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Can we forecast better in periods of low uncertainty? The role of technical indicators

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ABSTRACT

We examine the importance of periods of high versus low financial uncertainty when forecasting stock market returns with technical predictors. Our results suggest that technical predictors perform better in periods of low financial uncertainty and should be avoided due to poor forecasting performance in periods of heightened uncertainty. In-sample, we report disentangled R^2 statistics, and out-of-sample we show these results continue when forecasting the equity risk premium. We show similar results when forecasting the volatility of returns with technical predictors. We measure periods of heightened and low financial uncertainty in a regime switching framework. Overall, our results provide insight into the mechanism that suggests that, when uncertainty rises, investors' opinions polarize leading to a breakdown of predictability based on technical indicators.

1. Introduction

Since the seminal work of Welch and Goyal (2008), the debate over whether stock returns are predictable based on publicly available information has reignited. Papers such as Campbell and Thompson (2008), Cochrane (2008), Neely et al. (2014), Rapach and Zhou (2013) and Rapach et al. (2016), *inter alia*, suggest that stock returns are predictable based on a number of technical and fundamental predictors. Alongside this literature, it is also documented that return predictability is concentrated in recessions.[2] However, the source of return predictability still leaves a number of unanswered questions.

In this paper, we forecast stock market returns from a set of technical predictors. We show that technical predictors yield better results in low-uncertainty periods than in periods of high uncertainty. Furthermore, we find that this disparity persists when forecasting the volatility of returns. These results occur in- and out-of-sample. To define periods of low versus heightened uncertainty we rely on the financial uncertainty index of Ludvigson et al. (2021). Our first simple measure reports periods of heightened uncertainty when there is excess uncertainty (i.e., when the value of the index is above its mean). In our second approach,

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[2] Rapach et al. (2010) show that the combination forecast obtained from the macroeconomic variables used in Welch and Goyal (2008) performs better in periods of recession. Henkel et al. (2011) suggests that economic variables provide more useful forecasts in times of recession than the historical average, which works well in normal times. Dangl and Halling (2012) find that predictability is concentrated in periods of recession. Neely et al. (2014) show that technical indicators forecast stock returns more accurately in recessions compared to expansions, while Cujean and Hasler (2017) provide an equilibrium model to explain this phenomenon.

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high/low uncertainty periods are estimated using a regime-switching framework. The main conclusions from the two approaches remain unaltered.

We begin with a predictive regression framework that relates fourteen technical predictors to the monthly excess returns of the S&P 500 and disentangles predictive ability between good and bad times over a period 1960–2018. In-sample, we rely on the disentangled R^2 statistic, which has been previously used to assess the predictability differences between recessionary and expansionary periods (see, for example, Neely et al., 2014). Out-of-sample we compare forecasting performance across the different periods.

Whilst the general consensus is that predictability is more heavily concentrated in recessions, as classified by the national bureau of economic research (NBER), we provide evidence that predictability using technical indicators performs much better in low uncertainty times, and this persists both in- and out-of-sample. Even though our findings may appear to contrast that predictability is more heavily concentrated in recessions, only a small portion of our sample is officially classified as NBER dated recessions. Approximately ten percent of the sample over 1960–2018 is in recession according to the NBER dates. We also show that the historical average forecast performs much more poorly in recessions compared to expansions. For example, squared forecast errors are 144% greater when using the historical average forecast in recessions compared to expansions.[3] Therefore, there is a strong case that whilst predictability may be easier to come by in recessions, it may in fact be the case that the historical average forecast, the current benchmark used across the literature, is easier to beat. It is also important to note that NBER recessions are determined ex-post and therefore could not be used by market agents to forecast returns at particular periods in real-time.[4]

When forecasting the equity premium, we show that in-sample, the majority of the considered technical predictors perform better in periods of low financial uncertainty versus times of heightened financial uncertainty with larger disentangled R^2 statistics. Out-of-sample, we see that in periods of low uncertainty the technical predictors produce positive and statistically significant out-of-sample R^2's that are greater than the same statistic in periods of heightened uncertainty. With the full sample, the technical predictors appear to perform poorly. Neely et al. (2014) show that whilst all of the Campbell and Thompson (2008) out-of-sample R^2 statistics are positive for each of the technical predictors, only three of the fourteen are significantly greater than the historical average forecast at the 5% level or better when using a Clark and West (2007) test. Since out-of-sample forecasts are important for market agents seeking to time the market it is important to explore methods that can improve forecasts. We demonstrate that in periods of low financial uncertainty, predictability exists in an out-of-sample context as well. Therefore, the results reported show that disentangling the impact of uncertainty is not only important for our understanding of financial markets, but it provides practitioners with stronger signals about future returns during specific periods.

Why do technical predictors perform better in periods of low uncertainty? Our findings are specific to technical predictors and no such performance differential can be made with macroeconomic variables such as those used in Welch and Goyal (2008). This, therefore, suggests that our findings can coexist in the current literature which finds that predictability is concentrated to "bad" times. For example, Cujean and Hasler (2017) provide a compelling argument that in "bad" times, predictability is a result of the polarizing opinions of investors, with disagreement spiking when uncertainty rises. Therefore, it is plausible to suggest that trend chasing strategies, such as the use of technical indicators would break down in the event of heterogeneous opinions across the set of investors, thereby providing a parallel framework of why technical indicators can forecast better in periods of low uncertainty. Bali et al., (2017, p. 473), suggest that if investors' expectations or preferences towards economic uncertainty are dispersed, then investors with low aversion against uncertainty will remain, whilst investors with high aversion against uncertainty will 'cease or reduce their participation in the stock market'. It may also be the case that more generally, in periods of heightened uncertainty, investors flee the stock market in search of less risky assets, often termed a 'flight to quality' (Florackis et al., 2014), again breaking the chain of a particular market direction.

