Factor Investing in the UK Financial Market Before CRSP

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Abstract

This thesis investigates the robustness of factors in financial markets by conducting an out-of-sample analysis on the UK stock market, using untouched data from the Global Financial Database, spanning nearly two centuries until the start of the CRSP database. Addressing concerns about p-hacking raised by Harvey (2017), this study tests factors and factor enhancements in this out-of-sample dataset. Using long-short portfolios and Fama-MacBeth regressions, the analysis finds that short-term reversal, long-run reversal, size, value, and idiosyncratic volatility deliver a robust performance. On the other hand, momentum fails to deliver significant returns and alphas, reinforcing doubts about its reliability in the UK market put forward by Hon and Tonks (2003). The evidence concerning market beta remains inconclusive between the CAPM and the low-risk anomaly, and the seasonality factors yield strong returns, but no clear CAPM-alphas. The failure of enhanced factors to deliver a clear outperformance over their traditional counterparts highlights their susceptibility to p-hacking. Furthermore, the research underscores the impact of research design choices - such as bandwidth and market portfolio construction - on the outcomes, reaffirming the caution needed in avoiding p-hacking. The study contributes to the understanding of factor robustness and has implications for both researchers and practitioners of financial markets.

Keywords: empirical asset pricing, p-hacking, factor premia, factor enhancements, CAPM

1. Introduction

Higher returns without taking on higher risk; that is the appealing promise of factor investing. Ever since the days of Fama & French (1993) constructing the value and size factors, the field of factor research has expanded rapidly. Since then, it has produced several hundreds of factors, all of which promise this excess return over the prediction made by the Capital Asset Pricing Model (CAPM). These factors include the canonical Fama-French factors - value, size, investment, and profitability – as well as niche factors such as advertising expense, Research and Development, and deferred revenue. However, the past decade has been tough for advocates of factor investing. Over this period, most of the well-known factors have struggled to produce meaningful returns, with the value factor even yielding strong negative returns instead. While this could be explained simply by a blip in factor investing - a lost decade not meaningful enough to discard well-supported theories - it could also give support to the critique levelled against financial economic research by Harvey (2017). He finds that the incentives for researchers to only report their most significant results, a fundamental misunderstanding of the p-value, repeated testing on the same sample, and limited out-of-sample testing for robustness give rise to serious p-hacking concerns. This p-hacking may indicate that many factors currently supported by empirical research are merely spurious results and not indicative of robust factors capable of delivering excess returns in the future.

To address concerns about the robustness of factors and potential p-hacking, Harvey (2017) proposes a Bayesian weighting function of results, which is not just stricter than the standard critical t-statistic but is also based on the prior beliefs of the researcher. Although this approach has the advantage of favouring factors based on economic principles - which should be more likely to hold true than more randomised factors - it reduces the objectivity of empirical research. Therefore, wherever possible, out-of-sample tests should be conducted to test the robustness of the factors, with the critical note that it is often difficult to find an out-of-sample test with enough power to find evidence for the existence of these factors (Harvey, 2017). One potential solution to this problem is executed by Baltussen et al. (2021). They seek evidence for the four most well-known factors in a sample dating back to the 19th and early 20th century. If the factors are still significant in this sample, they are more likely to be an enduring characteristic of equity markets, solving the problem of repeated testing on the same sample (Baltussen et al, 2021). In their paper, they find that the most well-supported factors – value, low-risk, and momentum – are still significant in this out-of-sample test. However, evidence for a size premium is weak.

While the results of Baltussen et al. (2021) indicate that the most well-supported factors are robust, and not merely a result of p-hacking, the critique by Harvey (2017) was most concerned with the fringe factors that have a prior belief of low probability. It is the many factors not grounded in economic first principles and weakly supported by evidence that are most vulnerable to p-hacking, and thus least likely to hold up in out-of-sample testing. For a factor to be truly robust, it must appear consistently in before and during the coverage period of the Centre for Research in Security Prices (CRSP) and across both United Kingdom (UK) and the United States (US) financial markets. If all these conditions are met, the factor survives concerns about p-hacking, and is more likely to continue to deliver excess returns in the future. Therefore, the question this paper aims to answer is: "Which of the factors found in the CRSP sample hold up in the pre-CRSP sample in the UK stock markets?"

To investigate this question, this paper makes use of data from the Global Financial Database (GFD). Though less refined than data from more commonly used sources such as CRSP and Bloomberg, the GFD data goes back far beyond the start of most databases. For the UK, the CRSP database starts in 1985, whereas the GFD database extends back to 1694. This allows for an out-of-sample test in an untouched sample before the start of the CRSP database. In this sample, the Fama and French (1993), momentum, short-term reversal, long-term reversal, volatility, and seasonality factors are tested.

Additionally, the analysis covers factor enhancements such as a yearhigh interaction term for momentum, and residual momentum and reversal since they could be very prone to p-hacking. In each sample, the factors will be constructed through a high minus low construction, after which the average returns, median returns, and standard deviations can be calculated. Furthermore, a Fama-MacBeth (1973) regression will be executed to estimate the significance of the factor premia. Finally, the CAPM-alphas of the factors will be calculated, to ensure the factors deliver unique return, and do not simply load up on market beta to deliver returns. This analysis makes use of multiple bandwidths, sub-samples, market portfolio constructions, and lookback windows to analyse the potential for p-hacking (based on findings by Shoebag et al., 2022).

The analysis finds that several factors continue to deliver excess returns and alphas in this out-of-sample test. Short-term reversal, long-term reversal, size, and value continue to deliver returns. Additionally, idiosyncratic volatility unexpectedly delivers robust excess returns. For beta and seasonality, the evidence is mixed. Beta delivers returns in line with the CAPM expectations when using an equal-weighted market definition but underperforms these expectations when using a value-weighted market definition, leading to a low-volatility anomaly. Seasonality factors do yield positive returns, but these returns are inconsistent over time and mostly absorbed by the market-beta, leading to insignificant or even negative CAPM-alphas. Finally, the momentum factor delivers a significant underperformance, strengthening the findings by Hon and Tonks (2013) concerning the fickleness of momentum in the UK stock market.

Furthermore, factor enhancements deliver weak evidence. Residual momentum only worsens the underperformance of this factor, residual long-term reversal slightly underperforms the traditional factor, the momentum-yearhigh interaction term improves the returns, but fails to significantly improve the CAPM-alpha, and residual short-term reversal only yields a minor factor improvement. Lastly, research choices materially impact the outcomes, creating potential for p-hacking. The choices regarding bandwidths and market portfolio construction have a large impact on the results, and choosing different sub-samples over time has a small but clear impact. Changing the lookback window makes only a negligible difference in the factor returns, but a material impact on the ability of the CAPM to absorb factor returns. Figures 1-3 below summarise the main results of the paper, displaying the t-statistic for the factor portfolio returns across the entire sample, averaged over the three different bandwidths. Important to note here is that the size (MC_percentile) and the reversal (all factor portfolios containing “rev”) factor portfolios are constructed inversely with the standard small-minus-big (SMB) and reversal factors. Therefore, negative t-statistics for these factor portfolios equate positive factor returns.

The next section will cover the theoretical framework that leads to the four hypotheses of this paper. Section 3 will discuss the data, and Section 4 will discuss the methodology used to create factors and run the analysis. Section 5 will present the results of the paper per factor, and Section 6 will link these results back to the hypotheses and the theoretical framework. Finally, Section 7 will provide some concluding remarks.

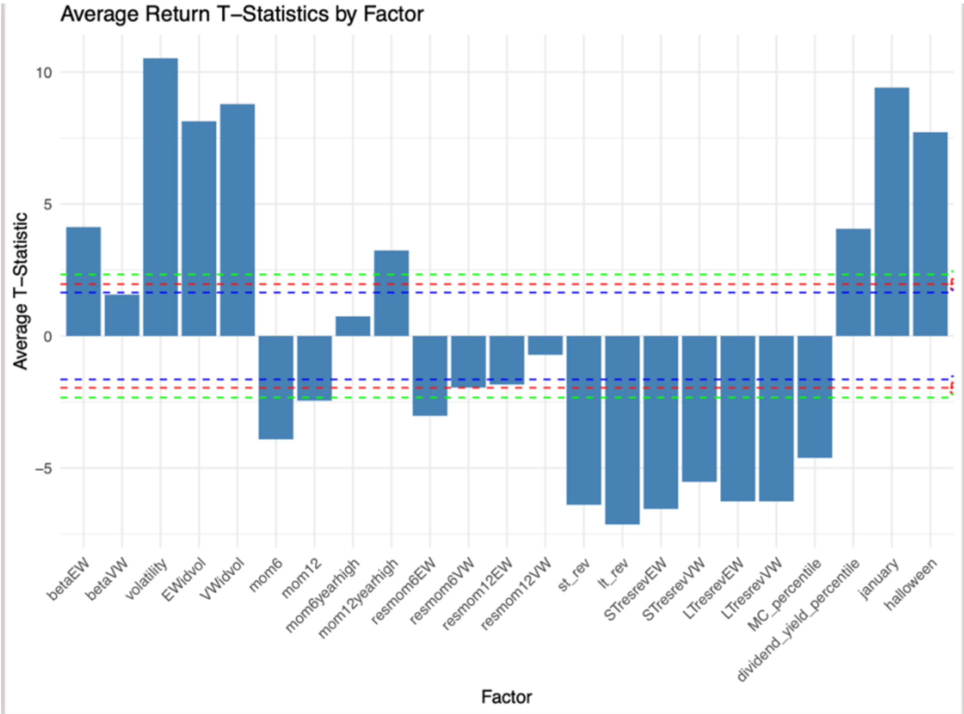

Figure 1: Average return t-statistics of the factors

The figure presents the full-sample average of the t-statistics of each factor's tercile, quintile, and decile long-short portfolio return. The lookback period for the beta and volatility factors is 36 months. The size and reversal portfolios run inversely to their standard factor constructions, meaning that the negative returns for both the MC and rev factor portfolios indicate positive factor profits. The t-statistics represent the average t-statistics of the tercile, quintile, and decile portfolios. The three lines indicate significance at the 10%, 5%, and 1% level respectively.

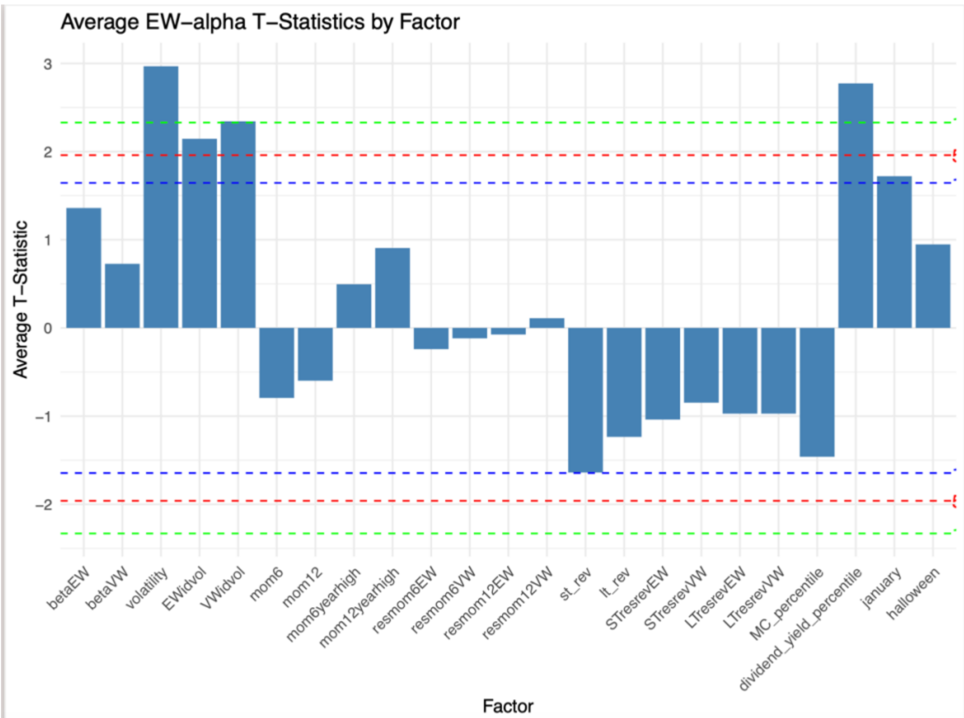

Figure 2: Average equal-weighted CAPM-alpha t-statistics of the factors

The figure presents the full-sample average of the t-statistics of each factor's tercile, quintile, and decile long-short portfolio CAPM-alpha based on an equal=weighted market construction. The lookback period for the beta and volatility factors is 36 months. The size and reversal portfolios run inversely to their standard factor constructions, meaning that the negative returns for both the MC and rev factor portfolios indicate positive factor alphas. The t-statistics represent the average t-statistics of the tercile, quintile, and decile portfolios. The three lines indicate significance at the 10%, 5%, and 1% level respectively.

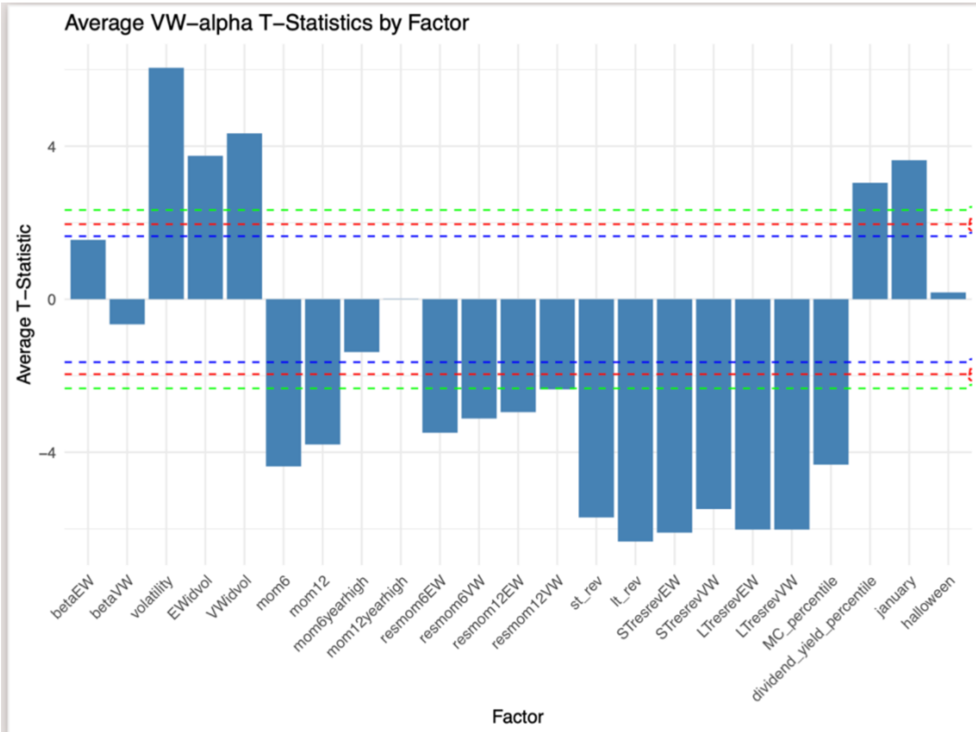

Figure 3: Average value-weighted CAPM-alpha t-statistics of the factors

The figure presents the full-sample average of the t-statistics of each factor's tercile, quintile, and decile long-short portfolio CAPM-alpha based on a value-weighted market construction. The lookback period for the beta and volatility factors is 36 months. The size and reversal portfolios run inversely to their standard factor constructions, meaning that the negative returns for both the MC and rev factor portfolios indicate positive factor alphas. The t-statistics represent the average t-statistics of the tercile, quintile, and decile portfolios. The three lines indicate significance at the 10%, 5%, and 1% level respectively.

2. Theoretical Framework

2.1 Modern Portfolio Theory

Academics have tried to develop a coherent theory of how financial assets are priced ever since stock markets became commonplace in the world. Simultaneously, practitioners have sought ways to consistently generate excess returns in financial markets without encountering higher risk. Despite this continuous search for model imperfections by both practitioners and academics, no conclusive asset pricing model has been discovered. To this day, the most used framework for asset pricing is based on Modern Portfolio Theory (MPT), developed by Harry Markowitz (1953) more than seventy years ago. MPT uses assumptions related to a homo economicus with mean-variance preferences investing in a frictionless financial market of infinitely divisible assets to find a perfect equilibrium: investors should invest in the entire financial market, under any and all conditions. Given the mean-variance preferences assumed by MPT, the optimal way to invest is to diversify away all idiosyncratic risk and bear only market risk.

Assuming there is a market of many risky assets and a risk-free asset, Sharpe (1964) has modelled the assumptions of MPT into an asset pricing model: CAPM. If every investor indeed invests in every asset, then all diversifiable risk is diversified away, with only non-diversifiable risk left, which is market risk. If investors are demanding higher returns for encountering higher risk, this must lead to a positive relationship between returns and market risk, measured in beta. In this model, only market risk is rewarded, as investors diversify away any idiosyncratic risk, meaning that this relation between returns and market risk is an absolute one, with market risk as the only determinant of returns above the risk-free rate. This risk-free asset is often operationalised as the long-term interest rate on the government bonds of a government with a negligible chance of defaulting, such as the United States or Germany (Berk & DeMarzo, 2017).

Finally, Fama (1970) completes the trilogy of seminal papers upon which the traditional asset pricing model is built. He proposes the efficient market hypothesis (EMH), based on findings that outperforming the market proves a very difficult task, and the wide availability of information in financial markets. The EMH states that any and all information is directly incorporated in security prices, meaning that excess returns without additional risk (so-called free lunches) are impossible. Therefore, assuming both the EMH and MPT to be true and a risk-free asset to be available, all assets are correctly priced according to the CAPM and have a correct risk-return relationship under this model. However, this does not mean that Fama believes the MPT to have a correct specification of risk.

2.2 Factors

While most investors still measure returns based on the CAPM and its basis in MPT, an ever-increasing body of academic work has analysed the many problematic assumptions required by these theories, as well as the inaccuracy of the predictions they yield. Simultaneously, a multi-trillion-dollar active asset management industry has claimed to find ways of delivering higher returns to its investors whilst keeping the risk profile in line with the broader market. While it must be noted that these claims are paired with a significant underperformance of most actively managed mutual funds (Fama and French, 2010), the breadth of research that uncovers flaws in MPT is too vast to ignore.

One of the major angles of critique lies within the absolute relationship between market risk and return that is present in the CAPM, with many empirical studies finding evidence for other factors that influence returns besides just market risk. These factors can be split into hypothesised additional risk factors - which contradict the CAPM but may still act in accordance with the EMH - and behavioural factors - which typically contradict both the CAPM and EMH.

A. Fama-French

While Fama (1970) formalised the EMH specifications that are often used alongside MPT, this does not mean that he believes the specification of the CAPM to be correct. Investors may have a more complex preference structure than simple mean-variance preferences. In arguably his most famous paper, written alongside Kenneth French, Fama introduced two additional risk factors beyond market risk, that deliver excess returns while not increasing market beta (Fama & French, 1993). These two factors, value (HML) and low size (SMB), are constructed through long-short portfolios of the high factor exposure minus the low factor exposure portfolio and used alongside market beta to explain stock market returns.

According to Fama and French (1993) these factors deliver excess returns through representing risk factors that are not included in the CAPM, such as liquidity and distress-related factors. The market prices securities efficiently, but with a more comprehensive definition of risk. However, later research has called into question the relationship between these factors and risk. For instance, De Groot and Huij (2018) find that - while the value premium and distress risk do often go together - it is not distress risk that is priced, but the value factor itself. This is concluded as, within the high-value portfolio, companies with lower distress risk outperform companies with higher distress risk. Equally problematic are several analyses documenting that the size anomaly has disappeared since the 1990s, at least in its unconditional form (Ahn et al., 2015). It is evident that establishing enduring risk-based stock market factors is not a simple task.

In later empirical work, Fama and French move away from their risk-based factor approach, and instead turned to economic factors. Fama and French (2015) introduce two additional factors: profitability (RMW) and investment (CMA), both derived from the dividend discount valuation model. However, this more comprehensive model yields additional problems. For one, the economic rationale may work, but in the case of profitability, runs directly against their earlier risk-based approach; after all, robust profitability should logically result in lower risk, and thus lower returns. More importantly, any factor model - including the Fama-French five factor model - needs to make choices regarding what factors to include. The choice for these economic and risk-based factors makes sense from the standpoint of EMH-supporting researchers, but leaves out several well-supported factors, such as low-volatility and momentum (Blitz et al., 2018). Furthermore, the most central factor aside from the market risk factor, size, has failed to deliver any meaningful returns ever since its discovery, leading to many researchers not considering size a valid factor anymore (Blitz and Hanauer, 2020). It is clear, therefore, that there must be more to asset pricing than just economic and risk-based factors, which is where behavioural finance provides some additional insights.

B. Momentum

Ever since the 1980s, more and more empirical studies have documented patterns in stock returns that are directly opposed to the EMH. Any factor constructed purely based on historical stock price movements that has predictive power over future returns is a direct breach of the EMH in all its forms. Arguably the most famous of these factors is the momentum factor. Jegadeesh and Titman (1993) - who popularised the momentum anomaly - found that the stocks that performed well over the most recent three to twelve months, continued to do so for the next three to twelve months. Similarly, stocks that performed poorly continue to do so. One critical note - which is especially relevant to this paper - is that the momentum factor has historically not been an enduring factor in the UK stock market, in contrast to other major financial markets (Hon & Tonks, 2003). Unlike some of the other anomalies, momentum has some hypothesised risk-based causes, most notably the finding of momentum crashes. Momentum strategies tend to have severe negative performances in times of heightened market anxiety and sharp market reversals, which are the cases where strong negative returns are least desired (Daniel & Moskowitz, 2018). However, behavioural theories propose momentum arises from an overreaction to perceived trends and overconfidence leading to exuberance (Daniel et al., 1998).

To combat the momentum crashes and firmly cement momentum in the behavioural anomalies category, Blitz et al. (2011) found evidence for a residual momentum factor - which is constructed not with absolute returns, but with residuals over the Fama-French three factor model - that yields similar returns while exhibiting lower volatility and downward potential when compared with the traditional momentum factor. By neutralising the momentum factor’s exposure to especially the market beta, it limits the effects of strong market reversals on the factor returns, and therefore provides a better risk-return trade-off (Blitz et al., 2011). Finally, empirical results have demonstrated that momentum works better when the stock is near the 52-week high than when it is far away from this reference point. Potential causes can be found in the heightened saliency of the momentum anomaly (George & Hwang, 2004). While some have argued that momentum delivered abnormally high returns in the 1970s and 1980s and is partially subsumed by market beta (Cenesizoglu et al., 2014), it continues to be regarded as one of the most important asset pricing factors (Asness et al., 2013).

C. Reversal

The next major anomaly in the pricing category is short-term reversal. Stocks that have performed well in the most recent month, tend to underperform in the upcoming month, while stocks that have performed poorly in the most recent month tend to overperform in the following month (De Groot et al., 2011). It is hard to find a risk-based justification for this short-term reversal premium. Instead, the existence of this anomaly tends to be attributed to a combination of liquidity constraints and irrational investor sentiment (Da et al., 2014). As with momentum, residualizing short-term reversal helps limit the factor loadings onto other factors, and consequently earn higher risk-adjusted returns than the traditional short-term reversal factor (Blitz et al., 2013).

The next reversal factor, popularized by Bondt and Thaler (1985), is long-term reversal. In their paper, they find that stocks that have fared poorly over a long period of time, tend to outperform stocks that have fared well. While this finding is also hard to explain through risk-based or economic theories, behavioural academists have hypothesized that herding behaviour - which leads to long-run momentum stocks becoming overpriced - is the main culprit of this anomaly. In contrast to short-term reversal and momentum, residual long-term reversal is not a proven enhancement. While absence of evidence is not evidence of absence, Blitz et al. (2011) provide a compelling reason for why residual long-term reversal should not yield great results. They find that one of the main benefits of residual momentum is that this enhanced factor is less prone to a reversal effect than the traditional momentum factor. Given that the long-term reversal factor relies on this reversal to take place, it then makes sense why residual reversal would not perform as well. Still, without empirical evidence, it is pre-emptive to completely rule out this possible enhancement.

D. Low risk

Another very peculiar anomaly that deserves a bit of attention – if only for it being the anomaly that most directly opposes the CAPM - is the low-volatility or low-risk anomaly.

Blitz and Van Vliet (2007) find that low-beta stocks have significantly higher risk-adjusted returns than high-beta stocks. They find that the relationship between return and market beta is not just flat, but even slightly inverted, as well as a CAPM-alpha of 12% for the low-minus-high risk portfolio. Similarly, high absolute volatility significantly underperforms low absolute volatility, an effect even stronger than the beta-related risk-adjusted return dispersion. This latter finding is supported by Ang et al. (2006), who find that high idiosyncratic volatility is detrimental for the returns of an asset. If high idiosyncratic volatility leads to lower returns, it is logical to conclude that the volatility anomaly would be stronger than the market beta anomaly. Baker and Hauger (2012) have demonstrated that this low-volatility anomaly holds in financial markets across the world.

Several hypotheses have been proposed, but the most well-supported hypotheses concern lack of access to liquidity to properly capitalize on this anomaly, and irrational investor preferences - the so-called lottery ticket effect (Blitz and Van Vliet, 2007; Blitz et al., 2013). While the CAPM would predict beta to be a significantly positive predictor of returns (Sharpe, 1964), the low-volatility anomaly suggests that the CAPM-alpha of a beta factor portfolio should be negative (Blitz & Van Vliet, 2006). In short, the two sides have strongly varying views on the relationship between beta and returns.

E. Seasonality

Finally, one of the oldest types of factors is the seasonality factors. As seasonality factors are solely based on calendar dates, they are typically deemed less sophisticated than more modern anomalies. Since they cannot be logically explained from a risk-based setting, they firmly fall into the category of behavioural factors. The two most famous seasonality anomalies are the January effect and the Halloween indicator. The January effect, popularised by Rozeff and Kinney (1976), refers to the finding that stocks demonstrate higher returns in January than in other months. The Halloween indicator is based on the adage “sell in May and go away. Just remember to come back in November”. Jacobsen and Zhang (2012) find that indeed, stock returns are abnormally lower in the months May through October than in the winter months. However, seasonality factors like the January effect and the Halloween indicator are the least robust of all the factors, as they fit the characteristics of potential data overfitting well (Lo and MacKinlay, 1990), and are the most suspect to p-hacking concerns discussed in the next section of the theoretical framework (Sullivan et al., 1999).

If there is not a risk-based or economic reason for an anomaly to exist, EMH would predict that anomaly to be arbitraged away by rational arbitrageurs. Therefore, EMH proponents tend to argue that these behavioural factors will be arbitraged away quickly after discovery. However, as Shleifer and Vishny (1997) point out, even a clear-cut mispricing opportunity - which is already unrealistic to present itself - may not be easy to arbitrage away due to noise traders worsening the mispricing in the short-term, forcing liquidity-constrained and highly leveraged arbitrageurs to close their positions prematurely. As long as arbitrageurs face some level of risk-aversion, these limits to arbitrage may suffice to prevent complete arbitrage of an anomaly. All in all, behavioural (pricing) factors form an important piece in the asset pricing puzzle. However, the argument against behavioural factors is that any empirical pattern can be defended by a behavioural explanation, regardless of its nature or persistence. As will be described in the next subsection, this problem has led to a true explosion of factors.

F. A multifactor world

In the 2000s, research into factor investing reached its peak, with new factors being proposed in rapid succession. These range from different specifications of the same factor – like value measured as price-to-sales or price-to-earnings (see Barbee et al., 1996)– to new factors such as net-debt-to-price (Penman et al., 2007) and intangible returns (Daniel and Titman, 2006). However, several of these factors are mere repackaging of other factors. For instance, the Piotroski F-score combines 9 other factors into one overarching value-quality factor. Similarly, quality factors like the Quality-Minus-Junk factor proposed by Asness et al. (2019) are often repackaged versions of other factors such as profitability and low-risk. While this may lead to better results when back-testing, this paper will soon delve into why this enlarges p-hacking problems significantly.

Equally interesting is the finding that factors tend to interact with each other. For instance, Blitz and Hanauer (2020) argue that size – although it may have disappeared as standalone factor – is a powerful catalyst for other factors, such as value and momentum. These factors seemingly work better in small-size stocks than in their larger counterparts. Furthermore, the negative correlations between some factors, such as value and momentum, may lead to diversification benefits of multifactor investing (Asness et al., 2013).

The final concern when looking at the factor landscape is the sheer volume of factors, many of which overlap intentionally, heavily load onto each other by accident, or seemingly disappear after the research has been published. While controlling for not just CAPM alpha but also five-factor alpha partially solves the issue of factor loadings, the problem of factor persistence nests itself in p-hacking, which will be discussed in the next section.

2.3 P-hacking

As mentioned before, many factors have faced struggles over the past decennium, to the point where researchers have called 2010-2019 a lost decade for factor investing (Blitz, 2020). While it is not strange for factors to have their ups and downs – after all, factors that perform all the time would not present limits to arbitrage as discussed by Schleifer and Vishny (1997) – the time scale and the number of factors that have underperformed has called into question whether the factors can provide a reliable source of excess returns in the future. In recent years, Harvey (2017) has fielded the strongest critique of the empirical financial body of research. His p-hacking may be the nail in the coffin for many factors, but it may also provide a path to drastically reduce the enormous factor field.

Harvey (2017) argues that a combination of repeated testing of factors on the same subsample, incentives for researchers to only publish their most significant results, limited out-of-sample testing, and a fundamental misunderstanding of the meaning of a p-value leads to many spurious correlations being interpreted as persistent investment factors. This partly explains the rapid expansion of the factor field. The p-value is formally defined as the probability of finding a certain sample given that the null hypothesis (H0) is true. However, it is often operationalized as the probability of H0 being true, given finding a certain sample.

This difference may seem insignificant at first but turns out to be of incredible significance in the p-hacking concern. A significant p-value is used as an argument to reject a null hypothesis and claim the discovery of a new factor. While the risk of a type 1 error is usually not big in an individual test, it becomes a big problem with repeated testing on the same sample. This happens especially in financial empirical studies, as the CRSP and Bloomberg datasets are the most complete, convenient, and correct datasets for financial data, so they tend to be used in most empirical work. If a researcher tests many different potential factors on one dataset, a few of them will be significant by default, regardless of the validity of the factors. Because of perverse incentives to publish, researchers may cherry pick these significant factors to base their paper around. They conveniently ignore the inversion of the meaning of the p-value and publish their work as if the significant p-value means the factor must exist. Because of a lack of valid out-of-sample tests- caused by the reliance on the same databases - these factors are then falsely upheld in academic literature (Harvey, 2017).

This problem is made even worse by the many choices that go into factor specifications. Choosing different breakpoints for the long-short portfolio construction, different rebalancing or holding periods, or different factor specifications, can lead to a wealth of different versions of a factor, with strongly varying returns and significances (Shoebag et al., 2022). This means that researchers can – whether intentionally or unintentionally - create significance in almost any factor they study. All these seemingly significant factors can lose their excess returns quickly, as they were a result of p-hacking a spurious correlation, rather than reflecting an enduring characteristic of financial markets. Since they are not based on any risk-based or economic fundamentals, behavioural factors are most prone to the effects of p-hacking. Therefore, the first hypothesis of the paper is as follows:

H1: The selection of breakpoints, lookback windows, and time periods has demonstrable impact on the returns of the factor portfolios.

While Harvey (2017) recommends thorough out-of-sample testing as the optimal solution to the p-hacking problem, he concedes that this is often not achievable in financial research, because outside of the standard databases, there are few datasets with another sample that allow for enough power to test the factor significances. Therefore, he recommends a Bayesian t-statistic, with stricter significance limits that are partly determined by the prior odds assigned to a factor. Though this allows for factors without economic foundations to be more stringently tested, it does leave space for subjectivity. Hence, the out-of-sample tests remain the preferred solution.

Baltussen et al. (2021) find a solution for this out-of-sample data problem. They use a US dataset that goes back until 1870, almost sixty years before the start of the CRSP database and investigate five of the most well-established anomalies – size, low-volatility, momentum, and value – with the aim to discover if these factors still hold up in this sample. By analysing the significance and magnitude of the factors in this analysis, they can draw conclusions about the out-of-sample decay present for each factor. They find that value, momentum, and low volatility hold up, while size demonstrates weak evidence (Baltussen et al., 2021). Therefore, the second hypothesis of this paper is as follows:

H2: Most of the well-supported factors - size, value, low-volatility, momentum, short-term reversal, and long-run reversal - maintain their significance out-of-sample.

While the traditional factors may maintain significance out-of-sample, the modern asset management research and practice is largely built on factor enhancements. Enhanced factors produce better risk-return trade-offs than their traditional counterparts in the researched samples. However, complicating factors with the goal of finding additional alpha is very prone to p-hacking, as there are more choices involved that are at the researcher’s discretion (see Harvey, 2017). While this p-hacking argument may hold true, factor enhancements are usually based on sound and enduring behavioural or financial theory, so a solid argument can be put forth as to why these enhanced factors should only demonstrate a similar level of out-of-sample decay as their traditional counterparts. Therefore, the third hypothesis is as follows:

H3: The well-established factor enhancements continue to outperform the traditional factors out-of-sample.

While these findings are interesting, they pertain only to the most well-established factors, most of which have an economic rationale to them as well. Since it is the behavioural factors, without any economic or risk-based rationale to them, that are most suspect to p-hacking concerns, this paper will follow the methodology outlined by Baltussen et al. (2021) to investigate mostly calendar- and price-based behavioural factors in a UK database - covering the entire period before the UK CRSP database commences in 1985 - and analyse whether they hold up out-of-sample. If these factors show strong excess returns, the factors are more robust to p-hacking, and thus more likely to be an enduring characteristic of markets, rather than a spurious correlation. Calendar-based factors such as the Halloween indicator are most easy to be cherry-picked and therefore face the most p-hacking accusations (Sullivan et al., 1999). Testing these factors in an out-of-sample universe will test the foundation of this argument. Therefore, the fourth and final hypothesis of this paper is as follows:

H4: The returns of calendar-based factors cannot be replicated out-of-sample; the momentum factor demonstrates diminished returns out-of-sample.

3. Data

3.1 Security data

This analysis uses data gathered from the Global Financial Data (GFD) database. This database contains data starting in the 17th century, and ending with the start of the CRSP dataset, in 1926 and 1985 for the US and the UK respectively. The database includes fundamental and price datasets (both split-adjusted and non-split-adjusted) for each security, which were downloaded using an API in RStudio. Unfortunately, for the UK database, the fundamental data was empty for all variables except for market capitalisation. These datasets were then merged into one overarching dataset containing price data, market capitalisation, and basic share information. For the price data, the split-adjusted close price was used, meaning that they are adjusted for stock splits and dividends. In case this data does not exist, non-split-adjusted close price data was used instead. Another problem is the large number of missing observations for both the market capitalisation data and the dividend data, which will be further elaborated upon in Section 4.

Using data from the 18th, 19th, and earlier 20th century inevitably comes with concerns surrounding data quality. For instance, the classification of stocks, bonds, and preferred stocks is not always consistent. Other concerns include the large number of missing observations and the low periodicity of many of the included securities. Therefore, several data quality filters were used to arrive at the universe of stocks for the analysis of this paper. The original dataset contains 25242 unique securities. Table 1 in Section 3.3 summarises each step in the filtering process, along with the number of observations and unique tickers removed. The first selection was made by filtering out any firms with a security classification other than common stock. Additionally, since there were still preferred stocks left after this filter, another filter was applied. This filter removes any securities with percentages in the stock name, as these typically represent preferred stocks and bonds.

After filtering out all securities but common stocks, 8554 unique stocks were left. Despite Fama and French (1993) filtering out financials, mostly because their value factor (book-to-market) has a different meaning for financials than for other stocks, this paper chooses not to do so. This decision was made because no book-value related measure is used in this analysis and because of the heavy weight of financials in the UK stock market. Taking out such a large sector could risk unilaterally tilting the remaining stocks away from the market composition.

Since many stocks only have price data with quarterly or annual frequency – insufficient to perform an analysis on price variables – these stocks were filtered out of the sample. First, any stock not containing “daily”, “weekly”, or “monthly” in the periodicity variable were removed, bringing the total amount of stocks down to 9226. Then, all dividend-only observations, which were created in the full-join merge between the datasets, were moved to the most recent price-data observation; otherwise, they would disappear in collapsing the dataset, leading to a total of 8554 stocks. To check for any potential mistakes in the periodicity filter, for every non-first observation, the observation is removed if the next observation is present and further than 59 days away. No additional tickers were removed in this step. Similarly, in removing any duplicate rows, no unique tickers were removed from the analysis.

For the next major step in the data handling, the data was collapsed into monthly data. For this, to be similar with the monthly observations, the first observation of the month was selected. The return of the month was computed as the percentage change between the close price of next month and the close price of the current month. Each time, the first observation of a month was taken as the close price of the month. For the daily and weekly observations, the first close price available was selected. For the monthly observations, the one known close price of each month was selected. To avoid infinitely large returns, negative close-price observations were removed, which included nine observations from separate tickers. Thereafter, observations containing less than twelve months of consecutive data were filtered out, as these observations would have no reliable price-based and volatility-based variables. Additionally, this step filters out any stock likely to be too illiquid to trade on a monthly basis. After this, 6242 unique tickers remained. Given that the analysis solely focused on the pre-CRSP period, any observation after 1984 was taken out of the dataset, removing two further tickers. Stocks with a price return above ten thousand percent were also removed, as to not bias the equal-weighted portfolios. This results in a final dataset of just over one million observations across 6239 unique tickers.

3.2 Interest rate and market portfolio

With regards to interest rates, the UK treasuries serve as risk-free rate for this analysis. Roughly 90% of the securities in the final dataset are London-based stocks, and out of the remaining 10%, half were based in Paris and another quarter in Vienna; all three relatively stable monetary unions. The final quarter was divided up between 11 more major cities. Due to the limited data availability for all countries but the UK in the very few databases that are available, it was infeasible to gather comprehensive data for these other stock markets. The UK treasury data from 1960 and onwards is taken directly from the OECD database. This database contains a dataset of monthly data about the 10-year UK treasury yield and can be reliably used without further complications. Given that most of the period under analysis falls before 1960, alternative sources of data had to be consulted. The GFD database also contains a dataset with monthly T-bill interest rate data from the major financial markets. Unfortunately, this data set also does not contain any observations before 1900.

