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Conditional mean reversion of financial ratios and the predictability of returns

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ABSTRACT

While traditional predictive regressions for stock returns using financial ratios are empirically proven to be valuable at long-term horizons, evidence of predictability at few-month horizons is still weak. In this paper, based on the empirical regularity of a typical dynamic of stock returns following the occurrence of a mean reversion in the US Shiller CAPE ratio when the latter is high, we propose a new predictive regression model that exploits this stylized fact. In-sample regressions approximating the occurrence of mean reversion by the smoothed probability from a regime-switching model show superior predictive powers of the new specification at few-month horizons. These results also hold out-of-sample, exploiting the link between the term spread and the credit spread as business cycle variables and the occurrence of mean reversion in the US Shiller CAPE ratio. For instance, the out-of-sample R-squared of the new predictive regression model is ten (four) times bigger than that of the traditional predictive model at a 6 (12) month horizon. Our results are robust with respect to the choice of the valuation ratio (CAPE, excess CAPE or dividend yield), and countries (Canada, Germany and the UK). We also conduct a mean–variance asset allocation exercise which confirms the superiority of the new predictive regression in terms of utility gain.

1. Introduction

The predictability of stock returns is of great importance not only for practitioners but also for academics with important implications for financial models of risk and return. In this paper, we provide evidence that financial ratios can predict in-sample and out-of-sample returns at a few month horizons, when considering that these financial ratios are persistent during some business cycle phases, while mean-reverting around other phases, and exploiting the informational content of some business cycle variables (term and credit spreads) about these phases.

The Cyclically-Adjusted-Price to Earnings (CAPE) ratio of Campbell and Shiller (1988), is well-known in characterising the strong relationship between an inflation adjusted earnings-price ratio and subsequent long-term returns. It has now become an often cited and followed measure of long-term equity market valuation by both academics and practitioners. More generally, a prolific number of academic papers have focussed on the usefulness of financial ratios for forecasting future stock market returns at multi-year horizons, including price-earnings (P/E), CAPE, dividend yield as well as book-to-market ratios

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(Rozeff, 1984; Fama and French, 1988; Campbell and Shiller, 1988; Cochrane, 1991; Hodrick, 1992; Goetzmann and Jorion, 1993; Lewellen, 2004 etc.). Moreover, these studies conclude that growth rates of fundamentals, such as dividends or earnings, are much less forecastable than returns, suggesting that most of the variation of financial ratios is due to variations in expected returns through mean reversion.[1] The underlying mechanism is that high market P/E ratios forecast low future stock returns, based on the inevitable correction in the market price, i.e. the decline in the ratio occurs almost exclusively from an adjustment in prices rather than in earnings. In other words, with mean reversion theory, when stock prices are very high relative to P/E indicators, then prices will eventually fall in the future to bring the ratios back to more normal historical levels (Campbell and Shiller, 1998; Campbell and Shiller, 2001).

Most of the existing empirical evidence has shown that this relation holds only for long-term stock market returns, with the consequence that P/E ratios revert to their historical average values over long horizons (Campbell and Shiller, 1998; Weigand and Irons, 2007 etc.).[2] For instance, Campbell and Shiller (1998) in their seminal paper showed that P/E ratios have considerable explanatory power in predicting only long-horizon future returns, with an explanatory power (as measured by the R-squared) of 20% or more in regressing future 4- and 5-year stock returns on initial P/Es. See also Weigand and Irons (2007) who studied a very long dataset (1871–2004) and found that high P/E ratios in the stock market are generally followed by a decade of lower than average real returns.[3]

However, as shown in Lettau and Van Nieuwerburgh (2008), the short-term predictive content in the valuation ratios can be recovered, if one relaxes the assumption of a fixed steady state mean of the economy. In other words, by assuming that the mean of a valuation ratio is regime-specific rather than global, short-term mean reversions can arise with a statistically significant predictive ability of the financial ratio for short-horizon returns. They indeed reported that dealing with regime changes by adjusting valuation ratios to their steady-state values increases their power in predicting returns over the next year.[4]

These findings have been analyzed from a more structural point of view by recent papers which try to link regime changes in the dynamic of valuation ratios to variables measuring the state of the business cycle. For instance, Arnott et al. (2017) by assuming that P/Es mean-revert toward levels that are suggested by macroeconomic conditions, rather than toward long-term averages, found that moderate rather than rock-bottom levels of inflation and real interest rates are associated with the highest valuation multiples. By incorporating these features in predictive regressions, they obtained significative improvements in the short-term forecasting power of the Shiller CAPE ratio for the US and other developed markets. See also Boucher (2006).

Against this background, our goal in this paper is to achieve short-term predictability of stocks' returns, but using a different approach. The core of our approach is that if one succeeds in identifying the *occurrence* of mean reversion in valuation ratios, the short-term predictability of returns can be recovered, based on the idea that the dynamic of returns following the occurrence of a mean reversion is usually different from the overall one. Our empirical investigations reveal indeed that average multi-period returns following a mean reversion in the US Shiller CAPE ratio are negative and range from -1.77% at 1 month up to -3.35% at 6 months. Episodes of mean reversion are identified by the levels of the smoothed probability estimated from a regime switching version of the mean reversion model of Jegadeesh (1991). Interestingly, this pattern appears more typical, when mean reversion episodes are associated with high levels of the CAPE ratio, with subsequent average multi-period returns of -16.46% at twelve months approximately. Predictive regressions exploiting the latter stylized fact show clear-cut superior predictive power at short-term horizons compared to the traditional predictive regression. For illustration, while the adjusted R-squared of the traditional predictive regression ranges from 0.03% (1 month) to 3.18% (12 months), the same statistic ranges from 7.65% (one month) to 11.83% (12 months).

One limitation of the above results is that the predictive powers are evaluated in-sample using the level of smoothed probabilities as an indicator of mean reversion regimes. Hence, they are not exploitable out-of-sample, because the smoothed probabilities estimated from the regime switching model are based on the whole available sample. To keep the power of our predictive regression out-of-sample, we use a simple strategy that consists of using a business cycle variable with a strong early-warning property regarding the occurrence of mean reversion in the US Shiller CAPE ratio, i.e. the US term spread.

The rationale of using the term spread springs from two pieces of evidence, i.e. the link between mean reversion in valuation ratios and economic recession, and the predictive power of term spread on the occurrence of economic recession. The first evidence is corroborated by some works that reported the predictive power of valuation ratios during recession (Rapach et al., 2010; Henkel et al., 2011; Dangl and Halling, 2012).[5] As for the second evidence, there is an abundant literature that highlights the early-warning nature of term spread on the occurrence of economic recession (Stock et al., 1989; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998). The theoretical basis of this typical behaviour goes back to the work of

[1] Note that Chen (2009) reports that part of the lack of dividend growth predictability stems from how dividends are constructed (through the reinvestment strategy). However, in the postwar period, dividend growth is unpredictable regardless of how dividends are constructed. Moreover, the author only performs in-sample tests and restricts the information set to dividend yield. See also McMillan and Wohar (2013).

[2] Short-term evidence of predictability based on financial ratios is at best unstable (Paye and Timmermann, 2006).

[3] A wide literature exists for the dividend price (dividend yield) as valuation ratio. See for example Campbell and Shiller (1988),Cochrane (1991), Fama and French (1988),Rozeff (1984), Lewellen (2004). These papers also conclude in predictability for long-horizon returns.

[4] Also McMillan (2019) documents that using cyclical (less persistent) components of financial ratios improves their predictability power.

[5] Moreover, Baltas and Karyampas (2018) highlight the economic importance of predictability in bad times, i.e. when it matters the most for asset allocators to retain assets and their client base intact. See also Hammerschmid and Lohre (2018).

Kessel (1965) who reported the cyclical behavior of the term spread and investigated the common variation of the term structure of interest rates and business cycles. Fama (1986) argued that this relationship could be consistent with the liquidity preference hypothesis and could be explained in an intertemporal CAPM framework. Harvey (1988) provided analytical evidence that the term spread was related to future consumption growth under the Consumption CAPM (CCAPM) framework. More recently, in a dynamic model with rational expectations, Estrella (2005) showed that the term spread contains information about expectations of future activity and is affected by current monetary policy.

Hence, we use lagged values of the term spread as an indicator of mean reversion in the US Shiller CAPE ratio, and observe that the forecast ability of our new predictive regression over short-term horizons continues to hold out-of-sample. Indeed, while the predictive powers of the traditional predictive regression, as measured by the out-of-sample R-squared, are very low, even negative at very short-term horizons, the new predictive regression shows higher predictive powers at the same horizons. Specifically, at the horizon of 1 (12) month, the out-of-sample R-squared is equal to -0.72% (2.28%) for the traditional regression, while it is equal to 0.64% (8.73%) for the new predictive regression. These findings also hold when considering other financial variables including the excess CAPE yield and the dividend yield, and other countries (Canada, Germany and the UK). Beyond the term spread, our results are also robust to the choice of the business cycle variable, as we obtain qualitatively similar results for the credit spread.

We also conduct a mean–variance asset allocation exercise which confirms the superiority of the new predictive regression in terms of utility gain. For instance, at the 1 month horizon and with a relative risk aversion parameter equal to 3, the utility gains or the annual portfolio management fees that an investor would be willing to pay to switch from the traditional model to the new proposed model, are equal to $2.06\%, 3.51\%, 2.04\%$ and 1.54% for the US, the UK, Germany and Canada, respectively.

Our contribution can be linked to a branch of the literature which sets the objective of increasing the short-term predictive power of valuation ratios regarding risk premiums, using models with time-varying parameters that fit business cycles, and specifically recession and expansion phases (Rapach et al., 2010; Henkel et al., 2011; Dangl and Halling, 2012; Gomez Cram, 2021). For example, Rapach et al. (2010) and Dangl and Halling (2012) documented that excess stock return predictability by the dividend-price ratio and the earnings-price ratio concentrates mostly in recessions, with valuation ratios having higher predictive power during recessions. Henkel et al. (2011) also provided the same evidence with the short-horizon performance of aggregate return predictors, such as the dividend yield and the short rate, that appear non-existent during business cycle expansions, but sizeable during contractions, with the phenomenon related to countercyclical risk premiums as well as the time-variation in the dynamic of the predictors.[6] Similarly, we relate the predictability of returns based on valuation ratios to the state of the business cycle, with the latter approximated via the early-warning property of the term spread regarding mean reversion in financial ratios. This contrasts with the contributions cited above which impose tight parametric restrictions on how predictive coefficients in their dynamic models evolve over time. In our framework, the dynamic comes from the term spread which helps in identifying a financial ratio's mean reversion in a forward looking manner.

Our results suggest that using the informational content of the term spread regarding the occurrence of mean reversion in valuation ratios, helps to improve the short-term predictability of stock returns. In this line, our paper shares the same objective as that of Moench and Tobias (2021) which confirmed the importance of the term spread for equity premium forecasts. Using recession probability forecasts based on the term spread as an explanatory variable, they achieved improvement in the equity premium predictability at short-term horizons. While the improvement as measured by the out-of-sample R-squared is of the same order as in our predictive regression, our out-of-sample approach is simpler, because it is based on a single step regression with only observed and non-estimated variables, and should therefore be robust to estimation risk across samples.

The rest of the paper proceeds as follows. Section 2 develops a dynamic mean reversion model in valuation ratios to identify a mean reversion regime, and analyses stocks' returns dynamic following mean reversion. Based on the empirical findings, our new predictive regression is introduced in this section and its predictive power is evaluated in-sample. Section 3 investigates the out-of-sample forecast ability of the new predictive regression, and Section 4 analyzes the implications for asset allocation. Section 5 evaluates the robustness of our results regarding the choice of the business cycle variable, and the last section concludes. Robustness checks regarding the choice of the financial ratio and the countries under investigation are reported in an Online Appendix.