The theoretical reasons why technical indicators are able to forecast the equity risk premium are not yet well established. Neely et al. (2014)[5] suggest that the current explanations are split into four facets. First, as news enters the market it can take time to reach investors. An additional angle to this argument is provided by Hong and Stein (1999) and Hong et al. (2007) with both papers indicating that due to investors' limited processing capabilities it can take time for investors to digest and act upon news. Treynor and Ferguson (1985) and Brown and Jennings (1989) show that technical analysis is useful for assessing whether news has been incorporated and is generating price signals. Second, Cespa and Vives (2012) provide a setting that shows why rational long-term investors follow trends. The authors show that asset prices can deviate away from their fundamental value under two scenarios, (i) persistence in liquidity trading and (ii) a positive level of asset residual payoff uncertainty. Third, that there can be overreaction and underreaction in stock markets, see Chan (1988), Conrad and Kaul (1993), Hong and Stein (1999) and Barberis and Thaler (2003), *inter alia*. Finally, investor sentiment can drive prices away from their fundamental value, see DeLong and Magin (2009).

In further analysis, we examine the accuracy of technical indicators in predicting volatility. We measure forecast accuracy with the proportion of explained variability (Blair et al., 2001; Poon and Granger, 2003). We find that technical indicators also provide more accurate volatility forecasts when the market is in low-uncertainty periods compared to high-uncertainty periods.

[3] We assess the performance of the historical average forecast with an initial sample of 200 months in a rolling manner over the period 1960–2018. The historical average forecast is a popular benchmark in the stock return predictability literature.

[4] The NBER chronology does not identify the precise moment that the economy enters a recession, it is instead is defined by a committee, see, https://www.nber.org/business-cycle-dating-procedure-frequently-asked-questions.

[5] Neely et al. (2014) find that technical predictors forecast better compared with macroeconomic variables that are widely used across the literature. However, through encompassing tests, Neely et al. (2014) highlight that forecasts from economic variables and technical predictors contain different information and gains are present when using the predictors in conjunction.

In sum, our main contribution is that when forecasting stock market returns, technical predictors perform better in periods of low economic uncertainty. This suggests that an investor should assess the current state of uncertainty before using technical indicators to forecast future returns.[6] The rest of the paper is organized as follows. Section 2 describes the data. The methodology and empirical analysis are presented in Section 3. Section 4 concludes the paper.

2. Data

Monthly volume and price data for the S&P 500 are collected from Stooq.com, log-returns are calculated along with fourteen technical indicators constructed in line with Neely et al. (2014). We measure financial uncertainty using the method of Ludvigson et al. (2021), who show that their methods may be better suited to measuring uncertainty when compared to using stock market volatility, which is the popular alternative across the literature (see, for example, Bloom, 2009).[7] Returns of the stock market are in excess of the risk-free rate measured using the one-month Treasury bill rate.[8] All data is collected over a period 1960:08 to 2018:12.

We employ fourteen technical predictors as in Neely et al. (2014). These technical predictors come from trend following strategies including moving averages, momentum and volume. The first moving average rule (MA), buy or sell decision ($BS1$) is obtained as follows:

$$BS1_t = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases} \tag{1}$$

where

$$MA_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} P_{t-i} \text{ for } j = s, l \tag{2}$$

P_t is the level of the stock price index, s the length of the short MA, l is the length of the long MA. Neely et al. (2014) explain that the MA rule can signal a change in the stock price trend, further details are provided in the paper. Next, the momentum strategy specifically traces prices. If current prices are greater than the prices m periods ago, we witness positive momentum, which in turn suggests we should purchase the market. If the opposite occurs, it suggest that we should sell the market.

$$BS2_t = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases} \tag{3}$$

The final strategy relies of on a combination of prices and volume data. Let

$$OBV_t = \frac{1}{j} \sum_{k=1}^{t} VOL_k D_k \tag{4}$$

where VOL_k is a measure of the trading volume during the period k and D_k equal to one if $P_k - P_{(k-1)} \geq 0$ and equal to minus one otherwise. The final trading signals are generating using the following decision rule:

$$BS3_t = \begin{cases} 1 & \text{if } MA^{OBV}_{s,t} \geq MA^{OBV}_{l,t}, \\ 0 & \text{if } MA^{OBV}_{s,t} < MA^{OBV}_{l,t} \end{cases} \tag{5}$$

with

$$MA^{OBV}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} OBV_{t-i} \text{ for } j = s, l \tag{6}$$

The premise behind the strategy is that recent price increases coupled with higher volume indicate a buy decision for market agents. For the MA rules $MA(s,l)$, we set $s = 1,2,3$ and $l = 9,12$. For the MOM rules $MOM(m)$, we have $m = 9,12$. Finally, for the VOL rules $VOL(s,l)$, $s = 1,2,3$ and $l = 9,12$.[9] The research of Neely et al. (2014) provides full details of the technical indicators (see Table 1).

3. Methodology and results

3.1. Defining periods of heightened/low uncertainty

A number of papers across the literature define periods of low and heightened uncertainty using recessions and expansions. However, it can be argued that the market reacts in a much more timely manner. In the asset allocation decision of investors, transferring from stocks to less risky assets (a flight to quality) will often happen prior to recessions as investors foresee negative times ahead. Our formal definition of low and heightened uncertainty regimes is based on the financial uncertainty index of

[6] Chu et al. (2022) also find an important role of different regimes when using non-fundamental predictors including technical indicators to forecast excess stock market returns, with their research differentiating between high and low sentiment periods.

[7] Bloom's (2009) method of measuring uncertainty is stock market volatility, defined as Chicago Board of Options Exchange (CBOE) VXO index of percentage implied volatility on a hypothetical at the money S&P100 option 30 days to expiration.

