# Momentum, echo and predictability

## Evidence from the London Stock Exchange (1820-1930)*

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April 5, 2019

**Abstract**

We study momentum and its predictability within equities listed at the London Stock Exchange (1820-1930). At the time, this was the largest and most liquid stock market and it was thinly regulated, making for a good laboratory to perform out-of-sample tests. Cross-sectionally, we find that the size and market factors are highly profitable, while long-term reversals are not. Momentum is the most profitable and volatile factor. Its returns resemble an echo: they are high in long-term formation portfolios, and vanish in short-term ones. We uncover momentum in dividends as well. When controlling for dividend momentum, price momentum loses significance and profitability. In the time-series, despite the presence of a few momentum crashes, dynamically hedged portfolios do not improve the performance of static momentum. We conclude that momentum returns are not predictable in our sample, which casts some doubt on the success of dynamic hedging strategies.

**Key words**: Momentum, echo, predictability, momentum crashes, dynamic hedging strategies, London Stock Exchange, factor analysis

**JEL classification**: G12

*The most recent version of the paper is available here.

# 1 Introduction

Momentum strategies buy securities with the highest past returns and short those with the lowest (Jegadeesh and Titman (1993)). In the U.S. equities post-1926, momentum has been highly profitable and volatile.[1] Recent literature uncovered two additional facts. First, realized volatility of momentum returns predicts future returns. Dynamically hedging a portfolio's exposure to momentum based on volatility avoids momentum crashes (Barroso and Santa-Clara (2015); Daniel and Moskowitz (2016)). Second, momentum in U.S. equities is better described as an echo: it is stronger when portfolios are formed 12 to 7 months ahead, than when formed 6 to 2 months ahead (Novy-Marx (2012)).

This paper studies momentum and its predictability in the context of the first modern stock market, the London Stock Exchange (LSE), from the 1820s to the 1920s.[2] The end of the Napoleonic Wars caused a large influx of both capital and investors in the City of London, at the expense of Amsterdam and Paris which were the other financial capitals at the time. So, by the 1830s the LSE was the largest stock market of the world, a status it maintained for the rest of the century. It also had light regulation and close to non-existing mandatory disclosures and audit (Michie (1999)), making for a good laboratory to test out-of-sample the performance and predictability of factors (Schwert (2003)).

In our cross-sectional tests, the size and market factors are highly profitable, while long-term reversals are not. Momentum is the highest-profitability factor, and the most volatile. We find strong evidence that momentum returns resemble an echo: they are high in long-term formation portfolios, and vanish in short-term ones. We also uncover momentum in dividends, which may proxy for earnings. When controlling for dividend momentum, the alpha of price momentum decreases in significance and drops by half.

In our time-series regressions, we uncover a few momentum crashes which make the distribution of momentum returns left skewed and leptokurtic, as it is in the U.S. equities.[3] However, dynamically hedging the momentum portfolio does not improve its performance, and sometimes it harms. We conclude that momentum returns are not predictable in our sample, which casts some doubt on the success of dynamic hedging strategies.

[1] In the CRSP sample, momentum's average return has been 13.7%, its volatility 24.3% and Sharpe ratio 0.43 (authors' calculations). See Asness, Moskowitz and Pedersen (2013) for recent evidence that confirms the profitability of momentum strategies across other asset classes and markets.

[2] We rely on data assembled in 2018 by Global Financial Database, a private company that collected all securities prices listed in two publications: the *Course of the Exchange*, and the *Times of London*. By the early 1830s, our dataset lists the prices of 250 companies' common shares. The number grows to 500 in the mid 1860s and reaches 1,400 at the beginning of the 20th century.

[3] See Geczy and Samonov (2016) for pre-1926 evidence; Daniel and Moskowitz (2016) for post-1926.

**Factors' performance.** Compared to the U.S. post-1926, we find that the market has been less profitable – averaging 5% annually – but also less volatile. Its Sharpe ratio has been 0.34, not too far from the 0.43 of CRSP.[4] The Small-Minus-Big (SMB) factor delivered a 4.85% average annual return, much higher than that found in U.S. post-1926. The risk-free rate, as proxied by the interest on British Government's consols, has been close to 3.3% throughout the period, despite the many large changes in suppy – i.e., in the outstanding stock of public debt. Due to almost non-existent disclosure and audit requirements, we cannot construct the High-Minus-Low (HML) book-to-market factor as in Fama and French (1993). To overcome this limitation, we rely on long-run reversals (e.g., De Bondt and Thaler (1985)). We do not find our proxy for the HML to be profitable, averaging at just 0.5% annually. As for momentum (UMD), consistent with the existing evidence it has been the most profitable factor – with an average annual return close to 9% – and the most volatile – with 20% annual standard deviation.

**Dissecting momentum returns.** Recent literature debates whether momentum is long or short term. In U.S. equities post-1926, Novy-Marx (2012) argues that long-term momentum is stronger than the short-term. His findings suggest that momentum can be better described as an *echo*, a puzzle for both behavioral and risk-based explanations of UMD returns (e.g., Barberis, Shleifer and Vishny (1998) and Johnson (2002)). In contrast, Goyal and Wahal (2015) find that long-term momentum does not consistently outperform its short-term counterpart in other 37 countries. In our sample, UMD profits strongly depend on the formation period: they average at 10.6% annually for long-term formation (12 to 7 months) and 3.8% for short-term formation (6 to 2 months). So, our out-of-sample test confirms that momentum is better described as a within-year echo.

It is particularly interesting to note this pattern because it refers to a market that had close to no disclosure requirement and no audited balance sheets. Therefore, either the price momentum we find reflects fundamental (earnings) momentum (as in Novy-Marx (2015)), and some information about earnings was available to investors despite the weak requirements, or it follows that there is more than earnings momentum in the data.

To shed further light on the relation between price momentum and fundamentals, we take advantage of another variable in our data: dividend policies. As shown in Braggion and Moore (2011), in the 19th century dividends were widespread and strongly associated with earnings. In addition, some confounding factors which affect contemporary dividend policies were absent at the time. First, dividends were considered as income, and the

[4]Our estimated Sharpe ratio for the market is remarkably similar to the 0.3 quoted by Golez and Koudijs (2018) on a sample obtained from the Course of the Exchange for the period 1813-1870.

marginal tax rate was about 5% flat, so that dividend policies were not influenced by tax-reduction objectives. Second, there were no legislative constraint on dividend issuance.

To investigate the role of fundamentals as drivers of price momentum, we construct two sets of earnings momentum portfolio. The first earnings momentum portfolio is constructed based on the past dividend paid by the firm relative to its market cap. The portfolio buys stocks of the highest dividend-paying firms over a 12 to 2 months formation period, and shorts the stocks of the lowest ones. We find strong evidence that our dividend momentum (DIV) strategy is profitable across our sample: it yields a 5% average annual return with a standard deviation of 12%.

The second earnings momentum portfolio is constructed based on the dividend innovations. Specifically, we look at the change of dividend year to year, and construct the $\Delta$-DIV portfolio. The portfolio buys stocks with the highest change in dividend paid and shorts the stocks with the lowest ones. The $\Delta$-DIV portfolio yield an over 24% return with a standard deviation of only 13.2%.

To discern whether price momentum seems driven by dividend momentum, we also test whether the alpha of the static UMD portfolio remains significant and positive after we control for the Fama-French three factors plus the dividend momentum portfolio. The conclusion depends on whether one focuses on value or equal weighted portfolios. Value-Weighting (VW) has the advantage of being consistent with momentum as commonly constructed in recent data, but it is somewhat noisy due to the the presence of a few very large firms. In contrast, Equal-Weighting (EW) is typically used in historical settings (e.g., Geczy and Samonov (2016) and Goetzmann and Huang (2018)) and it is less noisy.

In the EW sample, price momentum delivers excess returns of about 8.8% after controlling for the Fama-French three factors, significant at the 1%. However, introducing $\Delta$-DIV momentum reduces the alpha to 2.9%, and the alpha is insignificantly different from zero. The coefficient on $\Delta$-DIV is highly significant and positive, consistent with the results presented in Novy-Marx (2015). Conversely, the annualized alpha of $\Delta$-DIV strategy remains significant and close to 30% after controlling for price momentum, despite the fact that the coefficient on UMD is positive and significant. The explained variation of the regressions using equal-weighted portfolios is high, and does not change much across specifications.

As for VW portfolios, they deliver higher alphas but are less precisely estimated. In this case, the annualized alpha of price momentum drops by half from 11.2% to 5.8% after controlling for $\Delta$-DIV momentum. Similarly, the alpha of $\Delta$-DIV momentum does not change and remains around 28.8% after controlling for UMD. We suggest caution in inferring much from the value weighted rolling regressions, due to their low R-squared.

**Momentum crashes.** We find that the distribution of monthly momentum returns is left skewed and displays excess kurtosis, similarly to what has been documented in the CRSP sample, as well as in earlier U.S. data by Geczy and Samonov (2016). The largest negative monthly UMD returns in our sample are of a magnitude that falls in between the two episodes in Daniel and Moskowitz (2016) for the U.S., and those in Goetzmann and Huang (2018) for Imperial Russia. Within the five largest EW (VW) momentum crashes, investors lost 18% (26%) on average. The difference between the beta of the winners and that of the losers has been -2.4 (-3.5), on average, and the losses stemmed mostly from the performance of the losers, which averaged at 24% (21%) monthly return. We find little action in the winners portfolio, which returned on average 2% (-6%).

In light of the presence of a few momentum crashes, and because of the beta-gap between winners and losers, our data appear as a natural laboratory to test out-of-sample the validity of dynamic hedging strategies that leverage up and down the momentum portfolio based on realized volatilities, returns, etc. We shall consider a variety of dynamic hedging strategies, only constrained by the requirement that they should have been implementable in real time and not be subject to any look-ahead bias.

**Predictability and dynamic hedging.** Dynamic hedging consists in levering the portfolio when its realized volatility has been low and/or the market has been underperforming, and de-levering otherwise (Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016)). This strategy has been shown to successfully mitigate the consequences of the two main momentum crashes in U.S. equities post-1926: the one ensuing the Great Depression of 1929, and that following the Great Recession of 2007-2008.

After having identified a few momentum crashes, though of somewhat lower magnitude, we ask whether or not there is time series predictability in UMD returns. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find that, to the extent that momentum crashes occur as the market rebounds after a prolonged downturn, a dynamic strategy that levers up and down the momentum portfolio conditional on a few observables can substantially outperform the canonical static momentum strategy.

