Economic policy uncertainty as an indicator of abrupt movements in the US stock market

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Abstract

A two regime switching model is developed in an attempt to relate expected US stock market returns to deviations from fundamentals and to Economic Policy Uncertainty (EPU). The analysis is based on monthly data that cover the period from January 1900 to October 2022 and the EPU index is used as an explanatory variable. The findings suggest that the US stock market spends most of the time in a low-volatility regime, periodically switching to a high-volatility regime during times of financial instability. In an attempt to examine the forecasting ability of the model, out-of-sample probabilities of a crash and a boom are estimated recursively. The results provide evidence that our model is able to depict periods of abrupt movements in the US stock market. Finally, the estimated model and the associated probability of a crash are used to develop and evaluate a proposed trading strategy, in order to analyse the financial usefulness of the model. A simple simulation reveals that our trading rule produces statistically significant abnormal returns and manages to outperform the simple buy-and-hold strategy for the period before the Covid-19 crisis.

Keywords: economic policy uncertainty; stock market; regime switching model

JEL classification: C32; C50; G10

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1 Introduction

The Global Financial Crisis of 2008, the Eurozone economic crisis, and the Covid-19 pandemic have brought about increased interest in economic uncertainty. The Economic Policy Uncertainty (hereafter EPU) index, introduced by Baker, Bloom, and Davis (hereafter BBD, 2016), has been the subject of a significant part of the literature recently. In this paper, we try to evaluate the possible use of the EPU index in forecasting stock market bubble crashes.[1] The innovation of our approach lays on the use of a regime-switching model in an attempt to relate policy uncertainty with stock market bubbles. Most of the research on EPU so far focuses on its relationship with macroeconomic variables, thus only a few studies examine its relationship with the stock market. Though it is not the first study on the impact of policy uncertainty on the US stock market, very few so far have tried to detect the forecasting ability of EPU on stock market returns and, to the best of our knowledge, this is the first paper that relates EPU to stock market bubble crashes. Specifically, we evaluate the ability of EPU to serve as an early-warning indicator of abrupt movements in the US stock market, in a regime-switching framework. Moreover, to investigate the ability of our model to help investors predict bubble crashes, we form a trading rule utilising our estimated model that uses the EPU index as an early-warning indicator; a subject that, to the best of our knowledge, has not yet been addressed by the literature.

We use monthly data for the US stock market and the US EPU index since 1900 and apply a two-regime switching model, where we identify the *survival* and the *collapse* regimes. The in-sample analysis shows that the EPU coefficient is statistically significant, both in the conditional mean equation and the probability equation. We, then, proceed with the out-of-sample analysis to examine the actual forecasting ability of the model. The model seems to predict some of the bubble crashes, but not all of them. Finally, we propose a trading rule, which informs the investor when to exit and when to enter the market. This trading rule produces statistically significant abnormal returns and manages to outperform the buy-and-hold strategy for the whole out-of-sample period up to the Covid-19 crisis.

The rest of the paper proceeds as follows. Section 2 provides a brief literature review, Section 3 presents the empirical analysis that includes information about the data (Subsection 3.1), the bubble measures and the regime-switching model used in our study (Subsection 3.2), the in-sample (Subsection 3.3) and the out-of-sample (Subsection 3.4) results, and finally our

[1] Throughout the study we use the term "bubble" to refer to deviations from fundamentals.

trading rule (Subsection 3.5). Several robustness tests are presented in Section 4. Finally, Section 5 concludes the paper.

2 Literature Review

Hamilton (1989) model stock market returns through the Markov switching technique and later van Norden and Schaller (1993), and Schaller and van Norden (1997) use two-state regime switching models to identify the relationship between stock market returns and bubbles, or deviations from fundamentals as they aptly call them. They assume two states: the state in which the bubble survives and the state in which the bubble collapses. In their approach, van Norden and Schaller (1993) extend the model of Blanchard and Watson (1982), by allowing the probability of each state to be a function of the bubble size. More specifically, they suppose that the probability falls as the size of the bubble grows. Additionally, they allow for partial collapses of a bubble. Van Norden and Schaller's (1993) results prove that bubbles help in indicating regime switches in the US stock market. Later, in 1997, they further extend the Markov switching approach by introducing a multivariate specification in a regime-switching model trying to predict stock market returns. Contrary to other studies that focus only on the bubble size, Schaller and van Norden enrich the specification by adding other macroeconomic variables to the model, and show that the predictive power of the model can be improved. In addition, they also allow the transition probability to be affected by other economic variables.

A further innovative approach is later proposed by Brooks and Katsaris (2005) who follow the steps of van Norden and Schaller applying regime-switching models. Brooks and Katsaris add a third regime, the *dormant* regime, in which the bubble continues to grow steadily, at the fundamental rate of return. They find that in the three-regime model framework, deviations from fundamentals have explanatory power over the stock returns. They also create trading rules in an attempt to enhance the financial usefulness of their analysis.

Relative research has been conducted not only on the stock market, but on other markets as well, like the commodities and the foreign exchange markets. Roche (2001) applies a regime-switching model to detect the presence of bubbles in the housing market of Dublin and the results show evidence of a bubble in house prices. Another representative example is a study that uses both the van Norden and Schaller and the Brooks and Katsaris models to examine the existence of bubbles in the oil market (Shi & Arora, 2012).[2] Panopoulou and Pantelidis' (2015b) research on oil price predictability shows that both two- and three-regime switching models offer better price predictability than the Random Walk model. The same authors conduct a similar analysis for the foreign exchange market, trying to identify deviations from fundamentals for the British pound to US dollar exchange rate (Panopoulou & Pantelidis, 2015a).

Regarding the relationship between the EPU index[3] and the stock market only a few studies have been conducted so far, as most of the research focuses on the relationship of the index with macroeconomic variables. Karnizova and Li (2014) use both in-sample and out-of-sample analysis to examine the forecasting ability of EPU and find out that by adding the EPU index into a model with other financial variables, the forecasting accuracy for recessions is improved. These findings are in line with the results of Liu and Zhang (2015). They aim to examine the predictive ability of the EPU index to the realised volatility of the stock market. The in-sample results show a positive effect of EPU on stock market volatility and the out-of-sample analysis concludes that EPU helps to predict the realised volatility of the stock market. One of the first papers to examine the effects of policy uncertainty on stock prices is by Arouri et al. (2016). They use a sample that covers a very long period (monthly data from 1900 to 2014). Using a three-state Markov-switching process they conclude that the EPU-stock market relationship is not linear, it differs among different states, and the impact of EPU on the stock market is stronger and more persistent in the high volatility state. Evidence of a negative impact of the EPU index on the stock market but also on credit ratings is found in Boumparis et al. (2017). More recently, He et al. (2020) have studied the asymmetric volatility spillovers between the EPU indices and the S&P500 index. After examining the EPU of 6 countries, they find that the volatility of the stock market is a net recipient of EPU spillovers. Moreover, Luo and Zhang (2020) find that an increase in EPU has a significant positive effect on the aggregated stock price crash risk. A specific part of the literature also focuses on the case of China, examining the impact of the EPU index on the variation of Chinese stock market returns (Chen et al., 2017; Xu et al., 2021).

[2] Another study that examines the effects of the EPU index on oil markets is Bampinas et al. (2023).

[3] The Economic Policy Uncertainty index was introduced by Baker, Bloom, and Davis (2016) as a measurement that quantifies uncertainty about economic policies. It is a newspaper-based indicator, that captures both short- and long-run uncertainty about who will apply the economic policy, what economic regulations will be made, what will the results of these policy actions be, etc.. It is constructed by searching the digital archives of 10 large US newspapers, for the number of articles referring to economic policy uncertainty published per month. This means, the number of articles that include at least one word from each of the following 3 categories: Economy, Policy, Uncertainty.

The relative research proves that there is a negative relationship between EPU and stock market returns, both in an in-sample and an out-of-sample analysis. A positive relationship between policy uncertainty and stock price bubbles is also proven by research focusing on China (Cheng et al., 2021). Finally, recent evidence from van Eyden et al. (2023) show that both investor sentiment as well as the EPU index impact significantly the positive bubble indicators, which signal an abrupt increase in the stock market before the crash of a bubble.

