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Factor Timing in Asset Management: A Literature Review

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Abstract

While static factor-based investing is nowadays a common way of allocating portfolios, the next step, a dynamic progression towards time-varying components and factor cyclicity, is still far less established. This study offers a survey on the state of the art of factor timing in asset management and presents the main approaches discussed in the finance literature as well as empirical evidence on the performance of factor timing investment strategies. It becomes obvious that factor timing is much older than first assumed and that there is a diverse collection of approaches. In addition, empirical results on the economic benefits are conflicting. On the one hand, factor timing has the potential to generate economic wealth for long-term oriented institutional investors. On the other hand, high turnover and high transaction costs might limit returns. Furthermore, available data and literature are scarce, leading to challenges in comparing studies. These different perspectives are driving the debate in the finance literature.

Keywords: factor timing, factor investing, asset management, quantitative investing, smart beta

JEL Classification: G11, G23, G17, G24

I. Introduction

Strategic investment portfolio allocation is based on the assumption that the overall risk of a portfolio can be lower than the sum of the idiosyncratic risks of its individual investment components (*Bass* et al. 2017). Diversifying across asset classes such as stocks and bonds has been the standard approach for more than 60 years (*Bender* et al. 2018). However, in the aftermath of the Great Financial Crisis (GFC) of 2007 more recent evidence indicates incorrectly executed

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diversification based on asset classes (*Ilmanen/Kizer* 2012). This finding led to an increased interest in factor investing, suggesting a more sophisticated way to achieve robust portfolios through factor diversification (*Bender* et al. 2018). The idea of factors in asset management has been around at least since the discovery that small stocks tend to outperform large stocks (*Banz* 1981). Once it was established that risk factors exist, the challenge became to predict them over time.

With the discovery of time-varying components in factor returns, research is able to identify the forces that drive each factor. The idea is that with a sound knowledge of the mechanisms, the future performance of a factor should be predictable, which is the basis of factor timing. Knowing the direction and magnitude of fluctuations in factor returns makes it possible to identify a factor's good and bad times. This allows investors to adjust a portfolio's factor exposure, providing the opportunity to pursue active or defensive strategies. At first glance, factor timing promises solutions that sound like the "holy grail" of investing. A deeper dive into the state of the art on factor timing reveals a controversial debate as to whether there is indeed a statistically significant benefit, especially when transaction costs are taken into account. So far, a structured overview of the current state of empirical research is missing.

In literature, factor timing is presented as a new topic, but much of the underlying theory and basic research is decades old. What is striking is the scarcity of empirical research directly related to factor timing. Particularly missing is evidence about predicting future factor returns (*Bender* et al. 2018), which can be attributed to the ongoing debate about whether certain factors even exist. Consequently, this study aims to summarize the evidence about value creation by factor timing approaches. To this end, the study addresses three main questions:

1. How widespread is factor timing in the literature and what is the related field of research?
2. What are the approaches and how mature is factor timing?
3. Are there different groups (e. g., practitioners and academic researchers) and what are their attitudes and research findings regarding factor timing?

In line with these questions, factor timing is approached from a number of different angles, which is reflected in the structure of this study. Starting with the prediction of expected returns, followed by a presentation of the most common factor models, the fundamentals are introduced. Building on this foundation, the theory of portfolio allocation in the context of factor investing is presented. Once this theoretical foundation has been established, the next chapter is devoted to the topic of factor timing, covering both theory and empirical research. This part approaches the topic from different angles and discusses recent research findings using exemplary studies. For the purpose of this study, a literature review on factor timing was conducted and is presented in chapter V. The

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research includes an analytical part where the results are evaluated based on the time of publication and the use of keywords. A qualitative content analysis was also carried out to describe the literature landscape. After classifying the movements and approaches in research, the results of recent studies are discussed and an outlook on further directions is given. The study concludes in chapter VI. with a summary of the issues presented.

II. Prediction of Expected Returns

Keim/Stambaugh (1986) provide early evidence that asset prices, and hence asset returns, can be partially predicted by certain predetermined factors. These findings lead to a search for parameters and models, that indicate the future path of returns. For factors, *Ang* (2010) uses the analogy of the nutrients in our food. Just as each food has a unique composition of nutrients, each asset has a unique composition of factors. The factors reflect the risks and rewards of an asset. What the right mix of nutrients is for a healthy diet, a well-designed balance of factors is for an asset portfolio. Finding the right combination of factors for a particular investment strategy will reduce exposure to interest rate risk and default risk (*Ang* 2010).

In order to find this "right combination" of nutrients or factors, the way in which data is collected and processed plays a crucial role in building different models. The literature on predicting asset prices is divided into fundamental analysis, technical analysis, regression and Machine Learning (ML). Academic literature mostly uses linear regression models and provides expected process or price ranges, whereas practitioners mostly rely on technical indicators. For investment purposes, the practitioner approach is considered superior. Most technical indicators provide price movement classifications, rising/falling (2-classes) or rising/neutral/falling (3-classes). The dominance of the latter approach is illustrated by *Sezer* et al. (2020).

Recent research such as *Neely* et al. (2014) indicates that a combined approach can be superior to the individual approaches. They show that technical analysis of risk premia in the state of economic peaks delivers better predictions of economic downturns than regression analysis based on macroeconomic factors. Conversely, predicting the rise in risk premia based on macroeconomic factors at the peak of an economic downturn has superior predictive power (*Neely* et al. 2014).

Regardless of the approach taken, the two determinants of forecasting models are the data basis and the time horizon. At the long end, *Lo/MacKinlay* show that between 1962 and 1985 the variation in weekly US risk premia increased disproportionately with longer horizons. This leads to decreasing forecasting accuracy (*Lo/MacKinlay* 1988; *Lo* 2008). At the other end of the spectrum, *Fama/*

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French find that short periods do not solve the problem either. They report that 25 % to 40 % of return variation can be predicted from past returns over long time horizons (*Fama/French* 1988).

An emerging field of research that is gaining importance for factor timing in asset management is ML, a subset of Artificial Intelligence. The goal of ML is to improve prediction accuracy, reliability, and performance by learning through training. ML applications in financial market forecasting have received much attention in recent years. *Kumbure* et al. (2022) examine 138 studies published after 2000 related to ML applications in stock market forecasting. They report a significant increase in annual publications, as illustrated in Figure 1. *Sezer* et al. (2020) document similar findings.

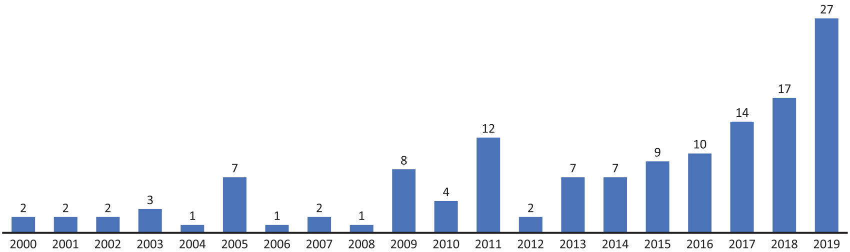

Figure 1: Number of publications related to ML applications per year[1]

While other areas exist, this study only examines the application of ML models for factor timing. Recently, some noteworthy results have been published such as *Digard/Bouzida* (2020) and *Dirkx/Heil* (2022), which give hope for a boost to the topic of factor timing.

III. Models and Portfolio Allocation

Predicting future asset returns is a key to successful participation in financial markets. The Capital Asset Pricing Model (CAPM) has dominated academic and practitioner research for predicting expected asset returns in portfolio management (*Fama/French* 1993). Although the empirical track record of the CAPM is poor (*Fama/French* 2004), its core idea that factors associated with an asset determine the asset risk premia paved the way for future models (*Ang* 2014).

[1] Illustration based on (*Kumbure* et al. 2022), own illustration.

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1. *Evolution of Asset Pricing Models*

The CAPM is derived from *Markowitz's* (1959) portfolio selection model and the core assumption of efficient markets. As it suffers from numerous inconsistencies most probably traced back to the simplifications in model assumptions such as homogenous expectations of investors, risk free borrow and lending and ultimately its empirical shortcomings of not fully explaining stock returns with so called anomalies, pointing in the direction of market inefficiencies. The first discovery was made by *Basu* (1977), who showed that companies with a low price-earnings ratio (P/E) tended to outperform those with high ratios.

Thus, a better empirical model for predicting asset returns was needed. *Fama/French* (1993) presented their three-factor model, ushering in the era of multi-factor models. They used the well-researched foundation of the CAPM and developed an empirical approach to improve the predictive power of the existing model. Their approach was to add two easy to measure variables, size (ME) and book-to-market-equity (BE/ME). These two factors are further associated with dept-to-equity (D/E) and price-earnings (P/E)-ratios, which allow to capture the cross-sectional variation in average stock returns (*Fama/French* 1993).

The choice of ME and BE/ME was favored by the fact that these two variables were well known at the time of their work and the relevant research supported this decision (*Fama/French* 2015a).

In their study *Fama/French* (1995) sorted common stock from NYSE, Amex and NASDAQ by ME and BE/ME. The size list is then split in half at the median, creating two groups small (S) and big (B). For the leverage list, *Fama/French* (1995) decided to differentiate into three categories, with breaking points at the lowest 30% low (L), 40% medium (M) and top 30% high (H). Assigned with these attributes, the stocks were sorted into six portfolios (S/L, S/M, S/H, B/L, B/M, B/H). SMB mimics the risk factor of return, associated with a company's size, by comparing the average return of the small stock portfolios (S/L, S/M, S/H) with the big stock's portfolios (B/L, B/M, B/H) on monthly base. This allows to compare the average return of small and big-stock portfolios, without the influence of leverage. HML is defined accordingly, comparing high leverage portfolios (S/H, B/H) with low (S/L, B/L). Therefore, HML represents the difference between average returns of high and low leverage portfolios, without the influence of size (*Fama/French* 1993).

$$R_{it} = R_{Ft} + \alpha_i + \beta_{\mathrm{ib}}(R_{Mt} - R_{Ft}) + \beta_{is} SMB_t + \beta_{ih} HML_t + e_{it} \,. \tag{1}$$

By adding the small minus big (SMB) and high minus low (HML) factors to the CAPM equation, the model can be described as shown in Equation 1.

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The original model was primarily based on data from the U.S. stock market. Researchers not only adopted the three-factor model for various geographic regions, but also used alternative factors to test the explanation of market anomalies (e.g. *Chen* et al. 2011; *Kiesel* et al. 2018).

Fama/French found that much of the variation in average stock returns attributable to investment behavior and profitability is left unexplained by their three-factor model from 1993. Their empirical research shows that different anomalies have the same five-factor exposure, suggesting that they are related to the same phenomenon (*Fama/French* 2015b).

$$
\begin{aligned}
R_{it} = {} & R_{Ft} + a_i + \beta_{ib}\left(R_{Mt} - R_{Ft}\right) + \beta_{is} SMB_t + \beta_{ih} HML_t + \beta_{ir} RMW_t \\
& + \beta_{ic} CMA_t + e_{it}\,.
\end{aligned}
\tag{2}
$$

Equation 2 shows the five-factor regression proposed by *Fama/French* (2015a), which extends the three-factor model by adding robust minus weak (RMW) and conservative minus aggressive (CMA). RMW_t represents the profitability factor by reflecting the difference between the returns of stocks with robust and weak profitability. Equivalent to RMW_t, CMA_t is a proxy for investment activity, expressing the difference in returns between firms with low and high investment. *Fama/French* estimate that their model describes between 74 % and 94 % of the cross-sectional variance of expected returns (*Fama/French* 2015a).