In particular, Barroso and Santa-Clara (2015) use volatility-scaling, and leverage momentum inversely to its average realized variance over the preceding six months. Namely, when the variance has been high their strategy de-levers the UMD portfolio, and vice versa. Daniel and Moskowitz (2016) use a similar scaling procedure, but condition not only on past variance of UMD returns, but also on UMD returns as forecasted by a (backward-looking) indicator for market downturns, past volatility and their interaction.

We begin our analysis by looking at whether this set of variables helps predicting momentum returns in our sample, and we find that it does not. Probably, this is because the crashes in our sample are more heterogeneous both in terms of origins and in terms of length. In particular, they do not necessarily occur when the market rebounds after a long downturn, and they tend to last for shorter periods of time. As a consequence, our out-of-sample test of the dynamic hedged UMD strategy shows that either it underperforms static momentum, or it does not improve its returns.

We also test whether aggregate dividends, adjusted for seasonality, carry information that helps predicting UMD returns. It turns out that dynamically hedging based on volatility and dividends is not different than dynamically hedging based on volatility alone, and the two yield similar returns as those from just investing in the static UMD portfolio. We conclude that in our sample momentum is not predictable, and dynamic hedging fails to improve the performance of static price momentum strategies.

The paper proceeds as follows: Section 2 describes the data and compares to existing benchmarks; Section 3 presents our cross-sectional tests; Section 4 describes the momentum crashes in our sample and presents our time-series tests; Section 5 concludes.

## 2 Dataset and preliminary analysis

**Dataset.** We obtain our sample from *Global Financial Data* (GFD), which digitalized in 2018 information about stocks traded at the LSE from two main primary sources: the *Times of London*, and the *Course of the Exchange*. These publications form the basis for most prior studies of LSE equities (e.g., Acheson, Hickson, Turner and Ye (2009)), and they are likely to cover most of the information available to non-member retail stock traders at the time. As such, it is the natural basis on which to form trading strategies that would have been implementable in real time.[5]

The variables we observe are: a date, a company identifier and name, the type of security (e.g., common or preferred stock, bond, etc.), the daily closing price, the number of shares outstanding (for equities), the stock exchange in which it was traded (e.g., London or New York), the currency and the sector (e.g., railways, banks, canals). The sample starts in 1810 and ends in 1929, and it contains 10,138 unique securities.

For our analysis, we restrict attention to common equities traded at the LSE in GBP (Great Britain Pounds), and exclude from the sample three outliers.[6] This leaves us with

[5]We also hand-collected information directly from the Course of the Exchange for a sub-sample of periods, in order to attest the accuracy of the GFD data we use, as this is the first paper – to our knowledge – that relies on it for academic research. We refer to our Appendix for a discussion of the data quality, which appears to be at least as accurate as previous data sources, but at higher frequency.

[6]The *Commercial Banking Company of Sydney Ltd.*, the *London Scottish American Trust Co.* and

4,260 securities. In addition, since we will be constructing dynamically-hedged portfolios, we restrict attention to stocks with at least weekly observations. This brings us to our final sample to 2,556 securities. Finally, to minimize potential data errors, we set stocks with a monthly return exceeding 500% as missing.[7]

Figure 1 plots the number of securities by type in our sample. We focus on common stocks, which evolve from around 200 in the 1820s to roughly 1,400 in the 1910s. Notice that there is a sharp increase in the number of securities in our sample in 1862. This is consistent with the findings of Acheson, Hickson, Turner and Ye (2009), and it appears to be due to the passage of the Companies Act in 1862, which concluded a process of gradual removal of most of the legal impediments to companies' incorporation in Britain and extended limited liability to all corporations, encouraging entry.

[ INSERT FIGURE 1 HERE ]

**Benchmarks.** Since we rely on a newly assembled database, we need to benchmark our dataset against the alternative sources which previous (mostly historical) research has relied upon. In the literature, there is an ongoing debate as to what sources can be relied upon for studying the *full* cross-section of LSE listed equities (see Hannah (2018) and Grossman (2018)). Some studies rely on the *Investors' Monthly Manual* (IMM), a supplement of the *Economist's* magazine introduced in 1864 by its editor, Walter Bagehot (e.g., Grossman (2018)). However, it has been shown by Hannah (2018) that the IMM's coverage relative to the LSE *Official List* (OL) varied substantially over time, and oftentimes it reflected editorial policies or constrains such as the number of published pages. In particular, Hannah argues that 'in 1869 most IMM securities were not in the LSE official list; by 1929 most LSE securities were not in the IMM'. On the other hand, the OL included many securities that were primarily traded outside of the LSE, in provincial exchanges and/or Oldham's pubs.

Alternatively, researchers have recently relied on a publication named *The Course of the Exchange* (COE), which has been published since the 18th century and throughout the 19th century (by-weekly prior to 1843, and daily afterwards), although due to the limitations and costs involved in digitizing this source they relied on monthly indices (e.g., Acheson, Hickson, Turner and Ye (2009), Hickson, Turner and Ye (2011) and Golez and Koudijs (2018)). Our data is – to our knowledge – the first to combine weekly (and after 1843 also daily) observations from two sources: the COE and the Times of London.

the *Metropolitan Trust Realisations Ltd.*. These three companies are reported to have an unreasonably large market capitalization. Including them in the analysis does not change any of our results.

[7] Our results are not sensitive to the specific threshold chosen.

Since we do not make claims about the exact LSE market size over the 19th century, we accept that our data does not cover the the universe of stocks traded in Britain at the time. However, we argue that these two publications probably covered most of the information set of a typical investor who was not a member of the LSE and, as pointed out by Acheson et al. (2009), they are likely to be biased toward the most liquid and actively traded securities. As a result, we find it natural to use them as the basis for portfolio strategies that could have been implementable by investors in real time.

Nevertheless, it is important to benchmark our data to the alternative sources. To this end, Table 1 shows that relative to Michie (1999), who relies on the OL and agrees with the numbers in Hannah (2018), our sample is larger in two instances: 1853 and 1873. In the other years reported, our sample has a lower coverage than the OL, especially in the late 19th century. As Michie (1999) himself points out, the higher coverage in early years might reflect the fact that not all traded securities were reported in the OL, especially in the early 19th century. However, the difference is not huge and it may depend on the exact point in time at which the prices had been measured. For subsequent years, the OL has a much larger coverage than our data. Although we cannot test this directly in the data, we conjecture that it may be partially due to international securities, as well as to the inclusion in the OL of stocks that were infrequently traded.

A more direct comparison of our data with previous research that hand-collected data from the COE, to validate the quality of our dataset, reveals positive news. As Table 2 shows, the average return by industry in our sample is fairly similar to that reported in Hickson et al. (2011). The main exception are Railways, which in our sample have a 6% (10%) higher EW (VW) return, and (in the VW case) Telegraph Cable & Express. The differences tend to be larger in the VW sample, which yet again suggests that relying on the EW sample is likely to reduce mis-measurements in the data.

[ INSERT TABLE 1 HERE ]

[ INSERT TABLE 2 HERE ]

# 3 Cross-sectional tests

In this section, we discuss how we construct the factors and we present our cross-sectional tests.

**Factor analysis.** In constructing the Small Minus Big (SMB) factor, we follow Fama and French (1993) and sort our cross-section of stocks by market capitalization into terciles (30%, 40% and 30%) at the end of June, each year. The SMB portfolio is formed by buying small stocks and selling large stocks from July to June of the subsequent year. As shown in Table 3, compared to the U.S. postwar sample, where the SMB factor had a Sharpe Ratio of -0.19 and an average return of 1.35%, in the UK sample we find SMB to be performing much better. The Sharpe ratio is 0.21 and average return 4.85%. It also appears that SMB was less volatile, although the difference is small and it reflects a general pattern of low volatility in the 19th century equity markets (see Schwert (1989)).

As for the High Minus Low (HML) factor, since we cannot rely on accounting information we proxy it with long-run reversals. Namely, we sort stocks by their cumulative return from year $t-5$ to $t-1$ into terciles (30%, 40% and 30%) at the end of June, each year. Together with size, we can split stocks into 3-by-3 blocks (size: small/medium/large, value: growth/neutral/value). We then form the proxied-HML portfolio by buying *small/value* and *large/value* stocks and selling *small/growth* and *large/growth* stocks from July to June of the subsequent year. Our HML-proxy portfolio does not perform well in the sample, and it is the only factor with a negative Sharpe ratio (i.e., -0.39).

Finally, we construct static momentum as in Jegadeesh and Titman (1993): we sort stocks into deciles based on their cumulative return from month $t-12$ to $t-2$. The UMD portfolio is created by buying the top-decile stocks and selling the bottom-decile ones. Unlike both SMB and HML, the UMD portfolio is rebalanced monthly. Momentum is the factor with the highest return (8.95%), but also the highest volatility (19.75%), as a result its Sharpe ratio is 0.28, slightly lower than that of the market. The final two rows of the table report separate statistics for the two legs of the UMD portfolio. The main takeaway from them, for our purposes, is that both legs delivered higher returns in the U.S. sample, but much more volatile than those in Britain in the 19th century.

[ INSERT TABLE 3 HERE ]

**Momentum or echo?** Following Novy-Marx (2012), we proceed to distinguish between long-term momentum (or echo) and short-term momentum, by altering the portfolio formation period. Long-term momentum is formed in months $t-12$ to $t-7$, whereas short-term momentum in the period $t-6$ to $t-2$. Figure 2 reports the cumulative performance over our sample period of the long-term momentum, the short-term momentum, as compared with the standard UMD portfolio. While the short-UMD underperforms the standard UMD, the long-term momentum over-performs both by a large margin.

[ INSERT FIGURE 2 HERE ]

Figure 3 clarifies that the discrepancy in performance reflects a persistent pattern over time. The Figure plots the 10 years rolling average abnormal return of long-term momentum (left panel) and short-term momentum (right panel). While long-term UMD consistently generates positive and (generally) significant alphas, the short-term UMD alpha is always close to zero and almost never statistically significantly positive. We conclude that our findings are consistent with momentum being better described as an echo phenomenon, as in Novy-Marx (2012) and unlike the findings of Goyal and Wahal (2015) for a sample of various equity markets.