3 Empirical analysis

3.1 Data

Our dataset consists of monthly US data and covers a period of more than a century, from January 1900 to October 2022. The data for the US EPU index are from Baker, Bloom, and Davis (2016).[4] The path of the data series is shown in Figure 1 and it can be seen that the EPU mean value and volatility increased during the Great Depression (1930) and the Global Financial Crisis (2008). For the estimation of the bubble, we need the S&P500 composite index as an indicator of the stock prices, the dividend, and the Consumer Price Index (hereafter CPI) as a proxy of the general price level. These three variables are retrieved from Shiller (2000)[5] and used to estimate the bubble size as explained in Section 3.2.

3.2 Methodology

3.2.1 Deviations from fundamentals

Shiller (2000) highlights the importance of understanding whether an increase in the stock market is a deviation from the fundamental values of the market, thus a speculative bubble, that will eventually at some point collapse. The query of whether and how asset bubbles can be detected has been the focus of many researchers for many years. An early research on this field of stock market bubbles is conducted by Blanchard (1979), Flood and Garber (1980), and Blanchard and Watson (1982). The term "bubble" is also used to refer

[4] Data are available at the website `http://www.policyuncertainty.com/` For the US there are two different measurements of the EPU index; the baseline overall index and the news-based policy uncertainty index. The first measurement is available only for the US, while the second one is also available for many other countries. This is why we choose to use the news-based policy uncertainty index, as it is the one that can be compared to other countries as well.

[5] Data are retrieved from the following website: `http://www.econ.yale.edu/~shiller/data.htm`.

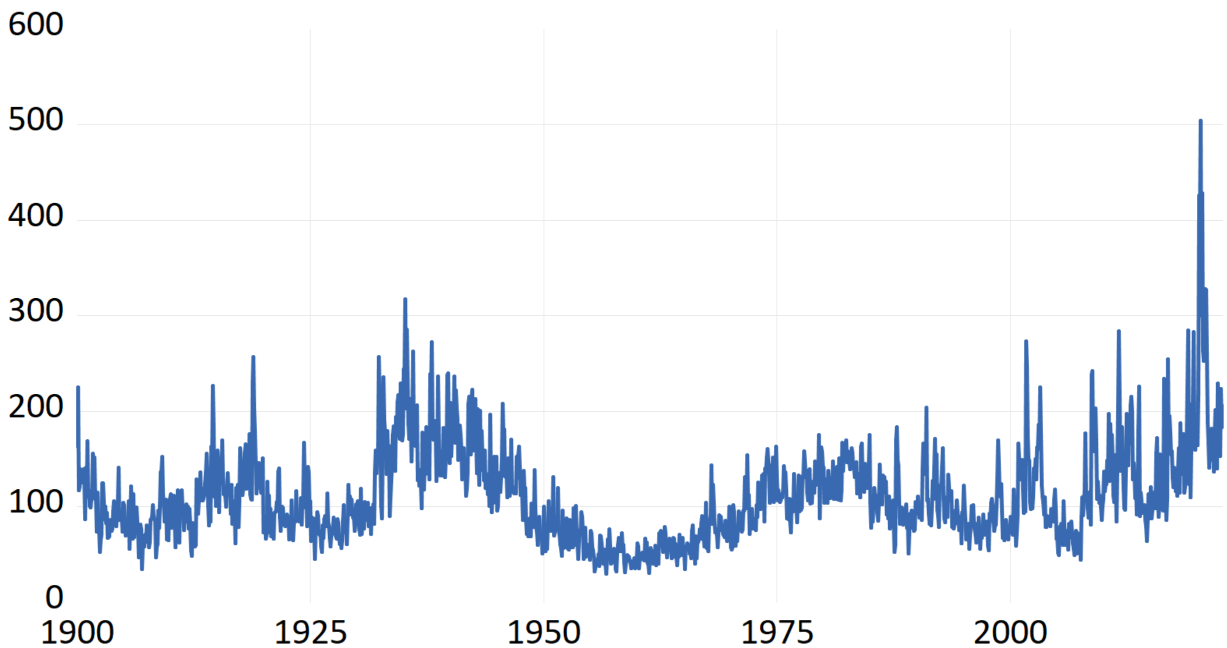

Figure 1: Economic Policy Uncertainty index, January 1900 - October 2022, USA

to rational deviations from the fundamental value. Fundamentals determine only one part of the price of the stock market index. There is also another part, that might be influenced by extraneous factors. So, rational deviations from the fundamental price might exist and this exact deviation from fundamentals is the so-called "rational bubble". Gürkaynak (2008) presents an analytic and critical review of the ways that bubbles can be identified. Much of the literature has focused on the field of stock market bubbles, like Diba and Grossman (1988), Hamilton and Whiteman (1985), Evans (1991), Froot and Obstfeld (1991), Enders and Granger (1998).

The literature proposes several ways of measuring bubbles. We choose to estimate two different bubble measures, to be able to test the robustness of our findings. The first way is with a constant dividend growth rate. We begin with the following arbitrage condition:

$$E_t(P_{t+1}) = (1 + r)(P_t + D_t), \tag{1}$$

where P_t is the stock market price, r is the constant rate of return and D_t is the dividend. To estimate the value of the bubble, we first need to have the value of the fundamental price, which according to Lucas (1978) is:

$$P_t^* = \rho D_t, \tag{2}$$

where $\rho = \frac{1+r}{exp(\alpha+\frac{\sigma^2}{2})-1}$.

The bubble equals the deviation of actual prices from the fundamental price, thus it is estimated as:

$$b_t^A = \frac{P_t - P_t^*}{P_t} = 1 - \rho \frac{D_t}{P_t}, \tag{3}$$

and ρ is the mean of the price-dividend ratio.

The second bubble measure assumes that the dividend growth rate is not constant but varies over time. Following the present-value model presented by Campbell and Shiller (1987), we assume that the present value of the stock prices is a linear function of the discounted value of the dividends:

$$P_t = E_t \sum_{i=0}^{\infty} \left(\frac{1+r}{r} \right)^i D_{t+i}. \tag{4}$$

Campbell and Shiller also use the term *spread*, defined as:

$$S_t = P_t^* - \frac{1+r}{r}, \tag{5}$$

which can be written in the form of a linear function of the dividends (D_t):

$$S_t = \frac{1+r}{r} \sum_{i=0}^{\infty} \left(\frac{1+r}{r} \right)^i E_t(\Delta D_{t+i}). \tag{6}$$

They note that in the case of stocks, this spread represents "the difference between the stock prices and a multiple of dividends". The spread is estimated by applying a Vector Autoregressive (VAR) model and then we get the second bubble measure:

$$b_t^B = 1 - \frac{S_t + \frac{1+r}{r} D_{t-1}}{P_t} = \frac{P_t - [S_t + \frac{1+r}{r} D_{t-1}]}{P_t}, \tag{7}$$

where $r = \frac{\bar{D}-1}{\bar{P}}$, $\bar{D}$ is the mean value of the dividend, and $\bar{P}$ is the mean value of the price. For the purposes of this research, we use both of these bubble measures, and the results we obtain do not show any important quantitative or qualitative differences, hence robustness is confirmed. The results presented later in the paper refer to the first bubble measure.

Figure 2 plots the bubble measure for the US stock market, as estimated by equation (3), in the same graph with the real stock market price level in logarithms. It is obvious that the path of the bubble is very similar to the path of the stock market price level. When the bubble moves away from the zero value, this means the stock market deviates much from its fundamental value and as it can be seen by the figure, this usually happens when the real stock market price falls sharply. High deviations from fundamentals are observed in 1931-32 during the Great Depression, in 1938 a year with a stock market crash triggered by the economic recession that was caused by the Great Depression and the high uncertainty about the effectiveness of Roosevelt's New Deal policy, in 1982 when a bear market was experienced due to a prolonged stagflation, and in 2008 when the Lehman Brothers collapsed and the Global Financial Crisis was triggered. Another observation worth noting is that the deviations from fundamentals were much sharper until the 1950s, and especially since 1990 the volatility of the bubble measure is much smoother than the years before, with only a sharp fall in 2008.

