

Can we forecast better in periods of low uncertainty?

The role of technical indicators.

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Overview

- 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 uncertainty**.
- We measure changes in uncertainty using a Markov Switching model.
- 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.

Motivation

The debate of whether or not stock market returns are predictable continues.

1. [Fama \(1970\)](#) - Efficient Capital Markets
2. 1970 - 2000s numerous papers for and against stock return predictability.
3. [Lettau and Ludvigson \(2001\)](#) - suggest that stock returns are predictable based on numerous predictors.
4. [Welch and Goyal \(2008\)](#) - question the viability of predictive regression forecasts in terms of timing the market **out-of-sample**.

Motivation

Since [Welch and Goyal \(2008\)](#) a new emphasis on finding predictability (new predictors, forecasting improvements, etc.).

1. [Rapach et al. \(2016, Journal of Financial Economics\)](#), 'short interest is arguably the strongest known predictor'.
2. [Neely et al. \(2014, Management Science\)](#), technical indicators (widely employed by practitioners) out-perform macroeconomic indicators.

Interesting findings...

Neely et al. (2014, Management Science)

1. Despite the positives of the paper, out-of-sample, predictability still remains weak.
 - Out-of-sample R^2 's, positive but small, often not statistically different to historical average forecast.
2. Predictability is concentrated in recessions
 - Technical indicators perform better in periods of recession compared to the historical average forecast.

Research Aims

1. Examine the predictive ability of technical predictors across periods of low versus high uncertainty.
2. Assess the out-of-sample implications of the results.
3. Examine the usefulness of technical predictors when forecasting the volatility returns.

All data is collected over a period 1960-2018.

1. Uncertainty data from [Ludvigson et al. \(2021\)](#).

- The authors use a FAVAR model to measure the unpredictable component of 147 financial time series, from valuation ratios to portfolios of equity returns.
- The measure of uncertainty conveniently aggregates uncertainty derived from all sources into one summary statistic

2. Monthly volume and price data collected for the S&P 500.

- Used to generate 14 technical indicators following the procedure in [Neely et al. \(2014\)](#).
- $BS1 = MA(1,9), MA(1,12), MA(2,9), MA(2,12), MA(3,9), MA(3,12),$
- $BS2 = MOM(9), MOM(12),$
- $BS3 = VOL(1,9), VOL(1,12), VOL(2,9), VOL(2,12), VOL(3,9), VOL(3,12).$
- Technical indicators rely on past price and volume patterns to identify price trends believed to persist into the future.

Technical indicators are based on trend following strategies, for example,

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

where

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

Comparing two moving averages, P_t is the level of a stock price index, $s(l)$ is the length of the short (long) $MA(s < l)$

Intuitively, the MA rule detects changes in stock price trends because the short MA will be more sensitive to recent price movements than the long MA.

In-sample analysis

We begin with a predictive regression framework that relates fourteen technical predictors to the monthly excess returns of the S&P 500.

$$r_t = \gamma_i + \lambda_i x_{i,t-1} + e_{it} \quad (3)$$

Table: Regression estimation results, in-sample

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

Defining periods of heightened/low uncertainty

A number of papers define periods of low uncertainty using recessions and expansions.