A key difference between the CAPM and multi-factor models is the definition of bad times. While the CAPM defines bad times as a period of low returns on a broad market portfolio, in multi-factor models each factor has its own definition of bad times. For the models themselves, this means that the risk of an asset is measured exclusively by beta in CAPM and by factor exposure for each factor in multi-factor models (*Ang* 2014).

In summary, multi-factor models provide a sound and, most importantly, well-researched basis for predicting expected average portfolio returns, as long as anomalies are not ignored. Although many researchers have successfully added more and more variables to improve existing models, the approach must be questioned. *Lewellen* et al. (2010) simulated artificial factors correlated with expected returns that produce zero true cross-sectional R^2s for the size and book-to-market (B/M) portfolios of *Fama/French*. They showed that, depending on the number of variables considered, the sample adjusted R^2 must be as high as 44 % for one factor and up to 69 % for five factors to be statistically significant.

In conclusion, it is not an option to endlessly increase the number of variables in multi-factor models. On the one hand, the required in-sample predictive power per variable must increase with each additional variable, as demonstrated by *Lewellen* et al. On the other hand, the autocorrelation of the factors will cause mathematical problems, as with all models based on linear regression.

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2. Factor Investing: Strategies and Time-Variability

Portfolio allocation refers to the composition of a portfolio to achieve specific goals. Many portfolio theories assume that investors primarily seek to increase the return on their investments while being risk averse. In the real world, these goals may vary from investor to investor. In traditional asset management, portfolios are constructed by broad diversification across the major asset classes (equities, commodities, fixed income, cash, and others). These asset classes can be further diversified by investing in different geographical markets or industries (*Bender* et al. 2018).

That the risk of assets does not depend on a single factor has been known at least since *Basu* (1977) discovered that value as a factor can describe the returns of ordinary shares. Factors are grouped into sets that describe a single asset or an entire portfolio. Factor sets can include fundamental macroeconomic variables such as growth, inflation, and volatility, or they can consist of investment-style factors. Examples of the latter are SMB and HML. The most influential factor discoveries are shown in Figure 2. Although the chart ends in 2013, the search for factors with explanatory power continues. Since it seems that most of the common financial variables have been examined, *Dichtl* et al. (2019) refer to "factor tilting", a topic related to factor timing, where the cross-section of factors is explored. In particular, the research on the relationships of factors within factors has gained popularity.

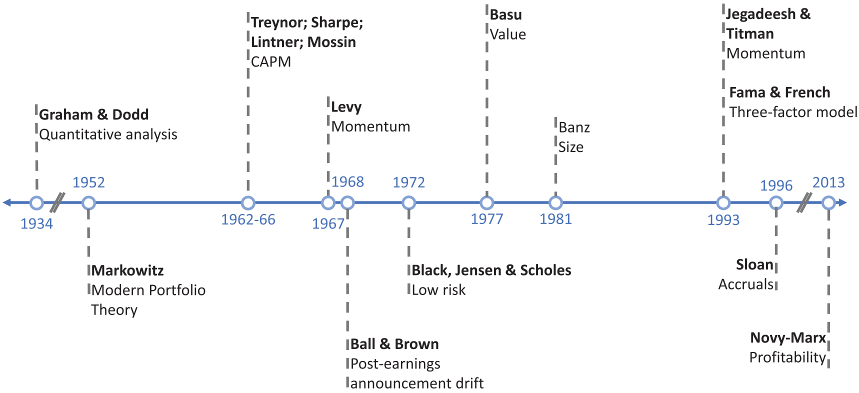

Figure 2: The development of Factor Investing (Smart Beta) Equity Strategies[2]

Ideally, when factors are used, their significance remains the same over time. *Fama/French* (2012) investigated the size effect discovered by *Banz* (1981) and

[2] Illustration based on *Alford* (2016), own illustration.

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could not find a statistically significant influence of a company's size on its risk premium, both in the U.S. and in international markets. According to *Ang* (2014) there are two possible explanations for this. First, the effect existed at the time of *Banz* (1981) and was subsequently exploited by the market until it was eliminated by rational investors bidding up small caps. Second, the effect never existed and is an artifact of data mining. Researchers tend to store 95% of their data that is insignificant and present only the 5% that is significant to the public. To judge significance, they use a standard p-value of 0.05. Therefore, the factor found may be significant by chance within 5% of the data, but it will fail out of sample (*Ang* 2014). In the case of *Banz's* size effect, smaller stocks still have higher returns on average than large firms, but unlike previously assumed, it is not size, but a combination of factors that are stronger in small firms. In addition, small stocks are more illiquid, which needs to be compensated for (*Ang* 2014).

To address this data mining problem, *Harvey* et al. (2016) investigate hundreds of factors to assess when a (newly discovered) factor has enough explanatory power for the cross-section of expected returns. They examine 313 articles (63 working papers and 250 published articles from top journals) with 316 different factors. Their results show that 70% of the factors they looked at had a Sharpe ratio of less than 0.5 per year, meaning that an investor is undercompensated relative to the risk taken. For newly discovered factors, they propose that they must exceed a t-statistic of 3.0, which corresponds to a p-value of 0.25%, compared to the CAPM market beta t-statistic (sample period 1935–1968) of 2.57 shown by *Fama/MacBeth* (1973). *Harvey* et al.'s justification for this high hurdle is threefold: first, the "low-hanging fruits" have been harvested, reducing the rate at which new truly significant factors are discovered. Second, unlike most scientific fields such as physics, financial research has a limited amount of data because artificial data cannot be generated for backtesting. Third, the cost of data mining decreased dramatically, allowing more factors to be tested – In the past, only the most promising were tried (based on economic principles). Despite the stated high hurdle, *Harvey* et al. see room for exceptions when a factor is derived from a theory, rather than through sorely empirical exercise without any theory behind it.

Factor strategies (also called smart beta strategies) are developed in two steps: first, the investable universe is defined by deciding which factors to invest in. Second, the factors are weighted to determine the actual composition of the portfolio. This clear approach avoids distortions due to personal preferences or impulsive actions by portfolio managers (*Amenc* 2013). It is important to note that these strategies do not incorporate timing information (*Hodges* et al. 2017). In traditional cap-weighted portfolio theory, a portfolio is sporadically rebalanced based on how its components have performed in the past. In smart beta strategies, the composition shifts continuously because factors tend to have a

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time-varying component. By combining active and passive investments, smart beta strategies build on the recent performance of its factors, compared to their historical performance (*Hodges* et al. 2017). If a factor is low relative to its historical valuation or relative to other factors, it is considered cheap and thus should be bought.

Since the inception of expected return forecasting models, researchers have been looking for predictable time-varying components. *Solnik* (1993) divided the literature at the time of his work into three approaches: (1) a first approach was to model the expected return based on past returns under a set of conditional variables; (2) the second approach is to model the risk premium as a function of the volatility of returns; and (3) a third approach was to use observable variables at the beginning of a period and incorporate this information into the forecast. For the last approach, good performance has been reported for U.S. stocks when dividend yield, term structure spread, default spread, short-term interest rates, or a seasonal factor was considered (*Solnik* 1993).

The commonality of the approaches presented by *Solnik* is to identify a conditional set of variables, to develop dynamic asset allocation strategies (*Hua* et al. 2012). However, in order to adapt to the new environmental conditions, it raises the necessity to find better prediction models. *Hua* et al. propose to start with an existing static model and then add a set of optimal conditioning variables. They suggest incorporating a process to assign the observed values to these variables, which converts the gathered information into factor weights.

For factor models, the results of *Ang/Chen* (2002) show that the factor exposure of certain assets can change over time and depending on market directions. The correlation between factors, assets represented by a bundle of factors, and time raises the question of how to model time-varying portfolios.

IV. Factor Timing Strategy

In this harsh environment since the global financial crisis of 2008, some factor models struggle with their static-quantitative approach, due to the extreme behavior of their factors. By the nature of their construction, these types of models perform well in static environments with long time horizons, but are vulnerable to rapid changes in market conditions. In particular, when market volatility persists, static models suffer from performance issues (*Hua* et al. 2012).

When investing in factors in the static way, the goal is to find a set of factors with the highest possible average returns. Naturally, these factors are subject to fluctuations that affect expected returns. From this point, it is possible to take advantage of these inevitable fluctuations by weighting the importance of a factor depending on its expected return – owning more of it when the return is above normal and reducing it when it is lower. In the extreme forms of success-

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ful factor timing, it is quite possible to drop a previously well-performing factor and invalidate it when the explanatory power is no longer present. This edge-case might occur when a certain factor has been exploiting potential market inefficiencies and too many investors have tried to take advantage of it (factor crowding). Regardless of academic or practitioner research, almost every presentation of factors asks whether they can be timed in some way. This underscores the importance of the discussion of whether factors can be reliably timed across the research landscape (*Asness* 2016).

Besides the lucrative prospects of reducing portfolio risk by using a mathematical model to avoid losses, the fundamentals of portfolio investing are still important. *Ilmanen/Kizer* (2012) argue that the apparent failure of diversification in the 2007 financial crisis was a "user error" because diversification was done incorrectly. The error they identify is incorrect diversification in the sense of diversifying in traditional assets rather than diversifying in factors. Another mistake they report is the wrong implementation of diversification. Over long horizons, a strategy of diversified portfolios reduces downside risk. In situations of short-term panic, this strategy is likely to fail.

While the value of factor diversification is now widely accepted, two questions remain. First, there is still uncertainty about the optimal management of factors, and second, whether additional value can be created through forecast-based factor allocation. Regarding the latter, *Dichtl*, et al. (2019) divide the research community into sceptics and optimists. The sceptics like *Asness* (2016), *Asness* et al. (2017) and *Lee* (2017) argue that the factor diversification strategy and factor timing are too highly correlated and the value added through diversification (passive factor allocation) exceeds the potential of factor timing (active factor allocation). Optimists represented by *Hodges* et al. (2017) and *Arnott/Becker* (2016) acknowledge the challenges of predictions based on macroeconomic and investment-style indicators. Nevertheless, they argue that investors with a reasonably long investment horizon and a good understanding can benefit from factor timing (*Dichtl* et al. 2019).

The latter distinguish between "factor timing" and "factor tilting" in active factor allocation. In this distinction, factor timing is defined as the use of time-series information of macroeconomic variables. The aim is to predict expected returns based on these fundamental variables. Factor tilting is defined as "factors within factors". In other words, the variables are derived from factors such as valuation and momentum and are described with their individual cross-section.

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1. *Timing Indicators*

Macroeconomic variables, market sentiment, and momentum are the most common groups of timing indicators. They have in common not to be static over time and follow at least partially predicable patterns, triggered by different events. In the framework of factor timing, indicators are used as triggers for models that derive actions such as buy and sell. In the following, we focus on the basics of these indicators. According to *Dichtl* et al., factors are used as indicators in a method they define as "factor tilting". With this exception, indicators generally mimic risk, whereas factors carry risk.

a) Macro Factors and the Business Cycle

As economies fluctuate in size and appear in cyclical waves, a number of factors have been identified in the search for the cause of contradictory and expanding economies. The first suspects are fundamental macroeconomic (macro) factors such as consumption, output and productivity (*Backus* et al. 1993). Although it is often said that fluctuations and shocks that cause a contradiction in an economy, are due to a specific event, empirical evidence suggests that it is a set of factors and the event acts as a trigger. *Zarnowitz* (1992) states that each downturn is due to a mix of common and unique characteristics, making it difficult to develop a unified business cycle model.