3.2.2 Regime-switching model

Following van Norden and Schaller (1993), we use a two-regime model that allows the bubble to change between two different states: *(i)* the *survival* (S) state, in which the bubble continues to survive, and *(ii)* the *collapse* one (C), in which the bubble crashes (even partially). The regime-switching model and the probabilities we use are described by the following equations:

$$R^s_{t+1} = b_{s0} + b_{s1} B_t + b_{s2} epu_t + e^s_{t+1}, \tag{8}$$

$$R^c_{t+1} = b_{c0} + b_{c1} B_t + e^c_{t+1}, \tag{9}$$

$$Pr(W_{t+1} = s) = n_t = \Phi(b_{n0} + b_{n1}|B_t| + b_{n2} epu_t), \tag{10}$$

$$Pr(W_{t+1} = c) = 1 - n_t, \tag{11}$$

where R_i is the expected excess return for regime i, B_t is the bubble size, epu_t the Economic Policy Uncertainty index, $e^i_{t+1} \sim N(0, \sigma^2_i)$ and Φ is the standard normal cumulative density

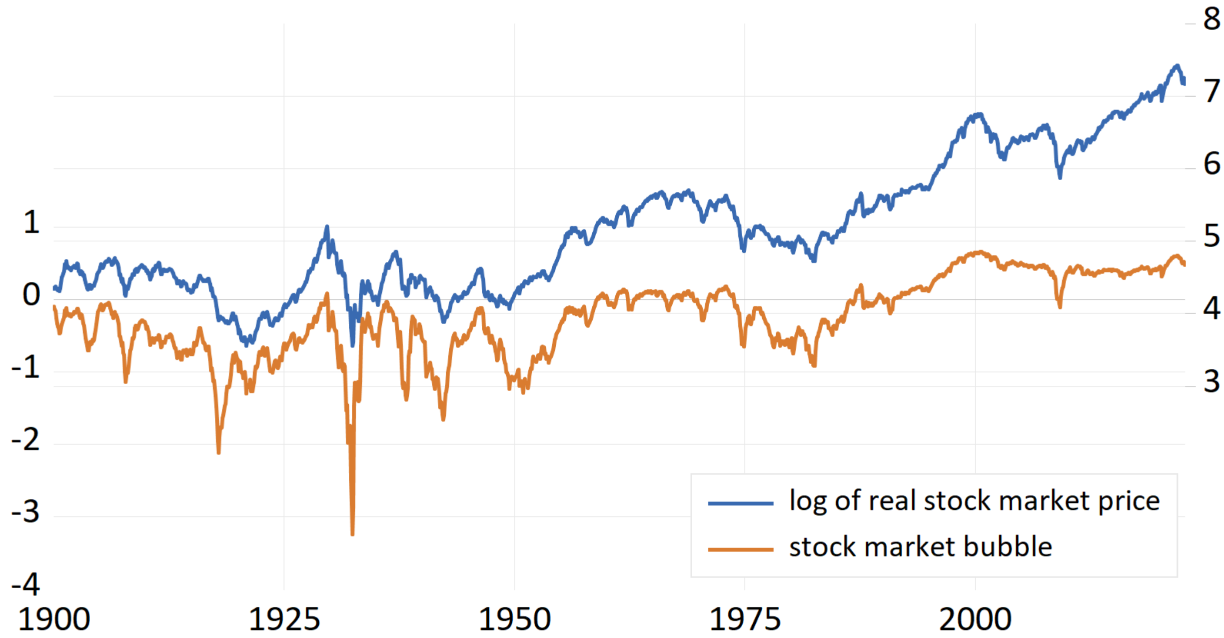

Figure 2: Stock market bubble and stock market prices, USA

Note: The blue line depicts the logarithm of the real stock market price, estimated as the stock market price over the CPI (labelled on the right-hand axis). The initial data have been retrieved from Shiller (2000, `http://www.econ.yale.edu/~shiller/data.htm`). The stock market bubble drawn in red is the authors' own calculations, estimated by equation 3 (labelled on the left-hand axis).

function. The expected excess return in regime S is a function of both the bubble size and the EPU index, while in regime C the expected return is only a function of the bubble size, $Pr(W_{t+1} = s)$ is the probability of being in the S regime and it is a function of the absolute value of the bubble and the EPU index, and $Pr(W_{t+1} = c)$ is the probability of being in regime C.

The model is estimated by maximising the likelihood function:

$$l(r_{t+1} \mid \xi) = \prod_t \left[\frac{n_t \phi \left(\frac{b_{s0} + b_{s1} B_t + b_{s2} epu_t - R^s_{t+1}}{\sigma_s} \right)}{\sigma_s} + \frac{(1 - n_t) \phi \left(\frac{b_{c0} + b_{c1} B_t - R^c_{t+1}}{\sigma_s} \right)}{\sigma_c} \right], \tag{12}$$

where ϕ is the standard normal probability density function (*pdf*) and σ_i is the standard deviation of $e_{i,t+1}$.

As presented above, the *ex-ante* probability of R_{t+1} being in regime S is n_t and in regime C is $1 - n_t$. The *ex-post* probabilities can be derived by the following equations:

$$p_t^{x,s} = \frac{\frac{n_t}{\sigma_s}\phi\left(\frac{e^s_{t+1}}{\sigma_s}\right)}{\frac{n_t\phi\left(\frac{b_{s0}+b_{s1}B_t+b_{s2}epu_t-R^s_{t+1}}{\sigma_s}\right)}{\sigma_s} + \frac{(1-n_t)\phi\left(\frac{b_{c0}+b_{c1}B_t-R^c_{t+1}}{\sigma_s}\right)}{\sigma_c}}, \tag{13}$$

$$p_t^{x,c} = \frac{\frac{1-n_t}{\sigma_c}\phi\left(\frac{e^c_{t+1}}{\sigma_c}\right)}{\frac{n_t\phi\left(\frac{b_{s0}+b_{s1}B_t+b_{s2}epu_t-R^s_{t+1}}{\sigma_s}\right)}{\sigma_s} + \frac{(1-n_t)\phi\left(\frac{b_{c0}+b_{c1}B_t-R^c_{t+1}}{\sigma_s}\right)}{\sigma_c}}. \tag{14}$$

The probabilities of unusually low returns can also be calculated. The case of more than two standard deviations above or below the mean return can be considered as an unusual movement of the returns. The conditional probability of a crash is given by:

$$Pr(r_{t+1} < k) = n_t\Phi\left(\frac{k - b_{s0} - b_{s1}B_t - b_{s2}epu_t}{\sigma_s}\right) + (1 - n_t)\Phi\left(\frac{k - b_{s0} - b_{s1}B_t}{\sigma_c}\right), \tag{15}$$

where the critical value is $k = E(R_t) - 2 * \sigma_{R_t}$.

3.3 In-sample results

In this section, we provide the results of the two-state regime switching model presented above for the first bubble measure (equations 8, 9, 10, 11). Table 1 presents the coefficient estimates and their standard errors. Almost all coefficients are statistically significant at the 1% level, and only b_{s0} and b_{s1} are not statistically significant.

Analysing the intercept estimates, in the survival regime b_{s0} is not statistically significant. On the other hand, in the collapsing regime b_{c0} is significant, its sign is negative, as expected according to the theory and the literature, and is equal to -0.046976. This means that in a collapsing regime, the expected excess return is almost -4.7% per month (assuming a bubble equal to zero). All slope coefficients are significant in both regimes. There is no expected sign according to theory for the slope coefficient of the bubble size in the survival regime. Moreover, the slope coefficient in the collapse regime is negative, meaning that in the collapse regime, stock returns fall when the bubble size increases, as expected. The slope coefficient of the EPU index in the survival regime is positive, implying that when uncertainty increases the

Table 1: Model coefficients

	Coefficient	Std. Error
b_{s0}	0.000560	0.002299
b_{s1}	0.000258	0.001865
b_{s2}	7.91E-05***	21.98E -05
b_{c0}	-0.046976***	0.016212
b_{c1}	-0.021604**	0.010440
σ_s	0.029068***	0.000776
σ_c	0.088838***	0.004671
b_{n0}	2.071499***	0.229402
b_{n1}	-0.791913***	0.206305
b_{n2}	-0.003373**	0.001348

Notes: The coefficients marked with ** and *** are significant at 5% and 1% significance level respectively.

expected return for the next period will increase. This makes sense, as increased uncertainty implies increased risk, which would require higher expected returns for the investors.

The estimated constant term for the probability of being in the survival regime is 2.071499 and by calculating the probability $1 - \Phi(b_{n0})$ we get that on average, if the bubble size and the EPU index were zero, the probability of remaining in the survival regime would be 98%. The coefficients of the bubble size and the EPU index are both negative, which connotes that when the bubble size or/and the EPU index increase, the probability of switching to the collapse regime increases as well.