Homer (1963), known as the father of modern bond research, has compiled his extensive research into bonds and treasuries together in his seminal work, ‘A History of Interest rates’. Table 19 contains data about the UK long-term treasury yield in the 19th century. These yields were taken as the interest rates for that year, with the middle point being chosen if a range was given for that year. Data for the 18th century is notably less precise. While Table 12 contains data about the long-term interest rate on UK government bonds, these are not complete; especially in the first half of the century, several years of data are missing (Homer, 1963). In these cases, the last known interest rate will be used. All interest rates were divided by twelve to ensure that they represent monthly returns. In comparing the 20th century bond rates from Homer (1963), extracted from Table 57, with the GFD interest rate data, there seems to be little difference between the two, with the clear exception being the failure of the former to capture the interest rate peg present during the Second World War. In conclusion, this paper will use OECD interest rates post-1960, GFD interest rates from 1900 to 1960, and Homer's (1963) interest rates pre-1900.

Additionally, given the lack of market capitalisation data, constructing a value-weighted market portfolio is infeasible. Instead, the value-weighted returns will be proxied by the FTSE-100 return. Starting in 1800, the GFD database also contains a dataset with the monthly returns of all major world indices. Given the aforementioned dominance of London-based stocks, the FTSE-100 was chosen as reliable proxy for market returns, especially given the hurdles in international investment in the pre-CRSP period. An equal-weighted market portfolio will later be constructed within-sample.

3.3 The final data

Figures 4.1 and 4.2 below display an annual count of unique tickers in the dataset. For the entire 18th century, the unique number of tickers in a year never exceeds thirteen. Since testing portfolio returns of a period with two stocks in the entire period does not produce any productive results, the analysis will only cover years with at least twenty unique stocks. This means that the sample period will run from 1806 to 1984, encompassing 6211 stocks. This will also solve the issue surrounding missing interest rates in the 18th century. Furthermore, the histogram clearly displays the effect of the First World War and the Great Depression, with about 70% of stocks disappearing between 1915 and 1935. Figure 1b shows the histogram of tickers after 1806.

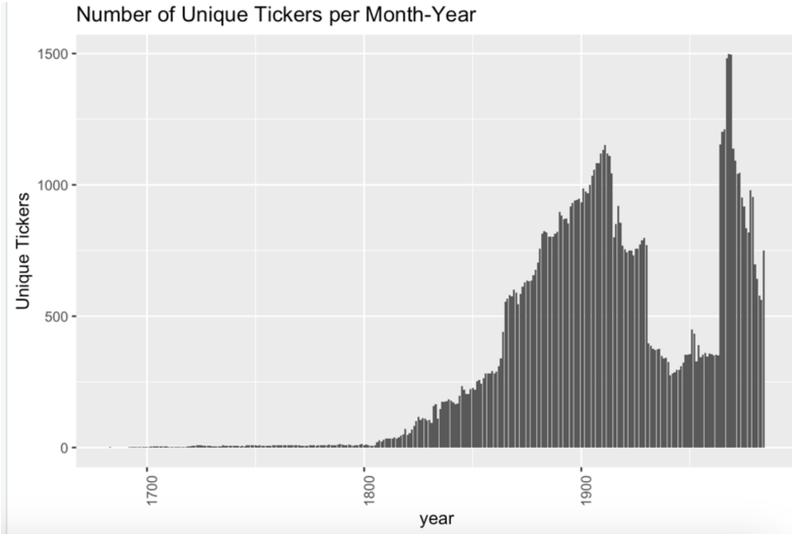

Figure 4.1 *Histogram of unique tickers over the total dataset*

The figure presents the total amount of stocks that have at least one price observation in a year, for each year in the total dataset.

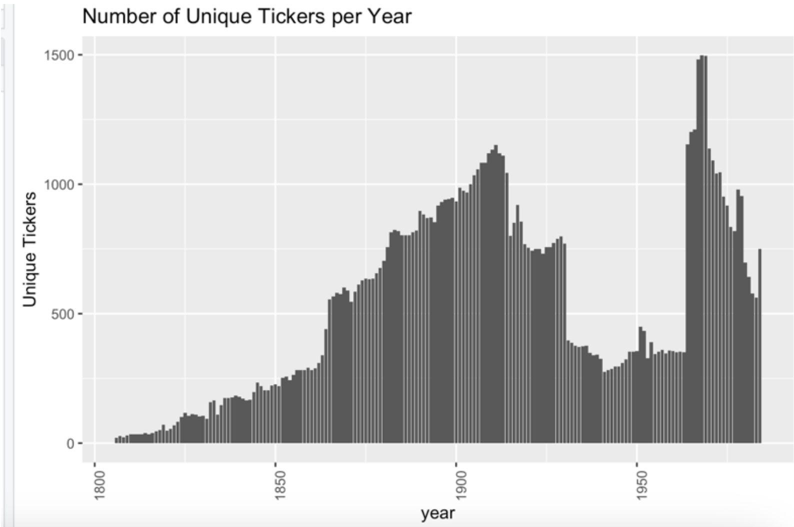

Figure 4.2 *Histogram of unique tickers after 1806*

The figure presents the total amount of stocks that have at least one price observation in a year, for each year after the 1806 cut-off point.

Step	**Unique Ticker Count**	**Observation Count**
Start	25242	31962607
Removing non-stocks	11406 (-13836)	11230049 (-20732558)
Removing stocks with low periodicity	9226 (-2080)	11175988 (-54061)
Absorbing and removing dividend only observations and removing tickers with no price observations	8554 (-672)	11094196 (-121548)

Removing long observation gaps (>59 days) and removing duplicate rows	8554 (-0)	11033525 (-60671)
Changing periodicity of the dataset into monthly and removing observations with negative close prices	8554(-0)	1057153 (-9976372)
Removing stocks with less than 12 consecutive months of data	6242 (-2312)	1047914 (-9239)
Removing observations after 1984	6240 (-2)	1040008 (-7906)
Removing observations with returns infinitely large or above ten thousand percent	6239 (-1)	1033602 (-6406)
Removing observations before 1806	6211 (-28)	1025492 (-8110)

Table 2 *Overview of the data filters*

This table portrays each data filter put in place to arrive at the eventual universe of stocks. The observation count and unique stock count are also portrayed, as well as the degree to which the filter impacts both. The filters are listed by their chronological order within the process.

The summary statistics can be found in Table 3 below. While some means and standard deviations are heavily inflated because of a select few extreme outliers, this only occurs in input variables for the factor portfolio construction process, and never in return variables. Given the well-behaved nature of the return variables, the sensible number of missing observations – which increase the larger the lookback window required to form a variable - and logical medians, the outliers are no cause for concern.

Name	**factor**	**mean**	**median**	**sd**	**min**	**max**	**na_count**	**observations**
Price Return	price_return	0.90	0.00	37.11	-100.00	9.90e+03	0	1.01e+06
Interest Rate	IR	0.38	0.27	0.27	0.02	1.36	0	1.01e+06
Value-weighted Market Return	VW_return	0.31	0.25	3.70	-22.25	53.96	0	1.01e+06
Equal-weighted Market Return	EW_return	0.90	0.66	3.80	-16.56	42.22	0	1.01e+06
6-month Momentum	mom6	1.67e+05	0.00	1.65e+08	-1.00	1.64e+11	3.70e+04	9.81e+05
12-month Momentum	mom12	1.63e+05	0.00	1.59e+08	-1.00	1.54e+11	7.37e+04	9.45e+05
6-month Momentum * distance year high	mom6yearhigh	1.67e+05	0.00	1.65e+08	-1.00	1.64e+11	3.70e+04	9.82e+05

12-month Momentum * distance year high	mom12yearhigh	1.63e+05	0.00	1.59e+08	-1.00	1.54e+11	7.37e+04	9.45e+05
Market Capitalisation	MC	11.40	0.30	1.04e+02	0.00	7.90e+03	3.09e+05	7.10e+05
Dividend Yield	dividend_yield	2.69	0.00	38.97	0.00	1.20e+04	6.79e+04	9.51e+05
Short-term Reversal	st_rev	1.71e+05	0.00	1.72e+08	-1.00	1.74e+11	6.17e+03	1.01e+06
Long-run Reversal	lt_rev	2.44e+05	0.00	2.19e+08	-1.00	1.98e+11	2.05e+05	8.134+05
Equal-Weighted Market Beta	betaEW	0.88	0.44	7.09	-39.74	6.94e+02	2.00e+05	8.19e+05
Value-Weighted Market Beta	betaVW	0.54	0.44	4.00	-4.24e+02	4.83e+02	2.00e+05	8.19e+05
Volatility	volatility	10.10	6.65	28.88	0.00	1.67e+03	2.00e+05	8.19e+05
6-month Equal-weighted Residual Momentum	resmom6EW	0.41	0.98	3.14e+02	-1.86e+05	3.54e+04	2.29e+05	7.89e+05
12-month Equal-weighted Residual Momentum	resmom12EW	-4.03e+03	0.96	3.32e+06	-2.42e+09	6.91e+08	2.58e+05	7.61e+05
6-month Value-weighted Residual Momentum	resmom6VW	1.02	0.99	11.46	-6.16e+03	2.97e+03	2.29e+05	7.89e+05
12-month Value-weighted Residual Momentum	resmom12VW	-3.00	0.97	2.44e+03	-1.86e+06	3.40e+05	2.58e+05	7.61e+05
Short-term Equal-weighted Residual Reversal	STresrevEW	1.00	1.00	0.36	-31.61	99.52	2.05e+05	8.14e+05
Short-term Value-weighted Residual Reversal	STresrevVW	1.00	1.00	0.34	-13.17	1.00e+02	2.05e+05	8.14e+05
Long-term Equal-weighted Residual Reversal	LTresrevEW	-1.38e+17	0.85	1.68e+20	-1.13e+23	7.15e+22	3.58e+05	6.61e+05
Long-term Value-weighted Residual Reversal	LTresrevVW	-1.38e+17	0.85	1.68e+20	-1.13e+23	7.15e+22	3.58e+05	6.61e+05

Table 3 *Summary Statistics of the main variables*

This table shows the summary statistics for each of the factors that will be used as input for the factor constructions. It includes the mean, median, standard deviation, minimum, and maximum observation, as well as the number of NAs and the number of observations. All numbers are rounded to two decimals and are in scientific notation if they are larger than 100. All return variables are in monthly percentages. The extreme outliers in some of the factors does not pose a major problem for the analysis, as the affected factors are only used as input variables for the portfolios.

4. Methods

4.1 Factor Creation

This section details the construction of all the factors, as well as any trade-offs and considerations made in the process. Due to the data quality, unconventional choices were necessary to construct certain factors. The factors can be categorised into five groups: volatility, momentum, reversal, Fama-French, and seasonality. The analysis was run on RStudio version 4.4.1.

A. Volatility

The first category is volatility-related factors. While in the literature, beta is the regression coefficient between the returns of an asset and the returns of the entire market, the data availability limits the possibilities for executing this regression using the complete market portfolio. Given that the value-weighted market portfolio comprises only the FTSE-100 index, the analysis was done using both this market portfolio and a within-sample constructed equal-weighted market portfolio. The equal-weighted market portfolio ensures all stocks are included but is biased toward stocks with smaller market capitalisations. The value-weighted market portfolio has the correct weights but does not contain all stocks. Therefore, both are used alongside each other for a comprehensive assessment. These regressions were executed over a 36-month window, with a one-month lag in the return variables, although this will be subjected to a sensitivity analysis later. Additionally, constructing the market portfolio based solely on UK stocks adds weight to Roll's critique (Roll, 1977). He critiques the assumption in asset pricing tests that the true market portfolio's composition – which includes any investable asset – can be known. Still, given the difficulties a UK-based investor in the 19th century would face investing in foreign asset markets, the validity of this analysis is no less than the reliability of most other asset pricing analyses.

Furthermore, volatility itself will also be considered. Given that idiosyncratic volatility should not be priced and may even be priced negatively (Ang et al. 2006), the volatility-factor portfolio should not deliver higher returns than the beta factor portfolio and should have a lower t-statistic due to higher random noise. This factor is constructed by a 36-month rolling-window volatility calculation of the returns of the stock, with prices lagged one month. Finally, this category also includes this volatility factor sorted within each of the equal-weighted and value-weighted beta portfolios, as a proxy for idiosyncratic volatility. This factor should yield little excess returns as most of the beta-related excess returns should be absorbed by the beta factor it is double-sorted into, and idiosyncratic volatility is not priced according to the CAPM and negatively priced according to Ang et al. (2006).

B. Momentum

The second group of factors consists of momentum-based factors. Momentum is constructed with both a 6-month and a 12-month formation period. The 6-month momentum variable is constructed as the percentage change between the close price 6 months ago and the close price of the month before last. The most recent month is skipped to avoid a potential one-month reversal effect as analysed by De Groot et al. (2011), which is standard practice in momentum factor construction (Asness et al., 2014). Similarly, the 12-month momentum variable is constructed as the percentage change between the close price 12 months ago and the close price of the month before last.

Based on the findings of George and Hwang (2004), interaction variables were constructed between the momentum factor and the nearness of a stock to its 52-week high, as measured by the percentage distance between the close price and the 52-week high. Since the latter is always negative, the interaction was constructed as momentum multiplied by one minus the percentage distance to the 52-week high. This ensures that the momentum variable is scaled down when the observation is far from the 52-week high.

Based on the findings of Blitz et al. (2011), a residual momentum is also analysed. While Blitz et al. (2011) use the residuals of a Fama-French three factor regression, the lack of data concerning the HML and SMB factors means that this paper will use the residuals of a CAPM-regression. Given that market beta is the most dominant factor and the leading explanation behind momentum crashes (Daniels et al., 2013), this CAPM-based residual momentum should still achieve most of what the Fama-French-based residual momentum would achieve. These residuals are derived from the CAPM-formula, through calculating the subtracting a firm's expected returns, based on beta and the market index, from their actual returns (Sharpe & Lindter, 1964). 6- and 12-month residual momentum is then calculated by a 6- and 12-month rolling window product of the gross residuals. This rolling window is again shifted by one month to prevent short-term reversal effects.

C. Reversal

Thirdly, the reversal factors consist of short-term and long-run reversal. The short-term reversal factor – based on the significant negative autocorrelation between stock returns over successive months (De Groot et al., 2011) – is constructed by calculating the percentage difference between last month's close price and the current month's close price. Because the long-short portfolios are constructed using a top-minus-bottom approach, this short-term reversal factor should produce negative returns to be in-line with academic literature. Similarly, the long-run reversal factor is created by taking the percentage difference between the close price of 36 months ago and the close price of this month. This factor too is expected to deliver negative results (Bondt & Thaler, 1985). Similar to residual momentum, the reversal anomalies also have a residual reversal counterpart. The short-term reversal factor equals the shifted CAPM-residuals from the past month, while the long-term residual reversal is the 36-month rolling-window product of the gross residuals. Long-term residual reversal follows the same construction procedure as residual moment, with a longer lookback period being the only difference.

D. Fama-French

The fourth category of variables consists of the Fama and French (1993) variables, size, and value. Baltussen et al (2021) include dividend yield as proxy for value. However, the majority of the stocks included in this analysis either did not pay dividends or do not have records of their payments in the GFD database - as evidenced by the many zeros in this column - so it is not a perfect proxy in this analysis. This dividend yield for each stock is calculated as the sum of the dividends in the trailing twelve (monthly) observations divided by the share price of that month. Unfortunately, this still gives scope to outliers as there may be insufficient observations to form diversified dividend portfolios. Size is more directly tested, as most companies in the dataset have market capitalisation data. As such, a top-minus-bottom portfolio can be constructed by ranking companies on their market capitalisation. While there are companies with missing market capitalisation data, the analysis still allows for general conclusions about the direction and magnitude of the size anomaly. Because of the erratic data in this category, the absolute size and dividend yield variables did not sort neatly into different portfolios. Therefore, stocks were sorted into size and dividend yield portfolios based on their percentile with regards to these two factors in that specific month. This transformation should not significantly affect the portfolio sorting, as the original size and dividend yield data is only used to sort the stocks into portfolios. However, the transformation does facilitate a smoother portfolio formation process.

E. Seasonality

The final category of variables is the seasonality factors. In this analysis, the January effect and the Halloween indicator will be tested. Since both variables are constructed based on the month of the observation, there can obviously be no long-short portfolios within a single month. Therefore, these two factors will be constructed on an annual basis. For the January effect, the long leg comprises the average returns of all observations during January of a specific year, while the short leg comprises the average returns of all observations during all other months of that year. Taking the average return means that the resulting long-short portfolio will have net-zero investment. Similarly, the Halloween indicator portfolio has a long leg, consisting of the average return in the months November to May of a specific year, and a short leg, consisting of the average return in the months June to October.

4.2 Empirical Analysis

Returns are defined as the difference between the first close price of this month and the first close price of the next month. Although this means the first day of each month is counted towards last month’s return, it is reasonable to assume that news was incorporated much slower in the stock markets before the rise of the internet.

In each month, every stock was ranked on each of the factors, with the exception of the previously discussed seasonality factors, after which the stocks were distributed into portfolios. To minimize the effects of p-hacking, portfolios were constructed using terciles, quintiles, and deciles. This standardises the analysis among factors, given that Fama and

French (1993) construct their factors as 3-minus-1 portfolios, whereas momentum is often constructed as 10-minus-1 portfolio (Jegadeesh & Titman, 1993). By performing the analysis with multiple breakpoints, the effect of breakpoints on the returns of anomalies can be studied. In every month, the average return of the bottom portfolio was subtracted from the top portfolio's return to construct the zero investment long-short portfolio. Due to the substantial missing market capitalisation data, portfolios were constructed as equal-weighted rather than value-weighted. While value-weighted portfolios align better with existing literature (see Baltussen et al., 2021), a strong size-tilt may enhance the magnitude of the factor returns observed in the analysis (Blitz & Hanauer, 2020).

For each of the factors, the average return of each long-short portfolio over time was calculated. This average was then divided by the standard error to get a t-statistic, following Fama and MacBeth's (1973) procedure. The returns of each long-short portfolio were then regressed on both the complete equal-weighted market portfolio and the incomplete value-weighted market portfolio to get the equal- and value-weighted betas of the factor returns. These betas were used to determine the CAPM alpha of each factor portfolio. These CAPM alphas are the returns of a factor portfolio minus its CAPM-based expected return. These expected returns are the risk-free rate plus the beta multiplied by the market portfolio return in less of the risk-free rate. The beta used is the beta of the factor portfolio over the entire analysis period. Fama-Macbeth regressions were used to test the significance of the factor returns. Due to the potential influence from extreme outloiers and high stock volatility, the median factor return was also computed to verify if it aligns with the average return.

To check for consistency of the factor premia across almost 200 years, the analysis was also conducted for both centuries separately. Some variation in the results is expected due to changing risk attitudes between generations (Malmendier & Nagel, 2011). However, for a factor to be an enduring characteristic of financial markets, it ought not to be solely determined by an extreme magnitude in one century offsetting absent or even negative results in others. Additionally, having a century of negative average performances makes a factor, no matter if it is an enduring characteristic of markets or not, completely uninvestable for most investors. Finally, a sensitivity analysis compares beta formation periods of 12 and 36 months. This affects both the beta and idiosyncratic volatility factor portfolios, as well as all the CAPM-alphas. Any formation period shorter than 12 months will suffer from wild swings in the resulting beta, as there are too little datapoints to run a thorough regression, so it captures too much noise (see Fama and French, 2010). On the other hand, any formation period longer than 36 months risks smoothing out real fluctuations in market beta that should be considered market risk, given the short evaluation windows in the financial industry (Berk & Green, 2004).

5. Results

This section briefly describes the returns and alphas of each of the factors analysed in this paper. Refer to Appendix A and B for a full overview of all results in the 36-month and 12-month beta formation analysis respectively, and Appendix C for figures presenting the average returns of the factor portfolios over time.

5.1 Volatility

When looking at the beta factors, there is no clear evidence for a value-weighted beta premium; the evidence for an equal-weighted beta premium is quite strong. The value-weighted beta yields insignificant returns of -2.3% annually in the tercile portfolio and 4.3% in the decile portfolio. The alphas are consistently negative and significant at the 10% level for the quintile and tercile portfolio constructions. On the other hand, the equal-weighted beta factor yields returns ranging from 7.7% to 11.0% and are significant at the 1% level for the quintile and decile sorts. The alphas hover around two to three percent and are consistently insignificant. Therefore, the value-weighted beta factor does not deliver any significant returns, and underperforms the CAPM expectation, while the equal-weighted beta factor delivers significant returns and performs in-line with the CAPM expectation. Interestingly, the median return for both beta factors is zero, and their median alphas are clearly negative, meaning that the beta factor in this sample mainly profits from strong positive outliers, while not generating any excess returns in most years.

When looking at the centuries individually, the 19th century aligns more with the CAPM, while the 20th century aligns more to the low-volatility anomaly. Additionally, the dispersion between the two beta factors is much smaller in the 20th century than it is in the 19th century. Changing the beta lookback window from 36 to 12 months slightly improves the returns of the value-weighted beta factor - making them consistently positive - but worsens the negative CAPM-alphas. The returns and alphas of the equal-weighted portfolio remain nearly unchanged. Furthermore, using an equal-weighted or value-weighted market portfolio to calculate the alphas does not materially impact the results. Nevertheless, the gap between the two beta factors is a noteworthy finding.

These findings extend themselves to the volatility factor. Given the significance of the equal-weighted beta factor, a significant volatility factor is not surprising. However, the high magnitude and significance of both the returns and alphas of the volatility factor are. The returns of the volatility factor are 40-60% higher than the returns of the equal-weighted beta factor, landing firmly in the double digits, and are all significant at the 1% level. The alphas, too, are in the double digits and significant at the 1% level. These returns maintain strong across the different portfolio constructions, individual centuries, and a shorter lookback window only strengthens their magnitudes. In similar fashion to the beta factors, however, the volatility factor mostly profits from strong positive outliers in returns, as its median return is in the low single digits annually, and its median alpha is indistinguishable from zero.

This finding logically corresponds with a positive return for the idiosyncratic volatility factors, given that volatility consists of market-based volatility and idiosyncratic volatility. The idiosyncratic factors also have double digit returns, but the equal-weighted idiosyncratic volatility factor faces extreme volatility as well, meaning that its t-statistics are only right at the border of the 1% significance level. The volatility of the value-weighted idiosyncratic volatility factor is much more in-line with the other factors, and coupled with its double-digit annualised return, produces t-statistics far beyond the 1% significance level.

That being said, the fact that the CAPM-alphas of the factor portfolio are roughly a third lower than the returns implies that there may still be some leakage of beta into this factor. The CAPM alphas of the equal-weighted factor are now mostly significant at the 10% or the 5% level, and the value-weighted factor's alphas lose about half the magnitude and significance of the absolute returns but are still significant at the 1% level. As before, the results are slightly improved with a shorter lookback period, but not by much. Finally, as with all volatility factors, the returns seem to be driven by positive outliers in the factor returns, as the medians of the idiosyncratic volatility factor returns are in the low single digits, and their median alphas are roughly zero. In short, both the bad performance of beta and the strong performance of volatility provide some puzzling results considering previous findings.

5.2 Momentum

The momentum factors also yield surprising results. The traditional momentum factors perform poorly, with insignificant and mostly negative returns, as well as consistently negative alphas across the board. The annualised returns range between -6.2% and 1.5%, and the alphas are between -2.0% and -13.2%. Except for 12-month momentum in the quintile sort, all traditional momentum factors deliver a negative alpha significant at the 10% level at least. However, the medians of the momentum returns are positive, and the alphas are nearly indistinguishable from zero, meaning that the negative average return is mostly caused by strong negative outliers. Despite momentum being typically constructed using narrow bandwidths, narrowing the bandwidths do not increase performance in this analysis. Furthermore, the findings are much stronger in the 19th century, whereas in the 20th century, they are much closer to zero. This makes a big difference for the alphas, as they lose their significance. Finally, there is little discernible difference between 6-month momentum and 12-month momentum.

When combining the momentum signal with the nearness to year high signal, the results are more positive. The quintile and decile portfolios of the 12-month interaction factor deliver strongly positive returns of about 8-10% annually, significant at the 1% level. However, this same cannot be said for the tercile portfolio, nor the 6-month interaction variable, which have mixed and insignificant returns. However, these returns lose 75% of their magnitude and all their significance when using CAPM-adjusted alphas, meaning that they do not provide any unique outperformance. The tercile portfolios even carry significantly negative alphas, showcasing why the decile formation may be most often used for momentum-based anomalies. After interacting the momentum with the yearhigh variable, there is no clear distinction between means and medians anymore.

Residual momentum delivers consistently negative returns, with annualised returns often in the double digits, and always significant at the 1% level. These results are consistent with both a six- and a twelve-month formation period and are more negative in the 20th century than in the 19th century. As before, the quintile sort produces more moderate results than the other two portfolio sorts, and the results hold regardless of the beta formation window. Additionally, the median return and alpha are a lot closer to zero, but do not counter the negative performance of the residual momentum factor. Finally, changing the beta formation period to twelve months only worsens the CAPM-alphas, which are now much more in-line with the absolute returns. In short, neither momentum, nor any of its enhancements, seem to deliver any meaningful returns or alphas in this analysis.

5.3 Reversal

When it comes to the third class, reversal, the results are much more in line with theory. Across all specifications and centuries, both short-term and long-run reversal have negative returns and negative alphas, and therefore positive factor returns, since the factors were inverted. The returns of short-term reversal are in the double digits across the overall sample and the individual centuries, all significant at the 1% level. Its alphas are stronger in magnitude and similar in significance compared to its returns, meaning that the short-term reversal returns are not the result of exposure to market beta. Residual short-term reversal shows marginally more significant returns and alphas than the traditional version, though the difference is minimal. Generally, higher significance, especially for the returns, is attributed to lower volatility rather than higher returns. Adjusting the beta formation period slightly improves the residual reversal results, though the improvement is not substantial. Furthermore, all versions of short-term reversal showcase stronger performance with narrower bandwidths - which is more pronounced for the residual version - and none of the short-term reversal returns are affected by a change in formation period of the market beta. Finally, the medians of both traditional and residual short-term reversal, though smaller in magnitude, are consistently negative, indicating that neither factor is solely driven by strong outliers.

Conversely, long-term momentum demonstrates double digit returns, significant at the 1% level. This factor is most effective in decile formation as well and performs well in both centuries, particularly excelling in the 20th century. Interestingly, long-term reversal performs worst with quintile bandwidths, which corresponds with the better performance of momentum with this formation. Additionally, the long-term reversal factor has double digit alphas as well, meaning that the returns are not caused by exposure to market beta. Residual long-term reversal performs well, with returns and alphas all significant at the 1% level, though it does not evidently outperform traditional long-term reversal. Changing the beta formation window has a negligible effect on the performance of this residual long-term reversal factor. Finally, the average returns and alphas of long-term reversal are mostly driven by strong outliers, as their medians are negative but close to zero.

5.4 Fama and French

The results for the Fama and French (1993) factors are in line with the existing theory. The value factor, measured by the dividend yield, delivers double-digit annual returns and double digit CAPM-alphas, both significant at the 1% level. Interestingly, the medians of the value factor are very close to zero, indicating that the value factor strongly benefits from significant positive outliers. The value effect is also much more pronounced in the 19th century than it is in the 20th century, where it only has an annual return of around 3%. The medians are roughly the same across both centuries, reflecting more severe positive outliers in the 19th century, and value performs better with broad bandwidths than with narrow bandwidths. These outliers are caused by the low number of sampled stocks in the 19th century combined with the low number of dividend payers in this data, causing many years to barely fulfil the 10 stocks minimum. This is problematic, as portfolio sorts assume zero idiosyncratic volatility, which is not achieved in this context. This also explains why the factor portfolio is interrupted on multiple occasions, as the amount of dividend payers drops below 10 due to attrition. Furthermore, the shorter lookback horizons increase the ability of the CAPM to absorb the value factor returns. Therefore, the CAPM-alphas are less significant in this sensitivity analysis than they are in the original analysis – most clearly so in the 20th century. All in all, the value premium is certainly present in this analysis, with some critical notes regarding its dependency on outliers to sustain itself and its ability to yield alphas with short lookback horizons.

The size factor delivers similarly positive and more robust results when compared to the value premium. The BMS portfolio constructed in this analysis, running contrary to the standard size factor, consistently delivers negative returns which run into the double digits. These returns are significant at the 1% level. While the equal-weighted CAPM-alpha is slightly less significant, the results remain clearly negative, and the value-weighted CAPM alpha is similar to the absolute return. Furthermore, the beta formation period has little impact in the ability of the CAPM to absorb the size factor returns, leading to similar alphas across specifications. Finally, size performs better with narrow bandwidths than with broader bandwidths. In short, the size factor delivers a strong performance in this out-of-sample test.

5.5 Seasonality

The January effect delivers an average annualised return of 10.4%, and the Halloween indicator delivers an average annualised return of 5.3% over the entire sample, both significant at the 1% level. However, this return is not distributed equally over the two centuries, as for both, the return has about twice the magnitude in the 20th century it has in the 19th century. While the returns portray a promising picture of seasonality factors, the alphas paint a mixed picture. Over the whole sample, the alphas are weakly significant for the January effect and completely insignificant for the Halloween indicator.

The 19th century alphas are negative for both factors, with the equal-weighted alphas significantly so at the 1% level. On the other hand, the 20th century portrays positively significant alphas for the January effect and insignificant alphas for the Halloween indicator. The equal-weighted alphas capture substantially more of the factor returns than the value-weighted returns, especially in this problematic 19th century. Furthermore, the medians are mostly near-zero, indicating a reliance on positive outliers, and changing the beta lookback window has very little impact on the results. In short, while both seasonality factors yield excess returns, they struggle to yield enduring alphas in the analysis. The Halloween indicator fails to do so throughout the analysis, and the January effect is solely reliant on a positive alpha in the 20th century.

6. Discussion

The main analysis of this paper examined the performance of several factors in the UK stock market in the 18th, 19th, and 20th centuries, until the start of the CRSP UK database. This section links the results to theory and literature, discussing each hypothesis in detail and then comparing with related studies. Sections 6.1 up until 6.4 will discuss each hypothesis separately, and Section 6.5 will compare the general findings of this paper with four closely related papers in the literature.

6.1 H1: p-hacking potential in research design

Regarding the potential influence of research design choices on p-hacking (H1), one of the most prominent effects is related to bandwidth selection. Using tercile bandwidths, the magnitude of short-term reversal may be overlooked, with the results being much stronger using narrower bandwidths. Similarly, quintile bandwidths are clearly more favourable to momentum factors, whereas decile bandwidths consistently favour reversal factors. On top of that, there is a clear low-beta anomaly in the tercile bandwidth construction, which is not significantly present with narrower bandwidths. Finally, the momentum-yearhigh interaction variable only delivers returns in narrow bandwidths, which emphasises the impact of bandwidth selection.

Another interesting choice concerns the choice between an equal- or value-weighted market portfolio. In this analysis, the equal-weighted market beta factor performs in-line with the CAPM predictions, while the value-weighted beta factor shows a clear low-beta anomaly, especially with lower bandwidths. Additionally, the equal-weighted market beta is significantly better at capturing factor returns in the alpha calculation, which results in lower CAPM-alphas, especially for the volatility and seasonality factors. On top of this, the equal-weighted idiosyncratic volatility factor outperforms the value-weighted counterpart. While there may be a hidden size bias in these results, it lends support to the conclusion that a broader market portfolio definition aids the returns of the market-based factors.

Furthermore, there were some differences in the returns and alphas between the centuries, especially for long-term reversal and beta, but not many were large enough to change the direction of a factor or make a material impact on its significance. The value factor and the January effect are the only clear exceptions. Value delivers a convincing performance in the 19th century – arguably due to outliers - but only yields moderate returns in the 20th century, whereas the January effect yields significant positive CAPM-adjusted returns in the 20th century, but clear negative ones in the 19th century. Therefore, there is some evident potential for p-hacking in the sample period selection. Finally, while the choice of lookback period of the volatility factors did not make a material difference for the performance of these specific factors, it significantly changed the extent to which the CAPM is able to absorb the factor returns. This effect is most pronounced for momentum, which carries more negative alphas with a shorter lookback period. In short, the choices that the researcher makes demonstrably impact the outcomes of the analysis. Therefore, this paper finds H1 to be well-supported.

A. Critical note to 6.1

One final critical note here is that even within this research paper, there is scope for p-hacking in areas not examined. Most prominently, the choice of data quality filters may strongly affect the results, especially when dealing with lower quality data. For instance, in contrast to Fama and French (1993), this paper chooses not to exclude financial stocks, given the lack of substantiated arguments to do so. Furthermore, only keeping observations with twelve months of trailing returns deliberately ignores any effect of a recent IPO on the factor returns. This may also induce attrition-related biases, given that the median listed stocks only remain listed for a dozen years.

Additionally, starting the sample period as early as in 1806 adds both additional scope, as well as additional idiosyncratic volatility concerns, given the low number of active stocks in this period. Starting the sample a few decades later could offer returns with tighter confidence intervals. Aside from this, the removal of the securities with quarterly or annual observation only may bias the results in certain directions, as the periodicity of stock market observations may correlate with certain factors. Which factors are affected, however, can only be left to speculation. Finally, the beta creation in this analysis could only be done on monthly basis. Changing this return interval could yield different results with regards to the beta factors and the CAPM alphas. In short, although this research tries to account for as many possible sources of p-hacking as possible, this provides a near impossible task. Further research could be done to assess the robustness of the results considering other research design choices.

6.2 H2: out-of-sample factor significance

Arriving at the main hypothesis of this paper, the second hypothesis can be answered by evaluating how well the returns and alphas of the traditional factors hold up in this out-of-sample analysis. In short, short-term reversal, long-term reversal, value (although somewhat problematically, given its reliance on large and unsustainable outliers in the 19th century), and size continue to deliver strong returns and alphas out of sample. Surprisingly, volatility delivers very high returns due to a strong performance of idiosyncratic volatility, in contrast to the findings by Ang et al. (2006). Value-weighted market beta behaves according to the low-volatility anomaly as found by Blitz and Van Vliet (2007), while equal-weighted market beta behaves according to the CAPM as prescribed by Sharpe (1964). Seasonality also yields mixed results, which will be further discussed in H4. Finally, momentum is the only traditional factor that fails to deliver any returns. This finding warrants some further discussion.

The unexpected deviation of the momentum factor warrants a discussion of potential causes. For one, it could hint at extreme outliers within the sample used in this analysis. While the average returns and alphas of the momentum factor are negative, the median returns are typically slightly positive. Additionally, it could be explained as momentum having periods of over- and under-performance, but no consistent significant effect in either direction. This finding aligns with the findings by Hon and Tonks (2003), who cover the fickle history of the momentum anomaly in the UK stock market. In this explanation, it makes intuitive sense that the momentum returns in the 20th century are significantly better than the momentum returns in the 19th century. Given that most research has so far focused on the 20th century, the potential for finding significantly positive results increases compared to the potential when analysing the whole period.

Since the analysis is a direct out-of-sample robustness test for the factors present in modern-day datasets, the strong results of the reversal and Fama-French factors demonstrate that they are more likely to be an enduring characteristic of financial markets, and not a result of p-hacking (Harvey, 2017). The findings of this paper yield largely inconclusive results for the debate between the low-risk anomaly and the CAPM, as the results of the value-weighted beta support the former, while the results of the equal-weighted beta support the latter. The dispersion of results between the two centuries seems to hint at a growing low-beta anomaly, perhaps aided by the introduction of the CAPM model in 1964 (Sharpe, 1964). The positive returns and alphas of the idiosyncratic volatility factor are puzzling findings to both theories, as neither assume positive idiosyncratic volatility to be priced, and is a finding that could be further studied in future research. Given that some factors pass the out-of-sample robustness test, where others fail to do so, means that H2 is partially supported. The factors that pass this test are less likely to be the result of p-hacking in one sample of stock market returns (Harvey, 2017).

6.3 H3: factor enhancements

The next hypothesis concerns factor enhancements. Several factor enhancements - residual momentum, residual short-term reversal, momentum interacted with the distance to the yearhigh, and residual long-term reversal - have been tested in this analysis. Most of these enhancements, except for residual long-term reversal, enjoy support in the literature, but none of them have delivered a convincing account of themselves. Some enhancements, such as residual short-term and long-term reversal, deliver returns and alphas roughly in the ballpark of the traditional factor. Short-term reversal may be preferred to traditional reversal, as the returns and alphas are slightly more significant given its lower volatility. On the other hand, residual long-term reversal slightly underperforms traditional long-term reversal, although this is not surprising given the arguments provided by Blitz et al. (2011).

What is surprising, however, is the failure of the momentum enhancements to significantly improve upon the poorly performing momentum factor. The interaction with the nearness to the yearhigh variable does yield significantly positive returns with narrow bandwidths, but these disappear when looking at the CAPM-alphas. What happens is that this interaction term loads up on beta in bull-markets, buying stocks that are soaring and breaking their year highs, and thereby yields strong returns without delivering strong alpha. This is compensated for in bear markets, where the high-momentum stocks are defensive stocks that do not slide as much, and therefore remain close to their year highs. This results in an average beta that moves around zero.

Furthermore, the residual momentum factor delivers an even worse performance than the traditional momentum factor. The residual momentum factor shares in the negative - though usually insignificant - performance of the traditional momentum factor, delivering negative and often significant alpha. Worse yet, this residual momentum factor continues to perform badly in the 20th century, and its medians are less positive than those of the traditional momentum factor. To sum it up, there are two enhancements that unconvincingly improve upon the original factor, one that marginally detracts from it, and one that clearly detracts from it. Therefore, this paper finds weak support for H3.

