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Alexandre Jasinski

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Membre de l'Université Paris Lumières

Alexandre JASINSKI

Trois essais en économie financière

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sous la direction de Christophe Boucher (Université Paris Nanterre)
et de Sessi Tokpavi (Université d'Orléans)

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À mon épouse, Natalia
À mes enfants, Mathilde et Augustin
Et à mes grands-parents, Irma et Tadeusz

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Three essays in financial economics

Abstract

This thesis makes a significant contribution to the field of asset returns forecasting. The first part introduces an innovative portfolio optimization paradigm, called "Smart Alpha," aimed at enhancing equity portfolio diversification while effectively managing exposure to risk factors. Recognizing the growing interest in factor investing due to the underperformance of purely active or passive strategies, Chapter 1 presents an active strategy of stock selection, which avoids betting on a-priori factors but focuses instead on an approach that minimizes the exposure of the portfolio to systematic sources of risk, while maximizing its potential alpha. Empirical evidence drawn from European stocks demonstrates the superiority of the Smart Alpha strategy over the European market index and over popular European factor investing and smart beta strategies. The second part of the research focuses on the critical task of short to medium-term return forecasting. While long-term predictive models using financial ratios have been well established, evidence for predictability over shorter horizons remains limited in the academic literature. In Chapter 2, a new predictive regression model is proposed, capitalizing on the observed dynamics of stock returns following mean reversions in the US Shiller CAPE ratio. This model displays superior predictive power, particularly at short horizons, from one to several months, both in-sample and out-of-sample. It leverages business cycle variables, such as the term spread and credit spread, to further enhance its predictability, particularly out-of-sample. The 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). Chapter 3 extends this approach by incorporating an extensive array of business cycle variables, employing penalization techniques. This extension arises from the absence of a consensus regarding which business cycle variables present the best predictive performance for mean reversion in valuation ratios and stock index prices. The results of the new predictive model demonstrate significant gains in short-term forecasting accuracy, spanning from one to several months. The superiority of the new predictive regression model is reaffirmed across various valuation metrics and individual US sectors. Both Chapters 2 and 3 perform a mean-variance asset allocation exercise that demonstrates improved utility gains, confirming the superiority of the new predictive regressions. Our results provide valuable insights and innovative approaches to asset returns forecasting, addressing both equity portfolios diversification via alpha maximization under factor's exposures constraints and short to medium-term tactical allocation, ultimately offering practical solutions for investors.

Keywords: Portfolio optimization, Factor investing, Zoo of factors, Sparse latent factors, Time varying factors, Return predictability, Valuation ratios, Mean reversion, Business cycle, Term spread, Credit spread, Penalization methods.

Trois essais en économie financière

Résumé

Cette thèse apporte une contribution significative au domaine de la prévision des rendements des actifs. La première partie présente un paradigme innovant d'optimisation de portefeuille, appelé « Smart Alpha », visant à améliorer la diversification du portefeuille d'actions tout en contrôlant efficacement l'exposition aux facteurs de risque. Reconnaisant l'intérêt croissant pour l'investissement factoriel en raison de la sous-performance des stratégies purement actives ou passives, le chapitre 1 présente une stratégie active de sélection de titres qui permet d'éviter de parier sur des facteurs a priori mais qui se concentre plutôt sur une approche visant à minimiser l'exposition du portefeuille aux sources de risque systématiques tout en maximisant le potentiel d'alpha. Les preuves empiriques du chapitre 1, basées sur les actions européennes, démontrent la supériorité de la stratégie Smart Alpha par rapport à l'indice de marché européen, ainsi qu'à l'égard des stratégies européennes populaires d'investissement factoriel et de smart beta. La deuxième partie de la recherche se concentre sur le domaine crucial de la prévision des rendements à court et moyen terme. Bien que de nombreux modèles prédictifs à long terme utilisant des ratios financiers semblent bien établis, les preuves de l'efficacité des prévisions à court terme restent limitées dans la littérature académique. Dans le chapitre 2, un nouveau modèle de régression prédictive est proposé, capitalisant sur la dynamique observée des rendements boursiers avec le phénomène de retour à la moyenne du ratio CAPE de Shiller aux États-Unis. Ce modèle présente une capacité prédictive supérieure, en particulier à court terme, à horizon d'un à plusieurs mois, à la fois dans l'échantillon et hors échantillon. Il exploite les variables du cycle économique, telles que la pente de la courbe de taux et le *spread* de crédit, pour améliorer encore la prévisibilité, en particulier hors échantillon. Les résultats sont robustes quant au choix du ratio de valorisation (CAPE, *excess* CAPE ou rendement du dividende) et des pays (Canada, Allemagne et Royaume-Uni). Le chapitre 3 étend cette approche en intégrant un large éventail de variables du cycle économique, en utilisant des techniques de pénalisation. Cette extension résulte de l'absence de consensus concernant les variables du cycle économique qui présentent la meilleure performance prédictive pour le retour à la moyenne des ratios de valorisation et des prix des indices boursiers. Le nouveau modèle de régression prédictive démontre ainsi des gains significatifs en matière de précision des prévisions à court terme, à horizon d'un à plusieurs mois. La supériorité du nouveau modèle de régression prédictive est réaffirmée en utilisant différentes mesures de valorisation et sur différents secteurs individuels aux États-Unis. Les chapitres 2 et 3 présentent un exercice d'allocation d'actifs de moyenne-variance qui montre des gains d'utilité améliorés, ce qui confirme la supériorité du nouveau modèle de régression prédictive. Nos résultats apportent des perspectives précieuses et des approches innovantes en matière de prévision des rendements des actifs à court terme, en abordant à la fois la diversification des portefeuilles d'actions via la maximisation de l'alpha sous contrainte d'expositions aux facteurs et l'allocation tactique à court et à moyen terme, offrant ainsi des solutions pratiques pour les investisseurs.

Mots clés : Optimisation de portefeuille, Investissement factoriel, Zoo de facteurs, Facteurs latents *sparse*, Facteurs variables, Prévisibilité des rendements, Ratios de valorisation, Retour à la moyenne, Cycle économique, Prime de terme, *Spread* de crédit, Méthodes de pénalisation.

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"It happens, however, that the energies and skill of the professional investor and speculator are mainly occupied otherwise. For most of these persons are, in fact, largely concerned, not with making superior long-term forecasts of the probable yield of an investment over its whole life, but with foreseeing changes in the conventional basis of valuation a short time ahead of the general public. They are concerned, not with what an investment is really worth to a man who buys it "for keeps," but with what the market will value it at, under the influence of mass psychology, three months or a year hence."

– John Maynard Keynes, 1936.

General Introduction

FORECASTING asset returns is a key aspect in finance, and its importance becomes particularly evident when applied to asset management, which even requires real-time forecasts of stock returns. The ability to predict future returns is hence not just an academic exercise but also a practical necessity that permeates numerous financial decisions, spanning from portfolio construction to risk management. Not surprisingly, anticipating bull or bear markets or selecting the stock with the greatest upside potential, are the biggest challenges for financial practitioners. They use a plethora of variables in an endeavor to forecast stock returns.

With a holistic perspective, investors navigate in an increasingly interconnected world. One must take into account not only each individual national features, but also international dynamics, and globalization, with its challenges since the Covid-19 pandemic crisis (Antràs et al., 2023) and the fragmentation of supply chains. Geopolitical tensions, trade agreements and currency fluctuations all play a central role in forecasting returns. Trade conflicts between major economic powers, like the US and China, or military conflicts, like the Russian invasion of Ukraine, have demonstrated how geopolitical events can introduce uncertainty into markets, affecting asset valuations and country and sectoral allocations.

Academic research strives to identify innovative methods for predicting stock returns¹ offering investors tools to allocate their wealth judiciously across countries and sectors, but also across diverse asset classes. Asset managers would shift their allocations toward more stable assets like bonds to protect their wealth in case of a prediction of a stock market downturn.

¹See Campbell and Thompson (2008), Welch and Goyal (2008), Rapach and Zhou (2013), Pettenuzzo et al. (2014), Atanasov et al. (2020), etc. Goyal et al. (2023) reviewed more than a thousand papers and identified 24 best papers from top-tier finance-related journals according to a performance methodology.

In the late 1990s, the technology sector surged, thanks to Internet-related companies,² through a collective bargain-hunting effect, as investors heavily relied on return forecasts and invested in these firms expecting short-term gains. However, this optimism abruptly ended with the bursting of the dot-com bubble in 2000, causing substantial losses for investors who had overly concentrated their portfolios in these stocks and lacked diversification. Prior to the 2008 global financial crisis, return forecasts played a crucial role in risk management within the banking and investment industry. Many financial institutions relied on over-optimistic forecasts for the housing market and complex financial products like mortgage-backed securities.³ When these forecasts proved inaccurate and the housing market collapsed, it triggered a global financial meltdown, demonstrating the implications of imperfect return predictions. David Viniar, who was Goldman Sachs' chief financial officer, famously said: "We were seeing things that were 25-standard deviation moves, several days in a row,"⁴ highlighting how extreme was the crisis and how impossible it was for the models to forecast such crisis.

These historical examples emphasize the potential for significant gains through return forecasting but also underscore the substantial risks of inaccurate predictions, accentuating the need for more precise and robust short-term return forecasts. The asset management industry is facing unprecedented challenges, with some investors having lost a significant amount of wealth. Investors' behavior and risk appetite have undergone profound changes, leading to a shift away from sophisticated products, an increased demand for refining portfolio selection and a renewed interest in de-risking investment portfolios.

The aftermath of the 2008 Global Financial Crisis ushered 15 years of unprecedented changes in financial markets. Central banks embarking on unconventional strategies like quantitative easing⁵ to stimulate economies and the resurgence of financial repression⁶ resulted in altered

²It has fueled the speculative frenzy surrounding the concept of the "new economy" and the "new era" (see Shiller, 2000; Stiglitz, 2003; Becker, 2006).

³Investors were attracted to higher-yielding mortgage securities, believing that higher ratings from Standard & Poor's and Moody's and reduced risk made them safe. These securities were sold to global pension funds and the biggest investment banks, which were seeking AAA-rated investments. Unfortunately, the return forecast of these financial instruments were done using techniques that failed to predict the risks of default in an already overheated real estate market.

⁴Thal Larsen, Peter. "Goldman pays the price of being big." *Financial Times*, 13 August 2007, <https://www.ft.com/content/d2121cb6-49cb-11dc-9ffe-0000779fd2ac>. Accessed 30 September 2023.

⁵The quantitative easing policy first introduced by Werner (1995), implemented by the Federal Reserve, the European Central Bank and the Bank of England would have prevented the 2008 debt crisis from a total blockage of the interbank market.

⁶See Reinhart and Sbrancia (2011), Reinhart et al. (2011), Perez (2015) and Chari et al. (2020).

interest rates. Ultra-low interest rates (even negative in Europe and Japan) pushed investors into riskier assets, creating the "TINA" effect.⁷ The technology sector has become a large component of the stock market, with the GAFAM⁸ stocks that distorted the market. The Covid-19 pandemic in 2020 brought extreme market volatility, followed by a sharp economic rebound and soaring inflation,⁹ prompting central banks to raise interest rates aggressively. Regulatory reforms aimed at preventing systemic failures reshaped the financial landscape, alongside emerging technologies like blockchain and cryptocurrencies (Girasa, 2018). Behavioral finance shed light on the role of human psychology in investment decisions, challenging the assumption of rational markets. Behavioral biases, such as FOMO and FOL,¹⁰ drove market exuberance and panic selling. Understanding these became crucial for effective risk management and investment decisions, ultimately shaping a more resilient investment landscape.

In this context, how can investors improve the optimization and diversification of their portfolio to maximize returns while managing exposure to the many types of risk? How can investors enhance their ability to predict short-term equity returns in this complex and uncertain landscape within the framework of tactical asset allocation?¹¹

The remainder of this general introduction is structured as follows. The first section reminds of the importance of equities in portfolio construction. The second section introduces the key aspects of return forecasting for portfolio optimization along with the role of factor models. The third section delves into the importance of short to medium-term return forecasting for tactical asset allocation and the role that valuation ratios and business cycle variables can play. The final section presents the thesis contribution to the field of forecasting returns in financial economics.

⁷TINA stands for "There Is No Alternative." Ultra-low interest rates aimed to stimulate borrowing, but affected savers and pushed investors into equities, pushing stock indices to record high.

⁸GAFAM for the five biggest US stocks in the late 2010s: Google, Apple, Facebook, Amazon, and Microsoft, whose sum of market capitalization as at 31 August 2023 is \$9.2 trillion and represents 23.2% of the S&P 500 index total or 3.6 times the size of the French CAC 40 index.

⁹Peaking at 9.1% for the US in June 2022 and 10.2% for the Eurozone in October 2022, the highest since the creation of the currency union.

¹⁰See Gärling et al. (2009) and Chan and Andrade (2011). Fear of missing out (FOMO) causes investors to rush into certain assets, driven by the fear that they will miss out on lucrative opportunities, leading to market exuberance and asset overvaluation (e.g. technology sector in the late 1990s and, more recently, cryptocurrencies). Conversely, fear of loss (FOL) can lead to panic selling during market downturns, thereby exacerbating higher volatility.

¹¹Tactical asset allocation (TAA) is a strategy which exploits short-term market dynamics to actively adjust portfolio asset allocation. Hence TAA capitalizes on short to medium-term market opportunities. On the contrary, strategic asset allocation (SAA) focuses on long-term target allocations

Why equity matters?

Equities are a fundamental constituent of portfolio construction due to their exceptional performance over extended time frames, outperforming all asset classes such as fixed income, commodities, and real estate. Figure 1 displays the dynamics of the total return of US traditional asset classes over 97 years from 1926 to 2023,¹² which are: equities, with a distinction between small and large capitalizations; government bonds, with a distinction between long-term maturity bonds (20-year and more) and medium-term maturity bonds (5-year); corporate bonds; and money market. Figure 2 displays, over the same period, the dynamics of the performance of alternative asset classes, which are: US housing and commercial real estate; crude oil; and gold. An important remark is that no other asset class, bonds, money market, commodities, or real estate displays the consistent and positive long-term returns as do stocks. They also provide a strong hedge against inflation.

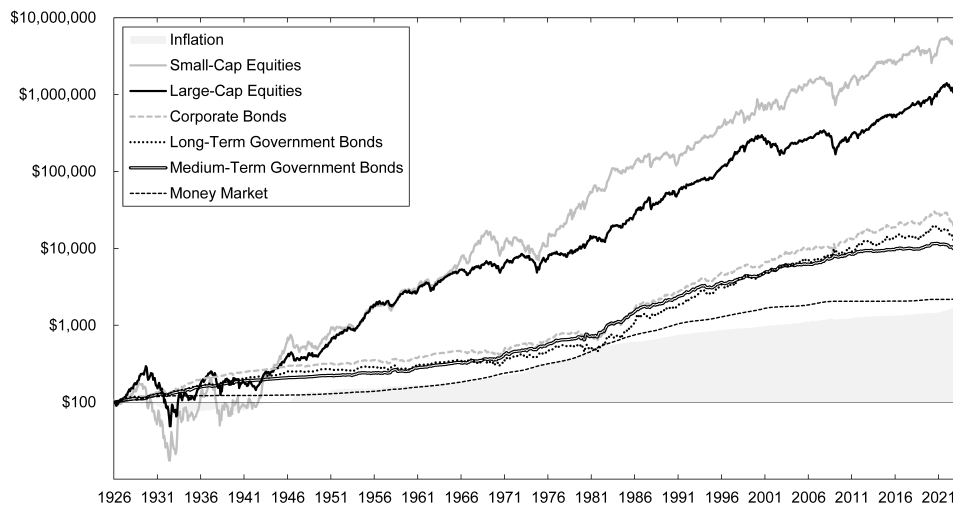


Figure 1: Dynamics of the total returns of US traditional asset classes since 1926

Source: Morningstar Direct, Bloomberg. The graph illustrates the total return nominal growth of a \$100 investment from 31 December 1925 through 31 August 2023. The US large-cap and small-cap equities, US long-term (20-year and more) high grade corporate bonds, US long-term (20-year and more) and medium-term (5-year) government Bonds and US money market (30-day US T-bills) are monthly total return indices from Ibbotson's *Stocks, Bonds, Bills and Inflation Yearbook*. Inflation is the US Consumer Price Index for all urban consumers.

¹²Data of S&P 500 are also available from 1881 using Shiller's database.

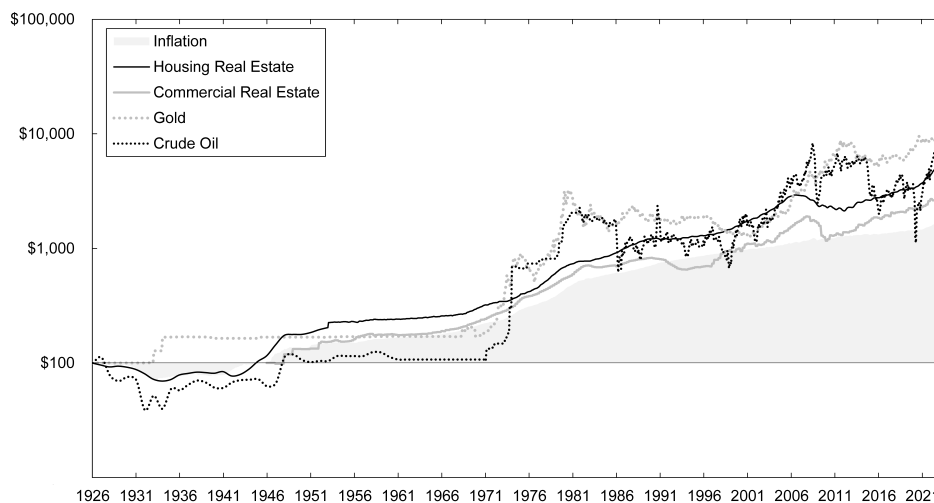


Figure 2: Dynamics of the total returns of alternative asset classes since 1926

Source: Bloomberg, Federal Reserve. The graph illustrates the total return nominal growth of a \$100 investment from 31 December 1925 through 31 August 2023. US Housing Real Estate is the S&P CoreLogic Case-Shiller US National Home Price Index. US Commercial Real Estate is from the National Real Estate Institute (1945–1996) and CoStar (1996–2023). The Gold Spot price is quoted as US Dollars per Troy Ounce. Crude Oil prices are from BP (British Petroleum) statistical review (1925–1950), Bloomberg Arabian Gulf Arab Light Crude Spot prices (1951–1983) and from Bloomberg West Texas Intermediate Cushing Crude Spot price (1983–2023). Inflation is the US Consumer Price Index for all urban consumers.

Table 1: Characteristics of traditional and alternative asset classes since 1926

	Large-Cap Equities	Small-Cap Equities	Long-Term Corp Bonds	Long-Term Govt Bonds	Medium-Term Govt Bonds	Money Market	Housing Real Estate	Commercial Real Estate*	Gold	Crude Oil
Annualized Return	10.25%	11.79%	5.65%	5.09%	4.84%	3.25%	4.06%	4.31%	4.76%	4.08%
Volatility	18.62%	28.00%	7.90%	8.66%	4.34%	0.87%	2.38%	3.31%	18.83%	36.35%

Source: Morningstar Direct, Bloomberg, Federal Reserve. Data from 31 December 1925 through 31 August 2023. The US large-cap and small-cap equities, US long-term (20-year and more) high grade corporate bonds, US long-term (20-year and more) and medium-term (5-year) government Bonds and US money market (30-day US T-bills) are monthly total return indices from Ibbotson’s Stocks, Bonds, Bills and Inflation Yearbook. Housing Real Estate is the S&P CoreLogic Case-Shiller US National Home Price Index. Commercial Real Estate is from the National Real Estate Institute (1945–1996) and CoStar (1996–2023). The Gold Spot price is quoted as US Dollars per Troy Ounce. Crude Oil prices are from BP (British Petroleum) statistical review (1925–1950), Bloomberg Arabian Gulf Arab Light Crude Spot prices (1951–1983) and from Bloomberg West Texas Intermediate Cushing Crude Spot price (1983–2023). *Data from December 1945.

However, with this potential for higher returns comes increased risk. Table 1 displays the volatility of the main asset classes as well as the alternative asset classes. Unsurprisingly, Equities are amongst the most volatile asset classes, with an annualized volatility of 18.62% for large-cap and 28.00% for small-caps since 1926. Commodities are more risky with a volatility of 36.35% for Crude Oil prices. Even gold, generally considered as a safe haven asset or a portfolio hedge,¹³ exhibits a slightly higher volatility (18.83%) than large-cap stocks since 1926. Stock markets, especially small-caps, are more subject to market fluctuations, economic cycles and company-specific events. This volatility can lead to significant short-term losses, making tactical asset allocation and portfolio optimization essential for asset managers, while seeking the best balance between risk and performance over time.

Portfolio optimization and the limits of factor investing

The work of (Markowitz, 1952) on optimized mean-variance portfolios and the subsequent development of the capital asset pricing model (CAPM) by Sharpe (1964) constitute essential milestones in the modern portfolio theory. Markowitz's research introduced the concept of diversification, highlighting how investors could minimize risk by constructing portfolios of assets with different risk-return profiles. This formed the basis for developing efficient portfolios aimed at obtaining the highest possible return for a given level of risk, a principle that remains central to modern finance. The capital asset pricing model, on the other hand, provides a systematic framework for understanding the relationship between risk and return and introduces the concept of market capitalization weighting. This approach suggests that in a well-diversified portfolio, the weighting of each individual assets should be proportional to their market value. Together, Markowitz's mean variance optimization and Sharpe's CAPM have revolutionized portfolio construction and asset allocation strategies, shaping the way investors approach risk management and portfolio choice.

Academic research investigating the presence of common risk factors beyond the market index, with roots dating back to Fama and French's seminal work in 1992, has unveiled factors capable of explaining variations in stock returns. Multi-factor models have become instrumen-

¹³See Baur and McDermott (2010), Akhtaruzzaman et al. (2021).

tal in portfolio management, providing a framework to identify and quantify potential return drivers within the market. After the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015) have further expanded the scope of factors to consider, incorporating to size, valuation and market factors, the momentum and quality, thereby offering a more comprehensive approach to understanding and managing risk and return in investment portfolios. Academic literature widely acknowledges the limitations of mean-variance optimized and market-capitalization weighted portfolios due to their constrained assumptions and poor out-of-sample performance (see for example Bloomfield et al., 1977; DeMiguel et al., 2009; Tu and Zhou, 2011; Behr et al., 2012; Kourtis et al., 2012). This has led to the emergence of alternative portfolio weighting approaches like equally weighted, minimum variance, and most diversified portfolios, often referred to as "smart beta" or "factor investing." These innovative methods aim to capture specific risk factors and associated premiums, offering investors a more diversified and potentially rewarding investment landscape beyond traditional approaches. This shift in portfolio construction recognizes the importance of considering alternative risk factors for superior risk-adjusted returns.

Multifactor models offer the possibility to measure, using systematic statistical methods, the common risk factors that drive stock markets. They have a rich history in finance and economics helping identify latent factors and test asset pricing theories (Ross, 1976; Chamberlain and Rothschild, 1983). Asset Pricing Theory (APT) tests date back to Roll and Ross (1980), Schipper and Thompson (1981), Connor and Korajczyk (1986), and Connor and Korajczyk (1988). Recent research extends multifactor models' possibilities, for exemple, in Kelly et al. (2019), Pelger (2019), Lettau and Pelger (2020a,b), Giglio and Xiu (2021). In macroeconomics, they also find use in business cycle forecasting (Stock and Watson, 2006).¹⁴

However, there are significant challenges to using factor models. The number of factors reported in the academic literature has become so numerous that Cochrane (2011) spoke of them as a "zoo of factors" in his 2011 presidential address to the American Finance Association. Portfolio managers face the challenge of choosing from this multitude of factors those that are truly relevant to their strategies. Harvey et al. (2016) categorized a total of 316 empirical

¹⁴Multifactor models are employed in large macroeconomic modeling (Forni et al., 2000; Favero et al., 2005; Gagliardini and Gourieroux, 2014), and monetary policy (Boivin and Ng, 2006).

factors sourced from 313 distinct publications featured in leading finance journals and ongoing working papers dating back to 1967. They examine the implications of this diversity of factors for portfolio optimization and show that the explanatory power of many of the factors suggested are spurious.¹⁵

More recently, Jensen et al. (2023) used a Bayesian model to find that a large majority of factors reported in the academic literature are in fact valid. Still, the main challenge investors face when optimizing the exposure of their portfolio to a specific factor, and hence to try to capture a specific risk premium, is predicting which factor will influence financial markets in the future and when.

Shiller (2018, 2019) investigates market "narratives" by highlighting a fundamental aspect of behavioral finance: the way investors interpret and react to economic events and financial information. Gennaioli and Shleifer (2018) dissects the global financial crisis, revealing the impact of beliefs held by home buyers, investors, and regulators and suggest a theory of belief formation, shedding light on the crisis's surprising nature and the persistence of financial and economic instability. A key finding of these studies is that markets are often driven by stories or collective narratives rather than objective, rational data. It is undeniable that markets are influenced by a multitude of factors, and it is difficult to anticipate which of these factors will be predominant at any given time. Narratives can evolve rapidly in response to economic, political, or even social events, making it even more complicated to predict which factor will come to the fore. Furthermore, optimizing a portfolio by anticipating the timing of narrative changes is a particularly delicate task. Markets may follow a certain narrative for a while, and then abruptly reject it in favor of a new one. Investors who poorly anticipate the timing of these changes may suffer significant losses in their portfolio.

Analyzing market narratives highlights the complexity of predicting financial market behavior. Investors must consider economic and financial indicators while remaining aware of how market sentiment interprets this information. A notable example is the 2016 election when expectations of a Hillary Clinton victory gave way to a surprising "Trump Rally" as financial markets reacted positively to Donald Trump's win, despite prior predictions of a negative out-

¹⁵See also Bai and Ng (2006), Lewellen et al. (2010) and Ahn et al. (2018).

come.¹⁶ This surprising reaction of the financial markets perfectly illustrates the difficulty of forecasting both event outcomes and subsequent market directions, highlighting the inherent unpredictability in markets drivers.

In this context, the success of factor investing depends on how accurately portfolio managers can predict when a given factor will be rewarded by the market. This task is inherently complex as factors and market loads can vary over time (Kelly et al., 2019). Factor risk premiums are tied to specific periods, difficult to predict and highly unlikely to repeat. Investors who choose to follow a particular style or factor that has already moved a long way in one direction are particularly vulnerable to sudden reversals, more commonly called "style rotations." Looking at the macroeconomic and geopolitical landscape, it is evident that the world is growing increasingly complex and dynamic. Shifts in leadership styles or factors may occur more frequently, posing challenges in predicting market trends and increasing the costs of implementing portfolio adjustments. As a result, investors who seek alpha generation will tend to diversify their portfolios away from the conventional practice of betting on specific factors and instead focus on stock selection with stronger emphasis on company-specific dynamics or investment strategies that are more independent from the main factors.

Return predictability and the link between equity valuations and the business cycle

The historical performance of equities displayed in Figure 1 vividly illustrates the strong correlation between equities and the business cycle. Stock values indeed heavily depend on corporate earnings, which are significantly influenced by the state of the business cycle. Economic expansion and higher activity growth tend to increase equity performance, while economic downturns often yield in reduced equity returns.¹⁷

Investors may potentially achieve better financial performance through tactical asset alloca-

¹⁶Zuckerman, Gregory and Chung, Juliet. "Billionaire George Soros Lost Nearly \$1 Billion in Weeks After Trump Election." *Wall Street Journal*, 13 January 2017, <https://www.wsj.com/articles/billionaire-george-soros-lost-nearly-1-billion-in-weeks-after-trump-election-1484227167>. Accessed 30 September 2023.

¹⁷Cochrane (2017) focus on the connection between asset prices and the business cycle. Macro-finance models were found to produce time-varying risk premia for different asset classes that are all tied to the state of the business cycle.

tion based on the timing of the business cycle. Tactically shifting allocation from stocks to cash or short-term bonds several months before a recession's onset and returning to stocks before its conclusion can lead to notable advantages compared to buy-and-hold strategies (Siegel, 1991). Of course, the best way to forecast short-term equity returns would be to time exactly the entry and exits of a recession, for each recession, which is obviously impossible. Successfully predicting the business cycle is a difficult task¹⁸ because it requires identifying economic peaks and troughs before they occur. Despite its difficulty, business cycle forecasting remains popular, thanks to the considerable benefits associated with the precise timing of these turning points.

The National Bureau of Economic Research (NBER), a private organization founded in 1920, is the reference in determining US business cycle dates based on macroeconomic indicators. Historical data underscores the connection between stock market movements and NBER economic recessions, with over 93% of the 48-recorded recessions since 1802 being preceded or accompanied by significant declines in the S&P 500 index. While NBER decisions hold political and economic significance, they tend to be announced well after cycles have commenced, rendering them less useful for market timing. The exceptional case of the recession caused by the Covid-19 pandemic lasted only 2 months, resulting in one of the shortest recessions in US history.¹⁹ At the end of a recession, the stock market typically rises, meaning that investors waiting for concrete signals of economic recovery often miss out on significant short-term gains on the market. Additionally, the NBER announces recession end dates well after the recovery begins.

Leading economic indicators can be used to time the level of economic activity with some precision, such as economic surveys based on purchasing managers' indexes (de Longis and Ellis, 2022). However, the US term spread, which is the spread between long-term Treasury yields and short-term Treasury bills, and particularly the phenomenon of yield curve inversion (when the yield of the short-term Treasury bills is higher than long-term Treasury yields), has proven to be a remarkable early warning indicator (See for example Stock and Watson, 1989; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998). It has consistently signaled imminent economic slowdowns over six decades. Similarly, movements in credit spreads are believed to contain

¹⁸During the 1974-1975 recession, economists failed to recognize the downturn's severity, leading to overestimations of GDP growth and underestimations of inflation. Similar forecasting issues persisted in later recessions, such as the 1981-1982 recession, and the 2007-2009 Great Recession, which experts failed to predict accurately.

¹⁹The announcements of the shutdown of economies by all governments in the world in March 2020 caused an extremely rapid fall in the US stock market in just a few weeks of almost 34%.

important signals regarding the evolution of the real economy and risks to the economic outlook. Welch and Goyal's seminal paper in 2008 suggests relevant predictors with powerful early-warning properties, which have been recently reaffirmed in Goyal et al. (2023).

Furthermore, a connection exists between equity valuation ratios and the prediction of equity returns, mainly when considering that these valuation ratios are persistent during some business cycle phases, while mean reverting around others phases. The works of Rapach et al. (2010), Henkel et al. (2011) and Dangl and Halling (2012) reported the evidence of predictive power of valuation ratios during recession.

A collection of metrics have been deployed to assess stock market valuations, typically quantifying the market's value relative to economic fundamentals like earnings, dividends, or book values, or to economic variables such as GDP and interest rates. The price/earnings ratio (P/E ratio) stands out as a central measure. It serves as a barometer of an investor's willingness to pay for each dollar of current earnings. The earnings yield, which is the reciprocal of the P/E ratio and akin to the dividend yield, measures earnings generated per dollar of market value and is closely aligned with long-term stock returns due to stocks' connection to real assets that appreciate with inflation.

Campbell and Shiller (1988) introduced the cyclically adjusted price/earnings ratio (CAPE ratio) a key valuation measure based on a 10-year average of real earnings to smooth business cycle fluctuations. Their research revealed that the CAPE ratio could predict long-term stock returns. When the CAPE ratio exceeds its long-term average, it predicts below-average future returns and vice versa. The CAPE ratio became famous when it indicated overvaluation in the late 1990s, coinciding with Alan Greenspan's "irrational exuberance speech."²⁰ In 2000, it reached a record high, accurately predicting a decade of poor equity returns.

Numerous academic papers have explored the predictive power of valuation ratios in the context of forecasting future stock market returns over multi-year horizons (Rozeff, 1984; Fama and French, 1988; Campbell and Shiller, 1988; Cochrane, 1991; Hodrick, 1992; Goetzmann and Jorion, 1993; Lewellen, 2004, etc.). These studies collectively suggest that while the growth rates of fundamentals like dividends and earnings are challenging to predict, variations in financial

²⁰Remarks by Chairman Alan Greenspan At the Annual Dinner and Francis Boyer Lecture of The American Enterprise Institute for Public Policy Research. Federal Reserve Board. 5 December 1996. <https://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm>. Accessed 30 September 2023.

ratios are primarily driven by expected returns through mean reversion.

Campbell and Shiller (1998, 2005) emphasize the importance of the stability of valuation ratios regarding mean reversion. If valuation ratios remain within historical ranges and do not deviate permanently or indefinitely, extreme levels should signal an impending correction. This correction can occur through either changes in dividends or changes in stock prices. Essentially, when stock prices are significantly elevated relative to P/E indicators, future price declines are expected to realign these ratios with historical norms. This contradicts the random walk theory, which asserts the unpredictability of stock price movements (Fama, 1965).

Nevertheless, empirical evidence largely supports the notion that this relationship holds strongest for long-term stock market returns as valuation ratios (whether it is P/E or dividend price) tend to revert to their historical averages over extended time horizons. Paye and Timmermann (2006) empirical work demonstrates that short-term evidence of predictability based on financial ratios is at best characterized by instability.

A debate has sparked on short-term stock return predictability using financial ratios and its link with the business cycle. Lettau and Van Nieuwerburgh (2008) assume that if 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 reconcile conflicting results in prior research by relaxing the assumption of a fixed steady-state mean of the economy, showing strong evidence of shifts. Furthermore, the results from McMillan (2019) shows that using cyclical components of financial ratios improves their predictability power.

Thesis Contribution

This thesis proposes three original contributions to the field of asset returns forecasting related to the main market features stressed above. It is split into two parts. The first part (Chapter 1) emphasizes the importance of the returns forecast for asset management, in particular for portfolio optimization introducing a new paradigm that improves equity portfolios' diversification while managing exposure to risk factors. The approach can be opposed to the Smart Beta of factor investing strategies. The second part addresses the importance of short-medium term

forecasting of returns for tactical allocation and is divided into two chapters (Chapter 2 and Chapter 3). Chapter 2 investigates ability to predict short-term equity returns with the role that valuation ratios and their mean reversion properties can play while Chapter 3 extend this ability using a broad set of business cycle variables.

Chapter 1 introduces an active investment approach, referred to as "Smart Alpha," offering an innovative perspective on equity portfolio allocation. Unlike traditional factor-based strategies, Smart Alpha focuses on capturing alpha, which represents expected returns uncorrelated with systematic risk factors, while minimizing exposure to these latent sources of risk. The methodology behind Smart Alpha relies on Sparse Principal Component Analysis (SPCA), a dimension reduction technique from machine learning, combined with a methodology for determining the optimal number of relevant factors, as outlined by Bai and Ng (2002). The Smart Alpha approach seeks to address the challenges to the efficiency of Markowitz (1952) mean-variance portfolios and Capital Asset Pricing Model (Sharpe, 1964) and the concerns from the relevance of alternative weighting schemes such as smart beta and factor investing. Three arguments qualify this concern: (1) the unstable optimal number of factors that drive the market; (2) the difficulty of timing factor rewards accurately; and (3) the persistence of stock alphas arising from various sources. Consequently, the chapter proposes the Smart Alpha strategy as an alternative approach to factor investing, focusing on minimizing systematic risk exposure while maximizing alpha, which is considered as the mispriced expected returns. This choice is supported by empirical evidence of alpha's predictability (Zaremba et al., 2019).

The success of Smart Alpha hinges on the correct specification of the asset pricing model and determining the optimal number of factors. A significant contribution of this chapter is its use of SPCA to estimate both alphas and betas, reducing the estimation noise and enhancing the stability of factor loadings. Smart Alpha shares similarities with the Betting-Against-Beta (BAB) investment rule (Frazzini and Pedersen, 2014b), but the new paradigm distinguishes itself by maximizing alpha, considering latent factors, and employing robust estimation methods. Empirical analysis using European STOXX 600 stocks demonstrates the superiority of the Smart Alpha portfolio in terms of returns, risk-adjusted returns, and downside risk compared to traditional factor investing strategies, BAB portfolios and other smart beta portfolios. Additionally, the chapter highlights the economic benefits of using SPCA to estimate stock exposures and

alphas, providing a robust foundation for the Smart Alpha strategy.

Chapter 2 delves into the critical issue of predicting stock returns at shorter horizon. By capitalizing on regime-specific mean reversion in valuation ratios, we present compelling evidence that these ratios possess predictive power for in-sample and out-of-sample returns over short horizons. This predictive capacity is harnessed by exploiting business cycle variables, such as term and credit spreads, to better understand these phases. Traditionally, financial research has emphasized the predictive power of valuation ratios like the CAPE for long-term stock market returns. However, this chapter builds upon the findings of Lettau and Van Nieuwerburgh (2008), which suggest that short-term predictive information in valuation ratios can be uncovered by accounting for regime-specific mean reversion. This approach leverages the relationship between changes in valuation ratios and business cycle variables, thereby enhancing short-term predictability (Arnott et al., 2017; Boucher, 2006).

In this context, the central idea of the chapter is that identifying instances of mean reversion in valuation ratios using a Markov-switching model, can enhance short-term return predictions, as the dynamics of returns following mean reversion differ from overall trends. Empirical analysis using a new predictive regression reveals that following mean reversion in the US Shiller CAPE ratio, average few month returns tend to be negative, especially when mean reversion episodes occur at high CAPE levels. To ensure the model's effectiveness in out-of-sample predictions, the chapter introduces the use of the US term spread as an indicator of mean reversion in valuation ratio. The rationale behind this choice stems from two critical evidence: (1) prior research has highlighted the connection between mean reversion in valuation ratios and economic recessions; and (2) the term spread has demonstrated robust predictive power in forecasting economic recessions. The results show that this new predictive regression, based on the term spread, outperforms traditional models in out-of-sample predictions, offering higher predictive power over short-term horizons.

This innovative approach is robust to the choice of the business cycle variable, as similar results are obtained for the credit spread. Besides, the out-of-sample results hold for various valuation ratio, including excess CAPE yield and dividend yield and across different countries, including the United States, the United Kingdom, Germany, and Canada. The chapter also conducts a mean-variance asset allocation exercise, demonstrating the superiority of the new

predictive regression in terms of utility gain for investors.

Chapter 3 extends the approach for predicting short-term stock index returns introduced in Chapter 2, by operating in a data-rich environment. This extension is accomplished by incorporating a comprehensive set of business cycle variables and implementing penalization techniques to facilitate parsimonious estimation. The new model broadens the relationship between mean reversion in the Shiller CAPE ratio and price dynamics by encompassing a wider range of early-warning business cycle variables. The primary objective of the chapter is to enhance the out-of-sample predictive power of the model proposed in Chapter 2. This extension stems from the absence of a consensus regarding which business cycle variables yield the best predictive performance for mean reversion in valuation ratios and stock index prices. Beyond the term and credit spreads examined in Chapter 2, the third chapter explores the predictive potential of global financial variables and macroeconomic indicators suggested by Welch and Goyal (2008). These predictors include stock index variance, net issuing activity, and bond returns.

To address model uncertainty, the chapter employs the least absolute shrinkage and selection operator (LASSO) method of Tibshirani (1996), which facilitates the variable selection and estimation simultaneously while mitigating overfitting. The empirical findings indicate that this extended approach significantly enhances short-term predictive power out-of-sample, with higher R-squared values for the optimal model. Importantly, the improvement in forecasting short-term stock returns does not arise from expanding the range of business cycle variables but rather stems from utilizing various lag-orders for the term spread. It underscores its central significance alongside the US Shiller CAPE ratio in predicting prices in the short term. These findings are robust to the choice of valuation metrics including the book-to-market ratio and the dividend yield. Furthermore, the robustness of the model is validated across different US industries, providing valuable insights for investors pursuing industry rotation strategies. Finally, the chapter conducts a mean-variance asset allocation exercise, which confirms the superiority of the new predictive regression in terms of utility gains for the broad US stock market and for the individual US sectors.

1

Smart Alpha: Active Management with Unstable and Latent Factors

1.1 Introduction

THIS chapter proposes an active investment approach for allocating equity portfolios. The strategy consists of betting on alphas, rather than on specified a-priori factors in the way that the factor investing approach does. This is done through a strategy we call "Smart Alpha," which maximizes alpha, or the expected return that is uncorrelated to various systematic sources of risk, while minimising the systematic risk from exposure to these risk factors. Computationally, the alphas of stocks and their exposures to driving factors are estimated using Sparse Principal Component Analysis (SPCA), a dimension reduction method from machine learning, coupled with a methodology for timing the optimal number of unknown relevant factors.

The efficiency of the Markowitz (1952) mean-variance optimized portfolios and of the market-capitalisation weighting derived from the Capital Asset Pricing Model (Sharpe, 1964) has recently been challenged. They use a rather "heroic" set of assumptions (stability in the expected returns and the variance-covariance matrix, no estimation risk, normal returns, no constraints on short selling, homogeneous expectations, and more) to guarantee that no other portfolios with the same risk have higher expected return. Furthermore, mean-variance optimized portfolios and market-capitalisation weighted portfolios perform relatively poorly out-of-sample (see for example Bloomfield et al., 1977; DeMiguel et al., 2009; Tu and Zhou, 2011; Behr et al., 2012; Kourtis

Joint work with Christophe Boucher, Patrick Kouontchou and Sessi Tokpavi. Published in *Quantitative Finance*, 21(6):893-909, 2021.

et al., 2012). The consequence is that alternative weighting schemes and heuristic approaches (equally-weighted, minimum variance, most diversified portfolio, equally weighted risk contributions, risk budgeting or risk parity)¹ have recently been proposed and have rapidly attracted asset managers and large institutional investors under the labels "smart beta" or "factor investing."² The idea underlying these approaches is to capture risk factors and thus risk premiums like low volatility, momentum, quality, value and size.

The rise of factor investing stems from the findings of academic research into the existence of some common risk factors beyond the market index. This strand of literature, which can be dated back to the seminal work of Fama and French (1992), has discovered many market variables or factors that may be able to explain the cross-sectional variations of stock returns. These include the size and value factors in Fama and French (1992) and the momentum factor in Jegadeesh and Titman (1993). The result is that what is traditionally called alpha in Sharpe's single index model appears instead as beta in disguise. This raises concerns in the financial world about how relevant active portfolio management is, as the alpha of a stock measured by the average excess returns over factor risk premiums naturally shrinks as more factors are identified and are subject to bets. However, there are three arguments that qualify this assertion.

The first is that the number of factors reported in the academic literature has become so numerous that Cochrane (2011) spoke of them as a "zoo of factors" in his 2011 presidential address to the American Finance Association.³ There have been some attempts in the empirical literature to gauge the relevance of these numerous factors,⁴ and Lewellen et al. (2010) for instance focus on biases in the cross-sectional regressions for asset pricing tests and show that the explanatory power of many of the factors suggested are spurious (see also Bai and Ng, 2006; Ahn et al., 2018; Harvey et al., 2016). The second issue is that beyond this uncertainty about the number of factors and which ones really drive the cross-sectional variations of stocks, the success of factor investing is anchored to how accurately portfolio managers can time when a

¹See Choueifaty and Coignard (2008), Meucci (2009), Maillard et al. (2010).

²Smart beta assets under management have grown by 500 per cent since 2008 to \$616 billion at the end of 2015 according to data from Morningstar ("Smart beta defenders dismiss fears, but doubts linger," 11/09/2016 Financial Times).

³In the same vein William Sharpe said "When I hear smart beta, it makes me sick" at the CFA Institute Annual conference in Seattle on 5 May 2014.

⁴Relevance means robust factors that are free of data snooping, and which approximate exposures to systematic sources of risk with consistent long-term risk premiums.

given factor is going to be rewarded by the market. This task is by nature complicated because the factors and loadings in markets are potentially time varying (Kelly et al., 2019) in response to changes in beliefs or in how markets price different stories (e.g. Shiller, 2017; Gennaioli and Shleifer, 2018). The third argument is that even in the ideal case when the factors rewarded are timed accurately, there is still a significant probability that stocks will have alphas that arise from stochastic mispricing relative to the asset pricing model, and from corrections of earlier over-reactions to news (de Bondt and Thaler, 1985, 1987), slow adjustments to firm-specific news (Jegadeesh and Titman, 1993), unanticipated increases in market illiquidity (Amihud, 2002), and the state of sentiment (Lee et al., 1991).

From these stylized facts, we propose an approach that can be viewed as an orthogonal take on the factor investing approach, and investigate its empirical properties. We call this approach "Smart Alpha," and it works by reducing exposures to various systematic sources of risk while maximising the expected return that is uncorrelated to these main risk factors. Rather than betting on specific a-priori factors as in the factor investing approach, we focus instead on an active approach that minimizes the portfolio's exposures to systematic latent sources of risk while maximising its alpha, which is given by the expected mispriced returns from an asset pricing model. Our choice is thus to bet on alphas instead of on alternative betas as the factor investing approach does. A further reason for this choice is that empirical regularities about alphas' predictability are reported in the literature. Zaremba et al. (2019) demonstrate predictive power over future returns from using alphas based on a multi-factor model with one year of data, allowing them to document an alpha momentum phenomenon for country and industry equity indexes in Europe. We hypothesize that it is likely that this phenomenon also holds for individual stocks, and our strategy intends to exploit this by maximising the portfolio's alpha.

The success of our strategy depends deeply on specifying the asset pricing model correctly in order to capture the alphas of the stocks over time as measured by the average mispriced returns. To achieve this we build on an exciting literature in statistics that focuses on estimating the number of factors in large dimensional latent factor models (Lewbel, 1991; Connor and Korajczyk, 1993; Donald, 1997; Bai and Ng, 2002; Onatski, 2010; Ahn and Horenstein, 2013). More precisely, we follow Bai and Ng (2002), who introduced statistics of the information criteria type into the framework of an approximate factor model to estimate the number of latent factors. Their

statistics are similar to the Akaike or Bayesian information criteria used for model selection in a linear regression model, and they are a compromise between the average variance of idiosyncratic returns and the number of factors. We use their method rather than more recent ones as it is simple to understand, like any information criterion is, and it has been shown not to be inferior to the other methods in our context, where the variance of the systematic part of stock returns is likely to be larger than the idiosyncratic part.⁵

The second main contribution of this chapter, besides determining the optimal number of factors to help avoid specification errors in the latent factor model and guarantee the stock's alphas are identified correctly, is to estimate the alphas of a stock based on the betas⁶ extracted from the sparse principal component analysis (SPCA). SPCA is a well-known methodology in machine learning that has applications in many fields including image processing, facial recognition, gene expression data analysis, multi-scale data processing, and more. In contrast to the traditional PCA, in which each factor is a linear combination of all the input variables, this method sets some of the loadings to exactly zero, so reducing estimation error. Small loadings (or exposures of a stock to latent factors) are indeed the most subject to irrelevant variability over time because they correspond to statistical noise. Sparsity thus introduces stability into the loadings of the stocks, or its betas, and consequently into its alphas.