The standard deviation of the error term in the collapse regime (0.088838) is almost three times higher than the respective standard deviation in the survival regime (0.029068). This is reasonable, as during a collapsing regime the stock returns are expected to fall suddenly and sharply, thus increasing the standard error.

The red line in Figure 3 captures the probability of remaining in regime S. As expected, the probability is, in general, very high but there are also significant drops implying that at these points in time, there is a high probability for the regime to change, hence for the bubble to (partially) collapse. Some sharp declines in the probability of remaining in regime S are observed during periods of market declines or rises or actual stock market crashes, Such declines happen in 1932 (Great Depression), in 1942 (2nd World War bear market), in 1982 (bear market due to long-lasting stagflation), in 2000 (dot-com bubble crash), in 2008 (Lehman Brothers and Global Financial Crisis) and in 2011 (Black Monday of August 8th).

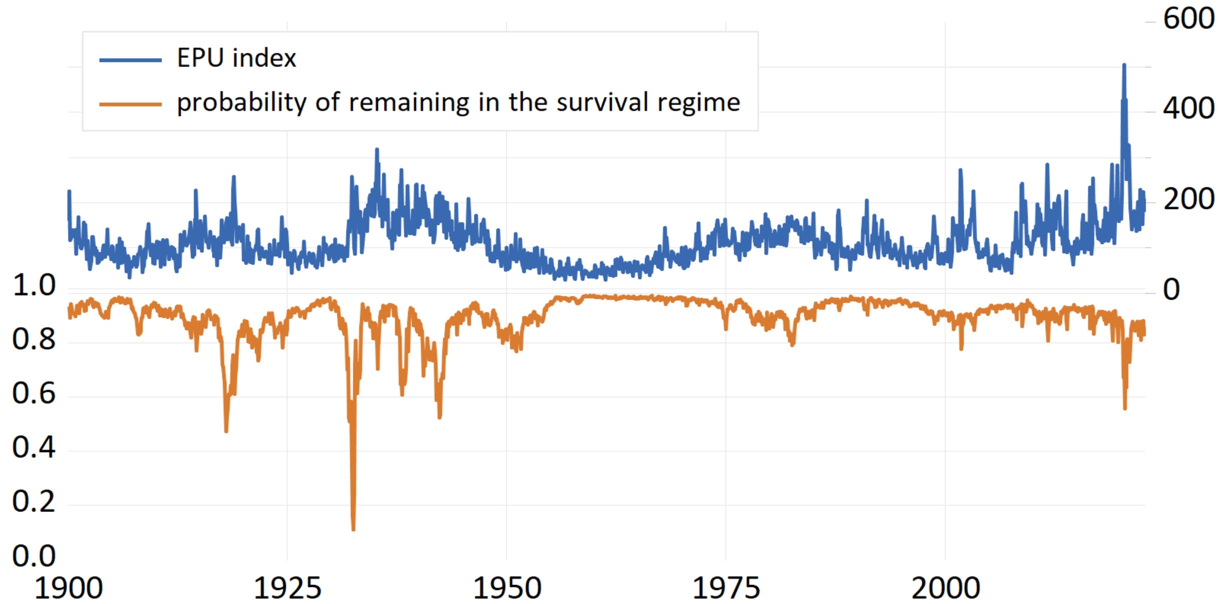

Figure 3: EPU and the probability of remaining in the survival regime

Note: The EPU index portrayed by the blue line is labelled on the right-hand axis, while the probability of remaining in the survival regime shown in red is labelled on the left-hand axis.

As it is suggested by the literature, there is a negative relationship between EPU and future stock market returns (Chen et al., 2017; Xu et al., 2021). The same graph also shows the path of the EPU index (blue line), indicating that uncertainty and the probability of remaining in the survival regime move coordinately in different directions throughout the sample.

The probability of remaining in any of the two regimes has so far been estimated based on the full sample. This provides information about the ability of our specification to fit the data in-sample. To test the predictive power of our model to depict abrupt movements in the US stock market, we need to perform an out-of-sample evaluation of our model. This is what we do in Section 3.4 where we estimate the expected probabilities of a bubble crash in a recursive manner.

To test whether the model succeeds in specifying the regimes properly, we estimate the Regime Classification Measure (RCM) proposed by Ang and Bekaert (2002). They suggest that a good regime-switching model should be able to classify regimes sharply, i.e. the ex-post probability of one regime should be close to 1 and the respective probability of the other regime should be close to 0 throughout the sample. The RCM takes values from 0 to 100 and for a two-state regime model is estimated by the following formula:

$$RCM = 400 * \frac{1}{T} \sum_{t=1}^{T} p_t(1 - p_t). \tag{16}$$

The lower the RCM value, the better the regime classification, since an RCM equal to 0 implies a perfect regime-switching model. In our model, the RCM is equal to 21. This RCM value suggests a relatively good (though not a perfect one) regime classification, as it is closer to zero than to 100.

3.4 Out-of-sample results

So far, we have examined the explanatory power of the model for stock market returns. All the aforementioned analysis is based on full-sample estimates. Thus, they do not reveal much about the actual forecasting ability of our model. However, investors would probably be more interested in the out-of-sample performance of the model. Therefore, this section presents the out-of-sample results in an attempt to investigate the actual forecasting ability of our model, and provide evidence that the EPU can serve as an early warning indicator and add to the literature that finds the EPU index to have significant impact on bubble indicators (van Eyden et al., 2023).

To draw conclusions for the out-of-sample predictive performance of our specification, we proceed with a recursive estimation of both the regime-switching model and the probability of a crash as described in equation (15). We first split the sample to obtain the initial estimation of the model using information from January 1900 to December 1939 and to estimate the probability of a crash. Then, we continue estimating the model and the probability of a crash each time adding one more observation to the sample until we reach October 2022 (recursive estimation). In this way we have a recursive estimation of the model and, more importantly, the probability of a crash in period $t + 1$ is estimated using only information that is available to the investor in period t. Thus, these probabilities can be considered as actual forecasts.

Figure 4 depicts the probability of a crash, which has been estimated using the recursive estimation explained above. When the probability of a crash increases sharply, this is often followed by a relatively large fall in stock prices. We can see from the graph that when the probability of a crash increases, there is actually a bear market or a stock market crash. The two highest peaks of the recursive probability of a crash are in September 2011 (0.17) when the stock market experienced a severe, but short-lived, bear market, and in April 2020 (0.22) when the Covid-19 pandemic started. Other high peaks of the probability of a crash are in

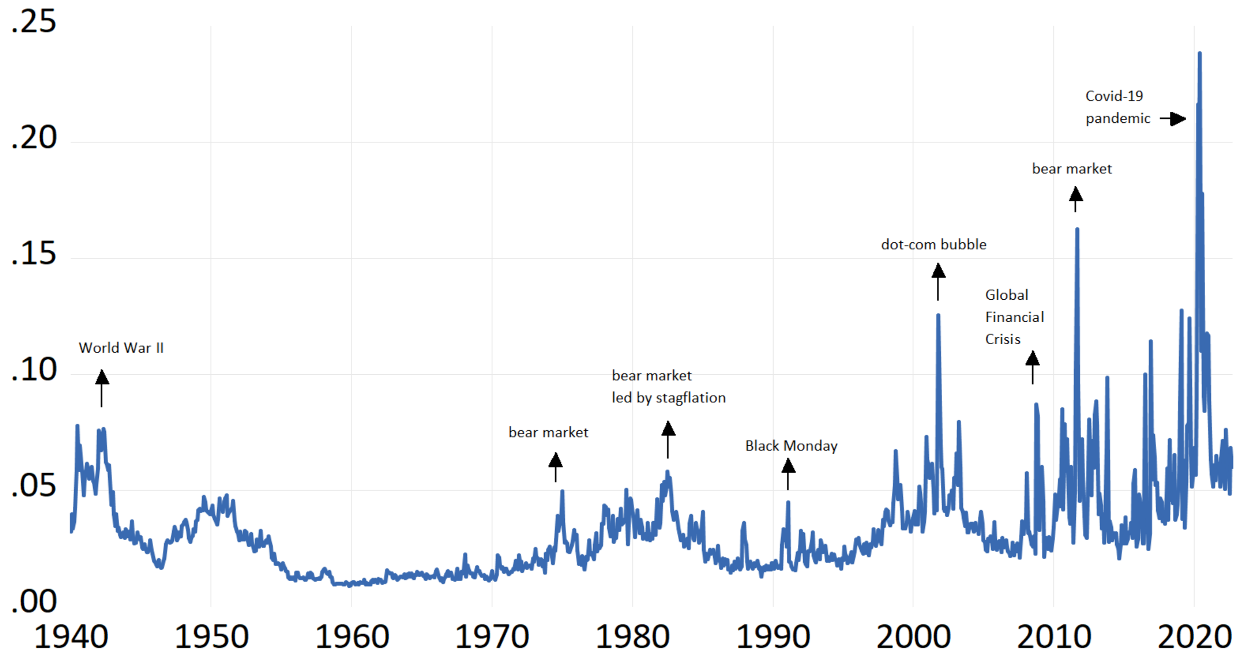

Figure 4: Recursive probability of a crash

2000 indicating the dot-com bubble crash, in 2008 which corresponds to the Global Financial Crisis, in 1942, corresponding to the bear market during the 2nd World War.