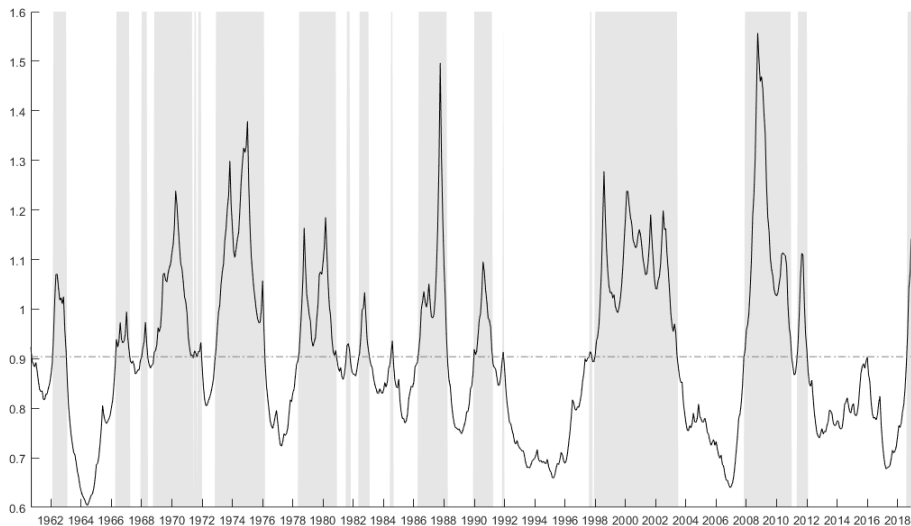
- Does the market react in a more timely manner?
- A flight to quality will often happen prior to recessions as investors foresee negative times ahead.

Our formal definition of low and heightened uncertainty regimes is based on the financial uncertainty index of [Ludvigson et al. \(2021\)](#).

- Our first simple measure is when the values of the index is above its mean:
 $FU - E(FU) > 0$
- The second measure uses a Markov-switching (MS) model - we switch based on financial uncertainty.

Defining periods of heightened/low uncertainty

The mean measure of uncertainty.



The Markov Switching Model

We consider a MS-model 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.
- 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

$$\Delta FU_t = \mu_{k_t} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_{k_t}^2) \quad (4)$$

- The uncertainty variable in model (4) is assumed to have a regime-dependent mean, μ_{k_t} , and a regime-dependent volatility, σ_{k_t} .

The Markov Switching Model

- 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

$$TP = \begin{bmatrix} tp^{00} = \mathbb{P}(k_t = 0 \mid k_{t-1} = 0) & 1 - tp^{11} \\ 1 - tp^{00} & tp^{11} = \mathbb{P}(k_t = 1 \mid k_{t-1} = 1) \end{bmatrix} \quad (5)$$

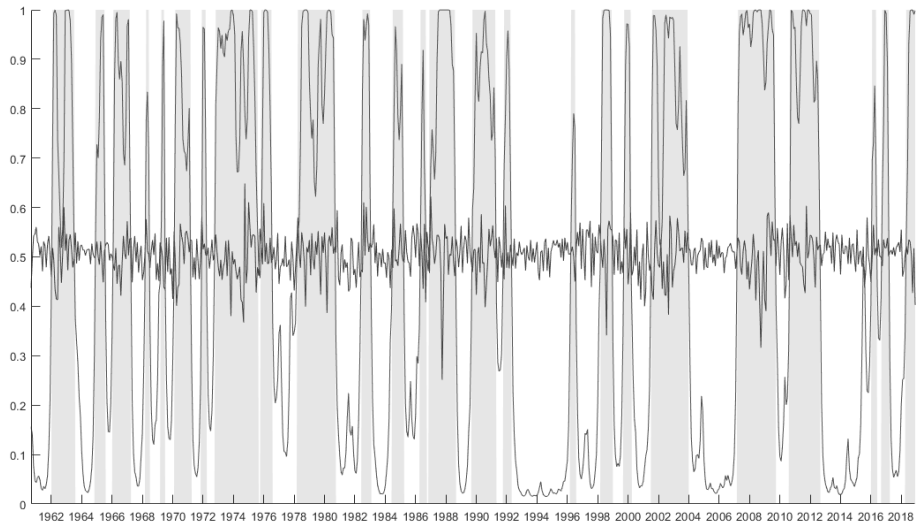
- We consider the logistic functional form for the state probabilities:

$$tp^{ii} = \mathbb{P}(k_t = i \mid k_{t-1} = i) = \frac{\exp(\theta_i)}{1 + \exp(\theta_i)}, \quad i = 0, 1 \quad (6)$$

- Since the mean in each regime is not significantly different from zero, we estimate the model assuming $\mu_0 = \mu_1$. That is, we examine a model that only switches in volatility.
- Periods of high (low) uncertainty are defined when the smoothed probabilities of being in the high (low) uncertainty regime is higher (lower) than 0.5.