6.4 H4: out-of-sample decay of different types of factors

The final hypothesis concerns which factors show convincing out-of-sample returns. The hypothesis was that the less rooted in economic theory the factors are, the more likely they are the result of p-hacking. The factors that have the weakest basis in economic theory are the seasonality factors. As such, the January effect and the Halloween indicator are the most suspect. Indeed, the analysis points out that these factors do yield returns, but that these results are often absorbed by the market beta, resulting in mixed CAPM-alphas. While the January effect performs better than the Halloween indicator, as it delivers CAPM-alphas in the 20th century at least, it fails to deliver a positive CAPM-alpha in the 19th century. In a similar vein, factor enhancements (which are typically more complex constructions than traditional factors) do not show convincing results in this analysis, meaning that the enhancements usually do not hold up well out-of-sample.

When looking at the rest of the factors, a more mixed picture appears. The reversal factors perform well, while momentum does not. On top of that, the beta factor yields mixed results itself, and the idiosyncratic volatility factor unexpectedly performs well. Finally, the traditional and well-established Fama and French (1993) factors deliver a mostly solid performance in this analysis. In short, the generally superior performance of the well-established factors compared to the weak performance of seasonality factors and the failure of factor enhancement reveals that that factors with weaker theoretical bases and factors with a more complex construction may be more susceptible to p-hacking. Therefore, H4 is mostly supported by this paper.

6.5 Comparison to prior research

In this final section, the results of this paper will be compared to other papers that have already conducted a similar analysis. All factors - except for seasonality - can demonstrably be found in the CRSP-period US stock markets, which is widely covered in the literature discussed in Section 2. Baltussen et al. (2021) conducted a similar pre-CRSP analysis, focussing on the US stock market, which can be used to compare the US and UK stock markets in this out-of-sample period. Furthermore, Grossman and Shore (2006) conducted an analysis specifically focused on the period 1870-1913, which is a subset of the period analysed in this paper. Similarly, Chabot et al. (2008) studied pricing factors in the UK stock market in the period 1866-1907. Both can be used to compare the conclusions of this paper with those of other analyses covering a similar period. Finally, Dimson et al. (2017) cover stock market anomalies in the CRSP period for both the US and the UK markets. These

CRSP period results can be used for comparison with the pre-CRSP sample results of this paper.

Since the methodologies of the different papers are dissimilar from each other, comparing the factor portfolio returns without context does not paint the full picture of the analysis. Instead, Table 4 below attempts to paint a general picture of both the conclusions each paper provides for each anomaly they study, as well as a brief overview of their research design choices. The conclusions from Dimson et al. (2017) are those that apply specifically to the UK stock market. The findings of this paper largely correspond to the findings of other analyses regarding the short-term reversal, long-run reversal, and value factors. Size and beta do not show a conclusive consensus, and the findings regarding momentum and idiosyncratic volatility directly contrast those of earlier research. Further research could be conducted to further explore the dynamics of these latter four factors in out-of-sample analyses.

Information	**This paper**	**Baltussen et al. (2021)**	**Grossman and Shore (2006)**	**Chabot et al. (2008)**	**Dimson et al. (2017)**
Sample Period	1806-1984, also split in 1806-1899 and 1900-1984	1866-1926	1870-1913	1866-1907	1955-2016
Market Construction	Both equal-weighted and value-weighted	Value-weighted	Both equal-weighted and value-weighted	Value-weighted	No CAPM alphas tested
Factor Portfolio Construction	Tercile, quintile and decile equal-weighted portfolios	Value-weighted quintile portfolios, with tercile and decile portfolios in the robustness tests	Equal-weighted portfolios constructed with 5% bandwidths	Tercile value-weighted portfolios	Factors constructed on individual basis, depending on original papers.
Return Calculation	Percentage difference between the first known close prices of successive months. Dividend and split actions handled by GFD.	Monthly closing price dataset. Dividend and split actions handled by GFD.	Monthly end of month return data from the Investors Monthly Weekly. Dividends included.	28-day period observations of returns. Dividends included	Monthly returns from CRSP data, the Fama-French libraries, and other contemporary sources
Beta	Inconclusive evidence for either low-volatility or CAPM.	Clear low-volatility anomaly; alpha of -6.8%, returns insignificant.	X	X	X

	Returns low to high single digits. Alphas negative to positive single digits.				
Idiosyncratic Volatility	Strong evidence for high-volatility premium Returns double digits, alphas high single digits to double digits.	X	X	X	Strong evidence for low-volatility premium (7.4%)
Momentum	Moderately negative momentum returns and alphas. Returns and alphas both negative with varying magnitudes.	Strong momentum return (8.2%) and alpha (11.5%)	X	Strong evidence but volatile. (0.1%-7.2% annualised returns; 4.1% alphas)	Strong evidence but volatile (10.2%)
Short-term Reversal	Strong evidence for a short-term reversal premium Double digit returns and alphas.	X	X	Strong evidence for a short-term reversal premium (untested magnitude)	X
Long-run Reversal	Strong evidence for a long-term reversal premium. High single to double digit returns and alphas.	X	Long-term reversal return premium, but U-shaped returns and alphas (3,1% and 2,8%)	Strong evidence for a long-term reversal premium (untested magnitude)	X
Size	Strong evidence for a small-size premium. Double digit returns and alphas.	Insignificant size return (-2.9%) or alpha (0.9%)	Clear size premium in extremes, likely caused by attrition (15.1% return and 14.2% alpha). Weak size premium in broader bandwidths.	X	Strong evidence (5.9%)

Value	Strong evidence for a (dividend) value premium. Double digit returns caused by strong outliers in 19th century.	Strong (dividend) value return (5.6%) and alpha (10.1%)	Clear, but low-magnitude (dividend) value premium (4.0% return, 4.3% alpha)	X	Strong evidence (both B/M (5.7%) and dividend yield (3%))
Seasonality	Moderate seasonality premium, but no clear CAPM-alphas. January effect outperforms the Halloween indicator. High single digit returns, slightly negative to low single digit alphas.	X	X	X	X

Table 3: *Comparison between the main findings of this paper and the main findings of related literature*

This table contains the most important research design information, as well as the main findings, of this paper and four closely related papers. For each of the papers, the included research design information consists of the sample period, the way the market portfolio is constructed, the way factor portfolios are constructed, and the way returns are calculated. Then, the main findings for every factor under analysis are covered. If a paper does not cover a factor, the cell is marked with an X. The paper by Baltussen et al. (2021) represents a similar pre-CRSP analysis conducted in the US stock market. Grossman and Shore (2006) cover size, value, and long-term reversal in a UK pre-CRSP period sample, with a sample period that falls within the sample period used in this paper. In a roughly similar sample period, Chabot et al. (2008) investigate momentum and reversal anomalies in the UK. Finally, Dimson et al. (2017) provide factor returns in the UK in the CRSP-period,

7. Conclusion

This thesis set out to investigate the robustness of factors in financial markets by examining their performance in an out-of-sample analysis, addressing concerns about p-hacking (Harvey, 2017) by testing their persistence in a different timeframe and market. Following Baltussen et al. (2021), who performed a similar analysis in the US database, the sample used was an untouched dataset of the UK stock market before the start of the CRSP database, taken from GFD. This dataset, spanning nearly two centuries, offers an out-of-sample environment with enough power to thoroughly test the factor's returns, something deemed rare by Harvey (2017).

The analysis found mixed results for the traditional factors. Factors like short-term reversal, long-term reversal, size, and value demonstrated robust performance, delivering consistent returns and alphas out-of-sample. These findings suggest that these factors are likely to be an enduring characteristic of financial markets rather than the result of p-hacking. Unexpectedly, idiosyncratic volatility demonstrated robust performance, warranting further investigation. Although existing literature generally views idiosyncratic volatility as negatively priced (Ang et al., 2006), our findings suggest potential for future research.

On the other hand, the momentum factor failed to deliver significant returns and alphas, especially in the 19th century. This challenges the reliability of momentum as a persistent factor in the UK stock market, echoing concerns previously raised by Hon and Tonks (2003). The seasonality factors generated positive returns but failed to produce significant CAPM-alphas, indicating a lack of robustness when accounting for market risk.

The investigation into factor enhancements found that most enhancements did not significantly outperform traditional factors. While some enhanced factors (residual momentum and residual long-term reversal) underperformed their traditional counterparts, others (residual short-term reversal and momentum-yearhigh) showed only marginal improvements. These results suggest that more complex enhanced factors may be more prone to p-hacking, and therefore less likely to hold up out-of-sample. One critical note is that the enhanced factors had a higher threshold to overcome than the traditional factors, seeing as they needed to both deliver strong returns and alphas, as well as materially improve upon the traditional factors they enhance.

Furthermore, this research underscores the impact of research design choices on outcomes. Bandwidth selection, the choice of market portfolio, and sub-sample periods significantly influenced the results, demonstrating the potential for p-hacking in empirical research. While changing the lookback windows on the volatility factors had negligible effects for the factors themselves, it did materially impact the ability of the CAPM to absorb factor returns, again highlighting the potential for p-hacking to influence results.

These findings have significant implications for both academics and practitioners. For researchers, the results reinforce the importance of out-of-sample testing and vigilance against p-hacking. Future studies should extend factor testing to diverse geographical and historical samples to assess robustness. Additionally, the failure of momentum and the abnormal positive performance of idiosyncratic volatility provide interesting openings for future research. For practitioners, the results suggest caution in relying on outdated investment factors like seasonality or on complex factor enhancements not rigorously tested out-of-sample, as the most fruitful factor enhancements in one sample may not yield the same returns in different contexts.

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Appendix

A. Analysis results with a 36-month beta lookback window

A.1 Full-sample results

Factor	Portfolio	Average	Median	T_stat	Mean_EWalpha	Median_EWalpha	EWt_stat	Mean_VWalpha	Median_VWalpha	VWt_stat
betaEW	3_minus_1	0,61	0,13	4.88***	0,98	-0,23	1.30	0,28	-0,23	1.54
betaEW	5_minus_1	0,69	0,05	4.14***	1,02	-0,25	1.34	0,32	-0,25	1.57
betaEW	10_minus_1	0,82	-0,01	3.34***	1,15	-0,21	1.44	0,44	-0,34	1.54
betaVW	3_minus_1	0,26	0,12	2.30**	0,56	-0,28	0.74	-0,14	-0,24	-0.83
betaVW	5_minus_1	0,23	0,09	1.47	0,55	-0,2	0.72	-0,15	-0,34	-0.72
betaVW	10_minus_1	0,23	-0,06	0.93	0,58	-0,3	0.73	-0,12	-0,4	-0.42
volatility	3_minus_1	1,33	0,49	10.41***	1,68	0,18	2.22**	0,98	0,24	4.91***
volatility	5_minus_1	1,95	0,65	10.76***	2,27	0,33	2.96***	1,57	0,45	6.31***
volatility	10_minus_1	2,67	0,79	10.39***	2,97	0,4	3.73***	2,27	0,6	6.92***
EWidvol	3_minus_1	0,97	0,39	8.54***	1,31	0,02	1.70*	0,6	0,09	2.98***
EWidvol	5_minus_1	1,26	0,45	8.57***	1,65	0,08	2.13**	0,94	0,13	4.02***
EWidvol	10_minus_1	1,68	0,46	7.29***	2,09	0,05	2.61***	1,38	0,11	4.25***
VWidvol	3_minus_1	1,08	0,41	9.36***	1,49	0,07	1.94*	0,78	0,18	3.86***
VWidvol	5_minus_1	1,44	0,52	9.25***	1,87	0,18	2.41***	1,15	0,27	4.74***
VWidvol	10_minus_1	1,79	0,53	7.74***	2,15	0,02	2.69***	1,44	0,15	4.41***
mom6	3_minus_1	-0,4	0,06	-2.75***	-0,14	-0,43	-0.18	-0,84	-0,41	-3.87***
mom6	5_minus_1	-0,9	-0,03	-4.25***	-0,56	-0,68	-0.70	-1,26	-0,55	-4.65***
mom6	10_minus_1	-1,88	-0,36	-4.75***	-1,31	-0,86	-1.50	-2,01	-0,9	-4.58***
mom12	3_minus_1	-0,11	0,28	-0.83	0,09	-0,28	0.11	-0,61	-0,16	-2.80***
mom12	5_minus_1	-0,49	0,21	-2.52***	-0,38	-0,44	-0.47	-1,07	-0,31	-3.97***
mom12	10_minus_1	-1,37	-0,03	-4.00***	-1,25	-0,43	-1.44	-1,95	-0,54	-4.62***
mom6yearhigh	3_minus_1	0,03	0,14	0.27	0,3	-0,44	0.39	-0,39	-0,36	-1.95*
mom6yearhigh	5_minus_1	0,11	0,24	0.77	0,32	-0,34	0.41	-0,38	-0,14	-1.71*
mom6yearhigh	10_minus_1	0,28	0,35	1.18	0,55	-0,08	0.68	-0,15	-0,02	-0.47
mom12yearhigh	3_minus_1	0,36	0,4	3.19***	0,62	-0,19	0.80	-0,07	-0,09	-0.38
mom12yearhigh	5_minus_1	0,53	0,49	3.33***	0,72	-0,05	0.92	0,03	0,04	0.11
mom12yearhigh	10_minus_1	0,67	0,67	3.19***	0,79	0,13	0.99	0,09	0,16	0.31
resmom6EW	3_minus_1	-0,29	0	-2.57***	0,05	-0,41	0.06	-0,65	-0,32	-3.38***
resmom6EW	5_minus_1	-0,47	-0,04	-2.82***	-0,13	-0,44	-0.17	-0,83	-0,37	-3.52***
resmom6EW	10_minus_1	-0,98	-0,23	-3.68***	-0,52	-0,53	-0.62	-1,23	-0,62	-3.58***
resmom6VW	3_minus_1	-0,16	0,01	-1.53	0,07	-0,36	0.09	-0,63	-0,21	-3.33***
resmom6VW	5_minus_1	-0,27	-0,03	-1.69*	-0,03	-0,47	-0.04	-0,73	-0,39	-3.06***
resmom6VW	10_minus_1	-0,7	-0,25	-2.63***	-0,34	-0,5	-0.41	-1,05	-0,59	-2.97***
resmom12EW	3_minus_1	-0,16	0,14	-1.48	0,12	-0,28	0.16	-0,57	-0,23	-2.96***
resmom12EW	5_minus_1	-0,27	0,14	-1.79*	-0,02	-0,29	-0.02	-0,71	-0,31	-3.05***
resmom12EW	10_minus_1	-0,6	-0,01	-2.23**	-0,31	-0,41	-0.36	-1,02	-0,33	-2.85***
resmom12VW	3_minus_1	0,05	0,23	0.50	0,32	-0,21	0.41	-0,38	-0,08	-2.02**
resmom12VW	5_minus_1	-0,12	0,18	-0.78	0,15	-0,3	0.19	-0,55	-0,19	-2.39***
resmom12VW	10_minus_1	-0,48	0,18	-1.85*	-0,23	-0,32	-0.27	-0,94	-0,21	-2.65***

st_rev	3_minus_1	-1,05	-0,56	-5.83***	-0,63	-1,02	-0.79	-1,32	-0,88	-5.55***
st_rev	5_minus_1	-1,79	-1,06	-6.26***	-1,21	-1,37	-1.46	-1,91	-1,35	-5.77***
st_rev	10_minus_1	-3,53	-1,79	-7.08***	-2,49	-2,24	-2.66***	-3,19	-2,19	-5.79***
lt_rev	3_minus_1	-0,69	-0,31	-6.31***	-0,43	-0,69	-0.56	-1,13	-0,71	-5.68***
lt_rev	5_minus_1	-1,16	-0,46	-7.40***	-0,89	-0,87	-1.13	-1,59	-0,97	-6.62***
lt_rev	10_minus_1	-2,09	-0,88	-7.70***	-1,69	-1,13	-2.02**	-2,4	-1,3	-6.70***
STresrevEW	3_minus_1	-0,61	-0,43	-6.24***	-0,35	-0,74	-0.45	-1,04	-0,75	-5.75***
STresrevEW	5_minus_1	-1,01	-0,64	-6.67***	-0,77	-0,95	-0.97	-1,46	-0,92	-6.29***
STresrevEW	10_minus_1	-1,72	-1,18	-6.73***	-1,42	-1,54	-1.70*	-2,13	-1,57	-6.26***
STresrevVW	3_minus_1	-0,44	-0,37	-4.63***	-0,16	-0,66	-0.21	-0,86	-0,5	-4.77***
STresrevVW	5_minus_1	-0,83	-0,59	-5.63***	-0,59	-0,92	-0.75	-1,29	-0,91	-5.67***
STresrevVW	10_minus_1	-1,61	-1,06	-6.29***	-1,32	-1,54	-1.58	-2,02	-1,5	-6.01***
LTresrevEW	3_minus_1	-0,63	-0,19	-5.78***	-0,39	-0,58	-0.50	-1,1	-0,56	-5.47***
LTresrevEW	5_minus_1	-0,91	-0,28	-6.09***	-0,68	-0,64	-0.85	-1,39	-0,76	-5.84***
LTresrevEW	10_minus_1	-1,49	-0,44	-6.92***	-1,32	-0,88	-1.57	-2,05	-0,84	-6.75***
LTresrevVW	3_minus_1	-0,63	-0,19	-5.78***	-0,39	-0,58	-0.50	-1,1	-0,56	-5.47***
LTresrevVW	5_minus_1	-0,91	-0,28	-6.09***	-0,68	-0,64	-0.85	-1,39	-0,76	-5.84***
LTresrevVW	10_minus_1	-1,49	-0,44	-6.92***	-1,32	-0,88	-1.57	-2,05	-0,84	-6.75***
MC_percentile	3_minus_1	-1,17	-0,4	-5.59***	-0,92	-0,76	-1.12	-1,62	-0,7	-5.39***
MC_percentile	5_minus_1	-1,61	-0,51	-4.63***	-1,35	-0,92	-1.50	-2,04	-0,81	-4.33***
MC_percentile	10_minus_1	-2,56	-0,63	-3.63***	-2,29	-0,94	-1.76*	-3,11	-0,99	-3.25***
dividend_yield_percentile	3_minus_1	2,07	0,36	4.13***	2,77	-0,09	2.71***	1,96	-0,05	3.40***
dividend_yield_percentile	5_minus_1	3,39	0,51	4.31***	3,86	-0,01	3.04***	2,99	0,01	3.33***
dividend_yield_percentile	10_minus_1	4,38	0,41	3.74***	4,7	-0,06	2.57***	3,67	0	2.40***
january	3_minus_1	0,87	0,21	9.40***	1,32	0,08	1.72*	0,63	0,15	3.63***
halloween	3_minus_1	0,44	0,28	7.72***	0,73	-0,21	0.95	0,03	-0,11	0.18

*The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

A.2 19th century results (1806-1899)

Factor	Portfolio	Average	Median	T_stat	Mean_EWalpha	Median_EWalpha	EWt_stat	Mean_VWalpha	Median_VWalpha	VWt_stat
betaEW	3_minus_1	0,78	0,16	4.25***	0,01	-0,21	0.07	0,42	-0,15	1.93*
betaEW	5_minus_1	0,94	0,07	3.45***	0,14	-0,3	0.56	0,54	-0,21	1.81*
betaEW	10_minus_1	1,26	0,01	3.10***	0,38	-0,37	0.87	0,79	-0,28	1.74*
betaVW	3_minus_1	0,35	0,18	1.98**	-0,5	-0,17	-1.93*	-0,1	-0,08	-0.44
betaVW	5_minus_1	0,27	0,21	1.03	-0,59	-0,06	-1.65*	-0,18	-0,16	-0.59
betaVW	10_minus_1	0,19	-0,09	0.45	-0,66	-0,45	-1.26	-0,24	-0,42	-0.52
volatility	3_minus_1	1,54	0,49	8.24***	0,74	0,12	4.39***	1,15	0,26	4.80***
volatility	5_minus_1	2,45	0,76	8.81***	1,57	0,37	5.88***	1,97	0,55	5.84***
volatility	10_minus_1	3,55	0,93	8.02***	2,75	0,35	5.76***	3,17	0,61	5.67***

EWidvol	3_minus_1	1,01	0,39	6.28***	0,15	-0,05	0.87	0,56	0,12	2.46***
EWidvol	5_minus_1	1,36	0,37	5.99***	0,61	-0,07	2.44***	1,02	-0,03	3.21***
EWidvol	10_minus_1	1,75	0,36	5.06***	0,98	-0,29	2.60***	1,39	-0,12	3.00***
VWidvol	3_minus_1	1,14	0,37	6.48***	0,39	-0,06	2.01**	0,8	0,09	3.26***
VWidvol	5_minus_1	1,48	0,49	6.59***	0,72	-0,03	3.00***	1,14	0,12	3.62***
VWidvol	10_minus_1	1,8	0,53	5.97***	0,93	-0,07	2.59***	1,35	0,08	3.36***
mom6	3_minus_1	-0,38	0,34	-1.50	-1,21	-0,35	-3.84***	-0,8	-0,24	-2.56***
mom6	5_minus_1	-1,15	0,16	-3.12***	-1,84	-0,51	-4.39***	-1,43	-0,35	-3.41***
mom6	10_minus_1	-2,65	-0,15	-3.87***	-2,95	-0,76	-4.04***	-2,54	-0,71	-3.46***
mom12	3_minus_1	-0,03	0,34	-0.14	-0,91	-0,25	-3.10***	-0,5	-0,1	-1.71*
mom12	5_minus_1	-0,56	0,22	-1.75*	-1,64	-0,44	-4.12***	-1,23	-0,26	-3.07***
mom12	10_minus_1	-1,92	-0,06	-3.26***	-3,12	-0,52	-4.35***	-2,71	-0,56	-3.77***
mom6yearhigh	3_minus_1	0,19	0,34	0.93	-0,62	-0,23	-2.35***	-0,21	-0,16	-0.80
mom6yearhigh	5_minus_1	0,25	0,41	1.05	-0,67	-0,16	-2.24**	-0,26	0,05	-0.85
mom6yearhigh	10_minus_1	0,45	0,57	1.07	-0,38	0,06	-0.72	0,03	0,32	0.06
mom12yearhigh	3_minus_1	0,54	0,47	2.85***	-0,24	-0,04	-0.94	0,17	0,08	0.66
mom12yearhigh	5_minus_1	0,75	0,54	2.77***	-0,19	0,03	-0.55	0,22	0,1	0.59
mom12yearhigh	10_minus_1	0,85	0,91	2.33**	-0,28	0,18	-0.59	0,12	0,41	0.25
resmom6EW	3_minus_1	-0,22	0,1	-1.20	-0,95	-0,27	-3.80***	-0,54	-0,18	-2.19**
resmom6EW	5_minus_1	-0,35	0,18	-1.23	-1,02	-0,21	-2.98***	-0,61	-0,02	-1.78*
resmom6EW	10_minus_1	-1,05	-0,13	-2.24**	-1,58	-0,35	-2.67***	-1,16	-0,3	-1.93*
resmom6VW	3_minus_1	0,06	0,23	0.33	-0,83	-0,19	-3.50***	-0,42	0,06	-1.79*
resmom6VW	5_minus_1	-0,03	0,14	-0.11	-0,88	-0,22	-2.60***	-0,47	-0,14	-1.38
resmom6VW	10_minus_1	-0,76	-0,12	-1.66*	-1,53	-0,32	-2.58***	-1,11	-0,3	-1.85*
resmom12EW	3_minus_1	-0,02	0,22	-0.12	-0,76	-0,2	-3.52***	-0,35	-0,06	-1.57
resmom12EW	5_minus_1	-0,12	0,1	-0.49	-0,91	-0,26	-2.96***	-0,51	-0,24	-1.56
resmom12EW	10_minus_1	-0,58	0	-1.27	-1,44	-0,43	-2.46***	-1,02	-0,29	-1.67*
resmom12VW	3_minus_1	0,27	0,29	1.80*	-0,48	-0,07	-2.38***	-0,07	0,05	-0.35
resmom12VW	5_minus_1	0,09	0,18	0.37	-0,7	-0,22	-2.35***	-0,29	-0,08	-0.93
resmom12VW	10_minus_1	-0,38	0,11	-0.87	-1,28	-0,34	-2.23**	-0,86	-0,02	-1.44
st_rev	3_minus_1	-1,13	-0,33	-3.63***	-1,69	-0,76	-4.21***	-1,29	-0,61	-3.54***
st_rev	5_minus_1	-2,11	-0,72	-4.18***	-2,46	-0,97	-4.07***	-2,06	-0,9	-3.64***
st_rev	10_minus_1	-4,62	-1,57	-5.25***	-4,23	-1,88	-4.22***	-3,82	-1,87	-3.85***
lt_rev	3_minus_1	-0,46	-0,25	-2.88***	-1,18	-0,65	-5.19***	-0,77	-0,58	-3.41***
lt_rev	5_minus_1	-1,05	-0,41	-4.10***	-1,79	-0,9	-5.31***	-1,39	-0,78	-4.10***
lt_rev	10_minus_1	-2,21	-0,78	-4.72***	-2,74	-1	-4.53***	-2,32	-0,92	-3.82***
STresrevEW	3_minus_1	-0,36	-0,06	-2.60***	-1,16	-0,39	-4.66***	-0,75	-0,32	-3.87***
STresrevEW	5_minus_1	-0,75	-0,22	-3.51***	-1,61	-0,61	-4.74***	-1,2	-0,52	-4.23***
STresrevEW	10_minus_1	-1,36	-0,63	-4.21***	-2,11	-0,99	-5.31***	-1,7	-0,88	-4.53***
STresrevVW	3_minus_1	-0,08	-0,03	-0.58	-0,83	-0,38	-4.20***	-0,42	-0,12	-2.39***
STresrevVW	5_minus_1	-0,36	-0,17	-1.82*	-1,14	-0,44	-4.22***	-0,73	-0,33	-2.95***
STresrevVW	10_minus_1	-1,18	-0,51	-3.48***	-1,94	-0,89	-4.89***	-1,52	-0,74	-4.05***
LTresrevEW	3_minus_1	-0,38	-0,09	-2.27**	-1,22	-0,37	-5.14***	-0,81	-0,32	-3.21***
LTresrevEW	5_minus_1	-0,72	-0,15	-2.94***	-1,61	-0,5	-4.80***	-1,19	-0,38	-3.37***

LTresrevEW	10_minus_1	-1,62	-0,25	-4.37***	-2,86	-0,73	-5.14***	-2,41	-0,64	-4.63***
LTresrevVW	3_minus_1	-0,38	-0,09	-2.27**	-1,22	-0,37	-5.14***	-0,81	-0,32	-3.21***
LTresrevVW	5_minus_1	-0,72	-0,15	-2.94***	-1,61	-0,5	-4.80***	-1,19	-0,38	-3.37***
LTresrevVW	10_minus_1	-1,62	-0,25	-4.37***	-2,86	-0,73	-5.14***	-2,41	-0,64	-4.63***
MC_percentile	3_minus_1	-1,47	-0,49	-4.30***	-2,43	-0,73	-4.51***	-2,02	-0,66	-4.01***
MC_percentile	5_minus_1	-2,14	-0,56	-3.42***	-3,12	-0,85	-3.39***	-2,71	-0,73	-2.98***
MC_percentile	10_minus_1	-4,1	-0,9	-2.77***	-5,82	-0,91	-2.53***	-5,32	-1,07	-2.33**
dividend_yield_percentile	3_minus_1	4,23	0,67	3.87***	4,6	0,25	3.35***	5,09	0,42	3.72***
dividend_yield_percentile	5_minus_1	7,49	1,09	4.16***	7,79	0,46	3.29***	8,34	0,68	3.52***
dividend_yield_percentile	10_minus_1	11,27	1,03	3.42***	11,53	0,28	2.15**	12,16	0,57	2.27**
january	3_minus_1	0,29	0,12	3.18***	-0,59	-0,25	-3.65***	-0,18	-0,06	-1.23
halloween	3_minus_1	0,34	0,4	5.56***	-0,59	-0,11	-4.36***	-0,18	-0,01	-1.53

*The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

A.3 20th century results (1900-1984)

Factor	Portfolio	Average	Median	T_stat	Mean_EWalpha	Median_EWalpha	EWt_stat	Mean_VWalpha	Median_VWalpha	VWt_stat
betaEW	3_minus_1	0,43	0,08	2.55***	1,83	-0,25	1.30	0,16	-0,36	0.56
betaEW	5_minus_1	0,43	0,02	2.30**	1,8	-0,2	1.27	0,13	-0,3	0.46
betaEW	10_minus_1	0,37	-0,03	1.36	1,81	0,09	1.25	0,14	-0,43	0.38
betaVW	3_minus_1	0,15	0,01	1.19	1,49	-0,38	1.06	-0,18	-0,38	-0.71
betaVW	5_minus_1	0,2	-0,01	1.12	1,56	-0,32	1.10	-0,12	-0,49	-0.42
betaVW	10_minus_1	0,28	-0,04	1.07	1,67	-0,26	1.17	-0,01	-0,38	-0.04
volatility	3_minus_1	1,09	0,49	6.38***	2,51	0,3	1.77*	0,84	0,21	2.68***
volatility	5_minus_1	1,42	0,55	6.22***	2,88	0,3	2.03**	1,21	0,43	3.36***
volatility	10_minus_1	1,75	0,67	7.12***	3,17	0,4	2.21**	1,49	0,59	4.00***
EWidvol	3_minus_1	0,93	0,38	5.79***	2,31	0,1	1.62	0,63	0,07	1.98**
EWidvol	5_minus_1	1,15	0,52	6.27***	2,55	0,18	1.79*	0,87	0,29	2.57***
EWidvol	10_minus_1	1,61	0,6	5.30***	3,04	0,26	2.10**	1,36	0,3	3.02***
VWidvol	3_minus_1	1,02	0,48	6.86***	2,43	0,23	1.72*	0,76	0,38	2.44***
VWidvol	5_minus_1	1,4	0,57	6.50***	2,84	0,44	2.00**	1,17	0,44	3.21***
VWidvol	10_minus_1	1,77	0,54	5.05***	3,19	0,23	2.20**	1,51	0,23	3.04***
mom6	3_minus_1	-0,42	-0,17	-3.39***	0,79	-0,51	0.55	-0,88	-0,61	-2.90***
mom6	5_minus_1	-0,63	-0,28	-3.40***	0,56	-0,88	0.39	-1,11	-0,7	-3.17***
mom6	10_minus_1	-1,04	-0,49	-2.93***	0,14	-0,89	0.09	-1,54	-1,09	-3.00***
mom12	3_minus_1	-0,21	0,23	-1.35	0,97	-0,29	0.67	-0,7	-0,28	-2.22**
mom12	5_minus_1	-0,42	0,18	-1.99**	0,73	-0,44	0.50	-0,94	-0,35	-2.55***
mom12	10_minus_1	-0,78	0	-2.41***	0,4	-0,33	0.27	-1,27	-0,53	-2.68***
mom6yearhigh	3_minus_1	-0,14	-0,03	-1.21	1,12	-0,66	0.78	-0,55	-0,63	-1.85*
mom6yearhigh	5_minus_1	-0,05	0,05	-0.36	1,19	-0,62	0.83	-0,48	-0,38	-1.53

mom6yearhigh	10_minus_1	0,1	0,16	0.51	1,37	-0,3	0.94	-0,31	-0,26	-0.85
mom12yearhigh	3_minus_1	0,16	0,33	1.44	1,38	-0,31	0.96	-0,29	-0,27	-1.00
mom12yearhigh	5_minus_1	0,28	0,44	1.90*	1,53	-0,13	1.06	-0,14	-0,02	-0.44
mom12yearhigh	10_minus_1	0,48	0,43	2.55***	1,74	0,03	1.21	0,06	-0,05	0.18
resmom6EW	3_minus_1	-0,36	-0,15	-2.92***	0,92	-0,71	0.64	-0,75	-0,58	-2.58***
resmom6EW	5_minus_1	-0,6	-0,23	-3.53***	0,65	-0,73	0.45	-1,02	-0,61	-3.15***
resmom6EW	10_minus_1	-0,89	-0,37	-3.92***	0,4	-0,63	0.27	-1,28	-0,88	-3.44***
resmom6VW	3_minus_1	-0,4	-0,2	-3.31***	0,86	-0,68	0.60	-0,81	-0,57	-2.82***
resmom6VW	5_minus_1	-0,54	-0,25	-3.04***	0,72	-0,67	0.50	-0,95	-0,63	-2.88***
resmom6VW	10_minus_1	-0,64	-0,3	-2.42***	0,68	-0,81	0.46	-1	-0,87	-2.45***
resmom12EW	3_minus_1	-0,32	0,08	-2.00**	0,9	-0,41	0.62	-0,77	-0,42	-2.50***
resmom12EW	5_minus_1	-0,44	0,15	-2.29**	0,78	-0,31	0.53	-0,9	-0,41	-2.67***
resmom12EW	10_minus_1	-0,63	-0,02	-2.22**	0,65	-0,39	0.44	-1,03	-0,43	-2.46***
resmom12VW	3_minus_1	-0,18	0,18	-1.23	1,03	-0,45	0.71	-0,64	-0,28	-2.19**
resmom12VW	5_minus_1	-0,33	0,19	-1.73*	0,89	-0,43	0.61	-0,78	-0,34	-2.35***
resmom12VW	10_minus_1	-0,59	0,2	-2.04**	0,66	-0,21	0.44	-1,02	-0,36	-2.41***
st_rev	3_minus_1	-0,96	-0,75	-6.07***	0,31	-1,34	0.22	-1,36	-1,27	-4.32***
st_rev	5_minus_1	-1,43	-1,31	-6.33***	-0,1	-1,71	-0.07	-1,77	-1,68	-4.75***
st_rev	10_minus_1	-2,35	-2,07	-5.78***	-0,96	-2,5	-0.63	-2,64	-2,48	-4.72***
lt_rev	3_minus_1	-0,93	-0,36	-6.37***	0,22	-0,85	0.15	-1,45	-1,01	-4.57***
lt_rev	5_minus_1	-1,27	-0,52	-7.33***	-0,09	-0,84	-0.07	-1,77	-1,13	-5.21***
lt_rev	10_minus_1	-1,97	-0,91	-7.50***	-0,79	-1,19	-0.54	-2,47	-1,56	-5.99***
STresrevEW	3_minus_1	-0,89	-0,75	-6.35***	0,37	-1,18	0.26	-1,3	-1,2	-4.40***
STresrevEW	5_minus_1	-1,29	-1,13	-5.99***	-0,02	-1,43	-0.02	-1,69	-1,61	-4.72***
STresrevEW	10_minus_1	-2,09	-1,67	-5.26***	-0,82	-2,27	-0.54	-2,5	-2,33	-4.58***
STresrevVW	3_minus_1	-0,84	-0,69	-6.00***	0,42	-1,11	0.29	-1,25	-1,02	-4.14***
STresrevVW	5_minus_1	-1,34	-1,11	-6.07***	-0,11	-1,54	-0.08	-1,78	-1,52	-4.86***
STresrevVW	10_minus_1	-2,07	-1,54	-5.36***	-0,78	-2,18	-0.51	-2,46	-2,11	-4.58***
LTresrevEW	3_minus_1	-0,9	-0,32	-6.39***	0,32	-0,89	0.22	-1,35	-0,95	-4.44***
LTresrevEW	5_minus_1	-1,1	-0,49	-6.63***	0,12	-0,97	0.08	-1,56	-1,09	-4.84***
LTresrevEW	10_minus_1	-1,35	-0,62	-6.18***	-0,09	-1,1	-0.06	-1,77	-1,02	-4.97***
LTresrevVW	3_minus_1	-0,9	-0,32	-6.39***	0,32	-0,89	0.22	-1,35	-0,95	-4.44***
LTresrevVW	5_minus_1	-1,1	-0,49	-6.63***	0,12	-0,97	0.08	-1,56	-1,09	-4.84***
LTresrevVW	10_minus_1	-1,35	-0,62	-6.18***	-0,09	-1,1	-0.06	-1,77	-1,02	-4.97***
MC_percentile	3_minus_1	-0,84	-0,32	-3.68***	0,41	-0,79	0.28	-1,26	-0,79	-3.62***
MC_percentile	5_minus_1	-1,04	-0,46	-3.92***	0,22	-0,96	0.15	-1,45	-0,98	-3.79***
MC_percentile	10_minus_1	-1,29	-0,39	-3.22***	0,01	-0,95	0.00	-1,67	-0,93	-3.18***
dividend_yield_percentile	3_minus_1	0,28	0,25	2.27**	1,56	-0,29	1.09	-0,11	-0,24	-0.38
dividend_yield_percentile	5_minus_1	0,3	0,34	1.56	1,59	-0,34	1.09	-0,09	-0,19	-0.27
dividend_yield_percentile	10_minus_1	0,67	0,21	2.94***	2,05	-0,35	1.42	0,37	-0,31	1.02
january	3_minus_1	1,51	0,36	9.17***	3	0,47	2.09**	1,33	0,55	4.51***
halloween	3_minus_1	0,54	0,02	5.53***	1,88	-0,32	1.31	0,21	-0,42	0.77

The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an *average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