A further analysis of the recursive probability of a crash indicates that not all of its peaks are followed by an actual market crash. In other words, in some cases, the models predict an increased probability of a crash but the stock market continues to produce positive returns. Once again, this shows that our model seems to have some predictive power for stock market crashes but, as expected, it is not a perfect one. Finally, another interesting point is that after 2000 the probability of a crash is much more volatile compared to the previous period.

3.5 Trading rule

The analysis proceeds with the introduction of a trading rule which is developed in an attempt to enhance the financial usefulness of the model. Once again, the evaluation period of the trading rule coincides with the out-of-sample period determined in the previous section, that is, it covers the period from January 1940 to October 2022. We consider two hypothetical investors who in January 1940 invest 1 US dollar each. However, the two investors follow different trading strategies. On the one hand, the first investor follows a simple buy-and-hold strategy, meaning that she enters the market in January 1940 and stays in the market until

October 2022. On the other hand, the other investor follows a different approach, applying an active trading strategy (which is similar to the one proposed by Brooks and Katsaris (2005)) as follows: each month she estimates the probability of a crash utilising our regime-switching model using all the information that is available to her until that period. She, then, decides whether she should stay in the market or exit the market by means of a simple rule. More specifically, when the recursively estimated probability of a crash is higher than the upper 90^{th} percentile of its 20-year historical value, the investor sells and exits the market, thus gaining only the risk-free rate. This position is maintained until there is a sign that the probability of a crash is relatively low, that is when the estimated probability of a crash falls below its 20-year historical median value. The median is used to avoid the decision being affected by very large past values of the probability of a crash. When the probability of a crash is below its 20-year historical median value, the investor should invest in the stock market. To make the approach more realistic and make sure that the investor is not using any information that is not available to her at the time she makes her decision, the median and the 90^{th} percentile of the probability of a crash are calculated using a fixed size window of the past 240 months (20 years). To ensure that the arbitrarily used 90^{th} percentile does not cause any bias, we also test the effectiveness of the trading rule using either the 80^{th} or the 95^{th} percentile and the results do not qualitatively change. We also assume that when the investor is not in the stock market, she gains the risk-free rate, which we set equal to the 3-month treasury bill rate. Moreover, we suppose there are transaction costs every time one exits or enters the stock market and consider this cost to be equal to 0.1% of the value of the trade. For both investors, we estimate the cumulative value of her portfolio in each period and we, then, compare them to examine whether our trading strategy is useful.

Even if our trading strategy generates a significant end-of-period profit, one could argue that this can be the result of pure luck. To have a clear picture of whether the estimated profit of our trading rule is indeed statistically significant, we use a simple simulation exercise. Specifically, we create 10,000 random trading paths by generating 10,000 series of zeros and ones, indicating when the investor is in or out of the market respectively. Each random series has the same length as our out-of-sample period (January 1940 to October 2022, that is, 963 observations) and it is generated by means of a binomial distribution, where the probability of success is set equal to the percentage of time our trading rule suggests that the investor is in the market. In this way, each one of the 10,000 random trading paths has similar characteristics (that is, equal length and, on average, equal frequency of being in and out of the market) with our trading strategy. We, then, compare the end-of-period profit of

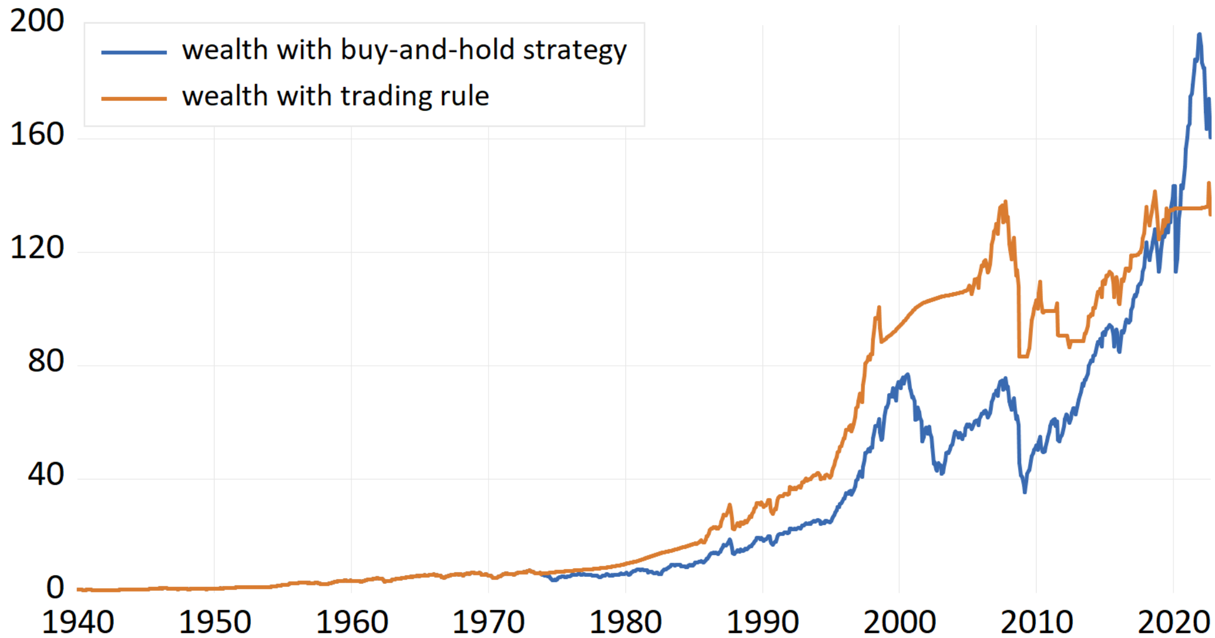

Figure 5: Wealth with and without the trading rule

our trading strategy with the end-of-period profit/loss of each random trading path. If, for example, our trading strategy outperforms 95 percent of the random trading paths, we can conclude that our profit is statistically significant at the 5 percent confidence level.

Initially, if we focus on the proposed trading rule, the investor who follows this strategy exits the market 14 times and stays out of the market approximately 32% of the time. Figure 6 provides the stock market prices in a common graph with the periods when the investor who follows the trading rule is out of the market (grey-shaded areas). Let us now compare our trading rule with the buy-and-hold strategy. According to Figure 5, until the early 1970s the wealth is equal for the two alternative strategies. However, after the mid-70s the investor seems to benefit from our trading rule, as the accumulated wealth starts to exceed the one generated by the buy-and-hold strategy. After 2000, the difference becomes even larger and continues like that for a long period. In other words, for more than four decades the trading rule that relies on the estimated probability of a crash that uses the EPU index as an early-warning indicator outperforms the simple buy-and-hold strategy.

However, the situation changes during the Covid-19 pandemic. During this period, our trading rule keeps the investor out of the market for a long period and the sharp increase in the stock market helps the buy-and-hold strategy to generate a higher profit. This can be rationally explained, since surprisingly the stock market was thriving, after an initial short-lived downturn, while the economy was struggling. The S&P500 fell by almost 35% between mid-February and mid-March 2020. Many people would expect that the stock market would continue falling, however the stock market began recovering gradually, with the US stock market fully recovering by August 2020. The Fed announcing that it will do whatever it takes and the congress pumping money into the economy are key actions that led to soaring stock market prices. Globally, governments and central banks took action to safeguard the economy helping the recovery of the stock market. Since the stock market is not only affected by the economy's condition but also by investors expectations, the stock market had an unpredictable reaction to the pandemic, thus leading the proposed trading rule to fail during this period.