2. Mean reversion in valuation ratios and in-sample short-term predictability of returns

This first section analyses the informational content of mean reversion in valuation ratios for the short-term dynamic of returns. The first part of the section provides a non-structural model for the occurrence of mean reversion in valuation ratios, and the second part evaluates to what extent this occurence has predictive power (in-sample) for the short-term dynamic of stock prices.

[6] Time-varying short-horizon predictability is also documented in the literature for sector portfolios (Guidolin et al., 2013).

2.1. Dynamic model for mean reversion in valuation ratios

For the description of our model of mean reversion in valuation ratios, let x_t be the natural logarithm of a given valuation ratio, here the US Shiller CAPE ratio recorded at month t. Unit root tests are the usual tools to check for mean reversion in a time series. Indeed, if x_t is nonstationary, it will exhibit no tendency to return to a long-run mean. This is the approach followed by Becker et al. (2012). Using unit roots and multiple structural break tests, they show that the P/E ratio is nonstationary globally, but is stationary around multiple breaks, which implies that this ratio will eventually revert to some local long-run means, confirming the regime-specific dynamic of valuation ratios as stressed by Lettau and Van Nieuwerburgh (2008). Although this approach is the most used in the literature, we do not follow it because it is about stationarity, and does not provide a model for the occurrence of the mean reversion phenomenon. We instead follow the methodology in Jegadeesh (1991) which provides a simple way to model mean reversion in a given time series through linear regression. For x_t the regression writes:

$$dx_t = \alpha_k + \beta_k\left(\sum_{s=1}^{k} dx_{t-s}\right) + \epsilon_{k,t}, \tag{1}$$

where $dx_t = x_t - x_{t-1}$ is the first difference of x_t, k is the holding period[7] and $\epsilon_{k,t}$ is an error term. The parameter of interest is β_k indexed by the holding period. Indeed, mean reversion occurs when $\beta_k < 0$, with the current value of x_t which adjusts to the past value x_{t-1} with regards to the level of lagged multi-period variations, i.e. $\sum_{s=1}^{k} dx_{t-s}$.

Table 1 displays the estimates of β_k using monthly data of the US Shiller CAPE ratio over a very long dataset (February, 1881 to April, 2020).[8] The evolution of this ratio is displayed in Fig. 1. For $k \in \{3, 6, 12\}$, the parameter β_k is positive and statistically significant at the 1% nominal risk level. For the other values of k, the same parameter is not significant at the usual nominal risk level. These results suggest the absence of mean reversion in the US Shiller CAPE ratio over the whole sample. Moreover, the explanatory power of the mean reversion equation as given by the value of the adjusted R-squared is overall very low.

This absence of mean reversion in the valuation ratio can result from the existence of instabilities in the estimated relationship, materialized by regime changes. To capture regime shifts, we consider the following Markov-switching extension (Goldfeld and Quandt, 1973; Hamilton, 1989; Hamilton, 1994; Kim and Nelson, 1999) of the mean reversion Eq. (1)

$$dx_t = \alpha_{k,S_{k,t}} + \beta_{k,S_{k,t}}\left(\sum_{s=1}^{k} dx_{t-s}\right) + \epsilon_{k,t}, \tag{2}$$

with $S_{k,t} \in \{0, 1\}$ a latent binary state variable which takes value 0 (1) when the first (second) regime is at stake. This state variable follows a first order Markov chain with the following transition matrix:

$$P = \begin{bmatrix} \Pr(S_{k,t} = 0 | S_{k,t-1} = 0) & \Pr(S_{k,t} = 1 | S_{k,t-1} = 0) \\ \Pr(S_{k,t} = 0 | S_{k,t-1} = 1) & \Pr(S_{k,t} = 1 | S_{k,t-1} = 1) \end{bmatrix} = \begin{bmatrix} p_{k,00} & p_{k,01} \\ p_{k,10} & p_{k,11} \end{bmatrix} \tag{3}$$

where $p_{k,ij}, (i,j = 0,1)$ denote the transition probabilities of $S_{k,t} = j$ given that $S_{k,t-1} = i$, with the equality $p_{k,i0} + p_{k,i1} = 1$. The transition matrix governs the random behavior of the state variable and is characterized by only two parameters, $p_{k,00}$ and $p_{k,11}$. For the estimation, we make the assumption of a zero-mean Gaussian distribution for the random error term $\epsilon_{k,t}$, with regime-specific variances, i.e. $\epsilon_{k,t} \sim (0, \sigma_{k,S_t})$. The full set of parameters is given by the vector $\theta = (\alpha_{k,0}, \alpha_{k,1}, \beta_{k,0}, \beta_{k,1}, \sigma_{k,0}, \sigma_{k,1}, p_{k,00}, p_{k,11})'$. This vector of parameters can be estimated by the method of quasi-maximum likelihood.

The estimation results (except for the transition probabilities to save space) of this model are displayed in Table 2 for the different values of the holding period parameter k. Focusing on the mean reversion parameters $\beta_{k,0}$ and $\beta_{k,1}$, we can observe that a regime's separation with the absence (presence) of mean reversion in the first (second) regime only occurs with $k \in \{24, 36, 48\}$. Indeed in these cases, $\beta_{k,1}$ is statistically significant and negative suggesting mean reversion in the second regime given by $S_{k,t} = 1$. At the same time $\beta_{k,0}$ is either statistically insignificant or significant and positive, indicating the absence of mean reversion in the first regime $S_{k,t} = 0$.[9] In particular, for $k = 36, 48$, this parameter is positive and statistically significant. This means that rather than being mean reverting, the process of the US Shiller CAPE ratio is persistent for these values of the holding period k. Indeed, as largely discussed by Marques (2004), mean reversion and persistence are inversely

[7] In the empirical applications, we will consider different values of the holding periods, $k \in \{3, 6, 12, 24, 36, 48, 60, 120\}$, corresponding to one quarter, one semester, and one, two, three, four, five and ten years, respectively.

[8] This very long sample has the advantage of numerous non-overlapped observations for traditional long-horizon regressions as well as covering a few episodes of recessions (while only 5 recessions have been recorded by the NBER over the past 40 years). Certainly, the disadvantage is to implicitly consider a unique data generating process despite different kinds of investors, markets, depth and liquidity. This is the reason why we consider different kinds of samples and countries as robustness checks.

[9] Recall that the identification of the absence (presence) of mean reversion in the first (second) regime is made via the sign of the estimated coefficients. Mean (no mean) reversion occurs when $\beta_{k,S_{k,t}} < 0$ ($\beta_{k,S_{k,t}} > 0$). Besides, the variance of the error term is also an element for identification, in the sense that it is supposed to be high (low) with mean (no mean) reversion.

Table 1
Estimation of the mean reversion parameter for the Shiller CAPE ratio.

k	3	6	12	24	36	48	60	120
Estimates	0.0603^{***}	0.0487^{***}	0.0263^{***}	0.0039	0.0037	0.0027	−0.0002	−0.0007
Std. Err.	0.0187	0.0126	0.0096	0.0074	0.0065	0.0048	0.0042	0.0030
R^2 (in %)	1.48	2.10	1.46	0.06	0.08	0.05	0.00	0.01

Notes: For different values of the holding period k, the table displays the parameter estimates of the slope parameter β_k in the mean reversion Eq. (1), followed by the Newey-West robust standard errors. The table also reports the explanatory power as given by the R-squared. *, **, and *** denote traditional significance at 10%, 5% and 1% levels, respectively.

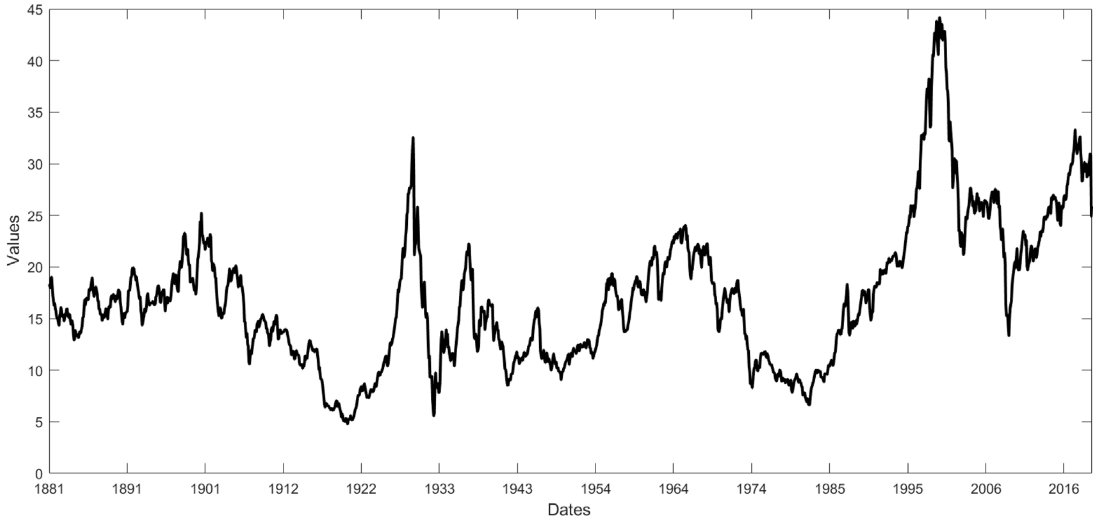

Fig. 1. Dynamic of the US Shiller CAPE ratio: 1881/02–2020/04. Notes: The ratio is computed based on a dataset that consists of monthly stock index prices, earnings data and the consumer price index (to allow conversion to real values). Monthly earnings data are computed from the S&P four-quarter totals for the quarter since 1926, with linear interpolation to monthly figures. Earnings data before 1926 are from Cowles and associates, interpolated from annual data. Stock price data are monthly averages of daily closing prices. The CPI-U (Consumer Price Index-All Urban Consumers) published by the US Bureau of Labor Statistics begins in 1913; the years before 1913 come from the CPI Warren and Pearson's price index.

Table 2
Regime-switching estimation of the mean reversion equation.

k	$\alpha_{k,0}$	$\alpha_{k,1}$	$\beta_{k,0}$	$\beta_{k,1}$	$\sigma_{k,0}$	$\sigma_{k,1}$	$dur_{k,0}$	$dur_{k,1}$
3	0.0037^{***}	-0.0231^{***}	0.0613^{***}	−0.0044	0.0009^{***}	0.0060^{***}	41.54	7.57
	(0.0008)	(0.0060)	(0.0131)	(0.0356)	(0.0000)	(0.0003)		
6	0.0024^{***}	0.0009	0.0519^{***}	0.0404	0.0009^{***}	0.0069^{***}	44.12	7.12
	(0.0008)	(0.0073)	(0.0074)	(0.0305)	(0.0000)	(0.0005)		
12	0.0037^{***}	-0.0251^{***}	0.0232^{***}	−0.0117	0.0009^{***}	0.0062^{***}	38.14	6.59
	(0.0008)	(0.0068)	(0.0046)	(0.0153)	(0.0000)	(0.0004)		
24	0.0051^{***}	-0.0334^{***}	0.0016	-0.0366^{***}	0.0009^{***}	0.0057^{***}	37.04	6.83
	(0.0008)	(0.0071)	(0.0033)	(0.0112)	(0.0000)	(0.0004)		
36	0.0049^{***}	-0.0355^{***}	0.0073^{***}	-0.0435^{***}	0.0009^{***}	0.0055^{***}	35.66	6.58
	(0.0009)	(0.0065)	(0.0027)	(0.0082)	(0.0000)	(0.0004)		
48	0.0050^{***}	-0.0326^{***}	0.0095^{***}	-0.0431^{***}	0.0008^{***}	0.0053^{***}	31.64	6.31
	(0.0008)	(0.0059)	(0.0023)	(0.0089)	(0.0000)	(0.0003)		
60	0.0041^{***}	−0.0008	0.0057^{***}	−0.0031	0.0008^{***}	0.0063^{***}	36.91	7.40
	(0.0009)	(0.0059)	(0.0021)	(0.0106)	(0.0000)	(0.0005)		
120	0.0051^{***}	-0.0233^{***}	0.0007	0.0124	0.0008^{***}	0.0060^{***}	31.26	6.31
	(0.0009)	(0.0057)	(0.0016)	(0.0088)	(0.0000)	(0.0004)		

Notes: For different values of the holding period k, the table displays the results of the estimation of the regime-switching mean reversion equation as given in (2). The parameter estimates are given followed by the standard error in parentheses. *, **, and *** denote traditional significance at 10%, 5% and 1% levels, respectively.

related, as high persistence implies low mean reversion and vice versa. Note also that the regime-specific variances of the error term are different, with estimated values ten times larger in the mean reversion regime $S_{k,t} = 1$.