Macroeconomic factors, such as inflation and economic growth, affect the return on assets in such a way that nearly everyone is affected, either positively or negatively. Compared to investment style factors, they are characterized by their persistence over time. For example, the next month's inflation is very likely to be close to today's inflation. Therefore, the level of a macroeconomic factor is much less important than its amplitude when it changes (*Ang* 2014). For factor-models, the state of an economy matters because it affects the factor exposure through the different behavior of the market. These models are designed to work at business cycle frequencies and are therefore of interest to investors with long investment horizons, such as pension funds. For factor investors, it is not the business cycle itself, but the numerous factors represented in it that will affect the economy. It is important for these investors to understand the impact on the market portfolio and the behavior of its components under changing macroeconomic conditions. For example, during shifts into recessions, government bonds yield higher returns, acting the opposite way of common stocks which decline (*Ang* 2014).

Beyond the economic intuition of the possibility to increase returns or hedge against risks, the question remains how to implement macro factors in asset management. *Varsani/Jain* (2018) assess four different indicators with regard to the US economy:

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1. Composite Leading Indicator (CLI)[3] published by the Organization for Economic Development (OECD)
2. US Purchasing Managers Index (PMI) published by the Institute for Supply Management (ISM), released on the first business day of each month
3. Chicago Fed National Activity Index (CFNAI), published monthly
4. The Federal Reserve Bank of Philadelphia ADS Index, published on a weekly basis

Among the various factors considered in the indicators, *Varsani/Jain* (2018) point out that one of the key differences is the amount of lag between the underlying data and the release date. They give the example of the CLI, which has a lag of two months and is published on a monthly basis, while the ADS is adjusted on a weekly basis. The time series of these indicators reveals the fluctuations with recognizable phases. Each of these phases has its own characteristics and represents a particular economic environment. A correct predicting of how market mechanism and related variables behave and change during and between these phases is critical to making sufficient predictions about asset returns. To determine factor exposure during different states of the economy, *Varsani/Jain* (2018) define four states: recovery, expansion, slowdown, and contraction. They follow *Bender* et al. (2013) and assign value, momentum, quality, low volatility, size, and dividend yield as factors representing each state in a given allocation as shown in Table 1. *Digard/Bouzida* (2020) follow *Varsani/Jain* (2018) and find that between December 1999 and November 2019, the U.S. economy was in expansion 42 % of the time, slowing 40 % of the time, contracting 9 % of the time, and recovering 9 % of the time.

Table 1

Economic states within a business cycle[4]

Macro state	**Allocation**
Expansion	Momentum, Size, Value
Slowdown	Momentum, Quality, Low Volatility
Contraction	Low Volatility, Quality, Value
Recovery	Value, Size, Yield

[3] The composite leading indicator (CLI) is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long term potential level. CLIs show short-term economic movements in qualitative rather than quantitative terms. (*OECD* 2023).

[4] Derived from *Varsani/Jain* (2018).

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Kwon (2022) takes an approach similar to *Digard/Bouzida* (2020) and *Varsani/Jain* (2018) to characterize macroeconomic regimes. Based on the characterization of macroeconomic regimes, he further investigates how they behave over a sample period from 1967 to 2021. His results, which cover a total of 657 months, are shown in Table 2.

Table 2

Transition matrix and distribution of economic regimes[5]

Transition Matrix					Total #
From/To	Recovery	Expansion	Slowdown	Contraction	
Recovery	94 %	5 %	0 %	1 %	172
Expansion	0 %	93 %	7 %	0 %	215
Slowdown	0 %	3 %	92 %	5 %	168
Contraction	10 %	0 %	0 %	90 %	102

Hodges et al. (2017) (real annualized US growth rate), *Varsani/Jain* (2018) (CLI, PMI, CFNAI & ADS) and *Digard/Bouzida* (2020) (PMI) identify recurring patterns in business cycles for various macroeconomic variables. They find evidence that macroeconomic indicators, when divided into different phases can act as timing indicators in dynamic models.

b) Market Sentiment

In general, sentiment describes investors' perceptions of the state of the world and is closely related to the economic environment. Sentiment captures the expected development of the market, which is not reflected in other financial data, such as macroeconomic variables. *Baker/Wurgler* (2006) describe the concept of sentiment as the "…propensity of investors to speculate" and the impact on common stock prices as follows:

> „When sentiment is estimated to be high, stocks that are attractive to optimists and speculators and at the same time unattractive to arbitrageurs – younger stocks, small stocks, unprofitable stocks, non-dividend- paying stocks, high volatility stocks, extreme growth stocks, and distressed stocks – tend to earn relatively low subsequent returns." (*Baker/Wurgler* 2006).

[5] Derived from *Kwon* (2022).

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Market sentiment indicators are closely related to macroeconomic indicators and follow a similar cyclical pattern over time. From a portfolio theory perspective, it is economically intuitive that when investor sentiment is low, investors will try to avoid risky investments in companies such as small, young, volatile, unprofitable, non-dividend paying, extreme growth, and stressed stocks. In a risk-on environment, factors such as low volatility, secure dividend yield, and quality outperform others over long time horizons (*Bender* et al. 2018).

Various indicators have been developed to capture market sentiment. These indicators can be divided into two groups. The first group is based on simple statistical methods and extracts information from asset prices. Known as market-based indicators, they are typically constructed using spreads of various asset classes or implied volatility, such as the Chicago Board Option Exchange (CBOE) Volatility Index (VIX). The second group is based on financial or economic models and is usually applied to a single financial market. An example of a model-based measure is the Goldman Sachs (GS) Risk Aversion Index. Although these indicators attempt to capture the same phenomenon, research has shown that the indicators behave differently, when responding to the same event. In their Financial Review of June 2007, the European Central Bank find that different indicators capture different "…facets of investors' risk appetite". When 14 sentiment indicators were challenged to principal component analysis (PCA), the first principal component explained only 38 % and the second 18 % of the total variance. This suggests that 5 principal components are needed for the Kaiser criterion and 6 for the Joliffe criterion. The low explanatory power of the first principal component suggests that the indices do not follow a common pattern, suggesting a considerable diversity in the methodologies of different indices (European Central Bank 2007). In addition to the skepticism about sentiment indicators, researchers have also reported statistical evidence to support the use of timing indicators to make economic gains. Sentiment indicators used in the factor timing literature are risk-tolerance indicators, diversification ratios and valuation indicators.

As described for macroeconomic variables, all factors show fluctuations in their historical time series. Valuation indicators attempt to capture the spread between the current price of a factor and its long-term historical value. Technical indicators such as the stochastic oscillator, the relative strength index or the Cyclically adjusted price-to-earnings ratio (CAPE), are used as valuation indicators. A factor often used to mimic investor sentiment is the CBOE Volatility Index. *Copeland/Copeland* (1999) show that large capitalization stock portfolios outperform small capitalization stock portfolios on the day that following an increase in the VIX. They find the same evidence for value and growth portfolios, with value portfolios outperforming growth portfolios. For both portfolio constructions, an inverse effect is observed on days following a decline in the VIX.

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Fergis et al. (2019) propose to consider economic growth, real interest rates, inflation, credit, emerging markets, and liquidity for their multi-factor model. For economic growth, emerging markets, and liquidity, they smooth the time-series of their factors using a modified Shiller CAPE, adjusted for each factor. According to the construction of the CAPE, a factor is fairly priced relative to its historical value when the valuation indicator is zero. Positive deviations indicate that a factor is cheap, while negative values indicate richness. In the case of liquidity, *Fergis* et al. (2019) consider the two effects that contribute to it, size (*Banz* 1981) and volatility selling (*Bakshi/Kapadia* 2003). Volatility selling again is a combination of the carry implied by the VIX term structure and the ratio of the current price, the spot VIX, to the fundamental value.

Digard/Bouzida (2020) take a different approach but utilize the VIX too, to capture market sentiment. They define three market states implied by the VIX future slope, which is derived from the prices of VIX future contracts with maturities ranging from one to six months. When the slope points upwards, the market state is in risk-on, and respectively for risk-off. They find that with this categorization, the VIX indicator sees the market in a risk-on environment 85 % of the time. Building on the work of *Varsani/Jain* (2018), *Digard/Bouzida* (2020) examine their top performing indicators and find similar results with few deviations, as shown in Table 3.

Based on their findings, *Digard/Bouzida* (2020) develop a market sentiment rotation strategy using these factors. At the beginning of each month, value, momentum, volatility, size, and quality are equally weighted at 20 %. Depending on changes in the VIX, the factors are increased to 100 % or decreased to 0 %. The portfolio weight is then normalized to 100 %. They show that the rotating portfolio approach slightly outperforms its static counterpart, which also outperforms its benchmark, the MSCI US.

Table 3

Comparison of best performing factors for market sentiment[6]

Market Sentiment	Allocation (*Varsani/Jain* 2018)	Allocation (*Digard/Bouzida* 2020)
Risk-on	Value, Momentum, Size	Value, Momentum, Volatility, Size, Quality
Risk-off	Volatility, Quality, High Yield	Volatility, Quality
Examined Factors: Volatility, Momentum, Size, Value, Quality and High Yield		

[6] Illustration based on *Digard/Bouzida* (2020).

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A third approach to capture investor sentiment with valuation indicators by *Digard/Bouzida* (2020) is the US High Yield Option Adjusted Spread (OAS). As the economy weakens, the yield curve steepens, with the steepest point typically occurring at the trough of a recession. Following their approach to defining market conditions for the PMI, market sentiment is categorized by comparing the 3-month and 12-month SMAs, as shown in Table 4. Again, the dynamic portfolio is constructed by equally weighting each factor at 20 % at the beginning of the month when market conditions change, and then rebalancing according to the current market state by increasing or decreasing the factors by 100 %. Finally, the portfolio is normalized to 100 % weight. The empirical results show the same results as for the VIX in terms of performance relative to both the static portfolio and the MSCI US benchmark.

Table 4

Classification of market sentiment on US High Yield Option Adjusted Spreads[7]

Market Sentiment	Classification
Risk-off	3-month SMA above 12-month SMA and spread increasing
Risk-on	3-month SMA below 12-month SMA and spread increasing
Neutral	Otherwise

c) Momentum

As several researchers have shown, momentum strategies can generate significant returns. The idea behind the momentum effect is the observation that stocks that have performed well in the past tend to outperform in the future. It is important to note that momentum gains in price and return do not persist and typically disappear within two years, as shown by *Jegadeesh/Titman* (1993). This is the basis for implementing a momentum-strategy rotation to take advantage of this pattern. Although the momentum effect has been extensively studied in the literature, the relation of factors and momentum is relatively new (*Varsani/Jain* 2018). Momentum can be divided into cross-sectional momentum and time-series momentum. Cross-sectional momentum refers to the relative performance of an asset compared to other assets over the previous period (*Jegadeesh/Titman* 1993). More recently, *Moskowitz* et al. (2012) propose time-series momentum as a framework for investment strategies. Here, the ab-

7 Derived from *Digard/Bouzida* (2020).

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solute performance of a stock over a period of time is put into perspective. They find that both momentum effects are consistent across numerous future contracts and multiple asset classes over a timeframe of 25 years. Although time-series momentum and cross-sectional momentum are different, they are related. Macroeconomic factors, market sentiment, and momentum have time-varying components. There is statistically significant evidence of the predictive power of certain factors for each of these topics. This provides a basis for implementing factor timing strategies. A critical aspect, as pointed out by *Bender* et al. (2018), is that sentiment and macroeconomic factors are more difficult to interpret than other factors.

2. *Factor Timing*

Factor timing is essentially time series forecasting with the goal of identifying and correctly predicting the good and bad times of a factor, and using this information to make a profit (active strategy) or hedge against risk (defensive strategy). In order to actively time factors, indicators such as those presented above are needed to dynamically adjust the forecasting model.