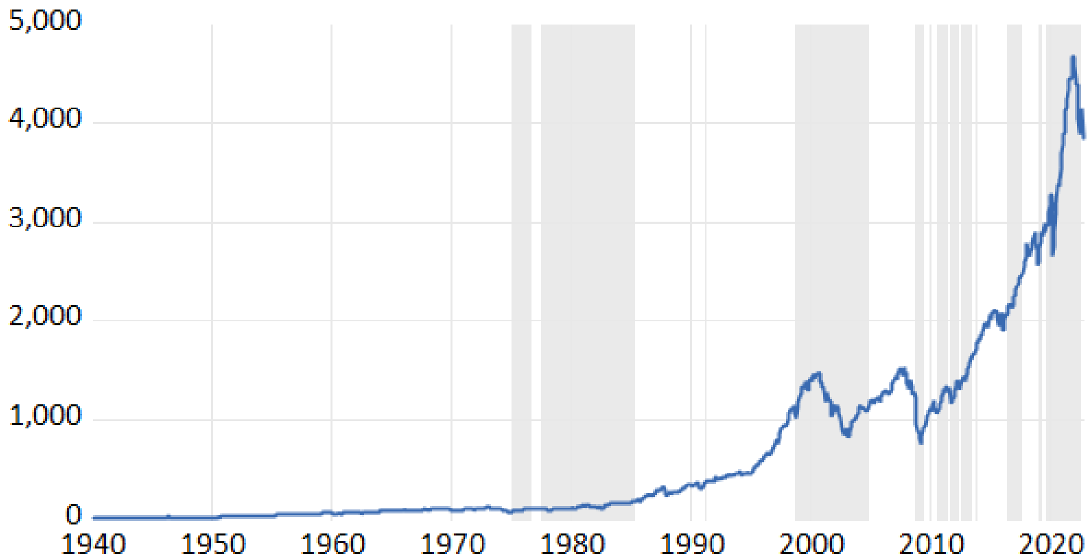

Figure 6: Stock market prices and timeline of when the investor who follows our trading strategy is out of the market

Note: The grey-shaded areas represent periods when the investor should be out of the stock market according to our trading rule.

In a nutshell, the investor who follows our trading rule gains throughout the whole period higher profits than the investor who follows the buy-and-hold strategy. The only exception is the recent Covid-19 period.

Finally, when it comes to the statistical significance of the end-of-period profit of our trading strategy, the simulation exercise suggests that the profit is statistically significant at the 3% significance level, outperforming about 97% of the random trading paths.

4 Robustness tests

We now proceed with some robustness tests to examine the sensitivity of our results to various factors that might affect our conclusions. As a first test, we check the sensitivity of the findings to the bubble measure. For this reason, we re-run the whole analysis using the 2nd bubble measure described in Section 3.1 and given by equations (4) to (7). The estimates of the regime-switching model are quantitatively and qualitatively similar and indicatively the estimated coefficients of the model are presented in Table 2. Additionally, we apply the same trading rule for the model that uses the second bubble measure, and the results are depicted in Figure 7. The wealth of the investor that follows our trading strategy follows a very similar path compared to the model that uses the 1st bubble measure, with marginal deviations in the last years of the sample (after 2018), where now the profit of the trading rule is slightly lower than the profit generated by the initial model. Thus, the overall results support the robustness of our findings to the way we calculate the deviations from fundamentals.

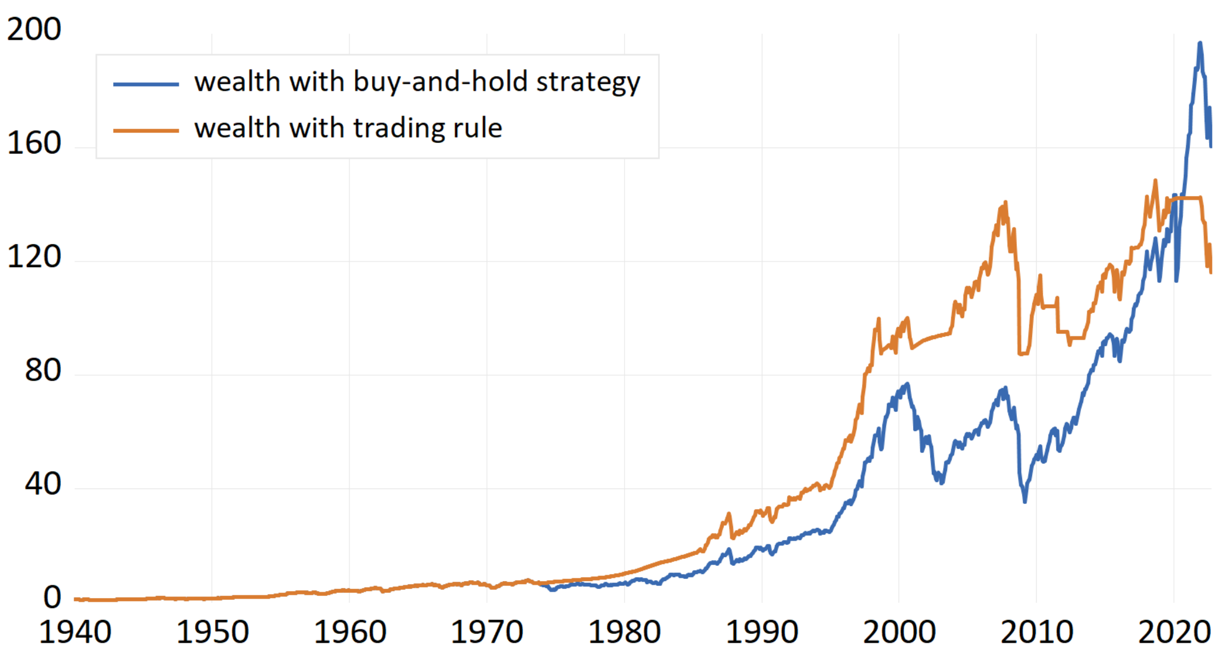

Figure 7: Wealth with and without our trading rule (model with the 2nd bubble measure)

There are two different historical EPU data series available, the old and the new one, since BBD keep updating the EPU keywords for the historical index, to be consistent with changes in the language usage and changes in the editorial standards of the newspapers over the years. For the main part of this research, the new EPU data series has been used, but the old version can also serve to support robustness. Using the old historical EPU index version, we conclude similar results, and we observe an even better performance for the trading rule, which is obvious in Figure 8.

Figure 8: Wealth with and without out trading rule (model with the old version of the historical EPU index)

Afterwards, as an additional test of the robustness of effectiveness of the trading rule that we proposed, we use different percentiles to determine the time the investor should exit the stock market. In the initial trading rule, we use the 90^{th} percentile (see Figures A1 and A2 in Appendix). We now use the 85^{th} or the 95^{th} percentile as a robustness check. Using the 85^{th} percentile the trading rule gives a relatively lower profit to the investor, while when we use the 95^{th} percentile the profit of the investor who follows our trading rule increases. So, our initial trading strategy is somewhere in between the two alternative percentiles considered here, and, in all cases, the similarity of the generated paths of wealth supports the robustness of our findings.

An additional robustness test we apply for the trading rule is to use different sizes of the fixed window that we use for the estimation of the median value and the 90th percentile of the probability of a crash, which is used as a signal to enter or exit the market, respectively.

Table 2: Model coefficients

	Coefficient	Std. Error
b_{s0}	0.000373	0.002375
b_{s1}	-0.000434	0.001749
b_{s2}	7.98E-05***	2.00E -05
b_{c0}	-0.051277***	0.017543
b_{c1}	-0.023033**	0.010713
σ_s	0.028809***	0.000785
σ_c	0.086984***	0.004354
b_{n0}	2.152323***	0.245325
b_{n1}	-0.719983***	0.179842
b_{n2}	-0.003926***	0.001342

Notes: The coefficients marked with ** and *** are significant at 5% and 1% significance level respectively.