Looking at the magnitude of the estimated values of $\beta_{k,1}$, results suggest that the strongest mean reversion phenomenon occurs with $k = 36$ (36 months or 3 years). With this value of the holding period k, the estimated values of the parameters $p_{k,00}$ and $p_{k,11}$ are equal to 97.20% and 84.80%, respectively. This means that the unconditional probability in staying in the first (second) no mean reversion (mean reversion) regime is equal to 97.20% (84.80%). The estimated values of expected durations for the two regimes are thus equal to:

$$dur_{k,0} = \frac{1}{1 - \widehat{p}_{k,00}} = 35.66, \tag{4}$$

$$dur_{k,1} = \frac{1}{1 - \widehat{p}_{k,11}} = 6.58. \tag{5}$$

Thus, compared to the absence of mean reversion, the presence of mean reversion is a short-lived event that lasts approximately half-a year. Fig. 2 which displays the estimates of the smoothed probability $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$, of mean reversion, confirms this stylized fact, with the probability of staying in this regime taking values higher to 0.5 in very few cases.[10] Periods of mean reversion match to some extent the NBER recession periods highlighted by the grey shaded areas, with a contemporaneous correlation equal to 33.21%. Although significant, this level of correlation shows that mean reversion in CAPE ratio contains a significant part of information not encompassed by NBER recessions. From the figure, we can observe that there are some cases with mean reversion events preceding NBER recessions, corresponding to the sequence of a crisis in the stock market followed a few months later by an economic recession. There are also other cases with mean reversion events following NBER recessions, corresponding to an exit from the crisis. Both correspond to more generally turning points of the business cycle (entry of recession and recovery) with lead-lag effects.

2.2. Return's dynamic following mean reversion and in-sample predictive regressions

A question of interest, which is at the heart of our methodology, is to evaluate the dynamic of the returns on the stock index in the period following the occurrence of a mean reversion state or regime, and to compare it to the same dynamic in the opposite state or regime (no mean reversion). Formally, let τ be a given horizon in month and $\widehat{\Pr}\left(S_{k,t} = i \middle| \Omega_T; \widehat{\theta}\right)$ the estimated smoothed probability of regime i at time t, with θ the vector of parameters.[11] Denote $Z_{t,i} = \mathbb{I}\left(\widehat{\Pr}\left(S_{k,t} = i \middle| \Omega_T; \widehat{\theta}\right) > \gamma\right)$the dummy variable taking value one when the smoothed probability of regime i is large and higher than a threshold γat time t, with $\gamma \in \{0.5, 0.6, 0.7\}$. Thus, this variable indicates whether regime i prevails or nor at time t. For a fixed time t with $Z_{t,i} = 1$, let us compute the multi-period return of the stock index in the subsequent period, i.e.

$$r_{t+1:t+\tau,i} = \sum_{s=t+1}^{t+\tau} r_s, \tag{6}$$

with r_s the monthly log-return of the index. By denoting n_i the number of observations (over the entire sample of length T) with $Z_{t,i} = 1$, we can compute the average value of $r_{t+1:t+\tau,i}$ given by:

$$\overline{r}_{i,\tau} = \frac{1}{n_i} \sum_{s=1}^{n_i} r_{t_s+1:t_s+\tau,i}. \tag{7}$$

Our goal is to compare $\overline{r}_{0,\tau}$ and $\overline{r}_{1,\tau}$ for the different values of τ, where $\overline{r}_{0,\tau}$ ($\overline{r}_{1,\tau}$) provides the average value of multi-period returns following a state without (with) mean reversion in the US Shiller CAPE ratio.

Fig. 3 compares these values (in %) for $\tau \in \{1:18, 24, 36, 48\}$ corresponding to one to eighteen months, two, three and four years. The figure reveals interesting stylized facts. First, the top panel shows that average multi-period returns following a mean reversion regime are negative from values of τ ranging from 1 month to 13 months. For instance, with $\tau = 1$ (1 month) and $\gamma = 0.5$, the recorded average multi-period returns is equal to -1.77%, and this value decreases up to -3.35% for $\tau = 6$ (6 months), followed by decreases in loss for higher values of τ. Precisely, for $\tau \geqslant 14$ months, the realized average multi-period returns become positive. Second, the bottom panel shows that in the absence of mean reversion in the US Shiller CAPE ratio, subsequent multi-period returns are always positive, with reported values increasing monotonously with τ.

These results provide strong evidence about short-term predictability of S&P 500 returns based on the occurrence of a mean reversion state in the US Shiller CAPE ratio. In other words, if we know that a mean reversion regime prevails at a given time, we will be able to predict market downturns in the subsequent months (1 month to approximately 1 year), with the

[10] The smoothed probability of a given regime corresponds to the likelihood of this regime at a given time t conditional to the set Ω_T of all available information from $t = 1$ to $t = T$, with T the sample length which here equals $T = 1635$ (monthly data from 1884/02 to 2020/04).

[11] We set here k to value 36 which corresponds to the best separation of the two regimes as displayed in Table 2.

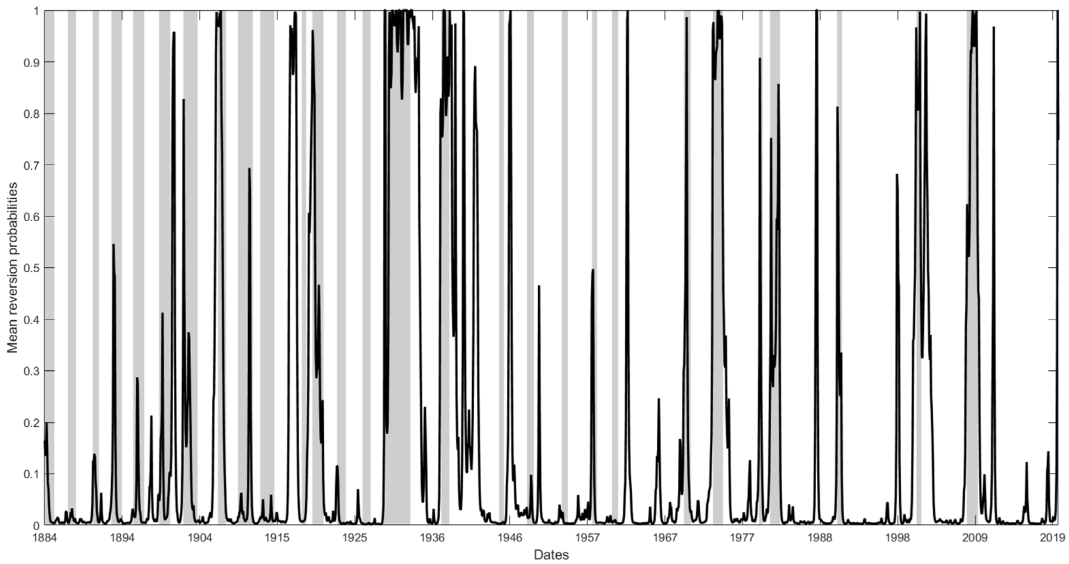

Fig. 2. Dynamic of smoothed probabilities of mean-reversion: 1884/02–2020/04. Notes: The figure displays the smoothed probabilities of the mean reversion regime that result from the estimation of the regime-switching mean reversion equation in (2). The estimation sample ranges from February, 1884 to April, 2020, with a total of 1635 monthly observations. The grey shaded areas correspond to the NBER recession periods.

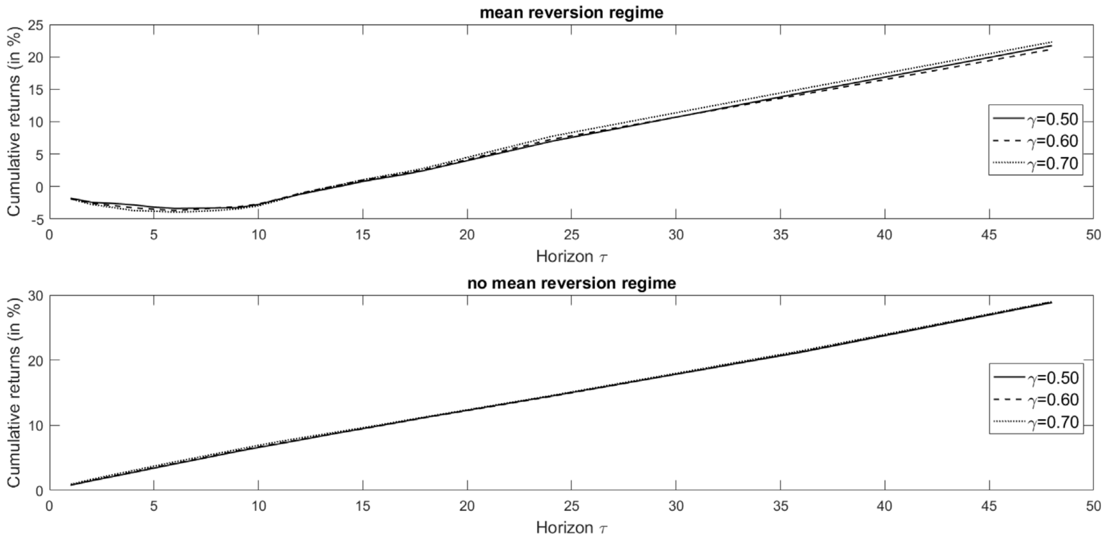

Fig. 3. Prevaling regimes and subsequent S&P 500 average returns. Notes: The figure compares subsequent S&P 500 average multi-period returns following the prevalence of a given regime (presence or absence of mean reversion) in the US Shiller CAPE ratio. Multi-period returns are indexed by the horizon τ in months, and the prevalence of a regime is given by the related smoothed probability exceeding a high threshold value $\gamma \in \{0.5, 0.6, 0.7\}$. The top (bottom) panel displays the average multi-period returns for the mean (no mean) reversion regime. Smoothed probabilities displayed in Fig. 2 are obtained from the estimation of the regime-switching mean reversion model in (2) using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations.

most severe cumulative loss in the sixth month. To confirm and evaluate the strength of this predictive power, we estimate the following stock return predictive regression for different values of the prediction horizon τ

$$r_{t+1:t+\tau} = a_0 + a_1 \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right) + u_{t+1:t+\tau}, \tag{8}$$

where again x_t is the natural logarithm of the US Shiller CAPE ratio, $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$ is the estimated probability of mean reversion regime at time t, a_0, a_1 some parameters, and $u_{t+1:t+\tau}$ the error term. It is worth noting that our predictive regression equation in (8) differs from the traditional equation which links multi-period returns to current values of valuation ratios as follows:

$$r_{t+1:t+\tau} = b_0 + b_1 x_t + \xi_{t+1:t+\tau}, \tag{9}$$

with b_0, b_1 some parameters, and $\xi_{t+1:t+\tau}$ the error term. The difference arises from using as predictor the prevalence of a mean reversion regime at time t as given by the estimated smoothed probability $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$ instead of the level of the valuation ratio. By doing so, our goal is to exploit the stylized facts observed in Fig. 3 which indicate that high and low values of this probability lead to different subsequent dynamics for stock prices.