It should be stressed that by minimising exposures to the various systematic sources of risk, Smart Alpha has some similarities to the Betting-Against-Beta (BAB) investment rule that was popularized by the prominent work of Frazzini and Pedersen (2014a). This rule states that a significant proportion of investors in the market are prohibited from using leverage or are limited in how much they may do so because of margin requirements. In consequence these investors go over-weight in risky or high-beta stocks instead of using leverage, and this then makes those stocks more expensive. High-beta risky stocks are consequently overvalued and are associated with low realized alpha. Obviously, a simple strategy for capitalising on this behaviour is to construct a low-beta portfolio like that used in the Smart Alpha strategy.

Our approach goes beyond the BAB investment rule in three essential points though. First,

⁵Empirical results, which are available upon request, show that using the more recent methods does not add value.

⁶It may be recalled that the alpha for a given stock corresponds to the average returns beyond the rewarded factor risk premiums that depend on their associated loadings or betas.

the Smart Alpha strategy not only minimizes the exposure or the beta of a portfolio, but it also aims to maximize the alpha of that portfolio. It differs in this from the BAB rule, which only selects a low-beta portfolio and allows its alpha to be realized following the promise of the negative relation between betas and alphas. The second difference is that traditional implementations of the BAB strategy are based on betas that are identified as exposures to a fixed number of empirical factors (market, size, value), while our approach considers latent factors, and the number of these may vary over time as market conditions change. The third point is that a robust approach (SPCA) is used to estimate both the alphas and the betas, and this cleans as much noise as possible.

Using stocks in the European STOXX 600 universe, we show empirically that our Smart Alpha portfolio is economically and statistically superior to many popular European factor investing indexes, the BAB portfolio, and more generally smart beta portfolios. The raw returns, average realized returns and risk-adjusted returns are, on average, higher than those of the competing portfolios, while the downside risk as measured by the maximum drawdown is lower. Moreover, we evaluate the economic value of using the SPCA to estimate the exposures and alphas of the stocks instead of the traditional PCA, and we observe significant economic gains.

This chapter is organized as follows. Section 2 presents the optimisation programme that underlies the Smart Alpha strategy together with a description of the latent factor model for asset pricing. Section 3 presents the method for identifying the optimal number of latent factors, and describes the SPCA methodology for estimating the exposures and alphas of the stocks. Section 4 compares the out-of-sample performances of the Smart Alpha portfolio with the MSCI factor investing indexes, BAB portfolios and popular smart beta portfolios, while Section 5 investigates the economic value of the new portfolio and its sensitivity to traditional factors. The last section concludes the chapter.

1.2 The Smart Alpha investment strategy

This section describes our Smart Alpha investment strategy. The first part of the section describes the underlying optimisation programme, and the second part specifies the statistical asset pricing model used for estimating the main inputs, which are the alphas and betas of the stocks.

1.2.1 The optimisation programme

To describe the Smart Alpha optimisation programme, let ω be a vector of length N with elements that are the weights of a given portfolio, where N denotes the number of stocks in the capitalisation universe. The main idea of our strategy is to bet on smart or intelligent alphas rather than on alternative betas or risk premiums. More specifically, the two objectives of the proposed strategy are to limit the exposures of the optimal portfolio to the systematic sources of risk, and to maximize its alpha given by the average mispriced returns from an asset pricing model. Starting from these two objectives, the optimisation programme can be written as follows:

$$\begin{cases} \tilde{\omega} = \arg \min_{\omega} \omega' \Sigma_S \omega \\ \text{u.c. } \omega' \alpha \geq \epsilon, \quad \omega \geq 0, \quad \omega \leq \bar{\omega}, \quad \omega' e = 1, \end{cases} \quad (1.1)$$

where $\alpha = (\alpha_1, \dots, \alpha_N)'$ is the vector of length N of the stock's alphas, $\alpha_p = \omega' \alpha$ is the portfolio's alpha, $\sigma_{S,p}^2 = \omega' \Sigma_S \omega$ is the systematic portfolio's variance with Σ_S as the (N, N) systematic covariance matrix from an asset pricing model, $\epsilon > 0$ is the required portfolio's alpha, $\bar{\omega}$ is the upper-bound on the portfolio weights for the purpose of diversification, and e is the unit vector of length N . The programme incorporates an alpha targeting constraint in the low systematic risk portfolio strategy. In empirical applications, the parameter ϵ is set to an extreme upper quantile of the estimated alphas of the stocks.⁷ We also consider stability issues by adding a turnover constraint to the programme, which is given by:

$$\sum_{i=1}^N |\omega_i - \omega_i^0| \leq \theta, \quad (1.2)$$

where ω_i^0 is the weight of stock i in the owned portfolio, and θ is the maximum value of wealth rebalancing for each optimisation, which we set to 20% in the empirical applications.

Two main remarks can be made about this optimisation programme. First, the Smart Alpha strategy limits the portfolio's exposures to the main systematic risk factors, unlike the factor investing approach, in which the philosophy is to increase exposures to empirical factors. Moreover, Smart Alpha minimizes the exposures of stocks to systematic risk factors, and so is in

⁷More precisely, we begin at the 99% quantile and decrease the order of the quantile by a small amount until convergence.

line with the desire of investors to see more risk management practices being used in portfolio construction. Since the most recent global financial crisis there has indeed been renewed interest in de-risking investment portfolios as investors increasingly demand portfolio strategies that could protect their wealth in volatile, falling markets. Long-only equity portfolios can de-risk by reducing or targeting the exposure of the portfolio to systematic risk factors.

As the second remark, it is worth stressing that by minimising the exposure of the portfolio to the main sources of systematic risk while maximizing its alpha, our strategy tries to maximize a risk-adjusted measure of performance defined as the ratio of the portfolio's alpha to its systematic volatility. It differs in this from the Markowitz view of an active portfolio strategy, in which the portfolio's expected return is maximized rather than its alpha, while the overall volatility of the portfolio is reduced rather than the systematic volatility. Interestingly, we can show that in the simplified case when the CAPM holds with the market portfolio as a single source of risk, this risk-adjusted measure is nothing else but that of Treynor (1965). In this case, and setting the risk-free rate to zero without loss of generality, we have:

$$\frac{\alpha_p}{\sigma_{S,p}} = \frac{\mu_p - \beta_p \mu_M}{\sqrt{\beta_p^2 \sigma_M^2}} = \frac{\mu_p}{\beta_p \sigma_M} - \frac{\mu_M}{\sigma_M}, \quad (1.3)$$

where μ_p is the portfolio's expected return, $\beta_p \mu_M$ and $\beta_p^2 \sigma_M^2$ are respectively the portfolio equilibrium expected return and systematic variance from the CAPM, β_p is the portfolio beta, and μ_M and σ_M are the expected return and volatility of the market portfolio. Taking μ_M and σ_M as exogenous, it appears from (1.3) that maximizing our ratio thus corresponds to maximizing the Treynor Ratio given by μ_p/β_p .

In the following section, we specify the factor model underlying the asset pricing model that we use to estimate the inputs of our optimisation programme.

1.2.2 Specification of the factor model

The asset pricing model we consider is based on the dynamic factor model (DFM) specification for asset returns (see Geweke, 1977; Sargent and Sims, 1977)

$$r_t = \lambda_0 f_t + \lambda_1 f_{t-1} + \dots + \lambda_s f_{t-s} + e_t, \quad (1.4)$$

where r_t is the vector of length N of returns on the stocks, f_t is a vector of length q with elements the dynamic factors, λ_j , $j = 0, \dots, s$, is a matrix of dimension (N, q) with elements the exposures of stocks on the q dynamic factors, and e_t is the vector of length N of idiosyncratic or residual returns at time t . In the terminology of Bai and Ng (2007), the q dynamic factors are called primitive shocks and are supposed to drive the cross-sectional variations of the returns on the stocks.

Note that this dynamic model admits a static representation given by:

$$r_t = \Lambda F_t + e_t, \quad (1.5)$$

where $F_t = (f'_t, f'_{t-1}, \dots, f'_{t-s})'$ is a vector of length $m = q(1 + s)$ of static factors, and $\Lambda = (\lambda_0, \lambda_1, \dots, \lambda_s)$ is a matrix of dimension (N, m) of exposures to static factors. Our object of interest here is the static representation of the dynamic factor model where the m static factors are identified and estimated. To put this differently we do not focus on identifying the s primitive shocks as we do not need to do this to estimate the two elements that are important for our investment strategy, which are the alphas and betas of the stocks. With the static specification in (1.5), the systematic covariance matrix Σ_S in the optimisation programme (1.1) has the following expression

$$\Sigma_S = \Lambda \Sigma_F \Lambda', \quad (1.6)$$

where Λ is once again the (N, m) matrix of the exposures of the stocks to static factors and Σ_F is the (m, m) matrix corresponding to the covariance matrix of static factors. As for α , which is the vector of length N of the alphas of the stocks in the same optimisation programme, it is equal to the difference between μ , the expected value of r_t , and μ^e , the vector of expected equilibrium value, which is

$$\alpha = \mathbb{E}(e_t) = \mu - \mu^e = \mu - \Lambda \bar{F}, \quad (1.7)$$

where \bar{F} is the vector of length m of expected returns on the m factors.

We should stress that in specification (1.5), we do not try to explain the cross-sectional variations of stock returns by considering the empirical factors that are identified in the literature like market, value, growth, small or large. This is because we want to avoid using spurious

empirical risk factors that suffer from specification and estimation errors and that typically have a high degree of multi-collinearity. When multi-collinearity exists, there are various pitfalls that can be exacerbated when estimating betas of a stock in a multi-factor regression. These pitfalls are that the estimated regression coefficient of any one variable depends on which other predictors are included in the model; the estimated regression coefficients become less precise as more predictors are added to the model; the marginal contribution of any one predictor variable to reducing the error sum of squares depends on which other predictors are already in the model; and the hypothesis tests on coefficients may yield different conclusions depending on which predictors are in the model.

Table 1.1: Correlations of the weekly returns of factor investing/smart beta European equity indexes, 2001–2018

Correlations	M	SC	LC	V	G	Q	MOM	MV
Market (M)	100%							
Small Capitalisations (SC)	90%	100%						
Large Capitalisations (LC)	100%	88%	100%					
Value (V)	99%	89%	98%	100%				
Growth (G)	98%	88%	98%	93%	100%			
Quality (Q)	94%	83%	94%	90%	96%	100%		
Momentum (Mom)	90%	84%	89%	85%	91%	92%	100%	
Minimum Volatility (MV)	91%	86%	91%	87%	93%	90%	98%	100%

Source: Bloomberg, Datastream, weekly data in EUR from 5 January 2001 to 25 May 2018. The European equity indexes are the MSCI Europe Total Return (M), MSCI Europe Small Capitalisation Total Return (SC), MSCI Europe Large Capitalisation Total Return (LC), MSCI Europe Value Total Return (V), MSCI Europe Growth Total Return (G), MSCI Europe Quality Total Return (Q), MSCI Europe Momentum Total Return (MOM), and the MSCI Europe Minimum Volatility Total Return (MV).

To give more insight into this last point, Table 1.1 presents the correlations between the weekly returns of eight MSCI factor investing/smart beta European Equity indexes over the period 2001–2018. The correlations between these long-only factors are high and can be explained by the existence of a significant market component. Indeed the correlation between each of the seven non-market factors individually and the market index averages 93%. A simple solution for dealing with factor correlations is to remove the market component from the other factors. However, the issue of factor dependencies remains even if the common market component is removed. To illustrate this point, Table 1.2 displays the correlations between the returns on the MSCI factors

cleaned of the market component. This cleaning is done by extracting the market component and calculating the excess returns over the market index adjusted for the beta from each factor. We observe that while the correlations decrease on average, some of the investable factors are still highly correlated, particularly the momentum (MOM) and the minimum volatility (MV) factors, which have a correlation of 91% over our sample.⁸ Note that this stylized fact is not specific to our sample, as we observe equally high correlations when using data over a longer period, though the factors involved are different.

Table 1.2: Weekly correlations of factor investing/smart beta European equity indexes (adjusted for the market beta): 2001–2018

Correlations	M	SC	LC	V	G	Q	MOM	MV
Market (M)	100%							
Small Capitalisations (SC)	0%	100%						
Large Capitalisations (LC)	0%	-76%	100%					
Value (V)	0%	-2%	8%	100%				
Growth (G)	0%	1%	-8%	-100%	100%			
Quality (Q)	0%	-13%	6%	-50%	51%	100%		
Momentum (Mom)	0%	18%	-23%	-40%	38%	49%	100%	
Minimum Volatility (MV)	0%	21%	-26%	-47%	45%	30%	91%	100%

Source: Bloomberg, Datastream, weekly data in EUR from 5 January 2001 to 25 May 2018. The European equity indexes are the MSCI Europe Total Return (M), MSCI Europe Small Capitalisation Total Return (SC), MSCI Europe Large Capitalisation Total Return (LC), MSCI Europe Value Total Return (V), MSCI Europe Growth Total Return (G), MSCI Europe Quality Total Return (Q), MSCI Europe Momentum Total Return (MOM), and the MSCI Europe Minimum Volatility Total Return (MV). The Small Capitalisation, Large Capitalisation, Value, Growth, Momentum, Quality and Minimum Volatility factor returns are the excess returns over the market index (adjusted for beta).

Moving from the long-only MSCI factors to the long-short Fama-French factors does not solve the dependence problem between factors, as Table 1.3 illustrates. The table reports the correlations of the weekly returns on the five Fama and French (2015) European Factors for the period from 2001 to 2018. The SMB (Small Minus Big) factor in this table is the average return on the small stock portfolios minus the average return on the big stock portfolios. The HML (High Minus Low) factor is the average return on the value portfolios minus the average return on the growth portfolios. The RMW (Robust Minus Weak) factor is the average return on the robust operating profitability portfolios minus the average return on the weak operating profitability portfolios. The CMA (Conservative Minus Aggressive) factor is the average return

⁸Statistical tests show that many of the correlations are statistically different from zero.

on the conservative investment portfolios minus the average return on the aggressive investment portfolios. The results show that the correlations between the market and the other Fama-French factors, and between the individual Fama-French factors are relatively low. Nevertheless, these factors are not completely orthogonal, since some correlations appear high in absolute terms and are statistically significant, especially the correlation of -66% between the market and SMB factors, and that of -50% between the RMW and HML factors.

Table 1.3: Correlations of weekly returns of the five Fama-French European factors, 2001–2018

Correlations	Market	SMB	HML	RMW	CMA
Market	100%				
SMB	-66%	100%			
HML	13%	-6%	100%		
RMW	-10%	3%	-50%	100%	
CMA	-30%	16%	38%	-18%	100%

Source: Fama-French European five-factor model, weekly data from 5 January 2001 to 25 May 2018.

Since latent factors extracted using statistical methods for dimension reduction are by construction orthogonal and do not suffer from this drawback, we consider the m factors in (1.5) as unobservable, and subsequently propose a methodology for estimating these factors along with our optimisation inputs Σ_S in (1.6) and α in (1.7). We begin by presenting the method for estimating the optimal number m of factors in our factor representation. This issue is crucial as accurate estimations of both inputs require a correct specification of the factor model, which depends heavily on m .

1.3 Estimating the latent factor model by Sparse Principal Component Analysis

This section presents the methodology used to estimate the latent factor model in (1.5). The first part of the section looks at estimating the optimal number m of latent factors that drive the cross-sectional variations of the returns on stocks. Taking this estimate, the second part describes the Sparse Principal Component Analysis (SPCA), the machine learning methodology

we estimate the latent factor model with, which provides the main inputs for the optimisation programme in (1.1).

1.3.1 Estimating the optimal number of latent factors

The literature has discussed widely how to infer the number of significant factors in approximate latent factor models (Stock and Watson, 1999; Connor and Korajczyk, 1993; Bai and Ng, 2002, etc.). Bai and Ng (2002) developed statistics of the information criteria type to estimate the number of latent factors. Their statistics are a compromise between the average variance of idiosyncratic returns and the number of factors, and so they share some similarities with the Akaike or Bayesian information criteria (AIC, BIC) that are usually mobilized for model selection in regression models. More recently, Ahn and Horenstein (2013) introduced two eigenvalue ratio statistics that attain their maximal values at an unknown number of latent factors. The rationale of these statistics arises because the leading eigenvalues of the covariance matrix grow without bounds as the number of stocks increases, while the remaining values are bounded.⁹

As already stressed, we use the approximate latent factor model of Bai and Ng (2002) as it is simple to understand and is not inferior to the other methods in our context of a factor model for stock returns. We may rewrite the factor model from (1.5) as follows:

$$R = F\Lambda' + E, \quad (1.8)$$

where R is the (T, N) matrix of returns, F is the (T, m) matrix of returns to latent factors, Λ is the (N, m) matrix of loadings, and E is the matrix of residual returns of dimension (T, N) .

We denote as V the (m, m) diagonal matrix with the m largest eigenvalues of RR' as elements. \tilde{F} is the principal component estimate of F under the normalisation $T^{-1}F'F = I_m$, with I_m as the identity matrix of dimension m . Then the elements of \tilde{F} are those of the eigenvector matrix associated with the m largest eigenvalues of the matrix RR' , multiplied by \sqrt{T} . The estimate of the factor loadings matrix Λ is $\tilde{\Lambda} = R'\tilde{F}/T$. The estimated matrix (T, N) of residual returns \tilde{E}

⁹For other references in this literature, see Lewbel (1991), Connor and Korajczyk (1993), Donald (1997), and Onatski (2010).

with the elements \tilde{e}_{it} , $i = 1, \dots, N$, $t = 1, \dots, T$ thus corresponds to

$$\tilde{E} = R - \tilde{F}\tilde{\Lambda}'. \quad (1.9)$$

Under this framework, Bai and Ng (2002) propose that m be estimated using statistics like information criteria. The idea is to find a balance between residual variance, which diminishes mechanically with the number of factors, and the complexity of the model that is increasing in the number of factors. We favour the following version of these statistics¹⁰

$$IC(k) = \ln(V(k, \tilde{F}^{(k)})) + k \left(\frac{N+T}{NT} \right) \ln(C_{TN}^2), \quad (1.10)$$

where $V(k, \tilde{F}^{(k)})$ is the average residual variance across stocks and time when the number of factors is set to k ,

$$V(k, \tilde{F}^{(k)}) = \frac{1}{TN} \sum_{i=1}^N \sum_{t=1}^T \tilde{e}_{it}^2, \quad (1.11)$$

and $C_{TN} = \min\{\sqrt{N}, \sqrt{T}\}$. The estimated value \hat{m} of the number of latent factors m corresponds to the value of k that minimizes the information criterion $IC(k)$, so

$$\hat{m} = \arg \min_{k \leq k_{\max}} IC(k), \quad (1.12)$$

with k_{\max} as the maximum number of factors, which we set to 50 in the empirical section. Under some regularity conditions, Bai and Ng (2002) show that $\Pr(\hat{m} \rightarrow m) \rightarrow 1$, as $T, N \rightarrow \infty$.

An illustration of this estimation procedure is given below, using the daily returns of all the stocks in the STOXX 600 universe over the period from November 2001 to May 2018. At the end of each month, we use the most recent one-year data (260 observations) for all the stocks in the capitalisation universe and run the methodology described above to estimate the number of latent factors \hat{m} . This process is iterated by repeatedly moving the estimation window one month forward, taking in the data for a new month and dropping the data for the earliest month, until the last observation is reached.

¹⁰The results available upon request show that a proposed investment strategy based on the other information criteria in Bai and Ng (2002) are less economically valuable. This is because they lead to optimal portfolios with lower realized alphas on an annual basis.

Figure 1.1 gives the time series dynamics of the number of estimated latent factors throughout the rolling-window procedure, with crisis periods highlighted. The crisis periods are the dot-com bubble financial crisis from September 2000 to March 2003, the global financial crisis, from June 2007 to March 2009, the European sovereign debt crisis from April 2011 to June 2012, and the fear of a hard landing for China from June 2015 to June 2016. The average number of estimated latent factors over the whole sample is four. We observe a substantial variation over time, with a clear-cut shape that corresponds to a significant increase at the beginning of crisis periods, and a decrease at the exit from them. The most important sharp increase occurred during the global financial crisis, when the number of latent factors extracted jumped from three to six significant factors in the two months from 4 September 2008 to 3 November 2008. This dynamic corroborates the results in Calomiris et al. (2012), who studied the sensitivities of stock returns to factors in crisis periods. They isolate three factors that explain the cross-sectional variation of stock returns during the 2007-2008 global financial crisis, looking beyond the usual factors that are associated with stock returns. These factors, which they called "crisis shocks," measure three market or economic states, which are a collapse of global trade, a contraction of the credit supply, and downwards pressure on the equity of firms because of selling. Most importantly, they show that these factors are not in play in various placebo samples that correspond to non-crisis periods. This then implies that the number of factors increases in crisis periods.

It is worth stressing that this increase in the number of factors in a crisis period is also observed for the other information criteria in Bai and Ng (2002), and in the method for estimating the number of factors in Ahn and Horenstein (2013). At first glance, this result might seem to contradict the empirical regularity that correlations increase in times of crisis. However, this regularity stems rather from the increase in the explanatory power of the first factor, notably the market, relative to the other factors in times of crisis, and is not incompatible with an increase in the number of factors in these periods. Figure 1.2 represents the relative explanatory power of the significant alternative factors, as measured by the ratio of the sum of the variances or eigenvalues of these factors over the variance of the first, market, factor. This figure shows that this power decreases in crisis periods, leading to the conclusion that the relative part of the variance of the market factor increases significantly in these periods.

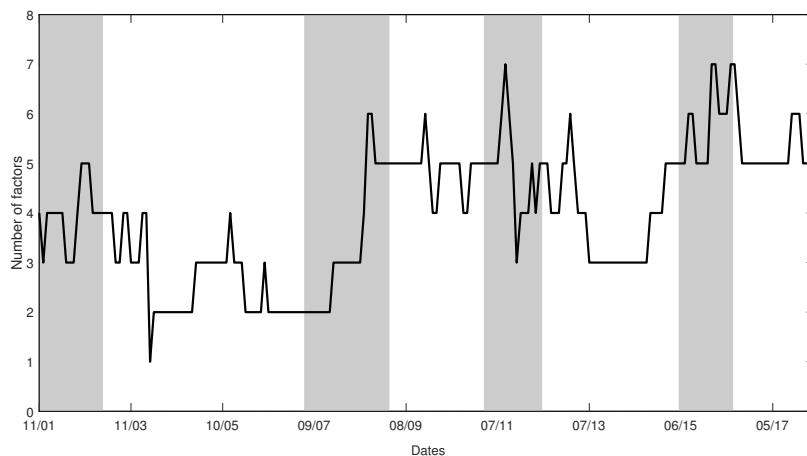


Figure 1.1: Dynamics of the estimated number of latent factors

Source: Bloomberg, daily data from 30 November 2001 to 28 May 2018. The four regions highlighted correspond respectively to the dot-com crisis period from 29 September 2000 to 31 March 2003, the global financial crisis period from 29 June 2007 to 31 March 2009, the European sovereign debt crisis from 29 April 2011 to 29 June 2012, and the fear of a hard landing for China from June 2015 to June 2016.

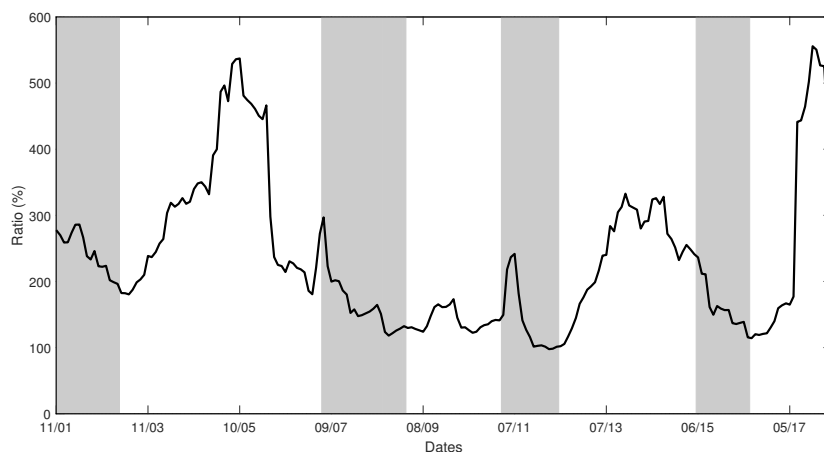


Figure 1.2: Relative explanatory power of significant alternative factors

Source: Bloomberg, daily data from 30 November 2001 to 28 May 2018. The relative explanatory power of the significant alternative factors is computed as the ratio of the sum of the variances of these factors over the variance of the first, market, factor. The four regions highlighted correspond respectively to the dot-com crisis period from 29 September 2000 to 31 March 2003, the global financial crisis period from 29 June 2007 to 31 March 2009, the European sovereign debt crisis from 29 April 2011 to 29 June 2012, and the fear of a hard landing for China from June 2015 to June 2016.

1.3.2 Description of the Sparse Principal Component Analysis

The success of the investment strategy that we develop in this chapter is based on estimating the alphas and betas of stocks efficiently. This section describes the Sparse Principal Component Analysis (SPCA) methodology that we use to estimate this set of inputs for our optimisation programme. Historically, this method aims to alleviate one of the main pitfalls of the traditional PCA, which is that the factors are hard to interpret. In PCA, the loadings or exposures to factors are non-zero, with the consequence that each factor is a linear combination of all the input variables. This makes it harder to interpret the factors extracted.

To achieve interpretability beyond data representation, SPCA sets some of the loadings, and hence the number of input variables that contribute to the variance of each factor, to zero. This can be done in an ad hoc way by choosing a threshold value and zeroing all the small loadings with absolute values lower than the threshold, but this approach has been criticized in the literature (Cadima and Jolliffe, 1995). More efficient methods (Jolliffe et al., 2003; Zou et al., 2006, etc.) introduced sparsity to the vector or matrix of loadings through penalisation methods such as the Lasso (least absolute shrinkage and selection operator) of Tibshirani (1996) or the Elastic Net of Zou and Hastie (2005). These introduce a bound for the sum of the absolute values of the loadings on each factor, forcing some of them to become zero.¹¹

In our context of estimating a latent factor model, SPCA has more virtues than just interpretability. First, by setting some of the loadings to exactly zero, it helps reduce estimation error. Indeed it is small loadings, or small exposures of stocks to latent factors, that are the most subject to irrelevant variability over time, because they correspond to statistical noise. Sparsity thus introduces stability in the loadings of a stock, which are its betas, and consequently in its alpha. Second, it makes sense to hypothesize that not all stocks are exposed to all factors, and therefore that only a certain set of stocks contributes to explaining the variability of each given factor. So if one of the latent factors extracted has a high level of correlation with, say, the small capitalisation factor as an empirical factor, it is reasonable to expect that stocks with large capitalisation will not load on this factor.

¹¹There are many variants of the Sparse PCA in the literature. See for example the SPCA method of Zou et al. (2006), the direct SPCA approach in d'Aspremont et al. (2007), the branch and bound method in Farcomeni (2009), the GPower method of Journée et al. (2010), the iterative elimination algorithm in Wang and Wu (2012), or the thresholding approach in Wu and Chen (2016). For a review, see Feng et al. (2016).

Here we use the SPCA methodology of Wu and Chen (2016), which is well suited for large dimensional problems. This method is introduced by in this chapter as an alternative to the SPCA approach in Zou et al. (2006). To describe the approach, we may consider once again our latent factor model given by:

$$R = F\Lambda' + E, \quad (1.13)$$

where R is again the matrix (T, N) of returns on stocks, F is the matrix (T, \widehat{m}) with columns given by the T returns of each latent factor, while \widehat{m} is the number of optimal factors obtained using the information criterion (see equations 1.10-1.12). The matrix Λ is of dimension (N, \widehat{m}) with the rows containing the betas or exposures of each of the N stocks to the \widehat{m} factors, and E is the matrix (T, N) of idiosyncratic or residual returns.

Given that this specification is based on the optimal number of latent factors, the traditional PCA methodology can be used to get the estimate $\widehat{\Lambda}_{pca}$ from the singular value decomposition of the matrix of returns R , with $\widehat{\Lambda}_{pca}$ corresponding to the first \widehat{m} columns of the matrix V , with

$$R = U\Omega V', \quad (1.14)$$

where the orthogonal matrices U and V are of dimensions (T, N) and (N, N) respectively, and Ω is a diagonal matrix of dimension (N, N) . As shown by Zou et al. (2006), the traditional PCA estimate of Λ as described above can be recast in a linear ridge regression framework. To do this, let $A = [a_1, \dots, a_{\widehat{m}}]$ and $B = [b_1, \dots, b_{\widehat{m}}]$ be the matrices of dimension (N, \widehat{m}) . For any $\psi > 0$, consider the following constrained ridge regression

$$(\widehat{A}, \widehat{B}) = \arg \min_{(A, B)} \sum_{j=1}^{\widehat{m}} \|Ra_j - Rb_j\|_2^2 + \psi \|b_j\|_2^2, \quad \text{u.c. } A'A = I_{\widehat{m}}, \quad (1.15)$$

where R is the matrix (T, N) of the stock's returns, $\psi > 0$ is the ridge parameter, and $I_{\widehat{m}}$ is the identity matrix of dimension \widehat{m} . As shown by Zou et al. (2006), the estimated matrix $\widehat{B} = [\widehat{b}_1, \dots, \widehat{b}_{\widehat{m}}]$ is equal up to some normalisations, to the estimated matrix $\widehat{\Lambda}_{pca} = [\widehat{\lambda}_{1,pca}, \dots, \widehat{\lambda}_{\widehat{m},pca}]$ from the PCA, so

$$\widehat{\lambda}_{j,pca} = \frac{\widehat{b}_j}{\|\widehat{b}_j\|_2}, \quad j = 1, \dots, \widehat{m}. \quad (1.16)$$

Following from this result, Wu and Chen (2016) add a thresholding constraint on this programme to obtain the sparse loadings of the stock, yielding

$$\left\{ \begin{array}{l} (\tilde{A}, \tilde{B}) = \arg \min_{(A,B)} \sum_{j=1}^{\hat{m}} \|Ra_j - Rb_j\|_2^2 + \psi \|b_j\|_2^2 \\ \text{u.c. } A'A = I_{\hat{m}} \quad B(i, j) = 0 \text{ if } G(i, j) = 0, \end{array} \right. , \quad (1.17)$$

where $G(i, j)$ is a sparse regularisation matrix with dimensions (N, \hat{m}) . The choice of the matrix G is crucial in this framework as it conditions the level of sparsity for the estimated loadings. Here we follow the suggestion of estimating G from a decision matrix based on the matrix of correlation of the stock's returns. The underlying idea is that a stock with a large variance should load on a significant factor, and the other stocks that are highly correlated with this benchmark stock should also load on this factor, and those that are less correlated should not.¹²

An equivalent form of the constrained penalized regression (1.17) is given by the authors. By letting D_j be the diagonal matrix with $D_j(i, i) = G(i, j)$, they show that (1.17) does indeed correspond to a constrained ridge regression

$$(\tilde{A}, \tilde{B}) = \arg \min_{(A,B)} \sum_{j=1}^{\hat{m}} \|Ra_j - RD_j b_j\|_2^2 + \psi \|b_j\|_2^2 \quad \text{u.c. } A'A = I_{\hat{m}}. \quad (1.18)$$

with the solutions

$$\tilde{b}_j = (D_j R' R D_j + \psi I_N)^{-1} D_j R' R \tilde{a}_j. \quad (1.19)$$

The connection to the hard thresholding rule arises in a large dimensional setting by letting $\psi \rightarrow \infty$, with (1.19) becoming

$$\tilde{b}_j = D_j R' R \tilde{a}_j, \quad (1.20)$$

and so the sparse loadings are defined as

$$\tilde{\lambda}_{j,spca} = \frac{\tilde{b}_j}{\|\tilde{b}_j\|_2}, \quad j = 1, \dots, \hat{m}. \quad (1.21)$$

Because in (1.20) \tilde{b}_j depends on \tilde{a}_j , Wu and Chen (2016) proposes an iterative algorithm that provides solutions to (1.17) or equivalently (1.18) by solving for B with A kept fixed, or for

¹²See the reference for more details on this issue.

A with B fixed.¹³ The full SPCA algorithm of Wu and Chen (2016) is displayed in Appendix 1.7.1.

With the estimated matrix (N, \widehat{m}) of sparse loadings $\widetilde{\Lambda}_{spca} = (\widetilde{\lambda}_{1,spca}, \dots, \widetilde{\lambda}_{\widehat{m},spca})$, the matrix (T, \widehat{m}) of the estimated factors is given by:

$$\widetilde{F}_{spca} = R\widetilde{\Lambda}_{spca}. \quad (1.22)$$

An empirical view of the estimated factors obtained with the SPCA methodology and their link with a-priori factors in the academic literature is given in Table 1.9 in Appendix 1.7.2, which presents the a-priori factors for each year that are most correlated with the estimated latent factors (best correlated factor with the fitted latent factor for each year). The estimated latent factors are presented in each column and the absolute value of the correlation coefficient is presented below the name of the a-priori factor. We considered a list of 49 potential a-priori factors available at a daily frequency, from oil price returns and equity sector returns to credit, term and sovereign spreads, implied volatilities, gold price returns and returns on typical indexes. The first point to note is that the main latent factor appears each year to be perfectly correlated with the market portfolio, which is the MSCI Europe index. The second is that we observe an instability in identifying the other latent factors since the most correlated a-priori factors change across the years. Moreover, the other latent factors present weak correlations with a-priori factors in most of the cases. These results explain why factor identification or timing is very difficult, and they justify our approach of betting on alpha rather than on these alternative risk premiums that were highlighted in the empirical literature on asset pricing.

Note that the degree of sparsity of each factor estimated is displayed in Table 1.10 in Appendix 1.7.2. For each year and factor, it corresponds to the proportion of the loadings of stocks that have estimated betas or exposures equal to zero. We observe that the degree of sparsity evolves over time and there is a lot of variation across factors. Interestingly, the degree of sparsity of the first factor is always equal to zero, though this result is expected as the first identified factor is nothing but the market. Overall, the degree of sparsity for each year decreases with the

¹³Note that for B fixed, A is obtained via the reduced rank Procrustes rotation. Formally, $A = \widetilde{U}\widetilde{V}'$ with \widetilde{U} and \widetilde{V} as the orthogonal matrices from the singular value decomposition of $R'RB$, so $R'RB = \widetilde{U}\widetilde{\Omega}\widetilde{V}'$. For more discussion, see Zou et al. (2006).

explanatory power of the factor. This means that the less a factor explains the variability of the data, the fewer stocks are exposed to it.

Lastly, let us note that with $\tilde{\Lambda}_{spca} = (\tilde{\lambda}_{1,spca}, \dots, \tilde{\lambda}_{\tilde{m},spca})$, the estimate of the vector $\alpha = (\alpha_1, \dots, \alpha_N)'$ of length N of stock's alphas is given by

$$\tilde{\alpha}_{spca} = \tilde{E} = \bar{R} - \tilde{F}_{spca} \tilde{\Lambda}'_{spca}, \quad (1.23)$$

where \tilde{E} , \bar{R} and \tilde{F}_{spca} are the sample means of \tilde{E} , R and \tilde{F}_{spca} , respectively. The feasible version of our Smart Alpha optimisation programme in (1.1) becomes

$$\begin{cases} \tilde{\omega} = \arg \min_{\omega} \omega' \tilde{\Sigma}_{S,spca} \omega \\ \text{u.c. } \omega' \tilde{\alpha}_{spca} \geq \epsilon, \quad \omega \geq 0, \quad \omega \leq \bar{\omega}, \quad \omega' e = 1, \end{cases} \quad (1.24)$$

where $\tilde{\Sigma}_{S,spca}$ is the systematic covariance matrix given by $\tilde{\Sigma}_{S,spca} = \tilde{\Lambda}_{spca} \tilde{\Sigma}_{F,spca} \tilde{\Lambda}'_{spca}$, with $\tilde{\Sigma}_{F,spca}$ as the covariance matrix of the \tilde{m} factors.

Note that for our optimisation programme in (1.24), the objective function is convex, which ensures that there is a unique global solution as soon as the systematic covariance matrix $\tilde{\Sigma}_{S,spca}$ is positive-definite. Moreover, even in the opposite case, the use of the constraints on the weights makes it possible to obtain a global solution. Indeed Jagannathan and Ma (2003) demonstrated that using the positivity constraint on the weights is equivalent to regularising the covariance matrix $\tilde{\Sigma}_{S,spca}$ in the quadratic form of the objective function. In practice, for the first optimisation of our backtesting exercise, we use the equally weighted portfolio as the initial solution, and for the following optimisations we use the portfolio held at the time of the optimisation.

1.4 The Smart Alpha and competing portfolios: comparison of performance

This section evaluates the Smart Alpha portfolio strategy empirically looking at the European equity market. It compares the performance of the Smart Alpha portfolio with those of European factor investing indexes and some competing smart beta portfolios. We start by describing the

database and the methodology used for the evaluation, and then we analyse the performance profiles of the strategies.

We consider the European stock market here because it has valuable characteristics in its size, liquidity, diversity of market conditions, and representativeness. Moreover it offers a significant regional diversification through different stock exchanges that operate independently, as 17 countries are represented within the STOXX 600 index, and so also through multiple currencies and then central banks that may drive the risks and returns of stocks. That means this market provides fertile ground for active strategies that try to capitalize on the alphas of stocks. The STOXX 600 serves as a benchmark for numerous actively managed funds and it underlies a variety of financial products.

We could equally well have used the US stock market for our backtesting exercise but we chose not to because over recent years, the US stock market has been dominated by just a few individual stocks from the technology industries. Stocks of the five biggest companies (Alphabet, Apple, Facebook, Amazon and Microsoft), known collectively as the GAFAM stocks, have been one of the main drivers of the entire US stock market for almost a decade. At 24.0%, their index weight represents nearly a quarter of the S&P 500 index as at 31 August 2020. Under these conditions, the results of an active stock-picking strategy will be very sensitive to the over or under-weighting of these few stocks.

Last but not least, the European market has experienced more episodes of financial disturbance than the United States market, with the euro area debt crisis from 2010 to end of 2012 and the Brexit crisis in 2016, which makes the backtesting exercises more robust.

1.4.1 Data and the evaluation methodology

The database comes from Bloomberg and Datastream, and includes the daily returns of all the constituents of the STOXX 600 index from 4 December 2000 to 28 May 2018. The database contains $N = 1,278$ stocks, which is all the stocks in the composition of the STOXX 600 index since 4 December 2000, and $T = 4,561$ daily observations. This database therefore takes account of survivorship bias, as it is not limited to only those stocks that are in the capitalisation universe at the end of the sample.

We use a rolling-window approach to this dataset to generate out-of-sample returns for the Smart Alpha portfolio. More precisely, we use the $n = 260$ daily returns that precede the date we set for the first optimisation of 30 November 2001 to find the solution $\tilde{\omega}$ for the optimisation programme in (1.24), restricting the investment universe to only the 600 stocks in the capitalisation universe at the optimisation date, and setting the upper bound $\bar{\omega}$ to the value 2%, meaning there are around 50 active stocks. This solution is implemented with a delay of one day, and the ex-post or realized daily returns for the strategy are recorded from the subsequent days with a holding period of one month.

This process is iterated by repeatedly moving the estimation window forward one month by including data for a new month and dropping the earliest month's data, until the final observation is reached. Traditional performance measures are computed for the realized returns net of transaction costs, with the proportional transaction cost set to 25 basis points per transaction.

1.4.2 The Smart Alpha portfolio: comparison with factor investing indexes and the BAB benchmark

Since our Smart Alpha portfolio strategy is by design orthogonal to factor investing, we compare its performances to those of eight MSCI factor investing indexes, which are the MSCI Europe Small Capitalisation Total Return (SC), the MSCI Europe Large Capitalisation Total Return (LC), the MSCI Europe Value Total Return (V), the MSCI Europe Growth Total Return (G), the MSCI Europe Quality Total Return (Q), the MSCI Europe Momentum Total Return (MOM), the MSCI Europe Minimum Volatility Total Return (MV), and the MSCI Europe Index (E). We also include the BAB strategy in the comparison as it shares some similarities with our strategy, as discussed in the introduction. The related optimal portfolio is obtained by minimising the exposures to the three Fama-French factors of market, size, and value.

The realized or ex-post performances of the Smart Alpha portfolio, the eight factor investing indexes, and the BAB portfolio are displayed in Table 1.4. For each strategy, the table displays absolute performance measures given by the raw return, the annualized average return, the annualized volatility, the Sharpe ratio and the maximum drawdown. Performance measures relative to the STOXX 600 index and given by beta, annualized residual risk, annualized alpha,

annualized average excess returns and the Appraisal ratio are also displayed.

Observing the absolute performance measures except volatility and maximum drawdown shows the best-performing factor investing index to be the MSCI Europe Small Capitalisation Total Return (SC). This index takes the highest values for the raw return at 410.99%, the annualized average return at 10.36%, and the Sharpe ratio at 0.61. However, this is beaten by our Smart Alpha portfolio (SA-SPCA), which delivers higher values for these three evaluation criteria, producing raw return of 584.01%, annualized average return of 12.33%, and a Sharpe ratio of 1.16. The Smart Alpha also delivers the best performance for the risk measures given by volatility and maximum drawdown. It has annualized volatility of 10.6% and maximum drawdown of -38.21%, which are lower than the 14.39% for annualized volatility recorded by the MSCI Europe Minimum Volatility Total Return and the maximum drawdown of -39.75% of the MSCI Europe Quality Total Return. The comparison with the BAB portfolio shows that our strategy performs better in these absolute metrics, except for volatility, which is of same order for both strategies.

This outperformance seems consistent when the measures of relative performance are considered. The annualized average excess return over the STOXX 600 index is 11.09%, which is much higher than the values for the competing strategies. Correcting the annualized average excess returns for the exposure to the market, or beta, does not eliminate this outperformance as the annualized alpha is instead 9.74%, which is still high. It may be noted that the beta of the Smart Alpha portfolio has the lowest value, which may partly explain its resilience in crises, as shown by it having the lowest value for maximum drawdown. This is also the case for the BAB portfolio. Finally, the value of the Appraisal ratio is 1.58 for the Smart Alpha portfolio, which is the highest value of any of the strategies.

1.4.3 Smart Alpha portfolio: comparison with popular smart beta portfolios

In this section, we compare the Smart Alpha portfolio with three smart beta portfolios and the market portfolio (STOXX 600). The first smart beta portfolio is the popular minimum volatility

Table 1.4: Ex-post performances of the Smart Alpha portfolio, MSCI factor investing indexes and BAB portfolio

	SA-SPCA	SC	LC	V	G	Q	MOM	MV	E	BAB
Raw Return (%)	584.01	410.99	106.41	104.54	137.67	249.22	351.04	196.74	123.21	347.18
Annualized Average Return (%)	12.33	10.36	4.48	4.42	5.37	7.85	9.53	6.80	4.98	9.47
Annualized Volatility (%)	10.60	16.89	19.77	21.41	18.04	16.80	17.58	14.39	19.38	10.56
Sharpe Ratio	1.16	0.61	0.23	0.21	0.30	0.47	0.54	0.47	0.25	0.89
Maximum Drawdown (%)	-38.21	-65.44	-57.26	-64.78	-51.20	-39.75	-50.84	-50.50	-58.22	-43.01
Beta	0.45	0.78	1.02	1.09	0.91	0.82	0.82	0.72	1.00	0.44
Annualized Residual Risk (%)	6.14	7.47	1.58	3.62	3.45	5.49	7.64	3.76	0.75	6.32
Annualized Alpha (%)	9.74	6.41	-0.28	-0.47	0.92	3.71	5.49	2.99	0.23	7.01
Annualized Average Excess Return (%)	11.09	8.68	-0.53	-0.65	1.25	5.29	7.61	3.68	0.49	7.53
Appraisal Ratio	1.58	0.86	-0.17	-0.13	0.27	0.67	0.71	0.79	0.31	1.11

Source: Bloomberg, daily data from 3 December 2001 to 28 May 2018. SA-SPCA refers to our Smart Alpha portfolio strategy based on the SPCA and the optimal number of factors, SC the MSCI Europe Small Capitalisation Total Return, LC the MSCI Europe Large Capitalisation Total Return, V the MSCI Europe Value Total Return, G the MSCI Europe Growth Total Return, Q the MSCI Europe Quality Total Return, MOM, the MSCI Europe Momentum Total Return, MV the MSCI Europe Minimum Volatility Total Return, and E the MSCI Europe Index. BAB is the Betting-Against-Beta portfolio strategy. The relative statistics (beta, residual risk, alpha, average excess returns, Appraisal Ratio) are computed with the STOXX 600 as benchmark.

portfolio, which is obtained as

$$\begin{cases} \tilde{\omega} = \arg \min_{\omega} \omega' \tilde{\Sigma} \omega \\ \text{u.c. } \omega \geq 0, \quad \omega \leq \bar{\omega}, \quad \omega' e = 1, \end{cases} \quad (1.25)$$

with $\tilde{\Sigma}$ as an estimate of the covariance matrix of stock returns. We do not consider the sample covariance matrix, which is not well conditioned in our case, because the number of stocks ($N = 600$) is higher than the length of the sample ($n = 260$). We instead use the shrinkage covariance matrix estimate in Ledoit and Wolf (2003). The goal of this is to exploit the usual bias-variance trade-off by reducing the variance or instability of the sample covariance matrix, at the cost of a small bias.

