asset prices below 20%, and Cambridge Associates (2019) identified a lower threshold of 15% to capture large changes in market behavior. In comparison, Tan and Tuluca (2021) used a pre-defined crisis period based on consensus from previous literature. In contrast, we will follow Patel and Sarkar (1998) who developed an approach to identify market crashes using the CMAX. By employing this definition we can take a more generalized approach without relying on arbitrary set crisis thresholds and duration, and thus find periods that significantly deviate from the regular movement of the market.

To identify periods with a significant decline in asset prices, using the CMAX index approach, we detected extreme prices in a defined period. By dividing the current price P_t, by the maximum price over the defined period P_{t-k} to get the CMAX value $CMAX_t$. The index can take all values between 0 and 1, where if $P_t = max(P_t, \ldots, P_{t-k})$ then CMAX is equal to 1 and converges to zero as prices P_t fall. To identify a crash, the CMAX has to fall below a predefined threshold set as the mean of all CMAX minus two times the standard deviation (Patel & Sarkar, 1998).

$$CMAX_t = \frac{P_t}{max(P_t, \ldots, P_{t-k})} \qquad (2)$$

Bussiere and Fratzcher (2002) stated the problem of either identifying the presence of a crash in a defined period, or the exact timing of a crash and found that the possibility of identifying when a crash is going to occur is a highly ambitious task with a low probability of success. Equally valuable is knowing if a crisis is going to occur in a defined period.

Choosing the span of the horizon encounters further problems as there exists a trade-off between the length and the reliability of the model which in turn is dependent on the frequency of the data. Additionally, as stated by Bussiere and Fratzscher (2002), from a policy-maker's perspective, it is more desirable to have an as early indicator as possible to take preemptive measures. To account for these parameters, we have chosen two time periods: 24 days for the higher volatility data (Bitcoin), and 6 months for the lower frequency data (S&P 500) (Equations 3 and 4)[1].

$$CMAX_t^{Bitcoin} = \frac{P_t}{max(P_t, \ldots, P_{t-24})} \tag{3}$$

$$CMAX_t^{Stock} = \frac{P_t}{max(P_t, \ldots, P_{t-6})} \tag{4}$$

Using the defined threshold and time period, we retrieve the indicators C_t^k:

$$C_t^k = 1 \; if \; CMAX_t^k < \overline{CMAX_t^k} - 2\sigma_t \tag{5}$$

$$C_t^k = 0 \; otherwise$$

The concept of a recession has somewhat competing definitions. One that is often stated is "a decline in the seasonally and calendar adjusted real gross domestic product (GDP) in at least two successive quarters" as defined by Shiskin (1974). Alternatively, the National Bureau of Economic Research (NBER), which is responsible for dating recessions, defines them as "... a significant decline in economic activity that is spread across the economy and lasts more than a few months. " (National Bureau of Economic Research, n.d.). In our analysis, we have chosen to base our study on the US recession periods documented by the National Bureau of Economic Research (Appendix 1) as done by Estrella and Mishkin

1 See Appendix 3 for a visual representation of the CMAX

(1998). This was made to ensure that our analysis aligns with recognized economic assessments, thereby enhancing the credibility and relevance of our findings.

3.4 Dependent Variable Definition

Using the crisis defined above, we construct three indicators Y_t^{Stock}, $Y_t^{Bitcoin}$, $Y_t^{Recession}$. To capture the movement of the independent variables in the leadup to the crash, as well as to consider if a crisis is going to occur in the coming twelve months, the Y_t^{Stock} and $Y_t^{Recession}$ indicators equal 1 for the crisis period and the twelve months preceding, and 0 for all other periods (as done by Coudert & Gex (2008); Estrella & Mishkin (1998)). For the $Y_t^{Bitcoin}$ indicator, as the bitcoin data is highly volatile, on a daily frequency, and has a short data period, we chose to have no leading dummy variable (Equation 7).

$$Y_t^{Stock} = \quad 1\ if\ \exists\ k = 1,\ldots,12\ s.t.\ C_t^{Stock} = 1 \tag{6}$$
$$Y_t^{Stock} = \quad 0\ otherwise$$

$$Y_t^{Bitcoin} = \quad 1\ if\ \exists\ C_t^{Bitcoin} = 1 \tag{7}$$
$$Y_t^{Bitcoin} = \quad 0\ otherwise$$

$$Y_t^{Recession} = \quad 1\ if\ \exists\ Date_k \ni\ NBER\ recession\ date\ s.t.\ t \in [Date_k - 12\ months] \tag{8}$$
$$Y_t^{Recession} = \quad 0\ otherwise$$

Additionally, to account for the post-crisis bias in the stock market indicator, another indicator J_t is defined where the 11 months after a crisis period are excluded from the sample, which is consistent with the methodology used by Coudert & Gex (2008) and Demirguc-Kunt & Detragiache (1998), who argue that by excluding this third distinction, the model leaves out the movement of the indicator in the period following a crisis, thereby avoiding the potential interference with the estimation of calm and crisis periods.