Table 3 displays the estimation results of our predictive regression. We report the estimates of parameters a_0 and a_1 in the first two columns and the last two columns display the adjusted R-squared of our predictive regression (Adj. R^2), and that of the traditional predictive regression (Adj. R^2 Tradi.). Inference is based on Newey-West standard errors.[12]

Two important trends emerge from the results. First, the parameter a_1 is statistically significant and negative for forecast horizons lower than 15 months, and the absolute values of the estimates appear higher at the prediction horizons $\tau \in \{9, 10, 11\}$, roughly one year. The negative value means that an increase in the probability of mean reversion leads to a decrease in short-term returns of the S&P 500 index. Second, the adjusted R-squared of our predictive regression is much higher than the one from the traditional predictive regression, notably at very short horizons. For instance, with $\tau = 1$ month, the adjusted R-squared is 177 times higher (5.31% against 0.03%). The highest predictive power is reached at the horizon $\tau = 6$ months. However, the predictive power of our regression model vanishes at longer time horizons.

These results are new and interesting and suggest that in predictive regressions, returns predictability at short-term horizons can be recovered using the occurrence of mean reversion as a predictor rather than the level of valuation ratios. As underlined in the introduction, this result shares some similarities with that of Moench and Tobias (2021), which shows that using the probability of recession in forecasting equity risk premiums increases the predictive power at short-term horizons. In our framework, we rather use the probability of mean-reversion in the US Shiller CAPE ratio, based on the stylized facts reported in Fig. 3.

Another interesting point that deserves to be investigated is to distinguish the two possible states underlying the prevalence of a mean reversion event, namely an increase (decrease) from low (high) values of the US Shiller CAPE ratio to get back to its average values. To do so, we reproduce the top panel of Fig. 3 (mean reversion regime) by separating these two states given by the Shiller CAPE ratio being lower or higher than the quantile of order 0.4.[13]

Fig. 4 which displays the results provides evidence that the patterns (negative average multi-period returns) observed in the top panel of Fig. 3 are attenuated by not taking into account which state (high or low levels of CAPE) of mean reversion is at stake. In other words, disentangling the patterns helps to discover significantly large decreases in the S&P 500 index prices in the months following a mean reversion in the CAPE ratio, when current CAPE ratio is very high (bottom panel). For instance, in this case, the cumulative multi-period returns decrease up to 16.46% for $\tau = 13$ (approximately one year). In the other case with low values of the CAPE ratio (top panel), subsequent multi-period returns are positive or negative, but close to zero.[14]

These new results call for a modification of our predictive regression in (8), in order to increase its predictive power reported in Table 3. We thus consider the following regression:

$$r_{t+1:t+\tau} = a_0 + a_1 \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right) + a_2 x_t \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right) + u_{t+1:t+\tau}, \tag{10}$$

where again x_t is the natural logarithm of the US Shiller CAPE ratio, $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$ is the estimated smoothed probability of mean reversion regime at time t, a_0, a_1 and a_2 the parameters, and $u_{t+1:t+\tau}$ the error term. In this new specification, we have:

$$\frac{\partial r_{t+1:t+\tau}}{\partial \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)} = a_1 + a_2 x_t, \tag{11}$$

which depends on the level of the US Shiller CAPE ratio, and takes value zero for $x^{\star} = -a_1/a_2$. With $a_2 < 0$ and $a_1 > 0, x^{\star}$ is positive, and with high (low) values of the Shiller CAPE ratio, i.e. $x_t > x^{\star}$ ($x_t < x^{\star}$), an increase in the occurence of mean reversion leads to negative (positive) subsequent short-term returns, a pattern compatible with the trends in Fig. 4.

Results in Table 4 confirm the expected figures, in the sense that the parameter a_1 (a_2) is positive (negative) and statistically significant for all forecast horizons. This suggests that conditioning the mean reversion regime to the level of the US Shiller CAPE ratio is valuable for predicting short-term horizon stock returns. Fig. 5 compares the explanatory power as given by the adjusted R-squared of this new predictive regression (last column in Table 4) and the predictive regression in (8) as displayed in the fourth column of Table 3. We observe an increase in the adjusted R-squared, notably for the horizons close to $\tau = 12$, i.e. approximately one year.

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[12] Results available from the authors upon request, show that an inference based on Hansen–Hodrick standard errors to deal with the overlapping nature of the data, leads to qualitatively similar results.

[13] This threshold value (0.4) is calibrated based on the data to obtain clear-cut differences.

[14] Note that we also considered separating the no-mean reversion regime into the states given by high/low values of the CAPE ratio. Results available upon request show that the multi-period subsequent cumulative returns are positive in both states, hence, with convergent dynamics.

Table 3
Estimation results of stock return predictive regressions.

τ	a_0	a_1	Adj. R^2 (%)	Adj. R^2 Tradi (%)
1	0.0098***	−0.0333***	5.31	0.03
2	0.0177***	−0.0542***	5.53	0.25
3	0.0245***	−0.0675***	5.38	0.46
4	0.0312***	−0.0792***	5.49	0.64
5	0.0380***	−0.0912***	5.79	0.84
6	0.0445***	−0.1021***	5.92	1.09
7	0.0506***	−0.1102***	5.79	1.38
8	0.0564***	−0.1162***	5.51	1.70
9	0.0620***	−0.1206**	5.16	2.05
10	0.0672***	−0.1227**	4.69	2.41
11	0.0719***	−0.1215**	4.09	2.79
12	0.0763***	−0.1185**	3.49	3.18
13	0.0806***	−0.1145*	2.96	3.57
14	0.0848***	−0.1095*	2.49	3.93
15	0.0889***	−0.1045	2.11	4.27
16	0.0933***	−0.1016	1.88	4.59
17	0.0978***	−0.0992	1.69	4.91
18	0.1021***	−0.0957	1.48	5.25
24	0.1265***	−0.0659	0.51	6.78
36	0.1794***	−0.0363	0.07	8.81
48	0.2391***	−0.0531	0.16	11.22

Notes: For different values of the prediction horizon τ, the table displays the estimation results of the stock return predictive regression as specified in (8). The last two columns display the adjusted R-squared of this predictive regression (Adj. R^2), and that of the traditional predictive regression (Adj. R^2 Tradi.). *, **, and *** denote traditional significance at 10%, 5% and 1% levels, respectively. Inference is conducted with the robust Newey-West standard error.

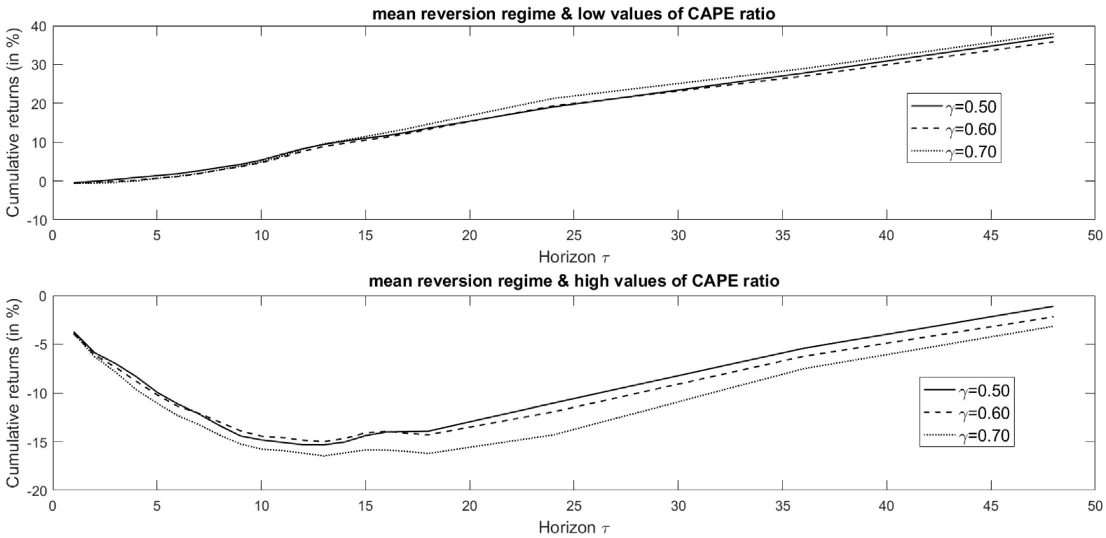

Fig. 4. Mean reversion regime, levels of CAPE ratio and subsequent S&P 500 average returns. Notes: The figure compares subsequent S&P 500 average multi-period returns following the prevalence of a mean reversion regime in two states regarding the levels of the US Shiller CAPE ratio. Multi-period returns are indexed by the horizon τ from 1 month to 18 months, and the prevalence of a mean reversion regime is given by the related smoothed probability exceeding a high threshold value $\gamma \in \{0.5, 0.6, 0.7\}$. Smoothed probabilities displayed in Fig. 2 are obtained from the estimation of the regime-switching mean reversion model in (2) using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations. The first (second) panel displays the average multi-period returns for the low (high) state of the CAPE ratio identified by the values of the latter being lower (higher) than the historical quantile of order 0.4.

To provide more insights about the new predictive regression, we investigate the stability of its overall good predictive power through time. We rely on the flexible time-varying parameter model of Farmer et al. (2022) to model predictive coefficients as a nonparametric function of time to identify pockets of return predictability. Precisely, we first use a local constant model to compute the estimator of time-varying vector of parameters a_t:

$$a_t = \arg\min_a \sum_{s=1}^{T} K_{hT}(s-t)[r_{t+1:t+\tau} - X_s a]^2, \tag{12}$$

Table 4
Additional estimation results of stock return predictive regressions.

τ	a_0	a_1	a_2	Adj. R^2 (%)
1	0.0101***	0.0845*	−0.0455***	7.65
2	0.0182***	0.1748**	−0.0887***	9.03
3	0.0252***	0.2481**	−0.1222***	9.54
4	0.0321***	0.3077**	−0.1498***	10.14
5	0.0389***	0.3617**	−0.1753***	10.85
6	0.0456***	0.4135**	−0.1996***	11.28
7	0.0519***	0.4734**	−0.2259***	11.55
8	0.0578***	0.5377**	−0.2531***	11.72
9	0.0635***	0.6022**	−0.2798***	11.76
10	0.0689***	0.6792**	−0.3104***	11.85
11	0.0738***	0.7660**	−0.3436***	11.91
12	0.0784***	0.8475***	−0.3739***	11.83
13	0.0829***	0.9112***	−0.3970***	11.53
14	0.0870***	0.9536***	−0.4115***	10.99
15	0.0912***	0.9838***	−0.4213***	10.43
16	0.0957***	1.0111***	−0.4307***	10.08
17	0.1002***	1.0464***	−0.4434***	9.91
18	0.1046***	1.0896***	−0.4588***	9.82
24	0.1292***	1.2358***	−0.5038***	8.45
36	0.1819***	1.1613***	−0.4635***	5.18
48	0.2420***	1.3498***	−0.5430***	5.65

Notes: For different values of the prediction horizon τ, the table displays the estimation results of the stock return predictive regression as specified in (10). The last column displays the adjusted R-squared of this predictive regression (Adj. R^2). *, **, and *** denote traditional significance at 10%, 5% and 1% levels, respectively. Inference is conducted with the robust Newey-West standard error.