B. Analysis results with a 12-month beta lookback window

B.1 full-sample results

Factor	Portfolio	Average	Median	T_stat	Mean_EWalpha	Median_EWalpha	EWt_stat	Mean_VWalpha	Median_VWalpha	VWt_stat
betaEW	3_minus_1	0,51	0,06	3.81***	-0,14	-0,34	-0.40	-0,04	-0,19	-0.19
betaEW	5_minus_1	0,65	0,12	3.39***	0	-0,35	0.01	0,1	-0,07	0.41
betaEW	10_minus_1	0,79	0,06	2.42***	0,12	-0,29	0.27	0,22	-0,07	0.59
betaVW	3_minus_1	0,36	0,18	2.93***	-0,34	-0,34	-0.97	-0,24	-0,22	-1.22
betaVW	5_minus_1	0,44	0,13	2.33**	-0,3	-0,43	-0.79	-0,21	-0,22	-0.84
betaVW	10_minus_1	0,35	0,07	1.15	-0,31	-0,42	-0.65	-0,21	-0,24	-0.59
volatility	3_minus_1	1,74	0,6	11.28***	1,14	0,17	3.44***	1,24	0,35	5.48***
volatility	5_minus_1	2,42	0,83	11.48***	1,78	0,37	4.98***	1,88	0,48	6.97***
volatility	10_minus_1	3,52	1	11.30***	2,89	0,46	6.95***	2,98	0,75	8.19***
EWidvol	3_minus_1	1,16	0,48	10.21***	0,56	-0,03	1.70*	0,66	0,2	3.22***
EWidvol	5_minus_1	1,44	0,56	9.75***	0,82	0,04	2.42***	0,91	0,2	4.03***
EWidvol	10_minus_1	1,74	0,59	9.19***	1,14	0,17	3.20***	1,23	0,15	4.75***
VWidvol	3_minus_1	1,3	0,52	10.06***	0,67	0,02	2.02**	0,76	0,15	3.56***
VWidvol	5_minus_1	1,71	0,55	9.83***	1,07	0,07	3.11***	1,17	0,25	4.74***
VWidvol	10_minus_1	2,07	0,54	8.68***	1,45	0,05	3.85***	1,54	0,22	5.15***
mom6	3_minus_1	-0,4	0,06	-2.75***	-1,05	-0,46	-2.85***	-0,95	-0,37	-4.17***
mom6	5_minus_1	-0,9	-0,03	-4.25***	-1,52	-0,69	-3.79***	-1,43	-0,54	-5.12***
mom6	10_minus_1	-1,88	-0,36	-4.75***	-2,43	-1,06	-4.55***	-2,33	-0,94	-5.29***
mom12	3_minus_1	-0,11	0,28	-0.83	-0,81	-0,26	-2.22**	-0,71	-0,15	-3.18***
mom12	5_minus_1	-0,49	0,21	-2.52***	-1,24	-0,31	-3.14***	-1,15	-0,21	-4.24***
mom12	10_minus_1	-1,37	-0,03	-4.00***	-2,15	-0,54	-4.25***	-2,05	-0,43	-5.03***
mom6yearhigh	3_minus_1	0,03	0,14	0.27	-0,58	-0,42	-1.65*	-0,48	-0,38	-2.28**
mom6yearhigh	5_minus_1	0,11	0,24	0.77	-0,52	-0,3	-1.49	-0,43	-0,16	-1.91*
mom6yearhigh	10_minus_1	0,28	0,35	1.18	-0,34	-0,21	-0.85	-0,24	-0,11	-0.79
mom12yearhigh	3_minus_1	0,36	0,4	3.19***	-0,27	-0,17	-0.79	-0,17	-0,07	-0.86
mom12yearhigh	5_minus_1	0,53	0,49	3.33***	-0,13	-0,08	-0.37	-0,03	0,08	-0.14
mom12yearhigh	10_minus_1	0,67	0,67	3.19***	-0,02	0,05	-0.06	0,08	0,35	0.27
resmom6EW	3_minus_1	-0,53	-0,06	-4.38***	-1,2	-0,49	-3.34***	-1,1	-0,41	-5.21***
resmom6EW	5_minus_1	-0,84	-0,13	-4.84***	-1,52	-0,71	-3.91***	-1,43	-0,54	-5.62***
resmom6EW	10_minus_1	-1,47	-0,38	-5.37***	-2,15	-0,9	-4.74***	-2,06	-0,84	-5.99***
resmom6VW	3_minus_1	-0,19	0,05	-1.77*	-0,88	-0,4	-2.50***	-0,78	-0,25	-3.84***
resmom6VW	5_minus_1	-0,4	0,02	-2.36***	-1,13	-0,49	-2.95***	-1,04	-0,31	-4.13***
resmom6VW	10_minus_1	-0,82	-0,22	-2.89***	-1,63	-0,72	-3.61***	-1,54	-0,71	-4.36***
resmom12EW	3_minus_1	-0,42	0,06	-3.32***	-1,03	-0,3	-2.87***	-0,94	-0,24	-4.42***
resmom12EW	5_minus_1	-0,72	0,05	-3.80***	-1,34	-0,38	-3.40***	-1,25	-0,28	-4.77***
resmom12EW	10_minus_1	-1,52	-0,16	-4.37***	-2,18	-0,57	-4.25***	-2,09	-0,49	-5.11***
resmom12VW	3_minus_1	-0,18	0,18	-1.40	-0,84	-0,31	-2.31**	-0,74	-0,08	-3.42***

resmom12VW	5_minus_1	-0,35	0,18	-1.90*	-1,04	-0,37	-2.65***	-0,94	-0,08	-3.65***
resmom12VW	10_minus_1	-1,09	0,01	-3.21***	-1,84	-0,32	-3.65***	-1,74	-0,24	-4.39***
st_rev	3_minus_1	-1,05	-0,56	-5.83***	-1,64	-1,15	-4.26***	-1,54	-0,95	-6.37***
st_rev	5_minus_1	-1,79	-1,06	-6.26***	-2,35	-1,59	-5.26***	-2,25	-1,58	-7.01***
st_rev	10_minus_1	-3,53	-1,79	-7.08***	-3,81	-2,52	-6.30***	-3,72	-2,39	-7.09***
lt_rev	3_minus_1	-0,69	-0,31	-6.31***	-1,33	-0,74	-3.76***	-1,24	-0,65	-5.97***
lt_rev	5_minus_1	-1,16	-0,46	-7.40***	-1,8	-0,95	-4.79***	-1,7	-0,9	-7.14***
lt_rev	10_minus_1	-2,09	-0,88	-7.70***	-2,7	-1,38	-6.09***	-2,6	-1,4	-7.81***
STresrevEW	3_minus_1	-0,73	-0,49	-5.48***	-1,31	-0,89	-3.61***	-1,22	-0,74	-5.64***
STresrevEW	5_minus_1	-1,38	-0,83	-7.79***	-1,99	-1,21	-5.04***	-1,89	-1,05	-7.52***
STresrevEW	10_minus_1	-2,47	-1,4	-8.15***	-3,11	-1,88	-6.56***	-3,01	-1,66	-8.24***
STresrevVW	3_minus_1	-0,63	-0,39	-5.43***	-1,25	-0,82	-3.56***	-1,16	-0,65	-5.59***
STresrevVW	5_minus_1	-1,14	-0,7	-6.45***	-1,73	-1,08	-4.44***	-1,64	-1	-6.51***
STresrevVW	10_minus_1	-2,21	-1,29	-6.94***	-2,78	-1,71	-5.68***	-2,68	-1,67	-7.06***
LTresrevEW	3_minus_1	-0,67	-0,18	-6.51***	-1,32	-0,7	-3.76***	-1,23	-0,57	-6.11***
LTresrevEW	5_minus_1	-1,02	-0,29	-7.53***	-1,69	-0,8	-4.58***	-1,6	-0,68	-7.27***
LTresrevEW	10_minus_1	-1,57	-0,57	-7.94***	-2,26	-1,08	-5.53***	-2,16	-0,94	-8.13***
LTresrevVW	3_minus_1	-0,67	-0,18	-6.51***	-1,32	-0,7	-3.76***	-1,23	-0,57	-6.11***
LTresrevVW	5_minus_1	-1,02	-0,29	-7.53***	-1,69	-0,8	-4.58***	-1,6	-0,68	-7.27***
LTresrevVW	10_minus_1	-1,57	-0,57	-7.94***	-2,26	-1,08	-5.53***	-2,16	-0,94	-8.13***
MC_percentile	3_minus_1	-1,17	-0,4	-5.59***	-1,78	-0,93	-4.36***	-1,68	-0,8	-6.08***
MC_percentile	5_minus_1	-1,61	-0,51	-4.63***	-2,2	-0,92	-4.36***	-2,11	-0,84	-5.15***
MC_percentile	10_minus_1	-2,56	-0,63	-3.63***	-3,17	-1,12	-3.70***	-3,12	-0,88	-3.96***
dividend_yield_percentile	3_minus_1	2,13	0,39	4.42***	1,53	-0,06	2.42***	1,6	-0,06	2.90***
dividend_yield_percentile	5_minus_1	3,46	0,47	4.46***	2,75	-0,1	3.00***	2,81	0,03	3.26***
dividend_yield_percentile	10_minus_1	4,14	0,5	3.59***	3,24	-0,13	2.49***	3,21	-0,1	2.56***
january	3_minus_1	0,87	0,21	9.40***	0,27	-0,13	0.81	0,37	0,13	1.97**
halloween	3_minus_1	0,44	0,28	7.72***	-0,14	-0,01	-0.41	-0,04	0,12	-0.22

*The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

B.2 19th century results (1806-1899)

Factor	Portfolio	Average	Median	T_stat	Mean_EWalpha	Median_EWalpha	EWt_stat	Mean_VWalpha	Median_VWalpha	VWt_stat
betaEW	3_minus_1	0,71	0,12	3.22***	-0,56	-0,35	-1.92*	0,34	-0,13	1.31
betaEW	5_minus_1	0,98	0,15	3.00***	-0,31	-0,48	-0.76	0,6	-0,03	1.64
betaEW	10_minus_1	1,22	0,11	2.09**	-0,05	-0,3	-0.08	0,86	-0,01	1.32
betaVW	3_minus_1	0,55	0,15	2.73***	-0,83	-0,38	-2.58***	0,08	-0,19	0.30
betaVW	5_minus_1	0,7	0,14	2.18**	-0,77	-0,52	-1.76*	0,13	-0,22	0.36
betaVW	10_minus_1	0,62	0,07	1.17	-0,67	-0,58	-0.99	0,23	-0,21	0.38
volatility	3_minus_1	2,26	0,73	9.24***	1,05	0,23	4.26***	1,96	0,54	6.85***

volatility	5_minus_1	3,26	1,06	9.40***	2,01	0,41	6.13***	2,92	0,72	7.54***
volatility	10_minus_1	5	1,29	9.20***	3,8	0,59	7.30***	4,71	1,07	7.81***
EWidvol	3_minus_1	1,38	0,55	7.80***	0,16	-0,01	0.79	1,07	0,34	4.74***
EWidvol	5_minus_1	1,66	0,57	7.22***	0,38	0,03	1.62	1,29	0,33	4.76***
EWidvol	10_minus_1	2,02	0,55	6.55***	0,81	0,06	2.74***	1,72	0,24	4.85***
VWidvol	3_minus_1	1,6	0,58	7.81***	0,33	0,04	1.46	1,24	0,32	4.92***
VWidvol	5_minus_1	2,08	0,63	7.51***	0,8	0,07	2.90***	1,71	0,43	5.32***
VWidvol	10_minus_1	2,64	0,6	6.36***	1,39	-0,11	3.55***	2,3	0,24	4.96***
mom6	3_minus_1	-0,38	0,34	-1.50	-1,66	-0,36	-4.76***	-0,75	-0,01	-2.50***
mom6	5_minus_1	-1,15	0,16	-3.12***	-2,38	-0,57	-5.29***	-1,47	-0,29	-3.61***
mom6	10_minus_1	-2,65	-0,15	-3.87***	-3,76	-1,1	-4.97***	-2,84	-0,74	-3.93***
mom12	3_minus_1	-0,03	0,34	-0.14	-1,39	-0,23	-4.23***	-0,48	0,02	-1.73*
mom12	5_minus_1	-0,56	0,22	-1.75*	-2,03	-0,43	-4.86***	-1,13	-0,04	-2.98***
mom12	10_minus_1	-1,92	-0,06	-3.26***	-3,47	-0,61	-4.96***	-2,55	-0,29	-3.83***
mom6yearhigh	3_minus_1	0,19	0,34	0.93	-1,03	-0,3	-3.73***	-0,12	-0,03	-0.49
mom6yearhigh	5_minus_1	0,25	0,41	1.05	-1	-0,24	-3.36***	-0,1	0,14	-0.35
mom6yearhigh	10_minus_1	0,45	0,57	1.07	-0,79	-0,12	-1.70*	0,13	0,32	0.27
mom12yearhigh	3_minus_1	0,54	0,47	2.85***	-0,7	-0,17	-2.76***	0,2	0,11	0.86
mom12yearhigh	5_minus_1	0,75	0,54	2.77***	-0,56	-0,13	-1.80*	0,35	0,32	1.11
mom12yearhigh	10_minus_1	0,85	0,91	2.33**	-0,53	0,02	-1.29	0,39	0,64	0.93
resmom6EW	3_minus_1	-0,61	0,08	-2.94***	-1,95	-0,47	-6.12***	-1,05	-0,32	-4.00***
resmom6EW	5_minus_1	-1,1	0,09	-3.70***	-2,47	-0,68	-6.02***	-1,57	-0,45	-4.38***
resmom6EW	10_minus_1	-2,08	-0,27	-4.38***	-3,47	-1	-5.81***	-2,56	-0,66	-4.67***
resmom6VW	3_minus_1	-0,03	0,3	-0.17	-1,41	-0,3	-4.80***	-0,5	0,12	-2.15**
resmom6VW	5_minus_1	-0,24	0,22	-0.89	-1,68	-0,33	-4.43***	-0,78	0,07	-2.36***
resmom6VW	10_minus_1	-0,92	-0,02	-1.84*	-2,53	-0,64	-4.16***	-1,62	-0,44	-2.83***
resmom12EW	3_minus_1	-0,47	0,14	-2.27**	-1,71	-0,28	-5.29***	-0,81	-0,13	-3.02***
resmom12EW	5_minus_1	-0,93	0,08	-2.87***	-2,18	-0,38	-5.04***	-1,28	-0,24	-3.34***
resmom12EW	10_minus_1	-2,19	-0,18	-3.61***	-3,53	-0,65	-4.93***	-2,62	-0,59	-3.84***
resmom12VW	3_minus_1	-0,08	0,3	-0.37	-1,37	-0,24	-4.29***	-0,47	0,03	-1.74*
resmom12VW	5_minus_1	-0,35	0,17	-1.12	-1,72	-0,4	-4.12***	-0,82	-0,01	-2.18**
resmom12VW	10_minus_1	-1,49	0	-2.51***	-3	-0,45	-4.33***	-2,09	-0,17	-3.17***
st_rev	3_minus_1	-1,13	-0,33	-3.63***	-2,3	-0,88	-5.64***	-1,39	-0,44	-4.15***
st_rev	5_minus_1	-2,11	-0,72	-4.18***	-3,26	-1,32	-5.65***	-2,35	-1,04	-4.61***
st_rev	10_minus_1	-4,62	-1,57	-5.25***	-5,27	-2,32	-5.71***	-4,37	-1,96	-4.84***
lt_rev	3_minus_1	-0,46	-0,25	-2.88***	-1,69	-0,74	-6.62***	-0,78	-0,51	-3.66***
lt_rev	5_minus_1	-1,05	-0,41	-4.10***	-2,27	-0,92	-6.84***	-1,35	-0,66	-4.53***
lt_rev	10_minus_1	-2,21	-0,78	-4.72***	-3,34	-1,42	-6.32***	-2,41	-1,04	-4.71***
STresrevEW	3_minus_1	-0,64	-0,16	-2.91***	-1,8	-0,6	-5.43***	-0,89	-0,38	-3.32***
STresrevEW	5_minus_1	-1,45	-0,4	-5.16***	-2,65	-0,9	-6.41***	-1,74	-0,6	-5.24***
STresrevEW	10_minus_1	-2,85	-0,75	-6.09***	-4,12	-1,49	-7.27***	-3,2	-1,12	-6.07***
STresrevVW	3_minus_1	-0,44	-0,1	-2.34***	-1,64	-0,5	-5.77***	-0,73	-0,31	-3.03***
STresrevVW	5_minus_1	-1,06	-0,19	-3.78***	-2,21	-0,69	-5.57***	-1,31	-0,35	-3.91***
STresrevVW	10_minus_1	-2,44	-0,75	-4.80***	-3,56	-1,39	-5.74***	-2,64	-0,77	-4.61***

LTresrevEW	3_minus_1	-0,59	-0,06	-4.41***	-1,87	-0,61	-6.96***	-0,95	-0,27	-4.91***
LTresrevEW	5_minus_1	-0,89	-0,12	-4.50***	-2,2	-0,77	-6.92***	-1,28	-0,39	-5.23***
LTresrevEW	10_minus_1	-1,64	-0,32	-4.95***	-3,02	-1,1	-6.84***	-2,05	-0,62	-5.59***
LTresrevVW	3_minus_1	-0,59	-0,06	-4.41***	-1,87	-0,61	-6.96***	-0,95	-0,27	-4.91***
LTresrevVW	5_minus_1	-0,89	-0,12	-4.50***	-2,2	-0,77	-6.92***	-1,28	-0,39	-5.23***
LTresrevVW	10_minus_1	-1,64	-0,32	-4.95***	-3,02	-1,1	-6.84***	-2,05	-0,62	-5.59***
MC_percentile	3_minus_1	-1,47	-0,49	-4.30***	-2,7	-1,01	-5.71***	-1,79	-0,76	-4.44***
MC_percentile	5_minus_1	-2,14	-0,56	-3.42***	-3,36	-0,99	-4.51***	-2,44	-0,83	-3.42***
MC_percentile	10_minus_1	-4,1	-0,9	-2.77***	-5,59	-1,48	-3.28***	-4,52	-1,16	-2.70***
dividend_yield_percentile	3_minus_1	4,5	0,81	4.30***	3,32	0,33	2.81***	4,43	0,52	3.74***
dividend_yield_percentile	5_minus_1	7,63	1,45	4.26***	6,29	0,48	3.10***	7,49	0,88	3.69***
dividend_yield_percentile	10_minus_1	11,19	1,04	3.45***	9,31	0,37	2.53***	10,7	0,9	2.91***
january	3_minus_1	0,29	0,12	3.18***	-1,05	-0,51	-4.73***	-0,14	-0,23	-0.91
halloween	3_minus_1	0,34	0,4	5.56***	-0,88	-0,16	-4.13***	0,03	0,15	0.17

*The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

B.3 20th century results (1900-1984)

Factor	**Portfolio**	**Average**	**Median**	**T_stat**	**Mean_EWalpha**	**Median_EWalpha**	**EWt_stat**	**Mean_VWalpha**	**Median_VWalpha**	**VWt_stat**
betaEW	3_minus_1	0,28	0,04	2.03**	0,3	-0,24	0.49	-0,42	-0,26	-1.36
betaEW	5_minus_1	0,3	0,04	1.58	0,32	-0,25	0.51	-0,41	-0,16	-1.21
betaEW	10_minus_1	0,32	0,03	1.34	0,3	-0,28	0.48	-0,43	-0,21	-1.19
betaVW	3_minus_1	0,14	0,19	1.13	0,16	-0,24	0.26	-0,56	-0,26	-1.86*
betaVW	5_minus_1	0,15	0,11	0.85	0,17	-0,22	0.27	-0,55	-0,23	-1.71*
betaVW	10_minus_1	0,05	0,09	0.21	0,06	-0,16	0.10	-0,67	-0,26	-1.79*
volatility	3_minus_1	1,18	0,45	6.53***	1,23	0,07	1.98**	0,5	0,09	1.44
volatility	5_minus_1	1,49	0,67	6.77***	1,54	0,32	2.41***	0,82	0,26	2.20**
volatility	10_minus_1	1,92	0,83	7.26***	1,96	0,46	3.03***	1,23	0,49	3.10***
EWidvol	3_minus_1	0,92	0,44	6.64***	0,97	-0,04	1.53	0,24	0,02	0.70
EWidvol	5_minus_1	1,21	0,55	6.64***	1,25	0,08	1.97**	0,52	0,05	1.45
EWidvol	10_minus_1	1,43	0,66	6.86***	1,48	0,25	2.27**	0,75	0,05	1.96*
VWidvol	3_minus_1	0,97	0,44	6.43***	1,01	-0,02	1.61	0,28	0,01	0.81
VWidvol	5_minus_1	1,3	0,44	6.45***	1,35	0,09	2.13**	0,62	0,1	1.67*
VWidvol	10_minus_1	1,46	0,5	6.91***	1,51	0,22	2.34***	0,78	0,21	2.07**
mom6	3_minus_1	-0,42	-0,17	-3.39***	-0,43	-0,6	-0.67	-1,16	-0,7	-3.36***
mom6	5_minus_1	-0,63	-0,28	-3.40***	-0,66	-0,82	-0.98	-1,38	-0,73	-3.64***
mom6	10_minus_1	-1,04	-0,49	-2.93***	-1,09	-1,05	-1.44	-1,82	-1,07	-3.63***
mom12	3_minus_1	-0,21	0,23	-1.35	-0,22	-0,3	-0.34	-0,94	-0,35	-2.69***
mom12	5_minus_1	-0,42	0,18	-1.99**	-0,44	-0,23	-0.66	-1,17	-0,39	-3.02***
mom12	10_minus_1	-0,78	0	-2.41***	-0,82	-0,51	-1.12	-1,55	-0,58	-3.31***

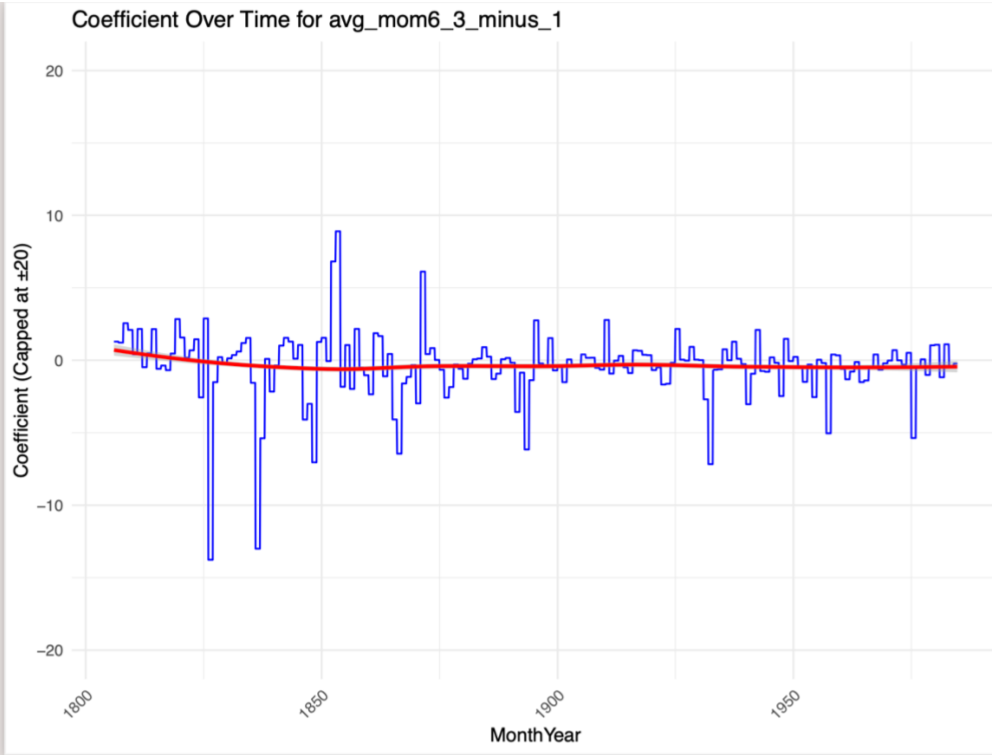
mom6yearhigh	3_minus_1	-0,14	-0,03	-1.21	-0,12	-0,54	-0.19	-0,85	-0,61	-2.48***
mom6yearhigh	5_minus_1	-0,05	0,05	-0.36	-0,04	-0,37	-0.06	-0,76	-0,51	-2.17**
mom6yearhigh	10_minus_1	0,1	0,16	0.51	0,11	-0,34	0.17	-0,62	-0,54	-1.59
mom12yearhigh	3_minus_1	0,16	0,33	1.44	0,17	-0,17	0.26	-0,56	-0,2	-1.68*
mom12yearhigh	5_minus_1	0,28	0,44	1.90*	0,3	0	0.47	-0,42	-0,13	-1.21
mom12yearhigh	10_minus_1	0,48	0,43	2.55***	0,49	0,08	0.75	-0,24	-0,02	-0.64
resmom6EW	3_minus_1	-0,44	-0,16	-3.88***	-0,44	-0,51	-0.67	-1,16	-0,55	-3.47***
resmom6EW	5_minus_1	-0,56	-0,2	-3.40***	-0,56	-0,74	-0.85	-1,29	-0,78	-3.56***
resmom6EW	10_minus_1	-0,81	-0,4	-3.28***	-0,82	-0,84	-1.21	-1,55	-0,93	-3.76***
resmom6VW	3_minus_1	-0,36	-0,14	-3.10***	-0,35	-0,51	-0.54	-1,07	-0,65	-3.18***
resmom6VW	5_minus_1	-0,57	-0,23	-2.94***	-0,57	-0,61	-0.86	-1,3	-0,69	-3.43***
resmom6VW	10_minus_1	-0,72	-0,4	-2.97***	-0,73	-0,76	-1.09	-1,46	-0,92	-3.55***
resmom12EW	3_minus_1	-0,35	0	-2.72***	-0,35	-0,31	-0.55	-1,08	-0,45	-3.24***
resmom12EW	5_minus_1	-0,49	0,03	-2.75***	-0,5	-0,36	-0.75	-1,22	-0,32	-3.42***
resmom12EW	10_minus_1	-0,81	-0,15	-2.58***	-0,83	-0,47	-1.13	-1,56	-0,43	-3.46***
resmom12VW	3_minus_1	-0,3	0,11	-1.97**	-0,3	-0,36	-0.46	-1,02	-0,21	-2.99***
resmom12VW	5_minus_1	-0,35	0,22	-1.99**	-0,35	-0,34	-0.53	-1,07	-0,23	-3.00***
resmom12VW	10_minus_1	-0,67	0,11	-2.19**	-0,67	-0,27	-0.92	-1,4	-0,29	-3.14***
st_rev	3_minus_1	-0,96	-0,75	-6.07***	-0,97	-1,38	-1.47	-1,69	-1,31	-4.85***
st_rev	5_minus_1	-1,43	-1,31	-6.33***	-1,43	-1,72	-2.09**	-2,15	-1,81	-5.53***
st_rev	10_minus_1	-2,35	-2,07	-5.78***	-2,34	-2,76	-3.01***	-3,07	-2,8	-5.78***
lt_rev	3_minus_1	-0,93	-0,36	-6.37***	-0,97	-0,73	-1.47	-1,7	-0,9	-4.78***
lt_rev	5_minus_1	-1,27	-0,52	-7.33***	-1,33	-0,98	-1.97**	-2,05	-1,11	-5.51***
lt_rev	10_minus_1	-1,97	-0,91	-7.50***	-2,06	-1,32	-2.91***	-2,79	-1,67	-6.52***
STresrevEW	3_minus_1	-0,82	-0,77	-5.99***	-0,82	-1,22	-1.26	-1,54	-1,21	-4.57***
STresrevEW	5_minus_1	-1,3	-1,25	-6.29***	-1,31	-1,59	-1.95*	-2,03	-1,6	-5.40***
STresrevEW	10_minus_1	-2,06	-1,77	-5.47***	-2,09	-2,3	-2.74***	-2,82	-2,33	-5.57***
STresrevVW	3_minus_1	-0,85	-0,71	-6.33***	-0,87	-1,13	-1.33	-1,59	-1,26	-4.72***
STresrevVW	5_minus_1	-1,22	-1,22	-5.98***	-1,25	-1,5	-1.85*	-1,97	-1,53	-5.24***
STresrevVW	10_minus_1	-1,96	-1,65	-5.32***	-2	-2,35	-2.64***	-2,73	-2,32	-5.46***
LTresrevEW	3_minus_1	-0,76	-0,27	-4.78***	-0,78	-0,85	-1.20	-1,5	-0,75	-4.27***
LTresrevEW	5_minus_1	-1,15	-0,42	-6.31***	-1,19	-0,84	-1.79*	-1,91	-0,89	-5.26***
LTresrevEW	10_minus_1	-1,49	-0,77	-7.05***	-1,54	-1,02	-2.27**	-2,27	-1,3	-5.91***
LTresrevVW	3_minus_1	-0,76	-0,27	-4.78***	-0,78	-0,85	-1.20	-1,5	-0,75	-4.27***
LTresrevVW	5_minus_1	-1,15	-0,42	-6.31***	-1,19	-0,84	-1.79*	-1,91	-0,89	-5.26***
LTresrevVW	10_minus_1	-1,49	-0,77	-7.05***	-1,54	-1,02	-2.27**	-2,27	-1,3	-5.91***
MC_percentile	3_minus_1	-0,84	-0,32	-3.68***	-0,84	-0,82	-1.26	-1,56	-0,83	-4.15***
MC_percentile	5_minus_1	-1,04	-0,46	-3.92***	-1,05	-0,86	-1.54	-1,77	-0,85	-4.42***
MC_percentile	10_minus_1	-1,29	-0,39	-3.22***	-1,3	-0,76	-1.73*	-2,03	-0,71	-3.96***
dividend_yield_percentile	3_minus_1	0,16	0,2	1.36	0,14	-0,32	0.22	-0,58	-0,22	-1.73*
dividend_yield_percentile	5_minus_1	0,32	0,21	2.46***	0,28	-0,41	0.44	-0,45	-0,43	-1.31
dividend_yield_percentile	10_minus_1	0,33	0,24	1.49	0,23	-0,36	0.35	-0,49	-0,37	-1.27
january	3_minus_1	1,51	0,36	9.17***	1,61	0,54	2.54***	0,89	0,52	2.61***
halloween	3_minus_1	0,54	0,02	5.53***	0,62	0,18	0.98	-0,1	0,05	-0.32

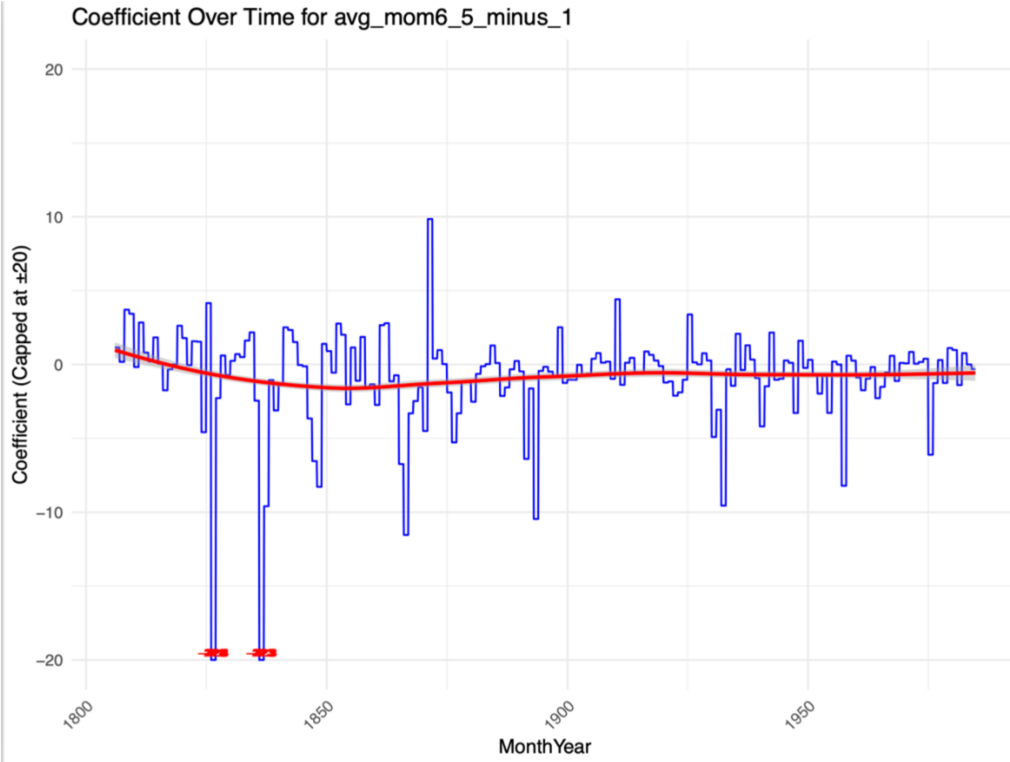
*The factor-portfolio bandwidth combination on the left, followed by the returns, equal-weighted CAPM-alpha and the value weighted-alpha. All returns and alphas contain an average, median, and t-statistic. ***, **, and * denote significances at the 1%, 5%, and 10% level respectively. The units of the returns and alphas are in percentage per month,*

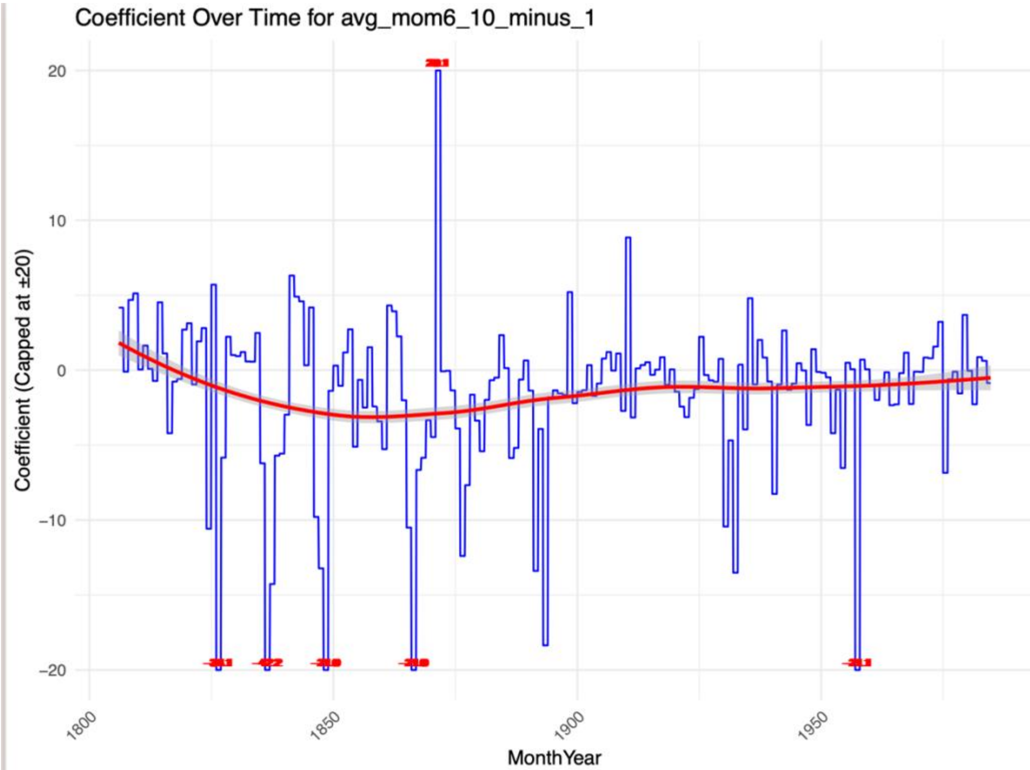
C. Factor portfolio returns over time

All graphs contain absolute factor portfolio returns over the entire sample.