$$(1) \qquad J_t^{Stock} = \quad 1\ if\ \exists\ k = 1,\ldots,12\ s.t.\ C_t^{Stock} = 1 \tag{9}$$
$$(2) \qquad J_t^{Stock} = \quad NA\ if\ \exists\ k = 1,\ldots,11\ s.t.\ C_t^{Stock} = 1$$
$$(3) \qquad J_t^{Stock} = \quad 0\ otherwise$$

3.5 The Models Used

Using the indicator definition above, stating a simple linear relationship of the model:

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{10}$$

where y is the dependent variable, x_k the independent variables, the β_k represents the coefficients of the independent variables, α the intercept, and the ε the error term, the expected value of the indicator will be equal to one due to our dependent variable being categorical:

$$E(Y) = Pr(Y = 0) \cdot 0 + Pr(Y = 1) \cdot 1 = Pr(Y = 1) \tag{11}$$

Thus, the linear regression will no longer be the best linear unbiased estimator (BLUE). The model violates the Gauss-Markov assumptions of homoskedasticity as the error terms are not constant, additionally, the error terms will not be normally distributed, furthermore, the model is non-linear in parameters as the dependent variable binary. Hence, we opted to use a discrete-dependent-variable approach utilizing a logistic regression model to evaluate the predictability of the independent variables, similar to previous literature (Frankel & Rose, 1996; Eichengreen, Rose & Wyplosz, 1995; Berg & Pattillo, 1999). Choosing the transformation to a logit-model enables us to express the dependent variable's log odds – the natural logarithm of the odds – as a linear function of the independent variables. The indicator value 0 is the reference category in the logit-model, as the regression calculates the log-odds of being in one category compared to the reference category given a unit change in the independent variable which gives the beta value.

To evaluate the performance of the indicators, we test them separately in univariate regressions, as well as jointly in a multivariate regression. By reason, we carried out two estimations in turn: First, we estimated the model for all binary dependent variables Y_t:

$$Pr(Y_t = 0) = \frac{1}{1+e^{\left(\beta_0+\beta_1 X_t\right)}} \tag{12}$$

$$Pr(Y_t = 1) = \frac{e^{\left(\beta_0+\beta_1 X_t\right)}}{1+e^{\left(\beta_0+\beta_1 X_t\right)}}$$

Where X_t is the value of the predictor variable at time *t,* β_1 is the intercept term for category 1 when compared to the reference category 0, and β_1 is the coefficients for the predictor X_t associated with the outcome 1, again relative to the reference category 0. Secondly, we evaluated the indicators in a multivariate logit model, for all binary dependent variables Y_t:

$$Pr(Y_t = 0) = \frac{1}{1+e^{\left(\beta_0 + \sum_{k=1}^{n} \beta_k X_t^k\right)}} \tag{13}$$

$$Pr(Y_t = 1) = \frac{e^{\left(\beta_0 + \sum_{k=1}^{n} \beta_k X_t^k\right)}}{1+e^{\left(\beta_0 + \sum_{k=1}^{n} \beta_k X_t^k\right)}}$$

Where β_k is the intercept term for category 1 when compared to the reference category 0 for predictor variable X^k_t at time *t*.

3.6 Assessing Regression Quality

To test if the relationship between the dependent and independent variables is significant we use the Wald test to test the hypothesis:

$$H_0: \beta_1 = 0 \ versus \ H_1: \beta_1 \neq 0 \tag{14}$$

The test statistics for the Wald test are calculated by dividing the maximum likelihood estimation (MLE) of the slope parameter $(\widehat{\beta_1})$ by the estimates of the standard error, $se(\widehat{\beta_1})$. Under the null hypothesis, this follows the standard normal distribution (Forthofer, Lee & Hernandez, 2007).

$$\frac{\widehat{\beta_1}}{se\,\widehat{\beta_1}} = test\ statistic \tag{15}$$

The produced test statistic is used to calculate the p-value which will indicate a significance level.

$$p\ value = [2 \cdot Prob(Z > test\ statistic)] \tag{16}$$

The fit of the model is evaluated with the pseudo R^2 developed by McFadden (1979 cited in Giselmar, Schons, Wieseke & Schimmelpfenning, 2018). Contrary to the OLS R^2, the R^2_{McF} does not represent the proportion of explained variance of the model but rather the increased log-likelihood compared to the null model. The maximum log-likelihood of the model estimation (LL_M) is divided by the maximum likelihood of the null model (LL_0) containing only the regression intercept (Giselmar et al. 2018).

$$R^2_{McF} = 1 - \frac{LL(L_M)}{LL(L_0)} \tag{17}$$

McFadden (1979 cited in Giselmar et al., 2018, p.511) recommends that values between 0.2 and 0.4 indicate a good fit, and values above 0.4 indicate an excellent fit.

To assess the predictive power of the indicators and evaluate their performance, we test if the model can identify a crisis period utilizing an in-sample estimation confusion matrix. The matrix contains rows that represent the instances of the actual classes or the true values of the indicators, and each column represents the instances of predicted classes, the predicted indicator value based on the independent variables. It thus makes it possible to evaluate to what extent the model predicts a calm-, crisis- or post-crisis period. The matrix plots each observed value – 0 or 1 – against the actual values.