The second smart beta alternative is the risk parity portfolio. This smart beta portfolio allocates wealth on a risk-weighted basis to avoid the pitfalls of the traditional capitalisation weighting scheme. The ultimate goal is to equalize each stock's total contribution to the overall risk in order to increase portfolio diversification. We consider here the simple but effective risk parity portfolio, with the weight $\tilde{\omega}_i$ on each stock i equal to:

$$\tilde{\omega}_i = \frac{\frac{1}{\tilde{\sigma}_i}}{\sum_{i=1}^N \frac{1}{\tilde{\sigma}_i}}, \quad (1.26)$$

where $\tilde{\sigma}_i$ is the sample standard deviation for the returns of stock i . Lastly, we consider the equally-weighted portfolio as a third alternative.

Table 1.5 displays the performance metrics of the Smart Alpha portfolio, the three competing smart beta portfolios, and the STOXX 600 index as the benchmark. Overall, the Smart Alpha portfolio has the best performances for raw return, annualized average return, annualized average excess return, annualized alpha and Appraisal ratio. Looking at the risk metrics displayed, we observe that the annualized volatility of the Smart Alpha portfolio is higher than that of the optimized minimum volatility portfolio (MV-OPT). This result is to be expected and naturally arises because our portfolio only minimizes the systematic part of the volatility, while the minimum volatility portfolio minimizes the total volatility, both systematic and specific. It can also be linked to the alpha constraint underlying our strategy that tightens the region in which the

Table 1.5: Ex-post performances of the Smart Alpha and popular Smart Beta strategies

	SA-SPCA	RP	EW	MV-OPT	Benchmark
Raw Return (%)	584.01	257.90	226.40	368.90	114.79
Annualized Average Return (%)	12.33	8.01	7.41	9.79	4.73
Annualized Volatility (%)	10.60	17.39	19.07	9.94	19.35
Sharpe Ratio	1.16	0.46	0.39	0.98	0.24
Maximum Drawdown (%)	-38.21	-60.95	-63.87	-41.15	-58.69
Beta	0.45	0.87	0.96	0.42	
Annualized Residual Risk (%)	6.14	4.15	4.63	5.61	
Annualized Alpha (%)	9.74	3.62	2.80	7.34	
Annualized Average Excess Return (%)	11.09	5.52	4.64	7.94	
Appraisal Ratio	1.58	0.87	0.60	1.31	

Source: Bloomberg, daily data from 3 December 2001 to 28 May 2018. SA-SPCA refers to our Smart Alpha portfolio strategy based on the Sparse PCA and the optimal number of factors, RP the risk parity portfolio, EW the equally-weighted portfolio, MV-OPT the optimized minimum volatility portfolio, and Benchmark the STOXX 600 Index.

minimum systematic risk portfolio is sought. It should be noted that the Smart Alpha portfolio is better for maximum drawdown than the minimum variance portfolio. The explanation for this result is that alpha is about return and dampens the severity of losses. Lastly, our portfolio using an active strategy has the highest value for the annualized residual risk.

1.4.4 The Smart Alpha portfolio: does sparsity matter?

We may recall that the Smart Alpha portfolio is based on a machine learning method, the SPCA version of Wu and Chen (2016, see Section 1.3.2 above), that allows the sparse exposures of a stock and then its alpha to be estimated. In this section, we evaluate the benefit of using SPCA rather than the traditional PCA. To do this, we consider the Smart Alpha portfolio optimisation programme in (1.24), with the systematic covariance and stocks' alphas estimated from a standard PCA with the optimal number of latent factors instead of the Sparse version of PCA, which is

$$\begin{cases} \tilde{\omega} = \arg \min_{\omega} \omega' \tilde{\Sigma}_{S, pca} \omega \\ \text{u.c. } \omega' \tilde{\alpha}_{pca} \geq \epsilon, \quad \omega \geq 0, \quad \omega \leq \bar{\omega}, \quad \omega' e = 1. \end{cases} \quad (1.27)$$

Comparing the performances of the two strategies in (1.24) and (1.27) will help in evaluating the relevance of estimating the systematic covariance matrix and the alphas, which are the two building blocks of the Smart Alpha strategy, using the sparse loadings of the stocks.

Table 1.6: SPCA versus PCA: performance comparison

	SA-SPCA	SA-PCA
Raw Return (%)	584.01	466.36
Annualized Average Return (%)	12.33	11.05
Annualized Volatility (%)	10.60	10.63
Sharpe Ratio	1.16	1.04
Monthly Turnover (%)	20.56	22.15
Maximum Drawdown (%)	-38.21	-38.83
Beta	0.45	0.46
Annualized Residual Risk (%)	6.14	5.90
Annualized Alpha (%)	9.74	8.42
Annualized Average Excess Return (%)	11.09	9.54
Appraisal Ratio	1.58	1.42

Source: Bloomberg, daily data from 3 December 2001 to 28 May 2018. SA-SPCA refers to our Smart Alpha portfolio strategy based on the Sparse PCA and the optimal number of factors, SA-PCA is its analogue based on the traditional non-sparse PCA.

Table 1.6 displays the results of the backtesting exercise. It shows the absolute performance or raw return of the Smart Alpha portfolio based on the SPCA to be much higher than that of its equivalent based on the traditional PCA. Over the entire period, the performance of the SPCA Smart Alpha portfolio is equal to 584.01%, while that of the PCA version is 466.36% for instance. This dominance also holds when the focus is on the annualized average return, the annualized average excess return, the annualized alpha, the Appraisal ratio, or to a lesser extent the annualized volatility and the maximum drawdown.

It is worth mentioning that sparsity has an interesting effect on portfolio turnover. While the turnover of the SPCA Smart Alpha portfolio is equal to 20.56, the value of the PCA equivalent is higher at 22.15. This result is expected because sparsity removes noise from the estimation of the stock's loadings by setting small values that are non informative and erratic over time to exactly zero. This de-noising process has the advantage of producing stable exposures and alphas for the stocks, and so there is less portfolio rebalancing and lower transaction costs. Though this difference may seem small at first glance, it should be noted that the figures displayed relate on average to a monthly rebalancing, and that over a long period like that of our backtesting, the gain in terms of transaction costs may be high.

1.5 Economic value of Smart Alpha strategy and sensitivity analysis

1.5.1 Economic Value

To calculate the value of the economic gains associated with our Smart Alpha strategy, this section uses the utility-based measure developed in Fleming et al. (2001, 2002). It is based on quadratic utility as an approximation of the true utility function of the investor and assumes that relative risk aversion (γ) is constant. Under these conditions, the average realized utility for a given portfolio (\bar{U}_p) is

$$\bar{U}_p(\cdot) = W_0 \left[\sum_{t=0}^{T-1} R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R_{p,t+1}^2 \right], \quad (1.28)$$

where W_0 is the initial wealth and $R_{p,t+1} = \tilde{\omega}'_t r_{t+1}$ are the returns on the portfolio (p). To measure the value of switching from a reference trading strategy to a candidate one, we then equate their average realized utilities,

$$\sum_{t=0}^{T-1} (R_{2,t+1} - \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{2,t+1} - \Delta)^2 = \sum_{t=0}^{T-1} R_{1,t+1} - \frac{\gamma}{2(1+\gamma)} R_{1,t+1}^2, \quad (1.29)$$

where $R_{1,t+1}$ and $R_{2,t+1}$ are the returns for the two strategies. To equate the average utilities, we subtract a constant, Δ , from each of the returns on the candidate strategy. This represents the cost that the investor would be able to pay, say for performance fees, while still having the same expected utility as under the reference strategy.

Table 1.7 reports the annual fees in per cent that an investor with a quadratic utility function and constant relative risk aversion equal to γ would be willing to pay to switch from the SPCA Smart Alpha strategy to each of the alternative competitive strategies considered in the sections above. The fees in the table are determined empirically as the value that equalizes the ex-post utility for the two different portfolios calculated from annual returns. The results show that all the values are positive, meaning that a rational investor switching from the SPCA Smart Alpha strategy to one of the alternative strategies has to pay some positive performance cost. To switch

Table 1.7: Willingness-to-pay for different strategies versus the Smart Alpha based on SPCA

	SA-PCA	SC	LC	V	G	Q	MOM
$\gamma = 1$	1.13	0.42	6.56	6.38	5.80	3.86	2.14
$\gamma = 3$	1.10	0.97	6.68	6.63	5.88	3.78	2.24
$\gamma = 5$	1.10	1.17	6.72	6.72	5.90	3.75	2.28
$\gamma = 10$	1.09	1.35	6.76	6.80	5.93	3.73	2.31
	MV	E	RP	EW	MV-OPT	BAB	
$\gamma = 1$	5.02	6.04	3.13	3.35	2.26	2.47	
$\gamma = 3$	5.03	6.19	3.39	3.71	2.23	2.50	
$\gamma = 5$	5.03	6.24	3.48	3.83	2.23	2.52	
$\gamma = 10$	5.04	6.29	3.56	3.95	2.22	2.53	

Source: Bloomberg, daily data from 3 December 2001 to 28 May 2018. SA-PCA refers to our Smart Alpha portfolio strategy based on the traditional PCA, SC the MSCI Europe Small Capitalisation Total Return, LC the MSCI Europe Large Capitalisation Total Return, V the MSCI Europe Value Total Return, G the MSCI Europe Growth Total Return, Q the MSCI Europe Quality Total Return, MOM, the MSCI Europe Momentum Total Return, MV the MSCI Europe Minimum Volatility Total Return, E the MSCI Europe Index, RP the risk parity portfolio, EW the equally-weighted portfolio, MV-OPT the optimized minimum volatility portfolio, and BAB the Betting-Against-Beta portfolio.

from the SPCA Smart Alpha strategy to its PCA analogue for instance, a rational agent with a quadratic utility function and a relative risk aversion coefficient $\gamma = 3$ must pay a cost equivalent to 1.10% per year over the full sample. It can be concluded from the table that all the alternative competing portfolios are inferior to the SPCA Smart Alpha portfolio.

1.5.2 Sensitivity Analysis

In this last section, we analyse the sensitivity of the (SPCA) Smart Alpha portfolio to the five long-short based Fama-French (1993, 1996 and 2015) European factors.¹⁴ The market factor is the return in euros on the European value-weighted market portfolio minus the US one month T-bill rate. The SMB (Small Minus Big) factor is the average return on the small stock portfolios minus the average return on the big stock portfolios. The HML (High Minus Low) factor is the average return on the value portfolios minus the average return on the growth portfolios. The RMW (Robust Minus Weak) factor is the average return on the robust operating profitability

¹⁴The Fama-French five factors are constructed using the six value-weighted portfolios formed on size and book-to-market, the six value-weighted portfolios formed on size and operating profitability, and the six value-weighted portfolios formed on size and investment.

Table 1.8: OLS regressions of the Smart Alpha strategy on the five Fama-French European factors

# Model	Intercept	Market	SMB	HML	RMW	CMA	R-Squared
<i>Panel A: Univariate OLS Regressions</i>							
(1)	9.792%*** (5.619)	0.447*** (30.918)					0.602
(2)	13.463%*** (4.356)		-0.279*** (-9.611)				0.134
(3)	12.852%*** (4.312)			0.073** (2.379)			0.005
(4)	12.888%*** (4.292)				0.020 (0.687)		0.000
(5)	13.088%*** (4.358)					-0.0706* (-1.681)	0.005
<i>Panel B: Multivariate OLS Regressions</i>							
(6)	9.757%*** (5.599)	0.450*** (28.353)	0.008 (0.599)				0.602
(7)	9.311%*** (5.581)	0.529*** (27.178)	0.140*** (5.883)	-0.228*** (-6.159)			0.628
(8)	9.228%*** (5.564)	0.506*** (21.281)	0.068 (1.610)	-0.240*** (-7.564)	0.112*** (3.004)		0.634
(9)	9.200%*** (5.563)	0.501*** (20.887)	0.074* (1.943)	-0.195*** (-4.143)	0.151*** (3.146)	-0.088* (-1.811)	0.635

Source: Bloomberg, Fama-French European five-factor model. Daily data from 3 December 2001 to 28 May 2018. The Newey-West corrected t-statistic of each parameter is displayed in parentheses below the estimated parameter. The \bar{R}^2 is the adjusted R^2 . The intercept is the annualized value of the estimated portfolio's alpha. *, **, and *** denote traditional significance at the 10%, 5% and 1% levels respectively.

portfolios minus the average return on the weak operating profitability portfolios. The CMA (Conservative Minus Aggressive) factor is the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios.

To measure the sensitivity of the Smart Alpha strategy to factors, we performed univariate and multivariate OLS regressions on the five Fama-French European factors. Table 1.8 displays the results for the whole sample ranging from 3 December 2001 to 28 May 2018. In Table 1.8, Panel A presents the estimated coefficients of the univariate OLS regressions and Panel B displays the estimated coefficients of the multivariate OLS regressions. We made a Newey-West correction (Newey and West, 1987) for the inference to deal with heteroskedasticity and autocorrelation.

In Panel A of Table 1.8, except for Model 1, which exhibits a moderately high R-squared, the other Fama-French factors (Model 2-Model 5) have weak explanatory powers with adjusted R-squared near 0 for HML, RMW and CMA factors. We observe that explanatory powers increase

from Panel A to Panel B, but these increases are marginal. Indeed, the adjusted R-squared reaches only 0.635 for the five Fama-French Factors regression (Model 9), while the univariate model with market factor has an adjusted R-squared of 0.602.¹⁵ This serves as evidence that the market factor is the only factor that can explain behind Smart Alpha portfolio strategy's dynamics, albeit only weakly. The incremental value of the other four factors appears limited.

This last observation is reinforced when both the values of the t-statistics and the estimated alphas are considered. Indeed, results in Harvey et al. (2016) provide guidance about inference in factorial regression analysis. These authors stress the data mining problem arising from the many empirical papers that try to explain the cross-section of expected returns. They use a multiple testing approach to analyse the significance of a factor given the previous tests on other factors, and they argue that a t-statistic with an absolute value that is greater than 3, and so is above the usual 1% critical value of the Student distribution, should be used instead for inference. Following this route, we can observe that most of the estimated coefficients in Table 1.8 are significantly different from 0 with a t-statistic higher than 3.0, except for HML, RMW and CMA in the univariate regressions. The estimated values for the alphas meanwhile are always positive and significant for all of the univariate and multivariate models in Table 1.8. The annualized alphas are between 9.311% and 13.463%.

All these results confirm that the sparse PCA methodology used in conjunction with the estimation of the optimal number of factors from the information criterion provides accurate estimates of the alpha of a stock and its exposures to latent factors, and so leads to optimal portfolios that meet the idea underlying the Smart Alpha strategy: reducing the exposures to latent factors while generating alpha.

1.6 Conclusion

In this chapter, we propose an active investing approach to allocating equity portfolios. The strategy consists of maximising alpha, which is the expected return uncorrelated to various systematic sources of risk, while minimising the exposures to those same systematic risk factors. The core idea is to bet on alpha rather than on alternative risk premiums in the way that the

¹⁵For comparison, the same exercise for the Risk Parity portfolio considered above leads to an adjusted R-squared of 0.865 for model 9.

factor investing approach does.

Methodologically, factors and the exposures and alphas of the stocks are extracted through a latent factor model estimated by Sparse Principal Component Analysis. In this framework, timing the exact number of relevant factors is crucial, and we achieve this by using the information criteria-like statistics in Bai and Ng (2002).

The empirical results confirm the value of our framework. The Smart Alpha portfolio has both lower risk and higher returns, alpha, than the market cap-weighted index, popular MSCI factor investing indexes, the Betting-Against-Beta strategy, and other heuristic or smart beta approaches such as the naïve equally-weighted portfolio, the risk parity portfolio and the minimum variance portfolio. Economically, our strategy also appears to perform best, because a rational investor who switches from our strategy to one of the alternatives has to pay a positive and significant performance cost. These results disprove the current folklore in the asset management industry about the death of alpha and the superiority of factor investing.

Moreover, we evaluate the economic value of estimating the exposures and alphas of the stocks using Sparse Principal Component Analysis instead of the traditional Principal Component Analysis, and we observe significant economic gains. Lastly, attribution analyses show that our strategy delivers ex-post returns that are not explained by the traditional empirical factors. This result is in line with the philosophy underlying the strategy of minimising the portfolio's exposures to the main sources of risk.

We may finish by noting that, because our framework is general and not specific to the equity market, the Smart Alpha portfolio methodology can be adapted to other asset classes and also to portfolio managers.

1.7 Appendices

1.7.1 Appendix: Sparse PCA algorithm

This Appendix presents the iterative SPCA algorithm of Wu and Chen (2016). In our context, the algorithm solves for the constrained penalized regression in (1.17) or equivalently (1.18) by alternately fixing one of the arguments A or B, and solving in the dimension of the free argument B or A. The normalized components $\tilde{b}_j, j = 1, \dots, \hat{m}$ of \tilde{B} are the sparse loadings of the stocks, with \hat{m} as the number of factors.

- Step 1. Let $A = [a_1, \dots, a_{\hat{m}}]$ start at $V[:, 1 : \hat{m}]$ with V as the stock's PCA loadings on the first \hat{m} principal components, obtained from the singular value decomposition (SVD) of R (see equation (1.14)).
- Step 2. Given a fixed A, apply the hard-thresholding rule in (1.20) to get sparse loadings, for $j = 1, \dots, \hat{m}$, with

$$\tilde{b}_j = D_j R' R \tilde{a}_j. \quad (1.30)$$

- Step 3. For a fixed $\tilde{B} = [\tilde{b}_1, \dots, \tilde{b}_{\hat{m}}]$, compute the SVD of $X' X \tilde{B} = \tilde{U} \tilde{\Omega} \tilde{V}'$, then update $A = \tilde{U} \tilde{V}'$.
- Step 4. Repeat Steps 2-3, until convergence.
- Step 5. Get sparse PCA loadings via normalisation, with $\tilde{\Lambda}_{spca} = [\tilde{\lambda}_{1,spca}, \dots, \tilde{\lambda}_{\hat{m},spca}]$, and

$$\tilde{\lambda}_{j,spca} = \frac{\tilde{b}_j}{\|\tilde{b}_j\|_2}, \quad j = 1, \dots, \hat{m}. \quad (1.31)$$

1.7.2 Appendix: Additional Tables

Table 1.9: Latent and a-priori factor matching (absolute value of the correlation coefficients)

Number of latent factors	1	2	3	4	5
Calendar years					
2001	Rm 1.00	Sect_Media 0.65	Sect_Travel 0.52		
2002	Rm 1.00	Sect_Tech 0.44	Sect_Media 0.40	Sect_Oil 0.32	Sect_Health 0.29
2003	Rm 1.00	LARGE 0.58	Sect_Chem 0.28		
2004	Rm 1.00	Sect_Media 0.49			
2005	Rm 1.00	SMALL 0.20	Sect_Basic 0.42		
2006	Rm 1.00	SMALL 0.75			
2007	Rm 1.00	Sect_Travel 0.51			
2008	Rm 1.00	LARGE 0.71	Sect_Bks 0.72	VALUE 0.24	GROWTH 0.39
2009	Rm 1.00	Sect_Bks 0.48	SMALL 0.64	Sect_Ins 0.60	QUALITY 0.39
2010	Rm 1.00	Sect_Bks 0.52	VALUE 0.69	SMALL 0.29	Sect_Chem 0.36
2011	Rm 1.00	Sect_Bks 0.76	LARGE 0.58		
2012	Rm 1.00	Sect_Bks 0.68	VALUE 0.73	LARGE 0.49	Sect_Ins 0.16
2013	Rm 1.00	Sect_Travel 0.72	VALUE 0.72		
2014	Rm 1.00	Sect_Bks 0.75	Sect_Oil 0.72	MOMENTUM 0.32	
2015	Rm 1.00	Sect_Oil 0.83	VALUE 0.16	QUALITY 0.61	Sect_Bks 0.43
2016	Rm 1.00	Sect_Basic 0.87	Sect_Bks 0.78	Sect_Travel 0.75	QUALITY 0.56
2017	Rm 1.00	Sect_Travel 0.16	Sect_Tech 0.66	Sect_Oil 0.47	MINIMUM VARIANCE 0.58
2018	Rm 1.00	Sect_Tech 0.51	SMALL 0.21	Sect_Bks 0.77	

Source: Bloomberg, DataStream; daily data from 30 November 2001 to 28 May 2018. Rm: MSCI Europe; VALUE: MSCI Europe Value; LARGE: MSCI Europe Large; SMALL: MSCI Europe Small; MOMENTUM: MSCI Europe Momentum; QUALITY: MSCI Europe Quality; MINIMUM VARIANCE: MSCI Minimum Variance; Sect_Basic: DS Equity Basic Resources; Sect_Bks: DS Equity Banks; Sect_Chem: DS Equity Chemistry; Sect_Oil: DS Equity Oil & Gas; Sect_Tech: DS Equity Technology; Sect_Travel: DS Equity Travel & Leisures; Sect_Media: DS Media; Sect_Ins: DS Insurance; Sect_Health: DS Health.

Table 1.10: Sparsity degree of estimated latent factors

Number of latent factors	1	2	3	4	5
Calendar years					
2001	Rm 0	Sect_Media 0.64	Sect_Travel 0.78		
2002	Rm 0	Sect_Tech 0.77	Sect_Media 0.82	Sect_Oil 0.89	Sect_Health 0.89
2003	Rm 0	LARGE 0.71	Sect_Chem 0.84		
2004	Rm 0	Sect_Media 0.87			
2005	Rm 0	SMALL 0.92	Sect_Basic 0.88		
2006	Rm 0	SMALL 0.82			
2007	Rm 0	Sect_Travel 0.71			
2008	Rm 0	LARGE 0.54	Sect_Bks 0.59	VALUE 0.63	GROWTH 0.64
2009	Rm 0	Sect_Bks 0.67	SMALL 0.69	Sect_Ins 0.71	QUALITY 0.75
2010	Rm 0	Sect_Bks 0.66	VALUE 0.67	SMALL 0.83	Sect_Chem 0.90
2011	Rm 0	Sect_Bks 0.74	LARGE 0.91		
2012	Rm 0	Sect_Bks 0.71	VALUE 0.82	LARGE 0.84	Sect_Ins 0.91
2013	Rm 0	Sect_Travel 0.84	VALUE 0.87		
2014	Rm 0	Sect_Bks 0.79	Sect_Oil 0.81	MOMENTUM 0.81	
2015	Rm 0	Sect_Oil 0.49	VALUE 0.87	QUALITY 0.51	Sect_Bks 0.92
2016	Rm 0	Sect_Basic 0.51	Sect_Bks 0.53	Sect_Travel 0.46	QUALITY 0.75
2017	Rm 0	Sect_Travel 0.86	Sect_Tech 0.82	Sect_Oil 0.87	MINIMUM VARIANCE 0.91
2018	Rm 0	Sect_Tech 0.80	SMALL 0.90	Sect_Bks 0.91	

Source: Bloomberg, DataStream; daily data from 30 November 2001 to 28 May 2018. Rm: MSCI Europe; VALUE: MSCI Europe Value; LARGE: MSCI Europe Large; SMALL: MSCI Europe Small; MOMENTUM: MSCI Europe Momentum; QUALITY: MSCI Europe Quality; MINIMUM VARIANCE: MSCI Minimum Variance; Sect_Basic: DS Equity Basic Resources; Sect_Bks: DS Equity Banks; Sect_Chem: DS Equity Chemistry; Sect_Oil: DS Equity Oil & Gas; Sect_Tech: DS Equity Technology; Sect_Travel: DS Equity Travel & Leisures; Sect_Media: DS Media; Sect_Ins: DS Insurance; Sect_Health: DS Health.

2

Conditional Mean Reversion of Financial Ratios and the Predictability of Returns

2.1 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 chapter, 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 (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

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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, 2005).

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

¹Note 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).

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

³A 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.

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

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 chapter 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 and Watson, 1989; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998). The theoretical basis of this typical behaviour goes back to the work of 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

⁵Moreover, 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).

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, 2022). 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, the chapter 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

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

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 chapter 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. The robustness checks regarding the choice of the financial ratio and the countries under investigation are reported in sections 6 and 7. The last section concludes.

2.2 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 occurrence has predictive power (in-sample) for the short-term dynamic of stock prices.

2.2.1 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:

$$dx_t = \alpha_k + \beta_k \left(\sum_{s=1}^k dx_{t-s} \right) + \epsilon_{k,t}, \quad (2.1)$$

where $dx_t = x_t - x_{t-1}$ is the first difference of x_t , k is the holding period⁷ 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 2.1: 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 equation (2.1), 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.

Table 2.1 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 Figure 2.1. 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

⁷In 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.

⁸This 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.

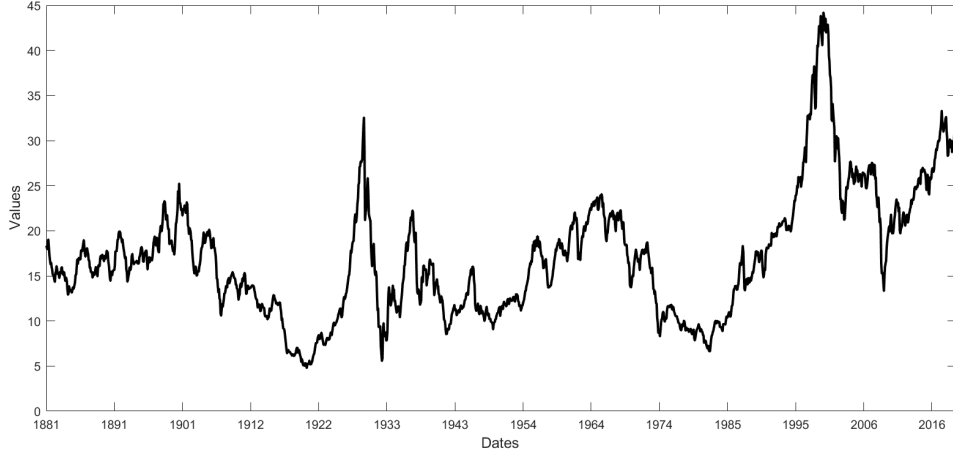


Figure 2.1: Dynamic of the US Shiller CAPE ratio: 1881/02-2020/04

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.

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, 1994; Kim and Nelson, 1999) of the mean reversion equation (2.1)

$$dx_t = \alpha_{k,S_{k,t}} + \beta_{k,S_{k,t}} \left(\sum_{s=1}^k dx_{t-s} \right) + \epsilon_{k,t}, \quad (2.2)$$

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:

$$P = \begin{bmatrix} \Pr(S_{k,t} = 0 | S_{k,t-1} = 0) & \Pr(S_{k,t} = 1 | S_{k,t-1} = 0) \\ \Pr(S_{k,t} = 0 | S_{k,t-1} = 1) & \Pr(S_{k,t} = 1 | S_{k,t-1} = 1) \end{bmatrix} = \begin{bmatrix} p_{k,00} & p_{k,01} \\ p_{k,10} & p_{k,11} \end{bmatrix} \quad (2.3)$$

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.

Table 2.2: 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*** (0.0008)	-0.0231*** (0.0060)	0.0613*** (0.0131)	-0.0044 (0.0356)	0.0009*** (0.0000)	0.0060*** (0.0003)	41.54	7.57
6	0.0024*** (0.0008)	0.0009 (0.0073)	0.0519*** (0.0074)	0.0404 (0.0305)	0.0009*** (0.0000)	0.0069*** (0.0005)	44.12	7.12
12	0.0037*** (0.0008)	-0.0251*** (0.0068)	0.0232*** (0.0046)	-0.0117 (0.0153)	0.0009*** (0.0000)	0.0062*** (0.0004)	38.14	6.59
24	0.0051*** (0.0008)	-0.0334*** (0.0071)	0.0016 (0.0033)	-0.0366*** (0.0112)	0.0009*** (0.0000)	0.0057*** (0.0004)	37.04	6.83
36	0.0049*** (0.0009)	-0.0355*** (0.0065)	0.0073*** (0.0027)	-0.0435*** (0.0082)	0.0009*** (0.0000)	0.0055*** (0.0004)	35.66	6.58
48	0.0050*** (0.0008)	-0.0326*** (0.0059)	0.0095*** (0.0023)	-0.0431*** (0.0089)	0.0008*** (0.0000)	0.0053*** (0.0003)	31.64	6.31
60	0.0041*** (0.0009)	-0.0008 (0.0059)	0.0057*** (0.0021)	-0.0031 (0.0106)	0.0008*** (0.0000)	0.0063*** (0.0005)	36.91	7.40
120	0.0051*** (0.0009)	-0.0233*** (0.0057)	0.0007 (0.0016)	0.0124 (0.0088)	0.0008*** (0.0000)	0.0060*** (0.0004)	31.26	6.31

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 (2.2). The parameter estimates are given followed by the standard error in parentheses. *, **, and *** denote traditional significance at 10%, 5% and 1% levels, respectively.

The estimation results (except for the transition probabilities to save space) of the regime-switching mean reversion model (2.2) are displayed in Table 2.2, 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 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:

$$dur_{k,0} = \frac{1}{1 - \widehat{p}_{k,00}} = 35.66, \quad (2.4)$$

$$dur_{k,1} = \frac{1}{1 - \widehat{p}_{k,11}} = 6.58. \quad (2.5)$$

Thus, compared to the absence of mean reversion, the presence of mean reversion is a short-lived event that lasts approximately half-a year. Figure 2.2 which displays the estimates of the smoothed probability $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$, 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

⁹Recall 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.

¹⁰The 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).

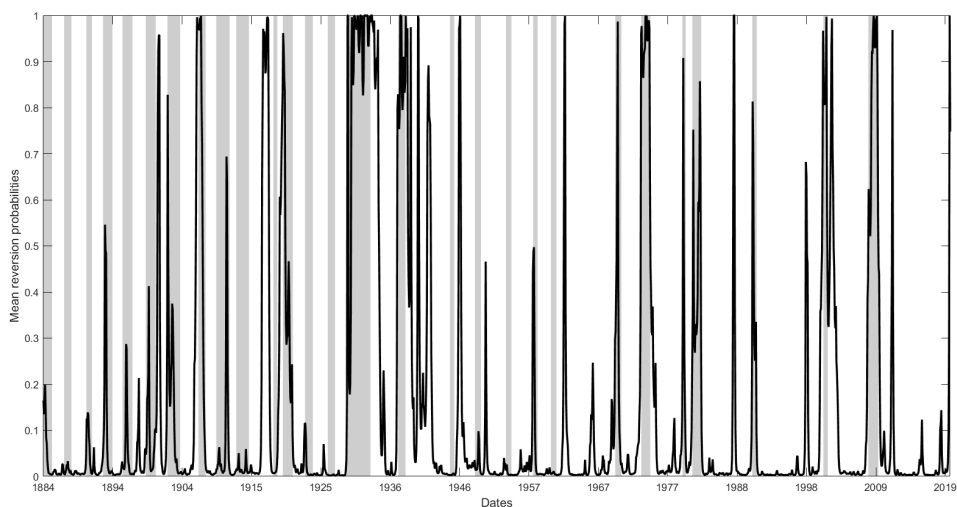


Figure 2.2: Dynamic of smoothed probabilities of mean-reversion: 1884/02-2020/04

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 (2.2). The estimation sample ranges from February, 1884 to April, 2020, with a total of 1635 monthly observations. The grey areas correspond to the NBER recession periods.

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.

2.2.2 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 $\widehat{\Pr}(S_{k,t} = i | \Omega_T; \widehat{\theta})$ the estimated smoothed probability of regime i at time t , with θ the vector of parameters.¹¹ Denote $Z_{t,i} = \mathbb{I}(\widehat{\Pr}(S_{k,t} = i | \Omega_T; \widehat{\theta}) > \gamma)$ the dummy variable taking value one when the smoothed probability

¹¹We set here k to value 36 which corresponds to the best separation of the two regimes as displayed in Table 2.2.

of regime i is large and higher than a threshold γ at time t , with $\gamma \in \{0.5, 0.6, 0.7\}$. Thus, this variable indicates whether regime i prevails or not 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.

$$r_{t+1:t+\tau,i} = \sum_{s=t+1}^{t+\tau} r_s, \quad (2.6)$$

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:

$$\bar{r}_{i,\tau} = \frac{1}{n_i} \sum_{s=1}^{n_i} r_{t_s+1:t_s+\tau,i}. \quad (2.7)$$

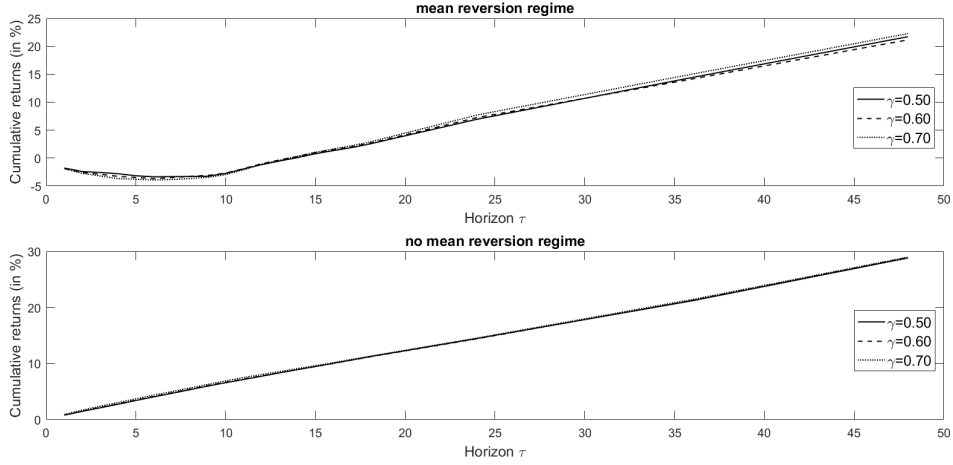


Figure 2.3: Prevaling regimes and subsequent S&P 500 average returns

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 Figure 2.2 are obtained from the estimation of the regime-switching mean reversion model in (2.2) using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations.

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

Figure 2.3 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 $\tau \geq 14$ 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 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

$$r_{t+1:t+\tau} = a_0 + a_1 \widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta}) + u_{t+1:t+\tau}, \quad (2.8)$$

where again x_t is the natural logarithm of the US Shiller CAPE ratio, $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$ 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 (2.8) differs from the traditional equation which links multi-period returns to current values of valuation ratios as follows:

$$r_{t+1:t+\tau} = b_0 + b_1 x_t + \xi_{t+1:t+\tau}, \quad (2.9)$$

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 $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$ instead of the level of the valuation ratio. By doing so, our goal is to exploit the stylized facts observed in Figure 2.3 which indicate that high and low values of this probability lead to different subsequent dynamics for stock prices.

Table 2.3: 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 (2.8). 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.

Table 2.3 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-

¹²Results available 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.

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 Figure 2.3.

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 Figure 2.3 (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

Figure 2.4 which displays the results provides evidence that the patterns (negative average multi-period returns) observed in the top panel of Figure 2.3 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

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

¹⁴Note 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.

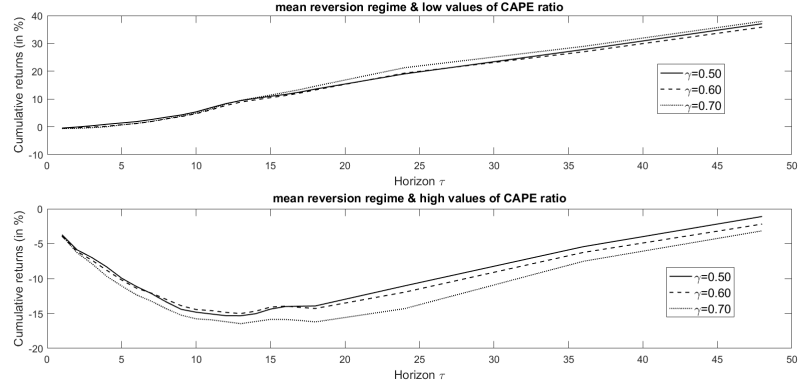


Figure 2.4: Mean reversion regime, levels of CAPE ratio and subsequent S&P 500 average returns

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 Figure 2.2 are obtained from the estimation of the regime-switching mean reversion model in (2.2) 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.

These new results call for a modification of our predictive regression in (2.8), in order to increase its predictive power reported in Table 2.3. We thus consider the following regression:

$$r_{t+1:t+\tau} = a_0 + a_1 \widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta}) + a_2 x_t \widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta}) + u_{t+1:t+\tau}, \quad (2.10)$$

where again x_t is the natural logarithm of the US Shiller CAPE ratio, $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$ 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:

$$\frac{\partial r_{t+1:t+\tau}}{\partial \widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})} = a_1 + a_2 x_t, \quad (2.11)$$

which depends on the level of the US Shiller CAPE ratio, and takes value zero for $x^* = -a_1/a_2$. With $a_2 < 0$ and $a_1 > 0$, x^* is positive, and with high (low) values of the Shiller CAPE ratio, i.e. $x_t > x^*$ ($x_t < x^*$), an increase in the occurrence of mean reversion leads to negative (positive) subsequent short-term returns, a pattern compatible with the trends in Figure 2.4.

Table 2.4: 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 (2.10). 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.

Results in Table 2.4 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. Figure 2.5 compares the explanatory power as given by the adjusted R-squared of this new predictive regression (last column in Table 2.4) and the predictive regression in (2.8) as displayed in the fourth column of Table 2.3. We observe an increase in the adjusted R-squared, notably for the horizons close to $\tau = 12$, i.e. approximately one year.

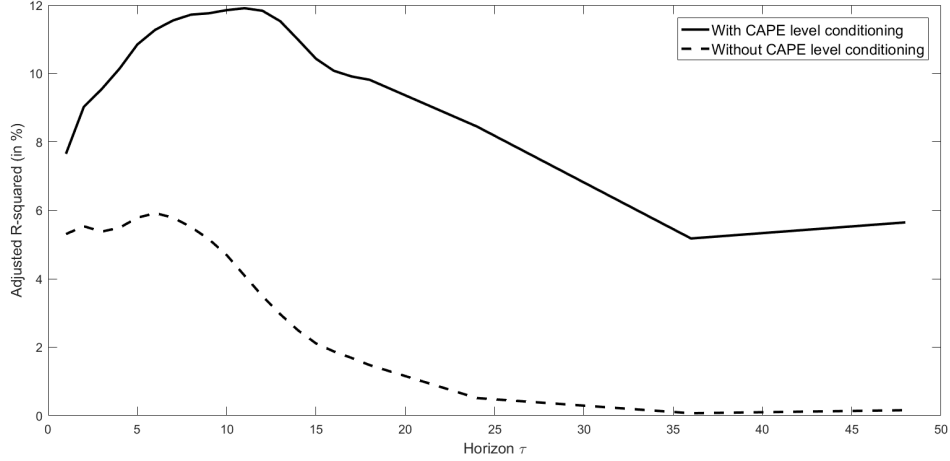


Figure 2.5: Explanatory powers of stock return predictive regressions

Notes: The figure compares the explanatory powers (adjusted R-squared) of two competing stock return predictive regressions. The first specified in (2.8) 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 (2.10).

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. (2023) to simulate 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 :

$$a_t = \arg \min_a \sum_{s=1}^T K_{hT}(s-t) [r_{t+1:t+\tau} - X_s a]^2, \quad (2.12)$$

with $X_t = (1, \widehat{\text{Pr}}(S_{k,t} = 1 | \Omega_T; \widehat{\theta}), x_t \widehat{\text{Pr}}(S_{k,t} = 1 | \Omega_T; \widehat{\theta}))$ 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:

$$K(u) = 1.5(1 - u^2)\mathbf{1}(-1 < u < 0). \quad (2.13)$$

Note that this (estimated) model is the time-varying counterpart of our predictive regression model in (2.10). Once the model is estimated,¹⁵ we compute the squared error difference (SED)

¹⁵The forecast horizon is set to $\tau = 12$ which corresponds to the highest level of explanatory power as displayed in Figure 2.5.

between our forecasts $\widehat{r}_{t+1:t+\tau}$ and the ones from the traditional predictive regression, $\bar{r}_{t+1:t+\tau}$, estimated with the same kernel method, with:

$$SED_{t+1:t+\tau} = (r_{t+1:t+\tau} - \bar{r}_{t+1:t+\tau})^2 - (r_{t+1:t+\tau} - \widehat{r}_{t+1:t+\tau})^2. \quad (2.14)$$

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 incurs a smaller (squared) forecast error. To identify such periods, Farmer et al. (2023) propose to project SED_t on a constant and a time trend

$$SED_t = \pi_{0,t} + \pi_{1,t}t + v_t, \quad (2.15)$$

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

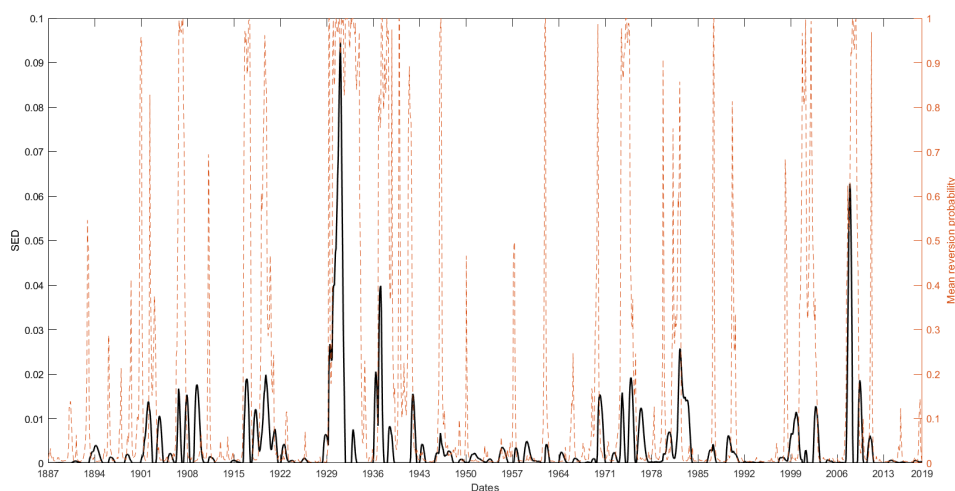


Figure 2.6: Pockets of predictability

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.

Figure 2.6 displays the time series behaviour of \widehat{SED}_t . Based on Farmer et al. (2023), 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. (2023). 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 occurrence 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:

$$y_t = w_0 + w_1 \widehat{\Pr}(S_{k,t-1} = 1 | \Omega_T; \widehat{\theta}) + \epsilon_t, \quad (2.16)$$

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 2.5 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 coefficients \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.

2.3 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 Figure 2.2) which are estimated using Ω_T the information set available over the entire period (t from 1 to T).

One solution to this problem is to check for the stylized facts reported in Figure 2.3 using the filtered probabilities rather than the smoothed counterparts. Note that the filtered probabilities

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

Table 2.5: 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.

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. Figure 2.7 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 latter 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 chapter 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:

$$r_{t+1:t+\tau} = a_0 + a_1 w_{t-m} + a_2 x_t w_{t-m} + v_{t+1:t+\tau}, \quad (2.17)$$

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.

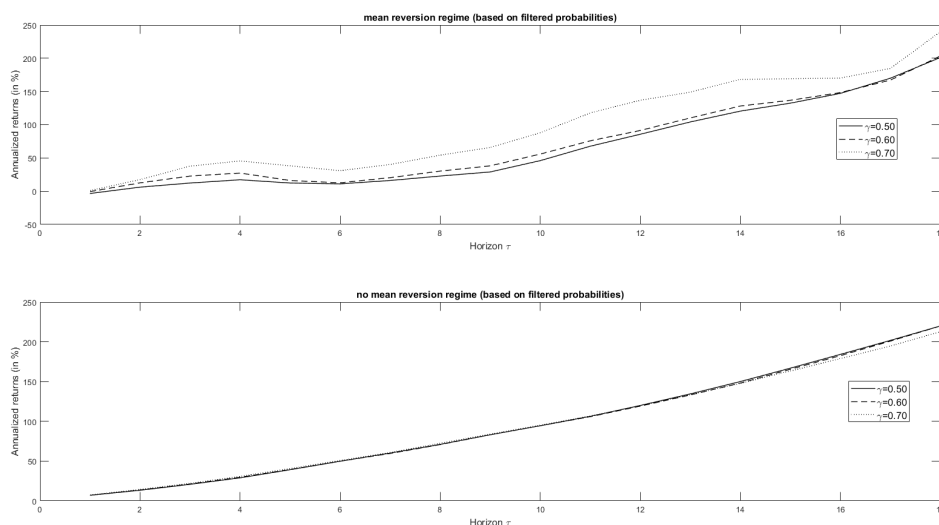


Figure 2.7: Prevaling regimes and subsequent S&P 500 average returns

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 (2.2) using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations.

Compared to the predictive regression in (2.10), 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 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 $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$, we observe that in periods of economic recession (expansion) the average value of $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$ 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 Figure 2.2, 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 and Watson, 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 Figure 2.8. This figure displays the correlations between lagged values of the term spread and the smoothed probability

¹⁷Note 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.

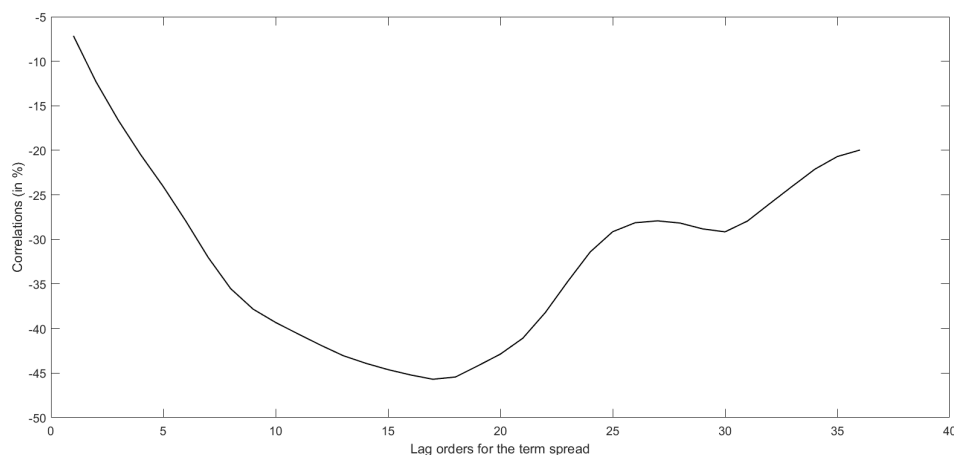


Figure 2.8: Correlations between the lagged values of the term spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio

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 (2.2) using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

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.