[ INSERT FIGURE 3 HERE ]

**Dividends and price momentum.** Having established that momentum resembles an echo in our sample, we ask the subsequent question of whether behind long-term momentum there might be momentum in fundamentals. For instance, Novy-Marx (2015) shows that, in the U.S. post-1926, there is momentum within innovations in firm's earnings, and once one controls for earnings momentum the profitability of price momentum vanishes.

To this end, we first construct a long-short portfolio based on the level of past dividends (denoted by DIV). The portfolio formation period is 12 to 2 months ahead of time, as for price momentum. Before describing the properties of the DIV portfolio, Figure 4 (upper panel) plots the aggregate dividends issued by the firms in our sample. The figure shows that there is substantial time variation in paid dividends, and a strong within-year seasonality. Figure 4 (lower panel) plots the aggregate dividends over the LSE market capitalization. Dividends paid are typically in the range of 0.5 to 2.5 percent of the LSE market cap.

[ INSERT FIGURE 4 HERE ]

Figure 5 presents rolling estimates for our DIV long-short portfolio over the sample. To construct DIV momentum, we first calculate the total dividend paid between month $t-12$ and $t-2$, relative to the market cap in month $t-12$. We then sort stocks by the past dividend relative to the market cap into deciles. The DIV strategy is constructed by buying the top decile stocks and selling the bottom decile stocks. Finally, we use a 10-year rolling window, and regress DIV returns on the Fama-French three factors, estimate the monthly alphas, and plot the estimates and 95% confidence interval. Dividends momentum earned on average 5.03% annually, with a standard deviation of 12.25%. Its alpha is almost always positive, and (especially since the mid 1860s) it is often statistically significant. This result suggests that there is momentum in dividends.

Next, we consider a portfolio based on dividends' innovations, which we label Δ-DIV. To construct the Δ-DIV momentum portfolio, we first calculate the total dividend paid between month $t-12$ and $t-2$, relative to the market cap in month $t-12$, as well as between $t-23$ and $t-13$, relative to the market cap in month $t-23$. Then we take the difference and sort stocks by the past change in dividend into deciles. The Δ-DIV strategy is constructed by buying the top decile stocks and selling the bottom decile stocks. Finally, we use a 10-year rolling window, and regress Δ-DIV returns on the Fama-French three factors, estimate the monthly alphas, and plot the estimates and 95% confidence interval. The results are presented in Figures 6 and 7.

[ INSERT FIGURE 5 HERE ]

[ INSERT FIGURE 6 HERE ]

[ INSERT FIGURE 7 HERE ]

Further, since Braggion and Moore (2011) argue that there is a tight link between dividends and earnings in these 19th century stocks. Indeed, in our sample dividend payout constitute 66.9% of the total return. A similar number (63%) is reported in Golez and Koudijs (2018). In addition, due to the institutional features that we mentioned about homogenous taxation and no legislative barriers to issuance, we argue that our DIV portfolio is likely to capture somewhat an underlying earnings momentum that cannot directly be observed in the data. Therefore, to test out-of-sample whether earnings momentum subsumes price momentum, we check if introducing it as a control affects the alpha of UMD. The regression results are presented in Tables 4 and 5.

Table 4, column (1) presents the regression of EW momentum returns on the Fama-French three factors. Consistently with the existing evidence, momentum has a negative loading on both the market and size, while our long-run reversal proxy for HML is not significant. The annualized alpha of UMD is 8.8% and significant. Column (2) adds our Δ-DIV strategy to proxy for Earnings UMD. It shows that regressing UMD on both the Fama-French three factors as well as our Δ-DIV factor, changes the results substantially. The alpha of UMD drops to 2.9%, and it looses significance. Column (3) uses the DIV factor instead of the Δ-DIV factor. The price momentum alpha drops to 5.6%.

However, earnings momentum is not explained by price momentum. In column (4), we regress $\Delta$-DIV returns on Fama-French three factors, and the annualized alpha is 30.72%. Moreover, earnings momentum loads positively on HML, unlike price momentum. Column (5) adds the price momentum as an explanatory variable, and the alpha of earnings momentum does not change.

We interpret this result as showing that price momentum seems mostly explained by dividends (or earnings, according to our interpretation) momentum, and not vice versa.

Table 5 replicates the same exercise but with value-weighted portfolios. In this case, price momentum survives the inclusion of $\Delta$-DIV as explanatory variable. The R-squared of the regression without controlling for $\Delta$-DIV is 0.003, which is much lower than that of our analogous equal-weighted regression. When including $\Delta$-DIV factor as an explanatory variable, we find it to be significant and positive. Moreover, the alpha of price momentum drops by half from 11.2% to 5.8%. However, since the R-squared remains very low, we are cautious in interpreting these results.

[ INSERT TABLE 4 HERE ]

[ INSERT TABLE 5 HERE ]

Now that we described the factor properties of the cross-section of stock returns, we shall focus squarely on momentum strategies and their predictability through time.

# 4 Momentum and predictability

The distribution of momentum returns is left skewed and displays excess kurtosis, similarly to what has been documented in the CRSP sample, as well as in earlier U.S. data by Geczy and Samonov (2016). Compared to Goetzmann and Huang (2018), who study the cross-section of stocks traded in Imperial Russia and document the absence of momentum crash episodes, our sample features a few episodes of larger magnitude. This makes it a natural laboratory to test out-of-sample if dynamic hedging strategies can improve on static momentum.

The magnitude of momentum crashes in our sample depends on whether we consider equal or value-weighted portfolios. Unlike Goetzmann and Huang (2018) and Geczy and Samonov (2016), who focus on Equal-Weighted (EW) momentum strategies due to data limitations, we have both prices and shares outstanding and so: (i) we can construct the Value-Weighted (VW) portfolio, which is more directly comparable to Daniel and

Moskowitz (2016); and (ii) we can control for other Fama-French factors. However, especially in the first half of the 19th century, the cross-section of traded shares by market capitalization was right skewed, with few very large firms and many smaller ones. To overcome the issue, we also study the performance of the EW momentum portfolio. Table 6 reports the ten highest (top panel) and lowest (bottom panel) monthly performance of the EW static UMD portfolio.

[ INSERT TABLE 6 HERE ]

**Momentum crashes.** The main crash that does not depend on equal versus value-weighting occurs in the month of December 1848, where VW (EW) momentum traders lose 27% (18%). Despite occurring in the aftermath of the Railways Bubble (1845), the crash has little to do with it. In contrast, it is driven by political and economics events in France, where in February 1848 the king of the July Monarchy, Louis Philippe I, was overthrown and replaced by a republican government (the Second Republic) guided by Alphonse de Lamartine. Political uncertainty drove down the prices of most France-related stocks listed at the LSE and lead to their inclusion in the losers portfolio.[8]

The turbulent months following the February Revolution did not allow France-related stocks to recover, mostly because the governing coalition was litigious and the conservatives soon begun organizing against the Lamartine's government. However, things changed in late 1848, when a large consensus begun to form around Napoleon III as candidate for president of the National Assembly, to be elected by popular vote on the 10th of December 1848. When the results were announced, on December the 20th, Napoleon III was declared president while winning 74% of the votes. France-related stocks listed at the LSE rallied, as evident from the astonishing 32% (22%) monthly return of the VW (EW) losers portfolio. Meanwhile, the portfolio of winners had a return close to zero.

In the two largest momentum crashes studied by Daniel and Moskowitz (2016), the crash is related to the time-varying betas for the winners and the losers, and in particular the fact that – while deep into a recession – the winners tend to be low-beta stocks, which do not suffer too much from the market downturn, while the losers mostly consist in high-beta stocks that tank because of the recession. As the market begins to rebound, the winners' return increases sharply – much more than that of the losers – and so the long-short UMD portfolio crashes. In light of this general intuition, it is informative to check if the two legs of our UMD portfolio have different betas in the 1848 crash episode.

[8] The VW losers portfolio featured 25% of *Northern of France Railway Co.* shares, 18% of *Paris and Orleans Railway* shares and 10% of *Paris and Rouen Railway* shares, to name the largest positions.

This turns out not to be the case: the difference between the beta of the losers and that of the winners is -0.84 (-0.11) in the VW (EW) portfolio. This is consistent with the crash not being related to a domestic market downturn, and calls into question the generality of the association of crashes to the time-varying UMD beta.

Two of the four largest EW momentum crashes occur in 1906, in the months of July and December. These times, the crashes are more similar – although of lower magnitude – to those ensuing the Great Depression and the Great Recession. It all appears to start with the San Francisco earthquake of April 1906. The quake, of Richter magnitude 8.3, spurred a large number of fires that destroyed four square miles of the city, or about half its size (Odell and Weidenmier (2004)). The shock caused a market crash in both New York and London. The shock in London was severe mostly because British insurance companies had issued an estimated \$87 million of policies in San Francisco and faced potential losses of \$46 millions (*The Economist*, August 11, 1906).

As the LSE market tanked in the aftermath of the quake, the UMD portfolio naturally started selling high-beta stocks – in particular, shares of gold mining companies which during the gold standard were particularly pro-cyclical – and purchasing those low-beta stocks that suffered less from the shock. This is clearly seen by comparing the betas of the EW momentum losers' portfolio (3.77) with that of the winners' portfolio (0.54). As soon as the LSE started to rebound, in mid-July 1906, the losers portfolio experienced a spectacular 30% rebound, while the winners' return was close to zero. As a result, static UMD traders faced a 22.3% monthly loss.

Despite the market rebound, during the late summer of 1906 Britain experienced a massive outflow of gold to the U.S., due to the settlement of the aforementioned insurance claims (about \$35 million, according to Odell and Weidenmier (2004)). Because of the gold standard, Britain was committed to redeem currency for gold at a fixed exchange rate. Therefore, the outflow of gold reduced the gold reserves at the Bank of England, forcing it into raising its discount rate from 3.5 to 4%, on September the 12th. The LSE inverted its upward trend and started another period of contraction.

As for the UMD portfolio, it again switched toward buying low beta and selling high beta stocks, which planted the seeds for the second crash of December 1906. As the market rebounded again, the losers' portfolio (with a beta of 4.6) gained 19%, while the winners' portfolio (with a beta of 0.53) returned just 1%. Despite the market rebound had been less severe in December relative to July, the gap in betas between the two legs of the UMD portfolio had been even higher (-4 in December, against the -3.2 of July), leading to an overall UMD monthly return of roughly -16%.