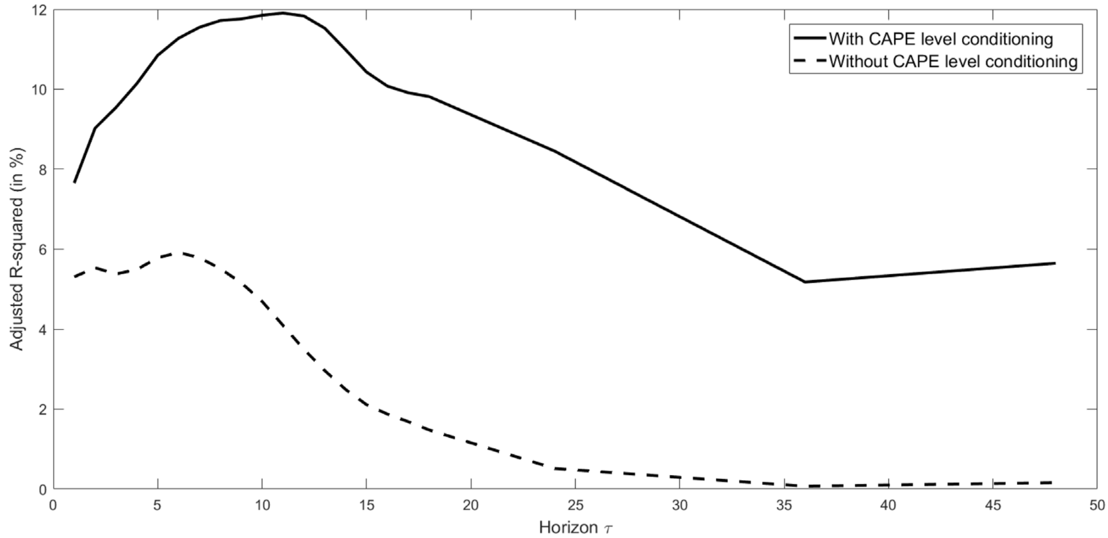

Fig. 5. Explanatory powers of stock return predictive regressions. Notes: The figure compares the explanatory powers (adjusted R-squared) of two competing stock return predictive regressions. The first specified in (8) uses the probability of mean reversion in the valuation ratio as the explanatory variable, while the second conditions this latter variable to the level of the ratio (10).

with $X_t = \left(1, \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right), x_t \widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)\right)$ the vector of predictors at time t, $a = (a_0, a_1, a_2)'$ the vector of parameters, $K_{hT}(u) \equiv K(u/hT)/hT$ a kernel function that controls weights on the local observations, where h is the bandwidth. In practice, we use the one-sided Epanechnikov Kernel with:

$$K(u) = 1.5(1 - u^2)\mathbf{1}(-1 < u < 0). \tag{13}$$

Note that this (estimated) model is the time-varying counterpart of our predictive regression model in (10). Once the model is estimated,[15] we compute the squared error difference (SED) between our forecasts $\widehat{r}_{t+1:t+\tau}$ and the ones from the traditional predictive regression, $\overline{r}_{t+1:t+\tau}$, estimated with the same kernel method, with:

[15] The forecast horizon is set to $\tau = 12$ which corresponds to the highest level of explanatory power as displayed in Fig. 5.

$$SED_{t+1:t+\tau} = (r_{t+1:t+\tau} - \bar{r}_{t+1:t+\tau})^2 - (r_{t+1:t+\tau} - \widehat{r}_{t+1:t+\tau})^2. \quad (14)$$

Periods in which $SED_{t+1:t+\tau} > 0$ mean that our predictive model produces a more accurate forecast (in a squared error sense) than the traditional model since it incurres a smaller (squared) forecast error. To identify such periods, Farmer et al. (2022) propose to project SED_t on a constant and a time trend

$$SED_t = \pi_{0,t} + \pi_{1,t}t + v_t, \quad (15)$$

using again the same one-sided kernel estimation, and to define pockets of predictability as periods for which $\widehat{SED}_t = \widehat{\pi}_{0,t} + \widehat{\pi}_{1,t}t > 0$.

Fig. 6 displays the time series behaviour of $\widehat{SED}_t$. Based on Farmer et al. (2022), both predictive models are estimated using a 2.5-year one-sided bandwidth, and the SED are computed using a one-year bandwidth. Only positive SED corresponding to identified pockets of predictability are displayed.

We observe in the figure, 47 identified pockets of predictability over the period which cover 66.71% of the total number of months in the sample. The observed durations of these pockets range from 5 months to 100 months (approximately 8 years) with associated values of local R-squared that range from 0.34% to 69.90%. The pocket with the highest level of predictability covers the stock market crash of 1929 and the subsequent Great Depression. The one with the second highest level of predictability matches the 2008 global financial crisis. For these two periods, we can observe that the probability of mean reversion is very high (close to one). Note that the other pockets of predictability are to some extent positively correlated with the probability of mean reversion, suggesting that factors that could be correlated with these pockets of predictability are those related to mean reversion in the Shiller CAPE ratio. As the latter phenomenon mostly covers crisis periods, thus market sentiment and uncertainty are likely to be correlated with the identified pockets of predictability as underlined by Farmer et al. (2022). Remark also that the pockets with the lowest levels of predictability are those associated to very short durations and are likely to be spurious. Overall, we can conclude that our predictive regression has a relatively high level of stability in its predictive power through time, this power peaking (collapsing) mostly around mean (no-mean) reversion episodes in the US Shiller CAPE ratio.

Another interesting question is to analyze the economic mechanisms underlying this established relation between the occurence of mean reversion in the CAPE ratio and subsequent prices dynamics. Formally, we use the Campbell (1991) and Campbell and Ammer (1993) vector autoregression (VAR) approach to decompose unexpected stock returns into discount rate news and cash flow news components. The goal is to assess which component is more or less predicted by the estimated probability of mean reversion in the Shiller CAPE ratio. This will allow a better understanding of the price dynamics highlighted above, and which follow the occurrence of a mean reversion phenomenon in the valuation ratio.

To do so, we consider the three-dimensional vector z_t with the first element being r_t the monthly return on the stock index at time t, and the remaining being the logarithm of the CAPE ratio, and the *relative bill rate* which is equal to the difference between the 3-month US treasury bill rate and its one-year backward moving average. We consider this last variable for its predictive power on stock returns as discussed by Campbell (1991). By considering a first-order VAR specification for z_t, with $z_t = Az_{t-1} + u_t, e1 = (1, 0, 0)'$, and $\lambda' = e1'\rho A(I - \rho A)^{-1}$, with ρ a discount coefficient, the discount rate news can then be conveniently expressed as $u_{ER,t} = \lambda' u_t$ and the cash-flow news as $u_{CF,t} = (e1' + \lambda')u_t$ (Campbell, 1991).[16]

We collect the three variables over the same time-span under investigation, i.e., from February, 1884 to April, 2020 with a total of 1635 monthly observations. We thus estimate the VAR model, extract the two time series of news $\widehat{u}_{ER,t}$ and $\widehat{u}_{CF,t}$, and consider the following regression:

$$y_t = w_0 + w_1 \widehat{\Pr}\left(S_{k,t-1} = 1 \middle| \Omega_T; \widehat{\theta}\right) + \epsilon_t, \quad (16)$$

with y_t either $\widehat{u}_{ER,t}$ or $\widehat{u}_{CF,t}, w_0$ and w_1 the parameters, and ϵ_t the error term.

Table 5 displays the estimation results. As from the theoretical decomposition of returns, unexpected returns are lower if future cash flows are lower than expected or future discount rates are higher than expected, the parameter w_1 should be negative (positive) when considering the regression model with cash-flow (discount rate) news as the dependent variable. The signs of the estimated coeefficients $\widehat{w_1}$ are as expected, with the conclusion that when the probability of mean reversion is high, unexpected returns are negative through both a decrease in cash flow news and an increase in discount rate news. With the reported explanatory powers, we can observe that price adjustments operate more through the discount rate component. Indeed, the associated R-squared is equal to 5.12%, four time higher than the one of the cash-flow news' regression.

3. Does the predictability hold out-of-sample?

Although interesting, these results are difficult to exploit empirically on an out-of-sample basis, because the identification of the mean reversion regime is based on the smoothed probabilities (see Fig. 2) which are estimated using Ω_T the information set available over the entire period (t from 1 to T).

[16] We choose ρ to be equal to 0.996 for our set of monthly data.

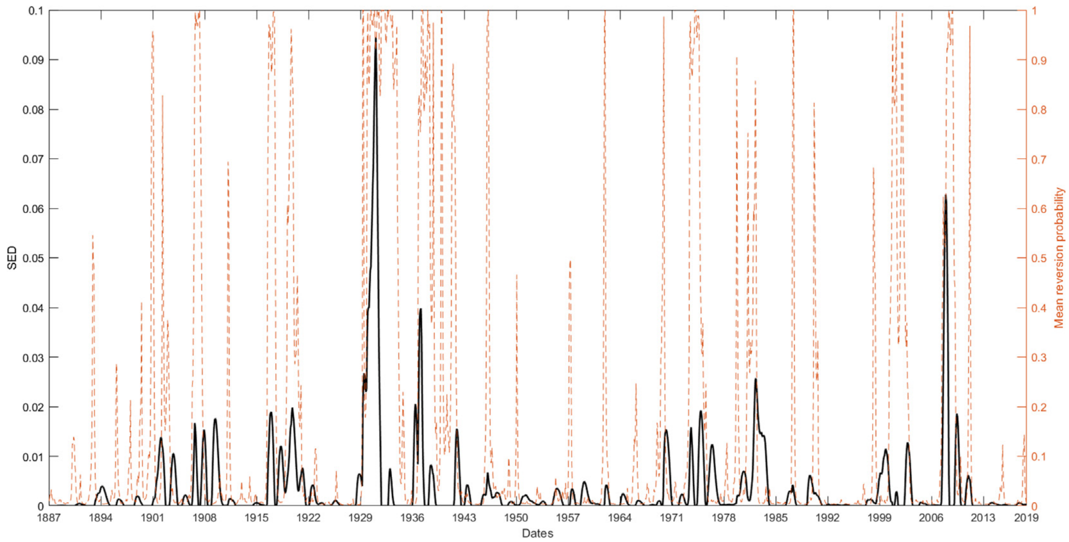

Fig. 6. Pockets of predictability. Notes: The figure (left yaxis, solid lines) displays the fitted squared error differences (SED) between our forecasts and the ones from the traditional predictive model. We only report positive SED corresponding to identified pockets of predictability, and we also display (right yaxis, dotted lines) the probability of mean reversion in the US Shiller CAPE ratio.

Table 5
Relations between mean reversion in CAPE ratio and unexpected returns components.

	w_0	w_1	R^2
Discount rate news component	−0.0020 (−4.4263)***	0.0132 (9.4248)***	5.12%
Cash-flow news component	0.0015 (2.2087)**	−0.0098 (−4.7028)***	1.21%

Note: The table displays the estimation results of the simple linear regression with each component of unexpected returns (discount rate news and cash-flow news) fitted by the probability of mean reversion in the CAPE ratio. We report the estimated coefficients along with their associated t-statistics in parentheses, and the R-squared. Significance level: * = 10 percent, ** = 5 percent, *** = 1 percent.

One solution to this problem is to check for the stylized facts reported in Fig. 3 using the filtered probabilities rather than the smoothed counterparts. Note that the filtered probabilities are defined conditionally to the information set Ω_t available at time t, and hence appear useful (to some extent) for a real-time forecasting exercise. Fig. 7 which displays the patterns, indicates that the prevailing regime (based on filtered probabilities higher than a given threshold) has no predictive power on average multi-period returns. Indeed, the latters are positive for both regimes, and this result is robust to the horizon τ and the probability threshold parameter γ. The fact that the smoothed probabilities rather than the filtered ones reveal the expected dynamic, namely negative returns following a mean reversion event, is purely statistical, because the former are based on past and future information, i.e. a complete knowledge of the dynamics of the observable.