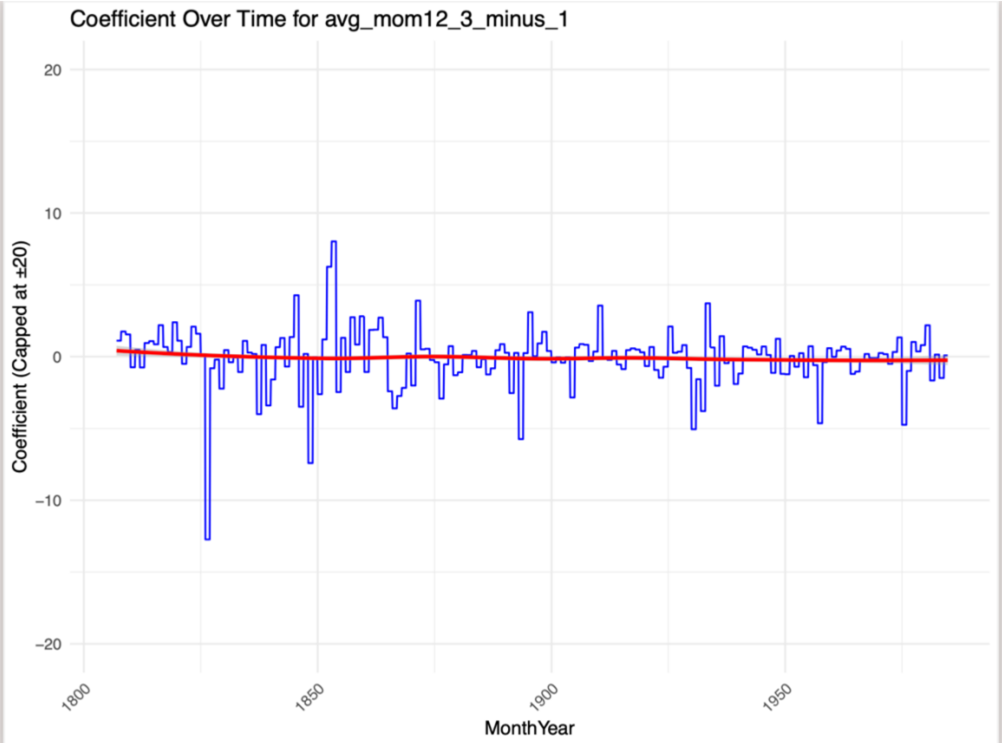
C.1 6-month momentum

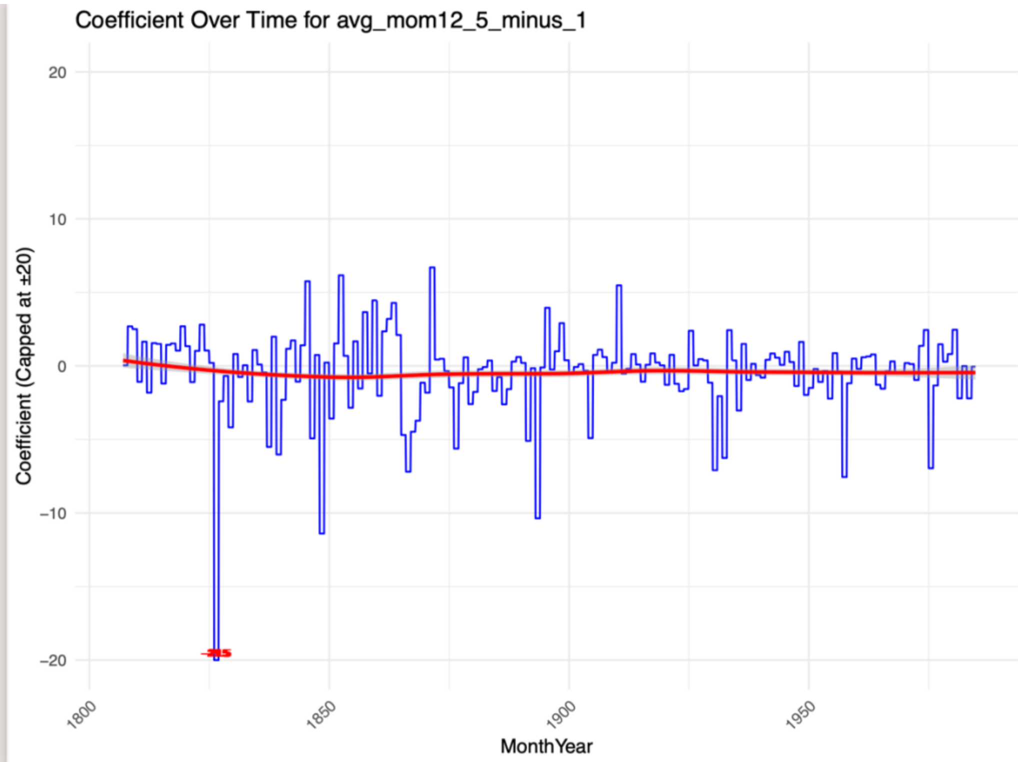


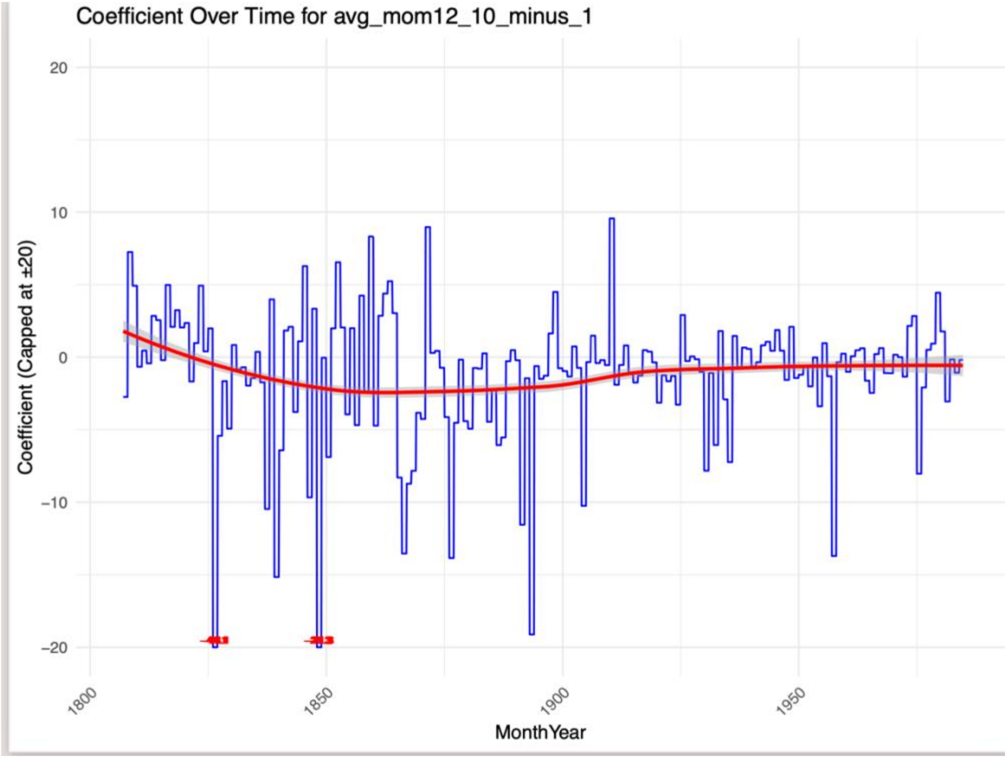




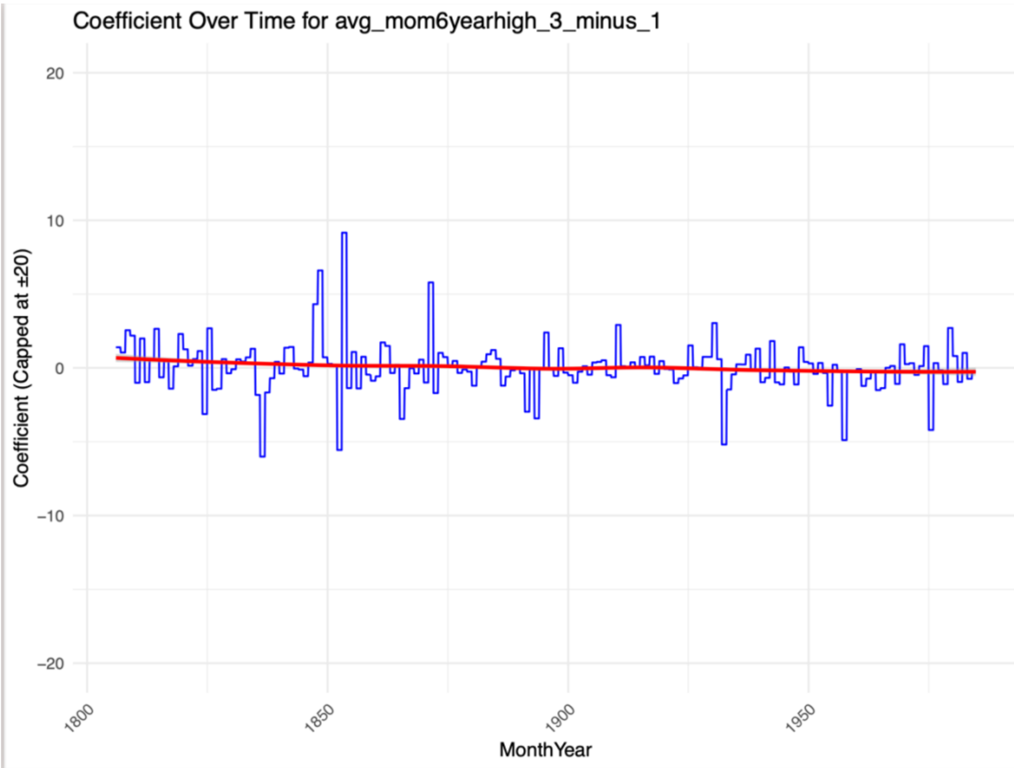
C.2 12-month momentum

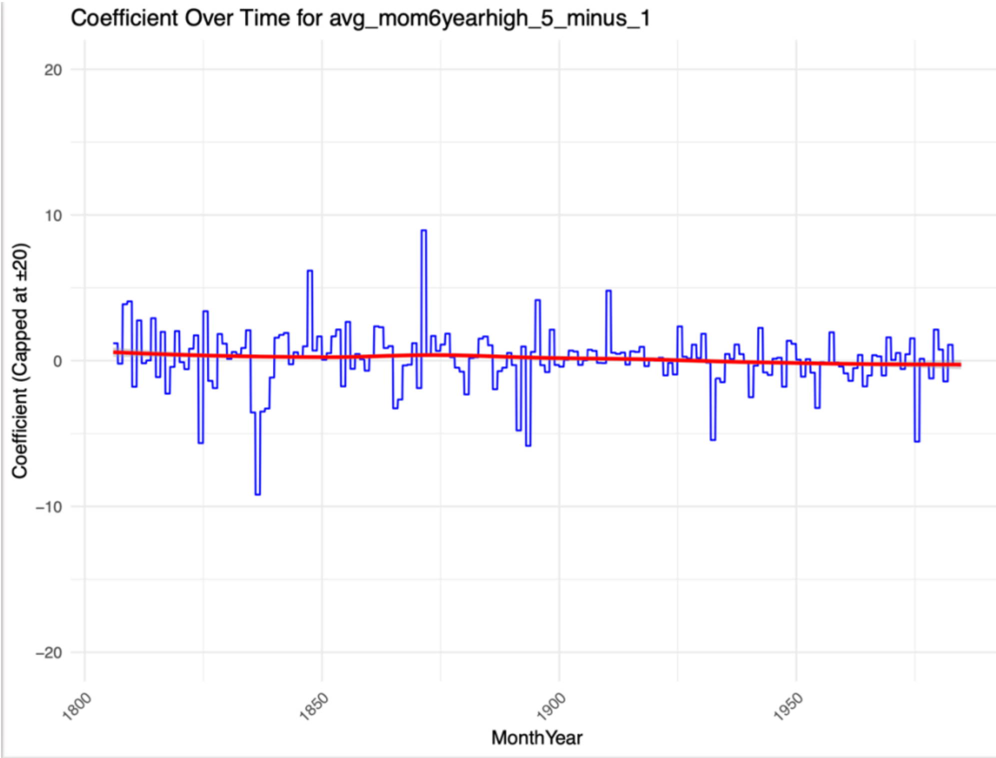

Coefficient Over Time for avg_mom12_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

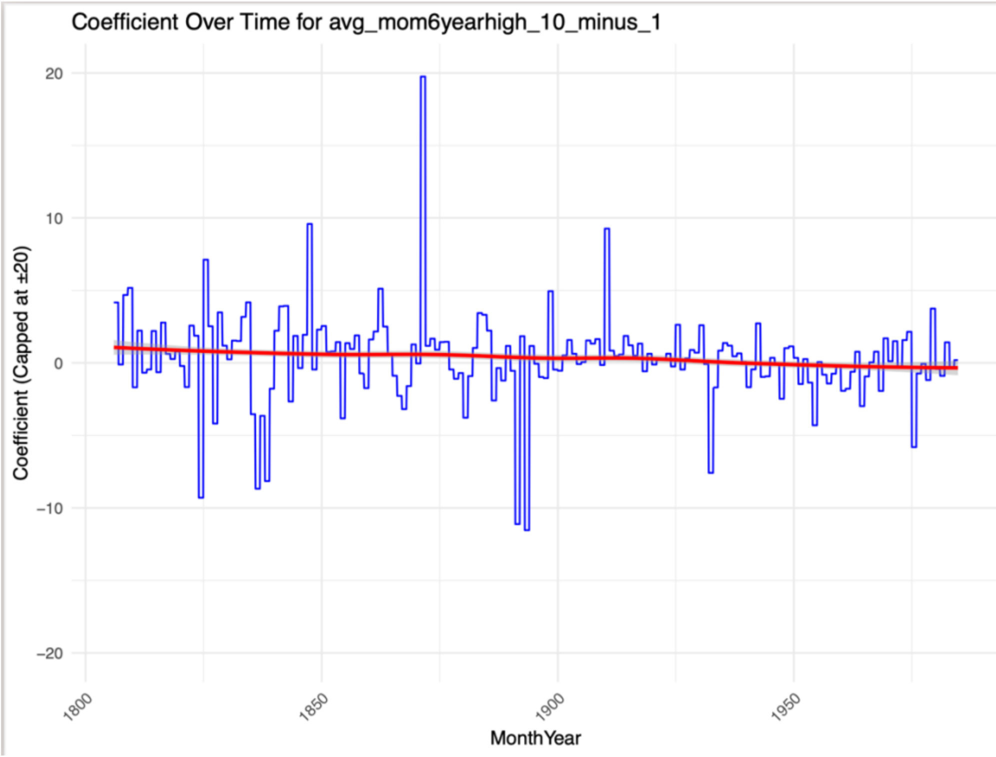

Coefficient Over Time for avg_mom12_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



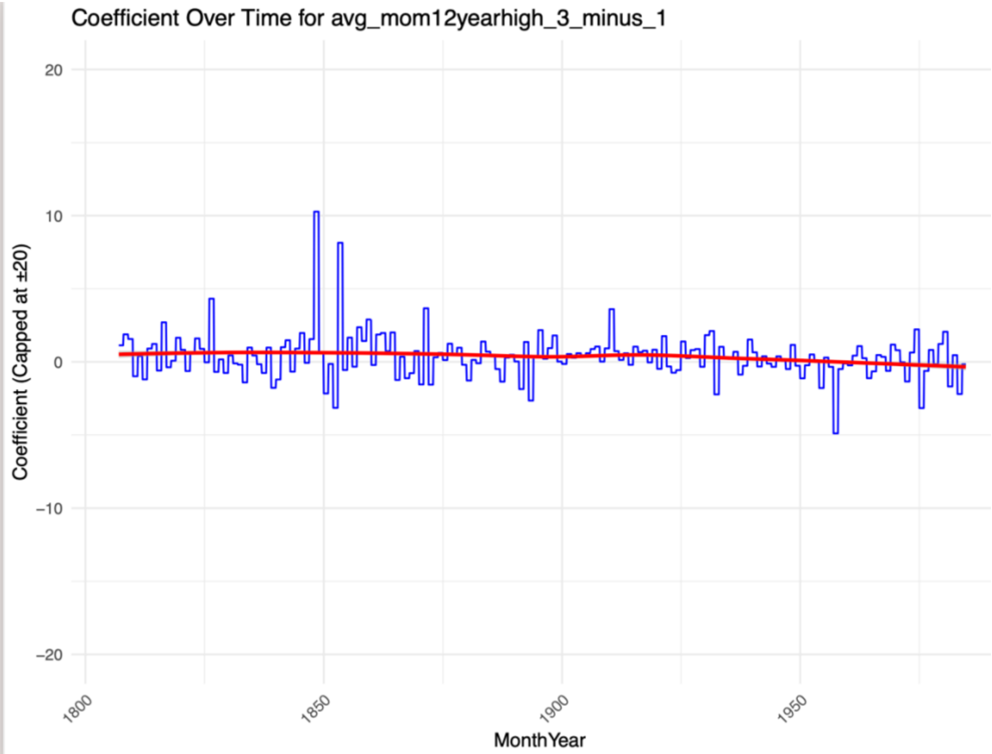
C.3 6-month momentum * distance to year high

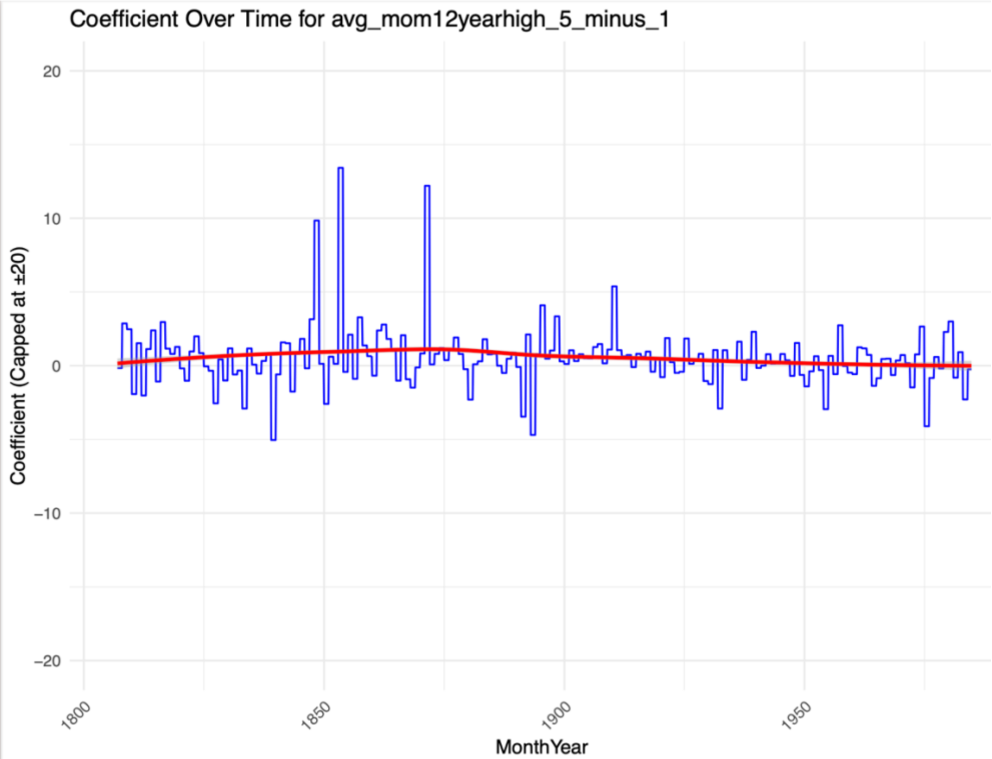


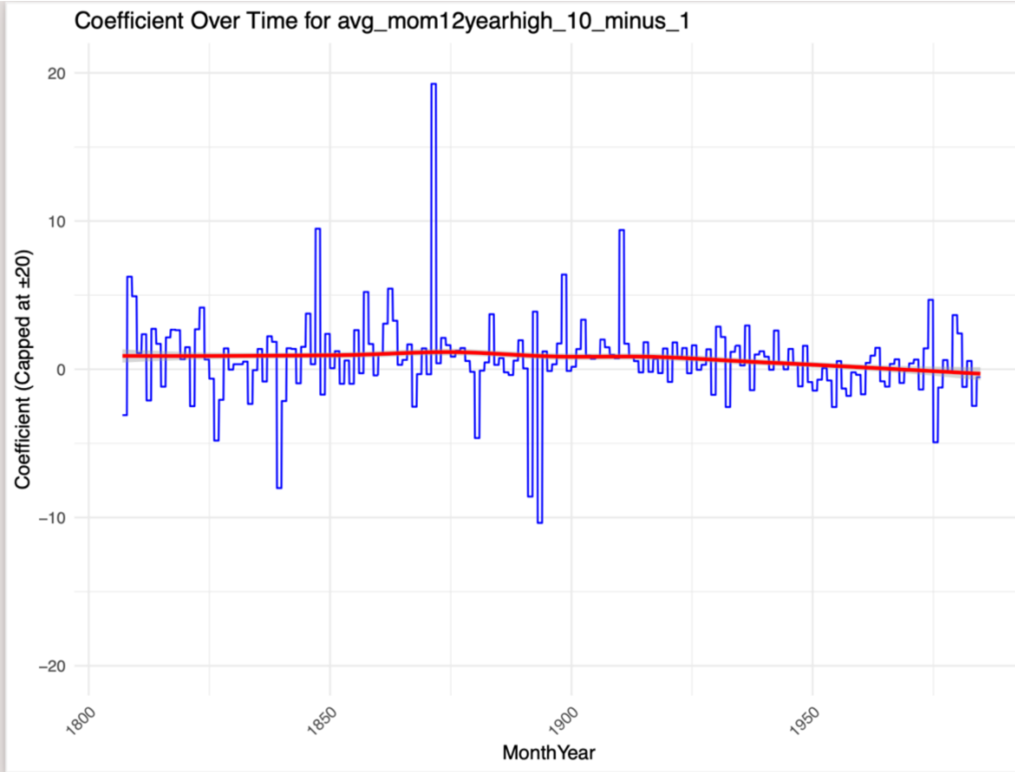




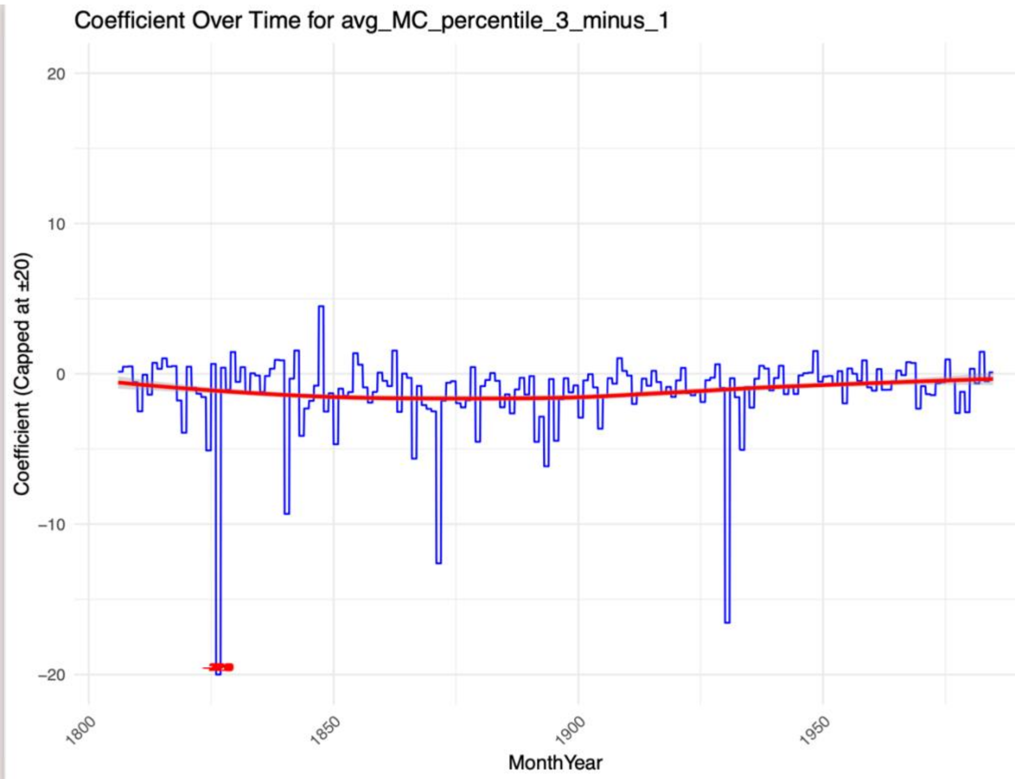
C.4 12-month momentum * distance to year high

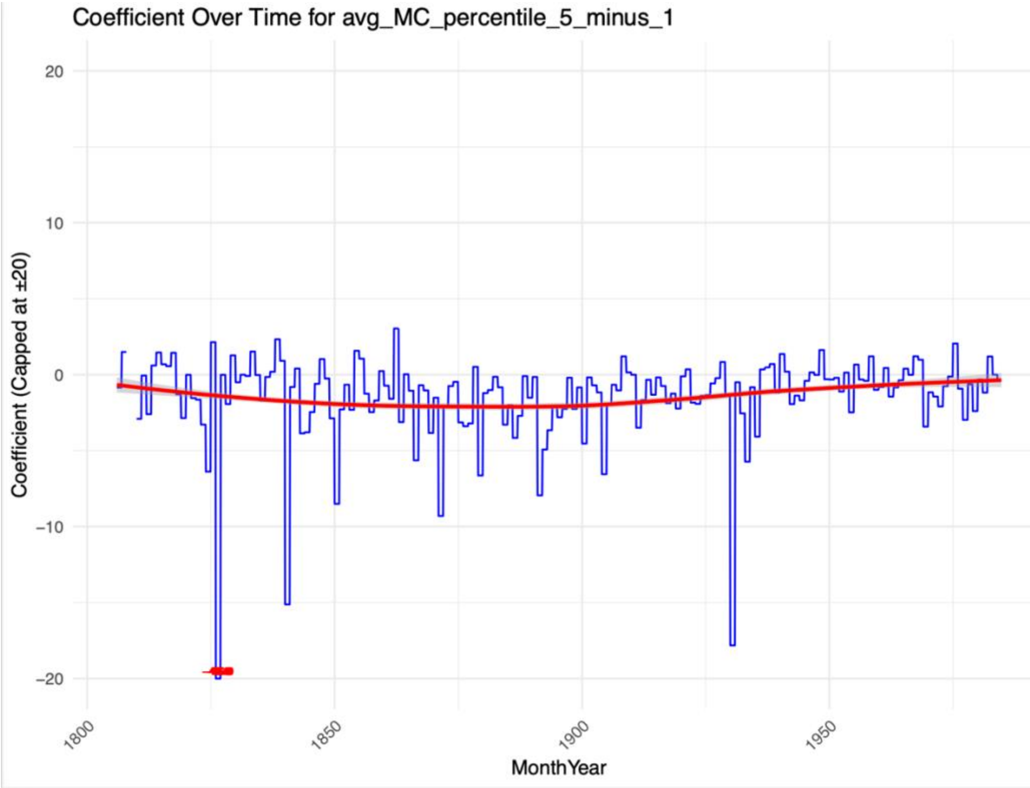

Coefficient Over Time for avg_mom12yearhigh_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

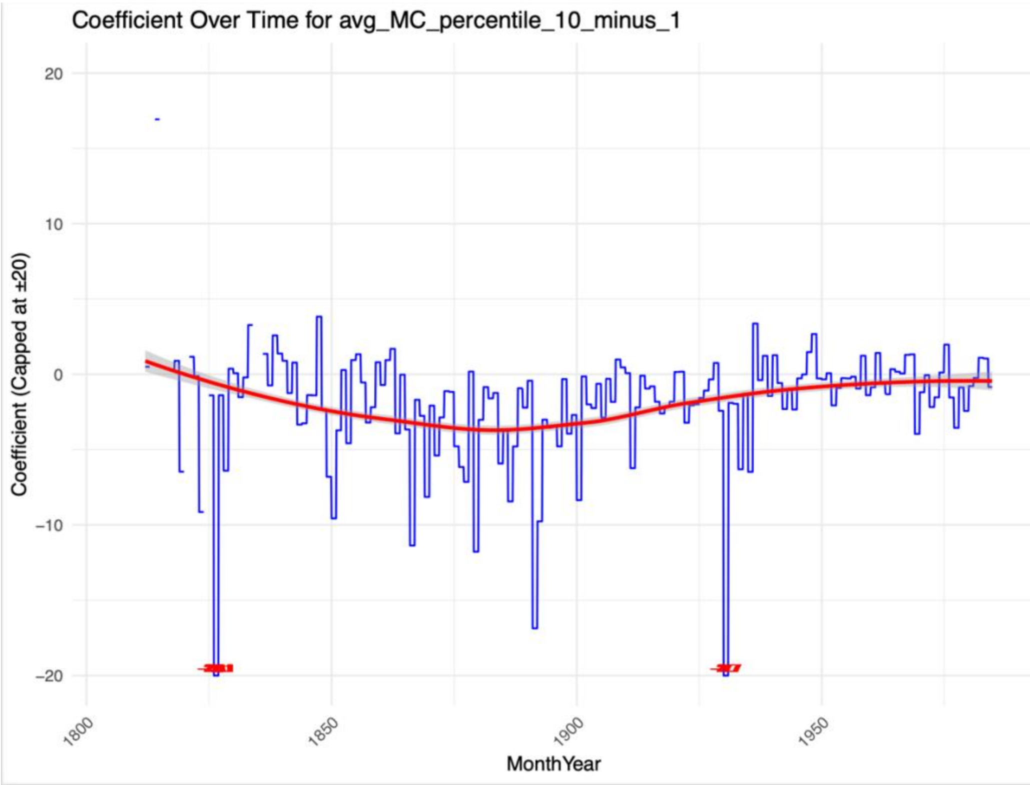

Coefficient Over Time for avg_mom12yearhigh_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



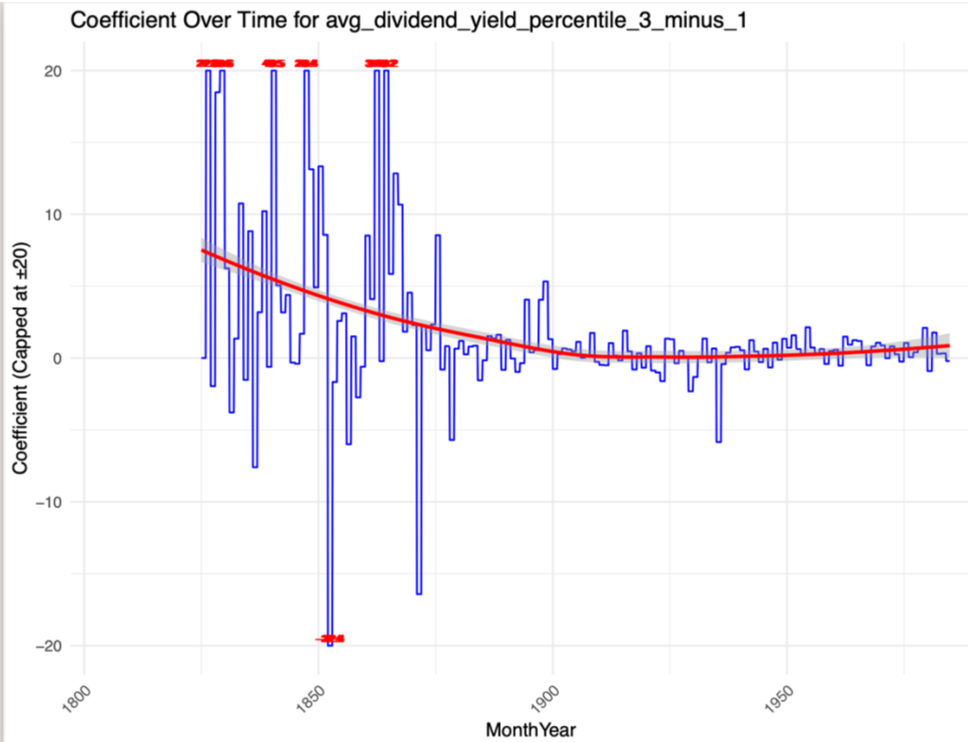
C.5 Market capitalisation

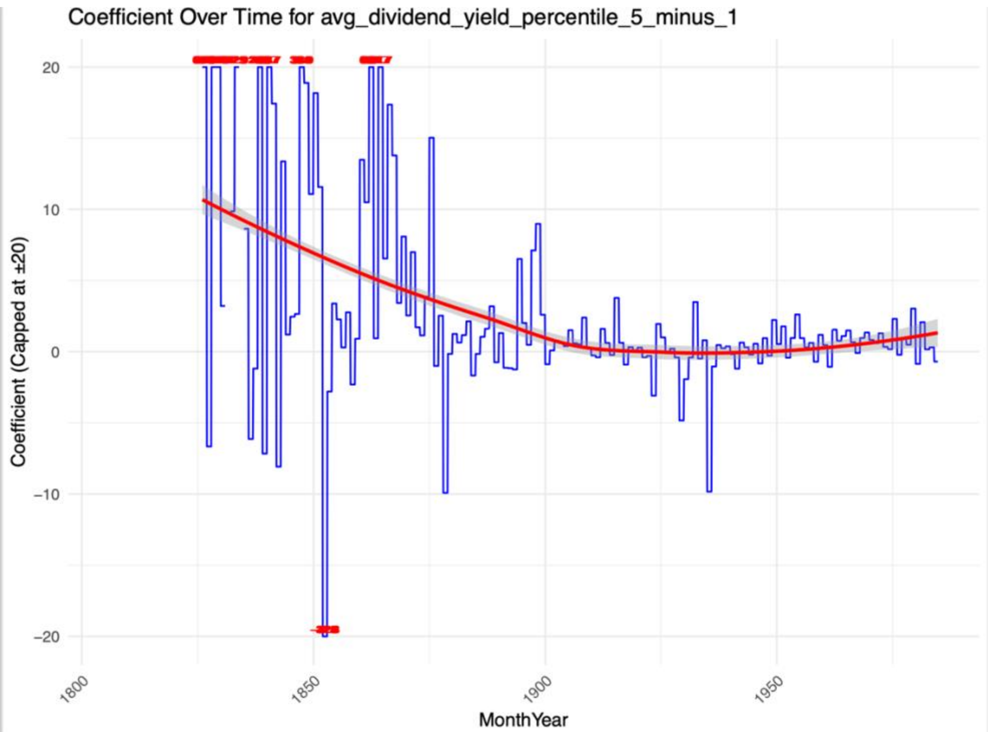


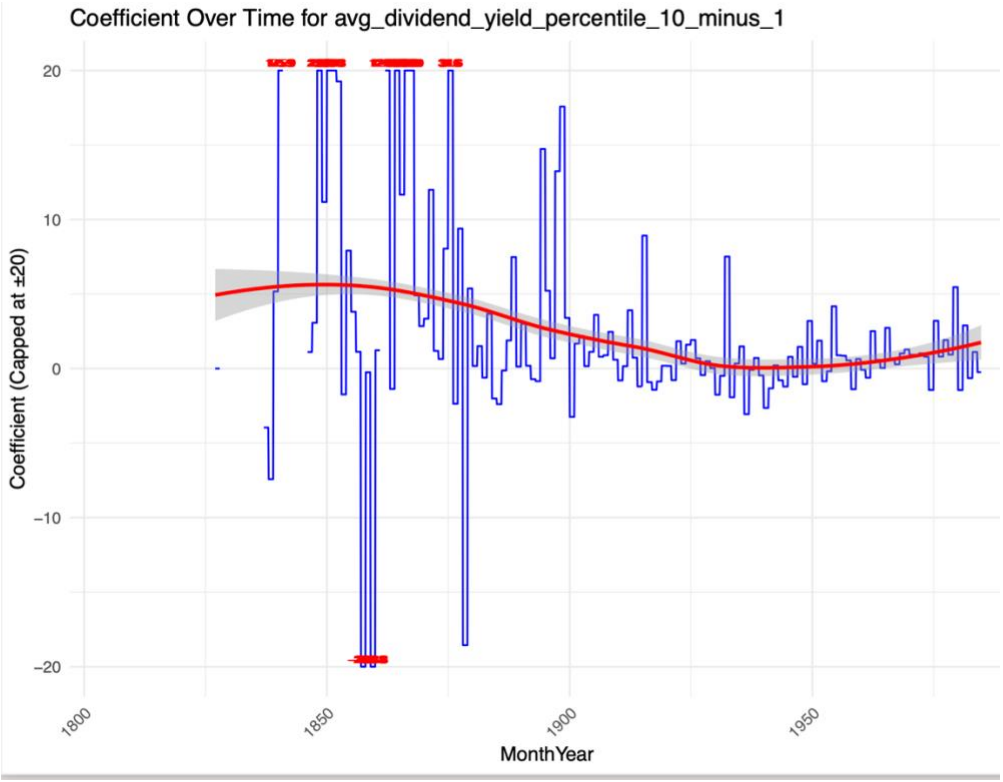




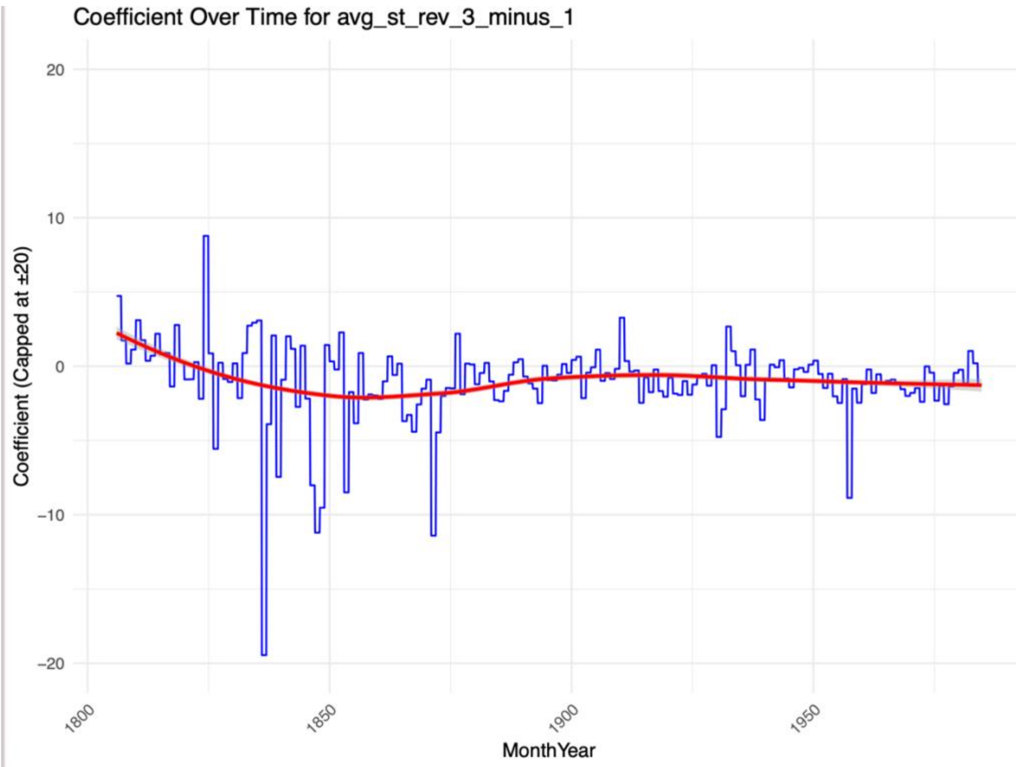
C.6 Dividend Yield

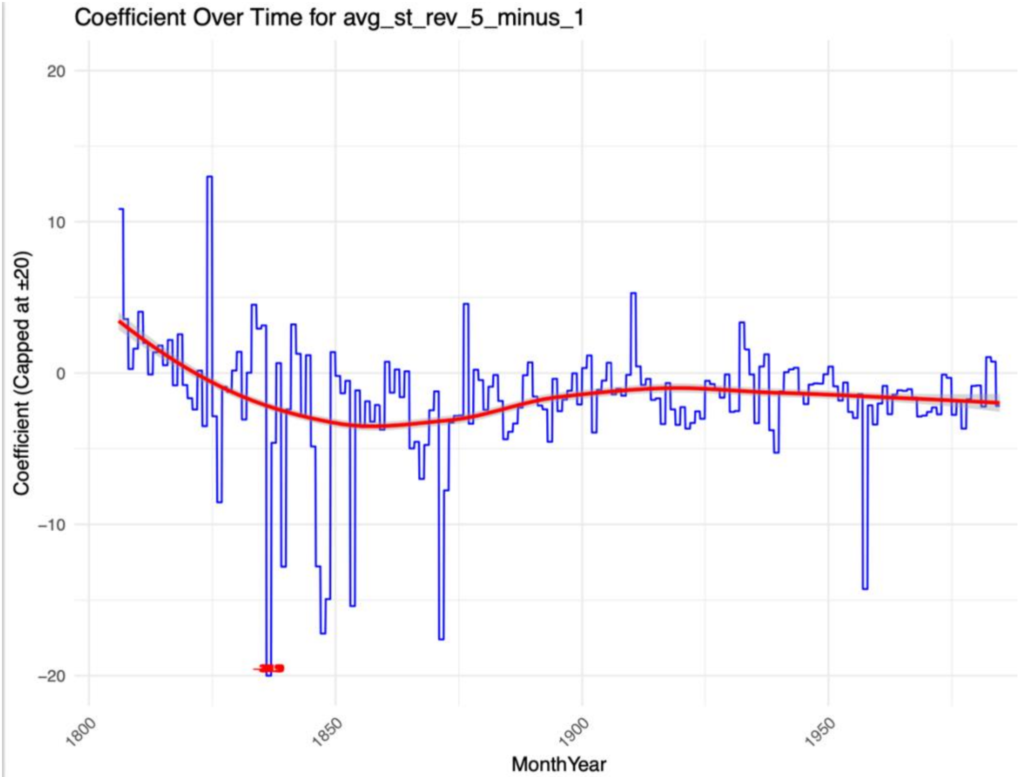

Coefficient Over Time for avg_dividend_yield_percentile_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