To evaluate if a crisis has been detected, a threshold must be set to where above the threshold, a crisis is predicted by the model, indicating that a crisis is pending. The problem with identifying an optimal threshold is that a low threshold will signal a large number of crises, and thus also a large number of observations where a crisis didn't occur (Type 2 error). A high threshold will have the inverse effect with a lower number of crises signaled, at the cost of not identifying actual crises (Type 1-error). Bussiere and Fratzscher (2002), Coudert and Gex (2008), and Berg and Pattillo (1999) all discussed this trade-off problem of choosing an optimal threshold. Berg and Pattillo (1999) discussed the problem of indicators carrying different optimal thresholds and thus finding an optimal threshold that works for all may be most effective. Similarly to Bussiere and Fratzscher (2002) as well as Coudert and Gex (2008), we will use a 20% threshold to test the goodness of fit.

We calculate four different values for predictions: True Positive (TP) if predicted is equal to one and the actual value is equal to one; True Negative (TN) if predicted is equal to zero and the actual value is equal to zero; False Positive (FP) if predicted is equal to one and the actual value is equal to zero; and False Negative (FN) if predicted is equal to zero and the actual value is equal to one. We evaluate the predictability of the models using three values: "percentage of correctly predicted crises" (Equation 18) which is calculated as the number of correctly predicted crises divided by the total crises observations; "false alarm" (Equation 19), which is calculated as the number of wrongly predicted crises divided by the number of crises predicted; and accuracy (Equation 20), which is the number of correctly predicted crises and calm periods, divided by the total number of observations.

$$Percentage\ of\ correctly\ predicted\ crises\ = \frac{TP}{(TP+FN)} \tag{18}$$

$$False\ alarms\ = \frac{FN}{(TP+FP)} \tag{19}$$

$$Accuracy\ = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{20}$$

To assess the efficacy of the indicators, each was initially evaluated independently against the two stock market dependent variables Y_t^{Stock} and J_t^{Stock} using univariate regression models. These two models will henceforth called Model 1 for Y_t^{Stock}, and Model 2 for J_t^{Stock}, using a misnomer. This evaluation, based on the Wald test, identified indicators significant at either the 1% level. Indicators failing to meet this significance criteria were subsequently excluded from the model. For Model 1, the remaining variables were examined collectively in all conceivable combinations and similarly, for Model 2, using multivariate regressions, testing each combination to determine the variables with the strongest predictive ability.

However, the inherent high correlation among the indicators precluded a straightforward multivariate regression analysis due to the presence of potential multicollinearity, which impedes the isolation of individual independent variable effects. To address this, we employed an in-sample estimation confusion matrix to evaluate the indicators, allowing for an analysis of multivariate regressions without the complications arising from multicollinearity, as this technique does not require differentiating between the indicators.

As an extension of this thesis, we tested if the variables with the highest predictive power from the multivariate regression were able to confidently predict other types of financial crises, in this case, U.S. recessions and Bitcoin to USD prices. To account for multicollinearity, the same approach of a confusion matrix prediction was employed, yielding an accuracy-, predictive power-, and false alarm percentage. Furthermore, to be able to further evaluate the variable's behavior, univariate regressions were run for each independent variable from both models 1 and 2 with the dependent variable $Y_t^{Recession}$. Only indicators with daily frequency are tested against the dependent variable $Y_t^{Bitcoin}$.

4 Results

4.1 Univariate Regression

As presented in Table 3, the indicators SANFRAN, EBP, VIX, BEX, and T10Y3M are significant at the 1% level. Consequently, excluding the indicators T10Y2Y, ONEYEI, TENYEI, MB, CCI, TWITTER, and ICI according to our criteria.

The negative coefficient of the SANFRAN shows that an increase in the SANFRAN leads to a decreased likelihood of the S&P 500 being in a crisis. This implies that sentiment in news information is correlated with the financial markets as shown by Boudoukh et al. (2012) which underscores the Efficient Market Hypothesis, that all available information is priced into assets. Our results further confirm Huang's et al. (2019) findings that news sentiment trends show predictive power prior to financial crises.

The positive coefficient of the EBP indicates that an increase in the EBP results in an increased likelihood of the stock market being in a crisis. As Gilchrist and Zakrajsek (2011) noted, an increase in the EBP reflects a reduction in the risk-bearing capacity of the financial sector. Previous literature (Favara et al., 2016) found that the EBP had an important role when predicting recessions. Our findings imply that it also has predictive power concerning the S&P 500.

The VIX and BEX had similar results, likely due to the strong correlation between the two risk aversion indicators. These results suggest that investors' expectations of near-term volatility, which originates from the assessment of future risks are influential in the likelihood of the S&P 500 entering a crisis. Underscoring the theory of CAPM, that all investors demand compensation for taking on more risk (Sharpe, 1964). This along with the findings by Danielsson et al. (2016) showed that volatility extremes are a significant predictor of a crisis. Further confirming Minsky's (1992) instability hypothesis which suggested that periods of low volatility can lead to an increased risk appetite among investors, potentially creating the beginnings of a crisis environment.