Another solution we retain in this paper and which is at the heart of our contribution, is to identify an early-warning business cycle variable which has high informational content on the smoothed probabilities. This variable can thus be used based on the information available at time t to infer the regime that prevails at that time in order to anticipate future evolutions in the stock market prices. To be more precise, if we denote w_{t-m} the value of such a variable observed at the date $t-m$, with m the lag-order, our predictive regression writes:

$$r_{t+1:t+\tau} = a_0 + a_1 w_{t-m} + a_2 x_t w_{t-m} + v_{t+1:t+\tau}, \tag{17}$$

with $r_{t+1:t+\tau}$ the multi-period returns, a_0, a_1 and a_2 some parameters, and $v_{t+1:t+\tau}$ the error term. Compared to the predictive regression in (10), the above specification considers lagged values of the business cycle variable w_t as a leading indicator for the occurrence of a mean reversion in the US Shiller CAPE ratio as evaluated by the level of the smoothed probability. This new specification thus circumvents the fact that the smoothed probability is based on the whole sample, and allows the deployment of an out-of-sample forecasting exercise based on w_{t-m}.

The choice of the business cycle variable w_t is here critical. We must choose a variable with strong predictive power on the occurrence of mean reversion in the US Shiller CAPE ratio. One approach is to consider a large panel of business cycle variables as regressors in a linear regression model for the smoothed probability. This model estimated along with a selection method like the least absolute shrinkage and selection operator (Lasso) of Tibshirani (1996), would help identify an

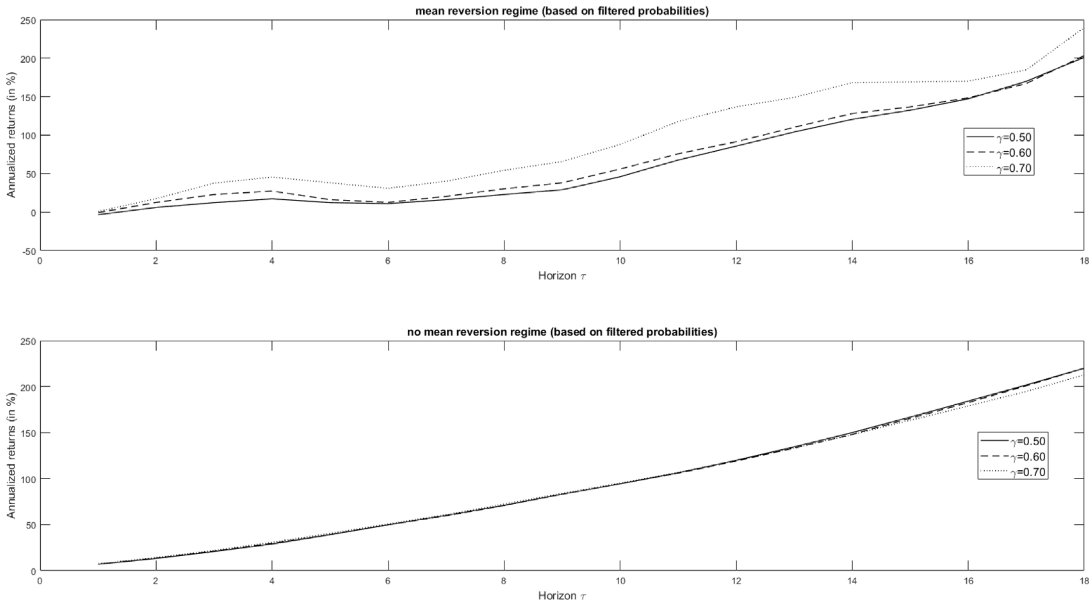

Fig. 7. Prevaling regimes and subsequent S&P 500 average returns. Notes: The figure compares subsequent S&P 500 average multi-period returns following the prevalence of a given regime (presence or absence of mean reversion) in the US Shiller CAPE ratio. Multi-period returns are indexed by the horizon τ from 1 month to 18 months, and the prevalence of a regime is given by the related filtered probability exceeding a high threshold value $\gamma \in \{0.5, 0.6, 0.7\}$. The first (second) panel displays the average multi-period returns for the mean (no mean) reversion regime. Filtered probabilities are obtained from the estimation of the regime-switching mean reversion model in (2) using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations.

index function (combination of selected business cycle variables) which can be used as a proxy for the smoothed probability. We do not follow such an approach here, as the selected variables are likely to change over time as well as their combination weights in the index function. We rather consider choosing a single business cycle variable, i.e. the term spread.

Our choice of the term spread is based on two pieces of evidence. On one side, there is a significant contemporaneous relationship between mean reversion in the US Shiller CAPE ratio and economic recession. Indeed, using the NBER recession indicator and our estimates of the smoothed probability of mean reversion $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$, we observe that in periods of economic recession (expansion) the average value of $\widehat{\Pr}\left(S_{k,t} = 1 \middle| \Omega_T; \widehat{\theta}\right)$ is equal to 31.9% (9.8%). This suggests some degree of concomitance between mean reversion in the valuation ratio and economic recession. Moreover, as observed in Fig. 2, there is also a lead-(lag) relationship between the two variables. On the other side, there is an abundant literature that stresses the predictive power of term spread on the occurrence of economic recession. Indeed, it is well known that the behaviour of the yield curve changes across the business cycle. During recessions, upward sloping yield curves not only indicate bad times today, but better times tomorrow. Guided from this intuition, many papers predict GDP growth in OLS regressions with the term spread. Furthermore, the term spread is successful at predicting recessions with dichotomous models (probit and logit models) in a univariate framework (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Moench and Tobias, 2021). The term spread is also an important variable in the construction of a leading business cycle indicator index (Stock et al., 1989). Inversion of the yield curve has come to be viewed as an early leading recession indicator. For example, every recession after the mid-1960s was predicted by an inverted yield curve within 6 quarters of the impending recession. Moreover, there has been only one false positive (an instance of an inverted yield curve that was not followed by a recession) during this time period.[17]

Taken together, these two stylized facts establish the link between the lagged values of the term spread and mean reversion in the US Shiller CAPE ratio. The horizon does indeed appear to be equal to 6 quarters or 18 months approximately, as we can see in Fig. 8. This figure displays the correlations between lagged values of the term spread and the smoothed probability of mean reversion in the US Shiller CAPE ratio.[18] The correlations are negative with the highest absolute value recorded at the lag-order 17.

[17] Note that, however, Rudebusch et al. (2007) highlight that the (linear) predictive ability of the term spread on economic activity is difficult to reconcile with DSGE structural models or some reduced-form models. In addition, Feroli (2004) pointed out that the predictive ability of the spread to forecast output fluctuations is contingent on the monetary authority's reaction function. Ang et al. (2006) provide evidence that the short rate has more predictive power than any term spread, but they are only considering relative short-maturity term spreads (from 4 to 20 quarters) and linear predictive regressions. Also, Haubrich and Dombrosky (1996) have documented weaker forecasting power during the 1985–1995 decade.

[18] Fig. A.1 in Appendix A displays the dynamic of the US term spread.

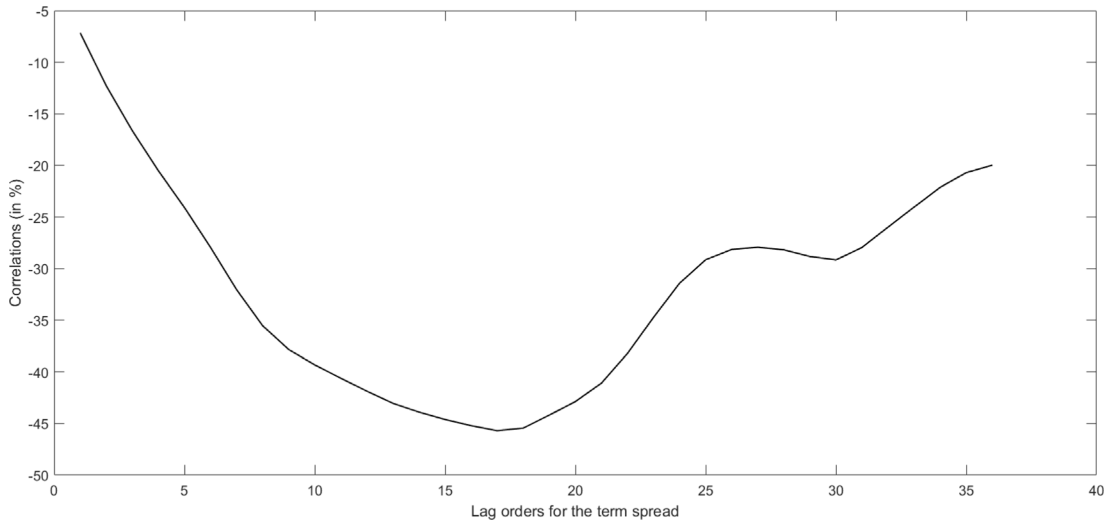

Fig. 8. Correlations between the lagged values of the term spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio. Notes: The figure displays the correlations between lagged values of the term spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio, for different values of lag-order from 1 month to 36 months, i.e. 3 years. The smoothed probabilities are obtained from the estimation of the regime-switching mean reversion model in (2) using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

Based on all the above results, we thus conduct a forecasting exercise to evaluate the out-of-sample power of our predictive model (17) with the business cycle variable w_t corresponding to the term spread, and $m = 17$. More precisely, we rely on a rolling-window forecasting scheme, i.e. for a fixed forecasting horizon τ from 1 month to 60 months (5 years), and for each month t, we use the available 360 monthly observations to estimate the predictive regression model (17). The estimated parameters are used to forecast the out-of-sample multi-period return $r_{t+1:t+\tau}$. The forecast values together with the realized values are used to compute the out-of-sample R-squared given by:

$$R^2_{OOS}(\tau) = 1 - \frac{\sum_{s=1}^{n_{oos}} \left(r_s(\tau) - \widehat{r}_s(\tau)\right)^2}{\sum_{s=1}^{n_{oos}} \left(r_s(\tau) - \bar{r}(\tau)\right)^2} \tag{18}$$

with n_{oos} the number of out-of-sample observations, $r_s(\tau) \equiv r_{t+1:t+\tau}$ the realized multi-period returns, $\widehat{r}_s(\tau)$ the forecast multi-period returns, and $\bar{r}(\tau)$ the average value of realized multi-period returns. Recall that the explanatory power of each model is evaluated using the model of historical average as benchmark. In other words, $R^2_{OOS}(\tau)$ is equal to 0 by definition for this benchmark model.

Fig. 9 displays the out-of-sample R-squared of our predictive regression in (17) with respect to the forecast horizon τ. For comparison, we also display the same statistic for the traditional predictive regression in (9).

Results in Fig. 9 are interesting as they confirm the trends observed with in-sample estimations. The predictive power of the traditional predictive regression is very low, even negative at very short-term horizons, and monotonically increases to reach high levels at long-term horizons. On the contrary, the trend observed for the new predictive regression shows a higher predictive power at short-term horizons, and a monotonic growth until horizon $\tau = 27$ (2 years and 1 quarter), followed by a decrease for higher horizons. For instance, at 12 months the out-of-sample R-squared is equal to 2.28% for the traditional regression, while it is equal to 8.73% for the new predictive regression. Thus, our new predictive regression model, that makes use of the informational content of the term spread regarding the occurrence of mean reversion in the US Shiller CAPE ratio, helps the recovery of short-term predictability of stock returns.[19]

Let us stress that our out-of-sample predictive regression benefits, at least to some extent, from the overall sample information set. Indeed, the lag m used for the business cycle variable is set according to the correlation of this variable with the smoothed probabilities of mean reversion in the CAPE ratio, which are estimated on the overall sample. To have a pseudo real out-of-sample exercise, we calibrate the parameter m through the rolling-windows. Fig. 10 compares the out-of-sample R-squared of our predictive regression in Fig. 9 and its analogue based on the full out-of-sample task. As we can see, even if there are differences, they remain marginal for the very short forecast horizons, not changing the central message of the paper.