The core of such a predictive model is often a traditional static model, such as the three- or five-factor models from chapter 3. A time-varying indicator is added to this model to allow dynamic adjustment to changing market conditions. The static model is often used as a second benchmark to evaluate model performance. According to *Leippold/Rüegg* (2021), the literature on the timing ability of risk factors focuses on both technical and fundamental predictors.

a) Active Strategy

Active strategies aim to generate profits by strategically timing market factors. *Bender* et al. (2018) utilize the *Fama/French* (2015a) five-factor model with size, value, profitability, investment, and momentum. They base their research on the *Fama/French* long factor portfolios, which consist of the top 30 % of securities (ranked by their factors), listed on the NYSE, AMEX and NASDAQ. These portfolios are challenged by market performance between 1963 and 2015. Similarly, *Leippold/Rüegg* (2021) examine three models based on long-only portfolios. First, a *Fama/French* (1992) three-factor model, second, a *Fama/French* (2015a) five-factor model; and third, an extended five-factor model, incorporating momentum, resulting in six factors. According to them, the long-only portfolios are chosen because most institutional investors, who are most likely to adopt such an approach, have long investment horizons.

Contrary to the previous approaches of equally weighting all factors, *Digard/Bouzida* (2020) decide to increase the two best performing indicators and de-

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crease the two worst by 100 % each for cross-sectional momentum. This strategy again significantly outperforms its benchmarks, but also suffers from high turnover. Over the period considered, from 1999 to 2019, this strategy significantly outperforms the benchmarks. The turnover, as with the time-series momentum, is high and may need to be slowed down to reduce transaction costs.

Building on the framework of *Campbell/Shiller* (1988a), which uses valuation as a signal and avoids factors when they are unusually expensive, *Bender* et al. (2018) construct a portfolio with four equally weighted factors and use factor portfolios from the MSCI World universe to test a dynamic strategy against a static strategy over a 20-year period. For the dynamic strategy, once a month, the four factors value, size, low volatility, and quality are sorted into quintiles based on their metrics. The dynamic strategy was able to generate an annualized return of 11.28 %, compared to the static approach's 7.57 % and the MSCI World index's 9.14 %.

Following the approach of *Hodges* et al. (2017) and *Ilmanen* et al. (2014), *Kwon* (2022) constructs a regime-dependent dynamic model with a macro indicator to time a portfolio. The goal for developing the indicator is to have a real-time business cycle with one-month increments. Therefore, Kwon uses a composite approach with five components, following the approach of *Fama/French* (2015a):

> "…yield spread between the 10-year treasury yield and effective federal fund rate, credit spread between the Moody's Baa corporate bond yield and 10-year treasury yield, four-week moving average of initial jobless claims, total units of building permits, and CBOE Volatility Index (VIX)." (*Kwon* 2022).

The sample period is set from 1967 to 2021, with the first 40 years used to initialize the experiment and the remaining span from 2007 to 2021 used for out-of-sample testing. He compares the dynamic portfolio to a risk parity portfolio, both restricted to an investment universe of US stocks. Both portfolios are allocated to the five equity factors size, value, momentum, profitability, and investment, which are widely known in the literature and show positive long-term premiums. A risk parity portfolio is a heuristic approach to portfolio construction. It follows the idea that each component of a portfolio contributes an equal share of risk (*Maillard* et al. 2010). The advantage of this approach is that it is easy to compute, as it does not require expected returns, but any measure of risk, such as volatility (*Blin* et al. 2021). Theoretically, any risk measure can be implemented as long as the weights are linear-homogeneous (*Maillard* et al. 2010).

The dynamic portfolio is rebalanced on a monthly basis according to the re-estimated covariance matrix. For comparison, the risk parity portfolio benchmark was also rebalanced on a monthly basis. Table 5 presents the regime-dependent factor allocations of the dynamic and benchmark portfolio. The dynamic portfo-

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lio increases its allocation to size to 79.5 % during recovery periods and to momentum to 54.4 % during expansion periods. In the slowdown and contraction regimes, the size factor experiences the largest change, being reduced to 0.0 % in both cases, followed by value with 3.8 % and 0.0 %, respectively (*Kwon* 2022).

Table 5

Benchmark and regime-dependent dynamic factor portfolios[8]

	Benchmark	Dynamic portfolios			
		Recovery	Expansion	Slowdown	Contraction
Size	23.1 %	79.5 %	23.5 %	0.0 %	0.0 %
Value	14.5 %	0.0 %	22.1 %	3.8 %	0.0 %
Momentum	13.5 %	0.0 %	54.4 %	27.3 %	25.9 %
Profitability	27.5 %	11.1 %	0.0 %	34.5 %	46.1 %
Investment	21.4 %	9.4 %	0.0 %	34.4 %	28.0 %

The out-of-sample results for the sample period 2007 to 2021 show that the dynamic, regime-timed approach can increase the absolute risk-adjusted returns relative to the untimed benchmark. Specifically, the regime-timed model was able to generate an information ratio of 0.626 at the expense of a high tracking error and higher volatility. As expected for dynamic strategies, turnover increased dramatically, in this case to 29.6 % per month. Once transaction costs are taken into account, this economic advantage remains statistically significant until costs are below 120 bps per two-way transaction. These results show that a dynamic approach, timed by market regimes, can generate economic wealth in real life applications (*Kwon* 2022).

b) Defensive Strategy

Defensive factor timing is an approach proposed by *Fergis* et al. (2019). The idea is to reduce portfolio risk during adverse market conditions by strategically overweighting and underweighting factors. The strategy aims to reduce the magnitude of losses and outperform a static, untimed benchmark. *Fergis* et al. (2019) select macro factors such as economic growth, real interest rates, inflation, credit, emerging markets, and liquidity. Individually, they describe the risk factor exposure in a multi-asset context over the long run, and are both eco-

[8] Derived from (*Kwon* 2022).

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nomically intuitive and historically persistent in terms of the non-diversifiable risk premium. They take a global portfolio of 14 major asset classes, with a timeframe from 2004 to 2017. Their principal component analysis, performed on the correlation matrix, shows that the first three principal components explain 82 % of the variation, and when expanded to six components, 92 %. *Fergis*, et al. (2019) conclude that global asset class returns can be represented by a manageable number of macroeconomic factors. While opportunistic factor timing attempts to generate excess returns, defensive factor timing periodically but infrequently reduces risk exposure to one or more given factors.

Another approach to defensive factor timing is volatility management. Some investors are interested in protecting their portfolio against volatility and therefore develop Volatility Managed Portfolios (VMP). *Moreira/Muir* (2017) propose a risk-parity multi-factor portfolio with fixed weights, where the relative weight of each factor does not vary. The risk exposure is adjusted according to the total volatility. During the sample period studied from 1926 to 2015, they show that their portfolio takes less risk during recessions and conclude that the volatility timing strategy is economically beneficial even after transaction costs. According to *Barroso/Detzel* (2021), the factors used by *Moreira/Muir* (2017) are expensive to trade because they do not use cheap-to-trade products such as ETFs or derivates. The factors are mostly represented in small-cap stocks, which are usually expensive to trade. *Barroso/Detzel* (2021) continue the idea of VMPs and follow *Moreira/Muir* (2017) with their portfolio scaling by the inverse of the realized variance on a monthly basis, which is not cost-optimized. They find that turnover is 15 times higher and transaction costs increase by 18.5 % per year compared to an unmanaged (buy-and-hold) portfolio. *Barroso/Detzel* find that such a strategy performs better only when sentiment is high, but underperforms in the long run. They also present important findings on transaction cost optimization and economic profitability. They examine strategies to reduce transaction costs, either by slowing down trading or by avoiding stocks that are expensive to trade. With one exception, they find that all strategies fail to make VMPs profitable. The only approach that stands out is a managed momentum strategy that is scaled by the realized volatility estimate.

DeMiguel et al. (2022) follow *Barroso/Detzel* (2021), but with a multi-factor portfolio where each factor weight is allowed to vary with the market volatility. Without the fixed-weight constraint of the *Moreira/Muir* (2017) study and optimized for transaction costs, *DeMiguel* et al. (2022) achieve a statistically significant 14 % higher Sharpe ratio than the unconditional mean-variance multi-factor portfolio. Over their sample period from 1977 to 2020, they report that the conditional portfolio significantly outperforms its unconditional counterpart in periods of high and low sentiment, which differs from the results of *Barroso/Detzel* (2021).

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c) Combining Factors and Models

There is significant evidence that models can benefit from additional factors while remaining robust and adaptive. The challenge is to find the superior number of factors and indicators to optimize models while avoiding overfitting. Among the pioneers, and often cited in the literature are *Bates/Granger* (1969), who show for the general case that two separate sets of forecasts can be improved by combining them into a composite forecast, resulting in a lower mean square error than eight of the original forecasts. Within the literature of factor timing, three general approaches to composite forecasting are identified:

- Different variables to mimic the same phenomena
- Same Model with different periods
- Different models

Different Variables – Same Phenomena: First, there is the most prominent of the different variables mimicking the same phenomena. Representatives of this approach are *Digard/Bouzida* (2020), *Hodges* et al. (2017), *Asness* et al. (2000) and *Dichtl* et al. (2019).

The basic approach tries to identify variables with the highest explanatory power, for which *Dichtl* et al. (2019) operationalize the dynamic portfolio selection of *Brandt/Santa-Clara* (2006). They examine a set of predictive factors, that synthesize the relevant information of 25 predictive variables and reduce the noise within the predictors including fundamental variables and technical indicators. To reduce the number of variables, a PCA in the sense of *Neely* et al. (2014) is performed for fundamental variables and technical indicators separately. In addition, the PCA generates orthogonal predictors to avoid multi-collinearity problems. As a result, the first principal component of the PCA of fundamental variables captures 27 % of the variation of the underlying variables. The first principal component of technical indicators captures even 93 %. The approach of *Brandt/Santa-Clara* (2006) then directly translates any predictive power embedded in the PCA factors into optimal portfolio weights. *Dichtl* et al. (2019) conclude that their approach can generate significant abnormal returns but due to high turnover, transaction costs erode most of the potential.

As already described, *Digard/Bouzida* (2020) take a very similar approach to examine timing strategies for the five factors value, momentum, quality, size, and low volatility. To assess whether a composite strategy outperforms the stand-alone strategies, they construct a three-compound approach with macro cycle-based, market sentiment-based, and momentum-based factor rotation. For the stand-alone strategy, they classify the market into different states based on indicators (macro (PMI), sentiment (VIX & high yield OAS spread) and momentum). Their results show that this simple strategy outperforms their benchmark, the MSCI US index, as well as the static, equally weighted portfolio before

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transaction costs. However, they admit to significant in-sample bias because the rotation rule is based on the best performing factors during the studied period (*Digard/Bouzida* 2020). Two years earlier, *Varsani/Jain* (2018) proposed this last approach as a four-component composite strategy.

Neuhierl et al. (2023) provide a comprehensive study of factors and indicators, which examines over 300 factors and 39 indicators during the sample period from 1926 to 2020. They first test each indicator for its forecasting performance and underline that the median improvement of a timed factor over its static counterpart is 2 % p. a. in return. In terms of forecasting accuracy, they are able to predict the sign of the actual return with 56 % accuracy and also show that there is a significant correlation between many indicators, suggesting that they describe the same phenomena. The results are then used to construct multi-factor portfolios with different indicators and generate a 20 % increase in return performance compared to the static approach. Additionally, they show that the best large-cap timing portfolio contains almost 200 stocks, which provides sufficient diversification.

Same Model – Different Periods: Dupleich Ulloa et al. (2012) explore a way to reduce risk through dynamic style rotation. In the post-2007 era regression models were challenged by structural breaks in the data. Attempts to counter this with dynamic models have their own problems. Depending on the responsiveness of such a model, important turning points may be missed, with negative consequences for portfolio performance. In addition, the potentially high turnover of such a strategy can dramatically increase transaction costs, diminishing returns. This is exacerbated by a high noise-to-signal ratio, which leads to unnecessary style rotations, further increasing transaction costs. In contrast to the majority of the literature, *Dupleich Ulloa* et al. (2012) weight and shift indicators according to the Information Ratio and adopt the work of *Pesaran/Timmermann* (2007) to address the issue of weight sensitivity to estimation error.