The results of these robustness tests are reported in the Appendix of the study. The initial size of the window we used was 20 years. We now consider a window of either 15 years or 25 years (see Figures A3 and A4 in Appendix). Our findings seem to be sensitive to the size of the window. When a 15-year window is considered, after the second half of 2016 the wealth for the investor who follows our trading rule is lower than that of the buy-and-hold strategy. The results for the 25-year window are even worse, since after 1997 the buy-and-hold strategy outperforms our trading rule. Thus, we can conclude that the window size of 20 years is the one that leads to the most effective trading rule.

A final test for the robustness of our findings is to re-estimate the regime-switching model and repeat the whole analysis excluding the EPU index from the specification. This is a crucial robustness test because it clearly reveals whether the inclusion of the EPU index in our specification helps the model generate more reliable estimates of the probability of a crash, resulting in a better trading strategy. We observe in Figure 9 that the recursively estimated probability of a crash does not capture very well the actual crashes of the stock market, thus connoting the importance of the use of EPU as an early-warning indicator in our model. Moreover, when we apply the trading rule using the probability of a crash from the model without the EPU index, we get the results presented in Figure 10. Apparently, the accumulated wealth of the trading rule in this case is much lower than that of the simple buy-and-hold strategy for the whole out-of-sample period. To further support the choice of the model that includes the EPU index as an early warning indicator, we apply the Log

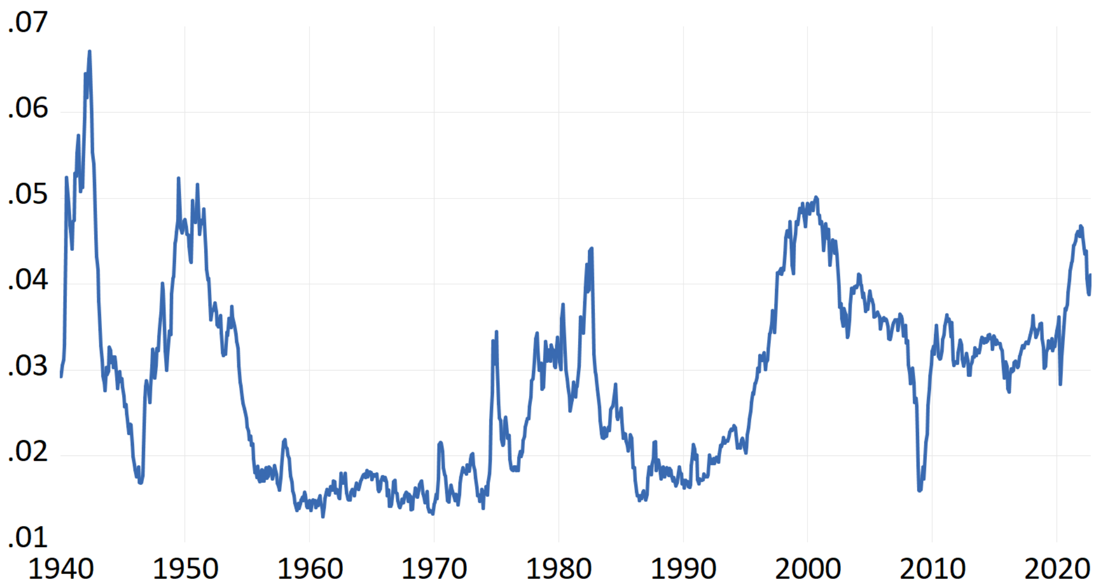

Figure 9: Recursive probability of a crash in the model without the EPU index

Likelihood (LR) test. We estimate the LR test where the general model is the one with the EPU index and the restricted is the one without the EPU index. The LR test is equal to $-2(logl_r - logl_g)$, where $logl_r$ is the maximised value of the log-likelihood function of the restricted model and $logl_g$ is the maximised value of the log-likelihood function of the general model. Based on the x^2 distribution, the null hypothesis is rejected and the LR test chooses the model with the EPU index. These results confirm our initial assumption that the EPU index plays a critical role as an explanatory variable in our regime-switching model. This confirms previous findings in the existing literature that support the ability of the EPU index to improve the forecasting performance of econometric models for financial markets (Karnizova and Li (2014).

5 Conclusion

Most studies in the literature that use the EPU index investigate its relation with various macroeconomic variables. Other studies focus on the relationship between the EPU index and the stock market volatility, while few studies examine the ability of EPU to provide reliable forecasts for stock market returns. This paper is the first one that tries to use the EPU index as an early warning indicator of abrupt movements in the US stock market. Specifically, we modify a standard two-state regime-switching model for the US stock market (that is often

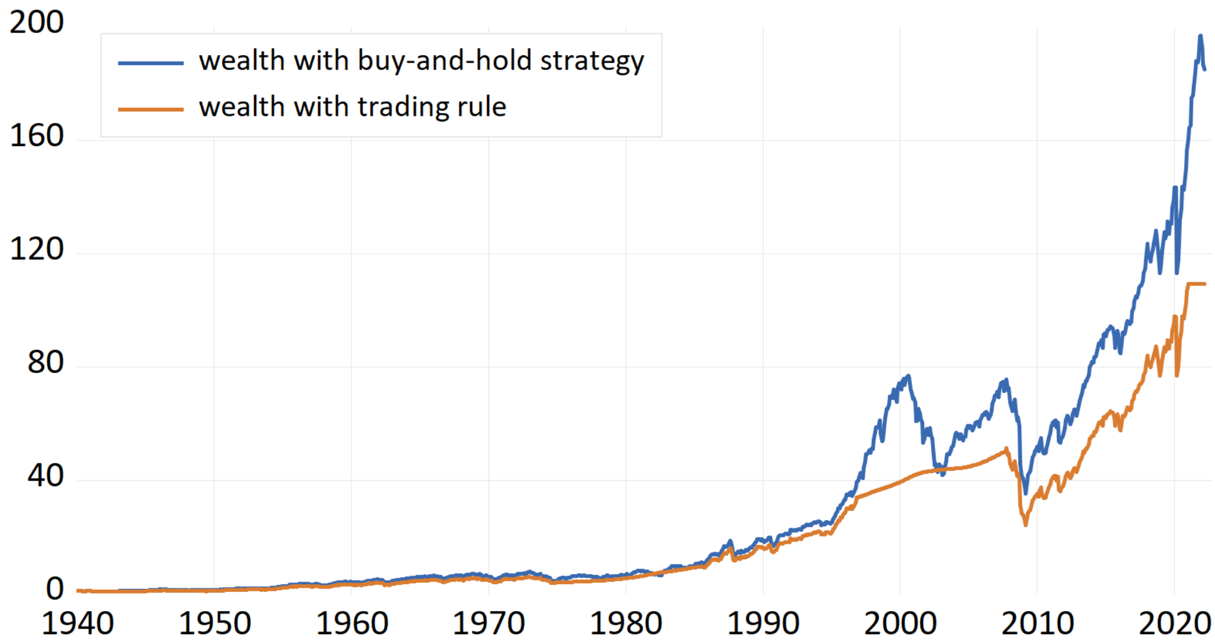

Figure 10: Wealth with and without the trading rule (model without the EPU index)

used in the context of the theory of self-fulfilling expectations) by including the EPU index in both the conditional mean and the probability equations.

Our estimates, based on monthly data from January 1900 until October 2022 suggest that EPU is statistically significant and the slope coefficients have the expected signs. The model seems to fit the data well in-sample. Moreover, we evaluate the out-of-sample predictive ability of our model and its usefulness to investors by developing a trading rule that uses the estimated probability of a crash to help the investor decide when to enter and when to exit the market. The proposed trading rule seems to outperform a simple buy-and-hold strategy for more than four decades (from the mid-70s until the Covid-19 pandemic), while it fails to beat the buy-and-hold strategy during the Covid-19 crisis. During Covid-19 the stock market was surprisingly thriving, contrary to the struggling economy. The Fed and the actions applied by the government assisted towards the full recovery of the stock market, after its initial downturn. As expected, our model was not able to predict these interventions and this is probably the reason our trading rule fails during the pandemic. Furthermore, a simple simulation exercise reveals that our trading rule generates an end-of-period profit that is statistically significant. Finally, various robustness tests confirm that our findings are qualitatively similar under alternative specifications. More importantly, if we repeat the analysis excluding the EPU index from the specification, the performance of our model collapses. This clearly reveals the usefulness of EPU in the context of our analysis.