To summarize, the largest negative monthly UMD returns in our sample are of a magnitude that falls in between the two episodes in Daniel and Moskowitz (2016) for the U.S., and those in Goetzmann and Huang (2018) for Imperial Russia. Within the five largest EW (VW) momentum crashes, investors lost 18% (26%) on average. The difference between the beta of the winners and that of the losers has been -2.4 (-3.5), on average, and the losses stemmed mostly from the performance of the losers, which averaged at 24% (21%) monthly return. We find almost no action in the winners portfolio, which returned on average 2% (-6%).

**Dynamic hedging.** After having identified a few momentum crashes, though of lower magnitude than the two ensuing the Great Depression and the Great Recession, we turn attention to the vexata quæstio of whether or not there is time series predictability in UMD profits. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) find that, to the extent that momentum crashes occur as the market rebounds after a prolonged downturn, a dynamic strategy that levers up and down the momentum portfolio conditional on a few observables can substantially outperform the canonical static momentum strategy.

In particular, Barroso and Santa-Clara (2015) use volatility-scaling, and leverage momentum inversely to its average realized variance over the preceding six months. Namely, when the variance has been high their strategy de-levers the UMD portfolio, and vice versa. Daniel and Moskowitz (2016) use a similar scaling procedure, but condition not only on past realized variance of UMD returns, but also on an indicator for market downturns, as well as on the interaction between these two variables. Importantly, their indicator is backward looking: it just considers whether or not in the past the market under or over-performed relative to its long-run average performance. So, the dynamically-managed UMD strategies proposed in both these papers are implementable in real time.

We begin our analysis by looking at whether the set of variables considered in Daniel and Moskowitz (2016) helps predicting momentum profits in our sample. To this end, we use a half-year rolling window to estimate market and UMD rolling variances. In addition, we use a 2-year rolling window to estimate the market's past returns. We then create a *bear dummy*, which is equal to one if market past return is less than zero, and zero otherwise. We also interact the bear dummy with the market's rolling variance, so that we can replicate their predictive regressions based on these three variables (past volatility, bear market and their interaction). Table 7 presents the result of our predictive regressions, where the dependent variable is the static UMD return. None of the coefficient is significant, and the same results hold if one changes the formation period behind past volatility measures and the bear indicator.

$\left[ \text{INSERT TABLE 7 HERE} \right]$

Given that the three variables constructed as in Daniel and Moskowitz (2016) fail to predict UMD returns in our sample, it is not very surprising that dynamically hedging UMD based on these variables does not improve its performance. Consistent with Daniel and Moskowitz (2016), our first dynamic hedging portfolio (which we label DYN) has a weight equal to $\frac{\lambda \times [\text{Predicted UMD return}]}{[\text{UMD rolling variance}]}$, where $\lambda$ is set so that the dynamically hedged portfolio has the same volatility as the static UMD portfolio. The CVOL portfolio dynamically hedged only conditioning on past volatility, as in Barroso and Santa-Clara (2015). In this case, the weight equals $\frac{\gamma}{[\text{UMD rolling variance}]}$, and $\gamma$ is chosen so that the volatility of the dynamically hedged portfolio is equal to that of the other two. Results are shown in Figure 8 for the value-weighted portfolio, and Figure 9 for the equal-weighted one.

In the figures, we also consider a dynamic DIV portfolio, which hedges based on both volatility and aggregate dividends. The portfolio is constructed as follows. First, we assume that dividends follow an AR(1) process with seasonality, captured non-parametrically by monthly dummies. We estimate the following rolling regressions:

$$\text{Aggregate Dividend}_t = \rho \times \text{Aggregate Dividend}_{t-1} + 12 \text{ Month Dummies} + \epsilon_t$$

and extract the regression's residuals, which we label *abnormal dividends*. The time series of abnormal dividends is plotted in Figure 10, while Figure 11 shows, as a check, the same plot obtained from similar regression run on the CRSP sample in the U.S. post-1926. While the range of abnormal dividends is the same, the variable is much more volatile in our sample than it is in the U.S.

We then construct three variables, DIV State, DIV Vol, and their interaction terms. DIV State is a dummy variable, which is equal to one if the past 2-year cumulative *abnormal dividends* is above zero, and zero otherwise. DIV Vol is the volatility of *abnormal dividends* in the past half year. We then estimate the next period momentum return using these three variables with a rolling window up to $t-1$. The estimation procedure is identical to the one used in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), except that we use a different set of predictors.

Next, we choose a time-varying portfolio weight that equals $\frac{\eta \times [\text{Predicted UMD return}]}{[\text{UMD rolling variance}]}$, and $\eta$ is chosen so that the volatility of the dynamically hedged portfolio is equal to that of the others. As shown in Figures 8 and 9, the also the dynamically hedged portfolio based on dividends fails to improve the performance of static UMD. We conclude that UMD returns in our sample cannot be predicted by the variables suggested in previous papers, which worked remarkably well in the U.S.. Even if we try to take advantage of dividends as a forecasting variable, we do not find predictability in the returns.

[ INSERT FIGURE 8 HERE ]

[ INSERT FIGURE 9 HERE ]

[ INSERT FIGURE 10 HERE ]

[ INSERT FIGURE 11 HERE ]

# 5 Conclusions

We conclude from our analysis that Fama-French factors – especially size and market – as well as momentum account for some of the cross-section variation in stocks since the earliest modern stock exchange was established, in London in the first half of the 19th century. Momentum is the most profitable factor, as well as the riskiest. Momentum returns resemble an echo: they are large for long-term formation periods of 12 to 7 months, while they vanish for shorter term formation periods.

We uncover strong profitability of dividends momentum strategies, which buy the highest dividend paying stocks and sell the lowest dividend paying ones. We interpret dividends momentum as capturing fundamental momentum, especially since there were close to non-existent disclosure and audit requirements at the time. When controlling for Fama-French factors and dividends momentum, price momentum's alpha drops by half and loses significance. However, dividends momentum's alpha does not change when controlling for price momentum. We interpret the evidence as suggestive that fundamentals are a key driving force behind price momentum.

Momentum profits are left-skewed and display excess kurtosis. In other words, it is prone to infrequent though devastating crashes. Often, such crashes occur when the market rebounds after a downturn. At these times, the winners portfolio underperforms because it mostly consists of low beta stocks, while the losers portfolio over-performs for specular reasons. While Daniel and Moskowitz (2016) document two such episodes, in the aftermath of the Great recession and in 2009, we show that a similar logic applied twice in 1906 – in July, when the market rebounded after the San Francisco earthquake, and in December, when it recovered after the Bank of England raised its discount rates to stop the drainage on its gold reserves. However, we also find episodes where momentum crashes for other reasons, and in which there is no gap in the beta of the winners vis à vis that of the losers. In particular, this happens for the December 1848 crash, associated with the French market rebound brought about by the election of Napoleon III.

The heterogeneous nature of momentum crashes in our sample translates into the lack of predictability of momentum profits. Our out-of-sample test on the performance of dynamically hedged momentum strategies concludes that they often underperform static momentum, especially if one uses a downturn indicator as a right-hand-side variable. Past realized volatility does a better job of predicting momentum returns, although the improvement from dynamic hedging in our sample is very small relative to what suggested in Barroso and Santa-Clara (2015). Abnormal dividends, adjusted for time and seasonality, do not help either in dynamically hedging static momentum. We conclude that there is no predictability in momentum returns, and cast some doubt on the efficacy of dynamic hedging strategies.

# References


**Acheson, G., C. R. Hickson, J. D. Turner, and Q. Ye**, "Rule Britannia! British stock market returns, 1825-1870," *The Journal of Economic History*, 2009, *69* (4), 1107–1137.

**Asness, C. S., T. J. Moskowitz, and L. H. Pedersen**, "Value and momentum everywhere," *The Journal of Finance*, 2013, *68* (3), 929–985.

**Barberis, N., A. Shleifer, and R. Vishny**, "A model of investor sentiment," *Journal of financial economics*, 1998, *49* (3), 307–343.

**Barroso, P. and P. Santa-Clara**, "Momentum has its moments," *Journal of Financial Economics*, 2015, *116* (1), 111–120.

**Bondt, W. F.M. De and R. Thaler**, "Does the stock market overreact?," *The Journal of finance*, 1985, *40* (3), 793–805.

**Braggion, F. and L. Moore**, "Dividend policies in an unregulated market: the London Stock Exchange, 1895–1905," *The Review of Financial Studies*, 2011, *24* (9), 2935–2973.

**Daniel, K. and T. J. Moskowitz**, "Momentum crashes," *Journal of Financial Economics*, 2016, *122* (2), 221–247.

**Fama, E. F. and K. R. French**, "Common risk factors in the returns on stocks and bonds," *Journal of financial economics*, 1993, *33* (1), 3–56.

**Geczy, C. C. and M. Samonov**, "Two centuries of price-return momentum," *Financial Analysts Journal*, 2016, *72* (5), 32–56.

**Goetzmann, W. N. and S. Huang**, "Momentum in Imperial Russia," *Journal of Financial Economics*, 2018, *130* (3), 579–591.

**Golez, B. and P. Koudijs**, "Four centuries of return predictability," *Journal of Financial Economics*, 2018, *127* (2), 248–263.

**Goyal, A. and S. Wahal**, "Is momentum an echo?," *Journal of Financial and Quantitative Analysis*, 2015, *50* (6), 1237–1267.

**Grossman, Richard S**, "Revising 'Bloody foreigners!'," *The Economic History Review*, 2018, *71* (4), 1357–1359.

**Hannah, L.**, "The London Stock Exchange, 1869–1929: new statistics for old?," *The Economic History Review*, 2018, *71* (4), 1349–1356.

**Hickson, C. R., J. D. Turner, and Q. Ye**, "The rate of return on equity across industrial sectors on the British stock market, 1825–70 1," *The Economic History Review*, 2011, *64* (4), 1218–1241.

**Jegadeesh, N. and S. Titman**, "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 1993, *48* (1), 65–91.

**Johnson, T. C.**, "Rational momentum effects," *The Journal of Finance*, 2002, *57* (2), 585–608.

**Michie, R.**, *The London stock exchange: A history*, Oxford University Press, USA, 1999.

**Novy-Marx, R.**, "Is momentum really momentum?," *Journal of Financial Economics*, 2012, *103* (3), 429–453.

_ , "Fundamentally, momentum is fundamental momentum," Technical Report, National Bureau of Economic Research 2015.