When choosing an estimation window for forecasting time-series with regression, the general approach to dealing with structural breaks is to use only post-break data. *Pesaran/Timmermann*, (2007) document that including (some) pre-break data in the estimation window, and thus trading off bias and forecast error variance, can be beneficial to the estimation process. Another challenge is to correctly identify and adjust the estimation-window, especially when dealing with small and multiple breaks. The authors present an extension to their model that allows them to deal with different types of model uncertainty.

Dupleich Ulloa et al. (2012) follow this approach by computing the expected return and covariance matrixes of a model with different estimation windows. An optimization function is used to compute the weight vectors that contain specific weights for each factor, which can then be averaged to obtain the optimal portfolio. The *Pesaran/Timmermann* (2007) approach allows time-series re-

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gressions in the absence of information on structural breaks such as point and size, to deliver reliable estimations (*Dupleich Ulloa* et al. 2012).

Different Models: Neely et al. (2014) point out that most macroeconomic variables exhibit a high degree of autocorrelation, resulting in poor performance. In addition, structural breaks plague the standard regression model with macroeconomic variables. *Rapach/Zhou* (2013) state that one percent explains ability as the upper bound, and thus view the practitioner approach as superior. *Neely* et al. find that analyses based on technical indicators that predict the decline in the equity risk premium in a market peak environment are superior to those based on macroeconomic variables. Similarly, the latter better capture the increase in the premium in a business cycle environment.

Consequently, compound approaches deliver better results for forecasting models. The need for robust models has increased since the financial markets left the calm waters following the 2007 crisis. Multiple authors such as *Fergis* et al. (2019) and *Asness* et al. (2000) plead for diversification of variables and models. *Fergis* et al. (2019) consider their "mosaic of indicators" as key elements to achieving robust defensive factor timing. They clearly see the benefits of having multiple defensive timing indicators in their strategy. *Asness* et al. (2000) report the same results when using a composite of industry-adjusted valuation indicators. They are able to achieve a far more robust, higher Sharpe ratio strategy. Based on their findings of better forecasting using macroeconomic factors and technical indicators, *Neely* et al. (2014) conduct further research to examine the connections between the two pools of information. By examining the different information captured by each, they expect to significantly improve the understanding of the economic forces that drive the equity risk premium.

d) Machine Learning

In the context of asset return forecasting and more specific factor timing, ML offers many benefits. First and foremost, ML algorithms can handle large amounts of data with ease, and models offer a variety of customizations. Many models do not require a deep understanding of the underlying data, such as regression models, which require detailed knowledge of data characteristics (for example structural breaks). On the other hand, ML models come with unique pitfalls such as training bias. Furthermore, the way in which models derive a solution is hidden from the users, not allowing them to comprehend and replicate the solution path.

To challenge their single factor strategy and the rule-based five-factor rotation compound strategy, *Digard/Bouzida* (2020) investigate the application of ML and compare the results. Again, they start with their five-factor model, represented by the three indicators PMI, VIX, and momentum. For each factor, a

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one-month forward performance is calculated and represented as a binary variable (negative/positive). The three indicator ML algorithm used is trained to identify patterns in the calculated probability of a factor's next month's return (up or down). The basic logic is, that if the probability of a factor's next month return is positive, the algorithm will suggest investing in that factor, independent of other factors. This is done independently for each of the five factors – therefore five independent ML-algorithms are needed. Once all results of the algorithms are available, an equally weighted portfolio of all factors with expected positive performance is created. The exposure is held for the remainder of the month and recalculated at the beginning of the following month. The predictive algorithm used by *Digard/Bouzida* (2020) is a tree-based predictive algorithm, with a CART[9] and a Random Forest[10]. The prediction process is performed in a two-step logic, with the CART selecting the variables with the highest predictive power, which are then fed into the Random Forest to predict whether a factor should be bought. This algorithm is able to detect non-linear relationships between variables and is resistant to outliers.

ML algorithms are designed to identify patterns in historical data, so the training window plays a critical role in the success of such a model. Longer and larger training sets contain more information and allow the algorithm to identify a more complete set of patterns. Short training windows increase the reactivity to new events and thus increase volatility, while longer training windows increase robustness. Another limiting factor is computational time, which increases with the size of the data set. *Digard/Bouzida* (2020) chose a 10-year rolling window, consisting of 8 years of training data and 2 years of validation data. Each month, five new algorithms (one for each factor) are trained based on the last 10 years.

To predict the optimal factor allocation, *Digard/Bouzida* (2020) investigate the two ways of time-series and cross-sectional forecasting. In an out-of-sample backtest between 2014 and 2020, the time-series approach outperforms both the equal-weighted static and the MSCI US benchmark. *Digard/Bouzida* (2020) report that the lead shrinks to be "razor-thin" when transaction costs are taken into account. The cross-sectional approach disappoints in terms of performance. Even without transaction costs, its performance lags both the five-factor static

[9] Classification and Regression Tree (CART), introduced by *Breiman* et al. (1984) is a feature selector to decide if a predictive variable has a high linear relationship with the target variable. The aim of employing CART is to avoid overfitting by variables that are not or weakly related to the target variable.

[10] Random Forest is a classification and regression approach introduced by *Breiman* (2001). It utilizes a combination of many prediction trees. Its strength is the efficient training when dealing with big datasets and the ability to recognize classes and the relationship between classes.

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and the MSCI US benchmark. When both approaches are applied to the European universe, both outperform their benchmarks.

Dirkx/Heil (2022) apply an entirely different approach and are the first to investigate how the low-risk anomaly can be harvested using an Artificial Neural Network with Long Short-Term Memory (LSTM). The focus is to innovate the timing of investment factors with the *Fama/French* (2015a) factors. The low-risk anomaly, discovered by *Haugen/Heins* (1975), describes the non-linear relationship between the risk and return of stock portfolios. In their study they find: "… over the long run, stock portfolios with lesser variance in monthly returns have experienced greater average returns than their 'riskier' counterparts" (*Haugen/Heins* 1975). According to *Dirkx/Heil* (2022), this different approach of forecasting risk rather than return has several advantages due to statistical characteristics such as less autocorrelation. *Dirkx/Heil* (2022) utilize a 3-layer LSTM with 256 nodes for each layer, followed by a dense layer and divide the sample period into 1994 – 2009 as the training data set and 2010 – 2019 as the forecasting data set. To evaluate whether more data improves the prediction quality, they test four different model configurations. The four models are then compared to a simple buy-and-hold long portfolio of the four *Fama/French* factors (SMB, HML, RMW and CMA), and show promising results. The long portfolio generates an average positive return across the four factors of 49.77 %, while the two worst performing models generate 60.83 %. When challenged with a Multilayer Perceptron (MLP), a GARCH model, and a LASSO regression, the LSTM outperforms. *Dirkx/Heil* (2022) conclude that, overall, the LSTM has slight advantages over the tested approaches and is well suited for forecasting risk and building a factor timing strategy around them.

3. *Problems and Pitfalls*

As shown so far, timing factors are not as trivial as they may seem at first glance. Different types of data, data processing and revisions, and different financial markets pose various challenges to researchers and practitioners. Beyond the obvious issues, *Bender* et al. (2018) identify time-varying relationships, data revisions, and cherry-picking of indicators as the main challenges in building a factor timing model. Most critical, they state, is the time-varying relationship between indicators and factors, which means that the nature of a factor may change over time, altering the relation (slope) between the factor and the indicator.

Cherry-picking is a particular problem in scientific work. Researchers tend to choose indicators that have proven to be the best predictors of a factor, based on historical data. This seems like a natural choice, but *Bender* et al. (2018) test 38 different predictors from 1970 – 1990 and 1990 – 2010 and find that of 18 that

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are statistically significant for size in the first period, only 1 was significant in the second. They find the same picture for investment and momentum, which changes from 10 to 0 and 9 to 1, respectively. This evidence shows that predictors that worked well in the past are not necessarily good predictors in the future. Only profitability does not change, with two out of two indicators remaining statistically significant. Over different time horizons, ranging from three months to six to twelve months, the results are similar. The third challenge is data revision, particularly for macroeconomic factors. This type of data is usually revised after its initial publication – for example, unemployment rates and GDP. This leads to incorrect estimates as not all data is correctly reflected at the time of publication (*Bender* et al. 2018).

Despite the challenges and pitfalls of factor timing, *Bender* et al. acknowledge its potential. However, they point out that "even a good factor timing strategy will not be successful in every period".

4. Conclusion of Factor Timing

Factor timing is a topic with controversial opinions and expectations, heavily depending on who is asked, and what settings and assumptions are discussed. Optimists like *Hua* et al. (2012), *Hodges* et al. (2017), *Bender* et al. (2018), *Dichtl* et al. (2019), *Fergis* et al. (2019), *Haddad* et al. (2020) and *Leippold/Rüegg* (2021) believe in the potential of timing factors strategically. Regardless of the defensive or active strategy studied, they report evidence of economic benefits compared to benchmarks such as static factor models or even market indices. *Haddad* et al. (2020) provide evidence that factor timing with an active strategy can increase expected return and that implementation is feasible in practice. They report that the gains from factor timing double the expected utility for investors relative to a static factor investing strategy. *Leippold/Rüegg* (2021) report similar results and show a significant excess return over their static multi-factor benchmark. Similar but less extreme results are reported by *Dichtl* et al. (2019). When ignoring transaction costs, they find statistically significant evidence for the beneficial application of factor timing strategies, whether for single, compound, or ML strategies.

Bender et al. (2018) recommend being cautious and parsimonious when choosing factors and indicators. Their recommendation is that it is better to decide on a few, theoretically intuitive factors and indicators with a good understanding. Regarding the model structure, the wide literature acknowledges the superior results of composite approaches, as started by *Bates/Granger* (1969). *Hodges* et al. (2017) show for the case of indicators that aggregated indicators consisting of economic regime, relative strength, and dispersion perform better than each of them individually.

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While a large number of research studies have been published in the field of factor timing that promise success in its application, the results should be taken with care. According to *Asness* (2016), there is an incentive to overstate the ability of factor timing because it has become the differentiating factor between active management and a cap-weighted index, that is done for a fee. In order to skim off these management fees, the majority of the financial industry hopes that factor timing will revive skill-based management. Skeptics like *Asness* et al. (2017) and *Lee* (2017) acknowledge the presence of a (theoretical) advantage in factor timing, but caution against being blinded by the promises. Both agree that factor timing may work under certain circumstances. For skeptics, the main concerns are the impact of transaction costs and the difficulty of implementation. Both *Asness* et al. (2017) and *Lee* (2017) suggest that the current achievements in factor timing should not replace a diversified portfolio of uncorrelated factors over the long term, but rather focus on timing risk premia over short horizons.

Lee (2017) argue that it would be more constructive to understand the underlying rationale of why risk premia rise before implementing a strategy to arbitrage them. This is supported by the optimists *Bender* et al. (2018) who raise the question for future research as to where temporary factor premia come from. In their extensive work, they also question the application over short horizons. The authors believe that cyclical timing of factors is possible but "short horizons and factor cyclicality don't mix".

> "That said, we believe timing of factors is possible as long as the horizon is sufficiently long, and the timing model is given enough time to add value." (*Bender* et al. 2018).

Finally, as noted by *Hua* et al. (2012), dynamic model weighting as used for factor timing is still in its infancy. This highlights the need for future research to test different models and compare different approaches, as done by *Dirkx/Heil* (2022).