The paper provides important insights and can prove to be helpful both for policy makers and investors. An interesting suggestion for future research is to apply the same analysis and examine whether the EPU index can serve as an early warning indicator for abrupt movements in the stock market of other countries, other than the US. Moreover, it would be interesting to investigate the performance of other categorical policy uncertainty indices for the US in a similar framework.

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Appendix

A1 Robustness tests (graphs)

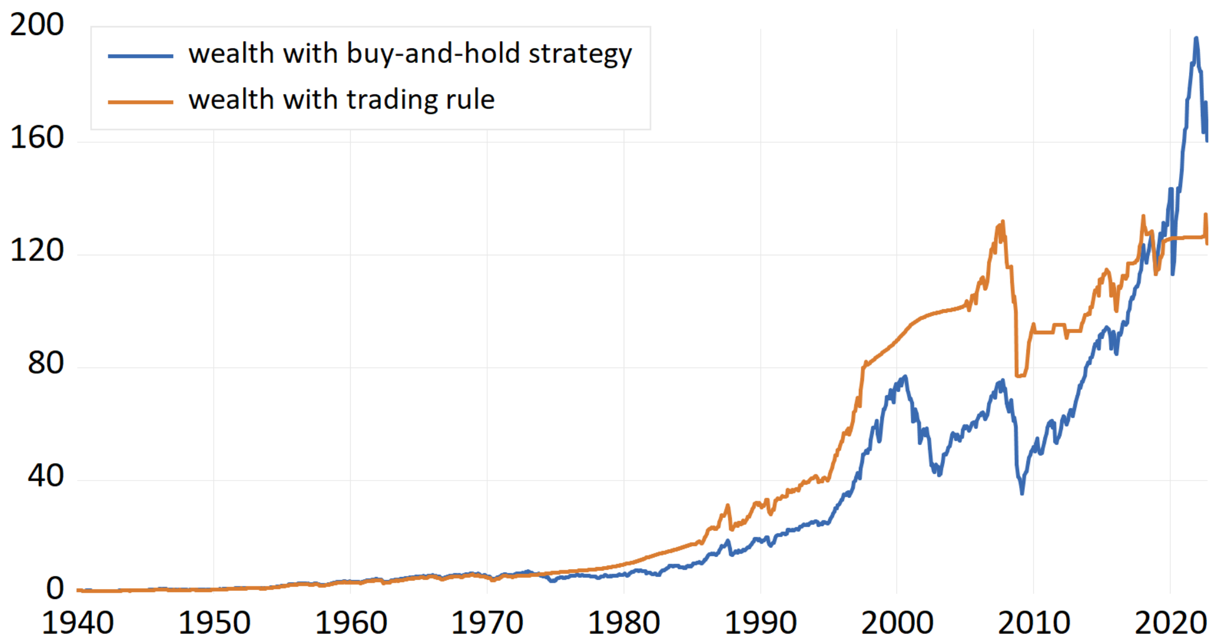

Figure A1: Wealth with and without the trading rule - 85th percentile

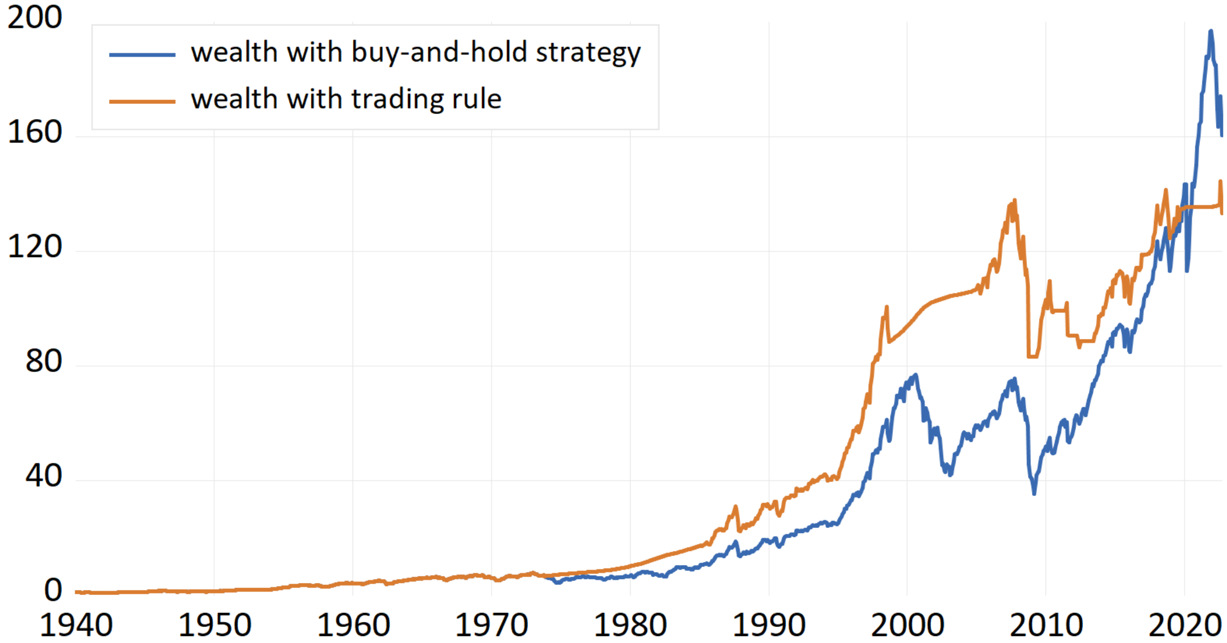

Figure A2: Wealth with and without the trading rule - 95th percentile

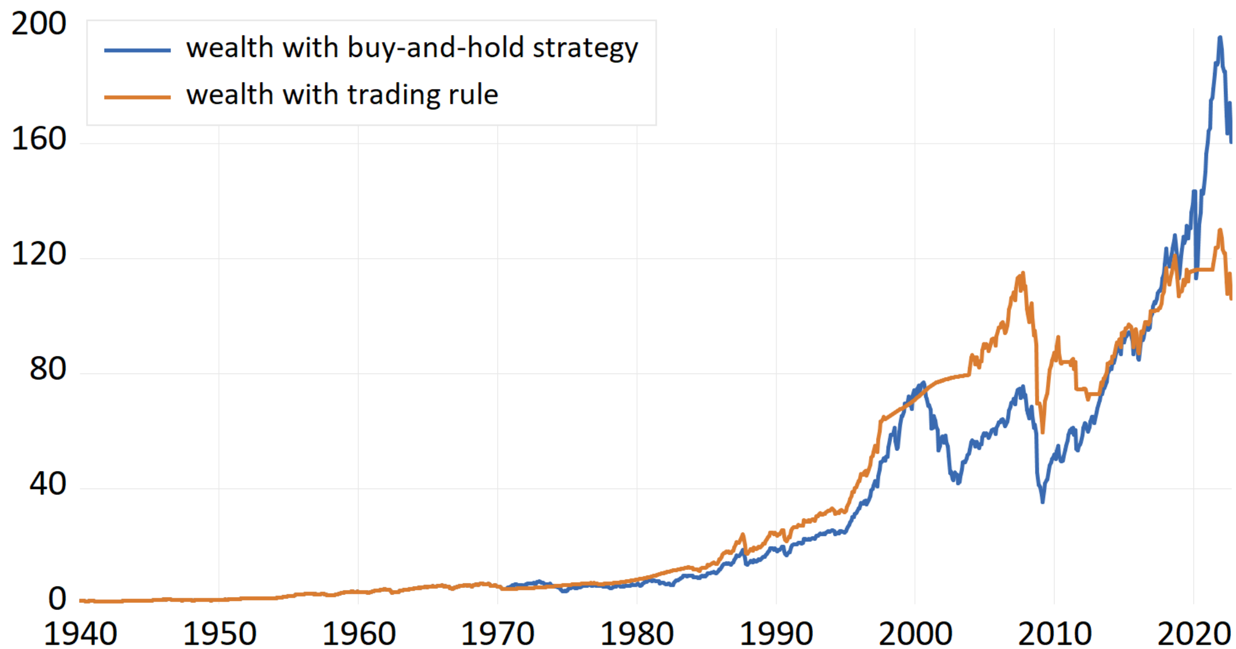

Figure A3: Wealth with and without the trading rule - 15-year window

Figure A4: Wealth with and without the trading rule - 25-year window