**Odell, K. A. and M. D. Weidenmier**, "Real shock, monetary aftershock: The 1906 San Francisco earthquake and the panic of 1907," *The Journal of Economic History*, 2004, *64* (4), 1002–1027.

**Schwert, G .W.**, "Why does stock market volatility change over time?," *The journal of finance*, 1989, *44* (5), 1115–1153.

**Schwert, G. W.**, "Anomalies and market efficiency," *Handbook of the Economics of Finance*, 2003, *1*, 939–974.

# Figures

Figure 1: Number of securities by type

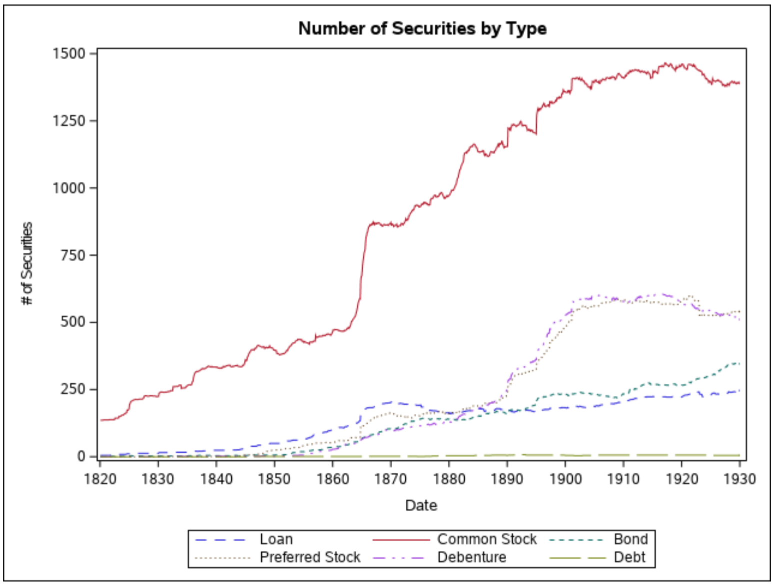
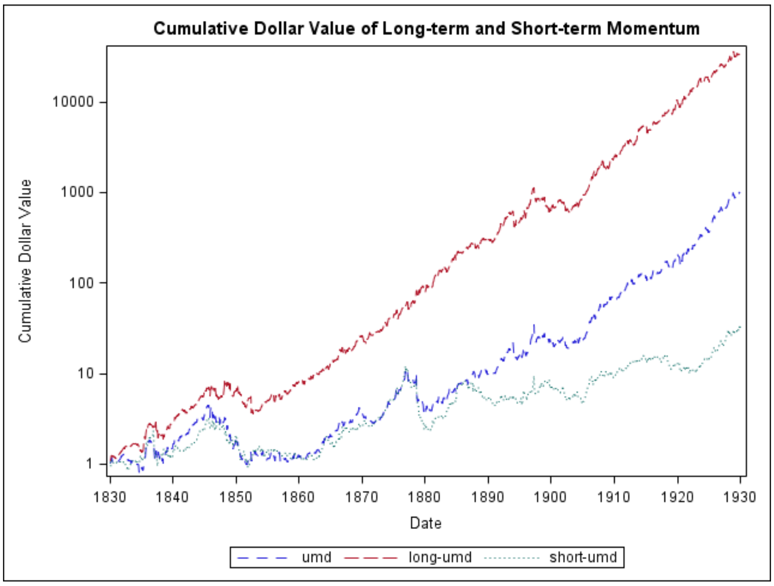
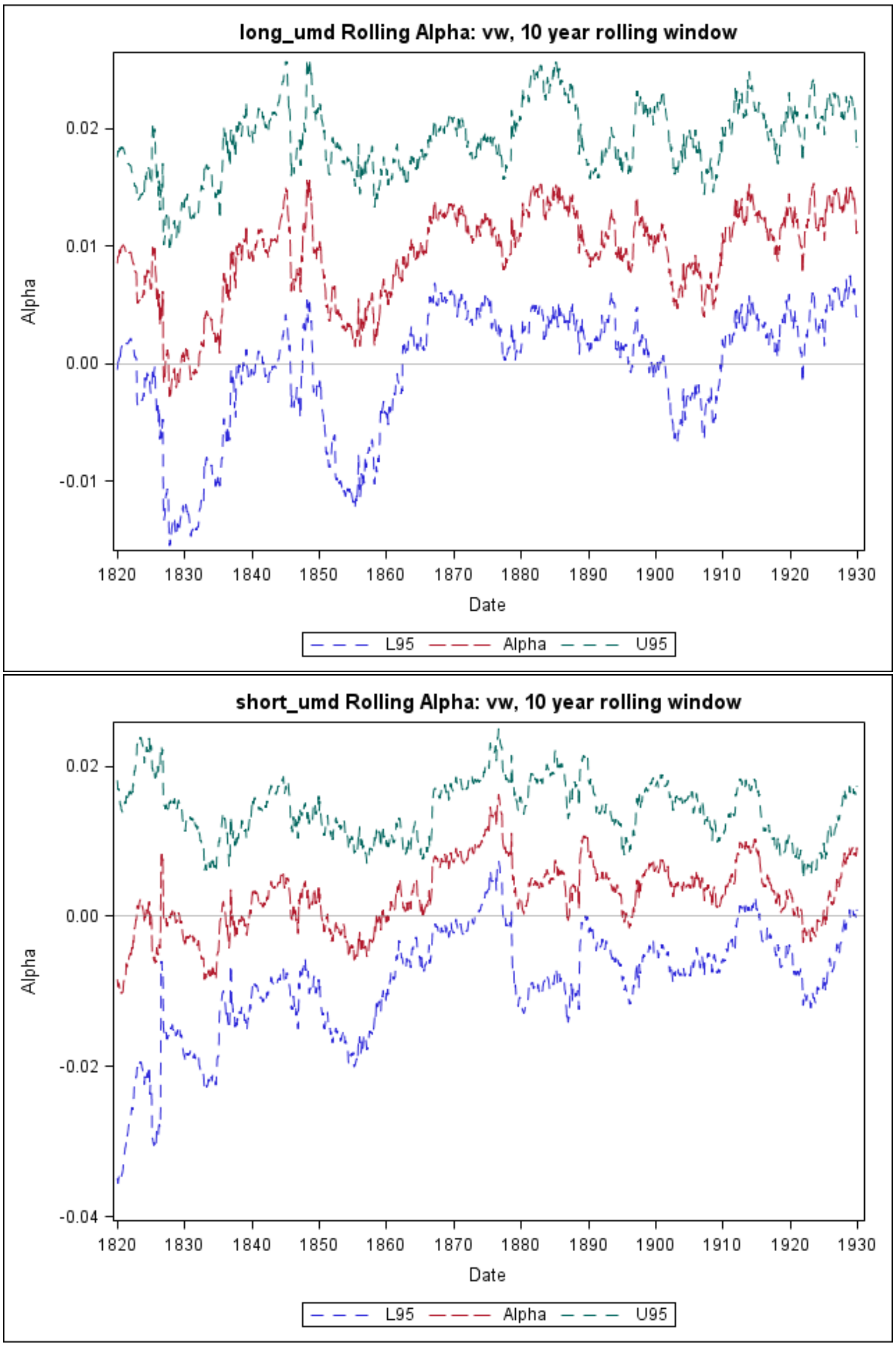



Figure 2: Long-term and Short-term Momentum: cumulative performance



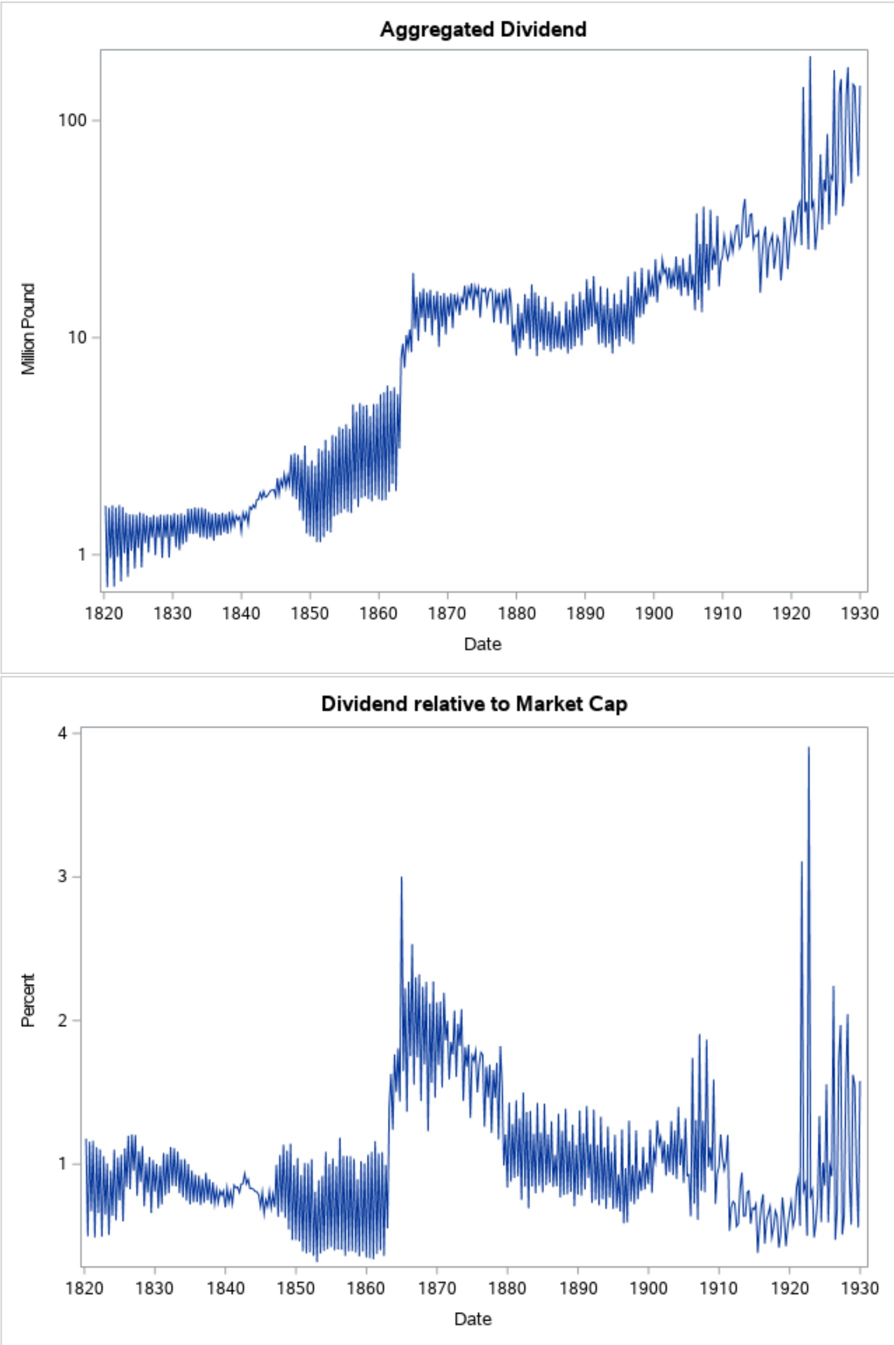

*The figure shows the cumulative \$-value of long-term, short-term, and traditional UMD. Traditional UMD is constructed by buying stocks with the highest decile of past performance and selling stocks with the lowest decile, between month* $t-12$ *to* $t-2$*. Long-term (short-term) momentum is constructed similarly, with past performance measured between month* $t-12$ *to* $t-7$ *(*$t-6$ *to* $t-2$*).*