The T10Y3M had a negative coefficient, indicating that an increase in the bond spread is associated with a decreased likelihood of the S&P 500 being in a crisis. In other words, a widening bond spread signifies a potential increase in investor confidence/risk appetite as they are willing to invest in more long-term securities in expectation of higher returns. Estrella & Mishkin (1998) found that the T10Y3M bond spread can explain future economic activity. Our findings suggest that the T10Y3M bond spread also has predictive power when it comes to the S&P 500.

Table 3: Log estimates 12 month dummy

	Estimation period: 1990/01-2022/12										2011/06	1998/10
	Number of observations = 395										139	302
	SANFRAN	T10Y3M	T10Y2Y	EBP	ONEYEI	TENYEI	VIX	MB	CCI	BEX	TWITTER	ICI
Constant	-1.0029***	-0.6063**	-0.8107***	-1.1823***	-0.9006**	-0.2729	-3.6670***	-1.1074***	8.0486	-5.6550***	-1.9083***	-0.3233
Indicator coefficient	-0.0299***	-0.0027**	-0.0022	0.0156***	-0.0599	-0.3218	0.1262***	0.0007*	-0.0908	1.5203***	0.0046*	-0.0055
Log likelihood	-214.6970	-223.1172	-225.3430	-197.4611	-226.5708	-224.7625	-195.7574	-224.5826	-226.1679	-398.5064	-134.0670	-174.671
Pseudo R^2_{McF}	0.0528	0.0156	0.0059	0.1288	0.0044	0.0084	0.1363	0.0092	0.0022	0.1209	0.0400	0.0011
Correctly predicted crises	77,67%	82,52%	95,15%	64,08%	100,00%	100,00%	78,64%	96,12%	100,00%	81,55%	14,29%	98,81%
False alarm	68,99%	73,77%	74,55%	67,16%	73,92%	71,07%	59,09%	74,22%	73,92%	57,58%	12,61%	100,00%
Accuracy	49,11%	34,94%	26,08%	56,46%	26,08%	35,95%	64,81%	26,84%	26,08%	66,33%	72,66%	28,52%

Significantly different from zero at the * 95%, ** 99%, ***99.9% confidence levels.

In Table 4 we find Model 2 with the 11 months post-crisis excluded. The significance of T10Y3M decreased to the 5 percentage level. Suggesting that T10Y3M's significance in Model 1 was partly explained by the post-crisis data. This has resulted in it falling below our criteria when choosing which independent variables to include in the multivariate regression for Model 2.

Both TENYEI and CCI were at a non-significant level in Model 1 (Table 3) but were significant at the 1 percent level in Model 2 (Table 4). Implying that the post-crisis period interfered with the prediction of the calm and crisis periods.

The TENYEI has a negative coefficient indicating that an increase in the indicator leads to a decrease in the likelihood of the S&P 500 being in a crisis. This is consistent with previous literature (Lintner, 1975; Bodie, 1976; Fama and Schwert, 1977; Jaffe & Mandelker, 1976; Nelson, 1976; Fama, 1981; Pindyck, 1984) that there is an inverse relationship between expected inflation and stock returns. Our findings are consistent with Boucher (2006), who underscored the predictive power of expected inflation on stock market fluctuations and asserted it as a key factor in financial forecasting.

Table 4: Log estimates 12 month dummy and 11 months post crisis

	Estimation period: 1990/01 - 2022/12										2011/06 - 2022/12	1998/10 - 2022/12
	Number of observations = 321										112	240
	SANFRAN	T10Y3M	T10Y2Y	EBP	ONEYEI	TENYEI	VIX	MB	CCI	BEX	TWITTER	ICI
Constant	-0.5012 ***	-0.3419	-0.5992**	-0.8380***	-0.4247	0.4378	-4.7013***	-0.8166***	27.3416**	-11.0777***	-2.7043***	-1.1466
Indicator coefficient	-0.0569***	-0.0026*	-0.0014	0.0196***	-0.1363	-0.4907**	0.2046***	0.0008*	-0.2802**	3.5602***	0.0176***	0.0069
Log likelihood	-171.8297	-198.5727	-200.9176	-167.7539	-201.0000	-197.7125	-151.7193	-199.2308	-197.5788	-149.8209	-53.5629	-153.5785
Pseudo R^2_{McF}	0.1469	0.0142	0.0026	0.1672	0.0022	0.0185	0.2468	0.0109	0.0191	0.2562	0.1495	0.0019
Correctly predicted crises	74,76%	82,52%	1,00%	64,08%	100,00%	96,12%	82,52%	96,12%	83,50%	81,55%	67,86%	100,00%
False alarm	45,87%	86,24%	100,00%	41,28%	99,54%	72,02%	26,15%	97,71%	94,04%	22,48%	21,43%	100,00%
Accuracy	49,37%	29,11%	26,08%	49,11%	26,33%	40,51%	62,28%	26,33%	25,06%	64,05%	61,67%	32,29%

Significantly different from zero at the * 95%, ** 99%, ***99.9% confidence levels.

The negative coefficient of the CCI shows that as consumer confidence increases, the likelihood of a market crash decreases. This is consistent with the results of Fisher et al. (2002) who showed the predictive power of consumer confidence in forecasting stock return fluctuations, and further affirms the theory of the CCAPM which shows the impact of consumer saving and consumption decisions on their investment behavior. Our findings further underscore that the CCI is a potential leading indicator in overall economic health.