Defining periods of heightened/low uncertainty

The mean measure of uncertainty.



Disentangled uncertainty

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:

$$R_c^2 = 1 - \frac{\sum_{t=1}^T I_t^c \hat{e}_{it}^2}{\sum_{t=1}^T I_t^c (r_t - \bar{r}_t)^2}, \text{ for } c=\text{low uncertainty (LU), heightened uncertainty (HU)} \quad (7)$$

- We estimate R_c^2 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.

Disentangled uncertainty

Table: Disentangled based on $FU - E(FU) > 0$

Predictor	$R^2_{LU} (%)$	$R^2_{HU} (%)$	Predictor	$R^2_{LU} (%)$	$R^2_{HU} (%)$
MA(1,9)	1.107	0.198	MOM(12)	0.273	0.369
MA(1,12)	1.324	0.502	VOL(1,9)	0.458	0.454
MA(2,9)	0.941	0.438	VOL(1,12)	0.621	0.869
MA(2,12)	1.339	0.903	VOL(2,9)	0.943	0.540
MA(3,9)	1.324	0.172	VOL(2,12)	0.881	0.671
MA(3,12)	0.951	-0.098	VOL(3,9)	1.007	0.114
MOM(9)	1.233	0.031	VOL(3,12)	0.855	0.713

Disentangled uncertainty

Table: Disentangled based on MS-model

Predictor	R_{LU}^2 (%)	R_{HU}^2 (%)	Predictor	R_{LU}^2 (%)	R_{HU}^2 (%)
MA(1,9)	1.803	-0.193	MOM(12)	1.146	-0.036
MA(1,12)	2.151	0.056	VOL(1,9)	0.581	0.395
MA(2,9)	1.547	0.119	VOL(1,12)	1.271	0.580
MA(2,12)	2.686	0.238	VOL(2,9)	2.119	-0.042
MA(3,9)	1.703	-0.086	VOL(2,12)	2.299	-0.012
MA(3,12)	1.345	-0.356	VOL(3,9)	1.940	-0.387
MOM(9)	1.800	-0.318	VOL(3,12)	2.263	0.040

Out-of-sample forecasts

Goyal and Welch (2008) - predictive regression models would not have helped a market agent time the market

- We assess out-of-sample forecasts in the following manner,

$$\hat{r}_{i,t} = \hat{\gamma}_i + \hat{\lambda}_i x_{i,t-1} \quad (8)$$

$$\hat{r}_t^{HA} = \frac{1}{t} \sum_{j=1}^t r_j \quad (9)$$

- We produce forecasts in an expanding window manner, with the initial forecast using 181 months.

Out-of-sample forecasts

The comparison between the predictive regression forecast and the historical average can be summarised using the out-of-sample R_{OS}^2 statistic. Following the framework provided in [Campbell and Thompson \(2008\)](#),

$$R_{OS}^2 = 1 - \frac{\sum (r_t - \hat{r}_{i,t})^2}{\sum (r_t - \hat{r}_t^{HA})^2} \quad (10)$$

To disentangle, we use a similar framework as the disentangled R^2 -statistic,

$$R_{OS}^2(c) = 1 - \frac{\sum (r_t - \hat{r}_{i,t})^2 I_t^c}{\sum (r_t - \hat{r}_t^{HA})^2 I_t^c}, \quad (11)$$

- for $c = \text{low uncertainty (LU)}$, heightened uncertainty (HU)
- if $R_{OS}^2 > 0$ the the predictive regression forecast outperforms the historical average forecast.