Based on all the above results, we thus conduct a forecasting exercise to evaluate the out-of-sample power of our predictive model (2.17) 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 (2.17). 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:

$$R_{OOS}^2(\tau) = 1 - \frac{\sum_{s=1}^{n_{oos}} (r_s(\tau) - \widehat{r}_s(\tau))^2}{\sum_{s=1}^{n_{oos}} (r_s(\tau) - \bar{r}(\tau))^2} \quad (2.18)$$

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

¹⁸Figure 2.22 in Appendix 2.9 displays the dynamic of the US term spread.

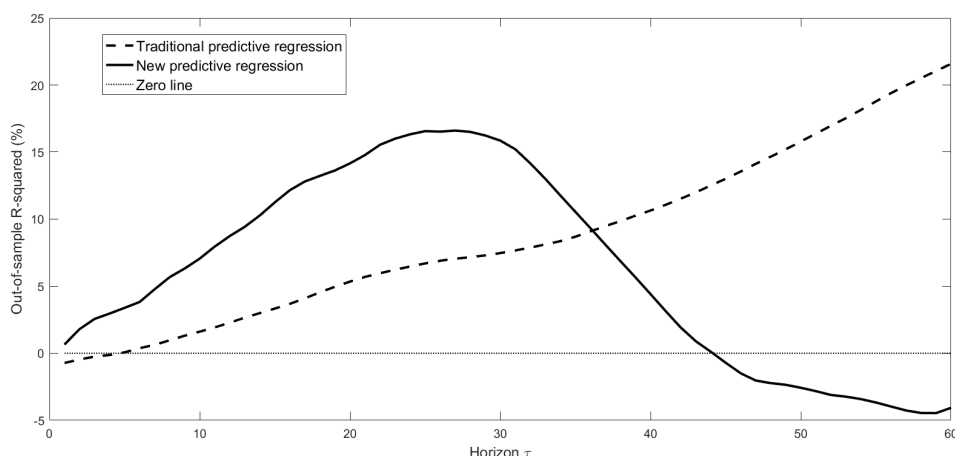


Figure 2.9: Out-of-sample predictive powers of competing predictive regressions

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression in (2.9) with the US Shiller CAPE ratio as the explanatory variable, and the new predictive regression in (2.17) 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.

of historical average as benchmark. In other words, $R_{OOS}^2(\tau)$ is equal to 0 by definition for this benchmark model.

Figure 2.9 displays the out-of-sample R-squared of our predictive regression in (2.17) with respect to the forecast horizon τ . For comparison, we also display the same statistic for the traditional predictive regression in (2.9). Results 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 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

¹⁹Results available 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.

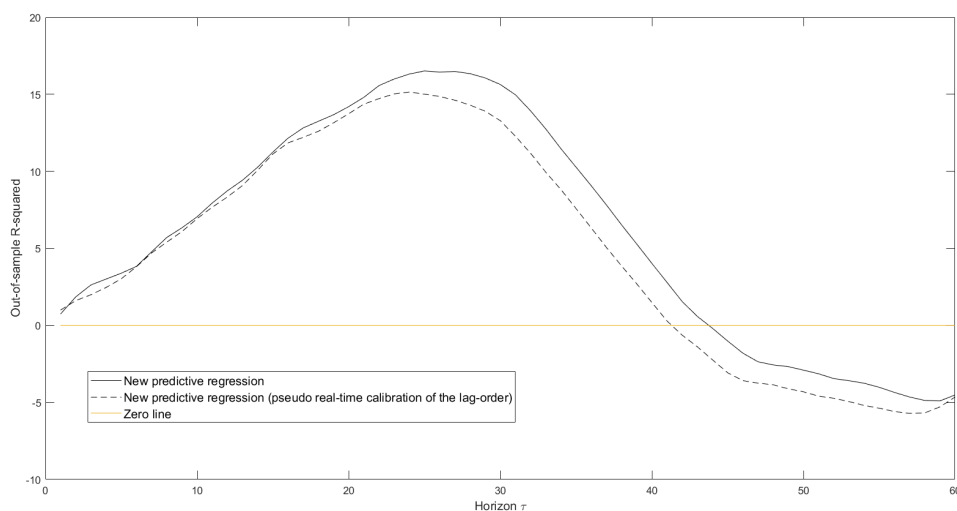


Figure 2.10: Out-of-sample powers of the new predictive regression

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.

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. Figure 2.10 compares the out-of-sample R-squared of our predictive regression in Figure 2.9 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 chapter.

Section 6 and 7 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) in section 6, (ii) and the country under investigation (Canada, France, Germany and the UK) in section 7. The results obtained are qualitatively similar.

2.4 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 Figure 2.9) 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 section 7), 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:

$$\widehat{w}_t = \frac{1}{\gamma} \frac{\widehat{R}_{t+\tau}}{\widehat{\sigma}_{t+\tau}^2}, \quad (2.19)$$

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 $\widehat{\sigma}_{t+\tau}^2$ 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:

$$r_{p,t+j} = w_t r_{t+j}. \quad (2.20)$$

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

$$\tilde{r}_{p,t+j} = r_{p,t+j} - c|\widehat{w}_t - \widehat{w}_t^+|, \quad (2.21)$$

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:

$$CER_p = \widehat{\mu}_p - \frac{1}{\gamma}\widehat{\sigma}_p^2, \quad (2.22)$$

with $\widehat{\mu}_p$ and $\widehat{\sigma}_p^2$ 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 2.6 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

Table 2.6: 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).

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.

2.5 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 and Watson, 1989; Lettau and Ludvigson, 2002), and stock returns (Lettau and Ludvigson, 2001).

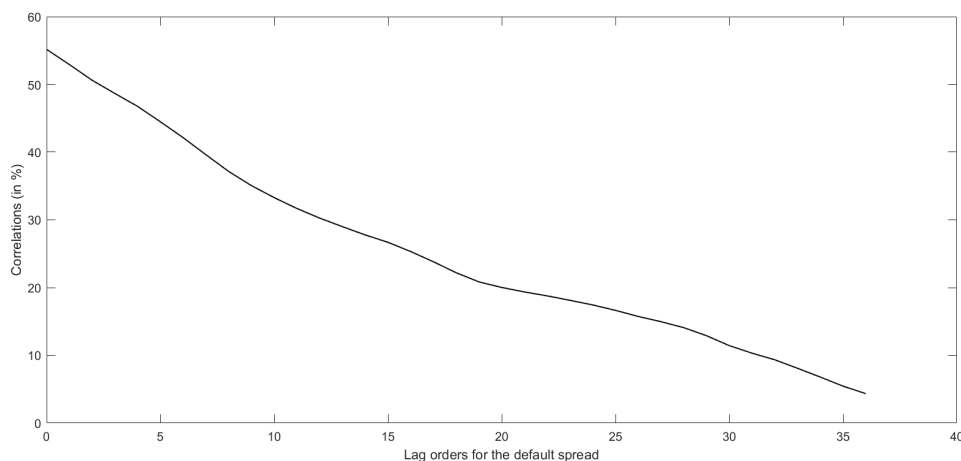


Figure 2.11: Correlations between the lagged values of the credit spread and the smoothed probabilities of mean reversion in the US Shiller CAPE ratio

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 (2.2). Correlations are computed using monthly data from January, 1919 to April, 2020, with a total of 1216 monthly observations.

Figure 2.23 in Appendix 2.9 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:

$$r_{t+1:t+\tau} = a_0 + a_1 w_{t-m} + a_2 x_t w_{t-m} + v_{t+1:t+\tau}, \quad (2.23)$$

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. Figure 2.11 which displays the correlations is the analogue of Figure 2.8 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.

Figure 2.12 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 Figure 2.9). The adjusted R-squared of the traditional predictive regression are low, even negative at

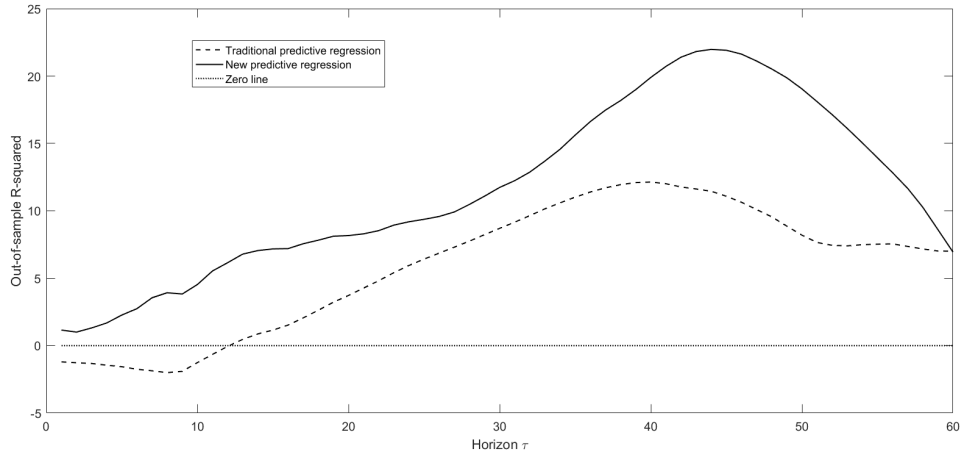


Figure 2.12: Out-of-sample predictive powers based on credit spread of competing predictive regressions: US

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression in (2.9) with the CAPE ratio as the explanatory variable, and the new predictive regression in (2.17) 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.

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 2.15 in Appendix 2.9 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.

2.6 Robustness checks: choice of the valuation ratio

This section evaluates the robustness of our results to the choice of the valuation ratio. First, we consider using the excess CAPE yield instead of the original CAPE ratio. The rationale of using this valuation ratio arises from the historically low interest rates over recent decades, which were playing a potential role in raising CAPE ratios. Theoretically, interest rates are a key component in determining prices. All things being equal, when interest rates fall, the discount rate goes

²⁰Note that the values obtained for the traditional model in Figures 2.12 and 2.9 differ, because the samples used are different. The US credit spread is available over a longer period.

down and stock prices are expected to rise. Thus, the never-ending decrease in interest rates since the beginning of the eighties could be a reason for the increases in stock prices and the CAPE ratio. The level of interest rates is therefore a particularly important element to take into account when evaluating stock prices. In this line, the excess CAPE yield recently introduced by Shiller and which takes into account both stock prices and interest rates, is a good indicator to capture this effect.

The excess CAPE yield is calculated by inverting the CAPE ratio to get a measure of the profits the S&P 500 index is delivering for each dollar investors are paying, minus the ten-year real interest rate (the US 10-year treasury bond). This thus represents the margin that stocks are paying over bonds and characterizes somewhat the risk premium associated with the stock market, taking into account the interaction between long-term changes in stock prices and interest rates. The higher this indicator is, the more attractive stocks are. Figure 2.13 displays the dynamic of the US excess CAPE yield.

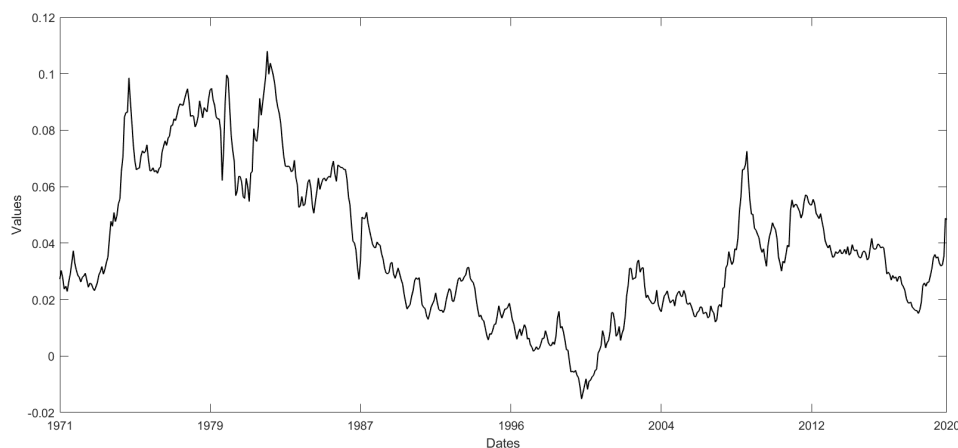


Figure 2.13: Dynamic of the US Excess CAPE yield: 1971/01-2020/04

Notes: The ratio is computed by inverting the CAPE ratio to get a measure of the profits the S&P 500 index is delivering for each dollar investors are paying, minus the ten-year real interest rate (the US 10-year treasury bond).

Results displayed in Figure 2.14 are similar to those obtained when using the original Shiller CAPE ratio. The new regression has very superior predictive powers at short-term horizons. For the one month horizon, the out-of-sample R-squared are equal to -0.02% and 0.57% for the traditional and the new predictive regression. Moreover, at the horizon of 12 (24) months, the

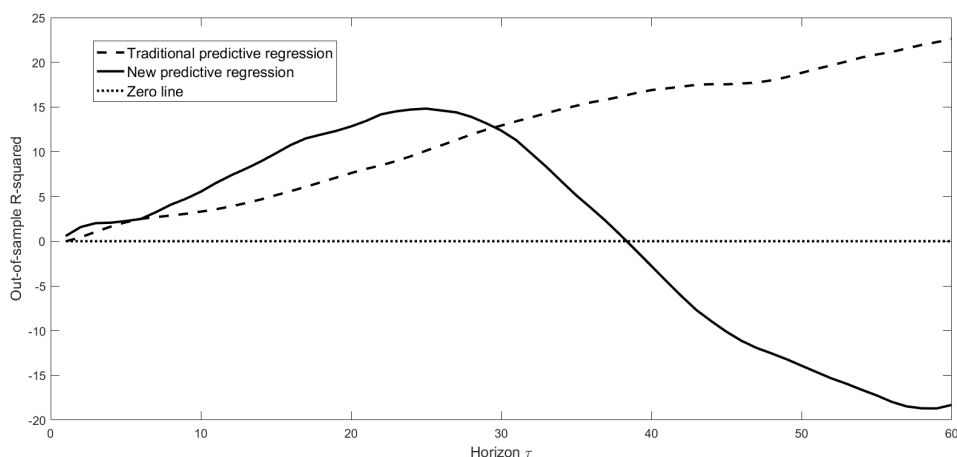


Figure 2.14: Out-of-sample predictive powers of competing predictive regressions: the US Excess CAPE yield

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the US excess CAPE yield as the explanatory variable, and the new predictive regression that conditions the influence of the US excess CAPE yield 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.

out-of-sample R-squared of the new predictive regression is equal to 7.35% (14.71%), while the recorded value for the traditional regression is equal to 3.88% (9.50%).

For more robustness checks, we also consider the US dividend yield as the predictive financial ratio. The choice of this financial ratio arises from its predictive content for long-term multi-period returns on the stock index (Rozeff, 1984; Campbell and Shiller, 1988; Fama and French, 1988; Cochrane, 1991; Lewellen, 2004). For instance, Rozeff (1984), based on the constant dividend growth model and the subsidiary Golden Rule of Accumulation view that real long-term growth equals the real rate of interest, presented evidence that dividend yields are directly related to and predict future stock returns. In particular, the author's predictive tests show that dividend yields provide superior predictions of equity risk premiums in terms of lower bias, a lower mean square error and a lower mean absolute error as compared with the method of using historical realized returns. Similar results are provided by Lewellen (2004) who corrected predictive regressions for small-sample biases, and showed that dividend yield predicted market returns during the period 1946–2000, as well as in various subsamples. Figure 2.15 displays the dynamic of the US dividend yield.

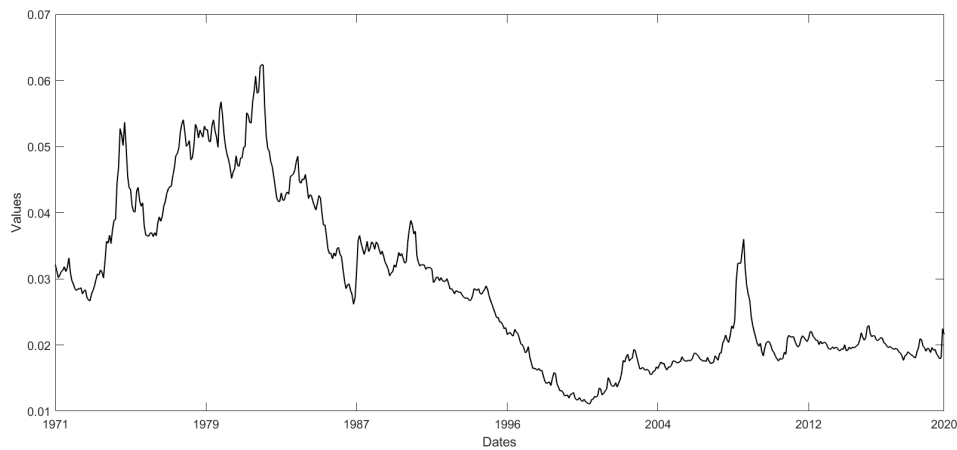


Figure 2.15: Dynamic of the US dividend yield: 1971/01-2020/04

Notes: Monthly dividend data are computed from the S&P four-quarter totals, with linear interpolation to monthly figures.

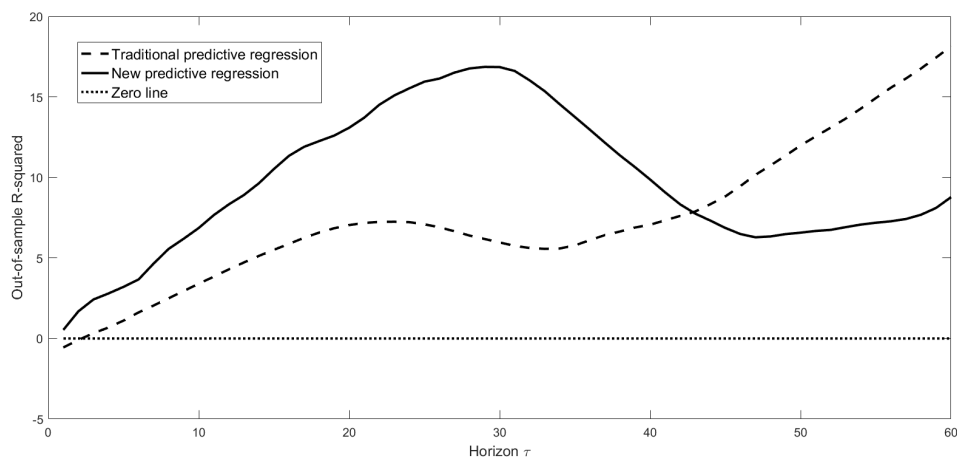


Figure 2.16: Out-of-sample predictive powers of competing predictive regressions: the US dividend yield

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the US dividend yield as the explanatory variable, and the new predictive regression that conditions the influence of the US dividend yield 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.

Figure 2.16 which compares our new specification to the traditional one, confirms once again the robustness of our results to the choice of the financial ratio.

2.7 International evidence

In this section, we investigate whether our results hold over other countries. We consider four additional countries including Canada, France, Germany and the UK. The first part of the section evaluates the robustness of our results in-sample, and the second part is devoted to out-of-sample analysis.

2.7.1 In-sample evidence

For in-sample evidence, we estimate for each country our predictive regression as specified in Eq. 2.10. Recall that the estimation of this regression requires as regressors the valuation ratio x_t and $\widehat{\Pr}(S_{k,t} = 1 | \Omega_T; \widehat{\theta})$, the estimated smoothed probability of mean reversion in the valuation ratio. The latter predictor is obtained estimating the regime switching mean-reversion model, with k the lag-order which leads to the best separation between the two regimes (mean-reversion versus no-mean reversion).

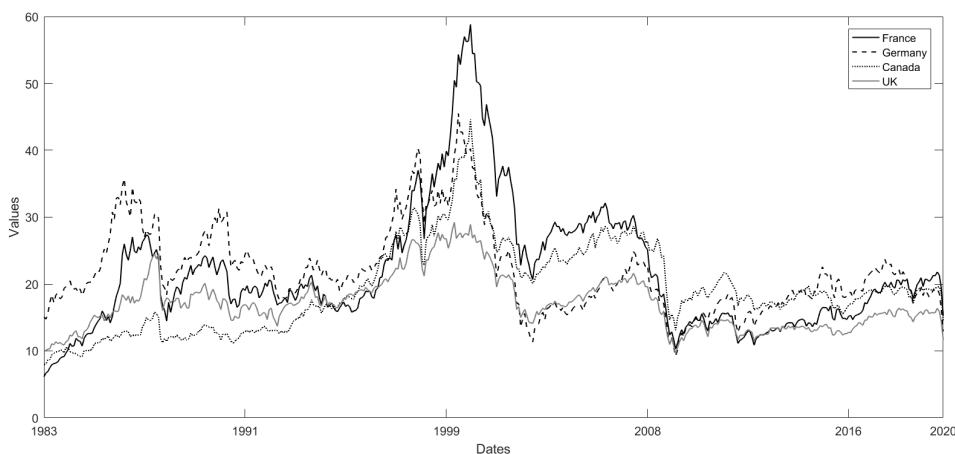


Figure 2.17: Dynamic of the CAPE ratio: 1983/01-2020/04

Notes: The ratio for each country 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 are computed from the latest annualised earnings of the last financial year or derived from an aggregation of quarterly earnings. Stock price data are monthly data of the first day of the month closing prices. The CPI-U (Consumer Price Index-All Urban Consumers) are published by the National Institute of Statistics and Economic Studies (INSEE) for France, the Federal Statistical Office (Statistisches Bundesamt) for Germany, the Office for National Statistics for the UK and by Statistics Canada, for Canada.

Table 2.7: Estimation results of stock return predictive regressions: Canada

τ	a_0	a_1	a_2	Adj. R^2 (%)	Adj. R^2 Tradi (%)
1	0.0088***	0.1488	-0.0608*	5.30	-0.09
2	0.0156***	0.3525**	-0.1300**	5.95	0.18
3	0.0222***	0.4881**	-0.1757***	6.05	0.47
4	0.0286***	0.6642***	-0.2338***	6.94	0.78
5	0.0349***	0.8344***	-0.2892***	7.85	1.13
6	0.0411***	0.9660***	-0.3312***	8.26	1.47
7	0.0474***	1.0589***	-0.3609***	8.37	1.80
8	0.0532***	1.0937***	-0.3706***	7.66	2.00
9	0.0592***	1.1252***	-0.3799***	7.18	2.19
10	0.0655***	1.1749***	-0.3957***	7.06	2.41
11	0.0716***	1.2397***	-0.4164***	7.10	2.66
12	0.0777***	1.3081***	-0.4376***	7.13	2.93
13	0.0835***	1.3107***	-0.4367***	6.53	3.08
14	0.0887***	1.2939***	-0.4275***	5.79	3.17
15	0.0938***	1.3050***	-0.4275***	5.48	3.24
16	0.0990***	1.3313***	-0.4330***	5.36	3.33
17	0.1045***	1.3904***	-0.4506***	5.58	3.38
18	0.1102***	1.4800***	-0.4787***	6.08	3.48
24	0.1473***	2.0763***	-0.6724***	10.30	3.75
36	0.2315***	1.0223**	-0.3585**	2.47	4.08
48	0.3073***	0.7481**	-0.2796**	1.80	3.51

Notes: For different values of the prediction horizon τ , the table displays the estimation results of the stock return predictive regression. The penultimate column displays the adjusted R-squared of this predictive regression (Adj. R^2), and the last column the adjusted R-squared of the traditional 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.

Figures 2.24-2.27 in Appendix 2.9 display the estimates of the smoothed probabilities of the two regimes for each country. Figure 2.17 displays the dynamic of the monthly values of the valuation ratio (CAPE) for each country over the sample that ranges from January 1983 to April 2020.

Table 2.7 displays the results of the predictive regression for Canada. The presentation is similar to that of Table 2.4 for the US, with an additional column that reports the adjusted R-squared of the traditional predictive regression for the purpose of comparison. As in Table 2.4 the parameter a_1 (a_2) is positive (negative) and statistically significant for all forecast horizons, except the horizon of 1 month for a_1 . These results are proof for this country, that our predictive

Table 2.8: Estimation results of stock return predictive regressions: the UK

τ	a_0	a_1	a_2	Adj. R^2 (%)	Adj. R^2 Tradi (%)
1	0.0117***	0.0915	-0.0374*	2.20	0.71
2	0.0185***	0.2268**	-0.0857**	3.59	2.00
3	0.0244***	0.3384**	-0.1248**	4.87	3.03
4	0.0297***	0.4491***	-0.1631***	6.23	3.98
5	0.0342***	0.6022***	-0.2154***	8.49	5.19
6	0.0386***	0.7626***	-0.2703***	11.01	6.44
7	0.0441***	0.8983***	-0.3173***	13.22	7.59
8	0.0502***	1.0201***	-0.3601***	15.15	8.55
9	0.0574***	1.1390***	-0.4027***	17.21	9.43
10	0.0637***	1.2576***	-0.4445***	19.20	10.26
11	0.0690***	1.3596***	-0.4798***	20.49	11.06
12	0.0743***	1.4410***	-0.5079***	21.20	11.81
13	0.0786***	1.5017***	-0.5280***	21.27	12.51
14	0.0824***	1.5561***	-0.5454***	21.24	13.19
15	0.0857***	1.6075***	-0.5614***	21.19	13.85
16	0.0884***	1.6847***	-0.5860***	21.73	14.52
17	0.0924***	1.7856***	-0.6199***	22.86	15.27
18	0.0970***	1.8818***	-0.6525***	24.03	15.97
24	0.1339***	2.2908***	-0.7969***	27.90	19.22
36	0.1791***	2.9484***	-1.0090***	32.53	24.58
48	0.2337***	2.9306***	-0.9980***	29.35	24.83

Notes: For different values of the prediction horizon τ , the table displays the estimation results of the stock return predictive regression. The penultimate column displays the adjusted R-squared of this predictive regression (Adj. R^2) and the last column the adjusted R-squared of the traditional 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.

regression, which relies on the mean reversion probability coupled with the level of the CAPE ratio, is valuable. The comparison of the predictive powers as measured by the adjusted R-squared confirms this statement. At short-term horizons, the values displayed for our approach are higher than those of the traditional model, the inversion of dominance being observed only at long horizons (36 and 48 months). Precisely, while the traditional model shows an adjusted R-squared of -0.09% (2.93%) at 1 (12) months, our model reaches a value of 5.30% (7.13%).

Tables 2.8-2.10 report the same compelling results for the remaining countries, i.e. the UK, Germany and France, respectively. For the UK (Table 2.8), the evidence appears to be stronger, because the explanatory power of our predictive regression model (R-squared) is higher than that

Table 2.9: Estimation results of stock return predictive regressions: Germany

τ	a_0	a_1	a_2	Adj. R^2 (%)	Adj. R^2 Tradi (%)
1	0.0212***	0.0286	-0.0254*	6.11	0.43
2	0.0326***	0.1576	-0.0712**	5.04	1.51
3	0.0433***	0.2422	-0.1016**	4.86	2.61
4	0.0530***	0.3204	-0.1287***	4.63	3.75
5	0.0632***	0.4233	-0.1642***	4.96	4.98
6	0.0722***	0.5529**	-0.2071***	5.49	6.17
7	0.0813***	0.6462**	-0.2383***	5.76	7.33
8	0.0932***	0.7185**	-0.2660***	6.50	8.41
9	0.1076***	0.8693***	-0.3221***	8.56	9.66
10	0.1189***	1.0604***	-0.3877***	10.44	10.94
11	0.1277***	1.2021***	-0.4344***	11.21	12.25
12	0.1388***	1.3061***	-0.4715***	11.98	13.58
13	0.1489***	1.4801***	-0.5302***	13.43	14.98
14	0.1591***	1.6093***	-0.5747***	14.52	16.21
15	0.1686***	1.6702***	-0.5962***	14.66	17.34
16	0.1773***	1.7545***	-0.6247***	15.01	18.47
17	0.1866***	1.8441***	-0.6556***	15.59	19.60
18	0.1969***	1.9433***	-0.6910***	16.60	20.62
24	0.2507***	2.6067***	-0.9155***	22.94	26.33
36	0.3305***	2.9883***	-1.0301***	23.63	34.43
48	0.4207***	3.3066***	-1.1317***	26.40	38.90

Notes: For different values of the prediction horizon τ , the table displays the estimation results of the stock return predictive regression. The penultimate column displays the adjusted R-squared of this predictive regression (Adj. R^2) and the last column the adjusted R-squared of the traditional 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.

of the traditional model across all horizons. The highest dominance is observed at the horizons of 10, 11 and 12 months.

Results of our approach are also robust for Germany as displayed in Table 2.9. There is a clear-cut superiority of our predictive regression compared to the traditional one, in particular for the short horizons (1 to 4 months), with a very marked difference at 1 month. Indeed, at this horizon, the adjusted R-squared is equal to 6.11% in our predictive regression against 0.43% for the traditional one. Even though the parameters a_1 and a_2 are not significant, similar results are obtained for France (see Table 2.10), with higher adjusted R-squared up to 3 months.

Table 2.10: Estimation results of stock return predictive regressions: France

τ	a_0	a_1	a_2	Adj. R^2 (%)	Adj. R^2 Tradi (%)
1	0.0164***	-0.0097	-0.0050	2.12	0.27
2	0.0257***	0.0477	-0.0254	1.88	0.97
3	0.0329***	0.1166	-0.0475	1.91	1.65
4	0.0400***	0.1772	-0.0670	2.10	2.29
5	0.0453***	0.2599	-0.0922	2.47	3.05
6	0.0497***	0.3553	-0.1205*	3.09	3.87
7	0.0536***	0.4414*	-0.1454*	3.73	4.70
8	0.0583***	0.5030*	-0.1633*	4.08	5.45
9	0.0637***	0.5810**	-0.1870**	4.74	6.25
10	0.0696***	0.6645**	-0.2130**	5.58	7.02
11	0.0754***	0.7522**	-0.2403**	6.41	7.93
12	0.0816***	0.8383***	-0.2673***	7.22	8.87
13	0.0874***	0.9232***	-0.2937***	8.00	9.79
14	0.0937***	1.0035***	-0.3192***	8.75	10.66
15	0.1002***	1.0735***	-0.3415***	9.35	11.50
16	0.1054***	1.1526***	-0.3658***	10.09	12.31
17	0.1106***	1.2495***	-0.3959***	11.15	13.12
18	0.1153***	1.3423***	-0.4241***	12.13	13.96
24	0.1454***	1.7898***	-0.5591***	16.84	18.80
36	0.2016***	2.3111***	-0.7158***	22.13	24.68
48	0.3002***	2.4208***	-0.7747***	21.49	31.15

Notes: For different values of the prediction horizon τ , the table displays the estimation results of the stock return predictive regression. The penultimate column displays the adjusted R-squared of this predictive regression (Adj. R^2) and the last column the adjusted R-squared of the traditional 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.

2.7.2 Out-of-sample evidence

This section investigates the out-of-sample robustness across countries (Canada, France, Germany, the UK), using the approach adopted for the US in Section 3 of the chapter. Formally, for a fixed forecasting horizon τ from 1 month to 60 month, i.e. 5 years, and for each month t , we use the available monthly observations to estimate the predictive regression model (2.17). The estimated parameters are used to forecast the out-of-sample multi-period return $r_{t+1:t+\tau}$, and compute the out-of-sample R-squared.

Recall that this regression requires the lagged value of the term spread w_{t-m} with m the

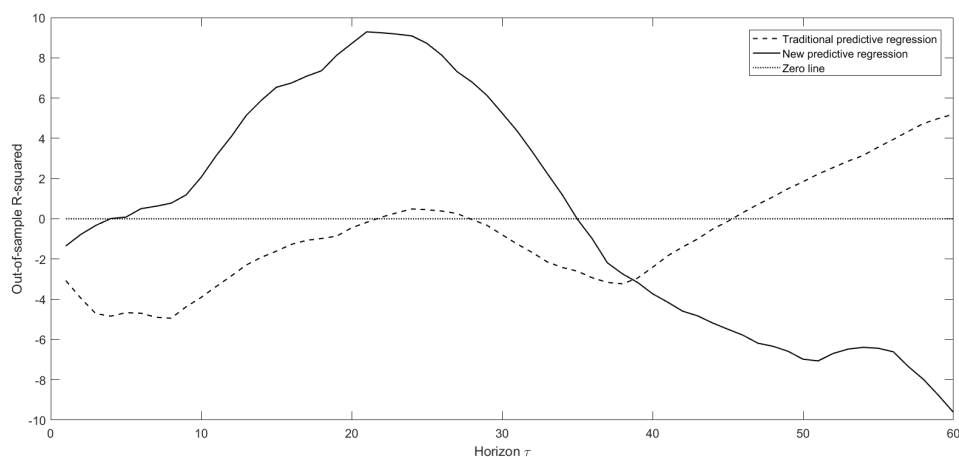


Figure 2.18: Out-of-sample predictive powers of competing predictive regressions: Canada

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the CAPE ratio as the explanatory variable, and the new predictive regression that conditions the influence of the CAPE 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, 1983 to April, 2020, with a total of 448 monthly observations.

lag-order. Figure 2.28 in Appendix 2.9 displays the dynamic of term spreads for each country. As done in section 3 for the US, we search for the optimal value of m , computing the correlation between lagged values of the term spread and the smoothed probabilities of mean reversion in the CAPE ratio (see Figure 2.8). The optimal lag-orders are equal to 21, 25, 6 and 9 for Canada, the UK, Germany and France, with the consequence that the early-warning property of the term spread holds over very short horizons for Germany (two quarters) and France (three quarters).

Figure 2.18 displays for Canada, the out-of-sample R-squared of our predictive regression with respect to the forecasting horizon. For comparison, the same statistic is reported for the traditional predictive regression. The patterns observed in the figure are qualitatively similar to those reported for the US in Figure 2.9. The new predictive regression has superior (inferior) predictive ability at short-term (long-term) horizons. For illustration, at the horizon of 12 (24) months, the adjusted R-squared is equal to 4.08% (9.09%) for the new approach, whereas it is only equal to -2.84% (0.49%) in the traditional approach.

Figures 2.19-2.21 display the same information for the UK, Germany and France, respectively. Results are similar, although the reported levels of adjusted R-squared are low and negative at

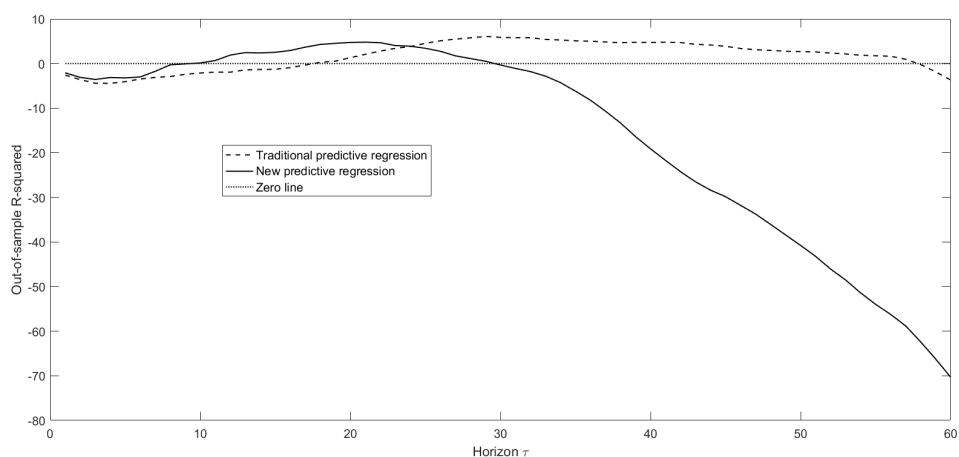


Figure 2.19: Out-of-sample predictive powers of competing predictive regressions: the UK

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the CAPE ratio as the explanatory variable, and the new predictive regression that conditions the influence of the CAPE 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, 1983 to April, 2020, with a total of 448 monthly observations.

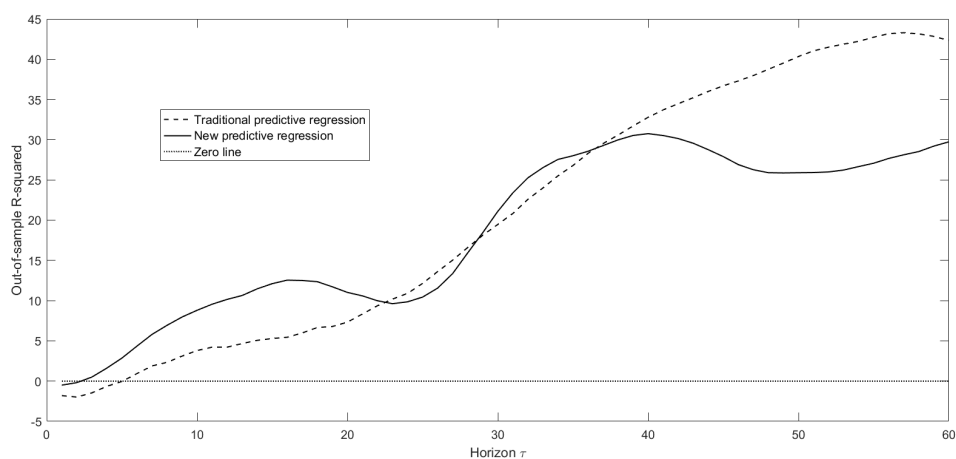


Figure 2.20: Out-of-sample predictive powers of competing predictive regressions: Germany

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the CAPE ratio as the explanatory variable, and the new predictive regression that conditions the influence of the CAPE 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, 1983 to April, 2020, with a total of 448 monthly observations.

very short-term horizons for France and the UK, even for the new predictive regression. In particular, for the UK (Figure 2.19), it should be noted that if the outperformance exists at

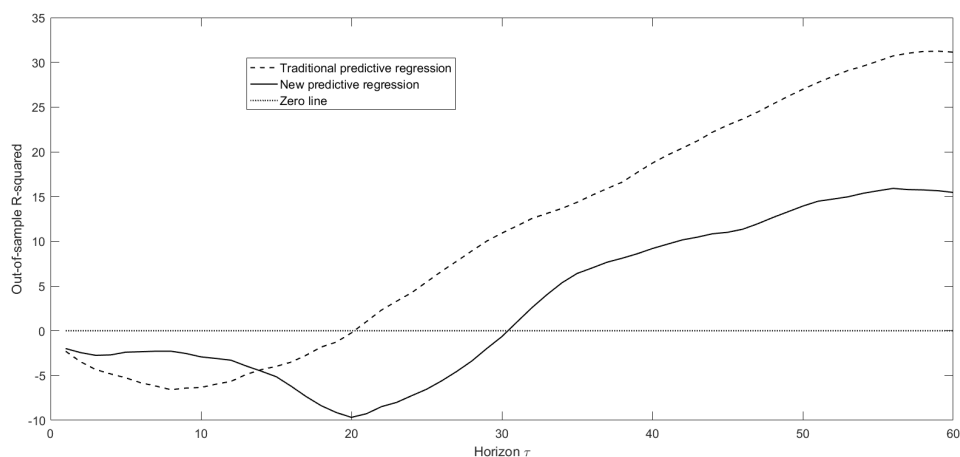


Figure 2.21: Out-of-sample predictive powers of competing predictive regressions: France

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the traditional predictive regression with the CAPE ratio as the explanatory variable, and the new predictive regression that conditions the influence of the CAPE 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, 1983 to April, 2020, with a total of 448 monthly observations.

short-term horizons, it remains lower compared to the other countries. This may stem from the fact that, contrary to the US, the term spreads for these countries have less predictive content regarding the business cycle, and further investigations are needed for the choice of the most suitable business cycle variable.

Finally, for France (Figure 2.21), results show that the out-of-sample R-squared of our model and that of the traditional linear model are negative for many short-term horizons, hence with the dominance of the historical average model in these scenarios. This qualifies the robustness of our results for this country.

2.7.3 Asset allocation

Table 2.11 displays the asset allocation results for the UK. Overall, we observe the same patterns compared to US (see Table 2.6), with high utility gains at the very short horizons that decrease with the horizons.

Tables 2.12-2.14 report the same information for France, Germany and Canada, respectively. For France (Table 2.12), we no longer observe the regularity of the evolution of CERs and utility

Table 2.11: CER and differences in CER: the UK

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	2.47	1.77	-1.05	-1.32	3.51	3.08
$\tau = 2$	2.94	2.16	-0.83	-1.41	3.77	3.57
$\tau = 3$	3.56	2.50	-0.54	-0.85	4.10	3.34
$\tau = 4$	3.81	2.82	0.43	-0.22	3.39	3.04
$\tau = 5$	2.90	2.23	1.53	0.09	1.37	2.14
$\tau = 6$	3.89	2.60	2.06	0.91	1.83	1.68
$\tau = 7$	2.66	1.91	0.96	0.10	1.70	1.81
$\tau = 8$	3.52	2.46	1.82	0.98	1.70	1.48
$\tau = 9$	2.70	1.55	2.14	1.60	0.56	-0.06
$\tau = 10$	3.78	2.32	3.01	2.26	0.77	0.06
$\tau = 11$	3.10	1.91	2.01	1.41	1.10	0.50
$\tau = 12$	2.54	1.45	2.87	1.94	-0.33	-0.49

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).

Table 2.12: CER and differences in CER: France

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	0.46	0.08	-0.44	-0.55	0.90	0.62
$\tau = 2$	1.45	0.68	-0.50	-0.85	1.95	1.53
$\tau = 3$	0.39	-0.17	-2.12	-2.06	2.51	1.89
$\tau = 4$	0.40	-0.14	-0.87	-0.71	1.27	0.57
$\tau = 5$	0.67	0.17	-2.10	-1.60	2.77	1.77
$\tau = 6$	1.28	0.52	-1.18	-1.22	2.46	1.74
$\tau = 7$	0.92	0.21	-2.19	-2.27	3.11	2.48
$\tau = 8$	1.30	0.45	-0.64	-0.79	1.94	1.24
$\tau = 9$	0.99	0.35	-0.44	-0.76	1.43	1.10
$\tau = 10$	-0.02	0.12	-0.26	-0.82	0.24	0.94
$\tau = 11$	1.14	0.25	0.75	0.06	0.39	0.20
$\tau = 12$	1.51	0.40	-0.54	-1.20	2.04	1.59

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).

Table 2.13: CER and differences in CER: Germany

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	2.56	1.11	0.51	-0.65	2.04	1.76
$\tau = 2$	2.10	0.85	0.54	-0.54	1.56	1.39
$\tau = 3$	1.07	0.27	-0.48	-0.95	1.55	1.22
$\tau = 4$	1.03	-0.04	1.27	0.41	-0.24	-0.45
$\tau = 5$	1.01	0.13	1.69	0.11	-0.68	0.01
$\tau = 6$	1.41	0.50	2.25	1.04	-0.84	-0.54
$\tau = 7$	-0.09	-0.64	0.79	-0.83	-0.87	0.19
$\tau = 8$	0.03	-0.77	2.37	0.78	-2.34	-1.56
$\tau = 9$	0.25	-0.96	3.48	2.46	-3.23	-3.42
$\tau = 10$	0.71	-0.83	3.48	2.30	-2.77	-3.13
$\tau = 11$	0.85	-1.12	3.29	2.32	-2.44	-3.44
$\tau = 12$	-0.38	-2.24	3.25	2.15	-3.64	-4.39

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).

Table 2.14: CER and differences in CER: Canada

	New model		Traditional model		Utility gain	
	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$	$\gamma = 3$	$\gamma = 5$
$\tau = 1$	3.59	2.57	2.04	0.72	1.54	1.85
$\tau = 2$	3.46	1.99	2.65	1.65	0.82	0.34
$\tau = 3$	2.96	1.73	2.98	2.15	-0.01	-0.41
$\tau = 4$	3.09	1.69	2.31	1.92	0.78	-0.23
$\tau = 5$	4.13	2.24	3.16	2.56	0.97	-0.32
$\tau = 6$	4.23	2.22	3.05	2.51	1.18	-0.29
$\tau = 7$	3.61	1.74	2.70	1.40	0.90	0.34
$\tau = 8$	3.08	1.46	3.00	2.06	0.07	-0.61
$\tau = 9$	2.09	0.60	2.83	2.00	-0.74	-1.40
$\tau = 10$	2.63	1.13	2.93	1.91	-0.29	-0.79
$\tau = 11$	2.17	0.81	3.17	1.94	-1.01	-1.14
$\tau = 12$	1.68	0.87	2.70	1.62	-1.02	-0.75

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).

gains as a function of the forecast or rebalancing horizon τ . However, the robustness of the results still holds with positive utility gains across all horizons. Finally, results in tables 2.13 and 2.14 show positive CERs at very short-term horizons, i.e. 1 to 3 months for Germany for both values of the relative risk aversion parameter γ , and 1 to 2 months for Canada with $\gamma = 5$. For $\gamma = 3$, the results are more erratic, even if we observe overall that all the CERs up to $\tau = 8$ are positive, except for $\tau = 3$.

2.8 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 chapter, 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 chapter would be to evaluate how our approach performs in forecasting sector-level or firm-level returns using micro-CAPE or micro-PE.

2.9 Appendix: Additional Figures and Tables

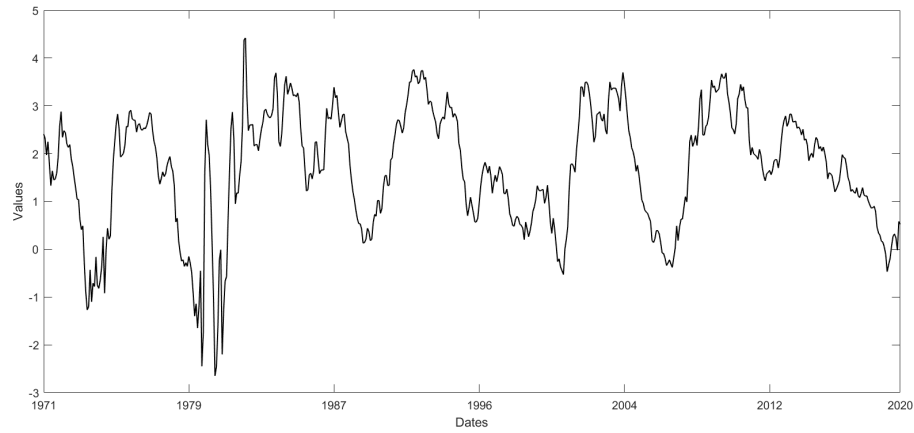


Figure 2.22: Dynamic of the US term spread: 1971/01-2020/04

Notes: The term spread is calculated as the difference between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity.