The positive coefficient of TWITTER indicates that an increase in economic-related uncertainty on Twitter increases the likelihood of a crisis in the S&P 500. It is similar to SANFRAN as they are both constructed using a lexical analysis. Baker et al. (2021) found that TWITTER is a strong uncertainty indicator. Our findings suggest that it is also able to be used as a significant indicator in stock market analysis.

Overall, the exclusion of the post-crisis periods led to an improvement in the regression quality as both the McFadden pseudo R^2 and log-likelihood were better in Model 2 (Table 4) compared to Model 1 (Table 3). The SANFRAN, EBP, TENYEI, VIX, CCI, and BEX will be used in testing the best combination of independent variables in the multivariate regression. TWITTER was also highly significant but due to its smaller data sample, will be excluded in the multivariate regression.

4.2 Multivariate regression

Table 5: Accuracy Logit normal Model 1

Combination	Category	Value
SANFRAN, BEX, T10Y3M	Accuracy	74.94%
	Correctly predicted crisis	72.92%
	False alarm	24.41%

See Appendix 5 for top 3 combinations

Table 6: Accuracy Logit post-crisis Model 2

Combination	Category	Value
SANFRAN, VIX, CCI	Accuracy	65.32%
	Correctly predicted crises	89.32%
	False alarm	23.85%

See Appendix 5 for top 3 combinations

Taking into account the results from the univariate regression models, we perform multivariate regressions to evaluate the performance of the independent variables when compared to each other. For Model 1 (Table 5) the SANFRAN, BEX, and T10Y3M resulted in the highest accuracy out of all possible combinations. Each independent variable is from a separate category of indicators, implying that a combination of independent variables captures unique market factors, resulting in the strongest predictive power.

For Model 2 (Table 6) the SANFRAN, VIX, and CCI had the highest accuracy out of all possible combinations. While the CCI and SANFRAN are technically both in the sentiment category, the CCI is also a part of the macroeconomic category, once again showing the importance of unique independent variables.

When comparing the results, the accuracy was lower in Model 2 (Table 6). However, this could in part be explained by the fact that 11 months were removed for each crisis by the post-crisis criteria. This resulted in the model not being able to predict anything during these months, automatically lowering the accuracy. So while accuracy was 9.62% lower in Model 2 (Table 6), the correctly predicted crisis increased by 16.4% and false alarms decreased by 0.56%. Indicating that when the model accounts for the post-crisis bias, the predictive power in general increases. This is consistent with previous literature that found when the model accounts for the post-crisis period, the estimations and quality of the regression overall improve (Bussiere & Fratzscher, 2002; Coudert & Gex 2008).

Taking into account the results from the univariate and multivariate regression models, we can evaluate the overall performance of the independent variables.

The univariate regressions highlighted the significance of SANFRAN, T10Y3M, EBP, VIX, and BEX at the 1% level in Model 1 (Table 3) and SANFRAN, EBP, TENYEI, VIX, CCI, AND BEX at the 1% level in Model 2 (Table 4). Their coefficients suggested varied relationships with the likelihood of a crisis in the S&P 500.

The multivariate regression approach gives us a more nuanced understanding by considering their interactions with each other. The combination with the highest accuracy from Model 1 included SANFRAN, BEX, and T10Y3M (Table 5). While SANFRAN, VIX, and CCI had the strongest performance in Model 2 (Table 6), indicating the robustness of these indicators when combined.

In conclusion, while each indicator provides unique insights, the strongest predictive power for stock market crises emerges from a combination of market sentiment indicators (SANFRAN and CCI), risk appetite measures (VIX and BEX, EBP), and macroeconomic factors (T10Y3M). This shows that the indicators capture substantial downward movements in the S&P 500 while also giving a comprehensive view of market dynamics, such as investor sentiment, risk appetite, and overall economic outlook.

4.3 Recessions & Bitcoin

As an extension of the thesis we wanted to test if the best-performing indicator variables from the multivariate regression model not only had predictive power for stock market crashes but also for other types of economic downturns such as US recessions. Previous literature found evidence that when stock prices fall, stock volatility increases. However, it also increases during recessions and other types of major financial crises (Schwert, 1989). Finally, we also evaluate the variables on a daily frequency for Bitcoin as a more experimental part of this thesis. This is done to gather a more comprehensive view of the predictive power of the variables and their effectiveness and applicability on different asset classes.

4.3.1 Results for Recessions and Bitcoin

4.3.1.1 Recession

Using the same multivariate estimation approach testing each possible combination, the best one was still the SANFRAN, VIX, and CCI (Table 8), indicating that no one variable could incorporate the information of the other any more than of stock market crises. Furthermore, the accuracy of the predictions yielded a higher value than that of the stock market crises. Even when accounting for the decrease in correctly predicted recessions (27.12% less), the indicators had good performance with essentially the same false alarm rate (1.49% lower). The prediction result of the CCI by itself shows an absence of correctly predicted crises and false alarms, indicating that it only predicted calm periods for the whole estimation. Conversely, both the VIX and SANFRAN indicators show high numbers of crises correctly predicted. The prediction results of the combination, when compared to the individual estimation show a large increase in the proportion of correctly predicted crises, and an increase in accuracy, which shows that they capture different indications of a future recession.