[19] Results available from the authors upon request, show that the differences in predictive performances are statistically significant, based on the test of predictive performances comparison of Giacomini and White (2006). This is the case for horizons ranging from 7 months to 33 months.

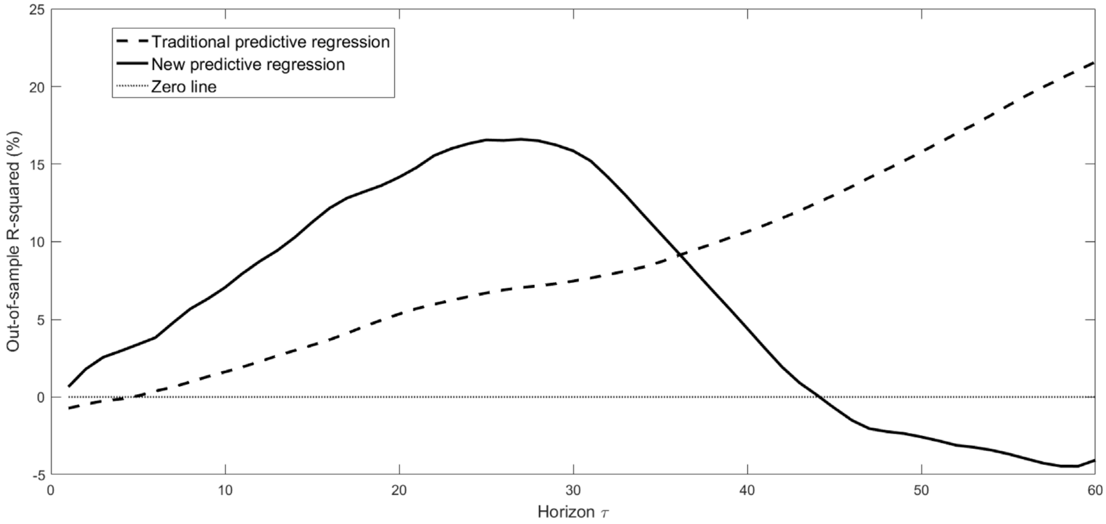

Fig. 9. Out-of-sample predictive powers of competing predictive regressions. Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression in (9) with the US Shiller CAPE ratio as the explanatory variable, and the new predictive regression in (17) that conditions the influence of the US Shiller CAPE ratio to the occurrence of mean reversion in this valuation ratio as approximated by lagged values of the term spread. Forecasts are obtained using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

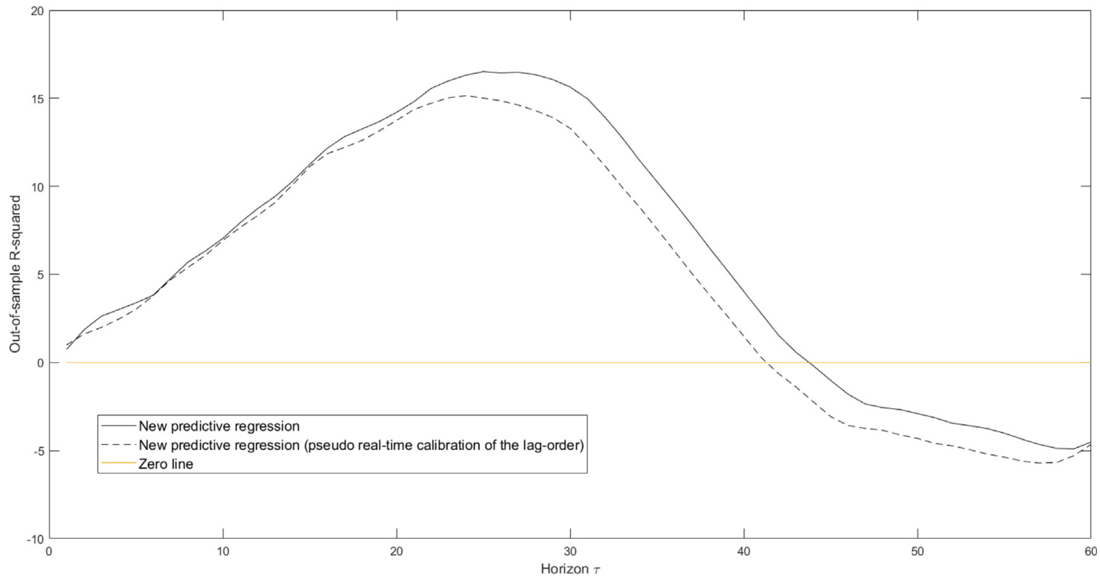

Fig. 10. Out-of-sample powers of the new predictive regression. Notes: The figure displays the out-of-sample predictive powers of our new predictive regression for two different out-of-sample configurations. The one with the lag-order of the term spread calibrated using the whole sample, and the one with this parameter calibrated using a pseudo real out-of-sample exercise. Forecasts are obtained using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

Note that an Online Appendix is available which presents additional investigations conducted to check for the robustness of the above results. Specifically, the robustness of the new predictive model is analyzed (i) with respect to the choice of the valuation ratio (excess CAPE yield, dividend yield), (ii) and the country under investigation (Canada, France, Germany and the UK). The results obtained are qualitatively similar.

4. Assessment of economic value

This section evaluates the economic value of the new predictive model for equity premium, based on an asset allocation exercise. We can expect that the robust out-of-sample forecast ability obtained for the US with positive out-of-sample adjusted R-squared at short horizons (see Fig. 9) should lead to economic gains for an investor that allocates his wealth between the S&P 500 and a risk-free instrument. For other countries, especially the UK and France, for which the new predictive model also dominates the traditional one, but with negative adjusted R-squared at very short horizons (see the Online Appendix), we can still achieve significant economic gains. Indeed, as underlined by Cenesizoglu and Timmermann (2012), the link between statistical and economic measures of forecast performance is positive but of low magnitude, with the consequence that negative out-of-sample adjusted R-squared can be associated with positive economic gains for investors.

Based on this, and for each country, we consider the standard mean–variance portfolio choice of an investor who chooses a portfolio in the universe of two instruments, i.e. the country stock market index and the risk-free asset (cash). Denote by r_t the returns on the stock index at month t. The investor has a rebalancing horizon τ for his portfolio that coincides with the forecast horizon for the risk premium. At time t, if we denote the optimal share of the wealth allocated to the stock index as w_t, we have:

$$\widehat{w}_t = \frac{1}{\gamma}\frac{\widehat{R}_{t+\tau}}{\widehat{\sigma}^2_{t+\tau}}, \tag{19}$$

with γ the relative risk aversion parameter, $\widehat{R}_{t+\tau}$ the forecast risk premium using a given predictive model (the traditional or the improved one) for the returns r_t, and $\widehat{\sigma}^2_{t+\tau}$ the variance of the portfolio returns computed here as the sample variance over a 10-year rolling window of past data, following Rapach et al. (2010) and Moench and Tobias (2021). Hence, $\widehat{w}_t$ differs only by the predictive model retained to forecast the risk premium $\widehat{R}_{t+\tau}$, and this allows a fair comparison between alternative models. The realized monthly portfolio return at time j between t and $t+\tau$ is given by:

$$r_{p,t+j} = w_t r_{t+j}. \tag{20}$$

If we consider a proportional transaction cost c, the portfolio's net return is given by:

$$\tilde{r}_{p,t+j} = r_{p,t+j} - c\left|\widehat{w}_t - \widehat{w}_t^+\right|, \tag{21}$$

where $\widehat{w}_t^+$ is the weight in the risky stock index at time t before rebalancing. The economic value of a given predictive model for risk premium can be evaluated based on the realized certainty equivalent return (CER) given by:

$$CER_p = \widehat{\mu}_p - \frac{1}{\gamma}\widehat{\sigma}^2_p, \tag{22}$$

with $\widehat{\mu}_p$ and $\widehat{\sigma}^2_p$ the mean and variance of the net portfolio's returns $\tilde{r}_{p,t+j}$. As in Moench and Tobias (2021), this value of CER is multiplied by 12 to interpret it as the annual risk-free rate that an investor would be willing to accept to not hold the risky portfolio. For each horizon τ we report the difference in CERs between our predictive model for risk premium and the baseline traditional model. This difference corresponds to the utility gain, i.e. the annual portfolio management fee that an investor would be willing to pay to switch from the traditional model to the new proposed model.

Table 6 displays for the US, the annualized value of CER (in %) of the new predictive regression, followed by the same statistic for the traditional predictive model. The utility gain is also reported. We consider different values for the forecast horizon between 1 and 12, and two values for the relative risk aversion parameter γ. The portfolio weight w_t is restricted to lie between 0 and 1, thus excluding short-selling and leveraging.

For $\gamma = 3$, our new predictive model has positive CERs that globally decrease with the forecast horizon, with positive and high values at very short horizons (1 month to 3 months) and negative values at the highest horizons (10, 11 and 12 months). For the traditional model, the CERs are positive at all forecast horizons, but lower for the values reported for the new model at the very short horizons. Hence, the utility gains are positive at these horizons (1 month to 3 months). For example, at the horizon of 1 month (3 months), the annual portfolio management fee that an investor would be willing to pay to switch from the traditional model to the new proposed model is equal to 2.06% (0.48%). For $\gamma = 5$ the utility gains are positive at all horizons, but globally decrease with the forecast horizons. All these results confirm the statistical evidence, i.e. the superior predictive power of the new model that decreases with the forecast horizon.

5. Robustness to the business cycle variable

In this last section, we evaluate the robustness of our out-of-sample forecasting model to the choice of the business cycle variable. Specifically, we consider the default yield spread or credit spread, rather than the term spread as the key variable for the incorporation of the dynamic in equity risk premium prediction.

The credit spread is defined as the yield difference between Moody's BAA bonds and Moody's AAA bonds. Credit spreads serve as a gauge of the degree of strains in the financial system. Movements in credit spreads are thought to contain important signals regarding the evolution of the real economy and risks to the economic outlook, a view supported by the insights from the large literature on the predictive content of credit spreads for economic activity (Stock et al., 1989; Lettau and Ludvigson, 2002), and stock returns (Lettau and Ludvigson, 2001). Fig. A.2 in Appendix A displays the evolution of the monthly US credit spread available from January, 1919 to April, 2020.

Recall that our predictive model is specified as follows:

Table 6
CER and differences in CER: the US.

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	2.75	1.40	0.69	−2.15	2.06	3.55
$\tau = 2$	2.53	1.22	0.65	−2.26	1.88	3.48
$\tau = 3$	2.60	1.36	2.12	−0.44	0.48	1.80
$\tau = 4$	1.81	0.74	1.99	−0.35	−0.18	1.09
$\tau = 5$	0.67	0.21	0.69	−2.08	−0.02	2.30
$\tau = 6$	1.76	0.93	2.07	−0.34	−0.31	1.27
$\tau = 7$	0.85	0.48	1.65	−0.87	−0.80	1.34
$\tau = 8$	0.82	−0.15	1.50	−0.73	−0.68	0.58
$\tau = 9$	0.31	−0.14	1.54	−0.64	−1.23	0.50
$\tau = 10$	−0.58	−0.81	1.03	−0.86	−1.61	0.05
$\tau = 11$	−0.08	−0.69	1.46	−0.76	−1.55	0.07
$\tau = 12$	0.91	−0.46	1.47	−0.51	−0.57	0.04

Notes: For different values of the relative risk aversion parameter γ and the forecast horizon τ, the table displays the annualized value of CER (in %) of the new predictive regression, followed by the same statistic for the traditional predictive model. The last two columns display the differences in CER (utility gain).

$$r_{t+1:t+\tau} = a_0 + a_1 w_{t-m} + a_2 x_t w_{t-m} + v_{t+1:t+\tau}, \tag{23}$$

with w_t the business cycle variable and m the optimal lag-order. Hence, for the estimation of the model, we first compute the correlations between the current values of the probability of mean reversion in the US CAPE ratio and current and lagged values of the credit spread. Fig. 11 which displays the correlations is the analogue of Fig. 8 for the term spread. We observe that the optimal lag-order m is equal to 0 with a correlation close to 55%. Therefore, and as usually reported in the literature, credit spread is a coincident business cycle variable.