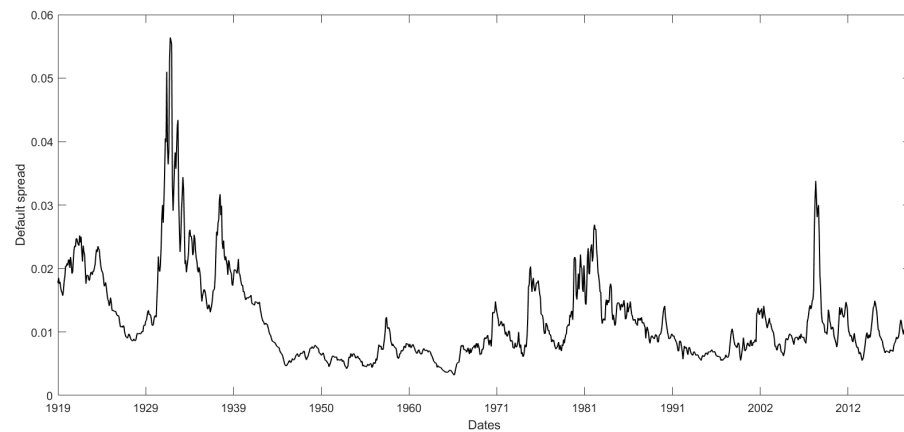


Figure 2.23: Dynamic of the US credit spread: 1919/01-2020/04

Notes: The credit spread is the difference between BAA and AAA rated corporate bond yields. The series is obtained from the FRED database.

Table 2.15: 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).

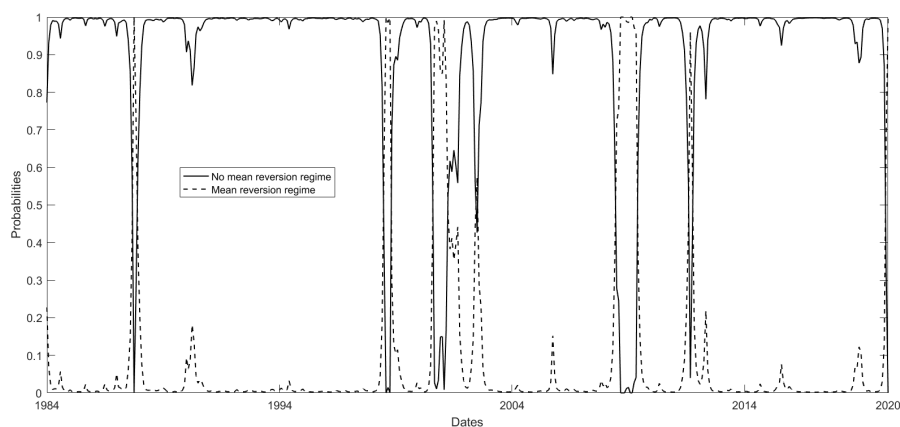


Figure 2.24: Dynamic of smoothed probabilities (Canada): 1984/02-2020/04

Notes: The figure displays the smoothed probabilities of the two regimes (no mean reversion/mean reversion) that result from the estimation of the regime-switching mean reversion equation in (2.2). The estimation sample ranges from February, 1984 to April, 2020, with a total of 435 monthly observations.

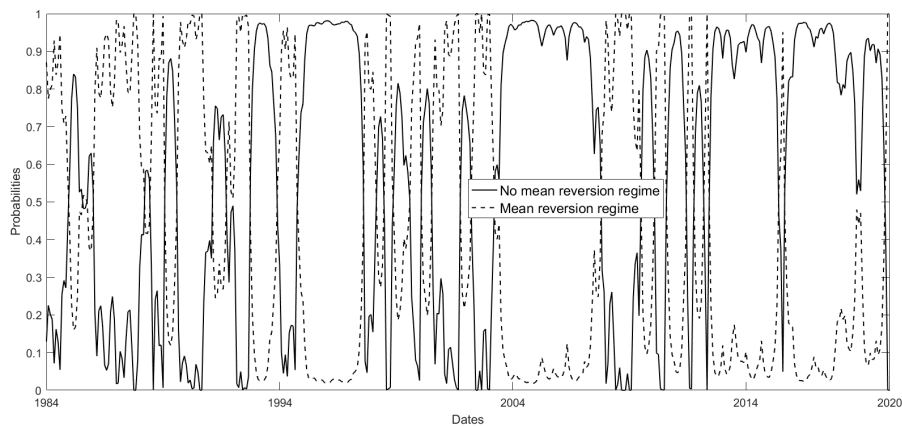


Figure 2.25: Dynamic of smoothed probabilities (the UK): 1984/02-2020/04

Notes: The figure displays the smoothed probabilities of the two regimes (no mean reversion/mean reversion) that result from the estimation of the regime-switching mean reversion equation in (2.2). The estimation sample ranges from February, 1984 to April, 2020, with a total of 435 monthly observations.

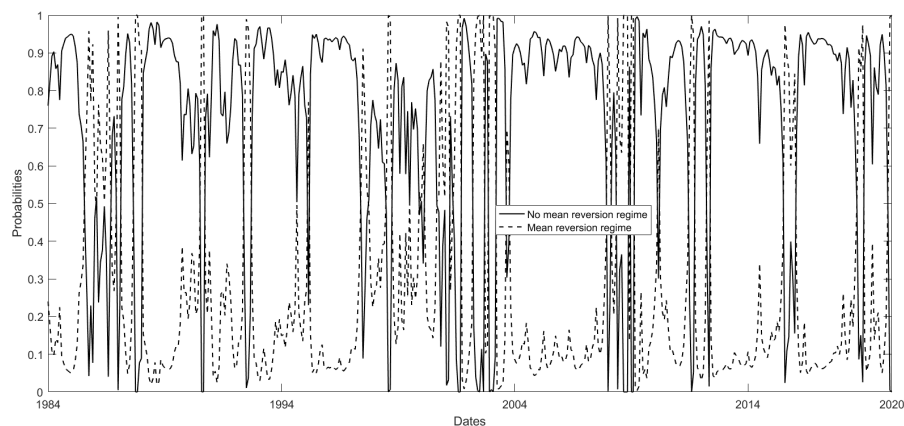


Figure 2.26: Dynamic of smoothed probabilities (Germany): 1984/02-2020/04

Notes: The figure displays the smoothed probabilities of the two regimes (no mean reversion/mean reversion) that result from the estimation of the regime-switching mean reversion equation in (2.2). The estimation sample ranges from February, 1984 to April, 2020, with a total of 435 monthly observations.

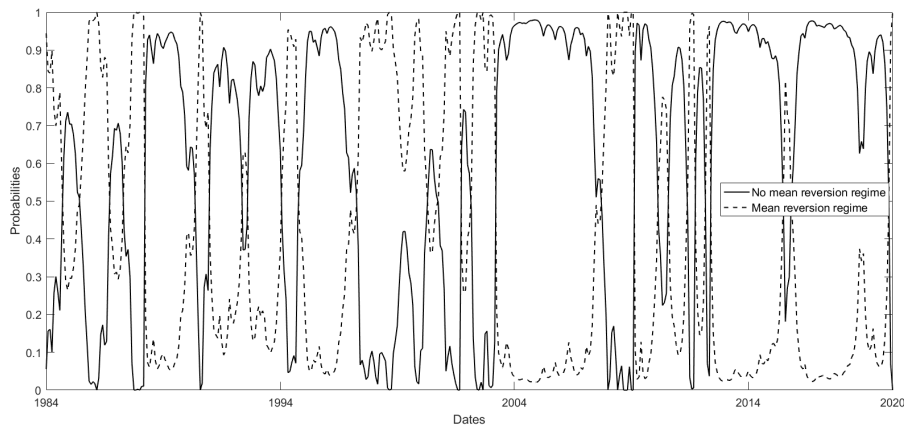


Figure 2.27: Dynamic of smoothed probabilities (France): 1984/02-2020/04

Notes: The figure displays the smoothed probabilities of the two regimes (no mean reversion/mean reversion) that result from the estimation of the regime-switching mean reversion equation in (2.2). The estimation sample ranges from February, 1984 to April, 2020, with a total of 435 monthly observations.

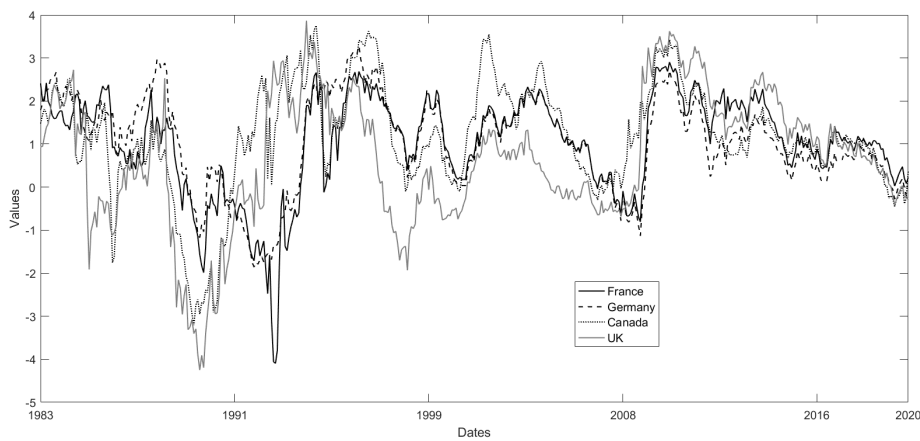


Figure 2.28: Dynamic of term spreads: 1983/01-2020/04

Notes: The term spreads are calculated as the spread between the rates of 10-Year Government Bonds Constant Maturity and 3-Month Government Bonds Constant Maturity. Data are from the OECD.

3

Predicting Equity Risk Premium: the Combined Effect of Valuation Ratios and Business Cycle Variables

3.1 Introduction

EQUITIES have long been regarded as an essential component of portfolio construction due to their exceptional performance over extended time frames, outperforming traditional asset classes such as fixed income, commodities, and real estate.

Building upon the methodology developed in Chapter 2, that proposed a straightforward specification for predicting short-term stock index returns out-of-sample, we extend the model in a data-rich environment by incorporating a comprehensive set of business cycle variables and employing penalization methods for parsimonious estimation. The approach of Chapter 2 capitalizes on the relationship between mean reversion in valuation ratios and price dynamics, along with the early-warning property of two business cycle variables, whereas our extension, employs a wider set of variables.

Numerous academic papers have explored financial ratios' usefulness like P/E, CAPE, dividend yield, and book-to-market ratios in forecasting multi-year stock market returns (Rozeff, 1984; Campbell and Shiller, 1988; Cochrane, 1991; Hodrick, 1992; Goetzmann and Jorion, 1993; Fama and French, 1988; Asness, 2003; Lewellen, 2004, etc.). These studies suggest that financial ratios' variation is driven by changes in expected returns through mean reversion, as fundamentals' growth rates are less predictable. This relationship primarily holds for long-term stock

Joint work with Christophe Boucher and Sessi Tokpavi.

market returns, with P/E ratios reverting to historical averages over extended periods (Campbell and Shiller, 1998; Weigand and Irons, 2007, etc.). However, Lettau and Van Nieuwerburgh (2008) showed that considering regime-specific means can recover short-term predictive content in valuation ratios, allowing for statistically significant short-term mean reversions and improved one-year return predictions.

Mean reversion in valuation ratios, often aligning with trend reversals in stock index prices, has been thoroughly examined in market history. The CAPE ratio, P/E ratios, dividend yields, and book-to-market ratios have demonstrated their effectiveness in forecasting future stock market returns (Rozeff, 1984; Campbell and Shiller, 1988; Cochrane, 1991; Hodrick, 1992; Goetzmann and Jorion, 1993; Fama and French, 1988; Lewellen, 2004, etc.). While their predictability remains robust over longer horizons (Fama and French, 1988), evidence points to weaker performance at short-term intervals.

To address the challenge of short-term predictability, subsequent research explores alternatives to assuming a fixed steady-state mean in the economy. One prevalent approach involves regime-dependent moments of valuation ratios, where regime timing improves short-term predictiveness (Rapach et al., 2010; Henkel et al., 2011; Dangel and Halling, 2012; Arnott et al., 2017; McMillan, 2019; Tsiakas et al., 2020; Gomez Cram, 2022; Moench and Tobias, 2021, etc.). This framework aligns with how investors process information based on the economy's state, as analyzed by Kacperczyk et al. (2016). Countercyclical risk premiums and investor disagreements about the economy's state also mold the predictive value of valuation metrics (Campbell and Cochrane, 1999; Bekaert et al., 2009; Cujean and Hasler, 2017, etc.).

Hence, valuation metrics' predictive ability can be contingent on the business cycle's observed state. Some studies employ models with time-varying parameters or structural breaks aligned with business cycles, particularly recessions and expansions, for efficient timing of these states (Paye and Timmermann, 2006; Lettau and Van Nieuwerburgh, 2008; Dangel and Halling, 2012, etc.). Others capitalize on time-varying links between price dynamics and valuation ratios, utilizing early-warning properties of business cycle variables for NBER recession occurrences or valuation ratio mean reversion (Moench and Tobias, 2021, etc.). Both papers underscore term and credit spreads' importance in effectively timing market regimes with powerful predictive regressions.

The objective of our study is to extend the out-of-sample predictive ability of the model proposed in Chapter 2 by employing a data-rich environment with an extensive set of business cycle variables. The primary motivation behind this extension stems from the absence of a strong consensus on which business cycle variables demonstrate the best predictive performance for mean reversion in valuation ratios and stock index prices.

Beyond the term and credit spreads investigated by Chapter 2 and other related studies, some global financial variables and macroeconomic indicators are suspected to contain informational content regarding stock index prices. Welch and Goyal (2008) seminal paper offers guidance, suggesting nine relevant predictors, excluding the five valuation ratios mentioned earlier. These predictors include stock index variance, net issuing activity, three-month Treasury bill, long-term government bond yield, return on long-term government bonds, default return spread, default yield spread, term spread, and inflation.

Addressing model uncertainty typically involves model averaging or forecast combination using all or a subset of these predictors (Avramov, 2002; Cremers, 2002; Rapach et al., 2010; Tsiakas et al., 2020, etc.). Avramov (2002) emphasizes the importance of model uncertainty over estimation risk, highlighting that investors neglecting model uncertainty face significant utility losses. However, recent findings by Tsiakas et al. (2020) challenge this, revealing that choosing economically motivated predictive variables results lead to better forecast combinations.

In our study, we adopt a model that incorporates all relevant predictors suggested by Welch and Goyal (2008) and focus on statistical rather than economic selection criteria to address the issue of model uncertainty. This approach enables a direct extension of the specification proposed by Chapter 2, which constitutes the central objective of the chapter. Building on the methodology of Chapter 2, we broaden the scope by incorporating a comprehensive range of business cycle variables and varying lag orders, which is likely to amplify predictive regression's efficacy, blending business variables and valuation ratios. Additionally, by including more lag orders, we expect to boost forecasting precision as the fixed lag order used in Chapter 2 could be overly restrictive for predicting out-of-sample returns across different horizons.

We use the least absolute shrinkage and selection operator (LASSO) method of Tibshirani (1996), which handles variable selection and estimation together, mitigating overfitting with numerous predictors. For the LASSO model estimation, we determine the tuning parameter

linked to a chosen number of predictors. This follows Tsiakas et al. (2020), who found using two predictors (one cyclical and one countercyclical) delivers valuable equity premium predictions in both economic phases. Their choice was economic-driven; we emphasize the LASSO's statistical selection power. Yet, we explore flexibility by considering three, four, and five variables.

Empirical applications show that this extension leads to superior predictive power. For instance, while the out-of-sample R-squared of the model specifications used in Chapter 2 ranges from 0.69% (1 month) to 14.03% (24 months), the same statistic for the optimal predictive regression model, which appears to be the one with three selected business cycle variables, ranges from 1.85% (1 month) to 20.07% (24 months).

We conduct a mean-variance asset allocation exercise,¹ 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 model proposed in Chapter 2 to the new proposed model, is equal to 2.52%.

We show for each business cycle variable and each lag-order from 0 to 18, how often each predictive variable is selected in the rolling-window forecasting procedure. The results highlight the significance of the term spread alongside the US Shiller CAPE ratio for forecasting prices one month ahead. Notably, only this variable, in its various versions (lag-orders), is chosen. This outcome validates the findings of Moench and Tobias (2021) and Chapter 2, emphasizing the robust predictive value of this business cycle indicator. These findings also hold when considering other financial variables including the book-to-market ratio and the dividend yield.

To explore the robustness of our new predictive regression, we investigate its performance across various US industries. This aspect is of particular interest, considering that investors often adopt industry rotation strategies and concentrate their holdings in sectors where they have more personal experience or private advantages (Kacperczyk et al., 2005; Roche et al., 2013; Narayan et al., 2017; Pham, 2021, etc.). Understanding how our predictive model performs across different industries provides valuable insights for investors and market participants seeking strategic portfolio allocation strategies.

¹We follow the same approach as in Chapter 2 to investigate the economic value of our new predictive regression model.

The rest of the chapter proceeds as follows. Section 2 develops a new predictive model which extends the setup of Chapter 2 with the introduction of a data-rich environment. The section 3 evaluates empirically the value-added of the new predictive regression by assessing in what extent it outperforms the specification in Chapter 2. In this section, the robustness checks are performed regarding the choice of the financial ratio. Section 4 deals with evidence of our new model on US individual sectors. The last section concludes.

3.2 Description of the new predictive model

In this section, we first review the main ideas underlying the predictive model of Chapter 2, and thus develop our new predictive model (specification and estimation) which extends their setup with the promise of improving the forecast ability.

3.2.1 Setup and specification

Mean reversions in valuation ratios are well-known and scrutinized phenomena in market history, often coinciding with trend reversals in stock index prices. For instance, the CAPE ratio introduced by Campbell and Shiller (1988) characterizes the connection between inflation-adjusted earnings-price ratio and subsequent long-term returns. This ratio, along with price-earnings (P/E) variables, dividend yields, and book-to-market ratios, is established in the literature as valuable for forecasting future stock market returns (Rozeff, 1984; Campbell and Shiller, 1988; Cochrane, 1991; Hodrick, 1992; Goetzmann and Jorion, 1993; Fama and French, 1988; Lewellen, 2004, etc.). Although the initial findings showed strong predictive power over multi-year horizons, explaining around 25%-40% of 3-5-year return variances (Fama and French, 1988), subsequent evidence has indicated weaker performance at short-term horizons.

Subsequent works tried to recover predictability at short-term horizons, relaxing the assumption of a fixed steady state mean of the economy. The common framework is to assume that the moments of valuation ratios are regime-dependent, and that the timing of the regimes can help increasing their powers in predicting returns over short-horizons (Rapach et al., 2010; Henkel et al., 2011; Dangl and Halling, 2012; Arnott et al., 2017; McMillan, 2019; Tsiakas et al., 2020; Gomez Cram, 2022; Moench and Tobias, 2021, etc.). One theoretical motivation of this

framework can be linked to the way investors process information depending on the state of the economy, as analyzed by Kacperczyk et al. (2016). In recessions, aggregate risk is higher and, consequently, investors care more about aggregate shocks. In expansions, aggregate risk is lower and, consequently, investors care more about idiosyncratic shocks. Another theoretical rationale is based on countercyclical risk premiums (Campbell and Cochrane, 1999; Bekaert et al., 2009), or countercyclical investor disagreement about the state of the economy (Cujean and Hasler, 2017).

Hence, the predictive content of valuation metrics may be linked to the observed state of the business cycle. In some papers, efficient timing of these states is conducted based on models with time-varying parameters or structural breaks that fit business cycles, and specifically recession and expansion phases (see for e.g. Paye and Timmermann, 2006; Lettau and Van Nieuwerburgh, 2008; Dangel and Halling, 2012). In other works, time-variations in the relation that links prices' dynamics to valuation ratios are achieved exploiting the early-warning property of business cycle variables on the occurrence of NBER recession (Moench and Tobias, 2021) or mean reversion in valuation ratios (cf Chapter 2). In this framework, both papers stressed the importance of term and credit spreads in timing market regimes in which the power of predictive regressions is high.

We focus on the methodology of Chapter 2, which is based on the observation that mean reversion episodes in the US Shiller CAPE ratio, identified via a regime-switching model, are followed by large decreases in the S&P 500 index prices, as reported in Figure 3.1.

The figure shows that average multi-period returns following a mean reversion regime are negative from values of τ ranging from 1 month to 13 months, while they are always positive in the absence of mean reversion in the US Shiller CAPE ratio. This suggests that timing mean reversion episodes can help predicting stock returns at short-term horizons.

Interestingly, by conditioning the occurrence of mean reversion in the CAPE ratio with the level of the latter, we obtained the stylized facts displayed in Figure 3.2. Hence, disentangling the mean reversion regimes in the top-panel of Figure 3.1 shows 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 of Figure 3.2), while with low values of the CAPE ratio (top panel of Figure 3.2), subsequent multi-period returns are positive or negative, but close to zero. We related these empirical features to the two types of mean reversion phenomenon (i.e. a crash

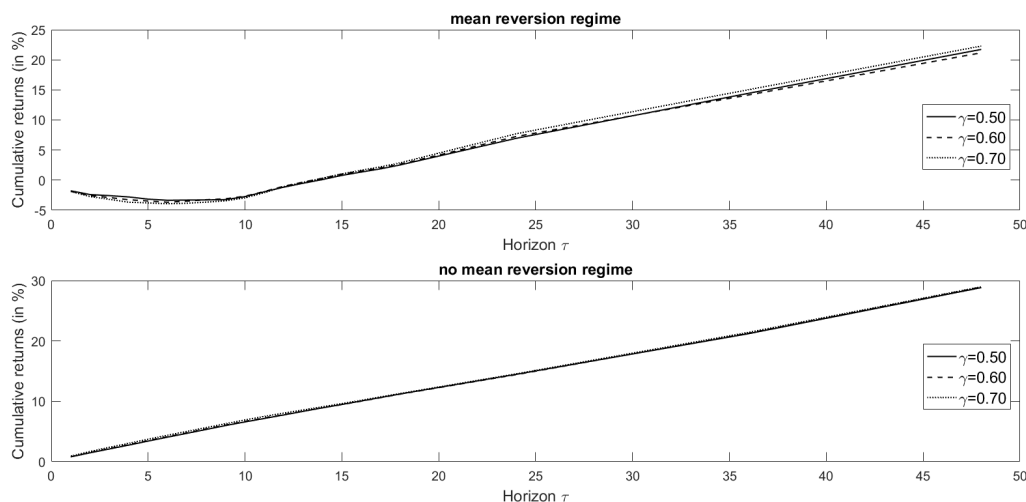


Figure 3.1: Prevaling regimes in the US CAPE ratio and subsequent S&P 500 average returns

Notes: The figure compares subsequent S&P 500 average multi-period returns following the prevalence of a given regime (presence or absence of mean reversion) in the US Shiller CAPE ratio, using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations. The prevalence of a regime is given by the related smoothed probability (estimated with a Markov regime switching model) exceeding a high threshold value $\gamma \in \{0.5, 0.6, 0.7\}$.

first then a recovery). On one side, a high level of the CAPE ratio corresponding to the beginning of a crisis on the equity market with subsequent negative returns, and on the other side a low level of CAPE ratio corresponding to the exit from the crisis and subsequent positive returns.

Based on these findings, we proposed, in Chapter 2, the following in-sample predictive regression:

$$r_{t+1:t+\tau} = a_0 + a_1 \widehat{\text{Pr}}_t + a_2 x_t \widehat{\text{Pr}}_t + u_{t+1:t+\tau}, \quad (3.1)$$

where $r_{t+1:t+\tau}$ is the multi-period returns over horizon τ , x_t is the natural logarithm of the US Shiller CAPE ratio, $\widehat{\text{Pr}}_t$ is the estimated smoothed probability of mean reversion regime at time t (estimated via a Markov switching model), a_0 , a_1 and a_2 the parameters, and $u_{t+1:t+\tau}$ the error term. Remark that the interaction between the probability of mean reversion and the level of the CAPE ratio in (3.1) allows modelling the two types of mean reversion phenomenon discussed above and which depend on the level of the CAPE ratio.

While this predictive model is shown to have relative good predictive performances over short-horizons, it is not suitable for out-of-sample forecasting exercise, because $\widehat{\text{Pr}}_t$ the smoothed

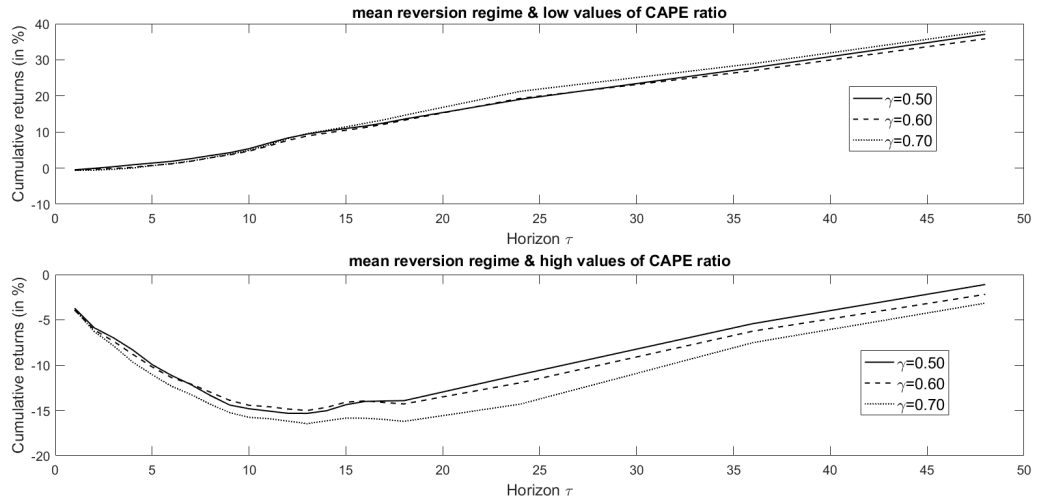


Figure 3.2: Mean reversion regime, levels of CAPE ratio and subsequent S&P 500 average returns

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, using monthly data from February, 1884 to April, 2020, with a total of 1635 monthly observations. 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 (estimated with a Markov regime switching model) 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 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.

probability of mean reversion regime at time t , is computed using the all sampling information (the whole history of the time series). To overcome this issue, we proposed, in Chapter 2, an operational out-of-sample predictive regression, approximating $\widehat{\text{Pr}}_t$ with a suitable business cycle variable, i.e., term spread or credit spread, yielding:

$$r_{t+1:t+\tau} = a_0 + a_1 w_{t-m} + a_2 x_t w_{t-m} + v_{t+1:t+\tau}, \quad (3.2)$$

with w_{t-m} the lagged value of the business cycle variable, a_0 , a_1 and a_2 some parameters, and $v_{t+1:t+\tau}$ the error term. The lag-order m is calibrated based on the empirical correlation between w_{t-m} and $\widehat{\text{Pr}}_t$.

As already stressed, our goal in this chapter is to extend this out-of-sample predictive regression, using a data-rich environment setup based on a large set of business cycles variables. The main motivation underlying our extension is the lack of a strong consensus on which busi-

ness cycle variables have the best predictive performance on the occurrence of mean reversion in valuation ratios, and more generally on stock index prices, as mean reversion in the CAPE ratio for example, mainly processes through prices adjustment.²

Beyond term and credit spreads mobilized by Chapter 2 and other works in the related literature, some global financial variables and macroeconomic indicators are suspected to have some informational content on stock index prices. A guidance on the relevant predictors can be found on the seminal paper of Welch and Goyal (2008). The authors suggest a list of 9 variables (excluding 5 valuation ratios, i.e., dividend yield, dividend-price ratio, earnings-to-price ratio, dividend-payout ratio, book-to-market ratio) including stock index variance, net issuing activity, three-month Treasury bill, long-term government bond yield, return on long-term government bonds, default return spread, default yield spread, term spread, and inflation.

The traditional way of dealing with model uncertainty using all or a subset of these predictors is through model averaging or forecast combination (Avramov, 2002; Cremers, 2002; Rapach et al., 2010; Tsiakas et al., 2020). The pioneering work of Avramov (2002) indeed showed that model uncertainty is more important than estimation risk, and investors who discard model uncertainty face large utility losses. They also stressed that the Bayesian approach is superior to that of model selection criteria. These findings are recently challenged by Tsiakas et al. (2020) who showed that economically motivated choice of predictive variables (dividend yield and the short rate) lead to simpler and superior forecast combinations.

Here, we rely on a model that includes all predictive variables, and focus on statistical instead of economic selection criteria to solve the issue of model uncertainty. This approach allows a direct extension of the specification of Chapter 2, which is the main objective of this chapter. For a given valuation metric x_t (CAPE ratio, book-to-market, etc.), a simple way to achieve this is to extend the specification in (3.2) using the $J = 9$ global financial variables and macroeconomic indicators in Welch and Goyal (2008), yielding:

$$r_{t+1:t+\tau} = \alpha + \sum_{j=1}^J \sum_{s=0}^m \beta_j^{(s)} w_{j,t-s} + \sum_{j=1}^J \sum_{s=0}^m \gamma_j^{(s)} x_t w_{j,t-s} + u_{t+1:t+\tau}, \quad (3.3)$$

²Indeed, 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, 2005).

where $w_{j,t}$, $j = 1, \dots, J$ is the value at month t of the j^{th} business cycle variable, α , $\beta_j^{(s)}$ and $\gamma_j^{(s)}$, $j = 1, \dots, J$, $s = 0, \dots, m$ are the parameters, and $u_{t+1:t+\tau}$ the error term. In practice, one can set the maximum lag-order m for the business cycle variables to $m = 18$ (a year and a half) to capture the long time-span underlying the early-warning property of some of them. For the term spread for example, stylized facts show that every recession after the mid-1960s was predicted by an inverted yield curve within 6 quarters of the impending recession, i.e., 18 months.

Remark that our specification extends that of Chapter 2 (see eq. 3.2) in two main directions. First, considering a large set of J business cycle variables instead of one, and including all lag-orders up to $m = 18$ months instead of one fixed lag-order. Our guess is that this data-rich environment should increase the power of the predictive regression that combines the effects of business variables and valuation ratios. For the lag-order, this improvement is expected based on the idea that a fixed lag-order, as considered in Chapter 2, is too restricted to forecast out-of-sample returns at all forecast horizons τ . For instance and as stressed above, a yield curve inversion 6 quarters ago, contains signals for market downturns at short horizons τ , but this predictive content is certainly weak for longer horizons τ . Hence, allowing for the possibility of all lag-orders should be valuable.

3.2.2 Estimation via Lasso

Our specification in (3.3) can be estimated via the ordinary least squares (OLS) method by minimizing the residual sum of squares:

$$RSS(\Theta) = \sum_{t=m+1}^T [r_{t+1:t+\tau} - \alpha - W_t' \Theta]^2, \quad (3.4)$$

where $W_t = (W_{1,t}', \dots, W_{J,t}')'$ is the vector of length $2J(m+1)$ of predictors, with $W_{j,t} = (w_{j,t}, \dots, w_{j,t-m}, x_t w_{j,t}, \dots, x_t w_{j,t-m})'$, $\Theta = (\Theta_1', \dots, \Theta_J')'$ is the vector of length $2J(m+1)$ of parameters with $\Theta_j = (\beta_j^{(0)}, \dots, \beta_j^{(m)}, \gamma_j^{(0)}, \dots, \gamma_j^{(m)})'$. Remark that the OLS estimation of this model is challenging due to the large number of predictors involved. For instance, if we consider the $J = 9$ business cycle variables, and the maximum number of lag-order $m = 18$, the dimension of the vector Θ is equal to $2J(m+1) = 342$, involving a large number of parameters to estimate, and hence making the OLS method fragile for estimation and forecasting. In such a context,

penalization methods such as the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996) are more appropriate. This method is designed to proceed to both the selection of variables and estimation to prevent overfitting issues in the context of many predictors.

The LASSO method operates by adding a penalty term to the objective function of the OLS method in (3.4), such that:

$$RSS(\Theta) = \sum_{t=m+1}^T [r_{t+1:t+\tau} - \alpha - W_t' \Theta]^2 + \lambda \|\Theta\|_1, \quad (3.5)$$

with $\|\cdot\|_1$ the 1-norm, and λ a tuning parameter that controls the intensity of the penalization and that is selected in such a way that the resulting model minimizes the out-of-sample error. The optimal value of the tuning parameter λ is usually obtained by relying on grid search with cross-validation or by using some information criteria. There is no closed-form solution to this optimization problem, and numerical procedures suitable for convex problems are needed, such as the least angle regression of Efron et al. (2004), which is the common algorithm to solve for the related selection method.

Let us remark that for the implementation of the LASSO here, we do not proceed to the selection of predictors among all $2J(m+1)$ available, but rather proceed, selecting first the most relevant business cycle variables. Precisely, we consider instead the following LASSO specification:

$$RSS(\Theta_1) = \sum_{t=m+1}^T [r_{t+1:t+\tau} - \alpha - \bar{W}_t' \Theta_1]^2 + \lambda \|\Theta_1\|_1, \quad (3.6)$$

where $\bar{W}_t = (\bar{W}'_{1,t}, \dots, \bar{W}'_{J,t})'$ is the vector of length $J(m+1)$ of current and lagged values of the J business cycle variables, with $\bar{W}_{j,t} = (w_{j,t}, \dots, w_{j,t-m})'$. The vector of parameters Θ_1 is thus of length $J(m+1) = 171$. Once the relevant business cycle variables are selected, we consider the non-linear model in the spirit of Chapter 2 that uses as predictive variables, these business cycle variables as well as their interactions with the current value of the valuation ratio x_t (see equation (3.2)). This non linear model is our final predictive regression that we estimate via OLS.

Moreover, for the estimation of the LASSO model in (3.6), we do not calibrate the tuning parameter λ using the usual cross-validation exercise. Instead, we find the value of λ that corre-

sponds to a given number $k \in \{2, 3, 4, 5\}$ of active or selected predictors. By restricting the number of selected predictors to a fixed and low number, we follow Tsiakas et al. (2020) who argued for parsimony, based on the findings that two predictors, one (the other) that generates cyclical (countercyclical) forecasts of stock index returns, are sufficient to deliver statistically significant and economically valuable equity premium predictions in both expansions and recessions. While their choice is economically motivated, our objective in this chapter is to choose these few relevant business cycle variables statistically, based on the selection power of the LASSO. Nevertheless, we allow for a bit more flexibility, considering three, four and five variables.

3.3 Empirical applications

In this section, we conduct empirical investigations to evaluate the value-added of the new specification. In particular, we assess in what extent it outperforms the specification in Chapter 2, both statistically and economically.

3.3.1 Data

The benchmark dataset includes monthly observations of nine (9) US global financial and macroeconomic variables over the period ranging from January, 1971 to April, 2020, with a total of 592 observations. This time-span is the one considered in Chapter 2, and we retain it to allow for a fair comparison. The 9 variables are those used by Welch and Goyal (2008) and include:

- Monthly realized stock index variance, computed as the sum of squared daily returns on the S&P 500 index. As reported in Chauvet et al. (2015), measures of volatility have predictive ability for economic activity, with high-volatility regime providing early signals of the Great Recession, which was associated with severe financial distress and credit disintermediation;
- Net issuing activity, defined as the ratio of twelve-month moving sums of net issues by NYSE listed stocks to the total market capitalization of NYSE stocks. Welch (2004) showed that this variable explains approximately two-thirds of variation in corporate leverage ratios;
- Three-month Treasury bill which rates are influenced by many factors related to the business cycle, including demand for risk-free instruments (e.g. flight-to-safety episodes), infla-

tion expectations and monetary policy actions. Typically, T-bill rates rise during periods of business expansion and fall during recessions;

- Long-term government bond yield;
- Return on long-term government bonds;
- Default yield spread, defined as the yield difference between Moody's BAA bonds and Moody's AAA bonds. Movements in this variable incorporate signals on the level of global financial risks and the economic outlook (Stock and Watson, 1989; Lettau and Ludvigson, 2002);
- Default return spread, sharing the same informational content with default yield spread;
- Term spread as the difference between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity. There is an abundant literature that highlights the early-warning nature of term spread on the occurrence of economic recession, through liquidity preference hypothesis (Fama, 1986) or expectations of future activity (Estrella, 2005);
- Inflation, as consumer price index for all urban consumers.

As for the valuation ratio x_t , we consider the US Shiller CAPE ratio over the same period. 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 500 four-quarter totals for the quarter since 1926, with linear interpolation to monthly figures. Stock price data are monthly averages of S&P 500 daily closing prices.

Figure 3.10 in Appendix 3.6 displays the dynamics of all ten variables over the period. The monthly realized stock index variance is characterized by the typical clustering phenomenon, and the other variables show different levels of variability, with some showing peaks coinciding with NBER recession periods. The next section runs an out-of-sample exercise to evaluate the relevance of the new specification, statistically.

3.3.2 Statistical evaluation

We rely on a rolling-window approach to stress the statistical relevance of the new predictive regression model. We set the size of the rolling-window samples to 360 (30 years of monthly data) and iterate each month, estimating the new specification and the one in Chapter 2, we refer as the benchmark predictive regression. This is done for each value of the forecast horizon $\tau \in \{1, 2, \dots, 60\}$. Out-of-sample returns $r_{t+1:t+\tau}$ are computed and compared to the naive model that relies on the in-sample mean of the stock's index returns as prediction, based on the out-of-sample R-squared given by:

$$R_{OOS}^2(\tau) = 1 - \frac{\sum_{s=1}^{n_{oos}} (r_s(\tau) - \widehat{r}_s(\tau))^2}{\sum_{s=1}^{n_{oos}} (r_s(\tau) - \bar{r}(\tau))^2} \quad (3.7)$$

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 in-sample multi-period returns.

Figure 3.3 displays the results. First, for all predictive regression models, the powers are low at very short-term horizons, albeit positive, and monotonically increase to reach high levels at medium-term horizons, and then decrease for subsequent higher forecast horizons. Second, the new predictive regression that exploits the selection of business cycle variables, dominates the benchmark regression model in Chapter 2 for the four configurations we consider. Without being regular, the out-of-sample R-squared increases on average with the number of selected business cycle variables. For instance, with $\tau = 24$ (2 years), the out-of-sample R-squared of the benchmark regression model is equal to 14.03%, while the recorded values are equal to 20.50%, 20.07%, 32.51%, and 38.43%, for the LASSO selection with 2, 3, 4 and 5 selected business cycle variables. Third, instability through the forecast horizon τ increases with the number of selected business cycle variables, sign of an increased instability in the selection process, when a larger number of variables is allowed. For high number of selected variables, results available upon request indeed show that this instability becomes very large, with performances ranging from high positive values to high (in absolute value) negative values, with low predictive powers on average.

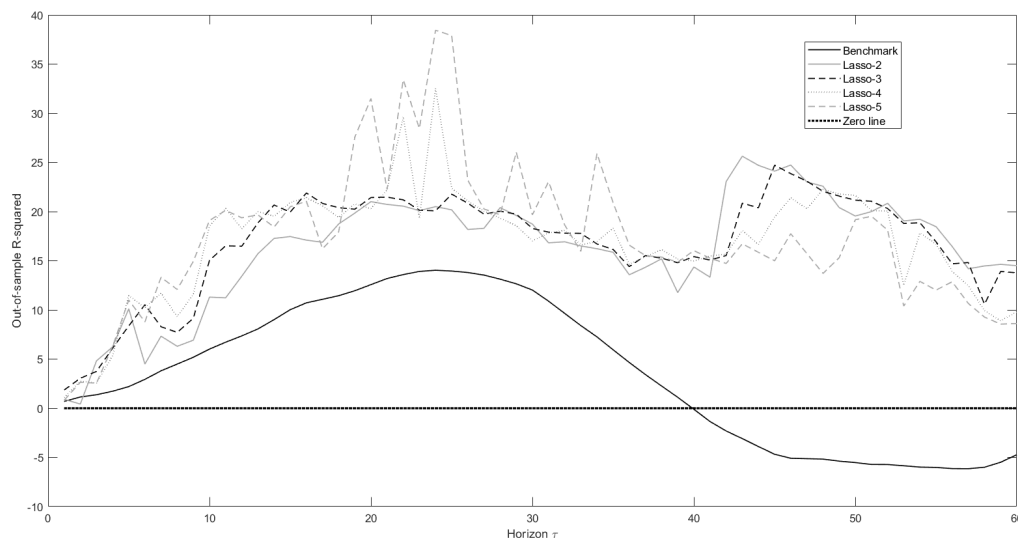


Figure 3.3: Out-of-sample predictive powers of competing predictive regressions for the S&P 500

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression, which is based on LASSO selection of business cycle variables, and their interaction with the US Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. Forecasts are obtained using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

Focusing on both performance and stability, our optimal predictive regression model appears to be the one with three selected business cycle variables. For this case, we observe an out-of-sample R-squared equal to 1.85%, 16.47% and 20.07% at the forecast horizons τ equal to 1, 12 and 24 months, whereas the same figures are equal to 0.69%, 7.36% and 14.03% at the same forecast horizons. Hence, the multivariate approach we retain, based on the selection of several business cycle variables rather than just one, is highly valuable.

For this optimal model, Table 3.1 shows for each business cycle variable and each lag-order from 0 to 18, how often each predictive variable is selected in the rolling-window forecasting procedure. The results are displayed for the forecast horizon $\tau = 1$. Recall that the optimal model considered is based on the selection of three variables over each rolling-window. This explains why the sum of the frequencies in Table 3.1 is equal to 3.

Table 3.1: Selected Variables through rolling windows for the S&P 500: $\tau = 1$

	Stock Var.	NIA	3M Tbill	LT Bong Yield	LT Bong Ret.	Default Ret. Spread	Term Spread	Term Spread	CPI
<i>Lag = 0</i>	0	0	0	0	0	0	0	67.92	0
<i>Lag = 1</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 2</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 3</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 4</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 5</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 6</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 7</i>	0	0	0	0	0	0	0	11.79	0
<i>Lag = 8</i>	0	0	0	0	0	0	0	98.11	0
<i>Lag = 9</i>	0	0	0	0	0	0	0	90.57	0
<i>Lag = 10</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 11</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 12</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 13</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 14</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 15</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 16</i>	0	0	0	0	0	0	0	0	0
<i>Lag = 17</i>	0	0	0	0	0	0	0	31.60	0
<i>Lag = 18</i>	0	0	0	0	0	0	0	0	0

Notes: the table displays the selection's frequencies (in %) of business cycle variables through rolling-windows, when predicting out-of-sample returns of the S&P 500 at the lag-order $\tau = 1$, based on our optimal predictive regression model that selects three business cycle variables. "NIA" refers to net issuing activity, "Var." to variance, and "Ret." to returns.

The results show in a remarkable way the importance of the term spread in conjunction with the US Shiller CAPE ratio, in forecasting the future dynamics of prices at one month horizon. Indeed, only this variable in its different versions (lag-orders) is selected. These results therefore confirm those of Moench and Tobias (2021) and Chapter 2, which underlined the strong predictive content of this business cycle variable. However, while Chapter 2 consider only the lag-order 17, based on stylized facts reported in the literature, our approach selects 5 lag-orders including the lag-order 17. Precisely the selected ones are 0, 7–9, and 17, with respective frequencies 67.92%, 11.79%, 98.11%, 90.57% and 31.60%. Remark that the Chapter 2's celebrated lag-order 17 ranks fourth in term of occurrence. This feature of the selection procedure underlying our predictive model, explains why it outperforms their predictive model.

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Tables 3.8 and 3.9 in Appendix 3.6 displays the same results for the forecast horizon τ equal to 12 (one year) and 24 (two years) months. Overall, we observe the same patterns, hence reinforcing the central role of the term spread. Indeed, contemporaneous and lagged values of this variable are the only selected business cycle predictors. The only exception is for $\tau = 24$ with the three-month Treasury bill at the lag-order 1, which is selected, albeit very marginally. It is interesting to note, by observing the tables 3.1, 3.8, and 3.8, that the number of selected variables increases with the forecast horizon τ . This can be explained by the fact that the more distant the horizon is, the higher is the uncertainty in forecasting returns, and the more it becomes necessary to mobilize a larger set of information to achieve a reliable prediction.

The results displayed show the relevance of our new predictive regression model that exploits

the non-linear effect (interaction) between selected business cycle variables and the US Shiller CAPE ratio as the valuation ratio. As an additional investigation, we check the robustness of our results to the choice of the valuation ratio, considering the book-to-market ratio. It is well known that this variable has significant predictive powers on the prices's dynamics (Kothari and Shanken, 1997; Pontiff and Schall, 1998; Lewellen, 2004, etc.).³

Figure 3.4, which is the analogue of Figure 3.3 compares the out-of-sample R-squared of the competing predictive regression models. The patterns are the same as those in Figure 3.3 for the US Shiller CAPE ratio as the valuation ratio. The new predictive regression models in its four variants consistently dominates the benchmark model in Chapter 2.

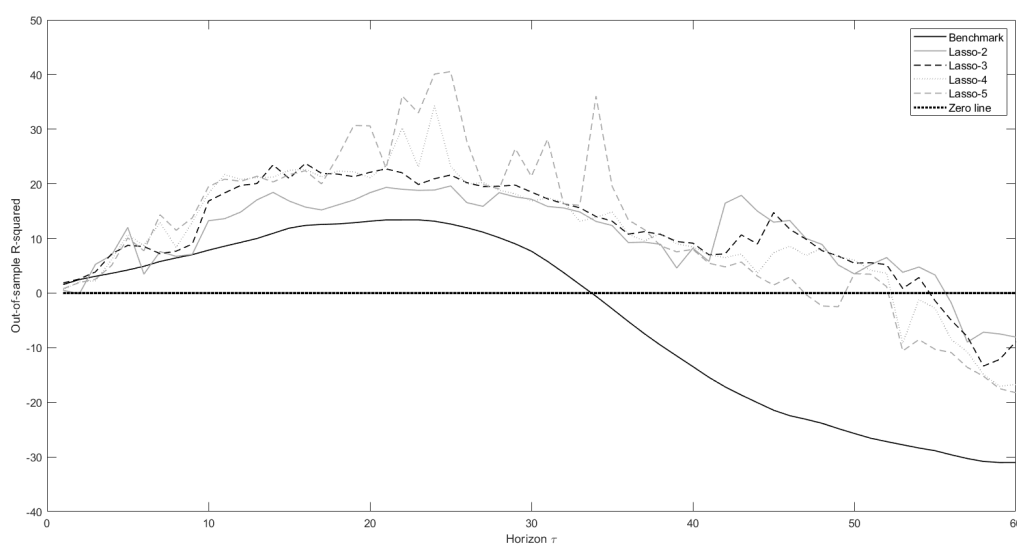


Figure 3.4: Out-of-sample predictive powers of competing predictive regressions for the S&P 500

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new model which is based on a LASSO selection of business cycle variables, and their interaction with the US book-to-market ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. Forecasts are obtained using monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

Once again, the version with 3 business cycle variables appears as the less volatile through the lag-orders τ .⁴

³Figure 3.11 in Appendix 3.6 displays the dynamic of the US book-to-market ratio.