[8] Data on the Treasury bill rate and macroeconomic variables that are used in unreported results are collected from Amit Goyal's webpage.

[9] The fourteen technical predictors are as follows, BS1 = MA(1,9), MA(1,12), MA(2,9), MA(2,12), MA(3,9), MA(3,12), BS2 = MOM(9), MOM(12), BS3 = VOL(1,9), VOL(1,12), VOL(2,9), VOL(2,12), VOL(3,9), VOL(3,12).

Table 1
Summary Statistics.

Predictor	Mean	Max	Min	Std.dev	Skew	Kurt
r_t	0.004	0.149	−0.248	0.043	−0.689	5.516
FU	0.904	1.557	0.604	0.166	0.765	3.591
MA(1,9)	0.698	1.000	0.000	0.46	−0.859	1.735
MA(1,12)	0.722	1.000	0.000	0.448	−0.988	1.975
MA(2,9)	0.699	1.000	0.000	0.459	−0.866	1.748
MA(2,12)	0.719	1.000	0.000	0.45	−0.972	1.944
MA(3,9)	0.705	1.000	0.000	0.457	−0.896	1.800
MA(3,12)	0.72	1.000	0.000	0.449	−0.980	1.959
MOM(9)	0.716	1.000	0.000	0.451	−0.957	1.914
MOM(12)	0.735	1.000	0.000	0.442	−1.061	2.124
VOL(1,9)	0.69	1.000	0.000	0.463	−0.822	1.674
VOL(1,12)	0.715	1.000	0.000	0.452	−0.949	1.899
VOL(2,9)	0.679	1.000	0.000	0.467	−0.765	1.584
VOL(2,12)	0.71	1.000	0.000	0.454	−0.926	1.856
VOL(3,9)	0.7	1.000	0.000	0.458	−0.873	1.761
VOL(3,12)	0.706	1.000	0.000	0.456	−0.903	1.814

Notes: This table reports the summary statistics for the log returns of the SP 500 in excess of the risk-free rate, (r_t), financial uncertainty, (FU), along with the fourteen technical predictors. Data for the returns and volume of the S&P 500 comes from Stooq.com, and are used to construct the technical predictors inline with Neely et al. (2014), financial uncertainty data is collected from Sydney Ludvigson's website.

Ludvigson et al. (2021). This measure extends upon the previous measure of macroeconomic uncertainty of Jurado et al. (2015), the extension allows for fluctuations that are not driven by the business cycle. The authors measure the unpredictable component of 147 financial time series, from valuation ratios to portfolios of equity returns. Heightened uncertainty from our definitions in Sections 3.1.1 and 3.1.2 covers 87% and 74% of NBER data recessions, respectively. While recessions make up 12% of the sample, periods of heightened uncertainty make up 43% and 46%, leaving a much larger window for market agents to use the variables to time the market. It is important to note that whilst heightened uncertainty and recessions are not entirely correlated, they are thought to be related. As is highlighted in Ludvigson et al. (2021), an important question within the literature has been whether uncertainty is a response to business cycle fluctuations or a source of such fluctuations. The authors show in their analysis that shocks to financial uncertainty appear to be a driver of economic fluctuations. This is important for our research as it signals that uncertainty can provide a prior warning of suppressed future economic conditions and therefore dictate certain investors' asset allocation decisions. Ludvigson et al. (2021) provide a number of arguments as to why Financial uncertainty differs to alternative types of uncertainty such as Macroeconomic uncertainty and Jurado et al. (2015), and Economic Policy Uncertainty of Baker et al. (2016). Ludvigson et al. (2021) provide evidence that positive shocks to financial uncertainty cause a sharp and persistent decline in real activity, lending support to the idea that heightened financial uncertainty is an exogenous impulse and creates economic downturns. Whereas the same does not appear to be true for macroeconomic uncertainty and economic policy uncertainty and where positive shocks to these do not appear to cause lower economic activity. Therefore, it appears than financial uncertainty empirically contains different information to alternative uncertainty measures.[10]

3.1.1. The baseline procedure

Our first simple measure, reports periods of low (heightened) uncertainty when the value of the financial uncertainty index, is below (above) its mean, that is when $FU - E(FU) > 0$. Heightened uncertainty periods obtained from this rule are shaded in grey in Panel A of Fig. 1. This procedure classifies 43% of the sample as in a high-uncertainty regime. As is seen in Fig. 1, financial uncertainty spikes across time, the two largest peaks being 'Black Monday' of 19th October 1987 and the 'Global Financial Crisis' of 2007/2008.

3.1.2. Markov-switching model for the financial uncertainty

We now consider a Markov-switching (MS) model[11,12] to detect periods of high and low uncertainty. We assume that the state of the market follows a first-order Markov chain with two regimes: the high-uncertainty regime and the low-uncertainty regime. Let $\Delta FU_t = \log(FU_t/FU_{t-1})$ be the log-difference time series of the financial uncertainty variable. We consider the following model:

$$\Delta FU_t = \mu_{k_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2_{k_t}) \tag{7}$$

[10] We compare financial uncertainty to alternative measures of uncertainty (Macroeconomic Uncertainty (MU) of Jurado et al., 2015, Economic Policy Uncertainty (EPU), News Based Economic Policy Uncertainty, (nEPU) of Baker et al., 2016, Investor Sentiment (IS) as defined in, Huang et al., 2015 and US Monetary Policy Uncertainty (MPU) of Husted et al., 2017), by computing their correlations. The largest in magnitude is the between FU and MU with a correlation coefficient of 0.676. The low correlation coefficient suggests that financial uncertainty contains information that is distinct from alternative uncertainty measure as is suggested in Ludvigson et al. (2021).