Given that the Consumer Confidence Index (CCI) reflects expected future households' consumption and savings patterns, and considering that recessions are characterized by a decrease in economic activity, it would be logical to infer that the CCI could serve as a reliable indicator of recessions. The observed insignificance of the CCI coefficient (Table 7) and the absence of correctly predicted crises (Table 8) does however not show this relationship, indicating that consumers' confidence in the future economic environment may not accurately reflect eventual economic realities.

Table 7: Recession (12 month)

	Estimation period: 1990/01-2022/12		
	Number of observations = 395		
	SANFRAN	VIX	CCI
Intercept 1	-1.3284***	-3.2338***	-0.6871
Indicator 1	-0.0339***	0.0903***	-0.0065
Log likelihood	-188.3641	-184.9709	-201.7451
Pseudo R^{2*}	0.0663	0.0832	0.00001
Correctly predicted crises	47.56%	41.46%	0%
False alarm	23.32%	21.41%	0%
Accuracy	70.63%	70.89%	79.24%

* McFadden R^2 Significantly different from zero at the * 95%, ** 99%, ***99.9% confidence levels.

Table 8: Accuracy, US Recession (Model 2)

Combination	Category	Value
SANFRAN, VIX, CCI	Accuracy	74.43%
	Correctly predicted	62.20%
	False alarm	22.36%

The significance of the VIX coefficient, and the high percentage of correctly predicted crises confirms Schwert's (1989) conclusion that stock market volatility increases when agents are uncertain of future returns, as a recession would imply a changed in the economic environment. Furthermore, Huang's et al. (2019) findings that sentiment spiked or had an upward trend ahead of financial crises – with the significance of the SANFRAN coefficient, and high prediction rate– show that news sentiment of financial articles takes into account the general perceived risk agents hold. To conclude, the multivariate regression shows that the indicator that had the best performance for predicting stock market crises had significant predictive power on US recessions as well.

4.3.1.2 Bitcoin

Table 9: Bitcoin, daily

	Estimation period: 2014/01-2022/12			
	Number of observations = 3246			
	VIX	SANFRAN	BEX	TWITTER
Intercept 1	-4.5880 ***	-2.9616***	-4.6332***	-3.2145***
Indicator 1	0.0759***	0.0144**	0.5185***	0.0022***
Log likelihood	-399.5928	-639.5022	-399.7603	-625.4037
Pseudo R^{2*}	0.0788	0.0075	0.0626	0.0166
Correctly predicted crises	0%	10.19%	10.38%	5.56%
False alarm	0%	0.065%	00.28%	0.14%
Accuracy	95.04%	95.09%	95.48%	94.94%

* McFadden R^2 Significantly different from zero at the * 95%, ** 99%, ***99.9% confidence levels.

Table 10: Accuracy Bitcoin

Combination	Category	Value
SANFRAN, BEX	Accuracy	95.52%
	Correctly predicted	10.38%
	False alarm	0.24%

See Appendix 5 for top 3 combinations

Among the indicators assessed at a daily frequency—VIX, SANFRAN, BEX, and TWITTER— each demonstrated a significant correlation with exceptional downturns in the Bitcoin to USD exchange rate in univariate regression analyses (Table 9). Notably, the combination of SANFRAN and BEX achieved the highest accuracy (Table 10). The relatively low percentage of correctly predicted crises and false alarm rates, compared to previous estimates, might be attributed to the design of the indicator. Its construction results in fewer identified crash observations, as it does not specify a lead-up period. Consequently, even if the indicators predominantly identify non-crisis periods, the model's accuracy appears deceptively high. Additionally, this result may also suggest that the indicators have a poor predictive power on major downward movements of Bitcoin to USD prices.

5 Conclusion

Our thesis aimed to evaluate the twelve independent variables' performance in identifying types of financial crises. We evaluated their performance on the S&P 500 and as an extension of our thesis, US recessions and Bitcoin. The indicators used in the logistic regression models are important variables in their respective categories to be used as proxies of sentiment, risk appetite, and overall economic health. They give investors an understanding of the various market factors that are significant during economic downturns.

We found that the logit model that took into account the post-crisis bias as described by Bussiere & Fratzscher (2002) period had the best regression quality as the independent variables' fit as well as predictive power for the S&P 500 improved. The variables that had the highest predictive power were the combination of SANFRAN, VIX, and CCI in the multivariate regression. It resulted in an accuracy of 65.32%, with correctly predicted crises of 89.32% and false alarms only at 23.85%. These three variables proved to be significant when evaluating them for recessions, resulting in an accuracy of 74.43%, with correctly predicted crises at 62.20% and false alarms only at 22.36%, indicating that the variables are strong leading indicators for both types of crises and that sentiment, risk appetite, and consumer confidence are important measures when considering what causes crises. Underscoring the theory of an efficient market. If a market is truly efficient, then all information, no matter its relevance should be immediately priced in.