⁴Results available upon request show similar trends when using the dividend yield as valuation ratio.

3.3.3 Economic evaluation

In this section, we follow the methodology of Chapter 2 and investigate the economic value of our new predictive regression model. Formally, we rely on the mean-variance framework of Markowitz (1952) and propose an allocation exercise between the S&P 500 index with return r_t at month t and a risk-free instrument (cash). With w_t the share of the wealth allocated to the index, the optimal solution writes:

$$\widehat{w}_t = \frac{1}{\gamma} \frac{\widehat{R}_{t+\tau}}{\widehat{\sigma}_{t+\tau}^2}, \quad (3.8)$$

with γ the relative risk aversion parameter, $\widehat{R}_{t+\tau}$ the forecast risk premium at the forecast horizon τ using a given predictive model (the benchmark or the one proposed in this chapter) for the returns r_t , and $\widehat{\sigma}_{t+\tau}^2$ 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).⁵

Remark that \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:

$$r_{p,t+j} = w_t r_{t+j}. \quad (3.9)$$

Using a proportional transaction cost c , the portfolio's net return is computed as:

$$\tilde{r}_{p,t+j} = r_{p,t+j} - c |\widehat{w}_t - \widehat{w}_t^+|, \quad (3.10)$$

with \widehat{w}_t^+ the weight in the risky stock index at time t before rebalancing. We evaluate the economic value of a given strategy through the realized value of the certainty equivalent return (CER) given by:

$$CER_p = \widehat{\mu}_p - \frac{1}{\gamma} \widehat{\sigma}_p^2, \quad (3.11)$$

with $\widehat{\mu}_p$ and $\widehat{\sigma}_p^2$ the mean and variance of the net portfolio's returns $\tilde{r}_{p,t+j}$.

Table 3.2 displays the CERs for the four versions of our predictive regression, as well as those from the benchmark model. As in Chapter 2, the CERs are multiplied by 12 to interpret them

⁵As in Chapter 2, the rebalancing horizon τ coincides with the forecast horizon for the risk premium.

Table 3.2: Certainty equivalent returns for alternative predictive regressions for the S&P 500: $\gamma = 3$

Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	5.06	5.27	4.88	4.61	2.75
2	7.05	6.26	6.34	5.00	2.53
3	5.77	5.49	4.04	3.50	2.60
4	4.53	5.67	4.82	5.45	1.81
5	2.19	2.44	2.22	2.28	0.67
6	2.14	2.82	4.24	3.69	1.76
7	0.76	0.94	1.68	1.56	0.85
8	1.63	1.05	1.02	1.24	0.82
9	0.60	0.17	-1.01	-0.66	0.31
10	1.91	1.91	1.20	1.66	-0.58
11	0.60	-0.72	-0.72	-0.72	-0.08
12	0.99	0.00	0.31	0.84	0.91

Notes: For the risk aversion parameter γ equal to 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

as the annual risk-free rate that an investor would be willing to accept to not hold the risky portfolio. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Results show that the LASSO selection adds economic value, because the highest CER is recorded for a given version of the new predictive regression. For instance, with τ equal to one month, the LASSO selection of three business cycle variables leads to a CER of 5.27% while the recorded value is equal to 2.75% for the benchmark model. The difference in CERs is thus equal to 2.52%, meaning that an investor would be willing to pay this level of utility gains or annual portfolio management fees to switch from the benchmark model to the new proposed model.

Remark that as the number of selected business cycle variables increases, our new predictive regression is less dominant. Indeed, while we observe ten forecast horizons where the LASSO-2 and LASSO-3 are the dominant strategies, only two (none) forecast horizons appeared for the LASSO-4 (LASSO-5). This arises from the instability of our predictive regression when the number of targeted business cycle variables increases (see Figure 3.3), which reduces the

Table 3.3: Certainty equivalent returns for alternative predictive regressions for the S&P 500: $\gamma = 5$

Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	3.55	3.87	3.28	3.39	1.40
2	5.54	4.91	4.84	3.58	1.22
3	4.39	3.61	2.23	2.35	1.36
4	3.44	4.53	3.92	4.34	0.74
5	1.67	2.00	1.71	1.51	0.21
6	1.58	2.33	3.90	3.42	0.93
7	0.46	0.39	0.80	0.51	0.48
8	0.18	-0.38	-0.50	0.12	-0.15
9	-0.23	-0.51	-1.48	-1.11	-0.14
10	1.39	0.72	0.34	1.32	-0.81
11	-1.12	-2.45	-1.10	-1.04	-0.69
12	-0.65	-1.23	-1.08	-0.80	-0.46

Notes: For the risk aversion parameter γ equal to 5, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

portfolio's net returns due to higher turnovers and transaction costs.

Table 3.3 displays the same results for $\gamma = 5$. The results are qualitatively similar to those reported in Table 3.2, except that the dominance over the benchmark model is less clear-cut. This is expected, as a higher risk aversion parameter γ is detrimental to unstable portfolio's strategies with higher volatilities. For robustness checks, Table 3.10 in Appendix 3.6 reports the same figures with the book-to-market as the valuation ratio. We observe the same patterns.

3.4 Evidence for US sectors

In this section, we investigate whether the relatively good performance of our new predictive regression holds across US industries.

3.4.1 Setup and universe of stocks for sector indices

Sector-level risk premia fluctuations are evident, demonstrated by Fama and French (1993) three-factor model. Predicting out-of-sample sectors' returns is valuable for asset allocation and can enhance portfolio performance in industry rotation-focused investment strategies.

There are some works that focused on this interesting issue, based on the idea that investors often pursue an industry rotation strategy or concentrate their holdings in sectors in which they have more personal experience or private advantages (Kacperczyk et al., 2005; Roche et al., 2013; Narayan et al., 2017; Pham, 2021, etc.). For instance, Kacperczyk et al. (2005) found that managers whose portfolios deviate from a well-diversified portfolio and are concentrated in a few industries perform better. Roche et al. (2013) argued that because of financial constraints and limited borrowing opportunities, household investors hold underdiversified portfolios with a few industries. Jame and Tong (2014) suggest that industry-level categorization influences the investment decisions of retail investors and even has a significant impact on asset prices. Under this type of behaviour, accurate predictive regression models should report heterogeneity in predictive performances both statistically and economically. This feature was documented by Pham (2021) who showed that stock returns are more predictable in industries with a large average firm size, and that dividend yields are not good proxies for predicting returns in some small industries.

Sector-level predictability could vary across industry sectors. Different sectors in the stock market may respond differently to various economic conditions, market cycles, and geopolitical events. Several factors influence the performance of sector stock indices, including industry-specific metrics, macroeconomic indicators, technological advancements, government policies, and global trends. Hence, some sectors exhibit more predictability than others. This divergence could stem from investors gaining more valuable pricing insights in specific industries or disparities in information possession and processing across sectors (Westerlund and Narayan, 2015). Phan et al. (2015) investigate the factors influencing out-of-sample predictability for each sector, focusing on industry characteristics. The study reveals robust evidence linking return predictability to specific industry traits, such as book-to-market ratio, dividend yield, size, price/earnings ratio, and trading volume.

Sector-level indicators are frequently utilized in predictability studies in the literature. However, models that explore the non-linear effect (interaction) between time-varying business cycle variables and the Shiller CAPE ratio as the valuation measure are seldom investigated at the sector level. Stalla-Bourdillon (2022) suggested sector-level returns forecasting using micro-CAPE or micro-PE. Similarly, we examine the key sectors in the US by applying our new predictive model on the Shiller CAPE ratio for each individual sector and subsequently on the aggregated dividend yield.

We analyze 7 of the main sectors in the US from the Global Industry Classification Standard economic taxonomy,⁶ which are Materials, Industrials, Health Care, Communication Services,⁷ Utilities, Financials and Information Technology sectors. Standard & Poor's has distributed in these sectors the most important listed companies in the US by market capitalizations (large- and mid-caps).

Our dataset includes monthly observations from S&P GICS indices of the prices and earnings of the seven (7) US individual sectors we consider over the period ranging from January, 1992 to April, 2020. Data are from Bloomberg. One exception is made for the Information Technology sector as we prefer the NASDAQ Composite index, which is a much more representative stock index of the broad US technology sector.⁸ We have increased the length of our database using Thomson Reuters Datastream sector indices from January, 1973 through December, 1991. The dataset includes a total of 568 observations. Figure 3.5 displays the dynamics of the seven US individual sectors' Shiller CAPE ratio we consider over the period.

As for the prior sections, we consider the US industries' Shiller CAPE ratio over the period. The ratio is computed based on a dataset that consists of monthly industries' stock index prices and earnings data and the US consumer price index (to allow conversion to real values). Stock price data are monthly averages of US industries' indices daily closing prices. Monthly earnings data are computed from the industries' indices four-quarter totals for the quarter since 1973, with

⁶In August 1999, in collaboration with Morgan Stanley Capital International (MSCI), Standard & Poor's issued the Global Industry Classification Standard (GICS), which is an economic taxonomy of business sectors. This classification is the benchmark for the S&P and MSCI indices in which each company is categorized according to its core business. These indices are the reference in the financial industry.

⁷The Telecommunications sector has been renamed Communication Services in November 2018 after the sector has been broadened.

⁸The Nasdaq Composite is a stock market index that includes almost all stocks listed on the Nasdaq stock exchange (more than 2500 stocks). The prices and Earnings of the NASDAQ Composite index are used from December, 2001 to April 2020. Data are from Bloomberg.

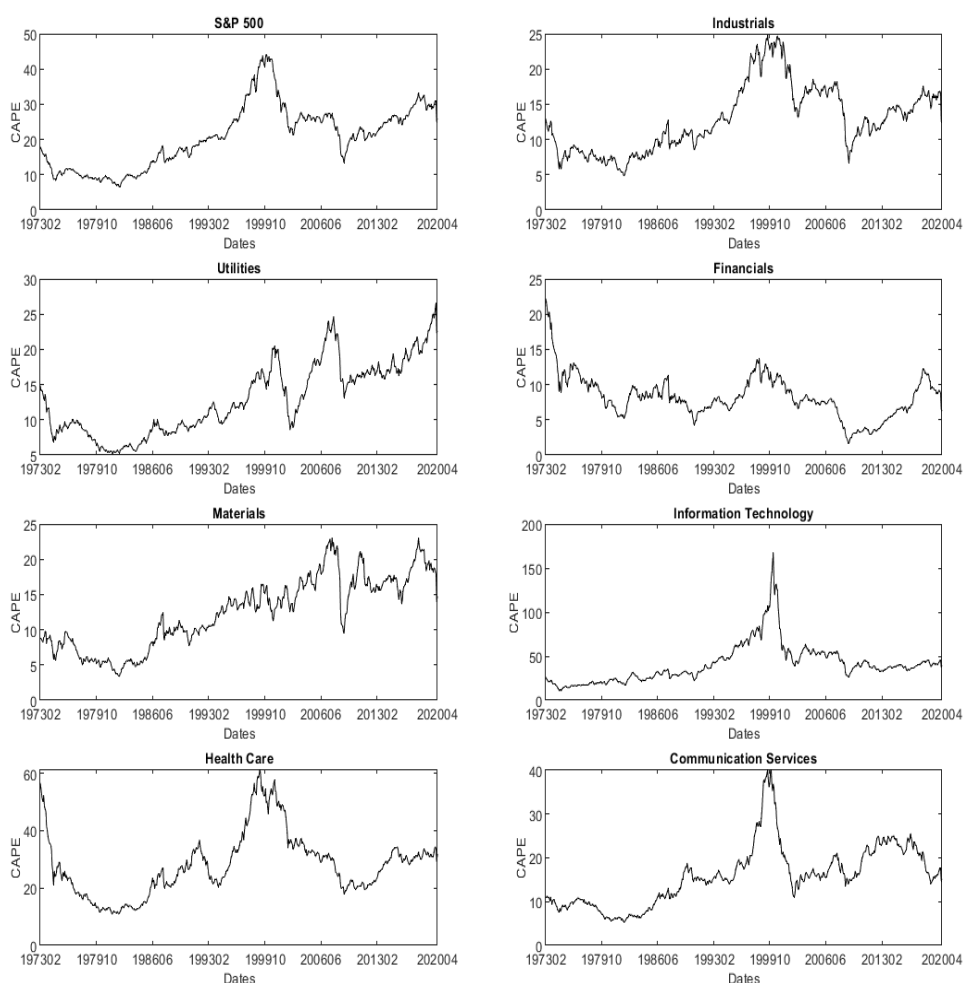


Figure 3.5: Dynamic of the US individual sectors' Shiller CAPE ratio: 1973/02-2020/04

Notes: The ratios are computed based on a dataset that consists of monthly individual sectors' stock index prices, earnings data and the consumer price index (to allow conversion to real values). Monthly earnings data are computed from quarterly totals since 1963, with linear interpolation to monthly figures. 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 1963.

linear interpolation to monthly figures. Because there was no industries earnings prior to 1973, we had to estimate it. For each individual sector, we estimated a regression for the period 1973 to 2020. The industries' earnings from January 1963 to December 1972 are approximated with predicted regression equations using the S&P 500 earnings. The R^2 of regressions has an average of 65.30%. The industries' earnings from January 1963 to December 1972 are approximated with predicted regression equations using the S&P 500 earnings. The average correlation for the

period 1973 to 2020 between the US individual industries' Shiller CAPE ratio computed using the industries' earnings and that computed using the predicted industries' earnings is 83.11%.

3.4.2 Statistical Evidence

We use exactly the same method as the section 3 with the overall S&P 500. Recall that we rely on a rolling-window approach to stress the statistical relevance of the new predictive regression model on the US individual sectors, using the same size of the rolling-window samples to 360 (30 years of monthly data) and iterate each month, estimating the new specification in (3.6). The specification in Chapter 2 is again referred as the benchmark predictive regression. This is done for each value of the forecast horizon $\tau \in \{1, 2, \dots, 60\}$. The out-of-sample returns per individual sector are computed and compared to the naive model that relies on the in-sample mean of the stock's index returns as prediction, based on the out-of-sample R-squared in (3.7).

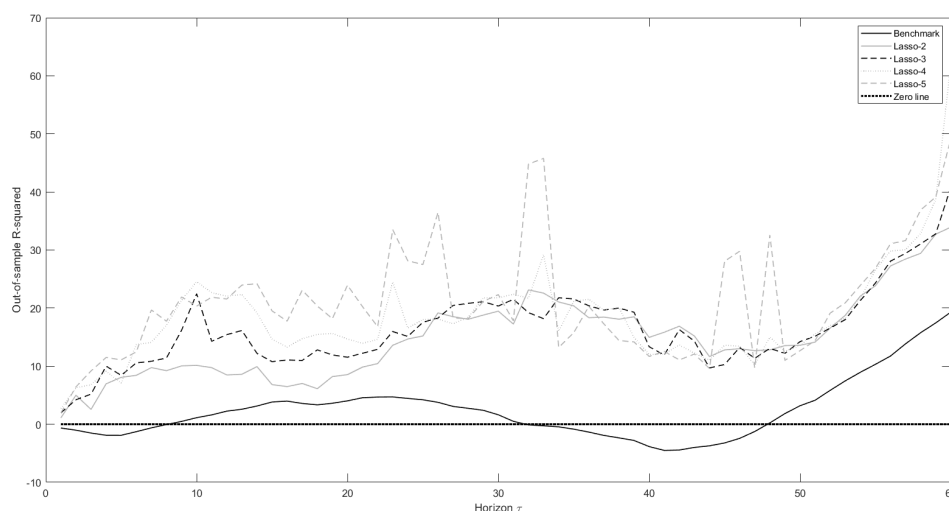


Figure 3.6: Out-of-sample predictive powers of competing predictive regressions for the US Industrials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Industrials sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

Figure 3.6 displays the results of the out-of-sample predictive regression models for the US Industrials sector. The pattern is relatively similar to the one for the overall S&P 500. The powers are low at very short-term horizons, albeit positive, and monotonically increase to reach

high levels at medium-term horizons. The new predictive regression for Industrials sector that exploits the selection of business cycle variables, dominates the benchmark regression model in Chapter 2 for the four configurations we consider. The out-of-sample R-squared are positive and increase on average with the number of selected business cycle variables. Remark that the out-of-sample R-squared of the benchmark regression model turns positive and starts to increase only from horizons τ equal to 48 months and stays around 0 for lower horizons. The instability through the forecast horizon τ increases with the number of selected business cycle variables, sign of an increased instability in the selection process, when a larger number of variables is allowed. Similarly to the overall S&P 500, for high number of selected variables, results show that this instability becomes very large.

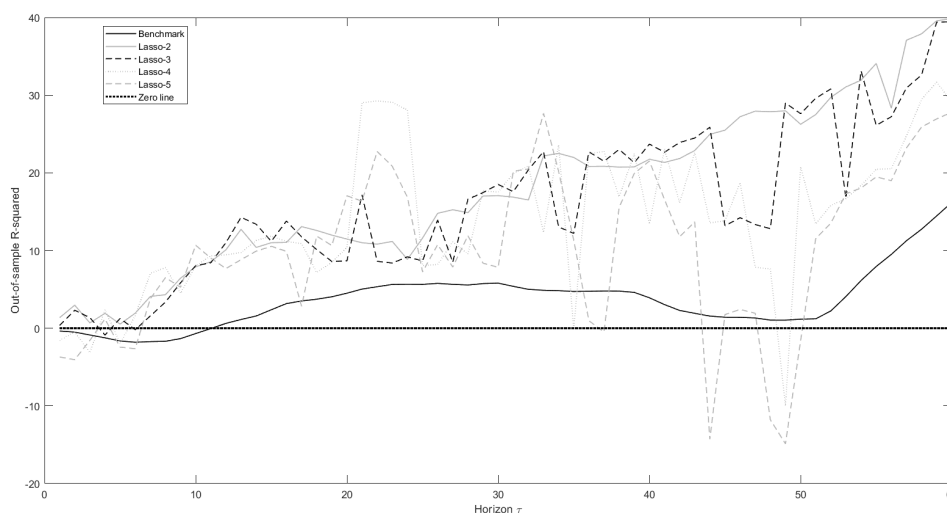


Figure 3.7: Out-of-sample predictive powers of competing predictive regressions for the US Information Technology sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Information Technology sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

Figure 3.7, and Figures 3.12-3.14 in Appendix 3.6 present very similar results for the Information Technology, Communication Services, Utilities and Materials sectors, respectively. The powers are low at very short-term horizons, albeit mostly positive, and monotonically increase to reach high levels at medium-term horizons. Again, the new predictive regression that exploits the selection of business cycle variables, dominates, for each of these sectors, the benchmark re-

gression model for the four configurations we consider. The out-of-sample R-squared are almost always positive and increase on average with the number of selected business cycle variables. The instability is also increased in the selection process when a larger number of variables is allowed. Remark that the out-of-sample R-squared of the benchmark regression model for Communication Services sector turns negative and monotonically decreases from horizons τ equal to 32 and for the Utilities sector, the out-of-sample R-squared of the benchmark regression model is negative for every horizon τ . For these two sectors, the new predictive model confirms its superiority. However, for high number of selected variables, results for the Information Technology sector show that the instability becomes even larger than for the other sectors, with the predictive power falling below the one of the benchmark and even turning negative for some forecast horizon τ .

Figure 3.15 in Appendix 3.6 presents the results for the Financials sector. In this specific sector, both our new model and the benchmark model fall short of outperforming the naive model, with negative out-of-sample R-squared values across all horizons τ . Nevertheless, our predictive regression model for the Financials sector, which employs selected business cycle variables, outperforms the benchmark regression model introduced in Chapter 2 across the four considered configurations, showing higher out-of-sample R-squared values. These R-squared values increase for each forecasting horizon as the number of selected business cycle variables grows.

Before the turn of the century, the Financials sector's valuation increased significantly, in line with the overall stock market and most other sectors. During this period, the Financials sector held substantial market weight. However, its decline in valuation, although less severe than the broader stock market and other sectors, was still noticeable. Leading up to the Global Financial Crisis of 2007-2009, the Financials sector did not experience noteworthy upward valuation shifts. The crisis inflicted such profound damage that it led to further valuation declines. It took nearly a decade, until 2018, for the Financials sector to fully recover.

This unique behavior observed in the sectors we consider in this section underscores the complexities inherent in predicting the Financials sector's performance. Recent research suggests that predictability of Financials sector stock returns depends on specific factors such as book-to-market ratios, profitability measures, and cost of capital related metrics. The model proposed by Adrian et al. (2015) helps address anomalies for Financials sector stocks by incorporating an

aggregate Financials sector profitability measure (return-on-equity) and a return spread factor (Financials minus non-Financials).

One sector exhibiting distinct characteristics is the Health Care sector, as depicted in Figure 3.16 in Appendix 3.6. Our new predictive model does not outperform the benchmark regression model in Chapter 2 until the horizon τ reaches 32 months. It is only from this point onward that our new model demonstrates better and progressively increasing predictive power across all four configurations we considered.

However, it's important to note that the benchmark regression model's predictive power in Chapter 2 for the Health Care sector displays the most stable increase among all individual sectors. It also attains the highest out-of-sample R-squared values for longer horizons, outperforming all individual sectors. In contrast to other individual sectors and the overall S&P 500, where predictability instability grows for longer horizons τ and with the number of selected business cycle variables, the predictability of the Health Care sector is notably more volatile for shorter horizons (1 to 32 months). It then stabilizes for horizons τ exceeding 32 months.

The Health Care sector is often characterized as acyclical or non-cyclical, meaning it is relatively agnostic to the business cycle and, thus, is not strongly influenced by changes in economic conditions and the business cycle variables used in our model. The performance of the Health Care sector and its demand for goods or services are relatively stable and not highly correlated with the fluctuations in the overall economy. The Health Care sector is known for providing essential services and products that are needed regardless of economic conditions. Medical care and pharmaceuticals, for instance, remain essential whether the economy is booming or facing a recession (Dillender et al., 2021).

As a result, the Health Care sector tends to be less affected by economic downturns, without being necessary recession proof (Erkmen et al., 2022). Consequently, our new predictive model with the four configurations we considered, with 2, 3, 4, and 5 selected business cycle variables, struggles to outperform the benchmark regression model in Chapter 2. Moreover, the Health Care sector is considered a defensive segment within the Financials industry. Its inherent traits contribute to its lower volatility when compared to other sectors. This lower volatility can act as a stabilizing force within an investment portfolio, especially during turbulent economic periods.

When focusing on both performance and stability for each individual sector, similarly to the

overall S&P 500, our optimal predictive model seems to be the one with three selected business cycle variables. The only exception is for the Information Technology sector, for which the optimal predictive model appears to be the one with two selected business cycle variables. Table 3.4 presents the out-of-sample R-squared at the forecast horizons τ equal to 1, 12, and 24 months of the optimal model for individual sectors and the benchmark.

Table 3.4: Out-of-sample R-squared at the forecast horizons τ equal to 1, 12 and 24 months

	Optimal Model			Benchmark		
	$\tau = 1$	$\tau = 12$	$\tau = 24$	$\tau = 1$	$\tau = 12$	$\tau = 24$
Industrials	1.95	15.42	15.11	-0.66	2.25	4.44
Information Technology*	1.35	10.10	8.86	-0.36	0.62	5.66
Materials	2.65	24.69	18.44	-0.46	3.11	11.82
Utilities	-1.91	20.42	14.76	-0.18	-18.43	-24.49
Communication Services	5.02	12.73	28.32	-0.71	9.86	6.83
Financials	-3.74	-7.31	-11.48	-2.59	-9.50	-16.36
Health Care	-4.21	0.10	18.61	-1.10	6.04	20.82

Notes: The Table displays the out-of-sample predictive powers of the optimal version of our new predictive regression for each individual sectors, which is based on LASSO selection of three business cycle variables, except for Information Technology* sector, which is based on LASSO selection of two business cycle variable and the predictive regression in Chapter 2 referred as "benchmark." We emphasize in bold the highest Out-of-sample R-squared. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

We observe a higher out-of-sample R-squared at the forecast horizons τ equal to 1, 12, and 24 months for each individual sector compared to the benchmark, with the exception of the Health Care sector and a few other exceptions at a short horizon τ equal to 1 month. Hence, similar to the overall S&P 500, the multivariate approach we retain, based on the selection of several business cycle variables rather than just one, is highly valuable.

Similarly to Table 3.1, Table 3.5 displays, for the optimal model per individual sector and for each lag-order from 0 to 18, how often the term spread is selected in the rolling-window forecasting procedure. Only the frequency for the term spread is represented because, as with the overall S&P 500, only this variable is selected in its different versions (lag-orders).

Table 3.5: Selection frequencies of the term spread for the US individual sectors through rolling windows: $\tau = 1$

	Financials	Health Care	Industrials	Information Technology*	Materials	Utilities	Communication Services
Lag=0	20.86	0	72.19	95.72	26.74	100.00	0
Lag=1	0	77.01	0	0	0	0	6.42
Lag=2	0	0	0	0	0	0	73.26
Lag=3	66.84	0	0	0	65.24	0	26.74
Lag=4	4.28	0	0	0	0	27.27	0
Lag=5	0	0	0	0	0	0	0
Lag=6	0	24.06	0	0	0	0	0
Lag=7	72.19	93.58	26.74	31.55	31.55	0	2.67
Lag=8	0	0	100.00	72.73	73.26	0	0
Lag=9	100.00	0	0	0	0	0	0
Lag=10	0	0	0	0	0	100.00	90.91
Lag=11	19.79	0	24.60	0	0	72.73	100.00
Lag=12	0	0	2.14	0	0	0	0
Lag=13	0	0	0	0	26.20	0	0
Lag=14	0	0	1.60	0	0	0	0
Lag=15	16.04	100.00	72.19	0	0	0	0
Lag=16	0	0	0	0	0	0	0
Lag=17	0	0	0	0	68.45	0	0
Lag=18	0	5.45	0.53	0	8.56	0	0

Notes: the table displays the selection's frequencies (in %) of the term spread amongst business cycle variables through rolling-windows, when predicting out-of-sample returns at the lag-order $\tau = 1$, based on our optimal predictive regression model that selects three business cycle variables, respectively two business cycle variables for the Information Technology sector*.

The results presented are for the forecast horizon $\tau = 1$. The optimal model considered involves the selection of three variables for each sector, except for the Information Technology sector, where two variables are chosen. Due to this selection process, the sum of the frequencies in Table 3.5 per column is equal to 3, except for the Information Technology sector, where it is equal to 2.

Once more, the results underscore the significant role of the term spread alongside the US individual sectors' Shiller CAPE ratio in forecasting price dynamics at a one-month horizon. These findings for US industry portfolios confirm the earlier studies of Moench and Tobias (2021) and Chapter 2, which highlighted the robust predictive power of this business cycle variable.

Tables 3.11 and 3.12 in Appendix 3.6 display the results for the forecast horizons τ equal to 12 (one year) and 24 (two years) months. Notably, we observe consistent patterns across these horizons for each individual sector, further reinforcing the significant role of the term spread in the forecasting process.

The results presented above reaffirm the importance of our new predictive regression model, which leverages the non-linear effect (interaction) between selected business cycle variables and the US individual sectors' Shiller CAPE ratio as the valuation ratio. To further investigate the robustness of our findings regarding the choice of the valuation ratio, we also consider the dividend-price ratio per individual sectors. Figure 3.17 in Appendix 3.6 illustrates the dynamics of the US individual sectors' dividend yield ratios.

A wide literature exists for the dividend-price ratio (dividend yield) as valuation ratio (Rozeff, 1984; Campbell and Shiller, 1988; Cochrane, 1991; Fama and French, 1988; Goetzmann and Jorion, 1993; Kothari and Shanken, 1997; Campbell and Shiller, 1998, 2005; Menzly et al., 2004; Lewellen, 2004, etc.), which aim at understanding the predictive ability of the dividend-price ratio. They found statistical validity of the predictive evidence of the dividend-price ratio and subsequent long-term returns.

Figures 3.8 and 3.9 display the out-of-sample R-squared of the predictive regression models with the dividend yield for respectively the Communication Services and Materials sectors. The patterns are the same as those reported in Figures 3.6 and 3.7 for the Shiller CAPE ratio as the valuation ratio. The new predictive regression models, in its four variants, consistently dominates the benchmark model in Chapter 2. Figures 3.18-3.22 in Appendix 3.6 report the

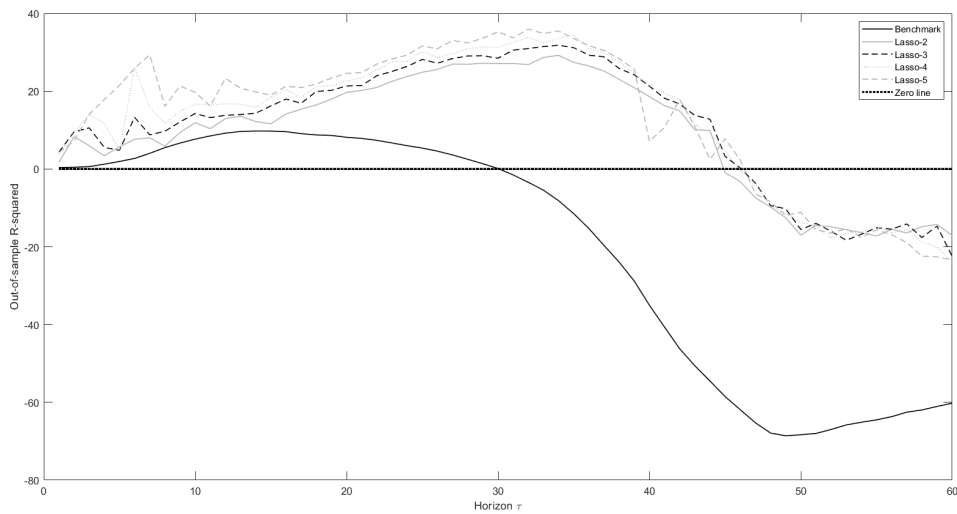


Figure 3.8: Out-of-sample predictive powers of competing predictive regressions for the US Communication Services sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Communication Services sector Dividend Yield as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

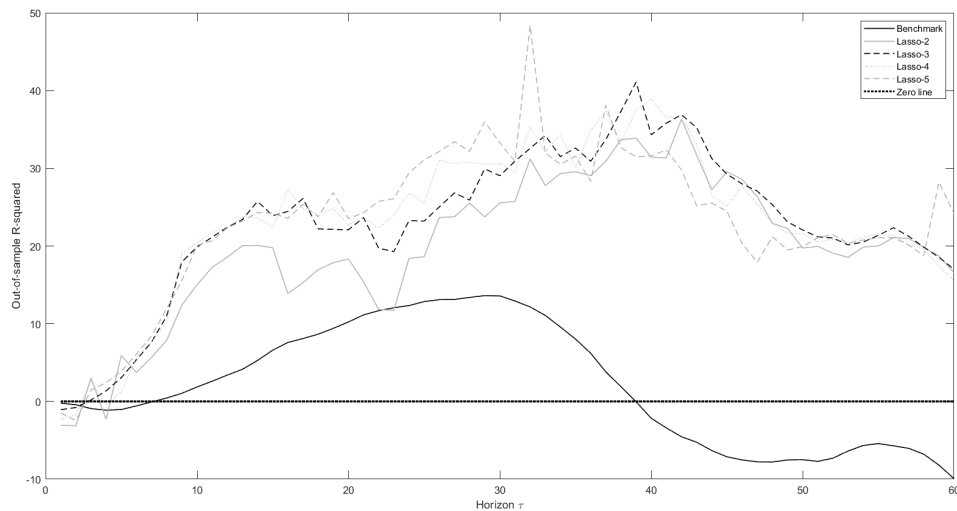


Figure 3.9: Out-of-sample predictive powers of competing predictive regressions for the US Materials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Materials sector Dividend Yield as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

same patterns for the Industrials, Information Technology, Utilities and Health Care sectors, respectively. Surprisingly, the results tend to be better for the Financials sector with positive out-of-sample R-squared at shorter horizons τ and more positive out-of-sample R-squared for the LASSO selection with 4 and 5 selected business cycle variables at longer horizons τ .

Once again, the version with 3 business cycle variables appears as the less volatile through the lag-orders τ .⁹

3.4.3 Economic Evidence

We use exactly the same method as the section 3 for the economic evaluation of our new model predictive model on individual US sectors through the realized value of the certainty equivalent return (CER) given by (3.11).

Tables 3.6 and 3.7 display the CERs for the four versions of our predictive regression for the US Industrials sector and the US utilities sector respectively, as well as those from the benchmark model. Results show that the LASSO selection for US individual sectors adds economic value, because the highest CER is recorded for a given version of the new predictive regression. For instance, for the US Industrials sector, with τ equal to one month, the LASSO selection of five business cycle variables leads to a CER of 5.26% while the recorded value is equal to 4.88% for the benchmark model. The difference in CERs is thus equal to 0.38%, meaning that an investor would be willing to pay this level of utility gains or annual portfolio management fees to switch from the benchmark model to the new proposed model. The Industrials sector has only two forecast horizons τ , where the benchmark has higher CERs.

Remark that the results show a lower dominance of the optimal model with 3 selected variables. The variability of our predictive regression dominance is closely tied to the characteristics of the individual sectors in the US. For instance, for the Industrial sector as displayed in Table 3.6, while we observe nine forecast horizons where the LASSO-4 and LASSO-5 are the dominant strategies, none (only one) forecast horizons appeared for the LASSO-2 (LASSO-3). For the Information Technology sector, as displayed in the upper panel of Table 3.13 in Appendix 3.6, while we observe seven forecast horizons where the LASSO-2 are the dominant strategies, only three forecast horizons appeared for the LASSO-5. Hence, the industrials sector suggests using

⁹Results available upon request show similar trends when using the book-to-market ratio as valuation ratio.

Table 3.6: Certainty equivalent returns for alternative predictive regressions for the US Industrials sector: $\gamma = 3$

Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	6.23	4.65	5.06	5.26	4.88
2	3.37	3.76	4.92	6.16	4.69
3	3.58	6.07	6.67	5.73	5.17
4	7.00	8.02	8.18	7.09	4.48
5	6.11	8.41	6.98	6.73	4.37
6	4.81	7.82	7.00	7.84	4.98
7	3.63	3.40	4.48	4.77	4.36
8	3.43	4.36	4.80	3.18	4.56
9	3.80	3.85	3.29	5.94	4.93
10	3.82	3.69	3.33	3.78	4.68
11	2.36	2.36	5.81	5.45	3.59
12	2.78	2.54	2.74	3.40	4.58

Notes: For the risk aversion parameter γ equal to 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US Industrials sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

more business cycle variables to achieve increased utility gain for our new predictive model in short-term periods. On the other hand, the Information Technology sector would only necessitate adding one extra variable to the term spread. Our new predictive model nevertheless validates the utility gain over the benchmark for the US sectors in its different configurations considered. Table 3.14 in Appendix 3.6 presents the results for the Materials and Financials sectors.

The Health Care sector is the only sector for which the benchmark has higher CERs for almost all forecast horizons τ (except for $\tau = 1$ month), as shown by the results displayed in Table 3.15 in Appendix 3.6. Meanwhile, the Health Care sector presents the second highest CERs, on average, after those of the Information Technology sector.

The results for $\gamma = 5$, displayed in Table 3.16 in Appendix 3.6, are qualitatively similar to those reported in tables 3.6 and 3.7.

The results confirm the robustness of our new predictive model.

Table 3.7: Certainty equivalent returns for alternative predictive regressions for the US Utilities sector: $\gamma = 3$

Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	4.47	3.62	4.62	3.16	4.42
2	5.20	3.63	4.21	3.40	4.75
3	3.97	4.12	4.49	3.68	4.43
4	6.26	3.75	4.52	4.22	4.42
5	4.29	4.60	4.80	4.54	3.80
6	4.73	3.57	3.78	3.56	3.91
7	4.06	4.78	5.71	5.93	3.12
8	2.30	2.83	3.79	3.79	2.93
9	3.67	5.05	3.68	3.22	3.11
10	3.85	3.67	1.97	2.27	2.70
11	4.19	3.12	3.85	3.38	2.90
12	3.61	3.16	4.13	3.74	2.82

Notes: For the risk aversion parameter γ equal to 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US Utilities sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

3.5 Conclusion

The literature reports evidence of forecast ability at short-term horizons is still weak. In Chapter 2, we presented a pioneering study that advances short-term prediction of stock index returns by incorporating mean reversion in valuation ratios and the early-warning properties of key business cycle variables, leading to significant statistical and economic gains.

The use of a data-rich environment and parsimonious estimation techniques further strengthens the model's predictive power. This research contributes to the growing body of literature on stock return prediction and offers practical implications for investors seeking to make informed decisions in short-term horizons. Empirical applications of our extended model demonstrate its efficacy in generating substantial and statistically significant gains in short-term stock return prediction. The model's ability to capture the intricate interplay between valuation ratios, a large set business cycle variables, and stock prices provides valuable insights for investors.

The robustness of the newly proposed predictive model is thoroughly validated across a comprehensive spectrum of factors, notably encompassing the selection of the valuation ratio (whether it is the Shiller CAPE ratio, the book-to-market ratio, or the dividend yield) as well as across various individual sectors within the US. This rigorous validation process underscores the reliability and versatility of the model, affirming its capability to yield consistent and meaningful insights regardless of the valuation metric employed or the specific sector under scrutiny.

Derived from an extensive range of variables, these results have significant implications for enhancing the comprehension of asset price dynamics and mean reversion in conjunction with the business cycle. Furthermore, their practical significance extends to dynamic asset allocations, particularly within sector allocation strategies.

3.6 Appendix: Additional Figures and Tables

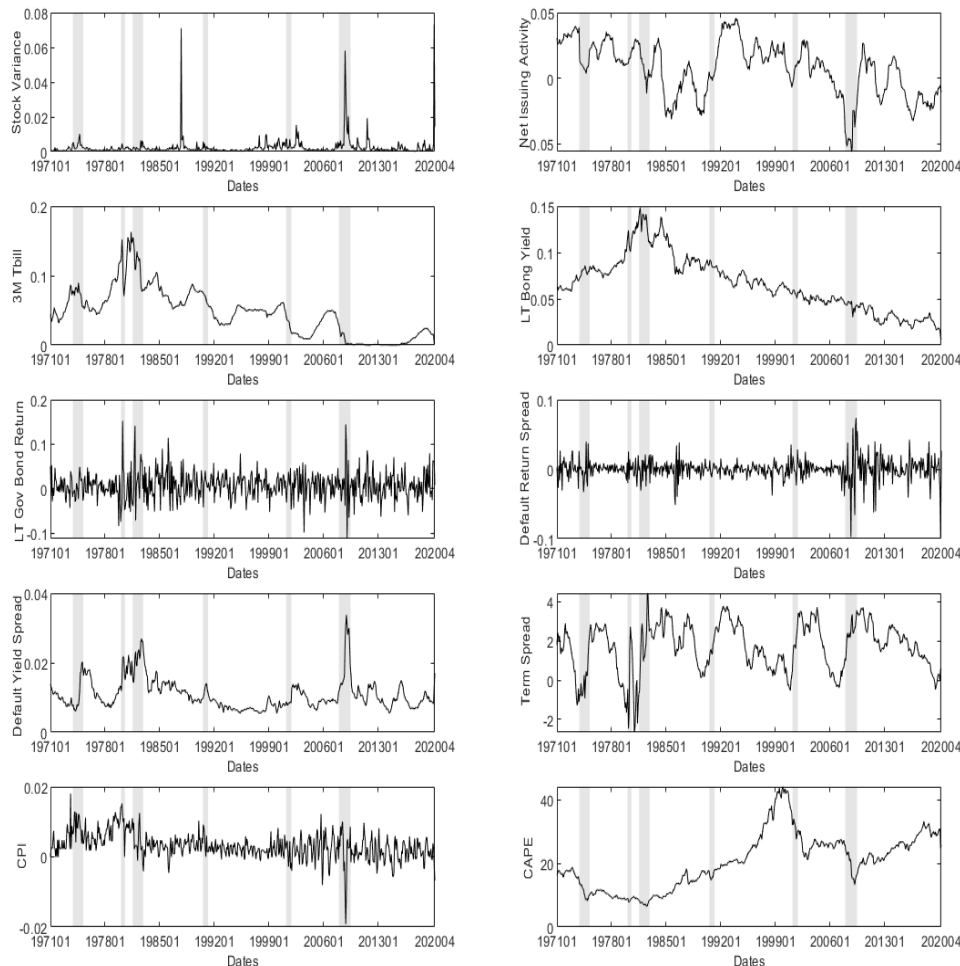


Figure 3.10: Dynamic of the US Shiller CAPE ratio and global variables

Notes: Data from January, 1971 to April, 2020, with a total of 592 monthly observations. Periods of NBER recessions emphasized with shaded bands. For stock index variance and Net Issuing Activity, we use data from the Center for Research in Security Prices (CRSP). The 3-Month US Treasury Bill is from the research database FRED from the Federal Reserve Bank of Saint-Louis. The Long-Term US Government Bonds' Yields and the Long-Term Government Bonds' Returns are from the Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook database. The Default Return Spread is computed with data from the Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook database. The Default Yield Spread from FRED. The CPI from the Bureau of Labor Statistics. The US CAPE ratio from the Shiller database.

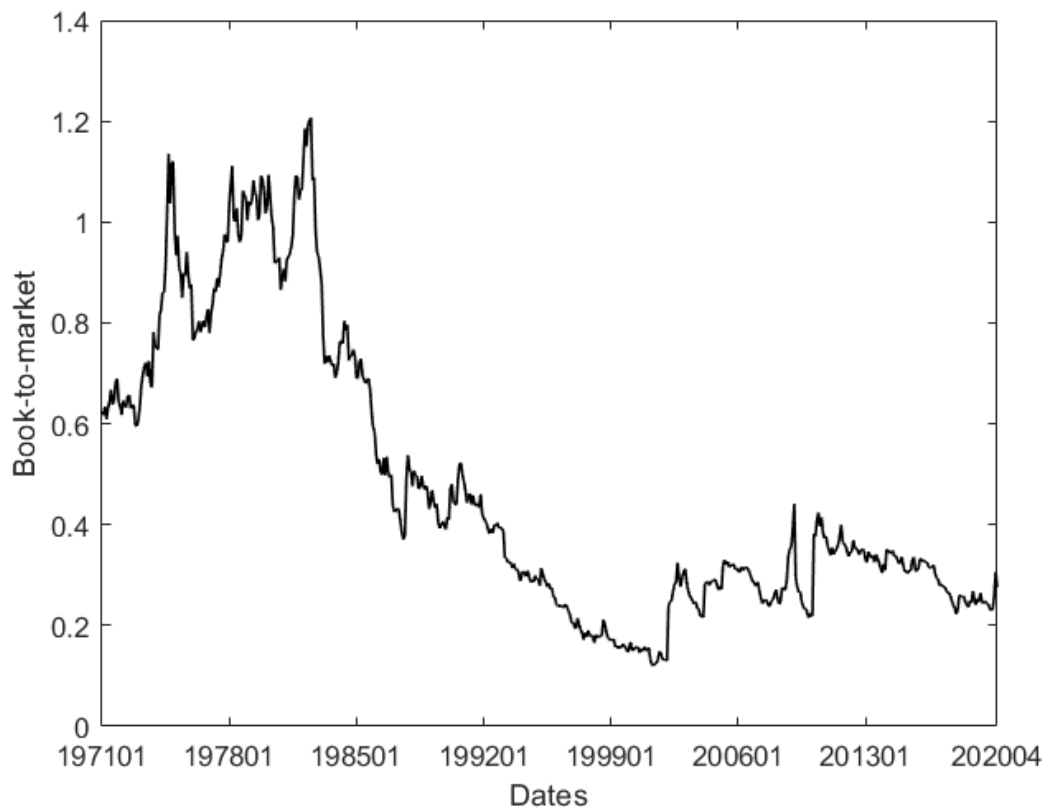


Figure 3.11: Dynamic of the US book-to-market ratio

Notes: Data from January, 1971 to April, 2020, with a total of 592 monthly observations.

Table 3.8: Selected Variables through rolling windows for the S&P 500: $\tau = 12$

	Stock Var.	NIA	3M Tbill	LT Bong Yield	LT Bong Ret.	Default Ret. Spread	Term Spread	Term Spread	CPI
Lag=0	0	0	0	0	0	0	0	34.33	0
Lag=1	0	0	0	0	0	0	0	52.24	0
Lag=2	0	0	0	0	0	0	0	10.45	0
Lag=3	0	0	0	0	0	0	0	1.49	0
Lag=4	0	0	0	0	0	0	0	0	0
Lag=5	0	0	0	0	0	0	0	0	0
Lag=6	0	0	0	0	0	0	0	99.50	0
Lag=7	0	0	0	0	0	0	0	65.17	0
Lag=8	0	0	0	0	0	0	0	0	0
Lag=9	0	0	0	0	0	0	0	0	0
Lag=10	0	0	0	0	0	0	0	0	0
Lag=11	0	0	0	0	0	0	0	0	0
Lag=12	0	0	0	0	0	0	0	0	0
Lag=13	0	0	0	0	0	0	0	0	0
Lag=14	0	0	0	0	0	0	0	0	0
Lag=15	0	0	0	0	0	0	0	0	0
Lag=16	0	0	0	0	0	0	0	0	0
Lag=17	0	0	0	0	0	0	0	0	0
Lag=18	0	0	0	0	0	0	0	36.82	0

Notes: the table displays the selection's frequencies (in %) of business cycle variables through rolling-windows, when predicting out-of-sample returns of the S&P 500 at the lag-order $\tau = 12$, based on our optimal predictive regression model that selects three business cycle variables. "NIA" refers to net issuing activity, "Var." to variance, and "Ret." to returns.