[11] The MS model allows us to capture more complex dynamics compared with alternative models that account for switching. It also allows us to switch based on state variables (financial uncertainty in our case).

[12] In an portfolio choice setting, Tu (2010), highlights the important role of market states, with the certainty-equivalent losses associated with not accounting for regime switching above 2% per annum and can be as high as 10%.

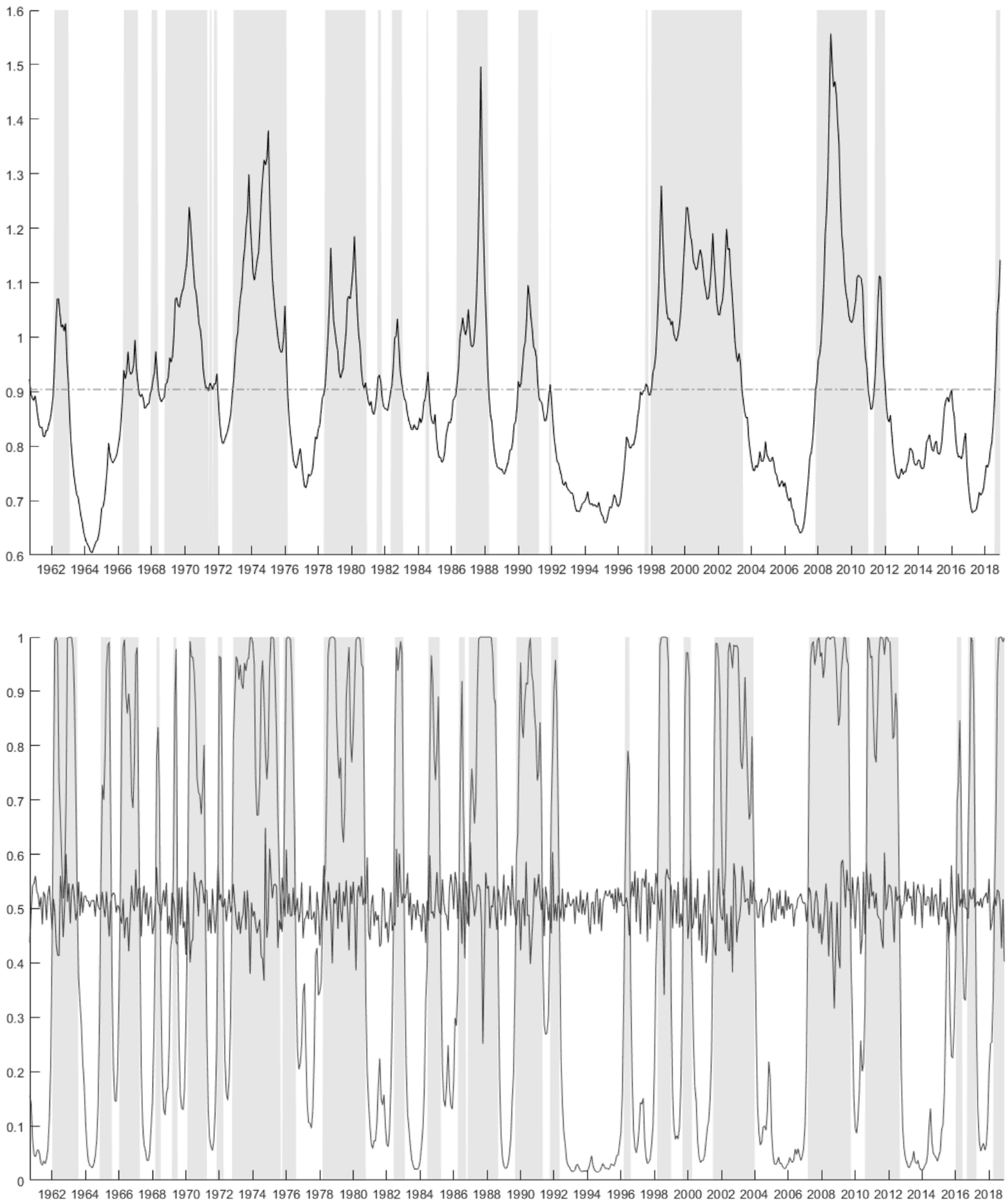

Fig. 1. Low-uncertainty and high-uncertainty states. Shaded areas indicate high-uncertainty regimes. High uncertainty regimes in Panel A are identified when the financial uncertainty variable is above its average mean over the sample period August 1960 to December 2018. Panel B shows the smoothed probabilities of being in the high-uncertainty state obtained from the Markov-switching autoregressive models in (7)–(9) with switches only in the variance. High-uncertainty regimes are identified when the smoothed probabilities are higher than 0.5. The time series $r_t + 0.5$ is also plotted.

The uncertainty variable in model (7) is assumed to have a regime-dependent mean, μ_{k_t}, and a regime-dependent volatility, σ_{k_t}. The variable $k_t \in \{0,1\}$ is a discrete random variable representing the regime at time t and is assumed to follow a homogeneous first-order Markov process with fixed transition probability matrix:

$$TP = \begin{bmatrix} tp^{00} = \mathbb{P}(k_t = 0 \mid k_{t-1} = 0) & 1 - tp^{11} \\ 1 - tp^{00} & tp^{11} = \mathbb{P}(k_t = 1 \mid k_{t-1} = 1) \end{bmatrix} \tag{8}$$

We consider the logistic functional form for the state probabilities:

$$tp^{ii} = \mathbb{P}(k_t = i \mid k_{t-1} = i) = \frac{\exp\left(\theta_i\right)}{1 + \exp\left(\theta_i\right)}, \quad i = 0, 1 \tag{9}$$

Table 2
Estimation parameters of the Markov-switching models.