V. Literature Research

The field of factor timing is relatively new, having emerged from business cycle theory and the study of macroeconomic variables. Recent research has drawn on the fundamental research of the past few decades, especially when it comes to factors. The line between basic research and factor timing is blurred because the idea is not new. The implementation of such a strategy has been discussed since the first discovery of the existence of a time-varying component. The actual application of factor timing has occurred in recent years, but is now being partially overtaken by ML approaches.

Next, we identify influential research and present the current literature landscape. This is done through a quantitative and qualitative review. We use the

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results to identify recent developments in factor timing. To better understand the results, a network analysis visualizes the interdependencies between studies.

1. Approach

Due to the paucity of publications dedicated on factor timing and the limited availability of recent study results, a qualitative first-hand review of the available research was undertaken. The process of gathering relevant research studies was structured in three steps. First, two databases (Web of Science and Google Scholar) were screened using the following key words: smart beta, factor timing, and factor investing. Figure 3 illustrates the studies found over the past 10 years related to the three search terms, 6 of which are found via 2 terms, adding up to 31. The results indicate a lack of literature related to the search terms. To be considered relevant, the search terms had to appear at least in the title, header, or classification, and a general relationship to factor timing had to be suspected (25 studies were identified in this step). Although smart beta is technically a sub-field of research, it was included because losses due to inconsistent naming could not be ruled out. The results were stored in a structured database.

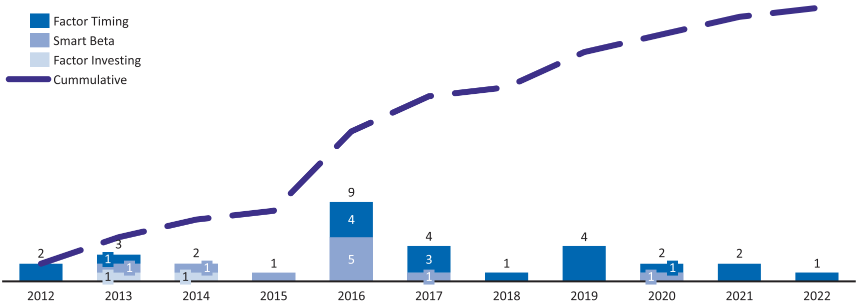

Figure 3: Yearly & cumulative publications

2. Literature Landscape

The structured database was created with the intention of better understanding the relationships between research studies. Therefore, we captured cross-references and classified the authors' attitudes/sentiments towards factor timing, which allows us to carry out various qualitative investigations. The initial screening of the available literature revealed a limited number of studies. In order to get to the bottom of why only a small number of studies were found through the structured search using predefined terms, the online tool Re-

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searchRabbit[11] (RR) was used to find similar studies, not necessarily related to the existing network at that time.

Factor investing, and therefore factor timing, is a relatively new area of research. By taking a multi-directional approach, searching through RR and examining the references of the studies found, the database was significantly expanded. Investigating this gap between the initial search and the lateral search with RR reveals that the topic of factor investing, and factor timing in particular, has been around for much longer. In fact, the foundations were laid in the late 1970s by critics of the CAPM. Finally, the great financial crisis of 2007 drew much of the attention to more robust approaches to portfolio diversification. Figure 4 shows publications that paved the way for factor timing, starting with *Campbell/Shiller* (1988a) and *Campbell/Shiller* (1988b) on the time-varying behavior of the market risk premium.

The potential timing ability of factor portfolios attracted much attention in the mid-2000s. The next wave of influential papers came in the mid to late 2010s with promising results from implementing factor timing models. With *Digard/Bouzida* (2020) and most recently *Dirkx/Heil* (2022), first steps towards ML approaches were made. However, there are more and earlier attempts to time investment strategies with ML, but many approaches lack economic theory, especially when using time-series of technical indicators instead of focusing on the development of ML-models.

What makes a structured literature search difficult are the different facets of academic and practitioner research. Different groups have different agendas and use inconsistent definitions, giving the impression that the topic of factor timing is not well defined and that the terminology is still evolving. In terms of content, these blurred lines continue, making it difficult in many cases to account for a particular topic within the broad scope of the literature reviewed. Many findings are critical of traditional portfolio theory, while others make use of previous research. An example of this is the business cycle theory, which can be traced back to the research of *Burns/Mitchell* (1964).

[11] https://www.researchrabbit.ai.

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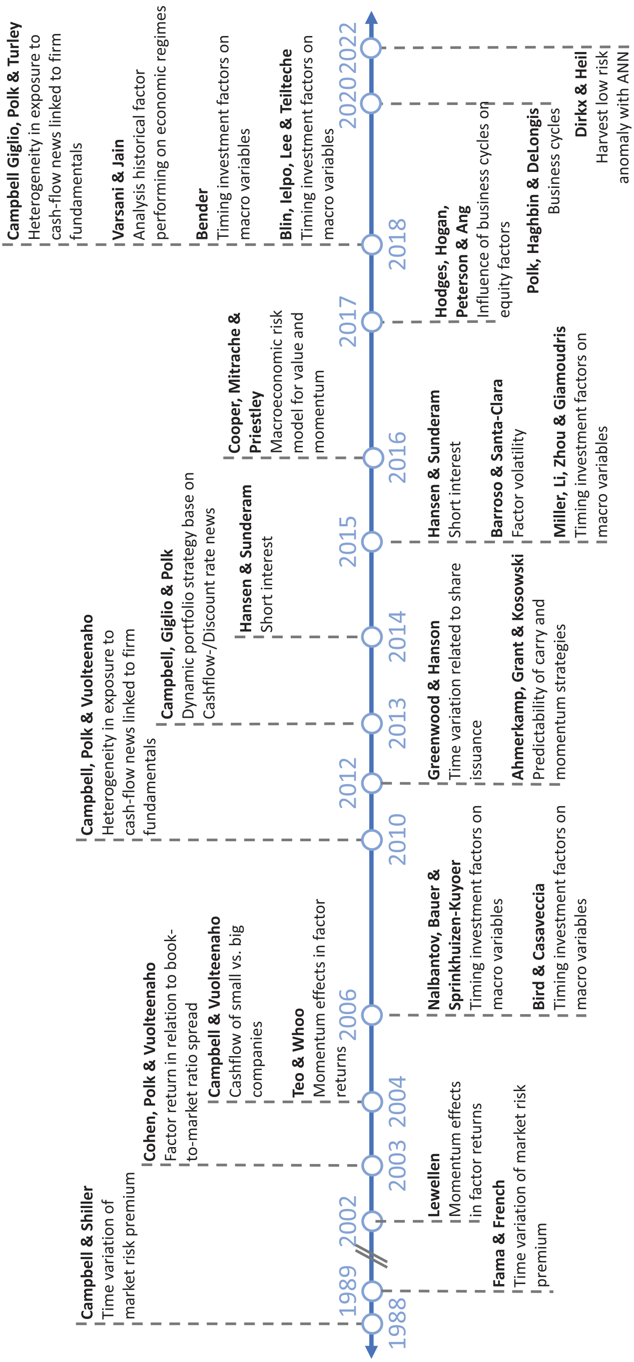

Figure 4: Milestone publications towards factor timing

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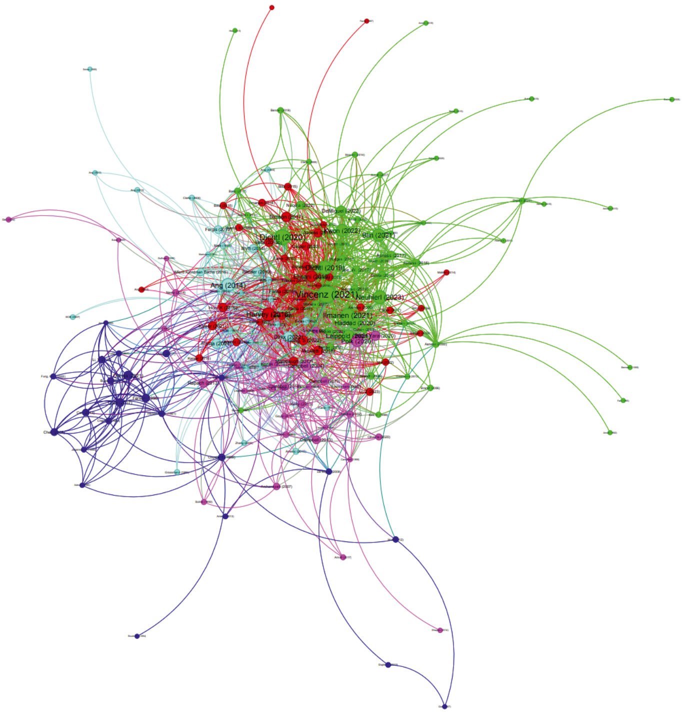

Figure 5: Gephi Network visualization with Yifan Hu Multilevel layout

For a better understanding of the relations between the research studies and the underlying discussions, we conducted a network analysis. The layout was first computed using the ForceAtlas 2 algorithm in Gephi, developed by *Jacomy* et al. (2014). ForceAtlas 2 is a force-directed layout based on a physical system, where nodes repulse each other and edges attract their nodes. Because the results were visually too dense, the graph was thinned using the Yifan Hu Multilevel layout (*Hu* 2005), which shows much clearer separation of highly connected studies. In network analysis, clusters are called communities.

This network analysis is based on qualitatively collected data. Some studies were cited as working papers, white papers, forthcoming or discussions at the time the citing study was written and later published with a different year or title. The methodology used to address this issue was to consider these studies under the final publication, resulting in some discrepancies when comparing study references and the year presented here. We apply similar approaches for authors, for example, *Goyal/Welch* (2008) and *Jensen/Black* (1972), where a different order of names was used. They were merged according to the higher number of publications for each nomenclature.

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The network is visualized in Figure 5 and contains 172 nodes representing studies, connected by 1,236 edges representing references. Due to the nature of references in the literature, the graph is unidirectional, with studies always referring to older studies (backwards relationship). The size of the nodes is ranked proportionally by the number of references to other publications, following the idea of the review to identify studies that contribute to factor timing research. We show an inverse illustration in Appendix C. Figure 10, where the size is proportional to the number of citations, allowing influential studies to be identified. Obviously, seminal studies such as *Fama/French* (1993) are among the most cited papers.

To further investigate the connections between studies, communities were identified using the Modularity[12] algorithm developed by *Bondel* et al. (2008). This algorithm clusters nodes based on how densely they are connected to other nodes. We identify five communities. For the community distribution results of the Modularity algorithm, see Figure 9 Appendix B. These results are visualized in Figure 5 by sorting the nodes shape according to their associated community.

Circle shaped nodes are mostly considered to be optimistic studies, clustering with respect to the center, in the upper right half of the network. This group is represented by research such as *Hodges* et al. (2017), *Polk* et al. (2020), *Scherer/Apel* (2020), *Blin* et al. (2021), *Kwon* (2022), *Dirkx/Heil* (2022) and *Neuhierl* et al. (2023). Building a very permeable partition are studies such as *Bender* et al. (2018) and *Dichtl* et al. (2019), which are primarily optimistic, but include criticism of the factor timing in their work. Pentagon shaped nodes represent mostly skeptical studies, running through the middle, with a large group at the top. Representatives of this group are *Asness* (2016), *Lee* (2017), *Blitz/Vidojevic* (2019), *Ilmanen* et al. (2021) and *Arnott* et al. (2016). Squares and hexagons are the foundation literature on factor investing and factor timing, found in the center and lower left, such as *Fama/French* (1993), *Fama/French* (2004), *Harvey* et al. (2016) and *Ang* (2014).