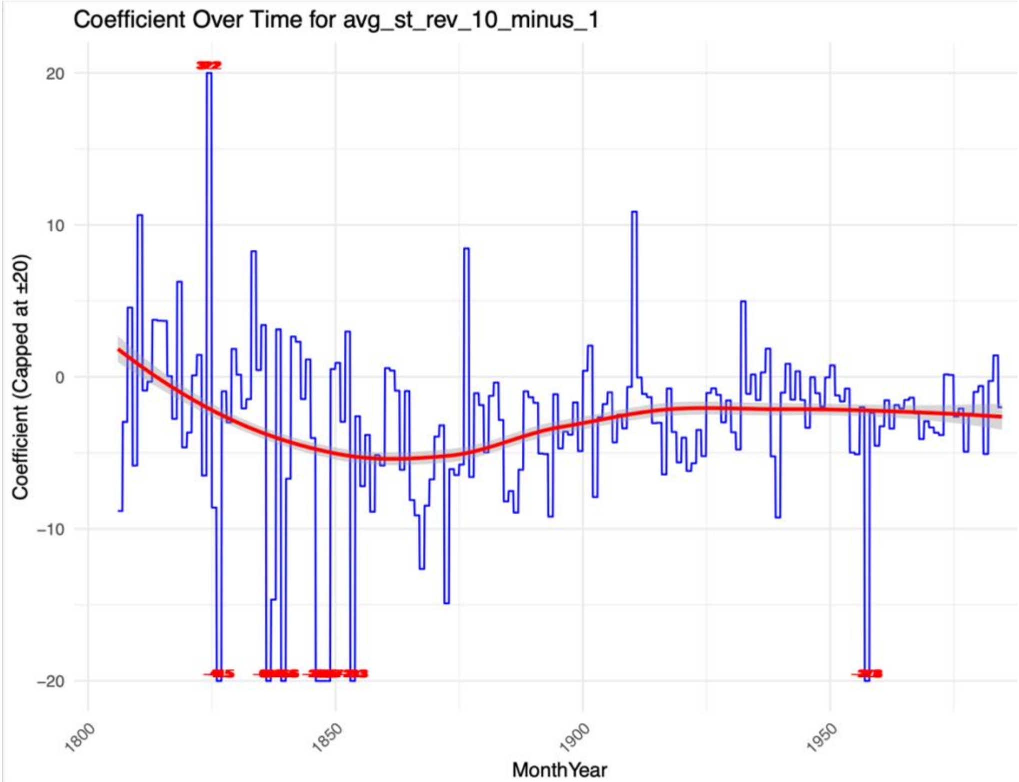

Coefficient Over Time for avg_dividend_yield_percentile_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



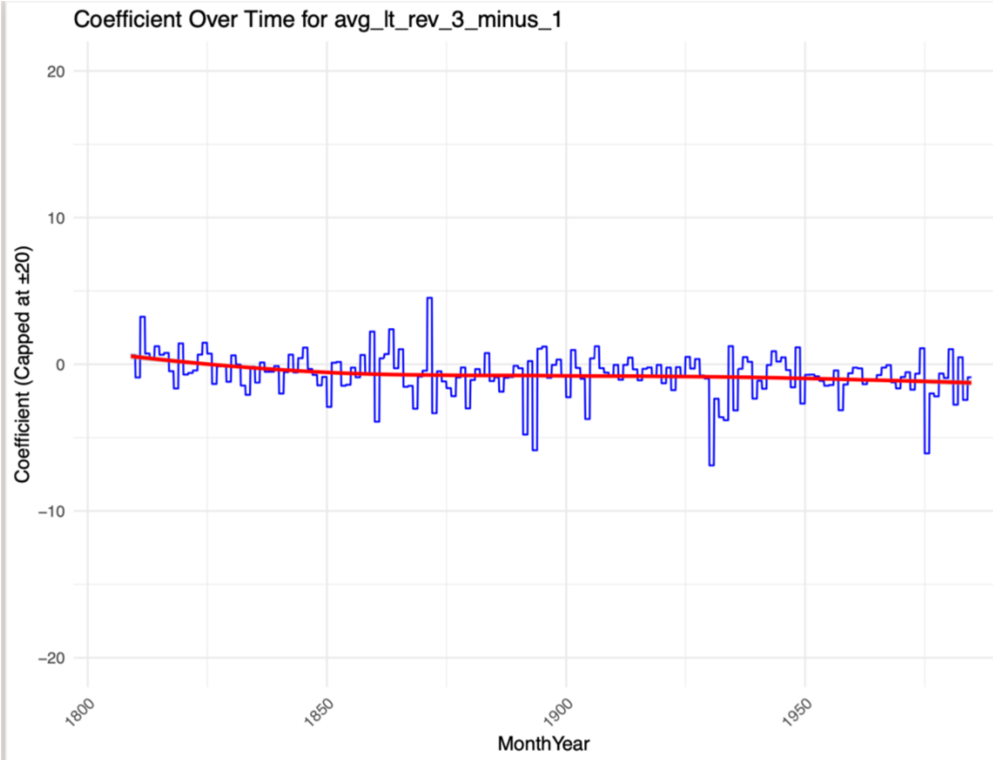
C.7 Short-term reversal

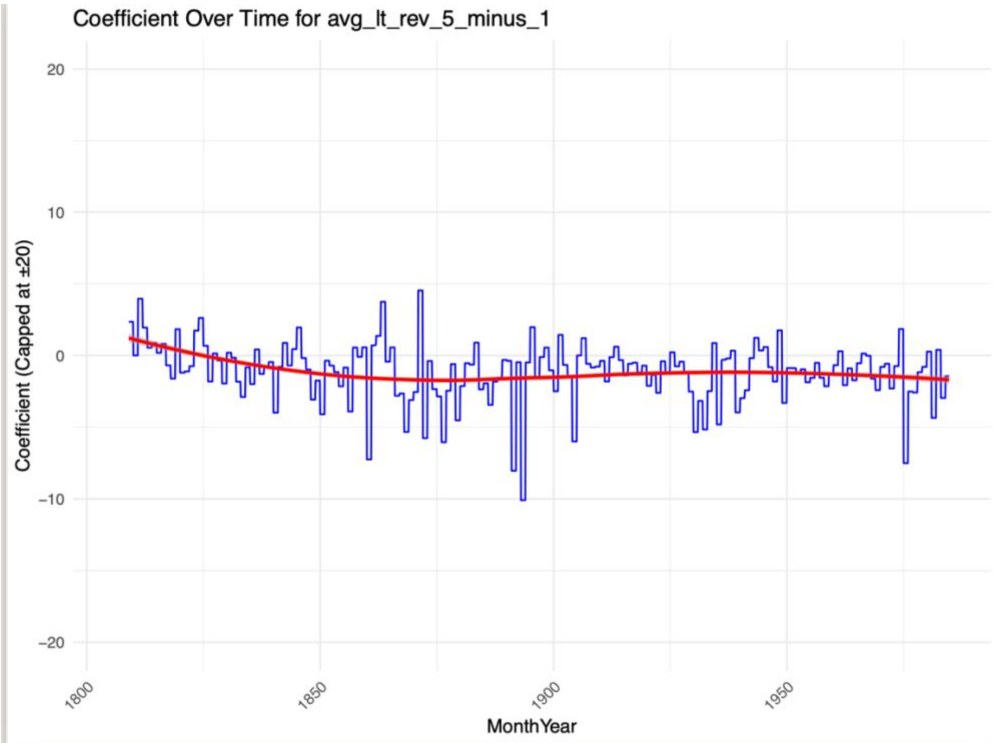


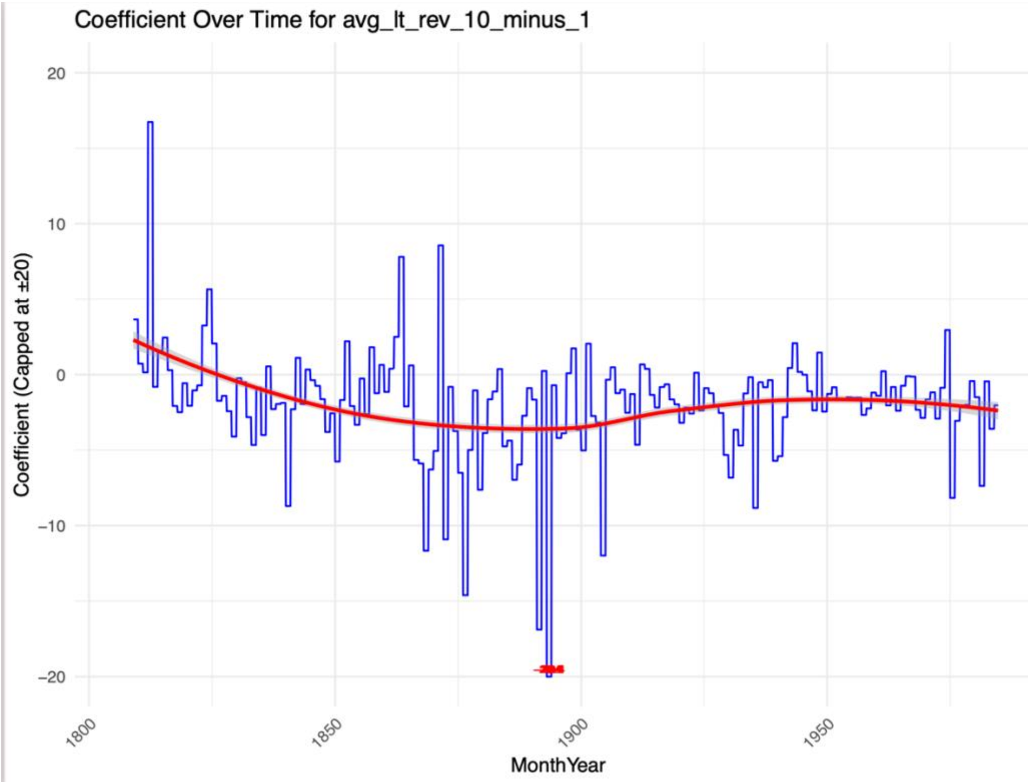




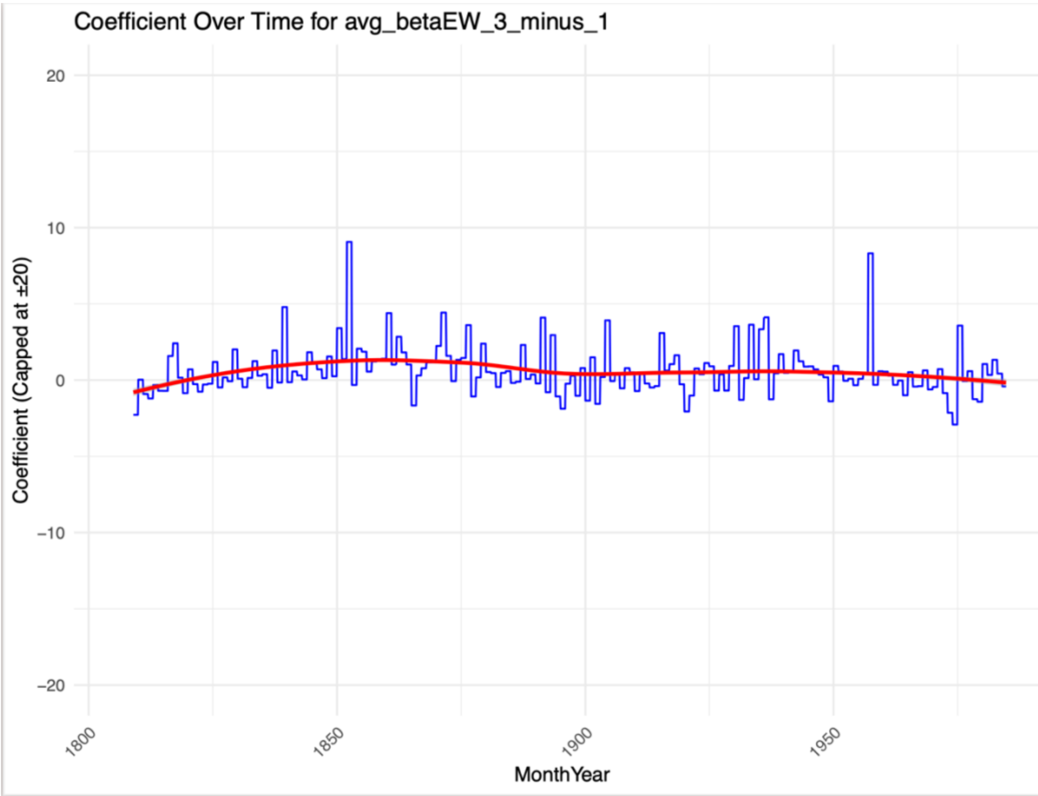
C.8 Long-term reversal

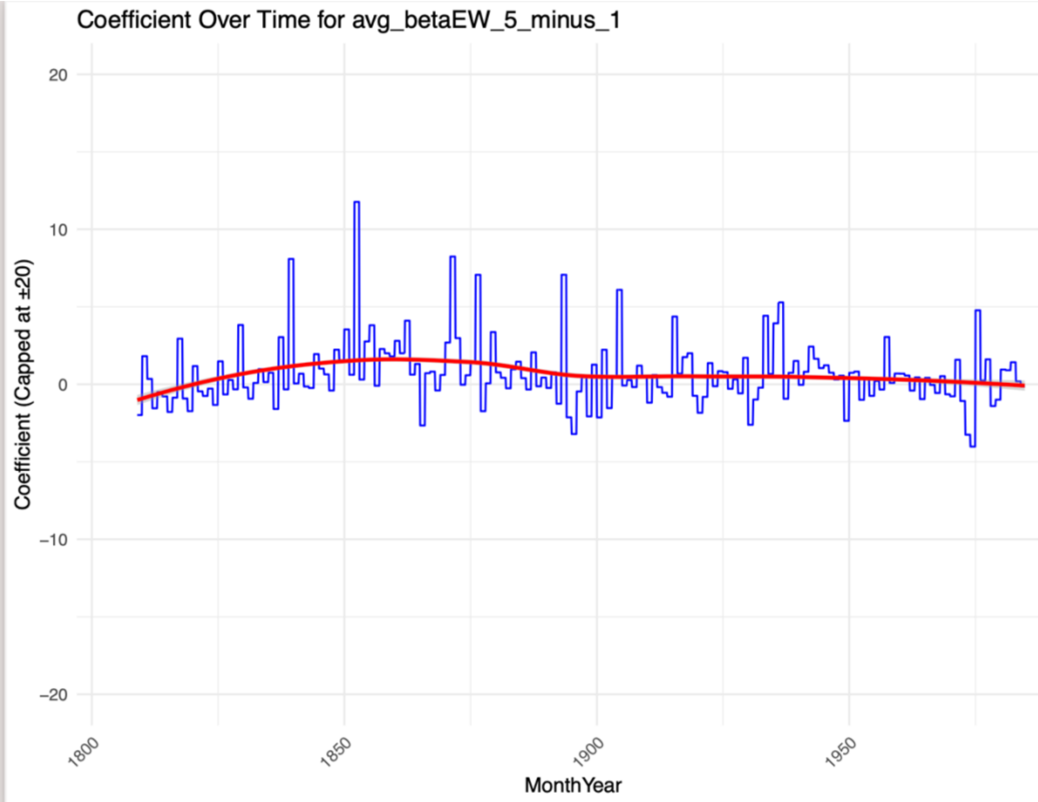

Coefficient Over Time for avg_lt_rev_3_minus_1
20
10
0
−10
−20
Coefficient (Capped at ±20)
1800
1850
1900
1950
MonthYear

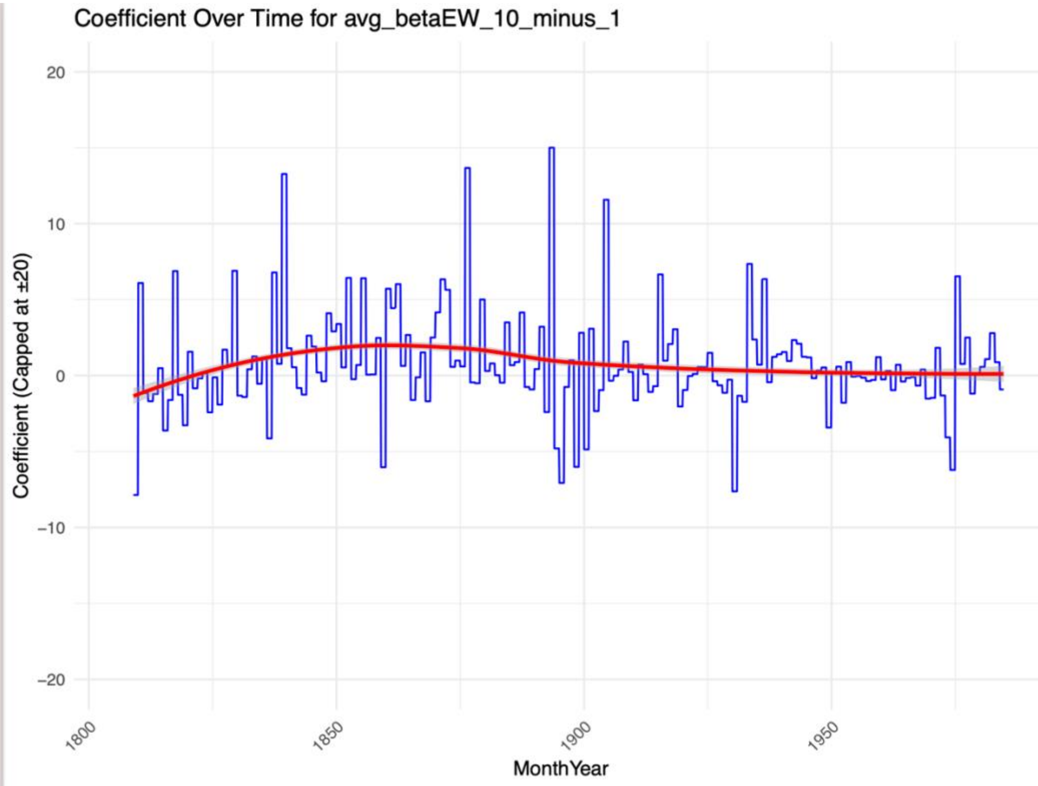

Coefficient Over Time for avg_lt_rev_5_minus_1
20
10
0
−10
−20
Coefficient (Capped at ±20)
1800
1850
1900
1950
MonthYear



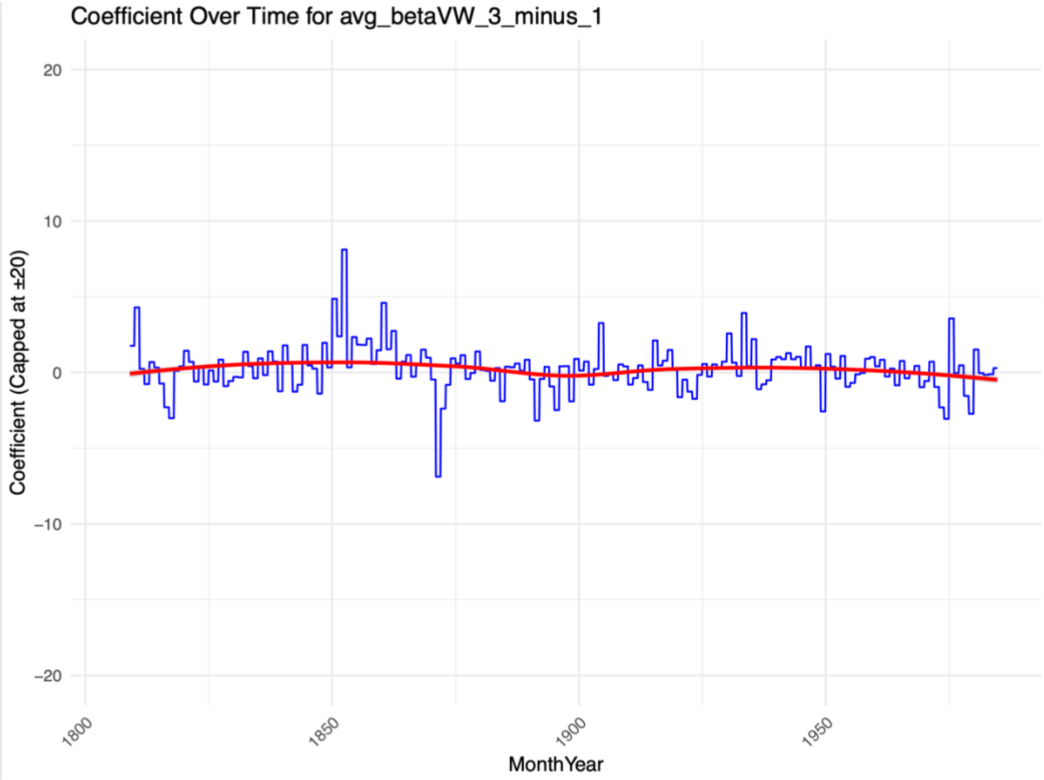
C.9 Equal-weighted market beta

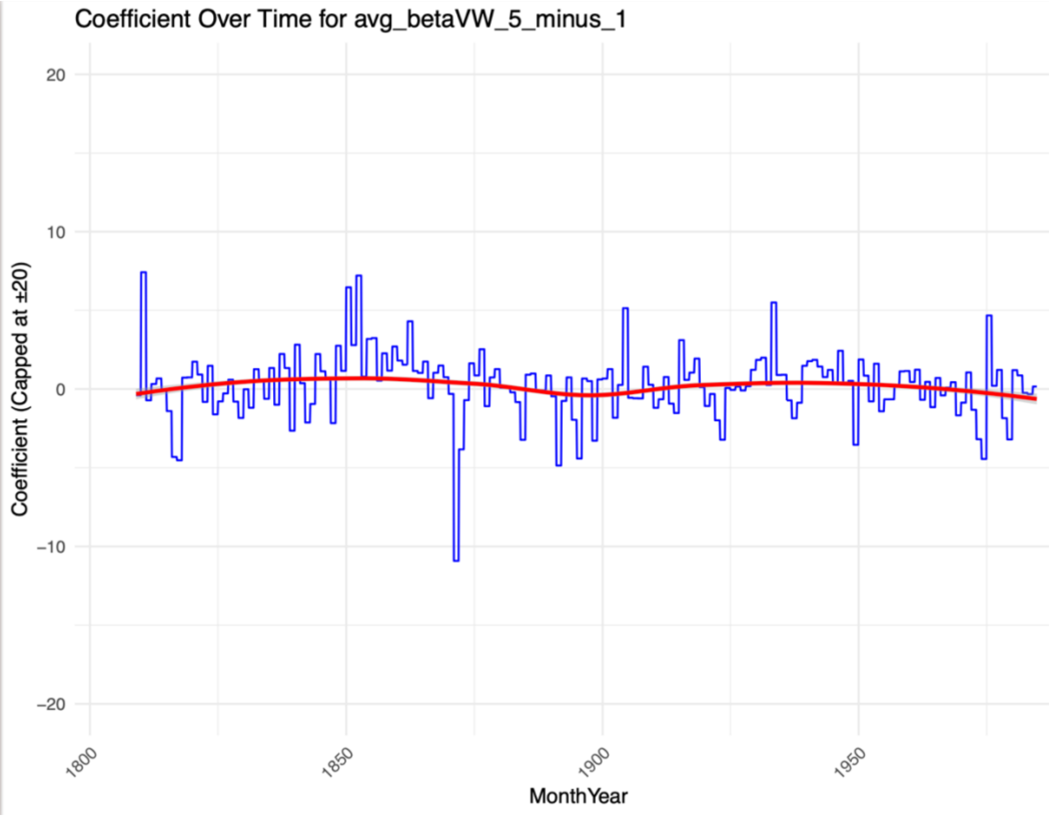


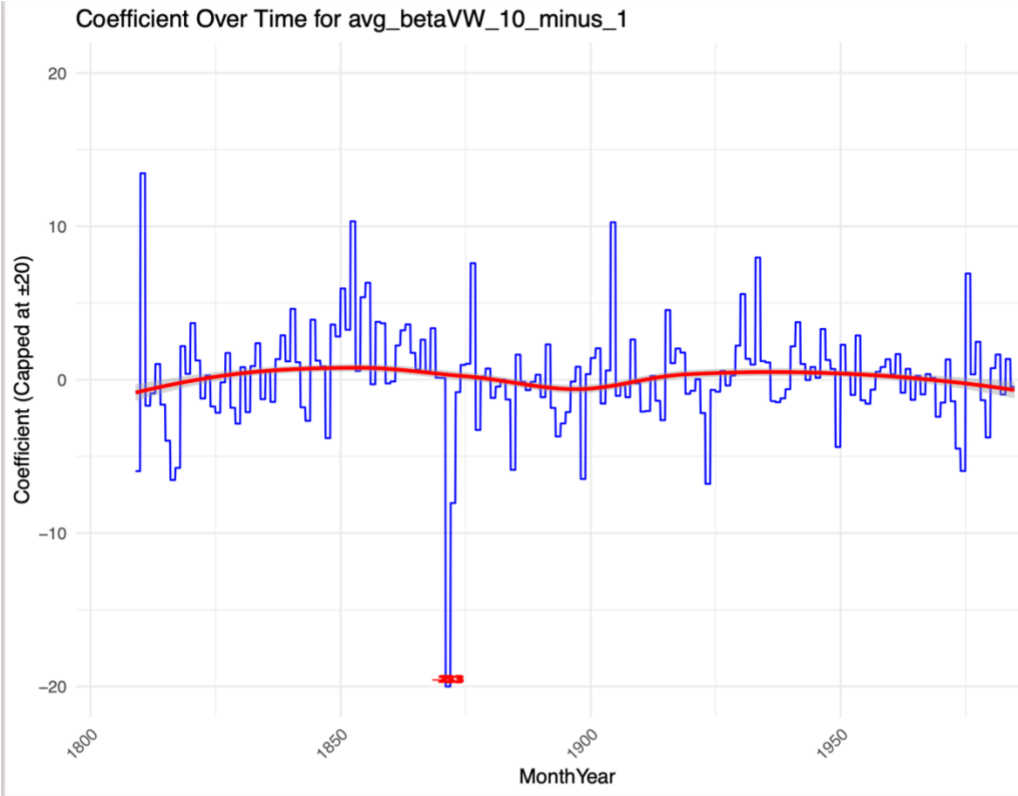




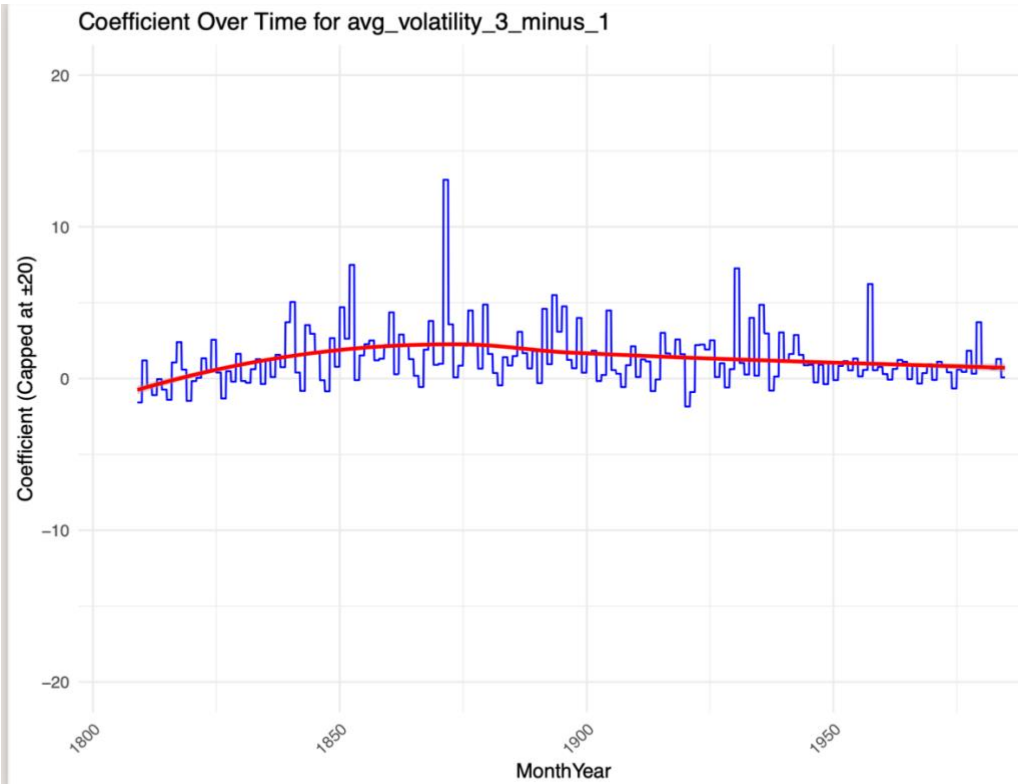
C.10 Value-weighted market beta

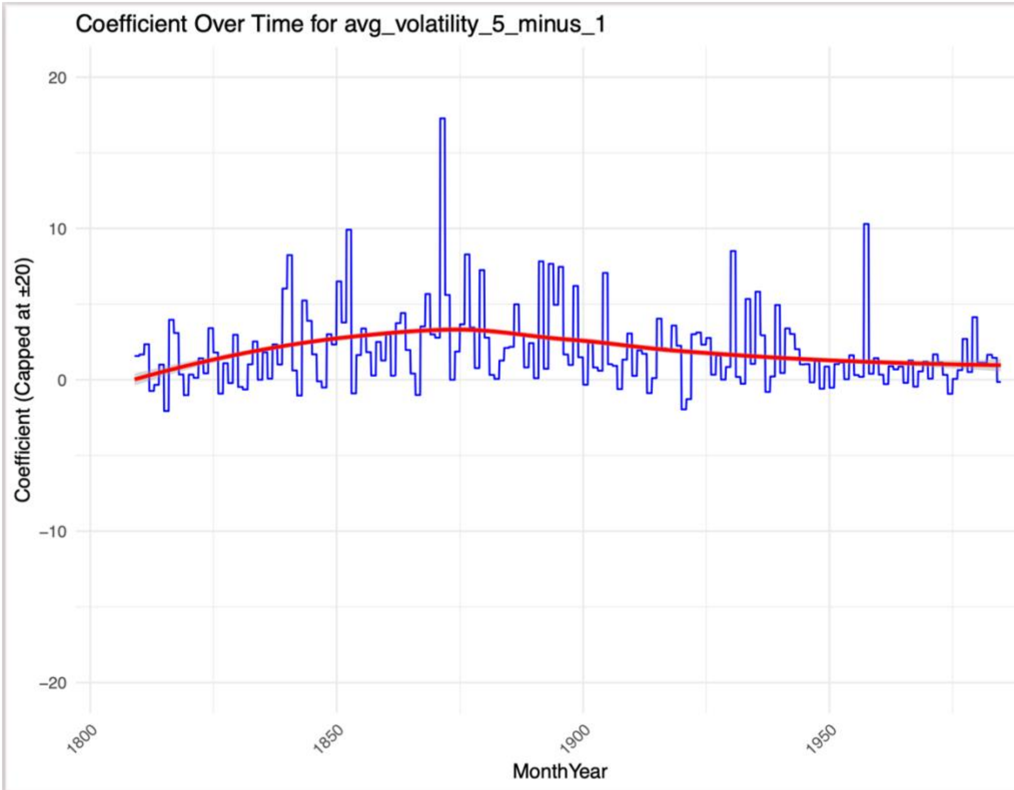

Coefficient Over Time for avg_betaVW_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

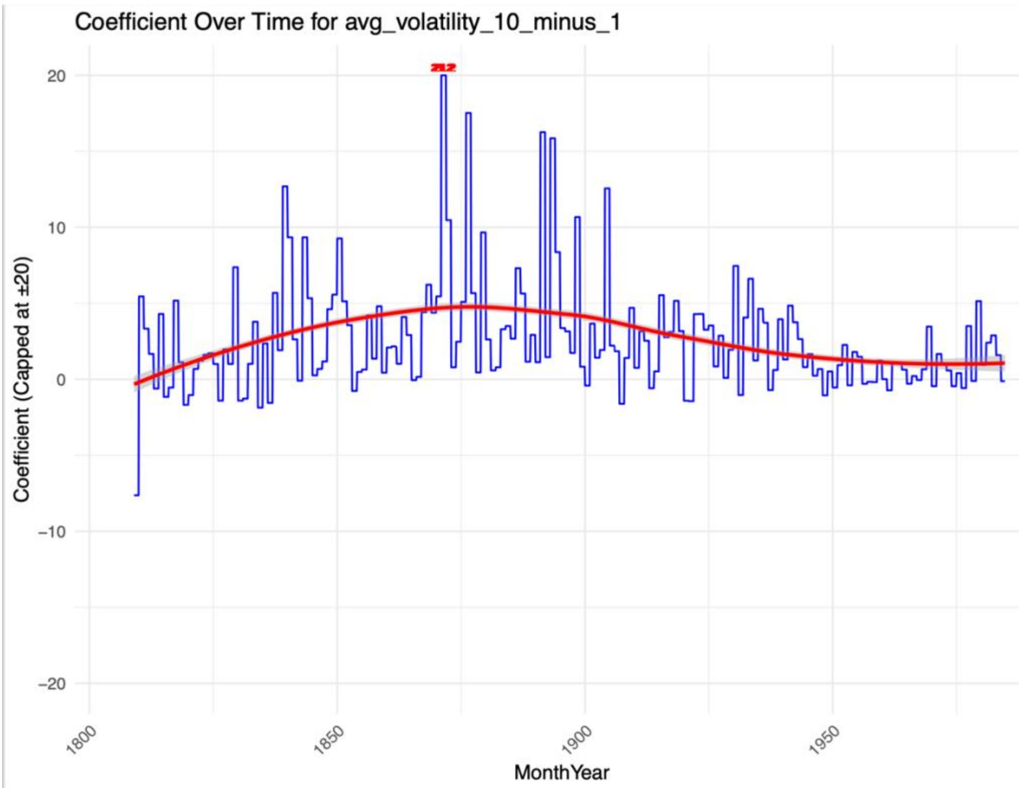

Coefficient Over Time for avg_betaVW_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