	ΔFU	
	MS-MV	MS-V
μ_0	−0.0014	0.0001
	(0.0039)	(0.001)
μ_1	0.0023	
	(0.0052)	
σ_0^2	0.0003***	0.0003***
	(0.0001)	(0.0000)
σ_1^2	0.0017***	0.0017***
	(0.0002)	(0.0002)
θ_0	2.2366***	2.2551***
	(0.2827)	(0.2707)
θ_1	2.1204***	2.1644***
	(0.3577)	(0.316)
LL	1494.179	1494.029
AIC	−2976.358	−2978.057
BIC	−2949.043	−2955.295

Notes: This table presents the in-sample estimation results from the Markov-switching models presented in Section 3.1. Standard errors are displayed as (·). ***, ** and * indicate 1%, 5% and 10% significance, respectively. MS-MV shows the estimation results from the Markov switching model that switches in both the mean and variance, whilst MS-V only switches in variance.

The Markov-switching model with time-varying mean and volatility in (7)–(9) is denoted as MS-MV model. Column 2 of Table 2 presents parameter estimates from this model. The model identifies a regime with a lower uncertainty mean ($\mu_0 = -0.0014$) and lower variance ($\sigma_0^2 = 0.0003$), and a regime with a higher uncertainty mean ($\mu_1 = 0.0023$) and higher variance ($\sigma_1^2 = 0.0017$). Since the mean in each regime is not significantly different from zero, we estimate model (7)–(9) assuming $\mu_0 = \mu_1$. That is, we examine a model that only switches in volatility. We label this model as MS-V. Column 3 in Table 2 provides results for the MS-V model.

A likelihood ratio test (LRT) to test the significance of switches in the mean does not reject the null of equal means with a LRT statistic of $2\,(1494.179 - 1494.029) = 0.301 < \chi^2(1)$, where $\chi^2(1)$ denotes the chi-squared statistic with 1 degree of freedom. Therefore, we consider the more restricted model MS-V for the identification of regimes. Periods of high (low) uncertainty are defined when the smoothed probabilities of being in the high (low) uncertainty regime is higher than 0.5. Panel B in Fig. 1 illustrates the high and low regimes obtained from the MS-V model. The model identifies 46% of the sample in a high-uncertainty state.

As is seen across the figures, for each model the periods of low versus high uncertainty can change. Whilst we do not expect both of the models to define the regimes identically, it is possible to form patterns across the different specifications. A notable difference is that both specifications record heightened uncertainty times in a much greater number than official recessions, this is important as we hope to pick up on the particular idiosyncrasies of the financial markets, which is not possible relying solely on business cycle fluctuations. Whilst the Markov Switching model as first addressed in Hamilton (1989) is a purely econometric procedure, that switches based on an unobservable variable. There are some papers in finance that try to understand why financial variables switch regimes. As is noted in Ang and Timmermann (2012), "regime models can match the tendency of financial markets to change their behaviour abruptly and the phenomenon that the new behaviour of financial variables often persists for several periods after such as a change".

Armed with the methods of classifying the uncertainty regimes, we now assess the significance of the different periods from a forecasting perspective.

3.2. In-sample analysis

We estimate the following predictive regression for each of the fourteen predictors,

$$r_t = \gamma_i + \lambda_i x_{i,t-1} + e_{it} \tag{10}$$

where r_t is the excess return of the S&P 500 and $x_{i,t}$ is one of the fourteen predictor variables. In Table 3, we report λ_i coefficients along with the R^2 from the regression. In order to disentangle the usefulness of the regressions in periods of low and heightened uncertainty in-sample we use the disentangled R^2 statistic (R_c^2) defined as follows[13]:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c \, \hat{e}_{it}^2}{\sum_{t=1}^{T} I_t^c (r_t - \hat{r}_t)^2}, \quad \text{for c} = \text{low uncertainty (LU), heightened uncertainty (HU)} \tag{11}$$

We estimate Eq. (10) separately for each predictor. I_t^{LU} (I_t^{HU}) signals the current state and takes a value of one when month t is in a low uncertainty (heightened uncertainty) state and zero on other occasions. Due to the setup of the calculation, it is possible for the disentangled R_c^2 to be negative; $\hat{e}_{it}$ is the fitted residual from (10), and $\overline{r_t}$ is the mean of the returns r_t for the full sample.

[13] See Neely et al. (2014) for further details.

Table 3
Regression estimation results, in-sample.

Predictor	λ_i	t_i	R^2 (%)
MA(1,9)	0.006	1.564*	0.468
MA(1,12)	0.008	1.935*	0.754
MA(2,9)	0.007	1.668*	0.529
MA(2,12)	0.009	2.184*	0.958
MA(3,9)	0.007	1.653*	0.510
MA(3,12)	0.004	0.907	0.160
MOM(9)	0.005	1.278	0.321
MOM(12)	0.005	1.243	0.303
VOL(1,9)	0.006	1.619*	0.477
VOL(1,12)	0.009	2.082*	0.830
VOL(2,9)	0.007	1.942*	0.678
VOL(2,12)	0.008	1.981*	0.756
VOL(3,9)	0.006	1.422*	0.378
VOL(3,12)	0.008	2.054*	0.780

Notes: This table presents the in-sample estimation results from the regression model $r_t = \gamma_i + \lambda_i x_{t-1} + e_{it}$, for each of the fourteen technical indicators across the full sample, 1960–2018. We report the estimated coefficient, λ, the t-statistic and R-squared (R^2). Significance is denoted at the * 10%, ** 5% and *** 1% level using the Wild bootstrap procedure which accounts for general forms of conditional heteroskedasticity and correlations between the equity risk premium and predictor innovations as in Neely et al. (2014). Hypothesis tests are reported for the one sided hypothesis test that $H_0 : \lambda_i = 0$ versus the alternative that $H_A : \lambda_i > 0$.