Figure 3: Long-term and Short-term Momentum: rolling alhpa



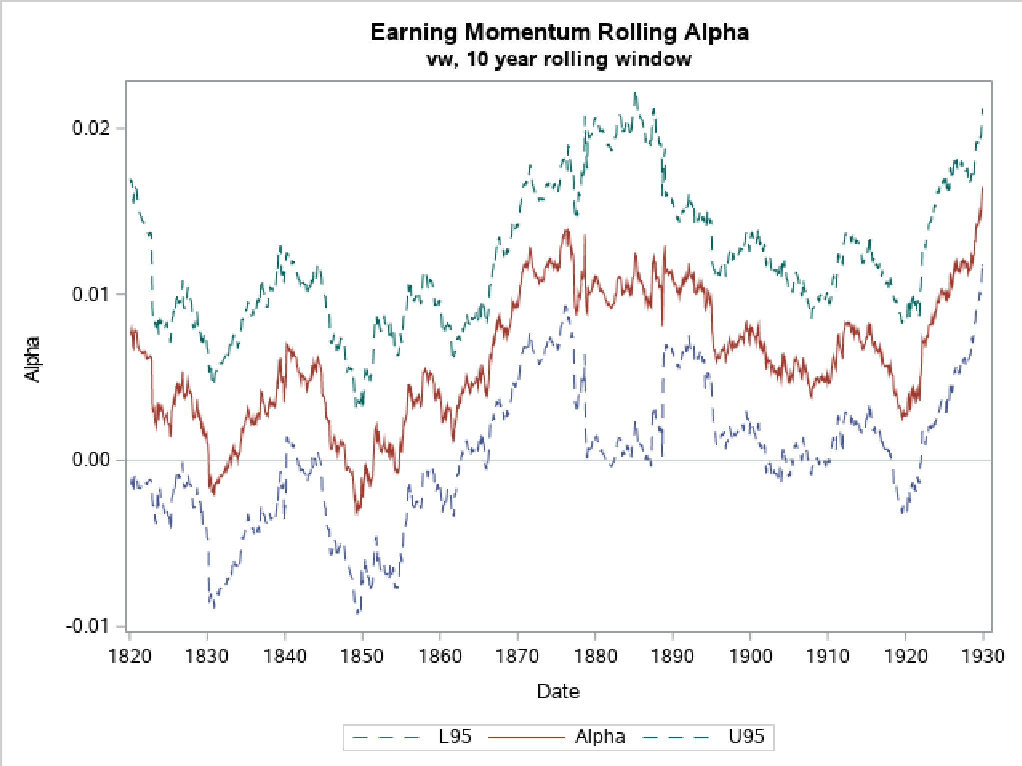

*The figure shows the rolling alpha of long-term and short-term UMD strategies. We use a 10-year rolling window, regress momentum returns on Fama-French three factors, and estimate the monthly alphas. We then plot the time-series of estimated alphas and their 95% confidence intervals.*

Figure 4: Aggregate dividends payout




*The figures show the aggregated $-amount of dividends and the percentage of dollar amount of dividends to the total market capitalization.*

Figure 5: VW Dividends Momentum – our proxy for earnings UMD




*The figure shows the rolling alpha of DIV momentum. To construct DIV momentum, we first calculate the total dividend paid between month $t-12$ and $t-2$, relative to the market cap in month $t-12$. We then sort stocks by the past dividend relative to the market cap into deciles. The DIV strategy is constructed by buying the top decile stocks and selling the bottom decile stocks. Finally, we use a 10-year rolling window, and regress DIV returns on the Fama-French three factors, estimate the monthly alphas, and plot the estimates and 95% confidence interval.*

Figure 6: EW Change in Dividends (Earnings) Momentum

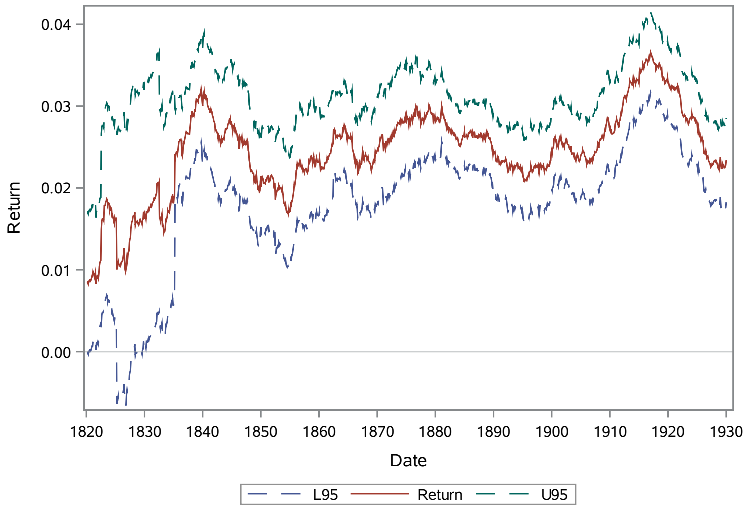
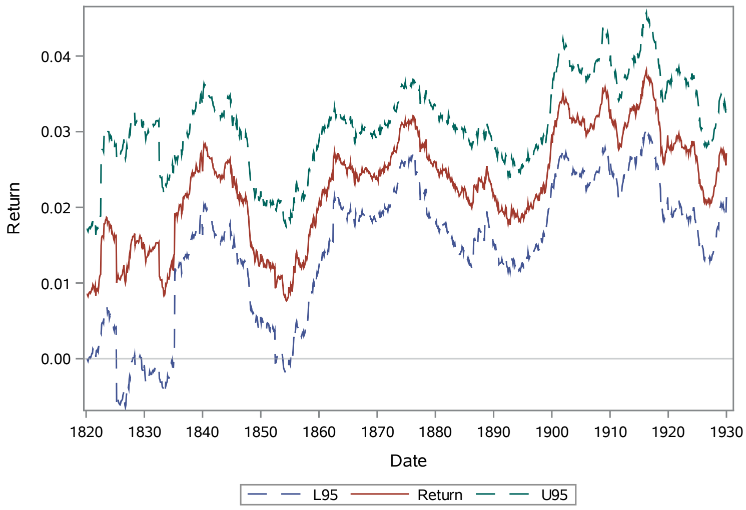
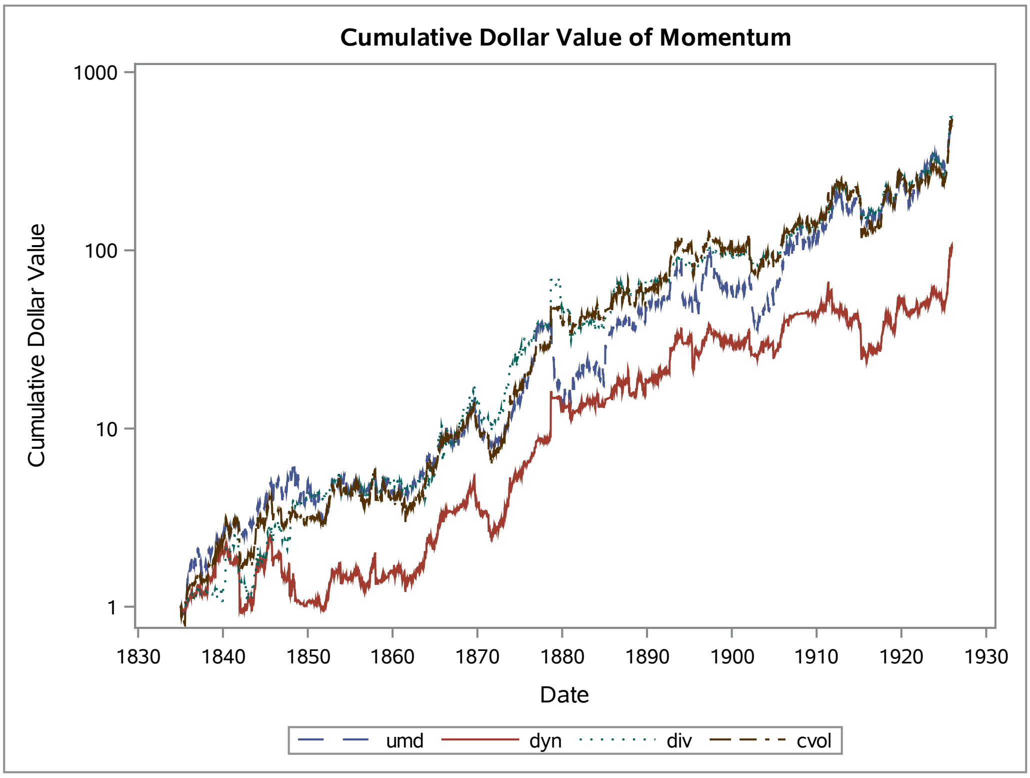