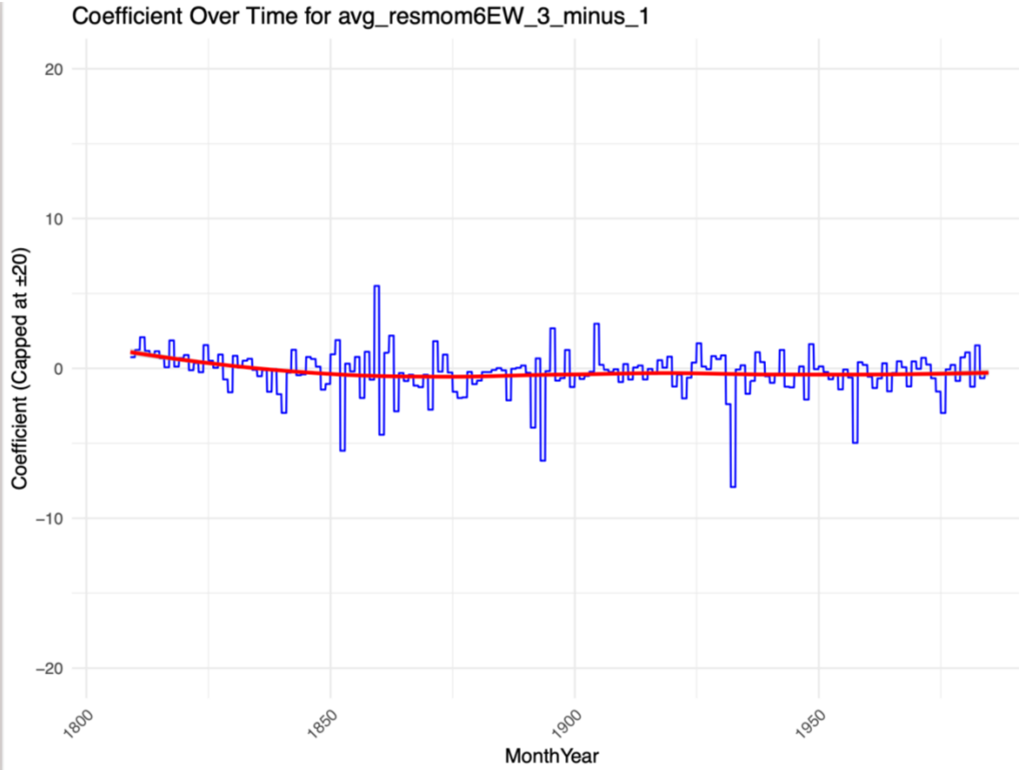
C.11 Volatility

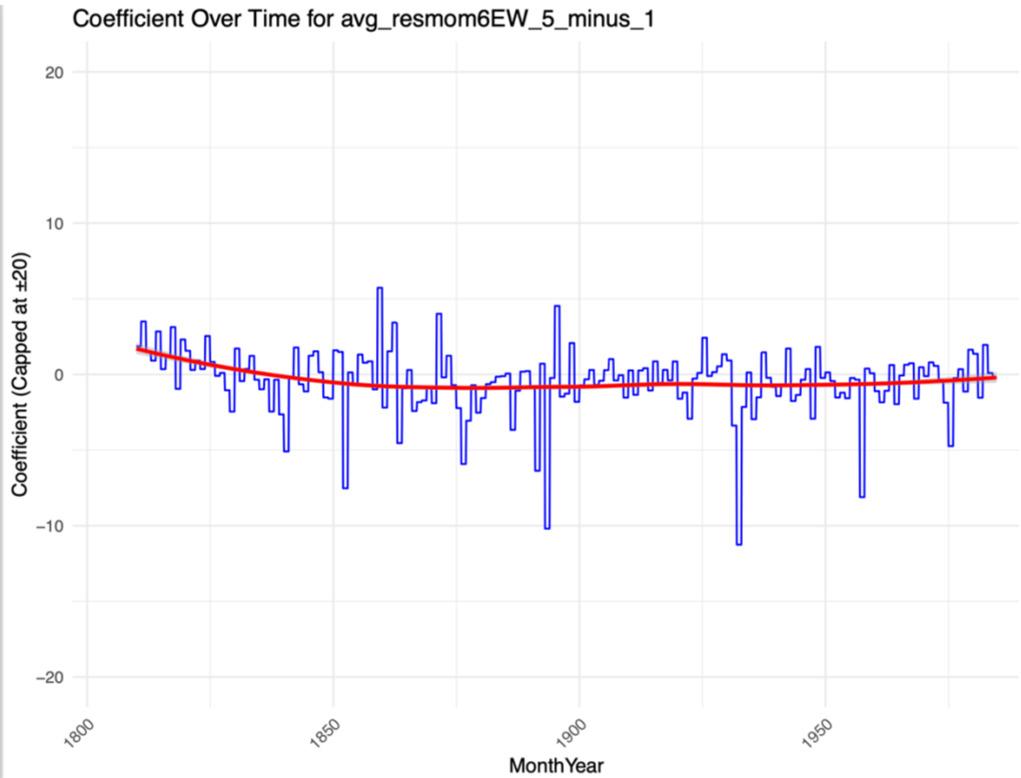


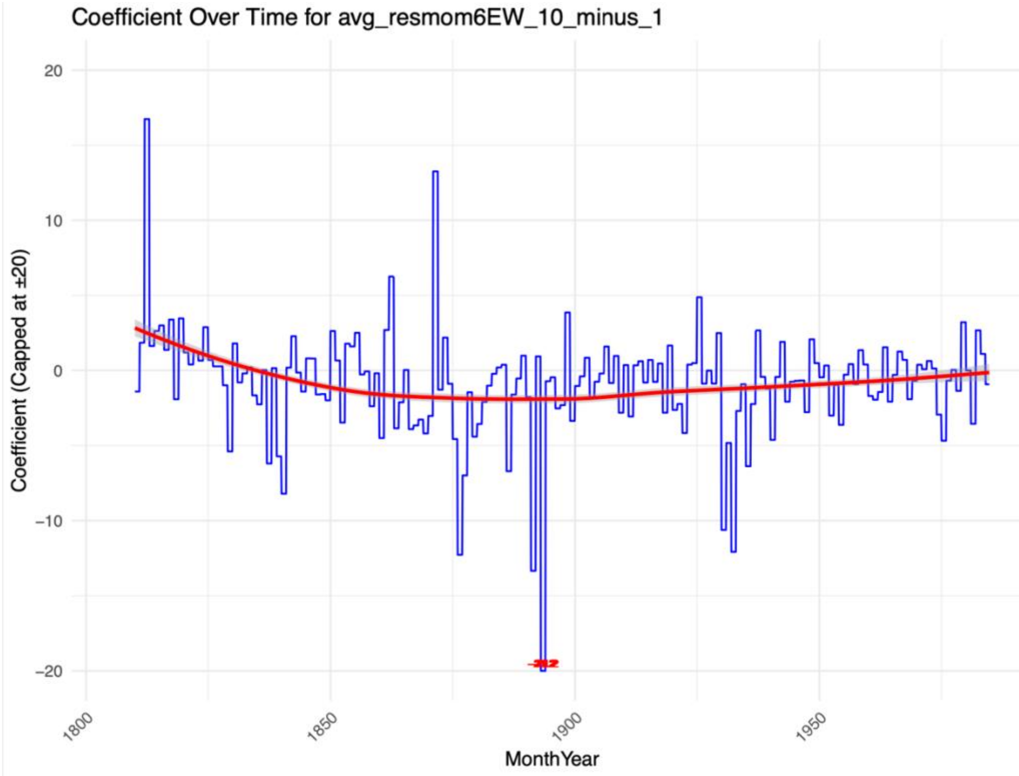




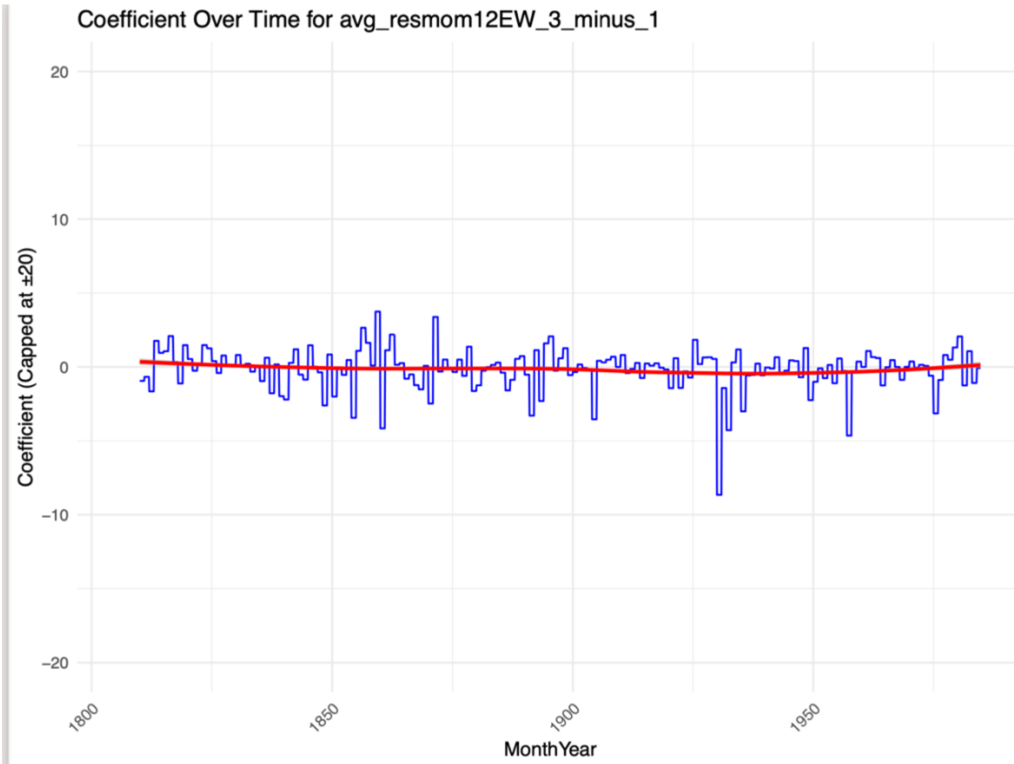
C.12 6-month equal-weighted CAPM residual momentum

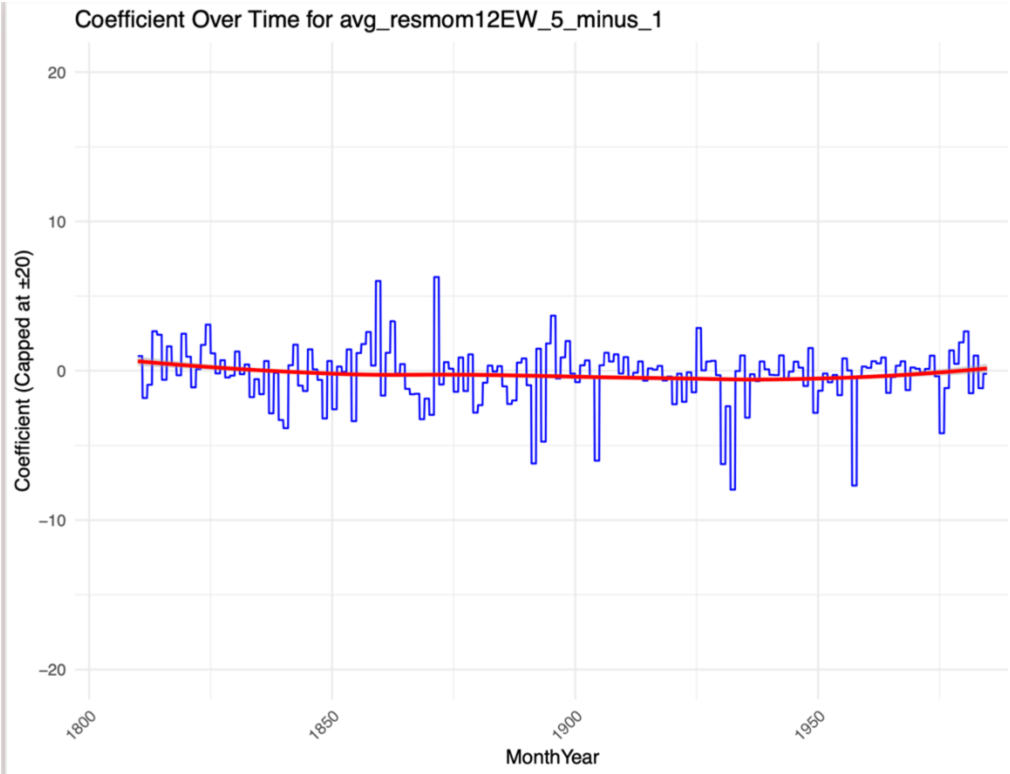

Coefficient Over Time for avg_resmom6EW_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

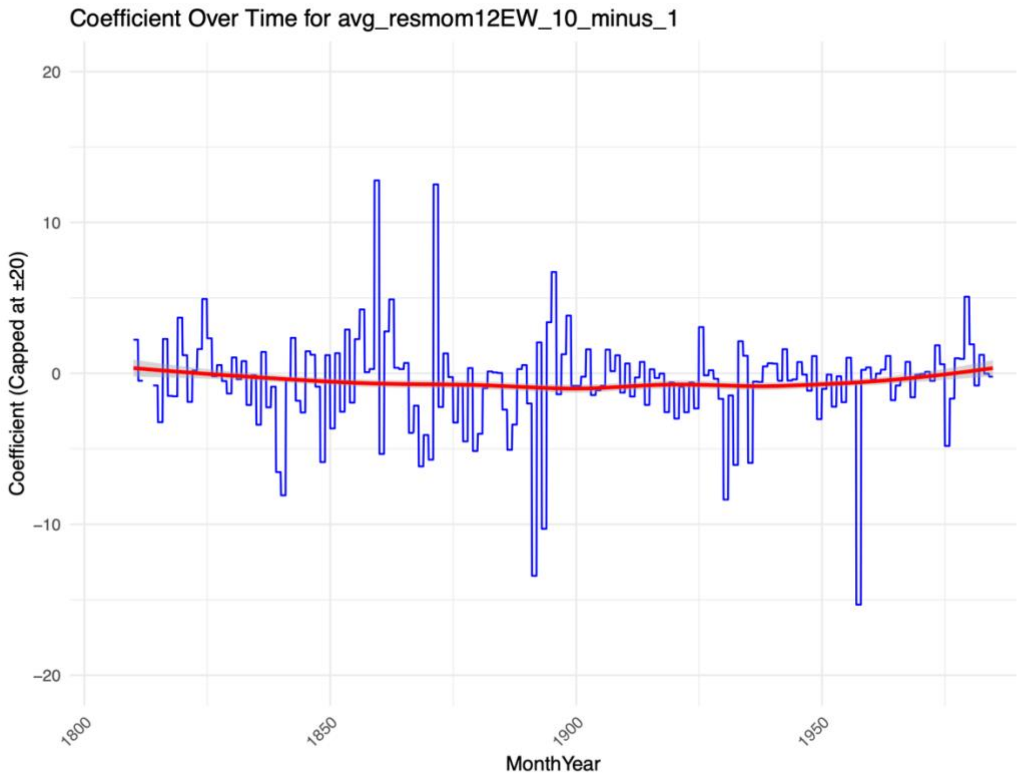

Coefficient Over Time for avg_resmom6EW_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



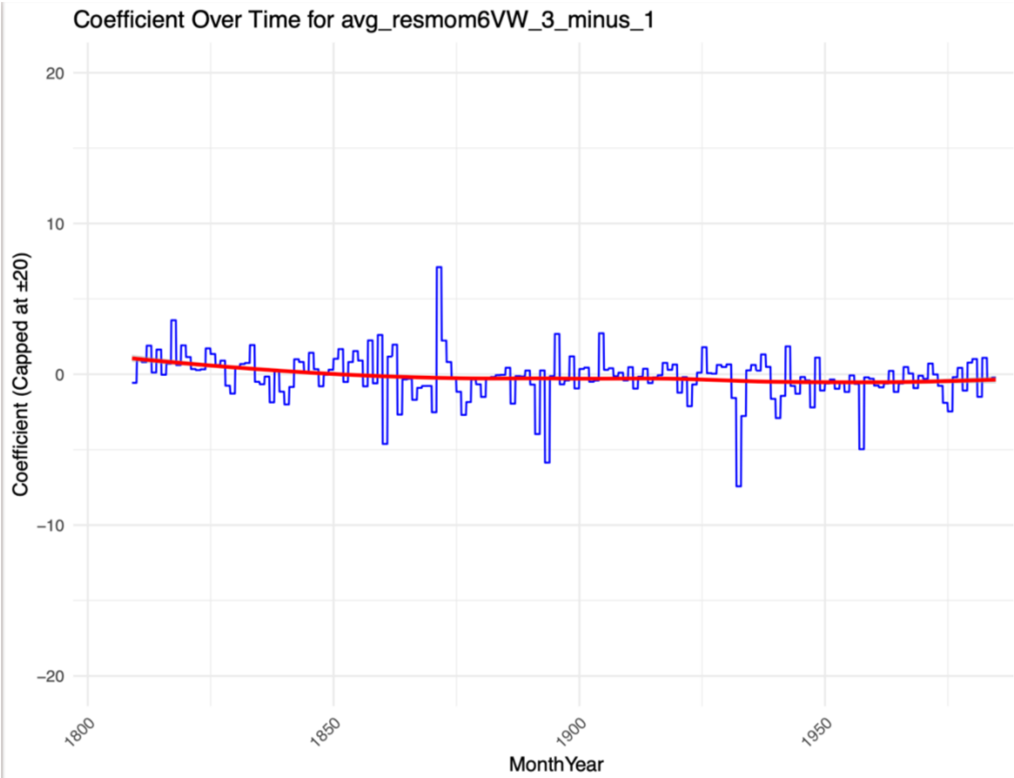
C.13 12-month equal-weighted CAPM residual momentum

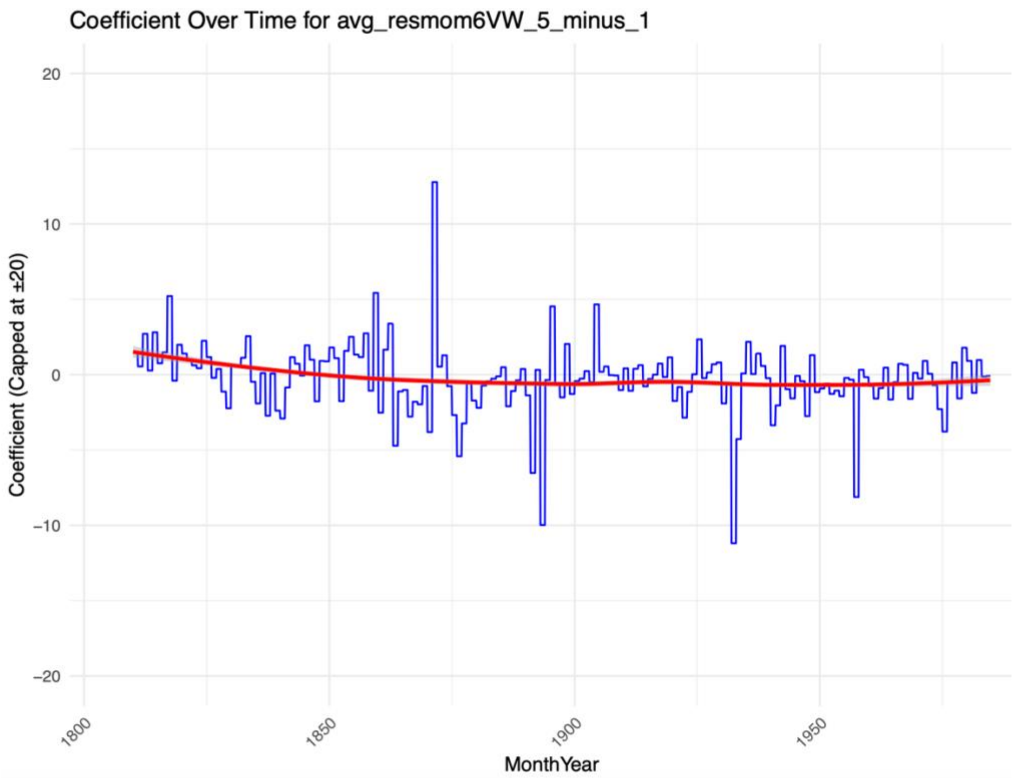


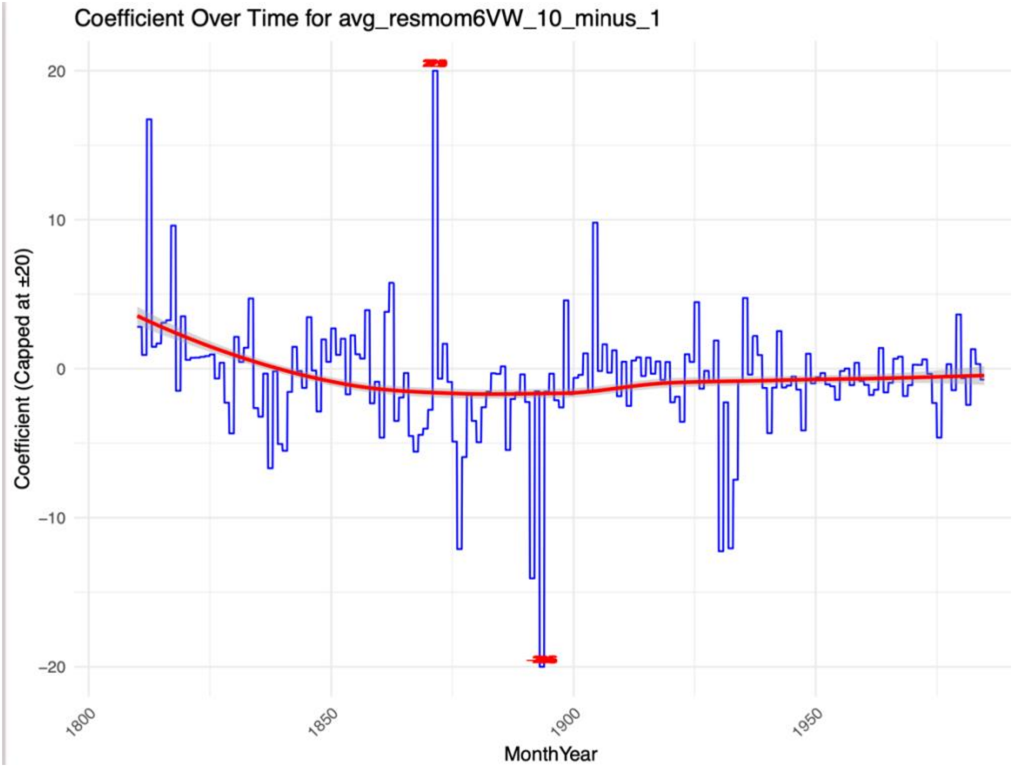




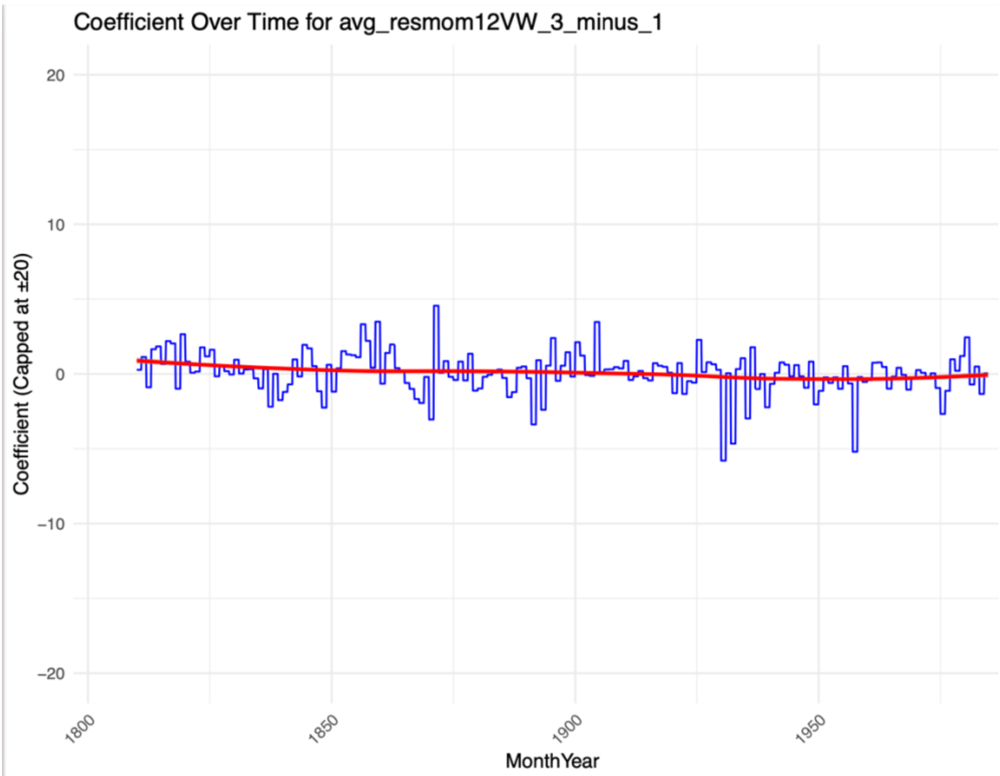
C.14 6-month value-weighted CAPM residual momentum

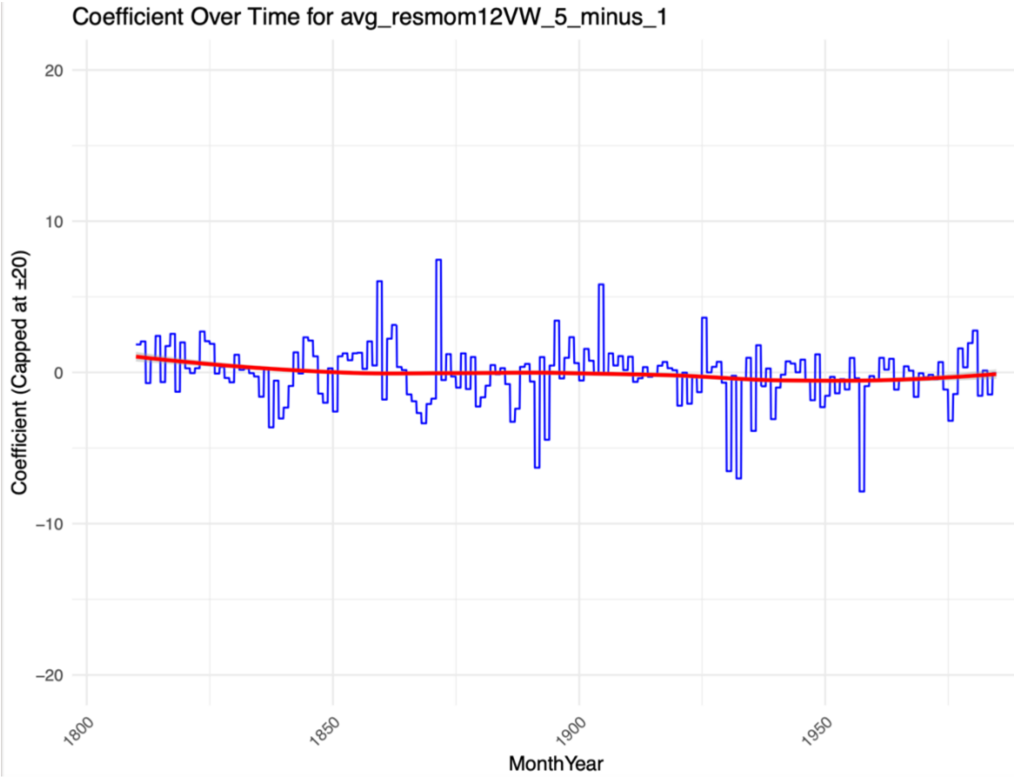

Coefficient Over Time for avg_resmom6VW_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

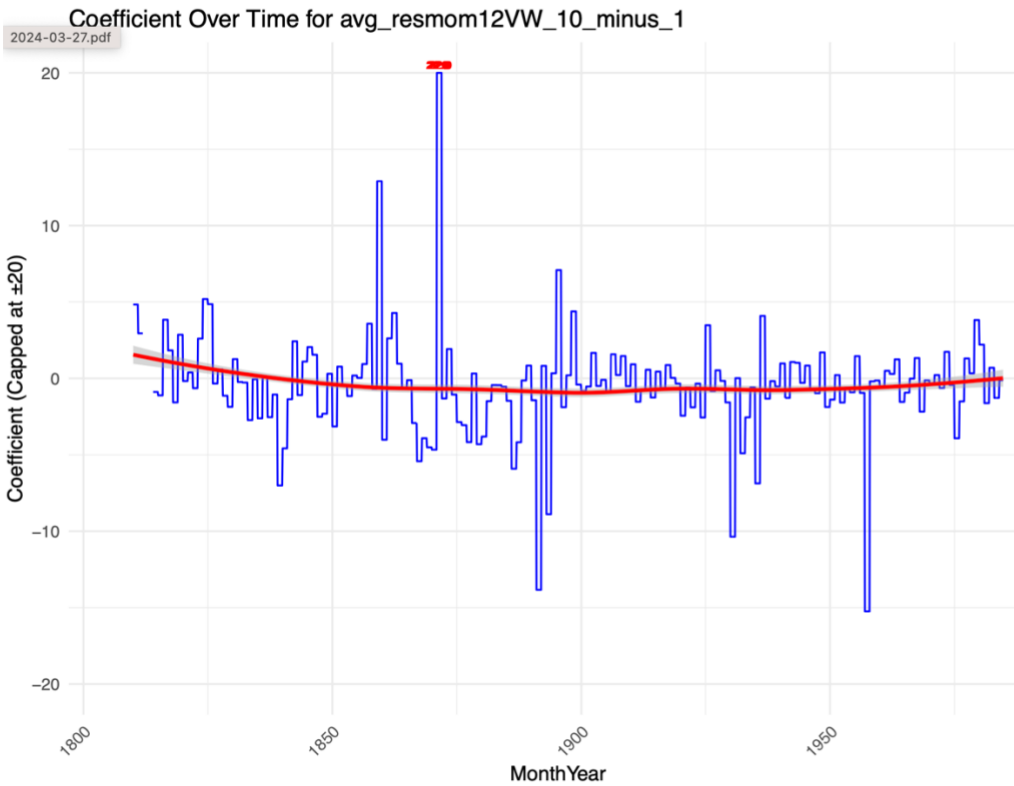

Coefficient Over Time for avg_resmom6VW_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



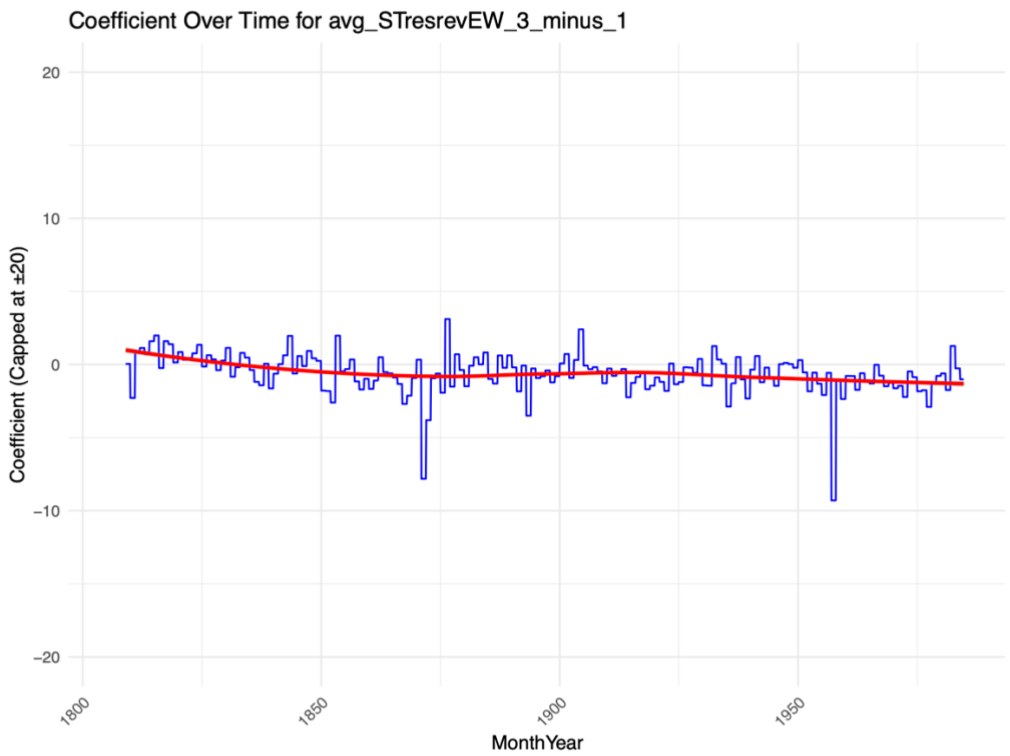
C.15 12-month value-weighted CAPM residual momentum



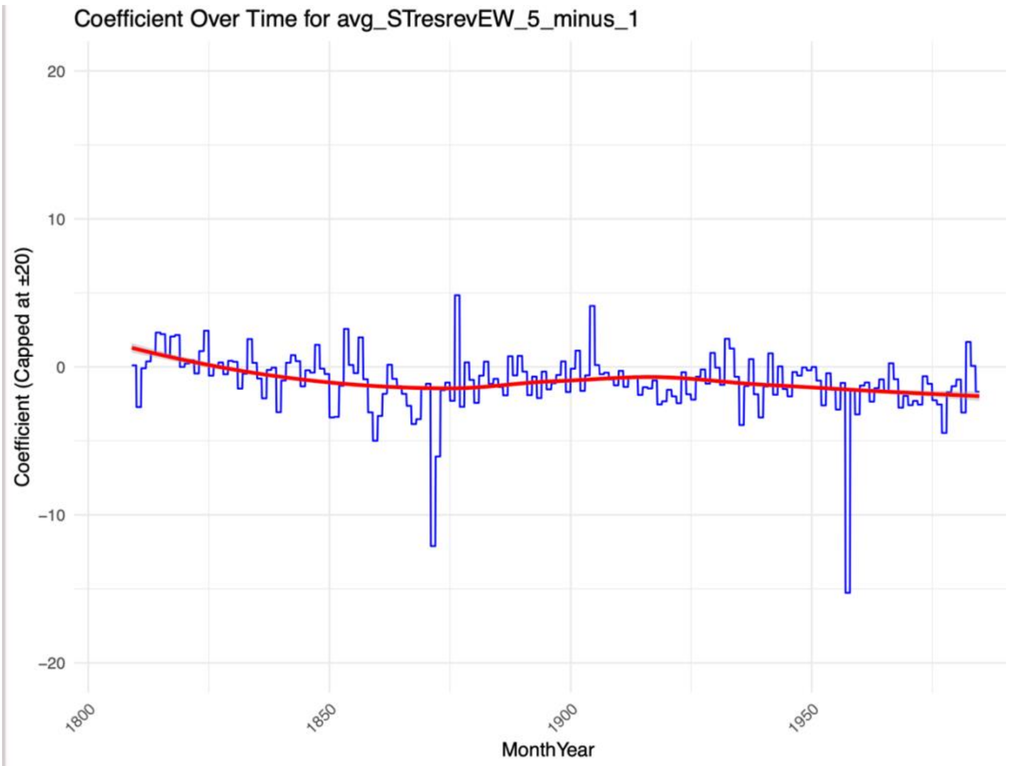




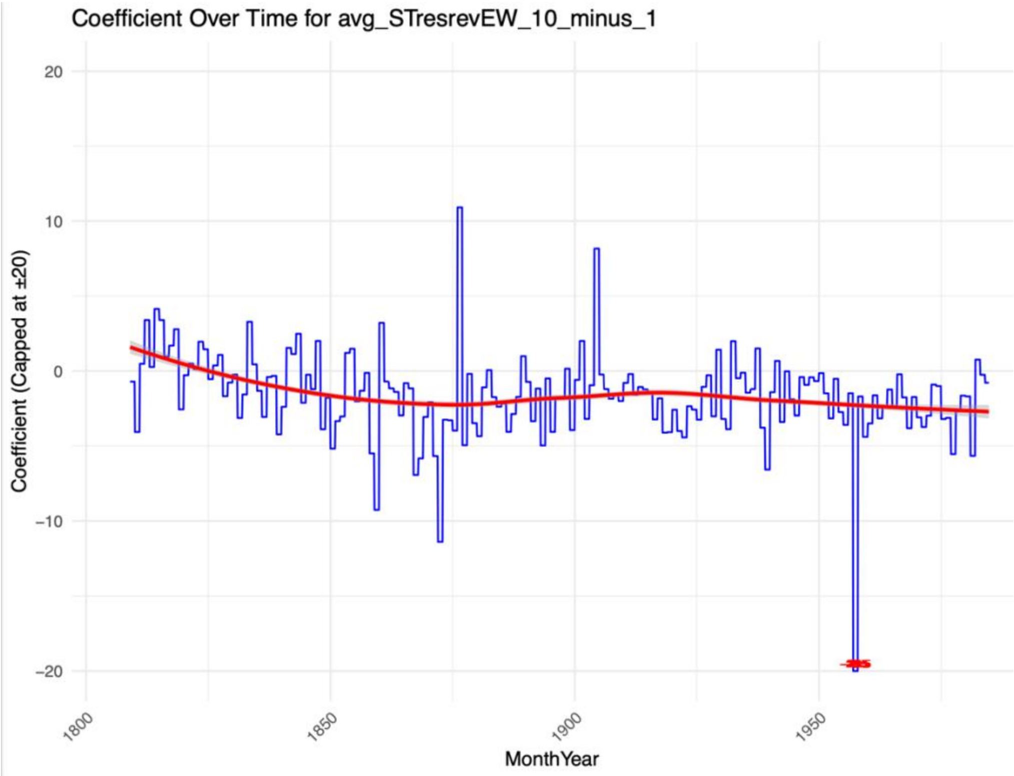
C.16 Short-term equal-weighted residual reversal



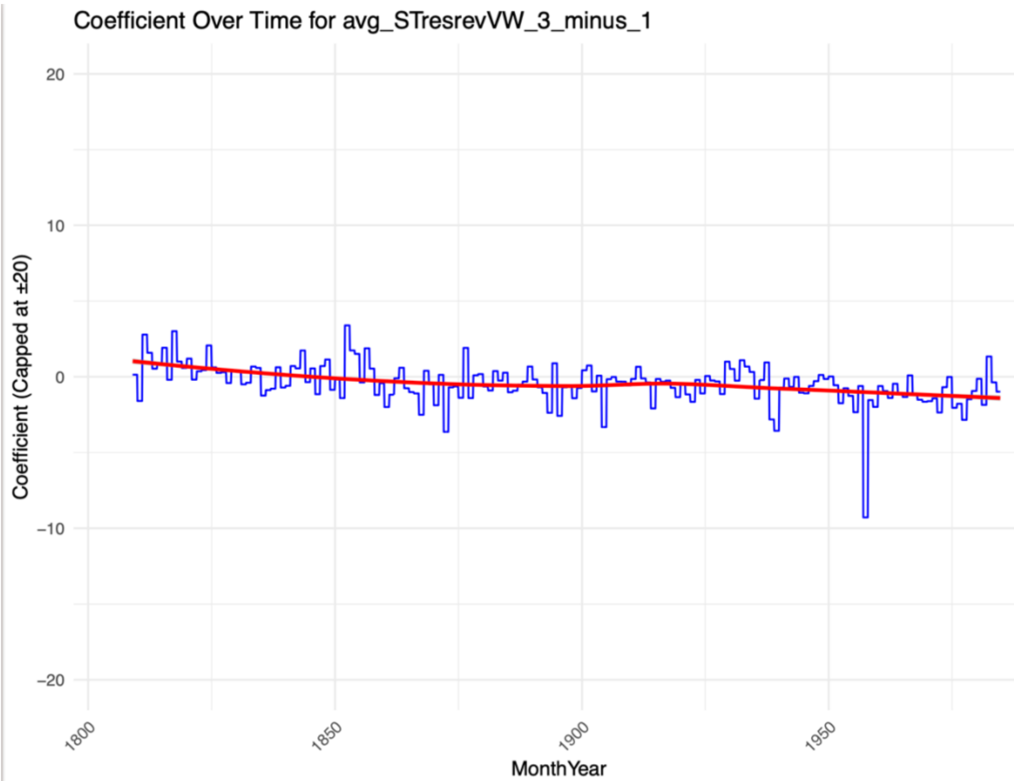
Coefficient Over Time for avg_STresrevEW_3_minus_1
20
10
0
−10
−20
Coefficient (Capped at ±20)
1800
1850
1900
1950
MonthYear