Table 4
Regression estimation results, in-sample disentangled.

Predictor	FU-mean		MS-V	
	R^2_{LU} (%)	R^2_{HU} (%)	R^2_{LU} (%)	R^2_{HU} (%)
MA(1,9)	1.107	0.198	1.803	−0.193
MA(1,12)	1.324	0.502	2.151	0.056
MA(2,9)	0.941	0.438	1.547	0.119
MA(2,12)	1.339	0.903	2.686	0.238
MA(3,9)	1.324	0.172	1.703	−0.086
MA(3,12)	0.951	−0.098	1.345	−0.356
MOM(9)	1.233	0.031	1.800	−0.318
MOM(12)	0.273	0.369	1.146	−0.036
VOL(1,9)	0.458	0.454	0.581	0.395
VOL(1,12)	0.621	0.869	1.271	0.580
VOL(2,9)	0.943	0.540	2.119	−0.042
VOL(2,12)	0.881	0.671	2.299	−0.012
VOL(3,9)	1.007	0.114	1.940	−0.387
VOL(3,12)	0.855	0.713	2.263	0.040

Notes: This table presents the disentangled in-sample estimation results from the regression model $r_t = \gamma_i + \lambda_i x_{t-1} + e_{it}$ for each of the fourteen technical indicators. The disentangled R^2 statistics, R^2_{LU} and R^2_{HU} are computed using the regimes as described in Section 3.1. R^2_{LU} (R^2_{HU}) attempts to capture good (bad) times (i.e. periods of low (heightened) financial uncertainty).

Table 3 reports in-sample tests for the full sample over the period 1960:08–2018:12, the coefficient λ_i is estimated via least-squares. The majority of technical indicators appear to produce statistically significant signals for the returns of the stock market. However, as has been shown by the previous literature it is important to interpret in-sample analysis with caution. With this in mind, we also report wild bootstrap p-values, which account for unknown forms of conditional heteroskedasticity as in Neely et al. (2014).[14] In Table 4, we disentangle the usefulness of the predictors in low and heightened uncertainty regimes twice (FU-mean and MS-V). The R^2_{LU} and R^2_{HU} relate to periods of low and heightened uncertainty, respectively. In the second and third column on Table 4, we see that when defining the regimes using the mean of the financial uncertainty index, the majority of the technical predictors produce larger R^2_{LU} compared with R^2_{HU}. This general theme is replicated and improved upon when using the switching regression where all fourteen predictors produce larger R^2_{LU} compared with R^2_{HU}.

3.3. Out-of-sample analysis

3.3.1. Forecasting the equity premium

Analysis from predictive regression frameworks is often critiqued for failing to aid a market agent when attempting to time the market (see, for example, Welch and Goyal, 2008). For our analysis, the in-sample results displayed across Table's 3 and 4

[14] The wild bootstrap procedure resamples whilst preserving the contemporaneous correlations in the data. Further details are found in the Online Appendix of Neely et al. (2014).

Table 5
Out-of-sample results, full sample.

Predictor	R^2_{OS}	CW-stat
MA(1,9)	0.000	0.561
MA(1,12)	0.444	1.300*
MA(2,9)	0.255	0.999
MA(2,12)	0.803	1.684**
MA(3,9)	−0.061	0.771
MA(3,12)	−0.067	0.19
MOM(9)	0.122	0.675
MOM(12)	0.149	0.700
VOL(1,9)	−0.294	0.421
VOL(1,12)	0.238	1.307*
VOL(2,9)	0.118	1.199
VOL(2,12)	0.659	1.614*
VOL(3,9)	−0.145	0.661
VOL(3,12)	0.561	1.536

Notes: This table presents out-of-sample R^2_{OS} statistics across the full sample, comparing the predictive regression forecasts using the technical predictors with the historical average forecast, see Welch and Goyal (2008). Significance in terms of the Clark and West (2007) statistics which tests whether the R^2_{OS} is greater than 0 is denoted at the 10%, 5%, and 1% level respectively, *, **, ***. Positive R^2_{OS} values indicate the predictive regression forecast outperforms the historical average in terms of mean-squared forecast error.

suggest a market agent should find more success with technical predictors in periods of low uncertainty. To show that these results persist out-of-sample, we generate forecasts in a predictive regression framework in (12) and compare mean-squared forecast errors against the historical average forecast in (13), the current benchmark in the stock return predictability literature. Many papers have previously highlighted that popular macroeconomic variables fail to beat it when using a similar framework,

$$\hat{r}_{i,t} = \hat{\gamma}_i + \hat{\lambda}_i x_{i,t-1} \tag{12}$$

$$\hat{r}^{HA}_t = \frac{1}{t}\sum_{j=1}^{t} r_j \tag{13}$$

The comparison between the predictive regression forecast and the historical average can be summarized using the out-of-sample R^2_{OS} statistic. Following the framework provided in Campbell and Thompson (2008),

$$R^2_{OS} = 1 - \frac{\sum (r_t - \hat{r}_{i,t})^2}{\sum (r_t - \hat{r}^{HA}_t)^2} \tag{14}$$

$$R^2_{OS}(c) = 1 - \frac{\sum (r_t - \hat{r}_{i,t})^2 I^c_t}{\sum (r_t - \hat{r}^{HA}_t)^2 I^c_t}, \quad \text{for } c = \text{low uncertainty (LU), heightened uncertainty(HU)} \tag{15}$$