Figure 7: VW Change in Dividends (Earnings) Momentum



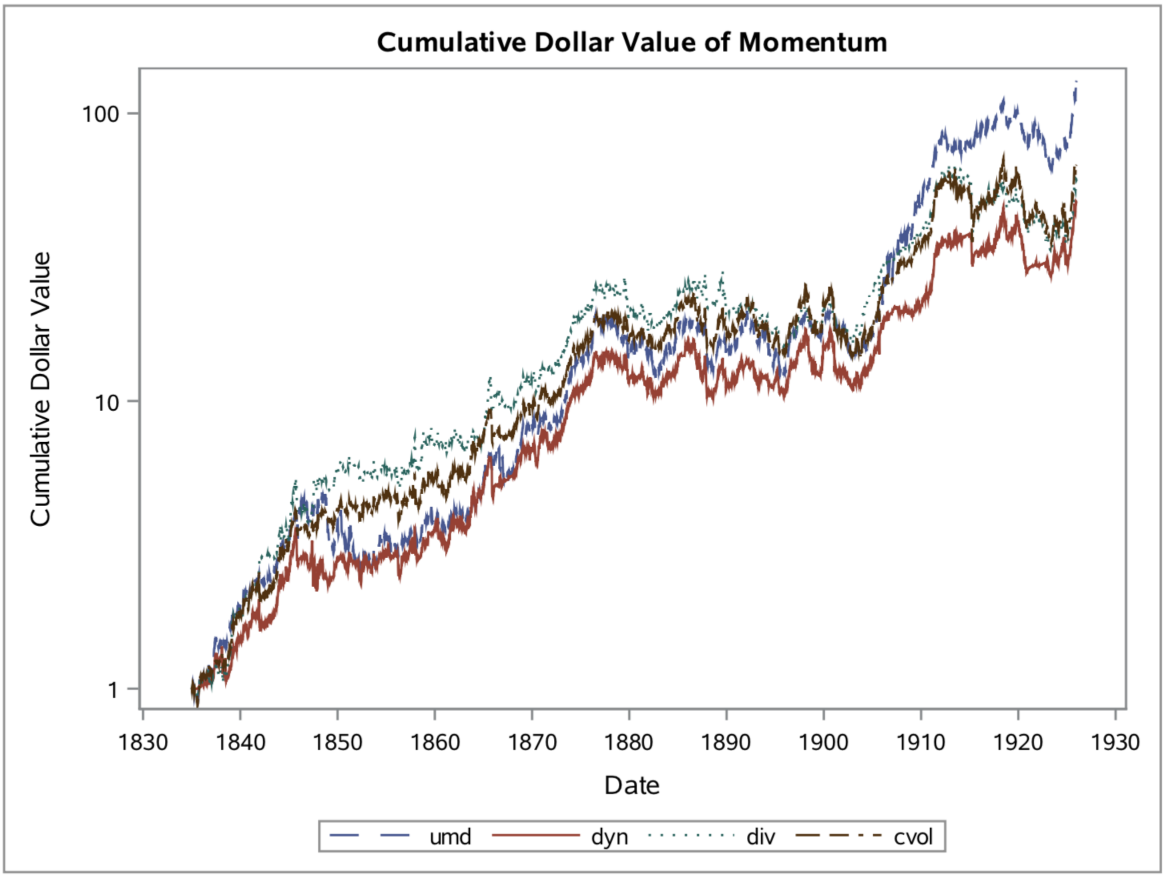

*The figures shows the rolling alpha of* $\Delta$*-DIV momentum. To construct the* $\Delta$*-DIV momentum portfolio, we first calculate the total dividend paid between month* $t-12$ *and* $t-2$*, relative to the market cap in month* $t-12$*, as well as between* $t-23$ *and* $t-13$*, relative to the market cap in month* $t-23$*. Then we take the difference and sort stocks by the past change in dividend into deciles. The* $\Delta$*-DIV strategy is constructed by buying the top decile stocks and selling the bottom decile stocks. Finally, we use a 10-year rolling window, and regress* $\Delta$*-DIV returns on the Fama-French three factors, estimate the monthly alphas, and plot the estimates and 95% confidence interval.*

Figure 8: Dynamic hedging of VW momentum portfolios



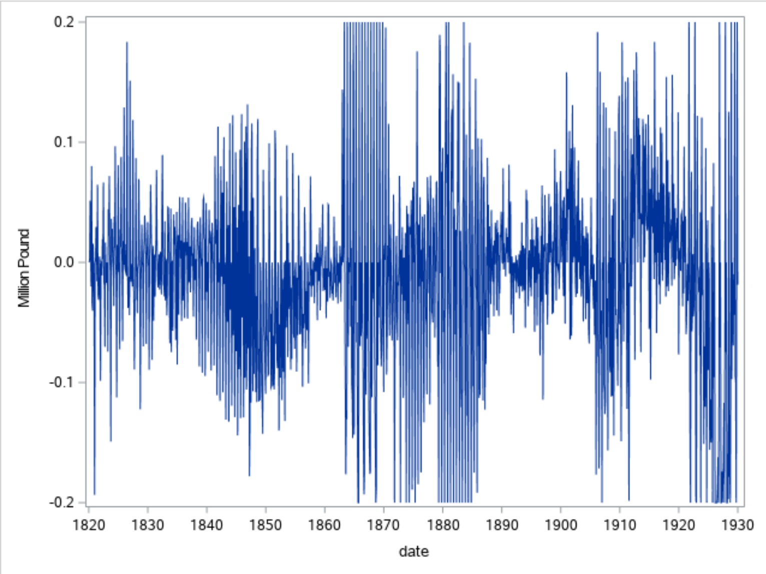

*The figure shows the cumulative dollar value of dynamic hedging VW momentum strategies. UMD denotes the static momentum. DYN denotes the dynamic hedging strategy employed by Daniel and Moskowitz (2016) using the interaction between the 'bear market' indicator and market volatility to predict UMD. DIV is the dynamic hedging strategy using dividend state and dividend volatility to predict UMD. CVOL is the constant volatility momentum strategy à la Barroso and Santa-Clara (2015).*

Figure 9: Dynamic hedging of EW momentum portfolios



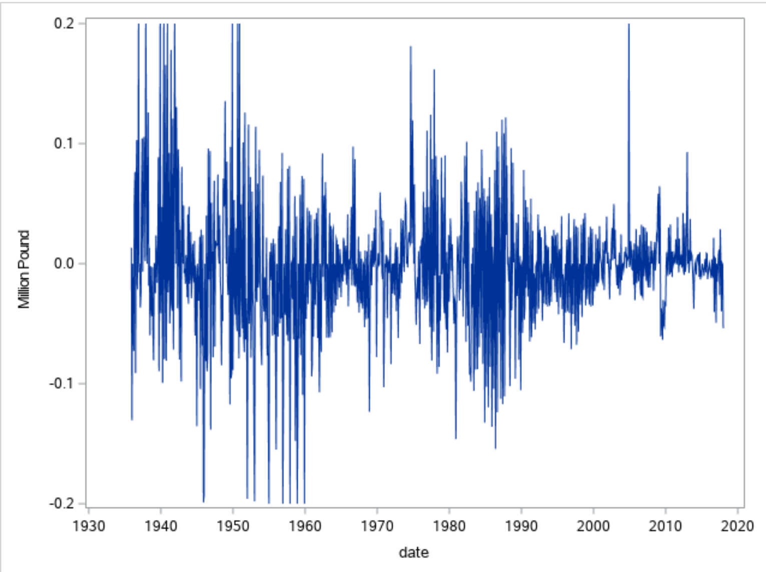

*The figure shows the cumulative dollar value of dynamic hedging EW momentum strategies. UMD denotes the static momentum. DYN denotes the dynamic hedging strategy employed by Daniel and Moskowitz (2016) using the interaction between the 'bear market' indicator and market volatility to predict UMD. DIV is the dynamic hedging strategy using dividend state and dividend volatility to predict UMD. CVOL is the constant volatility momentum strategy à la Barroso and Santa-Clara (2015).*

Figure 10: Abnormal dividends




*The figure plots the time-series of dividend residuals in our sample. The residuals are calculated on a rolling window, by regressing aggregate dividends in month $t$ on the previous month dividend and a set of monthly dummies. The plot is capped between -0.2 to 0.2 to exclude extreme observations.*

Figure 11: Abnormal dividends




*The figure plots the time-series of dividend residuals in the U.S. post-1926 CRSP sample. The residuals are calculated on a rolling window, by regressing aggregate dividends in month $t$ on the previous month dividend and a set of monthly dummies. The plot is capped between -0.2 to 0.2 to exclude extreme observations.*

# Tables

Table 1: Our sample coverage vs. Michie (1999)

| Year | Total Market Capitalization | | Gap |
|---|---|---|---|
| | Our sample | Michie 1999 | |
| 1853 | 418 | 292 | 126 |
| 1863 | 599 | 610 | -11 |
| 1873 | 1136 | 925 | 211 |
| 1883 | 1268 | 1745 | -476 |
| 1893 | 1574 | 2966 | -1392 |
| 1903 | 2599 | 4465 | -1866 |
| 1913 | 5486 | 6226 | -740 |

*The table compares the total market capitalization of stocks between our sample and that used by Michie (1999). We calculate the total market capitalization of stocks at the end of year from 1853 to 1913 in our sample. We also extract the total market capitalization from Michie (1999), after subtracting the government and colonial bonds.*

Table 2: Our industry returns vs. Hickson, Turner and Ye (2011)

| | Equally-Weighted | | | Value-Weighted | | |
|---|---|---|---|---|---|---|
| Industry | Our sample | Hickson et. al (2011) | Gap | Our sample | Hickson et. al (2011) | Gap |
| Market | 9.44% | 9.70% | -0.26% | 10.20% | 8.94% | 1.26% |
| Mining | 7.53% | 8.89% | -1.36% | 13.68% | 17.09% | -3.41% |
| Banks | 8.51% | 9.30% | -0.79% | 5.53% | 7.83% | -2.30% |
| Insurance | 6.51% | 6.94% | -0.43% | 5.11% | 6.97% | -1.86% |
| Canals and Docks | 4.09% | 4.23% | -0.14% | 5.28% | 4.44% | 0.84% |
| Railroads | 19.50% | 13.40% | 6.10% | 23.19% | 12.68% | 10.51% |
| Roads and Bridges | 0.09% | 1.95% | -1.86% | 1.17% | 0.27% | 0.90% |
| Utilities - Water | 7.04% | 6.68% | 0.36% | 9.98% | 6.52% | 3.46% |
| Telegraph Cable & Express | 15.28% | 15.13% | 0.15% | 34.89% | 19.15% | 15.74% |