Furthermore, in our experimental exploration of Bitcoin, we found that all four indicators used were highly significant, albeit with different and relatively poor model fits. The variables that performed the best were SANFRAN and BEX where the accuracy was relatively high at 95.52%. However, the model was quite weak when taking into account the correctly predicted crisis measure at 10.38%. With Bitcoin being a finite asset without an intrinsic value attached, it could prove hard for markets to fairly price the asset, leading to disparities between our indicators and the price of Bitcoin. Resulting in poor performance when evaluating them in relation to Bitcoin.

These findings show that multiple factors, that take into account sentiment, risk aversion, and macroeconomic data, are significant in different types of crashes, perhaps indicating that risk aversion is something individuals carry with them in most economic decisions. Further underscoring the importance of incorporating a broad combination of indicators — capturing unique information — when assessing the risk of financial downturns. However, it is important to note that the findings in this thesis do not aim to disprove, nor prove the theoretical background, but instead add to the ongoing discussion of efficient markets and asset pricing.

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APPENDIX

Appendix 1: Sources for data

Table 11: Sources for data

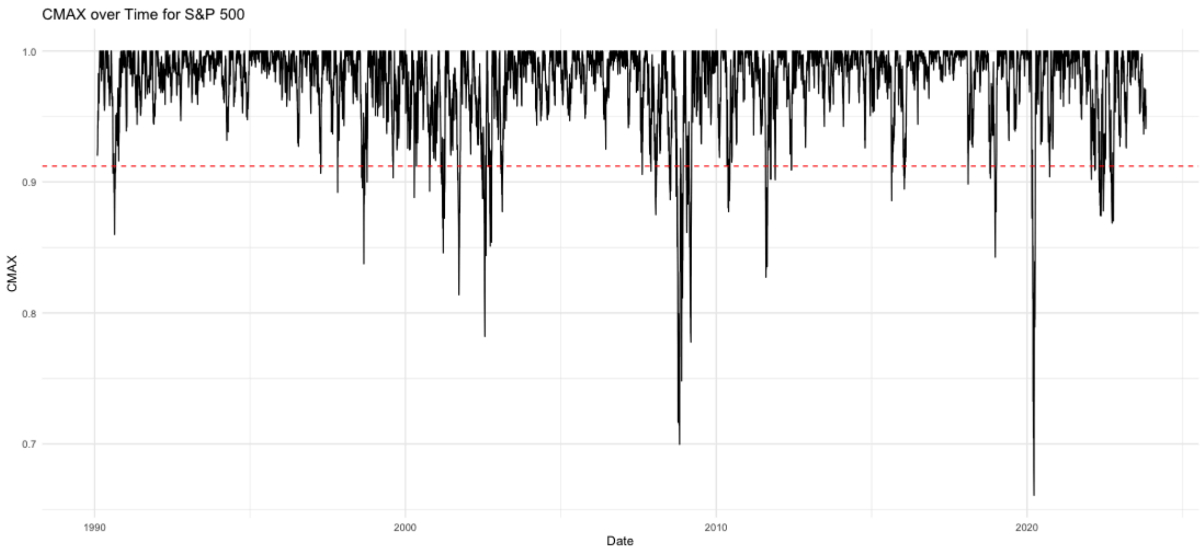
Data	Source
SANFRAN	Bloomberg terminal
ICI	Bloomberg terminal
TWITTER	https://www.policyuncertainty.com/twitter_uncert.html
VIX	Bloomberg terminal
BEX	Nancy Xu personal page https://www.nancyxu.net/risk-aversion-index
EBP	US Federal Reserve https://www.federalreserve.gov/econres/notes/feds-notes/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html
M0	St. Louis FED https://fred.stlouisfed.org/series/BOGMBASE
T10Y3M	St. Louis FED https://fred.stlouisfed.org/series/T10Y3M#0
T10Y2Y	Bloomberg terminal
CCI	OECD https://data.oecd.org/leadind/consumer-confidence-index-cci.htm
IE1	Cleveland FED https://www.clevelandfed.org/indicators-and-data/inflation-expectations
IE10	Cleveland FED https://www.clevelandfed.org/indicators-and-data/inflation-expectations
Recession	National Bureau of Economic Research https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions
Bitcoin	Yahoo Finance https://finance.yahoo.com/quote/BTC-USD/history/
S&P500	Yahoo Finance https://finance.yahoo.com/quote/%5EGSPC/history/