We report R^2_{OS} for low uncertainty, $R^2_{OS}(LU)$, and heightened uncertainty, $R^2_{OS}(HU)$, times by disentangling the predictive accuracy between periods (see Eq. (15)). In Eq. (14), r_t is the actual return, $\hat{r}_i$ is the forecasting from the predictive regression framework as in (12), and $\hat{r}^{HA}_t$ is the forecast from the historical average. Following the previous literature, we produce forecasts in an expanding window manner. For comparability to Neely et al. (2014), we set the initial window to be 181 months to produce the first one-step-ahead forecast. In Table 6, we report these results using our measures of the different regimes.[15] A positive R^2_{OS} indicates that the predictive regression forecast outperforms the historical average having a lower mean squared error. As is seen in Table 6, with the exception of defining the low and heightened uncertainty regimes using the mean of the financial uncertainty index, out-of-sample R^2 measures in low uncertainty times ($R^2_{OS}(LU)$) are entirely positive, with the majority being statistically significant using the Clark and West (2007) test method, where the null hypothesis $R^2_{OS} \leq 0$ is tested against the alternative that $R^2_{OS} > 0$. It is also apparent that even if a technical predictor produces a superior forecast compared with the historical average in heightened uncertainty times, i.e. $R^2_{OS}(HU)$ is positive, this is never statistically significant.

Interestingly, when analysing the usefulness of the fourteen technical predictors across the full sample (see Table 5), it would appear that whilst several predictors produce positive R^2_{OS} statistics, it is only MA(2,12), where this is statistically significant at the 5% level using the Clark and West (2007) test. The seemingly ordinary performance of technical predictors across the full sample sees significant improvements when we disentangle into low versus heightened uncertainty times.

3.4. A further application: volatility forecasting

Section 3.3.1 shows that return predictability from technical indicators is stronger during periods of low-uncertainty versus high-uncertainty. In line with these results, we compare the out-of-sample volatility forecasting accuracy of technical indicators and show that stock volatility predictability is also better when the market is in a low-uncertainty state.

[15] We also assess a median cut method to define periods of high and low uncertainty and allow for more than two regimes. The result that the technical indicators perform better in periods of low uncertainty remains, these results are available upon request. We would like to thank an anonymous reviewer for this suggestion.

Table 6
Out-of-sample results, disentangled.

Predictor	FU-mean		MS-V	
	$R^2_{OS}(LU)$	$R^2_{OS}(HU)$	$R^2_{OS}(LU)$	$R^2_{OS}(HU)$
MA(1,9)	1.119**	−0.438	1.148**	−0.59
MA(1,12)	1.522**	0.022	2.215***	−0.468
MA(2,9)	0.691*	0.084	1.03**	−0.144
MA(2,12)	1.385**	0.575	2.319***	0.023
MA(3,9)	1.132**	−0.529	2.473***	−1.365
MA(3,12)	0.686*	−0.362	0.998***	−0.614
MOM(9)	0.889**	−0.179	0.876**	−0.266
MOM(12)	0.455	0.029	0.758**	−0.165
VOL(1,9)	−0.222	−0.322	0.526	−0.716
VOL(1,12)	−1.015	0.728	1.646**	−0.487
VOL(2,9)	0.034	0.151	3.351***	−1.545
VOL(2,12)	0.608*	0.679	2.126***	−0.096
VOL(3,9)	0.167	−0.268	2.524***	−1.519
VOL(3,12)	0.006	0.779	2.154***	−0.258

Notes: This table presents out-of-sample R^2_{OS} that are disentangled, comparing the predictive regression forecasts using the technical predictors with the historical average forecast, see Welch and Goyal (2008). Significance in terms of the Clark and West (2007) statistics which tests whether the R^2_{OS} is greater than 0 is denoted at the 10%, 5%, and 1% level respectively, *, **, ***. Positive R^2_{OS} values indicate the predictive regression forecast outperforms the historical average in terms of mean-squared forecast error. The disentangled R^2_{OS} statistics, $R^2_{OS}(LU)$ and $R^2_{OS}(HU)$ are computed using the regimes as described in Section 3.1. $R^2_{OS}(LU)$ ($R^2_{OS}(HU)$) attempts to capture good (bad) times (i.e. periods of low (heightened) financial uncertainty).

We use monthly realized volatility as a proxy for the 'actual' volatility. The realized volatility for month t is computed as the squared root of the sum of squared daily returns,[16]

$$RV_t = \sqrt{\sum_{j=1}^{n_t} r_{j,t}^2} \tag{16}$$

where $r_{j,t}$ is the jth trading day return in month t and n_t denotes the number of trading days during month t.

Our volatility forecasts are obtained using the exponentially weighted moving average (EWMA) model introduced by Morgan and Reuters Ltd (1996). The one-period-ahead volatility forecast is given by

$$\hat{\sigma}_{i,t} = \sqrt{w\,\hat{\sigma}^2_{i,t-1} + (1-w)\,\hat{e}^2_{i,t}} \tag{17}$$

where $\hat{e}_{i,t}$ is the fitted residual from (10) using rolling windows of 200 observations. The parameter $w \in \{0,1\}$ is the so-called "decay-factor" that reflects how the impact of past observations decays while forecasting $\hat{\sigma}_{i,t}$. The most recent observation has the largest impact and the impact decays exponentially for past observations. The optimal decay factor is estimated for each individual stock by minimizing the heteroskedasticity adjusted mean absolute error (HMAE):

$$\text{HMAE} = \frac{1}{M}\sum_{t=1}^{M}\left|1 - \frac{RV_t^2}{\hat{\sigma}_t^2}\right| \tag{18}$$

where M is the out of sample size.

To measure volatility forecast accuracy, we employ a measure similar to the out-of-sample statistic of Campbell and Thompson (2008) used in Section 3.3.1. Specifically, we follow Blair et al. (2001) and use the proportion of explained variability

$$\text{PEV} = 1 - \frac{\sum_{t=1}^{M}(RV_t - \hat{\sigma}_{i,t})^2}{\sum_{t=1}^{M}(RV_t - \overline{RV}_t)^2} \tag{19}$$

where $\overline{RV}_t$ is the mean value of the monthly realized volatility in the out of sample period: $\overline{RV}_t = \frac{1}{M}\sum_{t=1}^{M} RV_t$. The measure PEV compares the sum of squared forecasts errors with the variation in realized volatility. Higher values of PEV correspond to more accurate forecasts, being PEV closer to 1 for small forecasts errors.