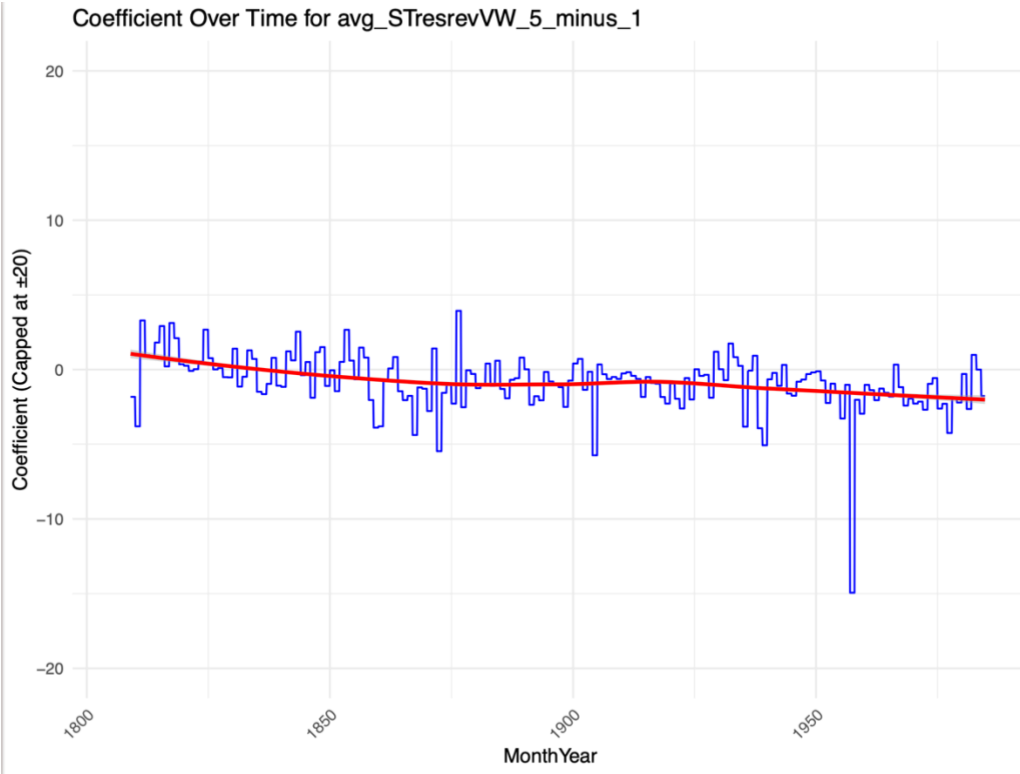


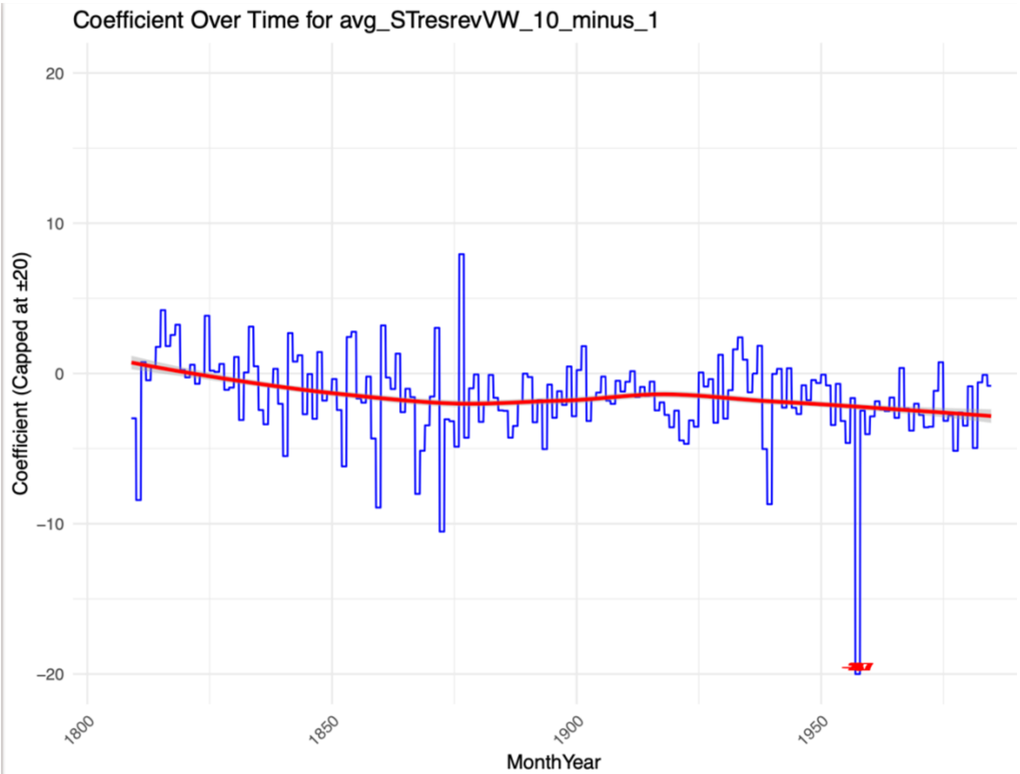
Coefficient Over Time for avg_STresrevEW_5_minus_1
20
10
0
−10
−20
Coefficient (Capped at ±20)
1800
1850
1900
1950
MonthYear



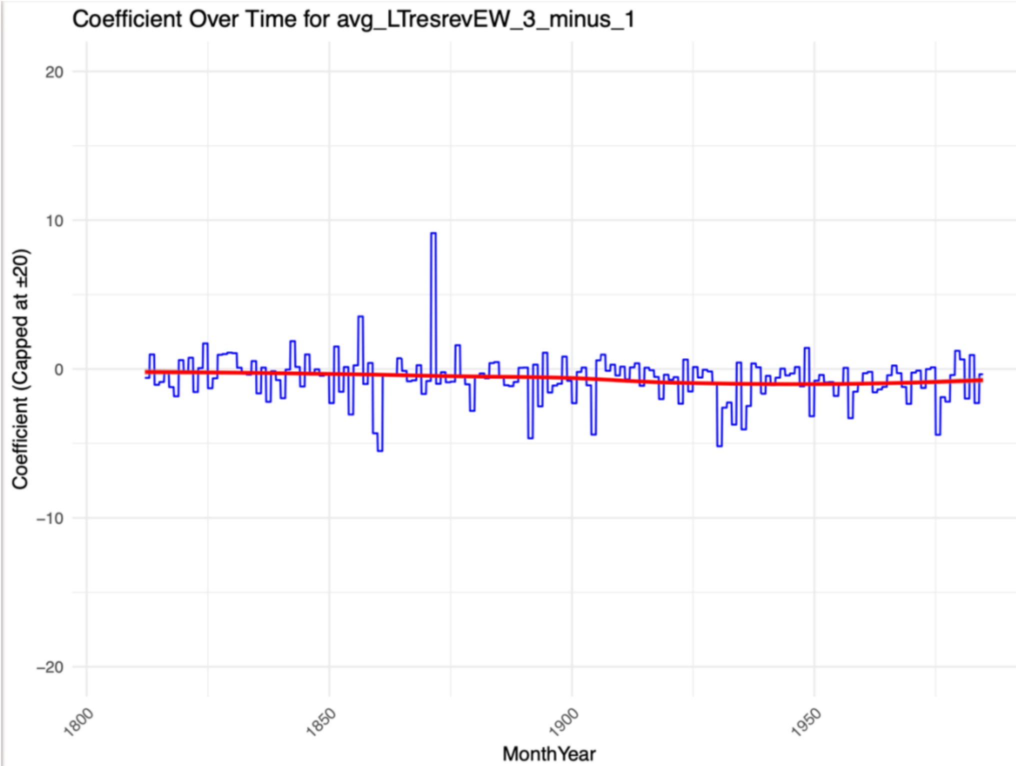
C.17 Short-term value-weighted CAPM residual momentum



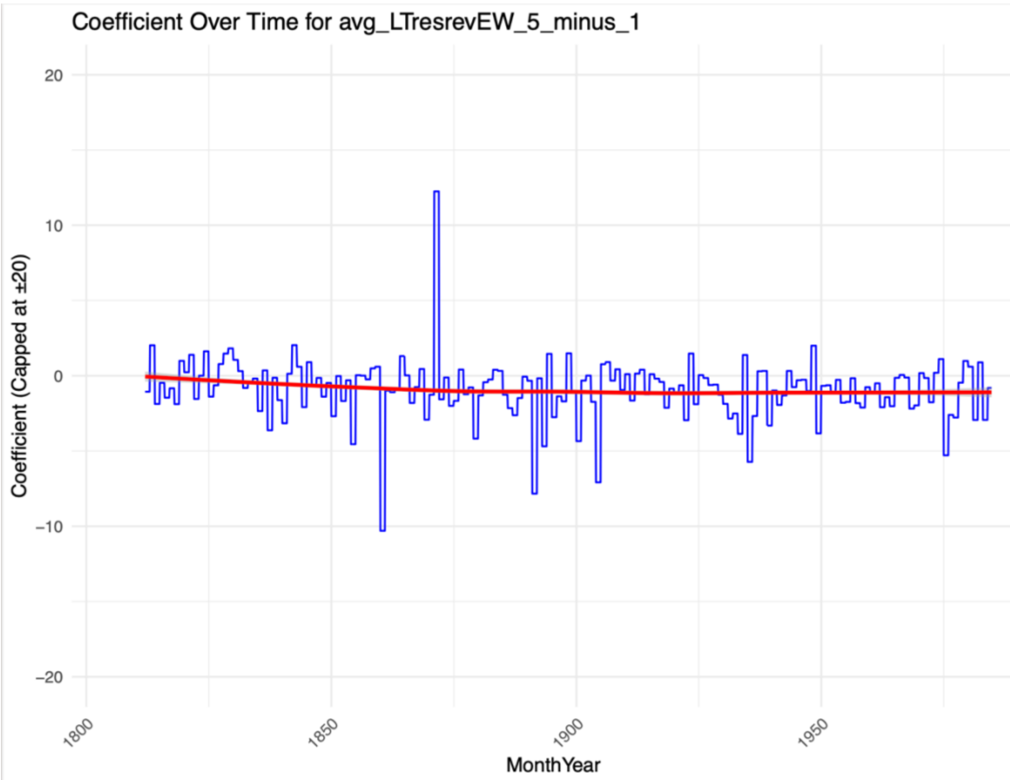




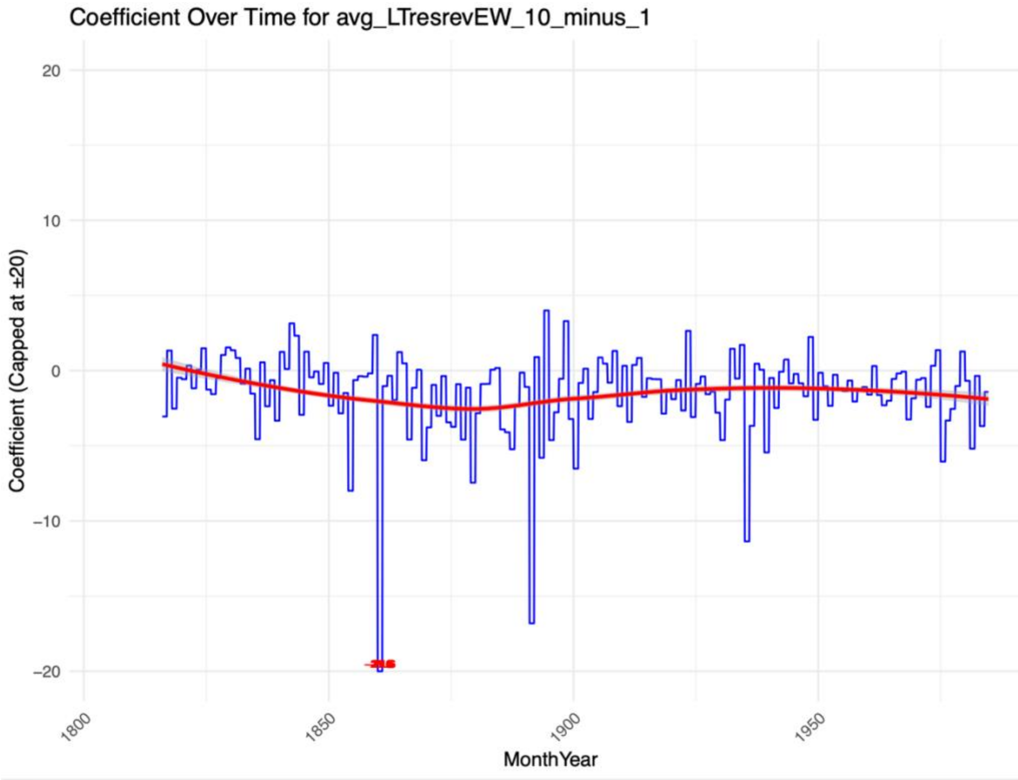
C.18 Long-term equal-weighted CAPM residual reversal



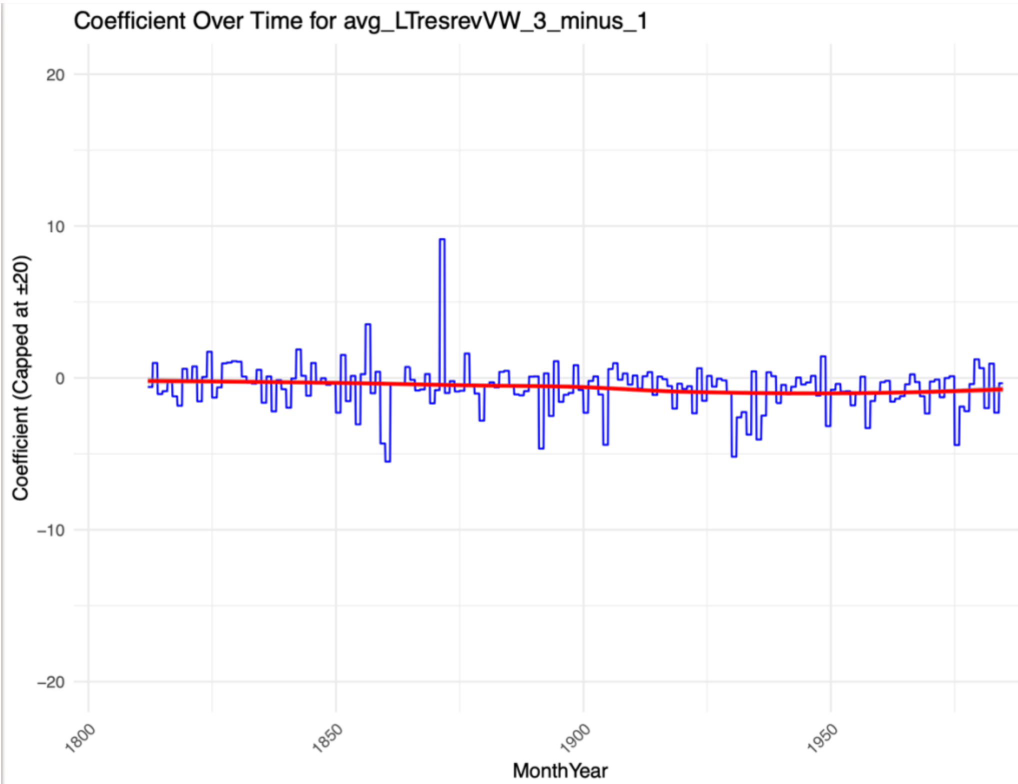
Coefficient Over Time for avg_LTresrevEW_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear

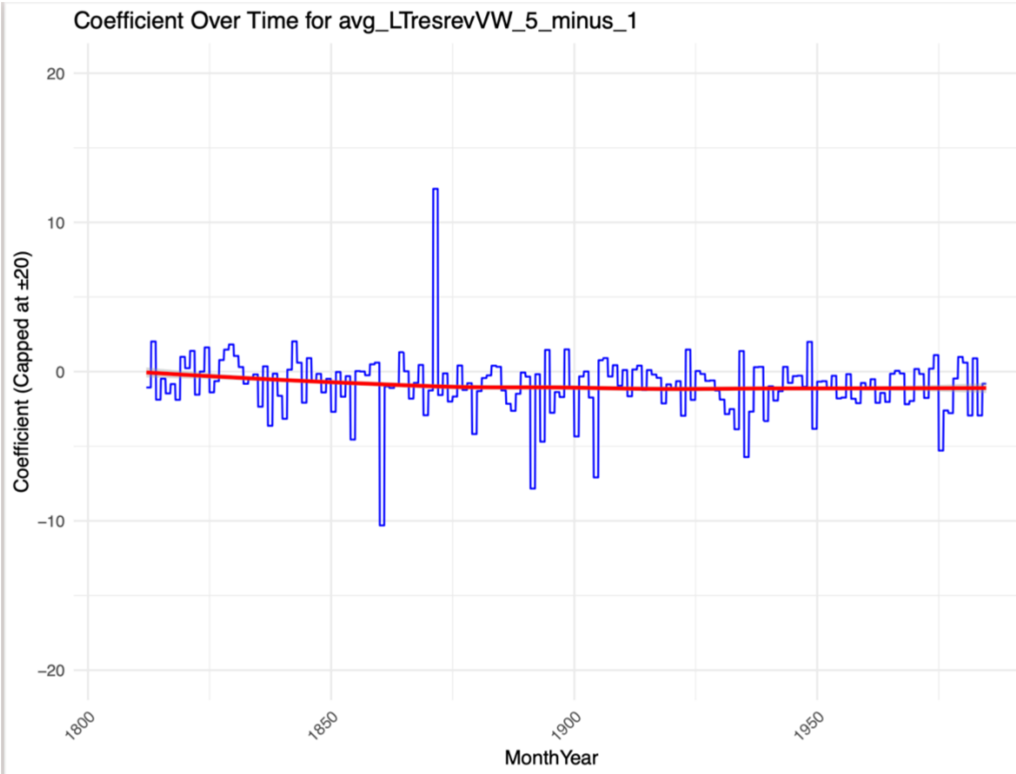


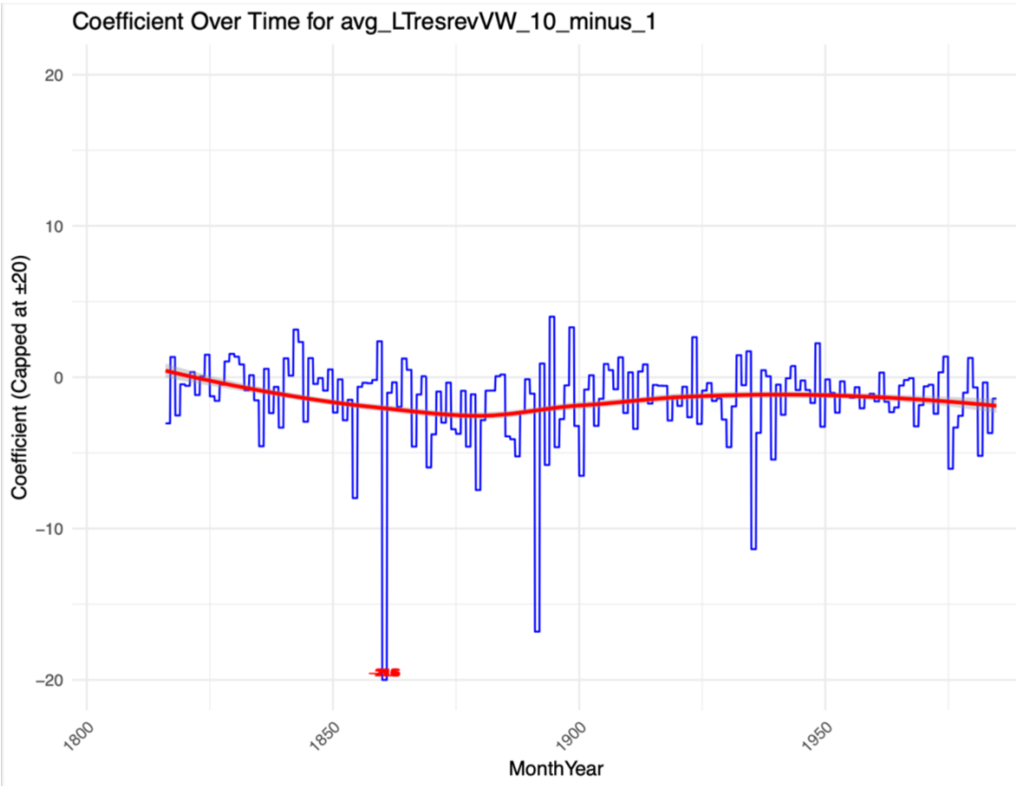
Coefficient Over Time for avg_LTresrevEW_5_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear



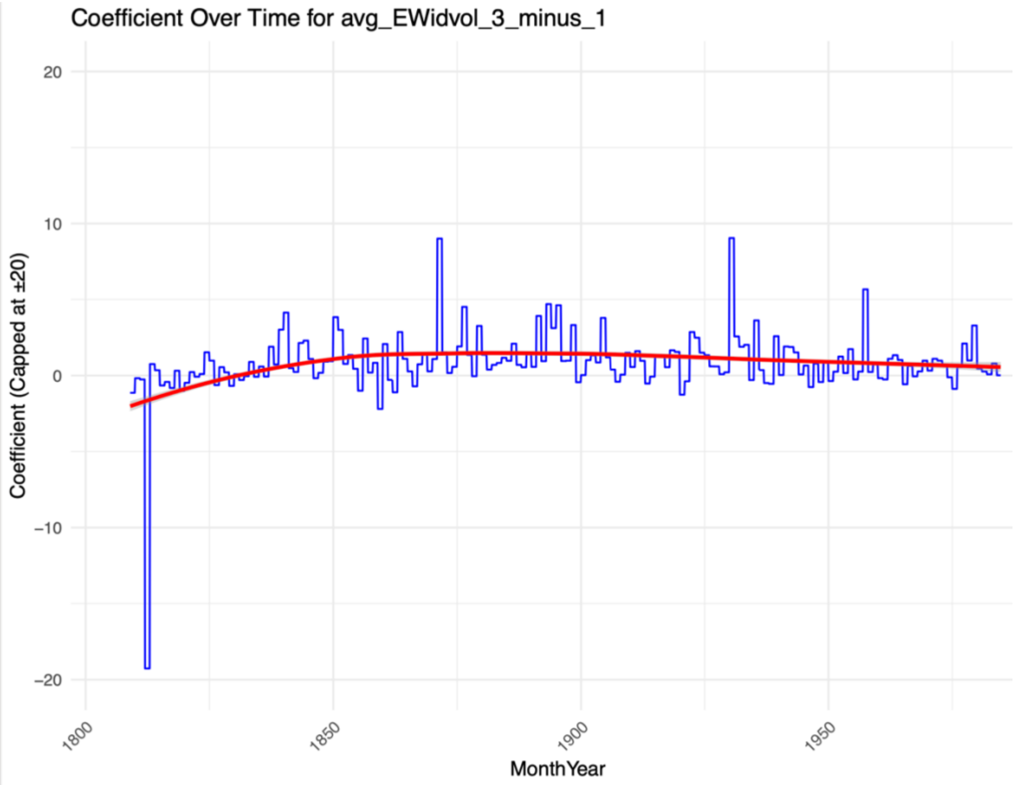
C.19 Long-term value-weighted CAPM residual reversal

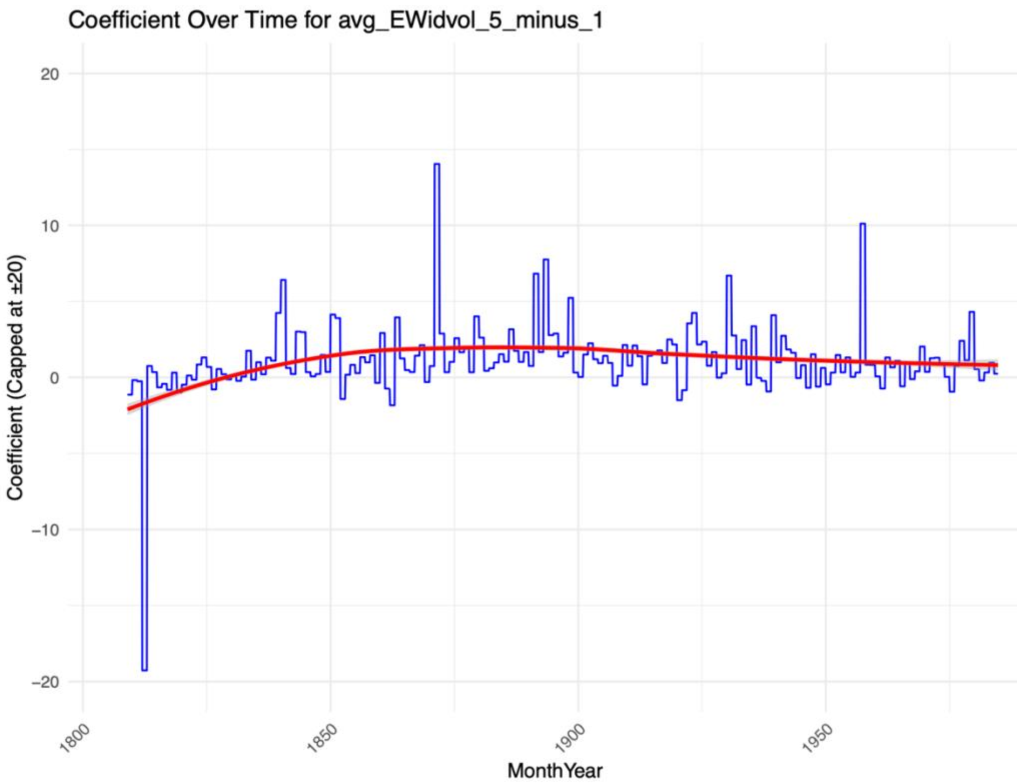






C.20 Equal-weighted idiosyncratic volatility


Coefficient Over Time for avg_EWidvol_3_minus_1
Coefficient (Capped at ±20)
20
10
0
−10
−20
1800
1850
1900
1950
MonthYear


Coefficient Over Time for avg_EWidvol_5_minus_1
Coefficient (Capped at ±20)
20
10
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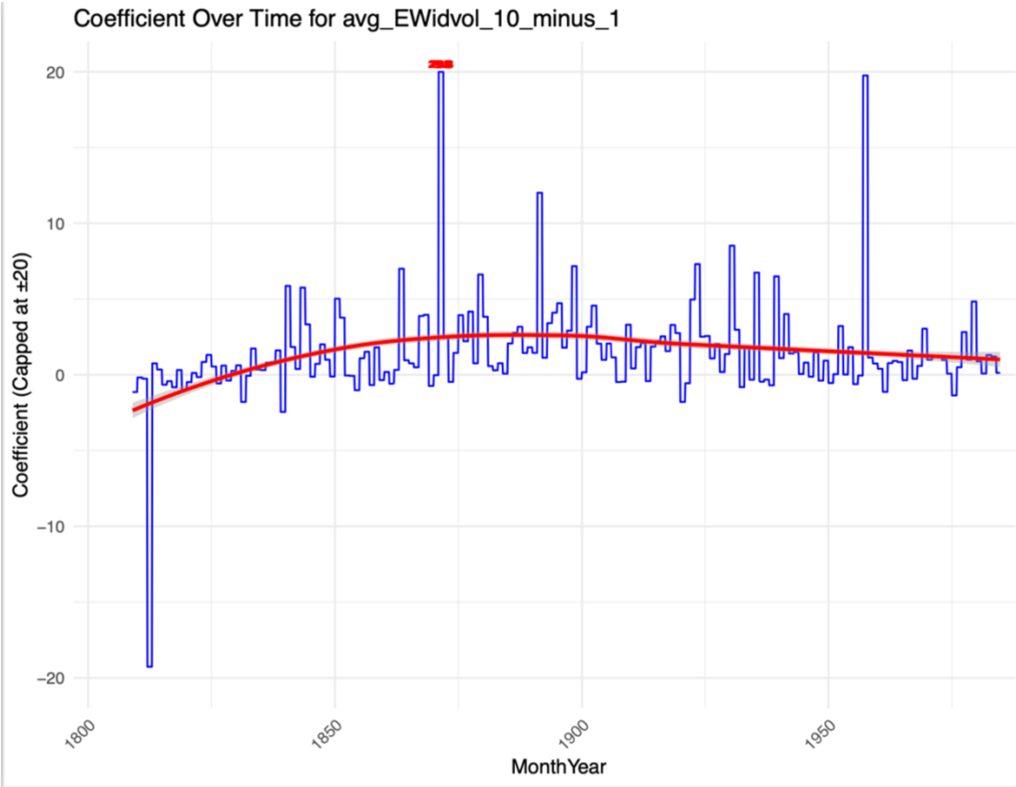
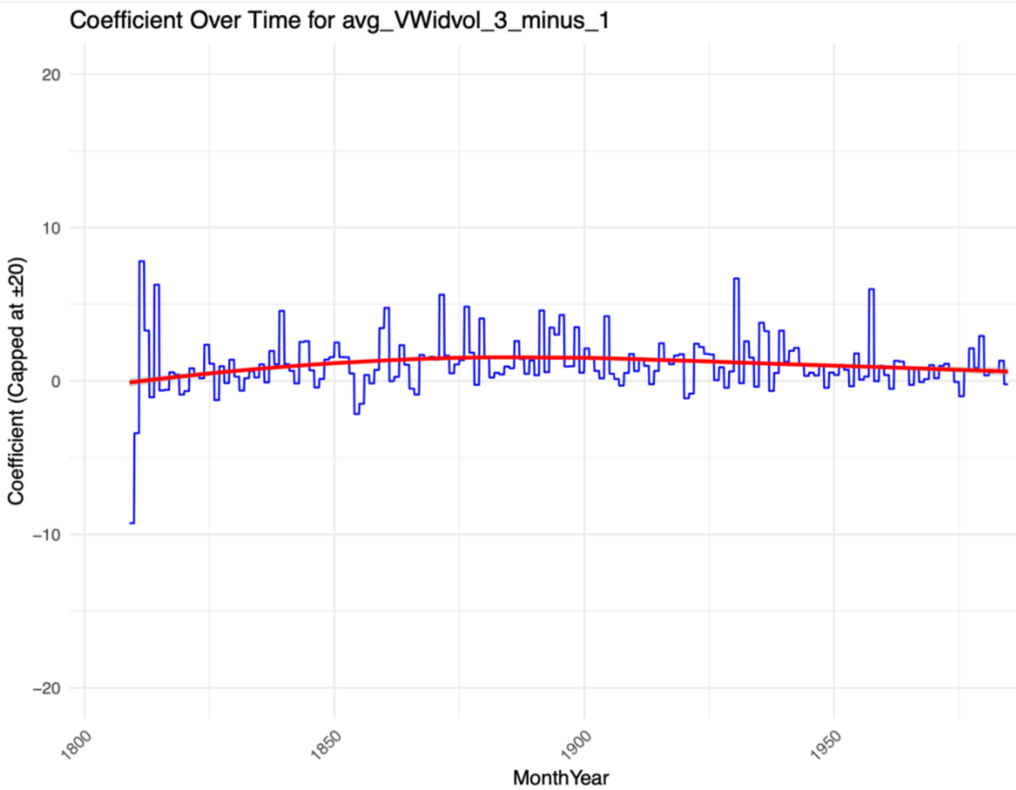
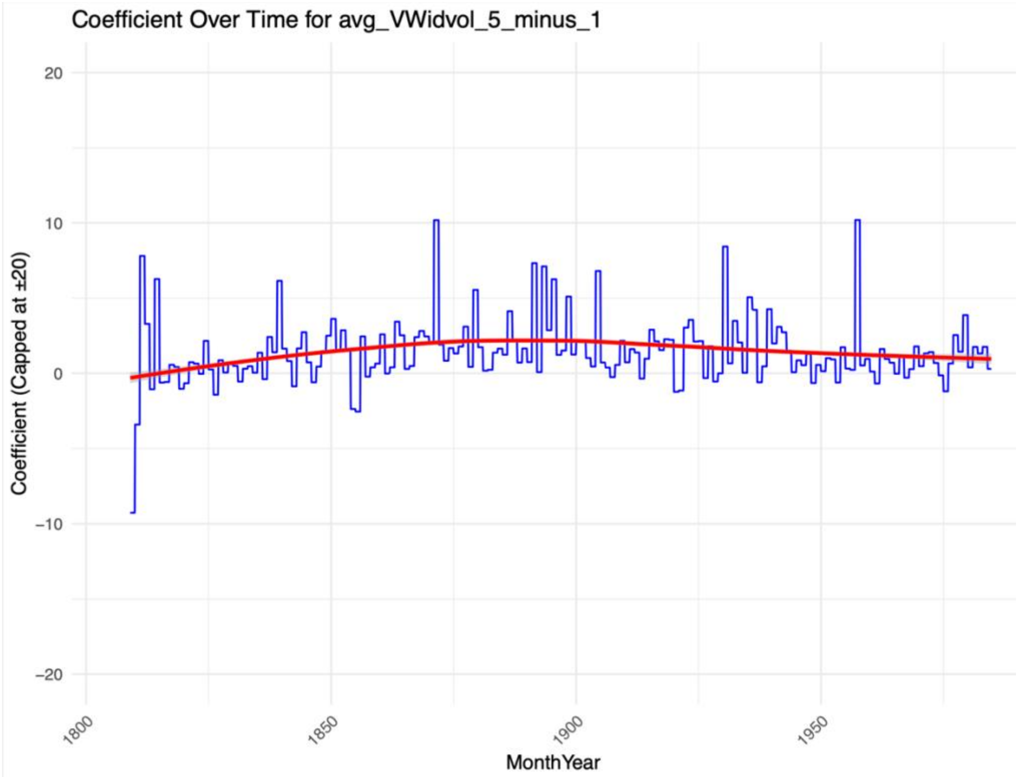
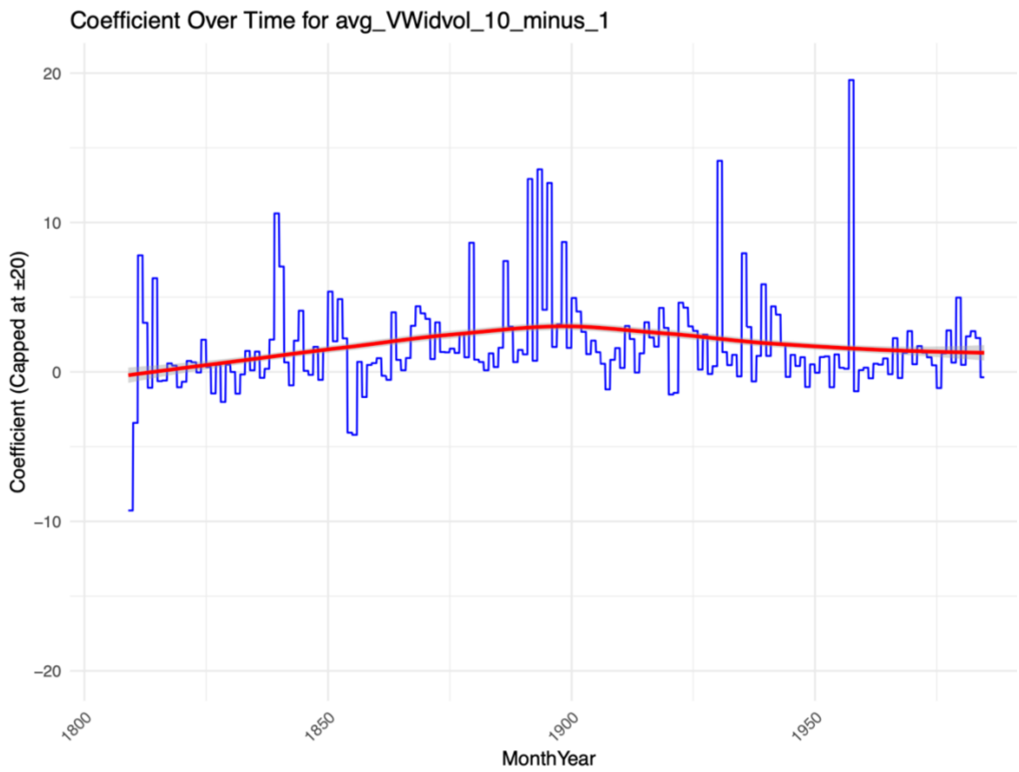
−10
−20
1800
1850
1900
1950
MonthYear



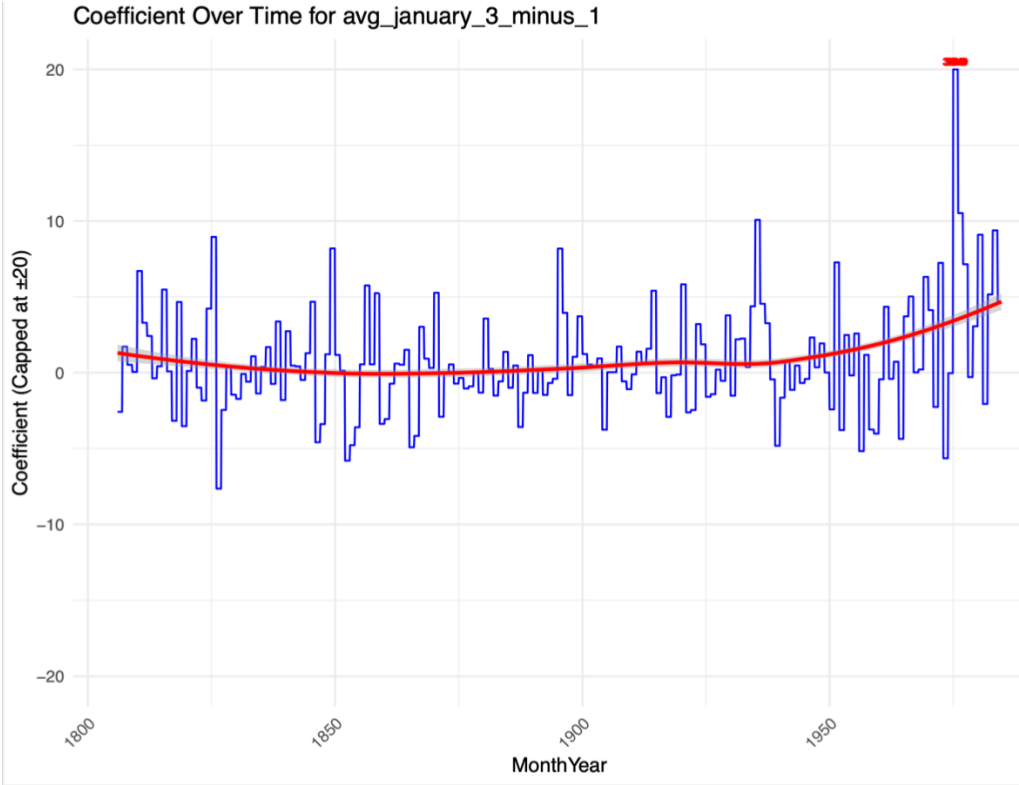
C.21 Value-weighted idiosyncratic volatility







C.22 January effect



C.23 Halloween indicator