Finally, there is one issue that stands out that has not yet been covered. On the left side of the graph there is a clearly separated cluster of triangles. The cluster assembles around *Osinga* et al. (2021), *Henriksson/Merton* (1981), *Ferson/Harvey* (1991), *Busse* (1999), and *Chen* (2007), which are dedicated to the timing ability of fund managers, but share the same seminal paper as factor investing.

In terms of interpretation, the shape coding has to be taken with care. They are not made qualitatively (manually), but they are generated according to the

[12] Modularity is a measure for the structure and density of a network, expressed in a value between -0.5 (non-modular cluster) and 1 (full modular cluster). Gephi uses the optimized Louvain method for detecting communities in large networks, developed by *Bondel* et al. (2008).

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communities found by the Modularity algorithm. Therefore, the grading is based on quantitative data. For example, *Harvey* et al. (2016) and *Dirkx/Heil* (2022) could obviously be organized in a different community.

The fact that foundational literature and seminal studies are predominantly close to the center, around which subsequent work is located, seems intuitive. What is surprising at first glance is the proximity of skeptics and optimists. In particular, the high density of connections between these two groups. This suggests that there are at least no strictly separated groups, indicating extensive exchange. Evaluation of these studies suggests that there may be statistical evidence for the benefits of factor timing. The criticism of the authors is mainly based on the fact that most of the benefits are diminished by transaction costs as well as the fear of wrong diversification, which leads to a cautious opinion on factor timing.

In addition, we performed a qualitative clustering to compare the results with the quantitative results presented above. In Table 6, Optimist, Skeptic, and Neutral represent the qualitative classification of a paper's attitude towards factor timing, while Base includes all papers not related to factor timing but cited in the literature. A graded graph based on the numbers in Table 6 can be found in Appendix C. Figure 11.

Table 6

Distribution of the qualitative literature classification

Sentiment	Share of literature in %	Modularity class in %
Optimist	35.92 %	34.90 %
Skeptic	18.45 %	25.50 %
Neutral	3.88 %	–
Base	41.75 %	39.69 %

Table 6 compares the qualitative sentiment classification (left) with the calculated Modularity Classes. For this calculation, the triangle community (timing ability of the fund manager) was excluded, as it was not classified in sentiment during the research. In short, the results show a similar position of the cluster, but a much higher diffusion rate, which supports the assumption of an extensive exchange rate.

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3. *Results*

As mentioned in the introduction, we conducted the research phase with three guiding questions. The results of this research are now presented according to these questions.

a) Leading Questions

1. How widespread is factor timing in the literature and what are the related research topics?

There is no simple or clear answer to the question of how widespread factor timing is, especially in practical applications. The available information on funds that actively time factors is scarce, and the reliability of this information is questionable. The fact that the authors of such studies are affiliated with certain companies suggests that at least the knowledge exists and may already be implemented in one way or another. What can be evaluated is the number of published studies on factor timing. Figure 6 illustrates the studies examined for this study that are directly related to factor timing, be it seminal literature that laid the groundwork or the development and testing of models.

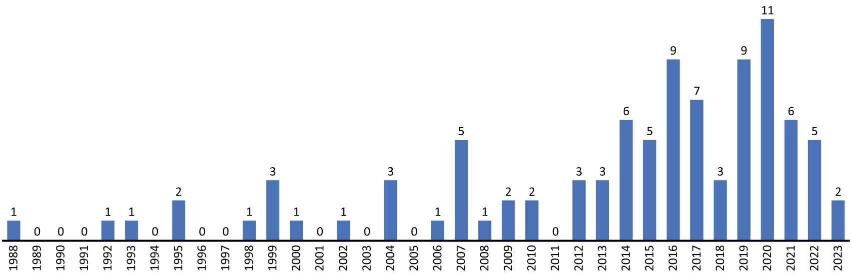

Figure 6: Number of factor timing related studies by year

Figure 6 shows 94 studies and scientific reports. The majority of the publications (70 %) was released in the past 10 years and 50 % since 2016. Although 2020 marks the current peak, this is expected to change in the coming years. In addition to the attention they have received, many studies from 2019 onwards have not yet been published in journals and are up for discussion.

Tracing the origins of factor timing reveals the related areas of research. The most obvious is portfolio management and all related theories such as diversification and volatility management. The study of macroeconomic factors and indicators, which can largely be summarized under the heading of business cycle

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theory, also plays an important role, as these are key elements in many factor timing strategies.

2. What are the approaches and how mature is factor timing?

There are two approaches to factor timing portfolios. First, the intent, which can be divided into two groups: Active and defensive factor timing. Active factor timing is an opportunistic approach that seeks higher returns first. The defensive approach primarily aims at a less volatile and more robust portfolio. Second, there is a technical side, which can be divided into conventional and ML approaches.

Remarkable progress has been made in recent years, from timing single factors to multi-factor models with one indicator like *Hodges* et al. (2017) to a global multi-asset model with six indicators like *Fergis* et al. (2019). However, these advanced approaches are followed by critical voices that the real-world success rises and falls with transaction costs. Studies such as *Hodges* et al. (2017) and *Digard/Bouzida* (2020) find significant evidence that rule-based factor timing can generate access return, even when transaction costs are considered. *Digard/Bouzida* (2020) are exemplary of the maturity of the field of factor timing and can be seen as a seminal study and starting point for future research. They incorporate transaction costs, consider US and EU markets, and use an ML algorithm. They also address the issue of using more than six macro indicators to make signals more resistant to noise. This basically summarizes the state of research in this area and highlights the need for further studies to challenge these results and provide arguments for or against factor timing in asset management.

3. Are there different groups (e. g., practitioners and academic researchers) and what are their attitudes and research findings regarding factor timing?

Obviously, there are clearly two groups: optimists and skeptics. The optimists focus on the economic benefits of timing, while the skeptics claim that factor diversification easily outperforms the potential of factor timing (*Kwon* 2022). The results of the network analysis suggest that this division is not so clear-cut in reality, and that skeptics are often cautious optimists. We identify no separation between practitioners and academics, partly due to the small number of publications by practitioners. We examined firms affiliated with individual researchers such as *Ang* (2014) and *Hodges* et al. (2017) Black Rock, *Arnott* et al. (2016) Research Affiliates, *Asness* et al. (2017) AQR and *Alford* (2016) GS, but we are not able to identify a separation in terms of attitude or sentiment towards factor timing.

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b) Further Findings

Research that goes beyond the main questions we address concentrates on the methodologies of the studies. Looking at the scope of the studies and the distribution of the markets considered, it is noticeable that the majority of the studies focus on the US market. Therefore, we expanded the literature database to include the market, the databases used, and the sample period. The results of the 25 most prominent and recent studies in this literature database are presented in detail in Appendix A. Table 7.

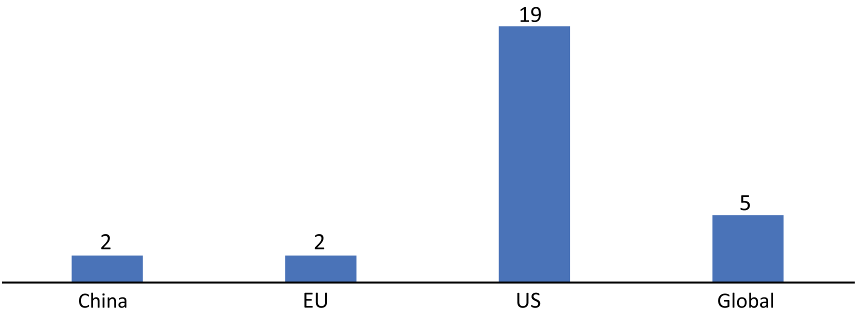

Figure 7: Examined regions in factor timing literature

The studies were classified according to the market they investigated, resulting in 28 results for 25 studies. As noted above, the vast majority of studies, 19, were conducted in US markets, followed by Global with 5, see Figure 7. More recently, two studies have been dedicated to China by *Ma* et al. (2023) and *Li* et al. (2023), which have become seminal studies for this region.

Figure 8 shows the databases used by the 25 studies. Considering the fact that most of the studies focus on US markets, it is obvious that US databases dominate. For US data, the most commonly used sources are Compustat, Bloomberg and CRSP. The Other section consists of databases that are used only once in the literature sample and contain either country-specific data or factors. For factors such as CMA, HML, RMW and SMB, Kenneth French's database[13] is the most frequently used, with 11 references.

[13] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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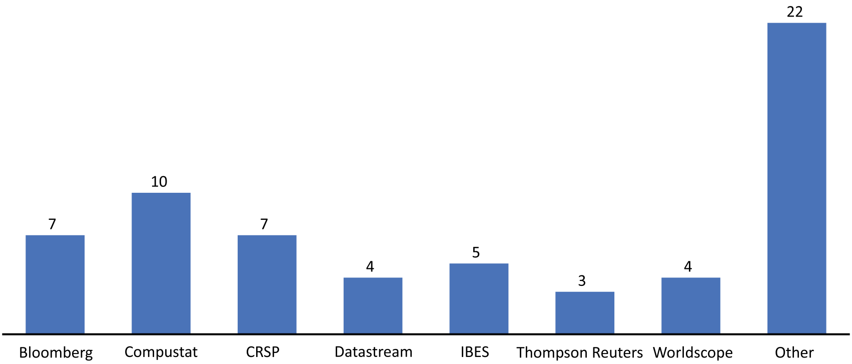

Figure 8: Count of used databases in factor timing literature[14]

4. Critical Evaluation

Factor timing is a controversial topic in the academic and practitioner literature. For some, it promises to be the "holy grail" of investing, but there are hurdles and dangers that should not be underestimated. First and foremost, factor investing, and factor timing in particular, is not suitable for the majority of investors. The complexity and understanding of the fundamentals required limits its application to large institutional investors. These investors need a long investment horizon and the financial strength to stay disinvested for long periods of time if necessary.

The research for this paper identified several weaknesses and gaps in the literature. To address these, they are discussed below and questions for further research are raised. On the one hand, there are promising results that suggest the widespread implementation of factor timing strategies. On the other hand, skeptics raise valid points when they criticize the following aspects of profitability: First, the excess return after transaction costs, in particular in relation to the complexity of implementation, and second, the lack of understanding of the factors and their underlying fundamentals.

There is also the problem of a limited database, especially for the design, training, and validating of models. In addition, there is a significant break in factor behavior and factor importance after the GFC 2007, as shown by *Dirkx/*

[14] Own illustration. Data based on Appendix A. Table 7; Other includes and were found only once: AQR Library, Citi, Consensus Economic, EPU, COT Report, FRED, IDC, Jeffrey Wurgler Website, Jonathan Wright Website, LLC, Lu Zhan Website, MSCI, NBER, Pastor Database, Penn World Tables, Research Affiliates, Robert Shiller Website, SDC, VIX, WIND and Xpressfeed.

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Heil (2022). This limits the useful database to about 200 data points on a monthly basis after 2007.

Although *Asness* et al. (2017) admit that tactical factor timing can prevent investing in "falling knives" in extreme market environments, they suggest building a diversified portfolio. Their diversification objection is partially undermined by the results of *Neuhierl* et al. (2023), who find in their study that almost 200 assets are required for their timed multi-factor portfolio. But even diversification is not "low hanging fruit". Given the lack of knowledge of factor fundamentals (*Bender* et al. 2018) compounded by effects such as correlation asymmetry, the question arises again as to how "true diversification" can be achieved.

Finally, the availability of research studies must be addressed. Publications examining factor timing are rare, as it can be considered an emerging field of research. There has been an increase in the number of studies published in recent years. Unfortunately, many studies are not freely available and the results are kept secret. First, there are academic journals, in particular portfolio management and quantitative investment journals, which restrict access to the publications. Second, much of the practitioner research is kept secret to protect their competitive advantage. Third, the number of ML applications, such as stock price forecasting, is increasing significantly (*Kumbure*, et al. 2022). In many cases, they lack economic theory, and due to the fast-moving field, critical discussions seem to be neglected.