Table 3.9: Selected Variables through rolling windows for the S&P 500: $\tau = 24$

	Stock Var.	NIA	3M Tbill	LT Bong Yield	LT Bong Ret.	Default Ret. Spread	Term Spread	Term Spread	CPI
Lag=0	0	0	0	0	0	0	0	65.08	0
Lag=1	0	0	1.59	0	0	0	0	0	0
Lag=2	0	0	0	0	0	0	0	0	0
Lag=3	0	0	0	0	0	0	0	2.65	0
Lag=4	0	0	0	0	0	0	0	6.88	0
Lag=5	0	0	0	0	0	0	0	1.59	0
Lag=6	0	0	0	0	0	0	0	1.59	0
Lag=7	0	0	0	0	0	0	0	58.20	0
Lag=8	0	0	0	0	0	0	0	28.04	0
Lag=9	0	0	0	0	0	0	0	2.12	0
Lag=10	0	0	0	0	0	0	0	5.29	0
Lag=11	0	0	0	0	0	0	0	0	0
Lag=12	0	0	0	0	0	0	0	0	0
Lag=13	0	0	0	0	0	0	0	0	0
Lag=14	0	0	0	0	0	0	0	0	0
Lag=15	0	0	0	0	0	0	0	0	0
Lag=16	0	0	0	0	0	0	0	67.20	0
Lag=17	0	0	0	0	0	0	0	18.52	0
Lag=18	0	0	0	0	0	0	0	41.27	0

Notes: the table displays the selection's frequencies (in %) of business cycle variables through rolling-windows, when predicting out-of-sample returns of the S&P 500 at the lag-order $\tau = 24$, based on our optimal predictive regression model that selects three business cycle variables. "NIA" refers to net issuing activity, "Var." to variance, and "Ret." to returns.

Table 3.10: Certainty equivalent returns for alternative predictive regressions for the S&P 500

$\gamma = 3$					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	4.44	4.04	3.97	5.19	2.96
2	6.51	5.58	5.61	5.13	4.06
3	5.39	5.18	4.53	3.82	2.51
4	4.47	5.74	4.96	5.96	3.08
5	2.23	2.10	1.98	1.78	2.52
6	2.11	2.68	3.50	3.49	2.09
7	0.59	1.12	1.53	1.63	0.31
8	1.14	0.90	0.68	0.64	1.43
9	0.82	0.82	-0.47	-0.50	0.84
10	1.91	1.91	1.41	1.90	1.91
11	0.46	-0.65	-0.64	-0.68	0.04
12	1.29	1.03	1.02	0.93	2.52

$\gamma = 5$					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	3.59	3.14	3.44	4.55	2.27
2	5.74	4.60	4.33	3.74	3.03
3	4.23	3.88	3.08	2.54	1.34
4	3.50	4.66	4.14	4.97	2.19
5	1.87	1.65	1.37	0.99	1.98
6	2.01	2.59	3.53	3.06	2.03
7	0.46	1.03	0.72	0.73	0.45
8	0.25	-0.25	-0.79	-0.26	0.39
9	0.20	0.27	-0.82	-0.91	0.01
10	1.28	0.88	0.48	1.50	0.67
11	-1.30	-1.92	-0.69	-1.00	-1.26
12	-0.37	-0.52	-0.52	-0.53	0.48

Notes: For the risk aversion parameter γ equal to 3 and 5, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US book-to-market ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1971 to April, 2020, with a total of 592 monthly observations.

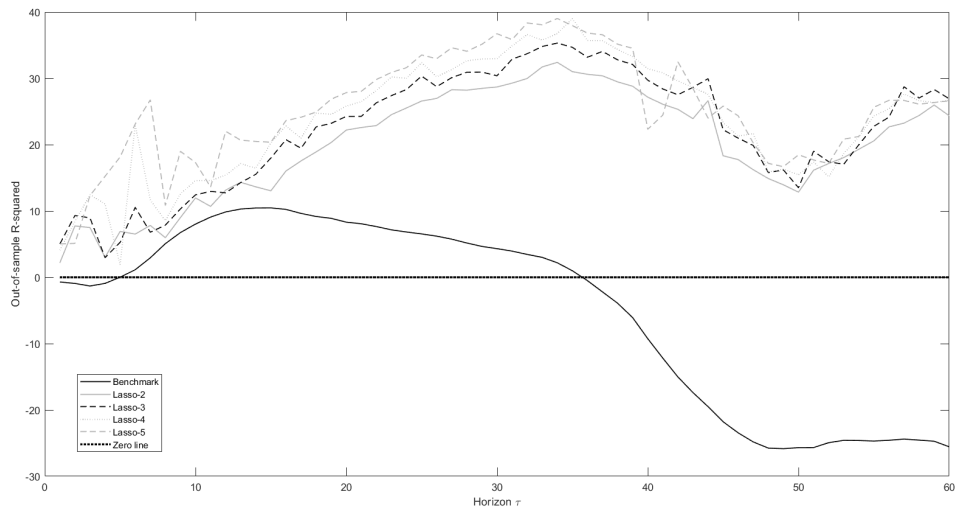


Figure 3.12: Out-of-sample predictive powers of competing predictive regressions for the US Communication Services sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Communication Services sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

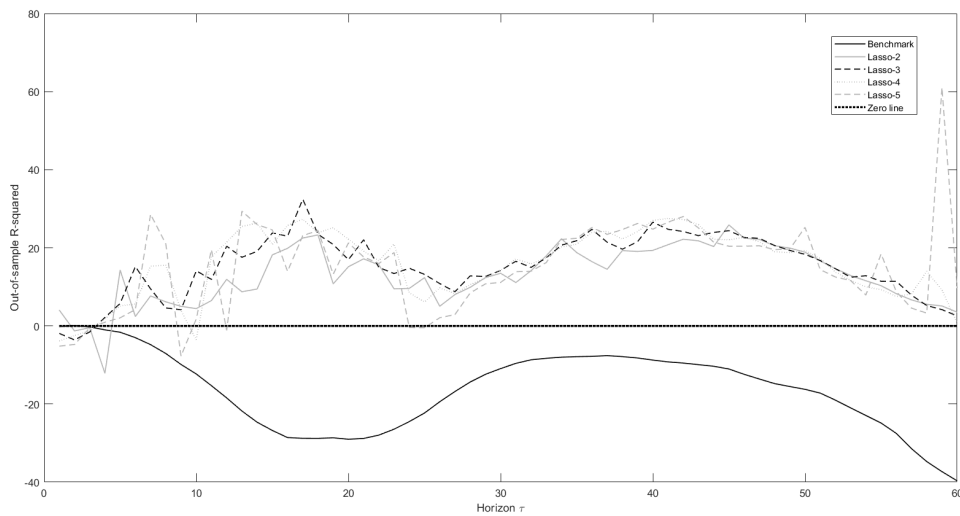


Figure 3.13: Out-of-sample predictive powers of competing predictive regressions for the US Utilities sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Utilities sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

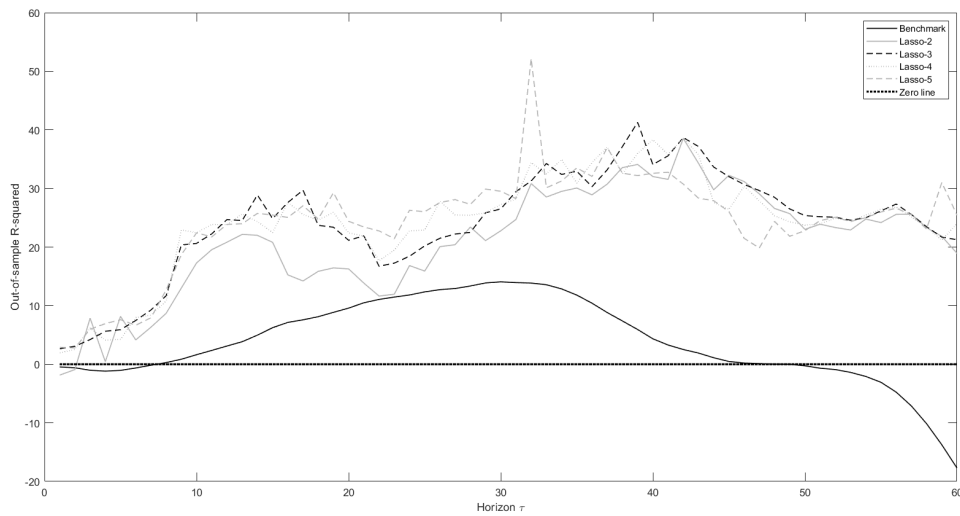


Figure 3.14: Out-of-sample predictive powers of competing predictive regressions for the US Materials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Materials sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

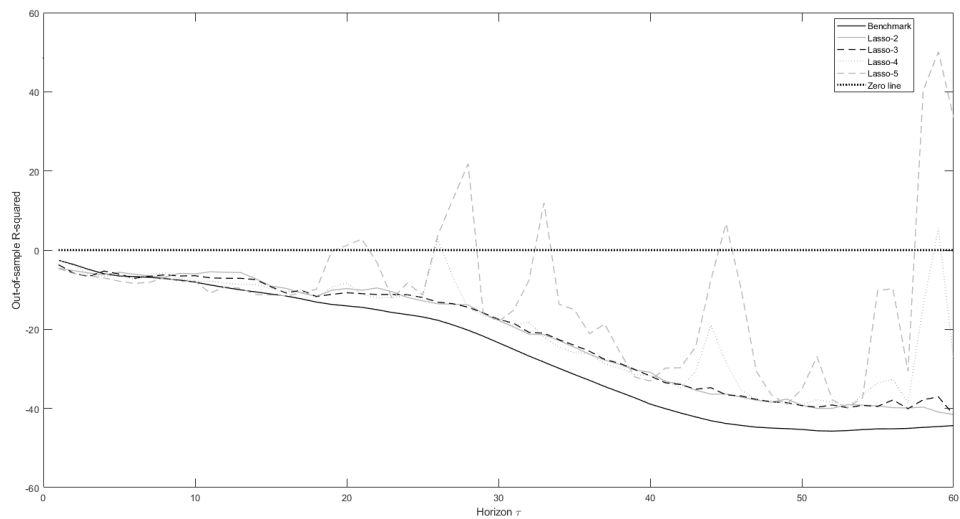


Figure 3.15: Out-of-sample predictive powers of competing predictive regressions for the US Financials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Financials sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

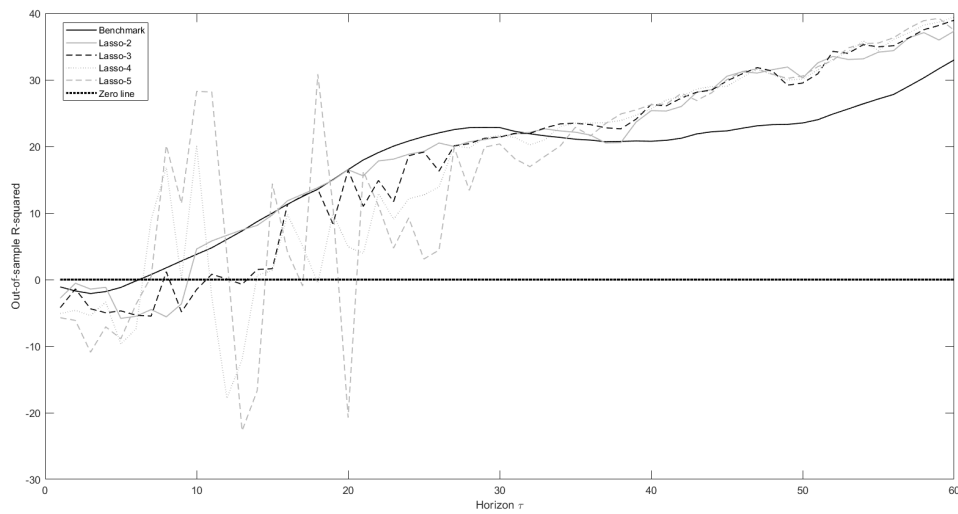


Figure 3.16: Out-of-sample predictive powers of competing predictive regressions for the US Health Care sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Health Care sector Shiller CAPE ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

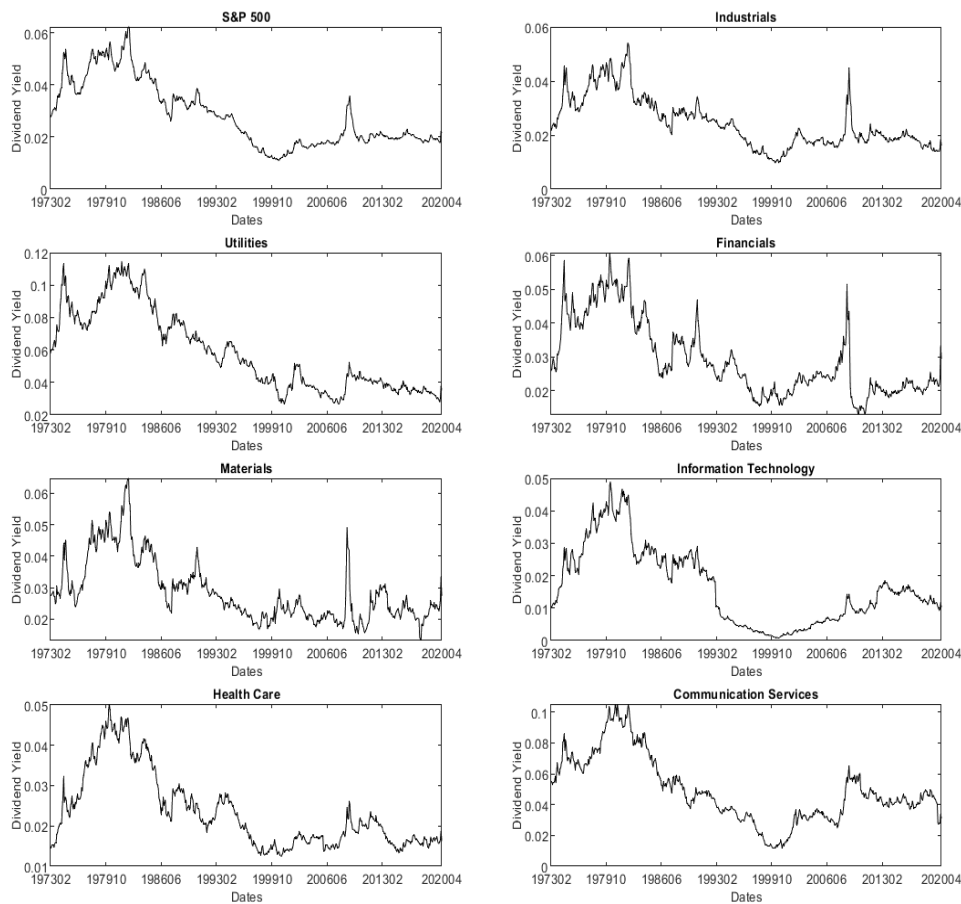


Figure 3.17: Dynamic of the US individual sectors' Dividend Yield: 1973/02-2020/04

Notes: The ratios are computed based on a dataset that consists of monthly individual sectors' stock index prices and dividend data. Monthly dividend data are computed from quarterly totals since 1973, with linear interpolation to monthly figures. Stock price data are monthly averages of daily closing prices.

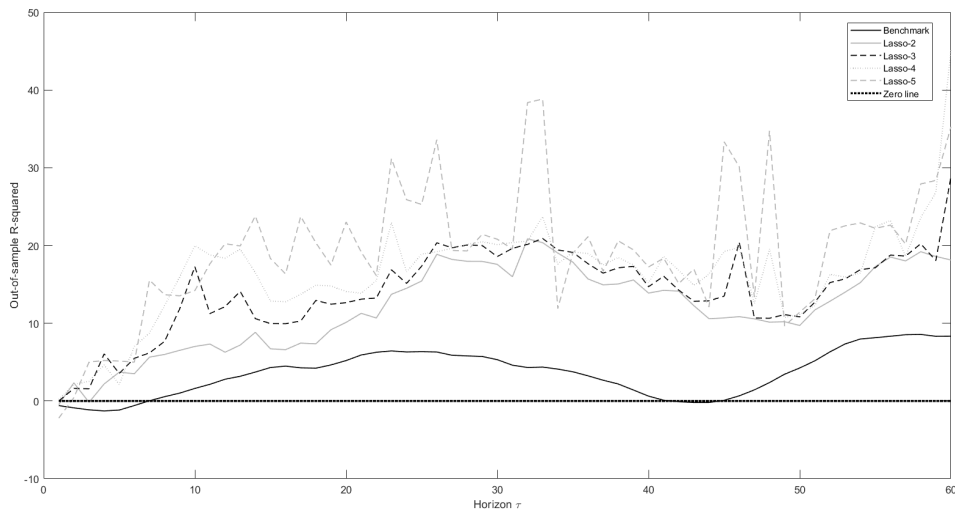


Figure 3.18: Out-of-sample predictive powers of competing predictive regressions for the US Industrials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Industrials sector Dividend Yield as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

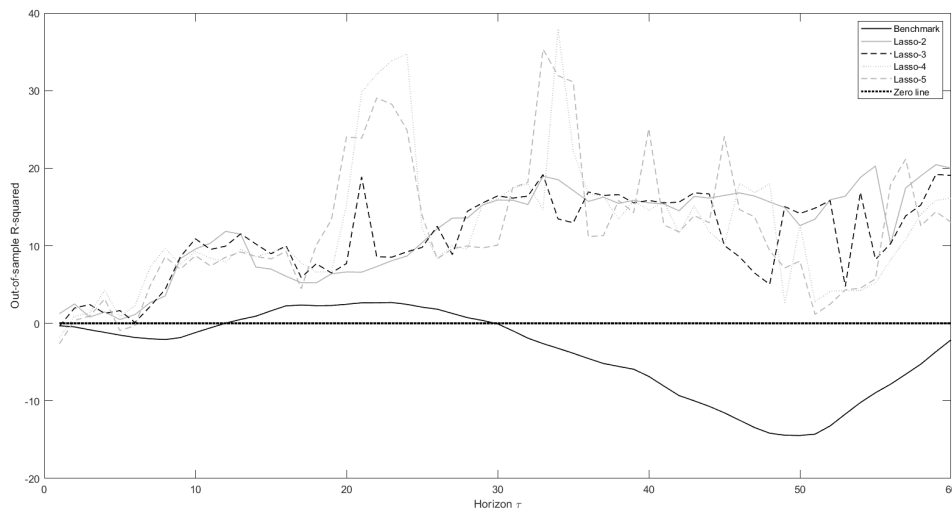


Figure 3.19: Out-of-sample predictive powers of competing predictive regressions for the US Information Technology sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Information Technology sector Dividend Yield as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

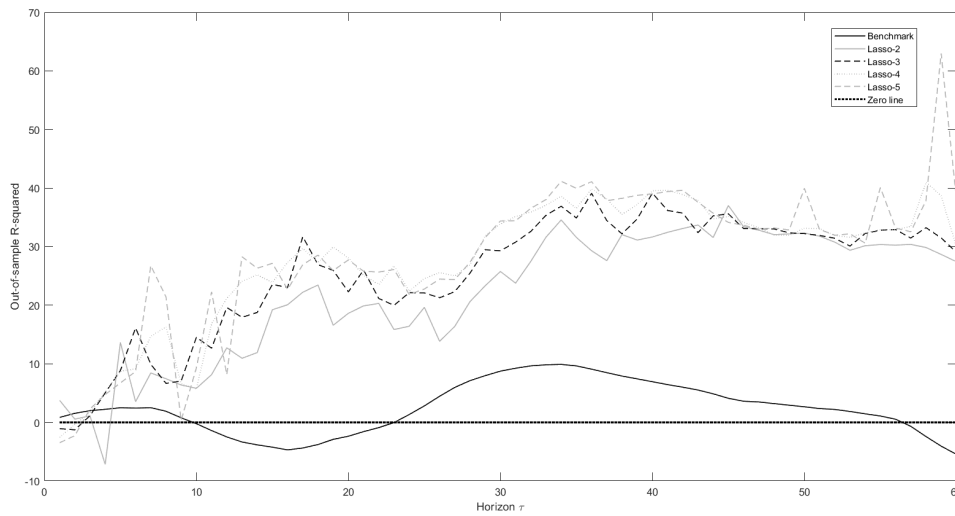


Figure 3.20: Out-of-sample predictive powers of competing predictive regressions for the US Utilities sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Utilities sector Dividend Yield ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

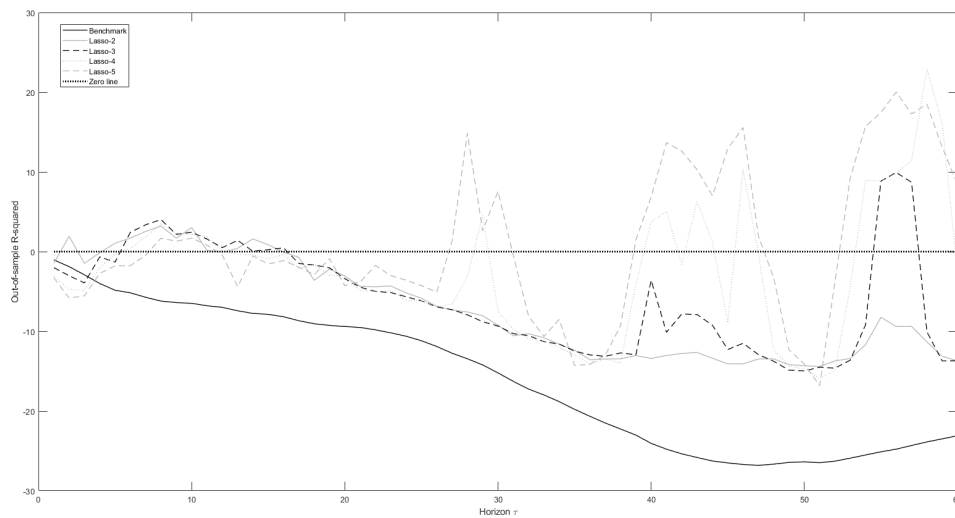


Figure 3.21: Out-of-sample predictive powers of competing predictive regressions for the US Financials sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Financials sector Dividend Yield as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

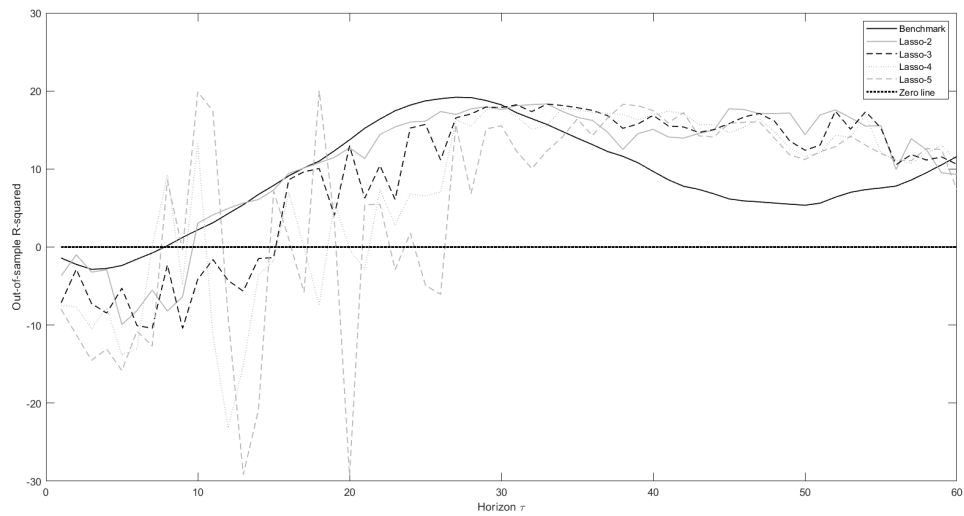


Figure 3.22: Out-of-sample predictive powers of competing predictive regressions for the US Health Care sector

Notes: The figure displays the out-of-sample predictive powers of alternative predictive regressions and their interaction with the US Health Care sector Dividend Yield ratio as valuation ratio. Forecasts are obtained using monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

Table 3.11: Selection frequencies of the term spread the US individual sectors through rolling windows: $\tau = 12$

	Financials	Health Care	Industrials	Information Technology*	Materials	Utilities	Communication Services
Lag=0	23.30	0	22.16	100.00	30.11	0	0
Lag=1	1.14	0	0	0	70.45	0	0
Lag=2	0	0	0	0	0	25.00	0
Lag=3	0	0	0	0	0	0	0
Lag=4	32.39	0	30.68	0	0	0	0
Lag=5	100.00	0	11.93	0	0	0	24.43
Lag=6	97.73	100.00	100.00	100.00	75.57	100.00	92.61
Lag=7	45.45	0	38.07	0	0	31.25	100.00
Lag=8	0	0	0	0	0	76.70	0
Lag=9	0	0	0	0	23.86	65.34	13.64
Lag=10	0	0	0	0	0	0	69.32
Lag=11	0	0	21.02	0	0	0	0
Lag=12	0	0	0	0	0	0	0
Lag=13	0	0	0	0	0	0	0
Lag=14	0	100.00	2.27	0	0	0	0
Lag=15	0	0	0	0	0	0	0
Lag=16	0	0	0	0	0	0	0
Lag=17	0	0	0	0	0	0	0
Lag=18	0	100.00	73.86	0	100.0	1.70	0

Notes: the table displays the selection's frequencies (in %) of the term spread amongst business cycle variables through rolling-windows, when predicting out-of-sample returns at the lag-order $\tau = 12$, based on our optimal predictive regression model that selects three business cycle variables, respectively two business cycle variables for the Information Technology sector*.

Table 3.12: Selection frequencies of the term spread the US individual sectors through rolling windows: $\tau = 24$

	Financials	Health Care	Industrials	Information Technology*	Materials	Utilities	Communication Services
Lag=0	26.83	0	17.07	91.46	16.46	23.78	0
Lag=1	0.61	0	0	0	0	72.56	0
Lag=2	48.17	0	0.61	0	0	100.00	6.71
Lag=3	14.63	0	2.44	0	0	28.05	4.27
Lag=4	73.17	0	1.83	0	0	0	100.00
Lag=5	90.85	0	25.61	0	38.41	0	92.68
Lag=6	45.73	0	100.00	77.44	65.85	75.61	92.68
Lag=7	0	0	94.51	8.54	3.05	0	3.66
Lag=8	0	0	57.32	0	65.85	0	0
Lag=9	0	0	0	0	0	0	0
Lag=10	0	0	0	0	0	0	0
Lag=11	0	0	0	0	0	0	0
Lag=12	0	0	0	0	0	0	0
Lag=13	0	0	0	0	0	0	0
Lag=14	0	98.78	0	0	0	0	0
Lag=15	0	100.00	0	0	5.49	0	0
Lag=16	0	1.22	0	0	36.59	0	0
Lag=17	0	0	0	0	6.10	0	0
Lag=18	0	100.00	0.61	22.56	62.20	0	0

Notes: the table displays the selection's frequencies (in %) of the term spread amongst business cycle variables through rolling-windows, when predicting out-of-sample returns at the lag-order $\tau = 24$, based on our optimal predictive regression model that selects three business cycle variables, respectively two business cycle variables for the Information Technology sector*.

Table 3.13: Certainty equivalent returns for alternative predictive regressions: $\gamma = 3$

US Information Technology Sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	8.71	8.14	6.85	5.61	8.32
2	8.91	8.18	8.51	8.38	7.78
3	8.33	8.71	8.90	9.14	8.90
4	8.89	9.71	10.12	10.44	8.57
5	8.95	8.75	7.77	8.08	8.78
6	9.03	8.78	8.18	7.03	8.53
7	8.43	8.18	7.49	4.90	8.26
8	8.26	7.86	5.21	3.33	7.94
9	8.43	8.10	7.67	7.27	8.17
10	7.91	6.68	7.70	8.13	8.19
11	7.43	7.76	8.20	8.45	8.10
12	6.75	7.40	8.28	6.26	8.58

US Communication Services sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	1.80	1.93	2.33	0.88	3.60
2	2.98	2.47	2.87	3.46	3.85
3	2.98	4.33	4.01	3.45	3.89
4	4.46	3.78	3.63	3.57	3.74
5	2.91	4.17	3.92	4.50	4.16
6	4.84	3.86	3.85	3.87	4.93
7	4.21	5.01	4.52	3.79	3.75
8	4.45	4.71	5.21	4.72	4.53
9	5.06	4.34	4.70	3.48	4.00
10	3.50	2.77	2.08	2.88	2.61
11	2.53	2.48	3.81	3.72	2.32
12	2.96	2.87	3.86	2.68	1.19

Notes: For the risk aversion parameter γ equal 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US individual sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 592 monthly observations.

Table 3.14: Certainty equivalent returns for alternative predictive regressions: $\gamma = 3$

US Materials Sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	0.45	-0.38	2.21	3.27	3.87
2	-0.22	-0.04	2.11	1.73	3.75
3	4.48	3.44	4.07	5.81	4.44
4	3.32	5.07	4.49	4.32	3.59
5	3.12	4.21	2.51	1.49	3.54
6	2.23	3.37	3.03	3.04	3.46
7	0.49	-0.22	-0.33	-0.28	3.18
8	4.09	5.55	1.70	2.22	3.53
9	2.58	5.22	4.93	4.17	4.09
10	1.92	0.61	1.13	0.93	3.60
11	4.43	4.65	4.28	4.98	4.00
12	1.02	1.16	1.67	1.57	2.85

US Financials sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	-1.42	-2.78	-1.55	-0.60	-0.76
2	-3.54	-3.56	-3.43	-1.37	-1.28
3	-3.14	-2.87	-2.27	-2.60	-1.23
4	-4.44	-3.42	-4.90	-4.33	-2.77
5	-4.21	-4.21	-5.32	-5.49	-2.87
6	-2.13	-3.06	-3.09	-3.38	-2.19
7	-1.61	-1.56	-2.22	-3.25	-2.28
8	-1.54	-1.62	-0.97	-4.22	-1.53
9	-2.15	-2.48	-1.30	1.17	-1.52
10	-1.63	-2.16	-2.24	-2.59	-1.66
11	-0.79	-0.68	-1.08	-1.43	-2.50
12	-1.26	-1.24	-1.08	-0.33	-1.41

Notes: For the risk aversion parameter γ equal 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US individual sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 592 monthly observations.

Table 3.15: Certainty equivalent returns for alternative predictive regressions for the US Health Care sector: $\gamma = 3$

Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	4.97	4.32	4.95	5.75	5.71
2	5.28	3.51	5.05	5.23	5.71
3	6.37	5.28	4.04	5.95	6.79
4	6.04	5.18	5.58	6.52	6.79
5	5.56	3.95	5.27	4.72	6.68
6	6.32	5.63	3.84	3.05	6.79
7	6.51	5.39	4.95	4.88	6.70
8	5.91	5.91	4.74	3.97	6.17
9	6.17	6.17	4.83	4.81	6.37
10	5.93	5.93	5.58	4.45	6.17
11	6.05	5.85	5.56	5.48	6.37
12	6.50	6.68	6.14	5.53	6.79

Notes: For the risk aversion parameter γ equal to 3, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US Health Care sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 568 monthly observations.

Table 3.16: Certainty equivalent returns for alternative predictive regressions: $\gamma = 5$

US Industrials Sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	4.95	2.43	3.48	3.12	3.66
2	1.37	2.32	2.79	3.24	3.53
3	1.70	5.01	5.67	4.18	3.94
4	5.29	6.27	6.38	5.34	3.38
5	4.56	5.76	5.42	4.93	3.23
6	3.68	5.83	5.22	5.58	3.77
7	2.24	2.21	3.48	3.89	2.97
8	2.53	4.35	4.53	3.13	3.32
9	2.62	2.40	1.81	4.82	3.39
10	1.52	1.69	1.20	1.81	2.74
11	1.90	1.87	4.34	3.81	2.03
12	1.09	1.04	0.90	1.49	2.94

US Utilities sector					
Forecast horizon τ	LASSO-2	LASSO-3	LASSO-4	LASSO-5	Benchmark
1	2.90	2.24	3.18	2.07	2.58
2	3.55	2.09	2.67	1.74	2.79
3	2.18	2.47	2.96	2.35	2.69
4	4.23	2.50	2.99	3.16	2.91
5	3.15	3.17	3.25	3.19	2.57
6	2.87	2.46	2.62	2.37	2.68
7	2.66	3.35	4.22	4.22	2.13
8	1.46	2.34	2.96	2.90	2.00
9	2.47	3.45	2.52	2.28	2.37
10	2.58	2.67	1.81	1.70	1.72
11	2.84	2.36	3.06	2.82	2.13
12	2.36	2.11	3.35	3.05	2.00

Notes: For the risk aversion parameter γ equal 5, the table displays the annualized values (in %) of certainty equivalent returns (CERs) for alternative predictive regressions: the predictive regression in Chapter 2 referred as "benchmark," and four versions of our new predictive regression which is based on LASSO selection of business cycle variables, and their interaction with the US individual sector Shiller CAPE ratio as valuation ratio. The four versions differs by the target number of selected business cycle variables ranging from 2 to 5. For each forecast horizon τ from 1 to 12 months, we emphasize in bold the highest CER. Computations are based on monthly data from January, 1973 to April, 2020, with a total of 592 monthly observations.

Conclusion

THIS thesis has made significant contributions to the field of financial economics. Through three empirical essays, it addressed the financial industry's growing concerns over the decline in alpha generation from active strategies, and to the need for more accurate prediction of returns over short to medium term for tactical asset allocations. Firstly, an original optimization paradigm for equity portfolios is presented, called "Smart Alpha," which properties are orthogonal to the extensive body of literature on factor investing. Secondly, we introduced a new robust predictive regression model that consistently improves out-of-sample forecasts of stock returns in the short and medium terms, a valuable contribution facing the numerous unsuccessful attempts in the academic literature. These two contributions are of a significant value for investors and the asset management industry, particularly for stock picking and for tactical portfolio allocation.

Chapter 1 introduced the "Smart Alpha" strategy, a novel optimization paradigm for equity portfolios. Unlike traditional factor investing, which bets on specific risk premiums, the new strategy focuses on alpha maximization, representing expected returns uncorrelated with systematic risk factors, while minimizing exposure to those factors. The smart alpha employs Sparse Principal Component Analysis through a latent factor model to extract the significant factors, stock exposures, and alphas. It demonstrated statistical and economic benefits compared to traditional Principal Component Analysis. The new approach also succeeded in timing the optimal number of relevant factors using an information criteria-like statistics.

Empirical results on the European stock market reveal the superiority of the Smart Alpha portfolio with both lower risk and higher returns compared to market cap-weighted indices and various heuristic or smart beta approaches. This challenges the prevailing belief in the asset management industry about the decline of alpha and the dominance of factor investing. Addi-

tionally, the strategy delivers ex-post returns that are not explained by the traditional empirical factors. Hence, it validates the philosophy of minimizing the portfolio's exposure to the many sources of risk, while maximizing a robust source of potential alpha. Importantly, the framework of the smart alpha strategy is general, flexible and not dependent to a specific stock market. It extends beyond equities, making it applicable to other asset classes.

Chapter 2 addressed the challenge of forecasting equity returns at short-term horizons by introducing a predictive regression model based on stock return dynamics following mean reversion in the US Shiller CAPE ratio. It shed light on the relationships among valuation ratios, business cycle, and stock price dynamics. In the literature, evidence of predictability has been only observed at long-term horizons, spanning several years. Previous short-term return forecasting often relied on models with over-parameterized time-varying coefficients to capture business cycles. In the new approach introduced in this chapter, we incorporated mean reversion in valuation ratios using a dynamic regime-switching variant of the model from Jegadeesh (1991). The model leverages the relationship between the term spread (credit spread) and the mean reversion phenomenon in valuation ratios. The in-sample and out-of-sample results demonstrate substantial and statistically significant improvements compared to traditional predictive regression methods, as they are able to improve predictability at a few months horizon.

These results are robust and hold across various valuation ratios (CAPE, excess CAPE, and dividend yield) and countries (Canada, Germany, and the UK). Furthermore, we conduct a mean-variance asset allocation exercise, affirming the enhanced utility gains provided by our new predictive regression. Our findings have significant implications for understanding asset price dynamics, mean reversion, and their connection to the business cycle, with practical implications for tactical asset allocation strategies.

Building on the success of Chapter 2, Chapter 3 extended the predictive model's capabilities, offering significantly improved short-term stock return predictions. We use a data-rich environment, with various business cycle variables and lag-orders, while employing parsimonious estimation techniques. The empirical analysis demonstrates the enhanced predictive power of the extended model, with significantly better short-term stock return predictions. The model's proficiency in capturing the intricate relationships among valuation ratios, business cycle variables, and stock prices dynamics provides valuable insights for investors. Importantly, the use

of multiple lag-orders for business cycle variables highlights how the term spread appears to be the most important early-warning indicator.

The model's validation across diverse valuation metrics (Shiller CAPE ratio, book-to-market ratio, dividend yield) underscores its robustness and reliability, ensuring consistent and meaningful insights for investors. In the same vein of Stalla-Bourdillon (2022) who suggested sector-level returns forecasting using micro-CAPE or micro-PE, the new predictive model provides improved out-of-sample stock returns on individual sectors within the US. These findings further carry substantial implications for advancing the understanding of asset price dynamics, mean reversion in tandem with the business cycle (bad and good times).

This thesis is devoted to the field of equity returns forecasting and its implication for the asset management industry, opening a wide field of possibilities for financial professionals. On the one hand, the smart alpha strategy can be easily implemented in long-only equity portfolios or alternative investment strategies like market neutral or long-short strategies. On the other hand, the new predictive regression model offers practical applications particularly useful for tactical asset allocation. It can be used in dynamic asset allocations, consistently improving the regional and sectoral asset allocation at short horizons (few months).

Keynes rightly observed that investors tend to focus on short-term market fluctuations. Various revolutions occurred in the financial world since the 1930s that have shaped the current market environment. One of the most significant changes since then is the increased availability and rapid dissemination of information among market participants. Future trends in portfolio management are expected to be heavily influenced by technological advancements that may enable much faster information processing. One prominent trend is the increasing integration of so-called "Artificial Intelligence" and machine learning into portfolio management processes. New techniques go beyond traditional fundamental analysis and allow to analyze vast amounts of real-time data including social media posts, news articles, financial forums, better assessing the market sentiment. It offers investors much faster information processing and thus potentially allowing them to improve market and asset returns predictability. An interesting extension of this thesis would be to evaluate how the new predictive regression model can be further enhanced by incorporating these new techniques, potentially leading to better timing of the business cycle, among other applications.

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Trois essais en économie financière

Résumé général

La prévision des rendements des actifs est un aspect clé de l'économie financière, et son importance devient particulièrement évidente lorsqu'elle est appliquée à la gestion d'actifs, qui nécessite même des prévisions en temps réel des rendements des actions. La capacité à prédire les rendements futurs n'est donc pas seulement un exercice académique, mais aussi une nécessité pratique qui imprègne de nombreuses décisions financières, allant de la construction de portefeuilles à la gestion des risques. Il n'est pas surprenant que l'anticipation des marchés haussiers ou baissiers ou la sélection d'actions présentant le plus grand potentiel de hausse soient parmi les plus grands défis pour les professionnels de la finance. Ils utilisent une multitude de variables dans le but de prévoir les rendements des actions.

Avec une perspective holistique, les investisseurs évoluent dans un monde de plus en plus interconnecté. Il faut tenir compte non seulement des caractéristiques nationales de chaque pays, mais aussi des dynamiques internationales et de la mondialisation, avec ses défis depuis la crise de la Covid-19 (Antràs *et al.*, 2023) et la fragmentation des chaînes d'approvisionnement. Les tensions géopolitiques, les accords commerciaux et les fluctuations des devises jouent tous un rôle central dans la prévision des rendements. Les conflits commerciaux entre les grandes puissances économiques, comme les États-Unis et la Chine, ou les conflits militaires, telle que l'invasion russe de l'Ukraine, ont montré comment les événements géopolitiques peuvent introduire de l'incertitude sur les marchés, affectant les valorisations des actifs et les allocations sectorielles et régionales.

La recherche académique s'efforce d'identifier de nouvelles méthodes de prédiction des rende-

ments des actions¹ en proposant des outils pour allouer judicieusement les actifs entre les pays et les secteurs, mais aussi entre les différentes classes d'actifs. Ainsi, les gestionnaires de portefeuilles pourraient ajuster leurs allocations d'actifs vers des classes d'actifs plus stables telles que les obligations pour protéger leur portefeuille en cas de prévision d'un retournement du marché boursier.

À la fin des années 1990, le secteur de la technologie a connu une forte croissance grâce aux entreprises liées à Internet², grâce à un effet de chasse aux aubaines collective, car les investisseurs s'étaient fortement appuyés sur des prévisions de rendement très optimistes et ont investi dans ces entreprises dans l'espoir de générer de forts gains à court terme. Cependant, cet optimisme a brusquement pris fin avec l'éclatement de la bulle Internet en 2000, entraînant des pertes importantes pour les investisseurs dont le portefeuille était trop concentré dans ces actions et manquaient de diversification. Avant la crise financière mondiale de 2008, les prévisions de rendement ont joué un rôle crucial dans la gestion des risques au sein du secteur bancaire et de la gestion d'actifs. De nombreuses institutions financières se sont appuyées sur des prévisions trop optimistes concernant le marché immobilier et les produits financiers complexes tels que les titres adossés à des créances hypothécaires³. Lorsque ces prévisions se sont révélées inexactes et que le marché immobilier s'est effondré, cela a déclenché une crise financière mondiale, démontrant les implications des prédictions imparfaites de rendement. David Viniar, qui était le directeur financier de Goldman Sachs, avait alors déclaré cette phrase devenue célèbre : « Nous observions des mouvements de 25 écarts-types, plusieurs journées d'affilée »⁴, mettant en évidence l'extrême gravité de la crise financière et la difficulté de prévoir de tels événements rares.

Ces exemples historiques mettent en évidence le potentiel de gains significatifs grâce à des prévisions précises des rendements, mais ils soulignent également les risques importants liés à

¹ Cf. Campbell et Thompson (2008), Welch et Goyal (2008), Pettenuzzo *et al.* (2014), Atanasov *et al.* (2020), etc. Goyal *et al.* (2023) ont étudié plus d'un millier de papiers de recherche et ont identifié les 24 meilleurs articles des revues financières de premier plan selon une méthodologie de performance.

² Cela a alimenté la frénésie spéculative entourant le concept de la « nouvelle économie » et de la « nouvelle ère » (cf. Shiller, 2000 ; Stiglitz, 2003 ; Becker, 2006).

³ Les investisseurs étaient attirés par les titres hypothécaires à rendement plus élevé, croyant que le risque limité et les notes élevées de Standard & Poor's et Moody's les rendaient sûrs. Ces titres ont été vendus à l'échelle mondiale à des fonds de pension et de grandes banques d'investissement à la recherche d'investissements notés AAA. Malheureusement, les prévisions de rendement de ces titres ont été faites à l'aide de techniques qui ont échoué à prédire les risques de défaut dans un marché immobilier déjà en surchauffe.

⁴ Thal Larsen, Peter. « Goldman pays the price of being big ». *Financial Times*, 13 août 2007, <https://www.ft.com/content/d2121cb6-49cb-11dc-9ffe-0000779fd2ac>. Consulté le 30 septembre 2023.

de fausses prédictions. Cela met en évidence la nécessité de mettre en place des méthodes de prévision de rendement à court terme appropriées et robustes. L'industrie de la gestion d'actifs fait face à des défis sans précédent, certains investisseurs ayant perdu une quantité importante de richesse. Le comportement des investisseurs et leur appétit pour le risque ont subi des changements profonds, les conduisant à (1) fuir les produits sophistiqués, (2) une demande accrue pour affiner la sélection de portefeuille et (3) un regain d'intérêt pour la réduction des risques dans les portefeuilles d'investissement.

Les conséquences de la crise financière mondiale de 2008 ont marqué 15 années de changements sans précédent sur les marchés financiers. Les banques centrales ont adopté des stratégies non conventionnelles telles que l'assouplissement quantitatif⁵ pour stimuler les économies, et la résurgence de la répression financière⁶ a entraîné une profonde modification des niveaux des taux d'intérêt. Les taux d'intérêt ultra-bas (voire négatifs, particulièrement en Europe et au Japon) ont poussé les investisseurs vers des actifs plus risqués, créant l'effet « TINA »⁷. Le secteur de la technologie est devenu une composante importante du marché actions, avec notamment les actions « GAFAM »⁸ qui ont perturbé le marché. La pandémie de la Covid-19 en 2020 a entraîné une volatilité extrême sur les marchés, suivie d'une forte reprise économique et d'une très forte inflation⁹, incitant les banques centrales à augmenter rapidement les taux d'intérêt. Les réformes réglementaires visant à prévenir les défaillances systémiques ont remodelé le paysage financier, face aux technologies émergentes telles que la blockchain et les cryptomonnaies (Girasa, 2018). La finance comportementale a par ailleurs mis en lumière le rôle de la psychologie humaine dans les décisions d'investissement, remettant en question l'hypothèse des marchés rationnels. Les biais comportementaux, tels que le syndrome FOMO, de l'anglais *fear of missing out* ou « peur de

⁵La politique d'assouplissement quantitatif, d'abord introduite par Werner (1995), mise en œuvre par la Réserve fédérale, la Banque centrale européenne et la Banque d'Angleterre, aurait empêché pendant la crise de la dette de 2008 de bloquer complètement le marché interbancaire.

⁶Cf. Reinhart et Sbrancia (2011), Reinhart *et al.* (2011), Perez (2015) et Chari *et al.* (2020).

⁷De l'anglais « *There Is No Alternative* » ou « il n'y a pas d'alternative ». Les taux d'intérêt ultra-bas visaient à stimuler l'emprunt, mais ont affecté les épargnants et ont incité les investisseurs, à la recherche de rendements, à se tourner vers les actifs plus risqués, telles que les actions, faisant grimper les indices boursiers à des niveaux records.

⁸GAFAM pour les cinq plus grandes actions américaines à la fin des années 2010, appartenant au secteur de la technologie : Google, Apple, Facebook, Amazon et Microsoft. La somme de la capitalisation boursière au 31 août 2023 représente 23,2% de l'indice S&P 500, soit 9 282 milliard de dollars ou 3,6 fois la capitalisation boursière totale de l'indice CAC 40.