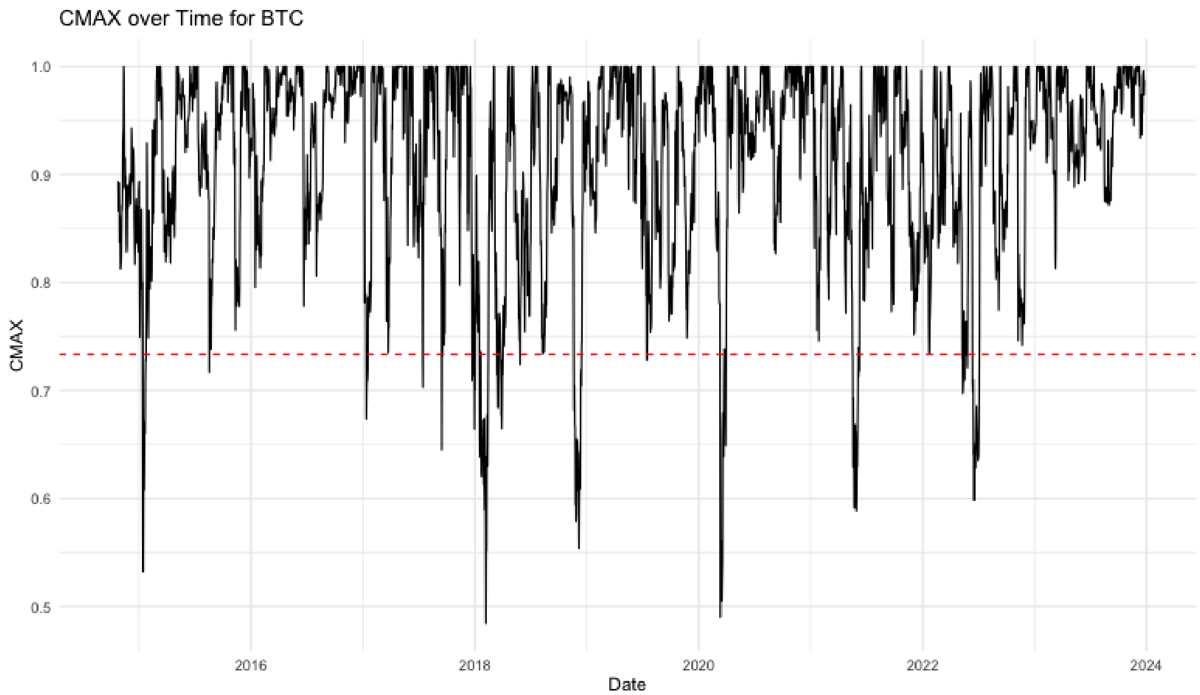
Appendix 2: Descriptive statistics for daily data

Table 12: Descriptive statistics (daily)

	Mean	Kurtosis	Skewness	Median	Min	Max	sd	n
SANFRAN	0.03	0.02	-0.51	0.05	-0.67	0.45	0.19	12183
VIX	19.59	8.21	2.15	17.71	9.14	82.69	7.96	12183
BEX	3.03	228.45	12.31	2.79	2.38	32.71	1.15	12183
TWITTER	104.49	26.92	3.98	73.77	0.00	1662.11	112.09	4202

Appendix 3: Visualization of CMAX





Appendix 4: Top three best performing iterations from multivariate regressions

Tabell 14: Accuracy Model 2

Combination	Category	Value
1. SANFRAN, VIX, CCI	Accuracy	65.32%
	Correctly predicted	89.32%
	False alarm	23.85%
2. SANFRAN, VIX, CCI, BEX	Accuracy	65.32%
	Correctly predicted	88.35%
	False alarm	23.39%
3. SANFRAN, VIX	Accuracy	64.81%
	Correctly predicted	89.32%
	False alarm	24.77%

Tabell 15: Accuracy Model 1

Combination	Category	Value
1. SANFRAN, BEX, T10Y3M	Accuracy	74.94%
	Correctly predicted	72.92%
	False alarm	24.41%
2. BEX, VIX, T10Y3M	Accuracy	72.91%
	Correctly predicted	64.58%
	False alarm	24.41%
3. BEX, EBP	Accuracy	72.66%
	Correctly predicted	54.17%
	False alarm	21.40%

Tabell 16: Accuracy Bitcoin		
Combination	Category	Value
4. SANFRAN, BEX	Accuracy	95.52%
	Correctly predicted	10.38%
	False alarm	0.24%
5. BEX	Accuracy	95.52%
	Correctly predicted	9.43%
	False alarm	0.19%
6. BEX, VIX	Accuracy	95.43%
	Correctly predicted	10.44%
	False alarm	0.33%

Appendix 5: Descriptive statistics of data

Table 17: Descriptive statistics

	Mean	Kurtosis	Skewness	Median	Min	Max	sd	n
SANFRAN	0.04	0.11	-0.55	0.05	-0.64	0.4	0.19	395
T10Y3M	1.66	-0.99	-0.02	1.60	-0.74	3.68	1.12	395
T10Y2Y	1.11	-1.17	0.17	1.06	-0.67	2.83	0.88	395
EBP	0.03	9.02	2.51	-0.12	-1.06	3.51	0.62	395
ONEYEI	0.02	0.28	0.08	0.02	0.00	0.05	0.01	395
TENYEI	0.02	-0.84	0.43	0.02	0.01	0.04	0.01	395
VIX	19.75	4.05	1.64	18.07	6.89	9.51	7.63	395
MB	0.78	34.80	4.61	0.53	-8.78	26.92	3.02	395
CCI	100.15	-0.01	-0.58	100.43	96.19	102.85	1.35	395
BEX	3.00	18.78	3.74	2.81	2.42	8.03	0.69	395
ICI	105.73	-0.56	-0.11	106.20	69.40	141.80	15.08	291
TWITTER	104.76	13.85	3.24	80.81	23.15	677.90	96.44	139