*The table compares the average industry returns between our sample and Hickson, Turner and Ye (2011). The sample period is between 1825 and 1870. Both the EW and VW annualized industry returns are calculated, and their gap is reported.*

Table 3: Factors in our data and in the U.S. post-1926

| | USA post-1926 (CRSP) | | | UK 1810-1926 (GDF) | | |
|---|---|---|---|---|---|---|
| | AVERAGE | ST.DEV | SR | AVERAGE | ST.DEV | SR |
| RF | 3.15% | 0.19% | 0.00 | 3.33% | 0.17% | 0.00 |
| MARKET | 10.50% | 16.91% | 0.43 | 4.90% | 4.66% | 0.34 |
| SMB | 1.35% | 9.29% | -0.19 | 4.85% | 7.20% | 0.21 |
| HML (proxy) | 4.13% | 9.29% | 0.11 | 0.49% | 7.29% | -0.39 |
| UMD | 13.69% | 24.31% | 0.43 | 8.95% | 19.75% | 0.28 |
| UMD-winners | 20.21% | 24.22% | 0.70 | 9.59% | 13.94% | 0.45 |
| UMD-losers | 6.51% | 28.18% | 0.12 | 0.65% | 18.70% | -0.14 |

*The table compares the Fama-French factors plus UMD between our UK sample and the U.S. post-1926 CRSP sample. The last two rows report the breakdown of the UMD portoflio in terms of the long leg (the winners) and the short leg (the losers) All returns and standard deviations are annualized.*

Table 4: Equal-weighted portfolios

| | (1)<br>UMD | (2)<br>UMD | (3)<br>UMD | (4)<br>Δ-DIV | (5)<br>Δ-DIV | (6)<br>Δ-DIV |
|---|---|---|---|---|---|---|
| MKTRF | -0.216*** | -0.236*** | -0.209** | 0.106* | 0.127** | 0.118** |
| | (-2.60) | (-2.86) | (-2.54) | (1.79) | (2.16) | (2.09) |
| SMB | -0.476*** | -0.461*** | -0.428*** | -0.0829* | -0.0365 | 0.00416 |
| | (-7.16) | (-6.97) | (-6.39) | (-1.75) | (-0.76) | (0.09) |
| HML | 0.0476 | 0.0219 | 0.0410 | 0.134*** | 0.129*** | 0.122*** |
| | (0.80) | (0.37) | (0.69) | (3.15) | (3.07) | (3.03) |
| Δ-DIV | | 0.192*** | | | | |
| | | (4.77) | | | | |
| DIV | | | 0.197*** | | | 0.353*** |
| | | | (4.41) | | | (11.62) |
| UMD | | | | | 0.0975*** | |
| | | | | | (4.77) | |
| Constant | 0.00736*** | 0.00245 | 0.00472*** | 0.0256*** | 0.0249*** | 0.0209*** |
| | (4.66) | (1.31) | (2.81) | (22.73) | (22.09) | (18.24) |
| N | 1200 | 1200 | 1200 | 1200 | 1200 | 1200 |
| r2 | 0.0659 | 0.0834 | 0.0808 | 0.0128 | 0.0313 | 0.113 |
| F | 28.12 | 27.17 | 26.27 | 5.183 | 9.653 | 38.09 |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*The table shows the regression results of EW price and dividends UMD. In columns (1) - (3), we regress price UMD on the Fama-French three factors and earnings momentum, proxied by Δ-DIV and DIV. In columns (4) - (6), we regress Δ-DIV on the Fama-French three factors, UMD, and DIV.*

Table 5: Value-weighted portfolios

| | (1) UMD | (2) UMD | (3) UMD | (4) Δ-DIV | (5) Δ-DIV | (6) Δ-DIV |
|---|---|---|---|---|---|---|
| MKTRF | -0.237* | -0.262** | -0.296** | 0.135 | 0.157* | 0.0956 |
| | (-1.92) | (-2.15) | (-2.45) | (1.58) | (1.84) | (1.13) |
| SMB | -0.0580 | -0.0643 | -0.0614 | 0.0338 | 0.0391 | 0.0315 |
| | (-0.76) | (-0.85) | (-0.82) | (0.63) | (0.74) | (0.60) |
| HML | 0.000761 | -0.0377 | -0.0155 | 0.205*** | 0.205*** | 0.194*** |
| | (0.01) | (-0.51) | (-0.21) | (3.99) | (4.02) | (3.84) |
| Δ-DIV | | 0.188*** | | | | |
| | | (4.56) | | | | |
| DIV | | | 0.292*** | | | 0.194*** |
| | | | (6.85) | | | (6.54) |
| UMD | | | | | 0.0910*** | |
| | | | | | (4.56) | |
| Constant | 0.00935*** | 0.00485** | 0.00530*** | 0.0240*** | 0.0231*** | 0.0213*** |
| | (4.91) | (2.28) | (2.70) | (18.07) | (17.39) | (15.55) |
| N | 1200 | 1200 | 1200 | 1200 | 1200 | 1200 |
| r2 | 0.00345 | 0.0205 | 0.0411 | 0.0156 | 0.0324 | 0.0496 |
| F | 1.381 | 6.245 | 12.80 | 6.323 | 10.01 | 15.59 |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*The table shows the regression results of VW price and dividends UMD. In columns (1) - (3), we regress price UMD on the Fama-French three factors and earnings momentum, proxied by Δ-DIV and DIV. In columns (4) - (6), we regress Δ-DIV on the Fama-French three factors, UMD, and DIV.*

Table 6: Best and worse performances of the EW static UMD portfolio

HIGHEST-PERFORMANCE MONTHS

| YEAR | MONTH | UMD return | MKT-RF | winner | loser | BETA GAP | WINNERS' AVG BETA | LOSERS' AVG BETA |
|---|---|---|---|---|---|---|---|---|
| 1925 | 11 | .20182 | .006318 | .15034 | -.04454 | .65707 | 2.26680 | 1.60973 |
| 1845 | 12 | .18302 | .043077 | .19814 | .01477 | 1.77706 | 2.22977 | .45271 |
| 1906 | 9 | .18068 | -.025409 | .01080 | -.15344 | -3.45766 | .58661 | 4.04427 |
| 1851 | 2 | .15756 | .047731 | .17122 | .01214 | .67292 | 2.30669 | 1.63377 |
| 1906 | 1 | .15720 | -.021537 | .03182 | -.11316 | -2.03587 | .55186 | 2.58773 |
| 1906 | 2 | .15070 | -.022716 | .02823 | -.11099 | -2.17008 | .52143 | 2.69152 |
| 1846 | 6 | .14943 | -.023150 | .01854 | -.11808 | -.12731 | 1.69828 | 1.82560 |
| 1851 | 4 | .13919 | .017240 | .10625 | -.03044 | 3.00190 | 3.54021 | .53831 |
| 1908 | 7 | .12686 | .003096 | .07282 | -.04912 | -1.11893 | 1.01273 | 2.13166 |
| 1925 | 9 | .12674 | .024972 | .12364 | -.00311 | .95920 | 2.34890 | 1.38970 |

LOWEST-PERFORMANCE MONTHS

| YEAR | MONTH | UMD return | MKT-RF | winner | loser | BETA GAP | WINNERS' AVG BETA | LOSERS' AVG BETA |
|---|---|---|---|---|---|---|---|---|
| 1906 | 7 | -.22266 | .058922 | .03709 | .30291 | -3.23506 | .53519 | 3.77024 |
| 1887 | 11 | -.20065 | .037708 | .01680 | .25545 | -2.83962 | .34745 | 3.18707 |
| 1848 | 12 | -.17998 | .051688 | .01364 | .22243 | -.10864 | 1.49098 | 1.59963 |
| 1906 | 12 | -.16353 | .042892 | .01013 | .19227 | -4.03569 | .53302 | 4.56871 |
| 1908 | 5 | -.15857 | .061795 | .03510 | .21030 | -1.77646 | .56308 | 2.33954 |
| 1866 | 8 | -.15186 | .047727 | .05548 | .22980 | -.36016 | 1.48038 | 1.84054 |
| 1850 | 5 | -.14829 | .036584 | .00853 | .17433 | -3.45853 | .82853 | 4.28706 |
| 1866 | 8 | -.14699 | .031919 | .03499 | .19902 | -.30079 | 1.49464 | 1.79542 |
| 1846 | 4 | -.14588 | .050235 | .05313 | .21254 | 1.09541 | 2.21357 | 1.11817 |
| 1853 | 11 | -.14229 | .043269 | .00420 | .16117 | -.39179 | 1.36957 | 1.76136 |

*The table shows the best and worst 10 months of EW momentum returns. Column umd return is the momentum return in the month. Column MKT-RF is the market excess return. Column winner (loser) is the return of the long (short) leg of the UMD portfolio. The winner's (loser's) average beta is the market beta of the long (short) leg of momentum portfolio. The beta gap is the difference between the winner's and loser's market beta.*

Table 7: Predictive regression for static UMD returns

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | umd | umd | umd | umd |
| bear | -0.000705 | | -0.000671 | -0.00104 |
| | (-0.91) | | (-0.86) | (-0.96) |
| mktvol | | -4.180 | -3.072 | -10.52 |
| | | (-0.44) | (-0.32) | (-0.59) |
| bear_mktvol | | | | 10.46 |
| | | | | (0.50) |
| _cons | 0.00198*** | 0.00183*** | 0.00207*** | 0.00231*** |
| | (3.91) | (3.54) | (3.52) | (3.04) |
| R-squared | 0.00 | 0.00 | 0.00 | 0.00 |
| No. Obs | 4988 | 4988 | 4988 | 4988 |
| F stat | 0.83 | 0.20 | 0.47 | 0.39 |

$t$ statistics in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*The table shows the weekly regression results when predicting UMD returns using the variables considered by Daniel and Moskowitz (2016). The dummy variable bear is equal to one if the past 2-year market cumulative return is below zero. The variable mktvol is the past 2-year market volatility. The interaction term bear$_m$ktvol is the product between the bear dummy and market volatility. We then regress the next period UMD return on these variables and report the regression results.*