Out-of-sample results - full sample

Goyal and Welch (2008) - predictive regression models would not have helped a market agent time the market

Table: Out-of-sample results - full sample

Predictor	R^2_{OS}	CW-Stat	Predictor	R^2_{OS}	CW-Stat
MA(1,9)	0.00	0.561	MOM(12)	0.149	0.700
MA(1,12)	0.444	1.300*	VOL(1,9)	-0.294	0.421
MA(2,9)	0.255	0.999	VOL(1,12)	0.238	1.307*
MA(2,12)	0.803	1.684**	VOL(2,9)	0.118	1.199
MA(3,9)	-0.061	0.771	VOL(2,12)	0.659	1.614*
MA(3,12)	-0.067	0.190	VOL(3,9)	-0.145	0.661
MOM(9)	0.122	0.675	VOL(3,12)	0.561	1.536

Clark and West (2007) test, where the null hypothesis $R^2_{OS} \leq 0$ is tested against the alternative that $R^2_{OS} > 0$.

Out-of-sample forecasts

Table: Out-of-sample results - disentangled

FU-mean					
Predictor	$R_{OS}^2(LU)$	$R_{OS}^2(HU)$	Predictor	$R_{OS}^2(LU)$	$R_{OS}^2(HU)$
MA(1,9)	1.119**	-0.438	MOM(12)	0.455	0.029
MA(1,12)	1.522**	0.022	VOL(1,9)	-0.222	-0.322
MA(2,9)	0.691*	0.084	VOL(1,12)	-1.015	0.728
MA(2,12)	1.385**	0.575	VOL(2,9)	0.034	0.151
MA(3,9)	1.132**	-0.529	VOL(2,12)	0.608*	0.679
MA(3,12)	0.686*	-0.362	VOL(3,9)	0.167	-0.268
MOM(9)	0.889**	-0.179	VOL(3,12)	0.006	0.779

Table: Out-of-sample results - disentangled

MS-Model					
Predictor	$R_{OS}^2(LU)$	$R_{OS}^2(HU)$	Predictor	$R_{OS}^2(LU)$	$R_{OS}^2(HU)$
MA(1,9)	1.148**	-0.59	MOM(12)	0.758**	-0.165
MA(1,12)	2.215***	-0.468	VOL(1,9)	0.526	-0.716
MA(2,9)	1.03**	-0.144	VOL(1,12)	1.646**	-0.487
MA(2,12)	2.319***	0.023	VOL(2,9)	3.351***	-1.545
MA(3,9)	2.473***	-1.365	VOL(2,12)	2.126***	-0.096
MA(3,12)	0.998***	-0.614	VOL(3,9)	2.524***	-1.519
MOM(9)	0.876**	-0.266	VOL(3,12)	2.154***	-0.258

The mechanism

Our results question the wisdom that predictability based on technical indicators should improve in recessions (or periods of uncertainty).

- Often as in [Neely et al. \(2014\)](#) in stock return predictability settings, researchers compare predictive regression model forecasts to the historical average forecast.
- 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.
- In a predictability setting with macroeconomic variables, [Cujean and Hasler \(2017\)](#) provide a compelling argument that in “bad” times, predictability is a result of the polarizing opinions of investors.
- [Bali et al. \(2017\)](#) find that if investors’ expectations or preference towards uncertainty are dispersed, then investors with low aversion against uncertainty will remain, whilst investors with high aversion against uncertainty will ‘cease or reduce participation in the stock market’.
- Trends should therefore break down in periods of high uncertainty.

The mechanism

Investors follow trends based which are useful for stock return predictability



A periods of uncertainty arises



Investors have dispersed aversion against financial uncertainty



When uncertainty rises investor disagreement spikes



Predictability based on technical indicators breaks down



This provides market agents with signals of when best to use technical indicators to forecast stock market returns

Further results

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.

- We forecast volatility using the exponentially weighted moving average model to produce one period ahead volatility forecasts.
- Estimated forecast accuracies are only significant in periods of low uncertainty with p-values smaller than 1% in all of the cases.

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. \(2021\)](#).
- The results persist in- and out-of-sample.
- 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.

Thank you and any questions?

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