⁹Atteignant 9,1% aux États-Unis en juin 2022 et 10,2% dans la zone euro en octobre 2022, soit les plus hauts niveaux depuis la création de l'union monétaire.

rater quelque chose », et la « peur de perdre » (le syndrome FOL, de l'anglais *fear of loss*)¹⁰ ont alimenté l'exubérance des marchés et les ventes paniques. Comprendre ces phénomènes est devenu essentiel pour une gestion efficace des risques et des décisions d'investissement, contribuant finalement à façonner un paysage d'investissement plus résilient.

Dans ce contexte, comment les investisseurs peuvent-ils améliorer leur capacité à prévoir les rendements à court terme au cœur de ce paysage complexe et incertain, dans le cadre de l'allocation tactique d'actifs¹¹ ? Comment les investisseurs peuvent-ils améliorer l'optimisation et la diversification de leur portefeuille pour maximiser leur rendement tout en gérant leur exposition aux nombreux types de risque ?

La suite de ce résumé est structurée comme suit. La première section rappelle l'importance du rôle des actions dans la construction de portefeuille. La deuxième section présente les principaux aspects de la prévision des rendements dans le cadre de l'optimisation de portefeuille ainsi que le rôle des modèles à facteurs. La troisième section se penche sur l'importance de la prévision des rendements à court et moyen terme pour l'allocation tactique d'actifs et le rôle que peuvent jouer les ratios de valorisation et les variables liées au cycle économique. La quatrième section présente la contribution de cette thèse au domaine de la prévision des rendements en économie financière. La cinquième et dernière section conclut.

Pourquoi les actions sont-elles importantes ?

Les actions sont un élément fondamental de la construction de portefeuille en raison de leurs performances exceptionnelles sur de longues périodes, surpassant toutes les autres classes d'actifs telles que les obligations, les matières premières et l'immobilier. La Figure 1 présente l'évolution des rendements, dividendes et coupons réinvestis, des classes d'actifs traditionnelles aux États-Unis sur 97 ans, de 1926 à 2023¹², à savoir : les actions, avec une distinction entre petites et

¹⁰Cf. Gärling *et al.* (2009) et Chan et Andrade (2011). Le syndrome FOMO pousse les investisseurs à se précipiter vers certains actifs, par peur de manquer des opportunités lucratives, ce qui entraîne une exubérance du marché et une surévaluation des actifs (par exemple, le secteur technologique à la fin des années 1990 et, plus récemment, les cryptomonnaies). En revanche, la « peur de perdre » (ou syndrome FOL) peut conduire à des ventes paniques lors des baisses du marché, exacerbant ainsi une volatilité accrue.

¹¹L'allocation tactique d'actifs (TAA) est une stratégie qui consiste à ajuster activement l'allocation d'actifs d'un portefeuille pour tirer parti des opportunités à court et moyen terme sur les marchés ou pour gérer le risque. Contrairement à l'allocation stratégique d'actifs (SAA), qui se concentre sur des allocations cibles à long terme, la TAA exploite la dynamique de marché à plus court terme.

¹²Les données de l'indice S&P 500 sont également disponibles depuis 1881 grâce à la base de données de Shiller.

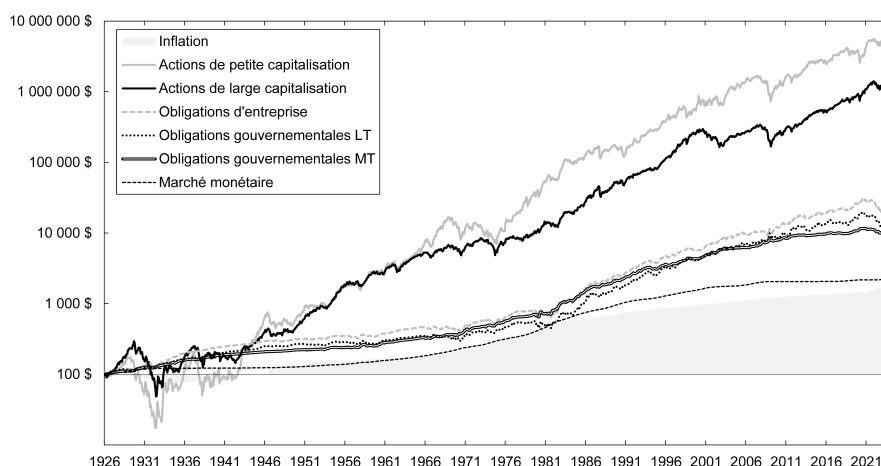


Figure 1 : Dynamique des rendements des classes d'actifs traditionnelles aux États-Unis depuis 1926

Source : Morningstar Direct, Bloomberg. Le graphique illustre la croissance nominale du rendement en dollars américains d'un investissement de 100 \$ du 31 décembre 1925 au 31 août 2023. Les actions américaines de grande et de petite capitalisation, les obligations d'entreprise de haute qualité à long terme (20 ans et plus), les obligations gouvernementales américaines à long terme (LT, 20 ans et plus) et à moyen terme (MT, 5 ans), ainsi que le marché monétaire américain (bons du Trésor américain à 30 jours) sont des indices de rendement mensuels, dividendes et coupons réinvestis, provenant de la base de Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook. L'inflation est mesurée par l'indice des prix à la consommation aux États-Unis.

grandes capitalisations ; les obligations gouvernementales, avec une distinction entre les obligations à long terme (20 ans et plus) et les obligations à moyen terme (5 ans) ; les obligations d'entreprises ; et le marché monétaire.

La Figure 2 présente, sur la même période, l'évolution de la performance des classes d'actifs alternatives, à savoir : le marché de l'immobilier résidentiel et commercial aux États-Unis ; le pétrole brut ; et l'or. La remarque la plus marquante est qu'aucune autre classe d'actifs, que ce soient les obligations, le marché monétaire, les matières premières ou l'immobilier, n'affiche des rendements à long terme aussi constants et positifs que les actions. Elles constituent en outre une solide protection contre l'inflation.

Cependant, avec ce potentiel de rendements plus élevés vient un risque accru. Le tableau 1 affiche la volatilité des classes d'actifs traditionnelles ainsi que les classes d'actifs alternatives. Sans surprise, les actions font partie des catégories d'actifs les plus volatiles, avec une volatilité annualisée de 18,62% pour les grandes capitalisations et de 28,00% pour les petites capitalisations

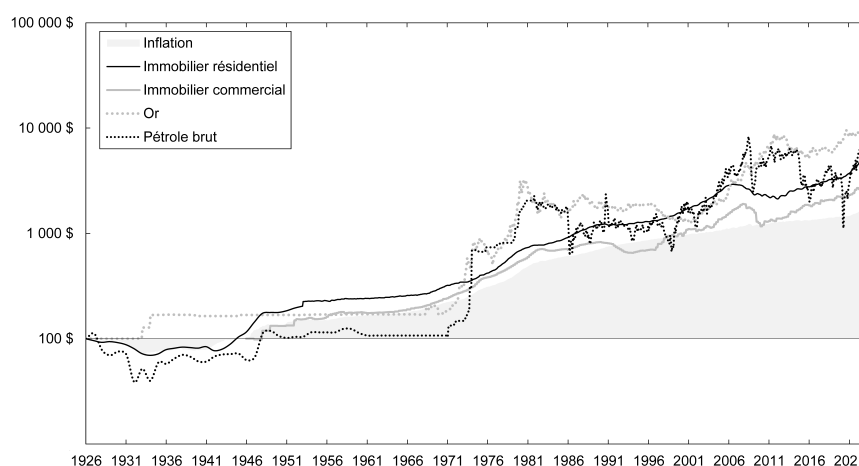


Figure 2 : Dynamique des rendements des classes d'actifs alternatives depuis 1926

Source : Bloomberg, Réserve fédérale. Le graphique illustre la croissance nominale du rendement en dollars américains d'un investissement de 100 \$ du 31 décembre 1925 au 31 août 2023. L'indice de prix de l'immobilier résidentiel américain est l'indice national des prix des logements de S&P/Case-Shiller. L'indice de prix de l'immobilier commercial américain provient de l'Institut national de l'immobilier (1945–1996) et de CoStar (1996–2023). Le prix de l'or est en dollars américains par once troy. Le prix du pétrole brut est en dollars américains par baril et provient de la revue statistique de BP (British Petroleum) (1925–1950), de l'Arabian Gulf Arab Light (1951–1983) et du West Texas Intermediate Cushing (1983–2023). L'inflation est mesurée par l'indice des prix à la consommation aux États-Unis.

Tableau 1 : Caractéristiques des classes d'actifs traditionnelles et alternatives depuis 1926

	Actions de grande capitalisation	Actions de petite capitalisation	Obligations d'entreprise	Obligations gouvernementales à long terme	Obligations gouvernementales à moyen terme	Marché monétaire	Immobilier résidentiel	Immobilier commercial*	Or	Pétrole brut
Rendement annualisé	10,25 %	11,79 %	5,65 %	5,09 %	4,84 %	3,25 %	4,06 %	4,31 %	4,76 %	4,08 %
Volatilité	18,62 %	28,00 %	7,90 %	8,66 %	4,34 %	0,87 %	2,38 %	3,31 %	18,83 %	36,35 %

Source : Morningstar Direct, Bloomberg, Réserve fédérale. Données du 31 décembre 1925 au 31 août 2023 en dollars américains. Les actions américaines de grande et de petite capitalisation, les obligations d'entreprise de haute qualité à long terme (20 ans et plus), les obligations gouvernementales américaines à long terme (20 ans et plus) et à moyen terme (5 ans), ainsi que le marché monétaire américain (bons du Trésor américain à 30 jours) sont des indices de rendement mensuels, dividendes et coupons réinvestis, provenant de la base de Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook. L'indice de prix de l'immobilier résidentiel américain est l'indice national des prix des logements de S&P/Case-Shiller. L'indice de prix de l'immobilier commercial américain provient de l'Institut national de l'immobilier (1945–1996) et de CoStar (1996–2023). Le prix de l'or est en dollars américains par once troy. Le prix du pétrole brut est en dollars américains par baril et provient de la revue statistique de BP (British Petroleum) (1925–1950), de l'Arabian Gulf Arab Light (1951–1983) et du West Texas Intermediate Cushing (1983–2023). *Données à partir de décembre 1945.

depuis 1926. Les matières premières apparaissent plus risquées avec une volatilité de 36,35% pour les prix du pétrole brut. Même l'or, généralement considéré comme une valeur refuge ou une couverture de portefeuille¹³, présente une volatilité légèrement plus élevée (18,83%) que les actions de grande capitalisation depuis 1926. Les marchés actions, en particulier les petites capitalisations, sont davantage soumis aux fluctuations du marché, aux cycles économiques et aux événements spécifiques aux entreprises. Cette volatilité peut générer d'importantes pertes à court terme sur les portefeuilles. Cela rend donc l'allocation d'actifs tactique et l'optimisation de portefeuille essentiels pour les gestionnaires d'actifs à la recherche du meilleur équilibre entre le risque et la performance.

Optimisation de portefeuille et limites de l'investissement factoriel

Les travaux de Markowitz (1952) sur l'optimisation de portefeuilles en fonction du rendement et de la variance, ainsi que le développement ultérieur du modèle d'évaluation des actifs financiers (MEDAF)¹⁴ par Sharpe (1964), constituent des jalons essentiels de la théorie moderne du portefeuille. Les recherches de Markowitz ont introduit le concept de diversification, mettant en évidence comment les investisseurs peuvent minimiser le risque en construisant des portefeuilles d'actifs présentant différents couple rendement-risque. Cela a constitué la base du développement des portefeuilles efficients visant à obtenir le rendement le plus élevé possible pour un niveau donné de risque, un principe qui reste central en finance moderne. Le modèle d'évaluation des actifs financiers, quant à lui, fournit un cadre systématique pour comprendre la relation entre le risque et le rendement et introduit le concept de pondération en fonction de la capitalisation boursière. Cette approche suggère que dans un portefeuille bien diversifié, la pondération de chaque actif individuel devrait être proportionnelle à sa valeur de marché. Ensemble, l'optimisation du couple moyenne-variance de Markowitz et le MEDAF de Sharpe ont révolutionné la construction de portefeuille et les stratégies d'allocation d'actifs, façonnant la manière dont les investisseurs abordent la gestion du risque et les choix de portefeuille.

¹³ Cf. Baur et McDermott (2010), Akhtaruzzaman *et al.* (2021).

¹⁴ *Capital asset pricing model* ou CAPM.

La recherche universitaire sur la présence de facteurs de risque communs au-delà du facteur de marché a révélé des facteurs capables d'expliquer les variations des rendements des actions. Les origines de ces recherches remontent aux travaux fondamentaux de Fama et French (1992). Les modèles multifactoriels sont devenus essentiels en gestion de portefeuille, fournissant un cadre permettant d'identifier et de quantifier les moteurs potentiels des rendements sur le marché. Après le modèle à trois facteurs de Fama et French (1993), le modèle à cinq facteurs de Fama et French (2015) a élargi davantage la portée des facteurs à considérer, incorporant à la taille de capitalisation, la valorisation et le facteur de marché, le facteur *momentum* et la qualité, offrant ainsi une approche plus complète pour comprendre et gérer le risque et le rendement dans les portefeuilles d'investissement.

La littérature universitaire a depuis largement reconnu les limites des portefeuilles optimisés en fonction du critère moyenne-variance et pondérés en fonction de la capitalisation boursière, en raison des hypothèses contraignantes de ces méthodes et de leurs performances médiocres hors échantillon (*Cf.* par exemple Bloomfield *et al.*, 1977 ; DeMiguel *et al.*, 2009 ; Tu et Zhou, 2011 ; Behr *et al.*, 2012 ; Kourtis *et al.*, 2012). Cela a conduit à l'émergence d'approches de pondération de portefeuille alternatives telles que les stratégies equi-pondérées, les stratégies de variance minimale ou bien les stratégies de diversification « maximale » de portefeuille, souvent appelés « smart beta » ou « investissement factoriel ». Ces méthodes innovantes visent à capturer des facteurs de risque spécifiques et les primes qui y sont associées, offrant aux investisseurs un paysage d'investissement plus diversifié et potentiellement plus gratifiant au-delà des approches traditionnelles. Ce changement dans la construction de portefeuille reconnaît l'importance de considérer des facteurs de risque alternatifs pour des performances ajustées du risque supérieures.

Les modèles multifactoriels offrent la possibilité de mesurer, à l'aide de méthodes statistiques systématiques, les facteurs de risque communs qui influent sur les marchés boursiers. Ils ont un très long historique en finance et en économie, participant, en particulier, à l'identification des facteurs latents et à tester les modèles d'évaluation par arbitrage¹⁵ (Ross, 1976 ; Chamberlain et Rothschild, 1983). Les tests des modèles d'évaluation par arbitrage remontent aux travaux de Roll et Ross (1980), Schipper et Thompson (1981), Connor et Korajczyk (1986) et de Connor et Korajczyk (1988). Des recherches récentes étendent les possibilités des modèles multifactoriels,

¹⁵ *Arbitrage pricing theory* ou APT.

par exemple dans Kelly *et al.* (2019), Pelger (2019), Lettau et Pelger (2020a,b) et Giglio et Xiu (2021). En macroéconomie, ils sont également utilisés dans la prévision des cycles économiques (Stock et Watson, 2006)¹⁶.

Cependant, il existe d'importants défis liés à l'utilisation des modèles factoriels. Le nombre de facteurs rapportés dans la littérature universitaire est devenu si nombreux que Cochrane (2011) les a qualifiés de « zoo de facteurs » lors de son discours présidentiel à l'Association américaine de finance en 2011. Les gestionnaires de portefeuille sont en effet confrontés au défi de choisir, parmi cette multitude de facteurs, ceux qui sont vraiment pertinents pour leurs stratégies. Harvey *et al.* (2016) ont recensé un total de 316 facteurs empiriques provenant de 313 publications distinctes depuis 1967 figurant dans les principales revues de finance et de *working papers*. Ils ont examiné les implications de cette diversité de facteurs pour l'optimisation de portefeuille et ont montré que la puissance explicative de nombreux facteurs suggérés est fallacieuse¹⁷.

Plus récemment, Jensen *et al.* (2023) ont utilisé un modèle bayésien pour montrer qu'une grande majorité des facteurs rapportés dans la littérature universitaire sont en réalité valides. Cependant, le principal défi auquel les investisseurs sont confrontés lorsqu'ils optimisent l'exposition de leur portefeuille à un facteur spécifique, et donc lorsqu'ils essaient de capturer une prime de risque spécifique, consiste à prédire quel facteur spécifique influencera les marchés financiers à l'avenir et surtout à quel moment.

Shiller (2018, 2019) explore le concept des « *narratives* » des marchés financiers en mettant en lumière un aspect fondamental de la finance comportementale : la manière dont les investisseurs interprètent et réagissent aux événements économiques et aux informations financières. Gennaioli et Shleifer (2018) dissèquent la crise financière mondiale de 2008, révélant l'impact des croyances des acheteurs de logements, des investisseurs et des régulateurs, et suggèrent une théorie de la formation des croyances, éclairant la nature surprenante de la crise et la persistance de l'instabilité financière et économique. Une conclusion clé de ces études réside dans le fait que les marchés sont souvent influencés par des histoires ou des récits collectifs dits *narratives* plutôt que par des données objectives et rationnelles. Il est indéniable que les marchés sont influencés

¹⁶Les modèles multifactoriels sont aussi utilisés dans de grands modèles macroéconomiques (Forni *et al.*, 2000 ; Favero *et al.*, 2005 ; Gagliardini et Gourieroux, 2014), et pour les problématiques de politique monétaire (Boivin et Ng, 2006).

¹⁷*Cf.* également Bai et Ng (2006), Lewellen *et al.* (2010) et Ahn *et al.* (2018).

par une multitude de facteurs, et il est difficile de prévoir lequel de ces facteurs prévaudra à un moment donné. Les *narratives* peuvent évoluer rapidement en réponse à des événements économiques, politiques ou même sociaux, rendant encore plus compliquée la prédiction du facteur qui sera prépondérant. De plus, l'optimisation d'un portefeuille en anticipant le moment exact des changements de *narratives* est une tâche particulièrement délicate. Les marchés peuvent suivre un certain *narrative* pendant quelques temps, puis le rejeter brusquement au profit d'un nouveau. Les investisseurs qui anticipent mal le *timing* de ces changements peuvent ainsi subir des pertes importantes dans leur portefeuille.

L'analyse des *narratives* de marché met en évidence la complexité de la prédiction du comportement des marchés financiers. Les investisseurs doivent à la fois tenir compte des indicateurs économiques et financiers et rester conscients de la manière dont le sentiment du marché interprète ces informations. Un exemple notable est l'élection présidentielle de 2016 aux États-Unis, lorsque les attentes d'une victoire d'Hillary Clinton, dont les sondages la plaçaient en tête¹⁸, ont cédé la place à un surprenant « *Trump Rally* ». Les marchés financiers réagissaient positivement à la victoire de Donald Trump, et ce, malgré toutes les prédictions antérieures d'un résultat négatif¹⁹. Cette surprenante réaction des marchés financiers illustre parfaitement la difficulté de prévoir à la fois le résultat des événements, qu'ils soient politiques ou économiques, et les orientations ultérieures des marchés, mettant en évidence l'imprévisibilité inhérente aux moteurs de la dynamique des marchés.

Dans ce contexte, le succès de l'investissement factoriel dépend de la précision avec laquelle les gestionnaires de portefeuille peuvent anticiper le moment précis où un facteur spécifique sera récompensé par le marché. Cette tâche est intrinsèquement complexe car les facteurs et les sensibilités du marché à ces mêmes facteurs peuvent varier dans le temps (Kelly *et al.*, 2019). Les primes de risque des facteurs sont liées à des périodes spécifiques, difficiles à prévoir et très peu susceptibles de se répéter. Les investisseurs qui choisissent de suivre un style ou un facteur particulier qui a déjà beaucoup progressé dans une direction, sont particulièrement vulnérables

¹⁸Parmi les derniers sondages effectués au cours de la semaine précédant l'élection, la victoire était donnée à la candidate démocrate Hillary Clinton, avec néanmoins une marge en baisse. Cf. *Latest Election Polls 2016*. *New York Times*, 8 novembre 2016, <https://www.nytimes.com/interactive/2016/us/elections/polls.html>. Consulté le 30 septembre 2023.

¹⁹Zuckerman, Gregory et Chung, Juliet. « Billionaire George Soros Lost Nearly \$1 Billion in Weeks After Trump Election ». *Wall Street Journal*, 13 janvier 2017, <https://www.wsj.com/articles/billionaire-george-soros-lost-nearly-1-billion-in-weeks-after-trump-election-1484227167>. Consulté le 30 septembre 2023.

aux retournements soudains. Ces retournements sont couramment appelés « rotations de style ». En examinant le paysage macroéconomique et géopolitique, il est évident que le monde devient de plus en plus complexe et dynamique. Les changements de style ou de facteurs peuvent se produire plus fréquemment, posant des défis pour la prédiction des tendances de marché et augmentant les coûts de mise en œuvre des ajustements de portefeuille. Par conséquent, les investisseurs à la recherche de génération d'alpha auront tendance à diversifier davantage leurs portefeuilles par rapport à la pratique conventionnelle qui consiste à parier sur des facteurs spécifiques²⁰. Les gestionnaires de portefeuille se concentreront davantage sur la sélection d'actions en mettant l'accent sur les dynamiques propres aux entreprises ou sur les stratégies d'investissement moins dépendantes des principaux facteurs.

Prévisibilité des rendements et le lien entre les valorisations des actions et le cycle économique

La performance historique des actions, telle qu'illustrée dans la Figure 1, met en évidence la forte corrélation entre les actions et le cycle économique. En effet, la valeur des actions dépend fortement des bénéfices des entreprises, qui sont significativement influencés par l'état du cycle économique. L'expansion économique et la croissance de l'activité ont tendance à augmenter la performance des actions, tandis que les périodes de ralentissement économique se traduisent souvent par des rendements plus faibles des actions²¹.

Une allocation tactique d'actifs basée sur le « *timing* » du cycle économique permettrait donc d'obtenir potentiellement de meilleures performances financières. Le changement tactique de l'allocation des actions vers les marchés monétaires ou les obligations à court terme quelques mois avant le début d'une récession, suivi d'un retour sur le marché actions avant la fin de cette même récession, peut conduire à des avantages notables par rapport aux stratégies de type « achat et conservation des positions »²² (Siegel, 1991). Bien sûr, la meilleure façon de prévoir

²⁰A l'instar des stratégies classiques de surpondération du style *value* au détriment du style croissance et *vice versa*.

²¹Cochrane (2017) se penche sur le lien entre le prix des actifs et le cycle économique. Les modèles macro-financiers permettent de produire des primes de risque variant dans le temps pour différentes catégories d'actifs, toutes liées à l'état du cycle économique.

²²Les stratégies de *buy-and-hold*.

les rendements à court terme des actions serait d'anticiper exactement l'entrée et la sortie d'une récession, pour chaque récession, ce qui est évidemment impossible. Prédire avec succès le cycle économique est une tâche difficile²³ car cela nécessite d'identifier les pics et les creux d'activité économique avant même qu'ils ne se produisent. Malgré sa difficulté, la prévision du cycle économique reste populaire, grâce aux avantages considérables associés au *timing* précis de ces points de retournement de l'activité.

Le Bureau national de recherche économique (NBER), une organisation américaine privée fondée en 1920, est la référence pour déterminer les dates du cycle économique aux États-Unis en se basant sur des indicateurs macroéconomiques²⁴. Les données historiques permettent de mettre en évidence la relation entre les mouvements du marché boursier et les récessions économiques identifiées par le NBER, avec plus de 93% des 48 récessions enregistrées depuis 1802 ayant été précédées ou accompagnées de baisses significatives de l'indice S&P 500. Bien que les décisions du NBER revêtent une importance politique et économique, elles sont généralement annoncées bien après le début des cycles, ce qui les rend moins utiles pour le *timing* du marché. Le cas exceptionnel de la récession provoquée par la pandémie de la Covid-19 a duré seulement 2 mois, ce qui en fait l'une des récessions les plus courtes de l'histoire des États-Unis²⁵. À la fin d'une récession, le marché boursier a généralement tendance à rebondir, ce qui signifie que les investisseurs qui attendent des signaux concrets de reprise économique manquent souvent des gains significatifs à court terme. De plus, le NBER annonce les dates de fin de récession bien après le début de la reprise économique.

Les indicateurs économiques avancés sont souvent utilisés par les gestionnaires d'actifs pour tenter d'anticiper le niveau de l'activité économique, tels que les enquêtes économiques basées sur les indices de sentiment des directeurs d'achat (de Longis et Ellis, 2023). Cependant, la pente de la courbe des taux d'intérêts aux États-Unis, qui est l'écart entre les rendements des bons

²³Lors de la récession de 1974–1975, les économistes ont échoué à reconnaître la gravité du ralentissement économique, ce qui a conduit à une surestimation de la croissance du PIB et à une sous-estimation de l'inflation. Des problèmes similaires de prévision ont persisté lors de récessions ultérieures, comme la récession de 1981–1982, où l'optimisme a cédé la place au pessimisme, et la Grande Récession de 2007–2009, que les experts n'ont pas réussi à prédire avec précision.

²⁴Ces indicateurs comprennent (1) le revenu personnel réel hors transferts, (2) l'emploi hors agriculture, (3) l'emploi tel que mesuré par l'enquête sur les ménages du *Bureau of Labor Statistics*, (4) les dépenses de consommation personnelles réelles, (5) les ventes en gros et au détail ajustées de l'inflation, ainsi que (6) la production industrielle.

²⁵Les annonces de la fermeture des économies par l'ensemble des gouvernements du monde en mars 2020 ont provoqué une chute extrêmement rapide des marchés boursiers mondiaux, le S&P 500 ayant perdu près de 34% en quelques semaines seulement.

du Trésor à long terme et des bons du Trésor à court terme²⁶, et en particulier le phénomène de l'inversion de la courbe de taux (lorsque les taux des bons du Trésor à court terme sont supérieurs à ceux des bons du Trésor à long terme), s'est avérée être un indicateur précoce remarquable (Cf. par exemple Stock et Watson, 1989 ; Estrella et Hardouvelis, 1991 ; Estrella et Mishkin, 1998). Il a systématiquement signalé des ralentissements économiques imminents au cours des six dernières décennies. De même, les mouvements des écarts de taux sur les marchés obligataires d'entreprises, ou les *spread* de crédit, contiennent des signaux importants concernant l'évolution de l'économie réelle et les risques pour les perspectives économiques. Les travaux fondamentaux de Welch et Goyal (2008) suggèrent une liste de variables prédictives pertinentes avec de puissantes propriétés d'alerte précoce, qui ont récemment été confirmées par les travaux de Goyal *et al.* (2023).

De plus, il existe un lien entre les ratios de valorisation des actions et la prédiction des rendements des actions, en particulier lorsqu'on considère que ces ratios de valorisation sont persistants pendant certaines phases du cycle économique, tout en revenant à leur moyenne autour d'autres phases. Les travaux de Rapach *et al.* (2010), Henkel *et al.* (2011) et Dangl et Halling (2012) ont notamment mis en évidence la puissance prédictive des ratios de valorisation pendant les récessions.

Une multitude de métriques ont été déployées dans le but d'évaluer les valorisations du marché boursier, quantifiant généralement la valeur du marché par rapport aux fondamentaux économiques tels que les bénéfices, les dividendes ou les valeurs comptables des entreprises, ou par rapport à des variables économiques telles que le PIB ou les taux d'intérêt. Le ratio cours/bénéfice (ou *P/E ratio*) se distingue comme une mesure centrale. Il sert de baromètre de la volonté d'un investisseur de payer chaque dollar de bénéfices actuels. Le rendement des bénéfices, qui est réciproque au ratio P/E et semblable au rendement des dividendes, mesure les bénéfices générés par dollar de valeur marchande et est étroitement lié aux rendements à long terme des actions en raison de la connexion qui existe entre les actions et les actifs réels qui augmentent avec l'inflation.

Campbell et Shiller (1988) ont introduit le ratio cours/bénéfice ajusté du cycle (*CAPE ra-*

²⁶Ou *term spread* en anglais.

tio)²⁷, une mesure clé de la valorisation des actions basée sur une moyenne mobile de 10 ans des bénéfices ajustés de l'inflation, pour lisser les fluctuations du cycle économique. Leurs recherches ont révélé que le ratio CAPE était capable de prédire les rendements à long terme des actions. Lorsque le ratio CAPE de Shiller dépasse sa moyenne à long terme, il prédit des rendements futurs inférieurs et vice versa. Le ratio CAPE est devenu célèbre lorsqu'il a indiqué une importante survalorisation des marchés à la fin des années 1990, coïncidant avec le discours d'Alan Greenspan sur « l'exubérance irrationnelle »²⁸ des marchés financiers. En 2000, le ratio CAPE a atteint un niveau record, prédisant avec précision une décennie de faibles rendements boursiers.

De nombreuses études universitaires ont exploré la puissance prédictive des ratios de valorisation dans le contexte de la prévision des futurs rendements boursiers sur des horizons de plusieurs années (Rozeff, 1984 ; Fama et French, 1988 ; Campbell et Shiller, 1988 ; Cochrane, 1991 ; Hodrick, 1992 ; Goetzmann et Jorion, 1993 ; Lewellen, 2004, etc.). Ces études suggèrent collectivement que, bien que les taux de croissance des fondamentaux, tels que les dividendes et les bénéfices, soient difficiles à prévoir, les variations des ratios financiers sont principalement liées aux rendements attendus par le biais du phénomène de retour à la moyenne.

Campbell et Shiller (1998, 2005) mettent l'accent sur l'importance de la stabilité des ratios de valorisation en ce qui concerne le retour à la moyenne. Si les ratios de valorisation restent dans les plages historiques et ne dévient pas de manière permanente ou indéfinie, des niveaux extrêmes devraient signaler une correction imminente. Cette correction peut se produire soit par des changements dans le niveau des dividendes, soit par des changements dans les prix des actions. Essentiellement, lorsque les prix des actions sont significativement élevés par rapport aux indicateurs P/E, on s'attend à ce que les futures baisses de prix réalignent ces ratios sur les normes historiques. Cela contredit la théorie de la marche aléatoire, qui affirme l'imprévisibilité des mouvements des prix des actions (Fama, 1965).

Néanmoins, les preuves empiriques soutiennent largement l'idée que cette relation est plus solide pour les rendements boursiers à long terme, car les ratios de valorisation (qu'il s'agisse du P/E ou du rendement des dividendes) ont tendance à revenir à leurs moyennes historiques

²⁷Pour *cyclically adjusted price/earnings ratio*.

²⁸*Remarks by Chairman Alan Greenspan At the Annual Dinner and Francis Boyer Lecture of The American Enterprise Institute for Public Policy Research*. Federal Reserve Board. 5 décembre 1996. <https://www.federalreserve.gov/boarddocs/speeches/1996/19961205.htm>. Consulté le 30 septembre 2023.

sur des horizons temporels prolongés. Les travaux empiriques de Paye et Timmermann (2006) montrent que les preuves de l'efficacité des prévisions à court terme basées sur les ratios financiers restent limitées et sont, au mieux, caractérisées par de l'instabilité.

Un débat a été lancé sur la prévisibilité des rendements boursiers à court terme en utilisant les ratios financiers et son lien avec le cycle économique. Lettau et Van Nieuwerburgh (2008) supposent que si la moyenne d'un ratio de valorisation est spécifique au régime plutôt que globale, des retours à la moyenne des ratios financiers peuvent survenir à court terme avec une capacité prédictive statistiquement significative pour les rendements à court terme. Ils concilient les résultats contradictoires des recherches antérieures en assouplissant l'hypothèse d'une moyenne à l'état stationnaire fixe de l'économie, en démontrant de solides preuves de changements. De plus, les résultats de McMillan (2019) montrent que l'utilisation des composantes cycliques des ratios financiers améliore encore leur pouvoir prédictif.

Contribution de la thèse

Cette thèse propose trois contributions originales au domaine de la prévision des rendements des actifs, en lien avec les principales caractéristiques du marché mises en avant ci-dessus. Elle est divisée en deux parties. La première partie (Chapitre 1) met l'accent sur l'importance de la prévision des rendements pour la gestion d'actifs, en particulier pour l'optimisation de portefeuille, en introduisant un nouveau paradigme qui améliore la diversification et la génération d'alpha des portefeuilles d'actions tout en gérant l'exposition aux facteurs de risque. Cette approche peut être opposée aux stratégies d'investissement basées sur les Smart Beta. La deuxième partie aborde l'importance de la prévision à court et moyen terme des rendements des actifs pour l'allocation tactique et est divisée en deux chapitres (Chapitre 2 et Chapitre 3). Le Chapitre 2 examine les possibilités de prédiction des rendements à court terme des actions en mettant en avant le rôle que les ratios de valorisation et leurs propriétés de retour à la moyenne peuvent jouer, tandis que le Chapitre 3 étend cette capacité prédictive en utilisant un large ensemble de variables liées au cycle économique.

Chapitre 1 : Smart Alpha : Gestion active avec des facteurs instables et latents

Le Chapitre 1 introduit une approche d'investissement active, appelée « Smart Alpha », offrant des perspectives innovantes pour l'allocation de portefeuille d'actions. Contrairement aux stratégies traditionnelles basées sur l'exposition aux facteurs, le Smart Alpha se concentre sur la capture de l'alpha potentiel, qui représente les rendements attendus non corrélés aux facteurs de risque systématiques, tout en minimisant l'exposition à ces sources latentes de risque. La méthodologie derrière le Smart Alpha repose sur l'Analyse en Composantes Principales *Sparse* (SPCA), une technique de réduction de dimension issue de l'apprentissage automatique, combinée à une méthodologie pour déterminer le nombre optimal de facteurs pertinents, comme l'ont exposé Bai et Ng (2002). L'approche Smart Alpha vise à relever les défis liés à la remise en question de l'efficacité des portefeuilles moyenne-variance de Markowitz (1952) et du MEDAF de Sharpe (1964), ainsi qu'aux préoccupations concernant la pertinence de schémas de pondération alternatifs tels que les smart beta et les stratégies d'investissement basées sur les facteurs. Trois arguments qualifient cette préoccupation : (1) l'instabilité du nombre optimal de facteurs qui influencent le marché ; (2) la difficulté de prévoir avec précision les gains liés aux facteurs ; et (3) la persistance des alphas des actions découlant de diverses sources. Par conséquent, le chapitre propose la stratégie Smart Alpha comme une approche alternative à l'investissement basé sur les facteurs, en mettant l'accent sur la minimisation de l'exposition au risque systématique tout en maximisant l'alpha, considéré comme les rendements attendus incorrectement évalués. Ce choix est soutenu par des preuves empiriques de la prévisibilité et de la persistance de l'alpha (*Cf. Zaremba et al., 2019*).

Le succès du Smart Alpha repose sur la spécification correcte du modèle d'évaluation des actifs et la détermination du nombre optimal de facteurs. Une contribution significative de ce chapitre est l'utilisation de la méthode SPCA pour estimer à la fois les alphas et les betas, réduisant le bruit d'estimation et améliorant la stabilité des sensibilités aux facteurs. Le Smart Alpha présente des similitudes avec la stratégie d'investissement *Betting-Against-Beta* (BAB)²⁹, mais le nouveau paradigme se distingue en maximisant l'alpha, en tenant compte des facteurs

²⁹ *Cf. Frazzini et Pedersen (2014b)*.

latents et en utilisant des méthodes d'estimation robustes. L'analyse empirique utilisant les actions européennes de l'indice STOXX 600 démontre la supériorité du portefeuille Smart Alpha en termes de rendements, de rendements ajustés du risque et de risque à la baisse par rapport à l'indice de marché, aux stratégies d'investissement basées sur les facteurs traditionnels, aux portefeuilles BAB et aux autres portefeuilles smart beta. De plus, le chapitre met en avant les avantages économiques de l'utilisation de la méthode SPCA pour estimer les expositions aux actions et les alphas, fournissant ainsi une base solide pour la stratégie Smart Alpha.

Le Smart Alpha remet en question la croyance dominante dans l'industrie de la gestion d'actifs concernant le déclin de l'alpha et la prédominance de l'investissement factoriel. De plus, la stratégie génère des rendements *ex post* qui ne sont pas expliqués par les facteurs empiriques traditionnels. Par conséquent, elle valide la philosophie de minimiser l'exposition du portefeuille aux nombreuses sources de risque tout en maximisant une source robuste de potentiel alpha. Il est important de noter que le cadre de la stratégie Smart Alpha est général, flexible et ne dépend pas d'un marché spécifique. La stratégie s'étend au-delà des actions, ce qui la rend applicable à d'autres classes d'actifs.

Chapitre 2 : Le retour à la moyenne conditionnel des ratios financiers et la prédictibilité des rendements

Le Chapitre 2 se penche sur la question cruciale de la prévision des rendements boursiers à court terme. En capitalisant sur le phénomène de retour à la moyenne des ratios de valorisation spécifique au régime de l'activité, nous présentons des preuves convaincantes que ces ratios possèdent un pouvoir prédictif pour les rendements en échantillon et hors échantillon sur de courtes périodes. Cette capacité prédictive est exploitée en tirant parti des variables liées au cycle économique, telles que la pente de la courbe de taux aux États-Unis et les *spreads* de crédit, pour mieux comprendre ces phases. Traditionnellement, la recherche financière a mis l'accent sur le pouvoir prédictif des ratios de valorisation comme le ratio CAPE pour les rendements à long terme du marché actions. Cependant, ce chapitre s'appuie sur les conclusions de Lettau et Van Nieuwerburgh (2008), qui suggèrent que des informations prédictives à court terme dans les ratios de valorisation peuvent être découvertes en tenant compte du retour à la moyenne spécifique au

régime de l'activité économique. Cette approche exploite la relation entre les variations des ratios de valorisation et les variables liées au cycle économique, améliorant ainsi la prévisibilité à court terme (*Cf.* Arnott *et al.*, 2017 ; Boucher, 2006).

Dans ce contexte, l'idée centrale du chapitre est que puisque la dynamique des rendements, suite à un retour à la moyenne, diffère des tendances générales, l'identification d'instances de retour à la moyenne dans les ratios de valorisation peut améliorer les prédictions de rendements des actions à court terme. L'identification d'instances de retour à la moyenne est réalisée à l'aide d'un modèle de changement de régime Markovien. L'analyse empirique à l'aide d'un nouveau modèle de régression prédictive révèle que, suite à l'occurrence d'un retour à la moyenne du ratio CAPE de Shiller aux États-Unis, les rendements moyens des actions sur quelques mois ont tendance à être négatifs, en particulier lorsque des épisodes de retour à la moyenne se produisent à des niveaux élevés du CAPE. Pour garantir l'efficacité du modèle dans les prédictions hors échantillon, le chapitre introduit l'utilisation de la pente de la courbe des taux aux États-Unis comme indicateur de retour à la moyenne du ratio de valorisation. Le choix de cette option découle de deux preuves critiques : (1) des recherches antérieures ont souligné le lien entre le phénomène du retour à la moyenne des ratios de valorisation et les récessions économiques ; et (2) la pente de la courbe de taux a démontré un pouvoir prédictif robuste dans la prévision des récessions économiques. La courbe de taux contient en effet des informations sur les anticipations d'activité future et est influencé par la politique monétaire actuelle (*Cf.* Estrella, 2005). Les résultats montrent que ce modèle de régression prédictive, basé sur la pente de la courbe de taux, surpasse les modèles traditionnels dans les prédictions hors échantillon, offrant une meilleure puissance prédictive sur de courtes périodes.

Cette approche innovante est robuste au choix de la variable liée au cycle économique, car des résultats similaires sont obtenus avec les *spreads* de crédit. De plus, les résultats hors échantillon sont valables pour différents ratios de valorisation, en particulier avec le rendement excédentaire du CAPE et le rendement des dividendes, et pour différents pays, notamment les États-Unis, le Royaume-Uni, l'Allemagne et le Canada. Le chapitre réalise également un exercice d'allocation d'actifs de type moyenne-variance, démontrant la supériorité du nouveau modèle de régression prédictive en termes de gain d'utilité pour les investisseurs.

Chapitre 3 : Prédiction de la prime de risque des actions : l'effet combiné des ratios de valorisation et des variables liées au cycle économique

Le Chapitre 3 étend l'approche de prévision des rendements des indices boursiers à court terme introduite dans le Chapitre 2 en opérant dans un environnement plus riche en données. Cette extension est réalisée en incorporant un ensemble complet de variables liées au cycle économique et en mettant en œuvre des techniques de pénalisation pour faciliter une estimation parcimonieuse. Le nouveau modèle élargit la relation entre le phénomène de retour à la moyenne du ratio CAPE de Shiller et la dynamique des prix, en incluant un éventail plus large de variables de prévision avancées du cycle économique. L'objectif principal du chapitre est d'améliorer la puissance prédictive hors échantillon du modèle proposé dans le Chapitre 2. Cette extension découle de l'absence de consensus concernant les variables du cycle économique qui offrent les meilleures performances prédictives pour le phénomène de retour à la moyenne des ratios de valorisation et des prix des indices boursiers. Au-delà de la pente de la courbe de taux et de des *spreads* de crédit examinés dans le Chapitre 2, le troisième chapitre explore le potentiel prédictif des variables financières mondiales et des indicateurs macroéconomiques suggérés par Welch et Goyal (2008). Ces variables prédictives comprennent la variance de l'indice boursier, l'activité nette d'émission et les rendements obligataires.

Pour faire face à l'incertitude du modèle, le chapitre utilise la méthode du « *Least Absolute Shrinkage and Selection Operator* » (LASSO) de Tibshirani (1996), qui facilite la sélection des variables et l'estimation simultanée tout en atténuant le surajustement. Les résultats empiriques indiquent que cette approche étendue améliore significativement la puissance prédictive hors échantillon à court terme, avec des valeurs de R^2 plus élevées pour le modèle optimal. De manière importante, l'amélioration de la prévision des rendements boursiers à court terme ne résulte pas de l'expansion de la gamme de variables du cycle économique, mais découle plutôt de l'utilisation à différents ordres de retard de la pente de la courbe de taux aux États-Unis. Cela souligne son importance centrale aux côtés du ratio CAPE de Shiller aux États-Unis pour la prédiction des rendements des actions à court terme. Ces résultats sont robustes au choix des mesures de valorisation, y compris le ratio cours/bénéfice (P/E) et le rendement des dividendes. De plus, la robustesse du modèle est validée pour différents secteurs américains, offrant des informations

précieuses pour les investisseurs utilisant des stratégies de rotation sectorielle. Enfin, le chapitre réalise un exercice d'allocation d'actifs de type moyenne-variance, confirmant la supériorité de la nouvelle régression prédictive en termes de gains d'utilité pour l'ensemble du marché actions américain et pour les secteurs individuels aux États-Unis.

Conclusion

Cette thèse a apporté des contributions significatives au domaine de l'économie financière. À travers trois essais empiriques, elle a abordé les préoccupations croissantes de l'industrie de la gestion d'actif concernant la diminution de la génération d'alpha par les stratégies actives, ainsi que la nécessité d'une prédiction plus précise des rendements à court et moyen terme pour les allocations d'actifs tactiques. Tout d'abord, un paradigme original d'optimisation de portefeuille d'actions est présenté dans le premier chapitre, appelé « Smart Alpha », dont les propriétés sont orthogonales à l'abondante littérature sur l'investissement factoriel. Deuxièmement, nous avons introduit, dans les chapitres 2 et 3, un nouveau modèle de régression prédictive robuste qui améliore systématiquement les prévisions hors échantillon des rendements des actions à court et moyen terme, une contribution précieuse face aux nombreuses tentatives infructueuses dans la littérature académique.

Ces deux contributions ont une valeur significative pour les investisseurs et l'industrie de la gestion d'actifs de manière générale, en particulier pour la sélection d'actions et l'allocation tactique de portefeuille. D'une part, la stratégie Smart Alpha peut être facilement mise en œuvre dans des portefeuilles d'actions de type « *long only* » ou des stratégies d'investissement alternatives permettant de mieux gérer, de façon dynamique, les expositions aux risques, telles que les stratégies decorréliées des marchés, de type « *market neutral* » ou « *long-short* ». D'autre part, le nouveau modèle de régression prédictive offre des applications pratiques particulièrement utiles pour l'allocation d'actifs tactique. Ce modèle peut être directement utilisé dans les stratégies d'allocations d'actifs dynamiques, améliorant systématiquement la performance d'un portefeuille avec une meilleure allocation d'actifs régionaux et sectoriels à court terme (à horizon de quelques mois).

Keynes avait observé à juste titre que les investisseurs ont tendance à se concentrer sur

les fluctuations à court terme du marché. Diverses révolutions ont eu lieu dans le monde financier depuis les années 1930, qui ont façonné l'environnement actuel du marché. L'un des changements les plus significatifs depuis lors est la disponibilité accrue et la diffusion rapide de l'information parmi les différents participants du marché. Les tendances futures en matière de gestion de portefeuille devraient être fortement influencées par les avancées technologiques qui permettront un traitement encore plus rapide de l'information. Une tendance majeure qui se dessine est l'intégration croissante de ce qu'on appelle « l'intelligence artificielle » et des modèles d'apprentissage automatique ou *machine learning*, dans les processus de gestion de portefeuille. Les nouvelles techniques vont au-delà de l'analyse fondamentale traditionnelle et permettent d'analyser de vastes quantités de données en temps réel, notamment des publications sur les réseaux sociaux, des médias, des articles de presse, des forums financiers, ce qui permettrait d'évaluer plus efficacement le sentiment du marché. Cela offre aux investisseurs un traitement de l'information beaucoup plus rapide et donc potentiellement la possibilité d'améliorer la prévisibilité des rendements des actifs. Une extension intéressante de cette thèse consisterait à évaluer comment le nouveau modèle de régression prédictive peut être encore amélioré en incorporant ces nouvelles techniques, ce qui pourrait potentiellement permettre une meilleure prévision du cycle économique, entre autres applications. Une autre extension de cette thèse, concernant la stratégie Smart Alpha, serait d'utiliser des modèles multi-factoriels en explorant les données de sentiments de marchés en temps réel, permettant ainsi d'affiner la détection systématique des facteurs significatifs moteurs de la dynamique des marchés financiers.