VI. Conclusion

While the fundamentals have been known since the 1960s, factor investing and smart beta have attracted attention in recent years, and some of this attention has focused on factor timing. The fact that factor-based portfolios have outperformed their conventional counterparts, which rely heavily on diversification across asset classes, leads some to believe that factor timing is the "holy grail" of investing.

This study reviews the origins and fundamentals of factor investing and factor timing. It then discusses empirical findings, pitfalls and implications, guided by the questions presented in chapter I. By reviewing the available literature on factor timing, this paper illustrates the literature landscape and provides an overview of the current directions and discussions on the topic. In addition, the literature is examined from both a quantitative and a qualitative point of view, and specific topics and related research are explored in depth.

It can be concluded that most academic and practitioner authors find evidence that the concept of factor timing has the potential to generate economic wealth. For real-world applications, skeptics criticize the high turnover of these dynamic strategies, resulting in the loss of additional return due to transaction

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costs. Despite the consensus, the empirical results should be treated with caution. This caution is justified by three facts:

First, the available literature, and therefore data, is limited. The number of studies published in reputable journals is even smaller, which calls into question the reliability of these results. Second, studies use many different approaches and sample periods. In addition, most studies are conducted on the US market and heavily weight common stocks as assets. Overall, this mix, combined with the small number of studies, makes it difficult to compare and benchmark results. Third and finally, the availability of real-world data is limited. The data available on a monthly basis is scarce by natural science standards, and it is not possible to generate artificial data, which drastically limits out-of-sample testing. This scarcity is exacerbated by structural breaks that further limit the usable data, although approaches have been found to mitigate these effects.

These weaknesses are also reflected in the methodology of this paper, in particular the limited number of published studies. Nevertheless, it has been possible to show that "digging deeper" reveals a broad landscape of fundamental literature and that the topic seems to be just beginning to gain momentum. In particular, the application of ML approaches has the potential to shape the topic of factor timing.

Indeed, factor timing has the potential to change the way portfolios can be managed in the future. The benefits it holds are obvious, and as *Haddad* et al. mention, "… factor timing is very valuable, above and beyond market timing and factor investing taken separately." (*Haddad* et al. 2020). However, many hurdles, such as optimizing transaction costs, must be addressed before it can become a mainstay of portfolio construction. Finally, diversification should not be neglected when considering a time-weighted factor portfolio. Factors are more effective at describing and managing risk compared to traditional asset classes.

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Appendix A

Table 7

Databases and examined markets by study[15]

Study Region	Database
(Ang, Madhavan, & Sobczyk, 2017) US	2006 – 2016: Kenneth French Database
(Arnott, Beck, Kalesnik, & West, 2016) US	1977 – 2016: Research Affiliates, LLC, CRSP, Compustat Worldscope, Datastream
(Asness, Friedman, Krail, & Liew, 2000) US	1963 – 1998: Compustat, IBES
(Asness, Chandra, Ilmanen, & Israel, 2017) US	1990 – 2016: IBES, Bloomberg, Datastream, Consensus Economics, Xpressfeed, MSCI Barra, Penn World tables
(Barroso & Detzel, 2021) US	1926 – 2015: CRSP, Compustat
(Bender, Se Sun, & Thomas, 2018) US	1963 – 2015: Kenneth French Database, Datastream, Bloomberg, Factset, Robert Shiller Website, Jeffrey Wurgler Website
(Blin, Ielpo, Lee, & Teiletche, 2021) MSCI World	1999 – 2020: Compustat, MSCI World, Bloomberg, Jonathan Wright zero-coupon database
(DeMiguel V. , Martín-Utrera, Nogales, & Uppal, 2020) US	1987 – 2014: CRSP, Compustat, IBES, Kenneth French Database, Lu Zhang Website
(DeMiguel, Martín-Utrera, & Uppal, 2022) US	1977 -2020: CRSP, Compustat
(Dichtl, Drobetz, Lohre, & Carsten, 2019) US	1997 – 2016: Worldscope Database, Kenneth French Database
(Digard & Bouzida, 2020) US, EU	1999 – 2019: MSCI smart beta
(Dirkx & Heil, 2022). US	1994 – 2019: Kenneth French Database, Bloomberg

[15] Data derived from literature database introduced in chapter V.2.

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Study Region	Database
(Fergis, Gallagher, Hodges, & Hogan, 2019) Global	2004 – 2017: Bloomberg
(Greenwood & Hanson, 2012) US	1963 – 2007: CRSP, Compustat, SDC data
(Gupta & Kelly, 2019) US, Europe & Pacific	1965 – 2017: Kenneth French Database
(Haddad, Kozak, & Santosh, 2020) US	1974 – 2017: CRSP, Compustat
(Hodges, Peterson, & Ang, 2017) US	1990 – 2015: Thompson Reuter, IBES Worldscope
(Hua, Kantsyrev, & Qian, 2012) US	1994 – 2009: Worldscope, IDC
(Ilmanen, Israel, Moskowitz, & Thapar, 2021) Global	1926 – 2020: Bloomberg, Thompson Reuter, Citi, Datastream, CRSP
(Kaiser, 2016) US	1989 – 2014: Thompson Reuter, Kenneth French Database, Pastor Database
(Kwon, 2022) US	1967 – 2021: Kenneth French Database, VIX, NBER
(Leippold & Rüegg, 2021) Global	1963 – 2018: CRSP, Compustat
(Li, Wan, & Wang, 2023) China	2000 – 2021: Baker EPU, WIND, Kenneth French Database
(Ma, Liao, & Jiang, 2023) China	2004 – 2020: CSMAR
(Micaletti, 2018) US	1997 – 2017: Bloomberg, COT Report, AQR Library Kenneth French Database
(Neuhierl, Randl, Reschenhofer & Zechner, 2023) US	1975 – 2020: CRSP, Compustat, IBES, FRED
(de Oliveira Souza, 2020) US	1990 – 2018: Kenneth French Database

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Appendix B

Modularity algorithm report

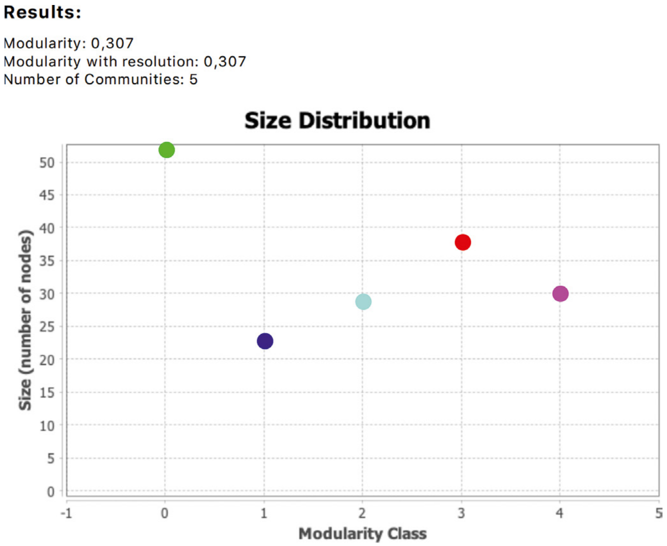

Figure 9: Modularity Class Report[16]

Figure 9 displays the report of the Modularity algorithms showing the five communities with 23 – 52 elements each. The shapes in Table 8 correspond with the shapes of classes in Figure 9.

Table 8

Shape code and distribution of communities

Shape	Modularity Class	Number of Studies	Share of Studies
	0	52	30.23 %
	3	38	22.09 %
	4	30	17.44 %
	2	29	16.86 %
	1	23	13.37 %

[16] Figure generated by Gephi, shape coding from Table 8 added for visibility.

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Appendix C

Network Analysis

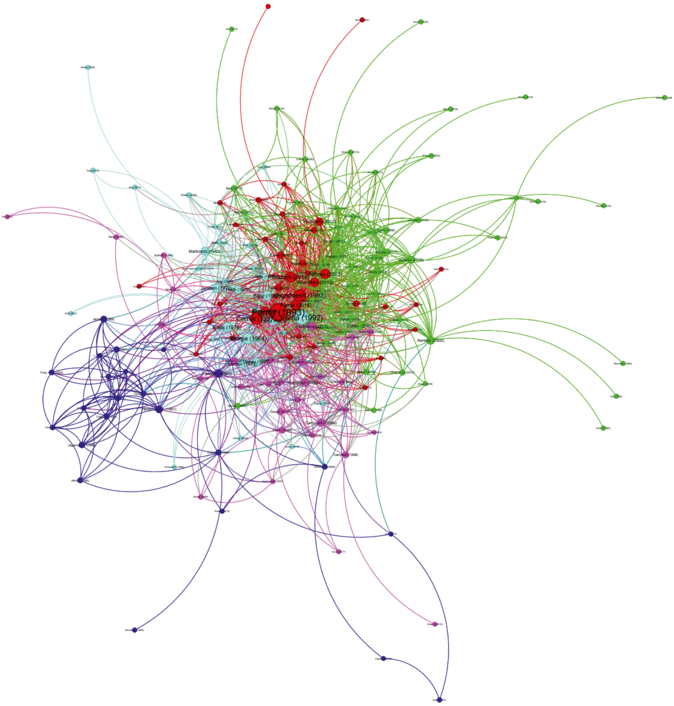

Figure 10: Network analysis with size of nodes according to the count of citations by other studies[17]

Circles are predominantly optimists, hexagons and squares base literature for factor investing and factor timing. Pentagons are mostly sceptics and triangles represent mostly literature affiliated with timing ability of fund manager.

[17] Own illustration. Data derived from literature database introduce in chapter V.2.

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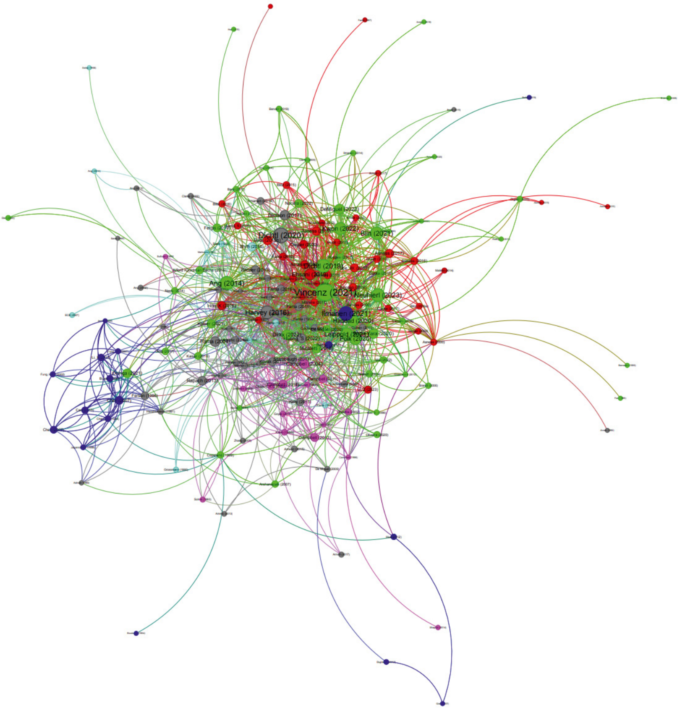

Figure 11: Authors attitude on factor timing[18]

The shape code of Figure 11 is as follows: hexagons: base literature, pentagons: optimist, triangles: sceptic, squares neutral, circles: no attitude towards factor timing. Sizes of nodes are based on the number of studies cited and the classification bases on the grading made for the literature database.

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[18] Own illustration. Data derived from literature database introduce in chapter V.2.

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