Fig. 12 summarizes the out-of-sample predictive ability of our forecasting model based on the credit spread. The results are similar to those obtained for the US term spread (see Fig. 9). The adjusted R-squared of the traditional predictive regression are low, even negative at very short-term horizons, and monotonically increase to reach high levels at long-term horizons. On the contrary, the trend observed for the new predictive regression shows a higher predictive power at short-term horizons, with a decrease for higher horizons.[20]

Table A.1 in Appendix A displays the outcome of the economic evaluation based on CER and differences in CER or utility gains. We observe utility gains at very short horizons, albeit lower than those obtained for the term spread, which decrease with the horizons.

6. Conclusion

Valuation is an important determinant of future returns, and the literature reported evidence of forecast ability at long-term horizons. Evidence about short-term horizons is still weak, and the available contributions reached short-term predictability by relaxing the assumption of a fixed steady regime of the economy. Recent papers achieved this task through models with time-varying parameters that fit business cycles, and specifically recession and expansion phases. However, these specifications usually impose tight parametric restrictions on how predictive coefficients in their dynamic models evolve over time.

In this article, we contribute to this literature proposing a new predictive regression model based on the observed dynamics of stock returns following the occurrence of a mean reversion in the US Shiller CAPE ratio, when the latter is high. First, the occurrence of mean reversion is approximated by the smoothed probability from a regime-switching version of the mean reversion model of Jegadeesh (1991). Second, to avoid model misspecification and allow our predictive regression to be operational for an out-of-sample exercise, we exploit the link between the term spread and mean reversion in valuation ratios. Both in-sample and out-of-sample predictions show large and significant improvement relative to the traditional predictive regression. We show that our results are robust with respect to the choice of the valuation ratio (CAPE, excess CAPE and dividend yield), and report robustness across countries (Canada, Germany and the UK). We also conduct a mean–variance asset allocation exercise which confirms the superiority of the new predictive regression in terms of utility gain. Beyond the term spread, our results are also robust to the choice of the business cycle variable, as we obtain qualitatively similar results for the credit spread.

These results have important implications regarding the understanding of asset price dynamics and mean reversion in relation with the business cycle (bad and good times) and then, practically, on dynamic asset allocations. Following Stalla-Bourdillon (2022), an interesting extension of this paper would be to evaluate how our approach performs in forecasting sector-level or firm-level returns using micro-CAPE or micro-PE.

[20] Note that the values obtained for the traditional model in Figs. 12 and 9 differ, because the samples used are different. The US credit spread is available over a longer period.

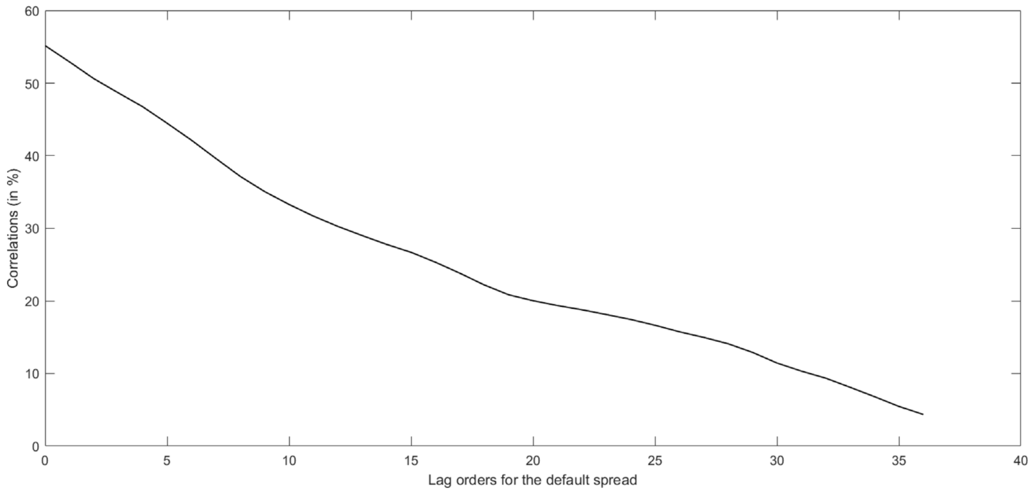

Fig. 11. Correlations between the lagged values of the credit spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio. Notes: The figure displays the correlations between lagged values of the credit spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio, for different values of lag-order from 0 month to 36 months, i.e. 3 years. The smoothed probabilities are obtained from the estimation of the regime-switching mean reversion model in (2). Correlations are computed using monthly data from January, 1919 to April, 2020, with a total of 1216 monthly observations.

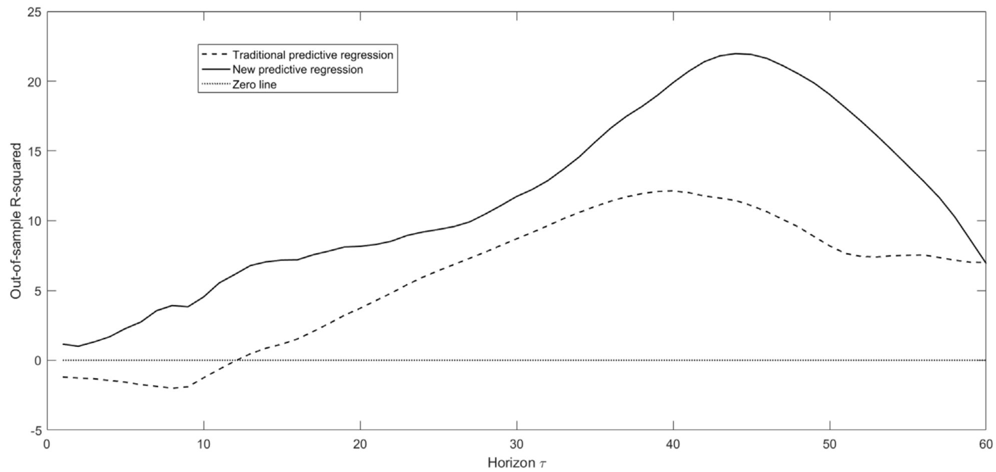

Fig. 12. Out-of-sample predictive powers based on credit spread of competing predictive regressions: US. Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression in (9) with the CAPE ratio as the explanatory variable, and the new predictive regression in (17) that conditions the influence of the CAPE to the occurrence of mean reversion in this valuation ratio, as approximated by lagged values of the credit spread. Forecasts are obtained using monthly data from January, 1919 to April, 2020, with a total of 1216 monthly observations.

Data availability

Data will be made available on request.

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.

Appendix A. Appendix A: Additional Figures and Tables

Figs. A.1,A.2.
Table A.1.

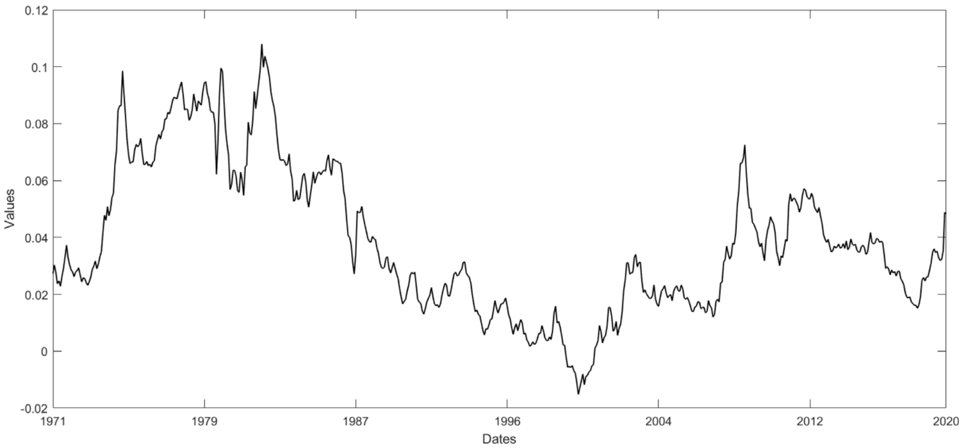

Fig. A.1. Dynamic of the US term spread: 1971/01–2020/04. Notes: The term spread is calculated as the difference between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity.

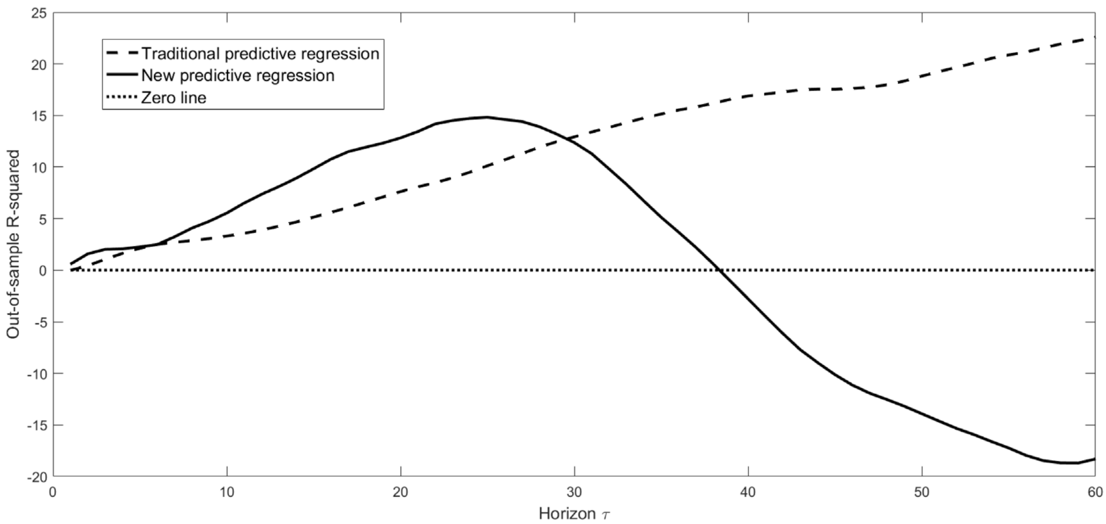

Fig. A.2. Dynamic of the US credit spread: 1919/01–2020/04. Notes: The credit spread is the difference between BAA and AAA rated corporate bond yields. The series is obtained from the FRED database.

Table A.1
CER and differences in CER based on credit spread: US.

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	4.14	2.39	3.78	1.77	0.36	0.62
$\tau = 2$	3.85	2.28	3.38	1.54	0.48	0.74
$\tau = 3$	4.20	2.52	3.74	2.06	0.45	0.47
$\tau = 4$	4.12	2.56	3.67	2.13	0.46	0.43
$\tau = 5$	3.94	2.36	3.57	1.91	0.36	0.45
$\tau = 6$	3.32	1.98	3.60	2.09	−0.28	−0.11
$\tau = 7$	3.16	1.95	3.11	1.67	0.05	0.28
$\tau = 8$	2.83	1.61	3.46	1.99	−0.64	−0.37
$\tau = 9$	2.72	1.65	3.43	2.07	−0.71	−0.42
$\tau = 10$	2.95	1.57	3.45	1.89	−0.49	−0.32
$\tau = 11$	2.89	1.31	3.39	2.03	−0.50	−0.72
$\tau = 12$	2.64	1.64	3.40	2.04	−0.76	−0.40

Notes: For different values of the relative risk aversion parameter γ and the forecast horizon τ, the table displays the annualized value of CER (in %) of the new predictive regression based on the credit spread, followed by the same statistic for the traditional predictive model. The last two columns display the differences in CER (utility gain).

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2023.102907.

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