Over periods of heightened and low uncertainty, conditional forecast accuracy is computed as:

$$\text{PEV}_c = 1 - \frac{\sum_{t=1}^{M}(RV_t - \hat{\sigma}_{i,t})^2 I_t^c}{\sum_{t=1}^{M}(RV_t - \overline{RV}_t)^2 I_t^c},\ \text{ for c = low uncertainty (LU), heightened uncertainty(HU)} \tag{20}$$

A measure similar to (20) has recently been used by Li and Zakamulin (2019). The authors examine how volatility predictability changes across bull and bear states of the market, where the regimes are identified using the dating algorithms of Pagan and Sossounov (2003) and Lunde and Timmermann (2004).

[16] Many studies advocate the use of high-frequency intraday data to estimate the latent volatility (see, for example, Andersen et al., 2003). We do not consider intraday data in our analysis since the purpose of this paper is to compare predictability ability during good versus bad times rather than obtaining the highest possible volatility forecasting accuracy.

Table 7
Volatility forecast accuracy.

Predictor	PEV (%)	FU-mean		MS-V	
		PEV_{LU} (%)	PEV_{HU} (%)	PEV_{LU} (%)	PEV_{HU} (%)
MA(1,9)	39.983	42.683***	39.292	48.979***	37.423
MA(1,12)	39.244	42.300***	38.461	48.913***	36.492
MA(2,9)	40.604	42.387***	40.147	48.986***	38.219
MA(2,12)	38.879	42.600***	37.926	49.187***	35.945
MA(3,9)	41.357	42.483***	41.069	48.933***	39.202
MA(3,12)	40.917	43.150***	40.345	49.224***	38.553
MOM(9)	39.697	42.819***	38.898	49.01***	37.047
MOM(12)	40.517	43.033***	39.872	49.052***	38.088
VOL(1,9)	41.246	42.686***	40.877	49.191***	38.985
VOL(1,12)	39.787	42.244***	39.158	48.948***	37.180
VOL(2,9)	40.163	41.536***	39.811	48.767***	37.714
VOL(2,12)	39.424	42.752***	38.572	49.513***	36.553
VOL(3,9)	41.201	42.301***	40.919	49.448***	38.855
VOL(3,12)	39.556	43.315***	38.593	50.543***	36.429

Notes: This table presents volatility forecast accuracies in (19)–(20). PEV (%) captures the percentage of volatility explained by the forecasts over the out-of-sample period. PEV_{LU} (%) (PEV_{HU} (%)) represent the percentage of volatility explained by the forecasts in low- (high-)uncertainty times. The significance of the forecasts are measured using bootstrapping procedures as explained in Section 3.4. Low- and high-uncertainty periods are identified using the procedures described in Section 3.1

For each technical indicator, we test the hypothesis $\text{PEV}_c \leq 0$ against the hypothesis of predictive ability $\text{PEV}_c > 0$. We follow Li and Zakamulin (2019) and compute the p-values from these tests by resampling the data used to compute PEV_c. In particular, we use the stationary block-bootstrap of Politis and Romano (1994) to resample the nonzero elements in the sequences $\left\{(RV_t - \hat{\sigma}_{i,t})^2 I_t^c\right\}_{t=1}^M$ and $\left\{(RV_t - \overline{RV}_t)^2 I_t^c\right\}_{t=1}^M$, for c = low uncertainty (LU), heightened uncertainty(HU). The optimal block length is obtained following Patton et al.'s (2009) procedure. The resampled data is then used to compute a resampled version of PEV_c in (20). We repeat this procedure $N = 10{,}000$ times. Let q be the number of times the resampled version of PEV_c is negative. An estimate of the p-value for testing $\text{PEV}_c \leq 0$ is calculated as q/N.[17]

Column 2 in Table 7 contains the volatility forecasts accuracies over the full out-of-sample period measured by (19). The remaining columns of Table 7 provide the forecasts accuracies in low uncertainty and heightened uncertainty times as identified by the models in Section 3.1. Technical indicators provide greater forecast accuracies when the market is in a low-uncertainty state as identified by any of the procedures in Section 3.1. Furthermore, the estimated forecasts accuracies are only significant in periods of low uncertainty with p-values smaller than 1% in all cases. On the other hand, none of the accuracy measures are significant in high-uncertainty periods or when considering the full sample.

4. Conclusion

In this paper, we find that technical predictors such as moving averages provide superior forecasts of the equity risk premium in periods of low financial uncertainty. We measure low versus heightened uncertainty using the financial uncertainty index of Ludvigson et al. (2021). In-sample, we report disentangled R^2 statistics. In an out-of-sample exercise, we show the superior performance of the technical predictors when compared against the historical average forecast. As robustness checks, we consider alternative methods of disentangling between periods of low and heightened financial uncertainty. The results that technical indicators perform better in periods of low financial uncertainty remains throughout. We also show significant gains from forecasting the volatility of stock market returns in low uncertainty regimes. Overall, our results provide further evidence for the mechanism that suggests when uncertainty rises investors' opinions polarize, leading to a breakdown in trend-chasing strategies. It may also be the case that periods of heightened uncertainty may drive certain investors away from the financial market in search of safer assets. This mechanism appears to lead to a deterioration of predictability when using technical predictors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[17] Due to the latent nature of volatility, we are not able to use Clark and West's (2007) test as in Section 3.3.1.

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