The Cross-Section of Stock Returns before CRSP

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Abstract

This study examines the cross-section of stock returns out-of-sample using a novel database of U.S. stocks between 1866 and 1926. Over this 'pre-CRSP' era (i) the relationship between market beta and returns is flat, (ii) value, momentum, low-risk, and seasonality factor premia are sizable and significant, and (iii) size, short-term reversal, and long-term reversal premia are weak. On average, the studied equity factor premia do not materially decay out-of-sample when unaffected by post-publication arbitrage. Additionally, we provide novel insights into economic explanations of factor premia over the combined pre-CRSP and CRSP 'super' sample covering 159 years of cross-sectional stock data.

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I. Introduction

Seminal studies reveal factors that predict cross-sectional differences in stock returns. Among others, Fama and French (1992, 1993) show that size and value are priced stock characteristics. Jegadeesh and Titman (1993, 2001) and Carhart (1997) identify momentum, Ang, Hodrick, Xing, and Zhang (2006), Blitz and Van Vliet (2007), and Frazzini and Pedersen (2014) identify low-risk via (idiosyncratic) volatility or beta, Jegadeesh (1990), and Lehmann (1990) identify short-term reversal, and Keloharju, Linnainmaa, and Nyberg (2016) identify return seasonality. Many of these factors are by now heavily studied with a wide industry actively allocating to them. More recent studies highlight a potential 'factor zoo' of hundreds of anomalies in the cross-section of stock returns (e.g., Harvey, Liu, and Zhu, 2016). At the same time, studies by Harvey (2017) and Fama and French (2018), amongst others, have raised concerns regarding the robustness of findings in the cross-section of stock returns, particularly highlighting the issue of p-hacking. Numerous predictive variables found in the cross-section of stock returns that seem important in-sample lose explanatory power, or even fail to hold up, out-of-sample.[1]

To illustrate this point, Figure 1 summarizes the t-statistics of the CAPM alphas of prominent equity factors – size, value (based on dividend yield – the value measure used throughout the paper), momentum, short-term reversal, low-risk, long-term reversal, and seasonality – based on standard 2x3 portfolio sorts across both their respective in-sample periods and subsequent out-of-sample periods. The

[1] As a case in a point, Harvey, Liu, and Zhu (2016) find that of over 300 documented stock-level anomalies many become questionable after analyzing these in a rigorous testing framework that allows for multiple hypotheses testing bias. Related, Hou, Xue, and Zhang (2020) conduct a large-scale replication study of 447 anomalies and find that 65% are insignificant at the 5% level using conventional critical values and 85% are insignificant using a critical value of three. Chordia, Goyal, and Saretto (2020) show that of about 2.1 million possible trading strategies only a small group survives after correcting for a multiple hypothesis testing bias.

in-sample period spans the sample period of the original studies (Black, Jensen, and Scholes, 1972, Banz, 1981 and Fama and French, 1992, Basu, 1977 and Fama and French, 1992, Jegadeesh and Titman, 1993, Lehmann, 1990 and Jegadeesh, 1990, Keloharju, Linnainmaa, and Nyberg, 2016, De Bondt and Thaler, 1985), while the out-of-sample period spans the period thereafter until the end of 2024. Consistent with the earlier studies, all factors except size exhibit significance over the in-sample period. However, results look materially different over subsequent out-of-sample periods with most factors losing their significance at traditional confidence levels. Only momentum remains significant, whereas others are insignificant over the more recent sample. This decay in the performance of equity factors raises concerns about their validity potentially attributable to p-hacking and underscores the need for independent out-of-sample tests.[2]

INSERT FIGURE 1 HERE

In this study we address this challenge and thoroughly examine equity factors out-of-sample. A complicating factor for independent out-of-sample studies is factor performance decay due to post-publication arbitrage as noted by McLean and Pontiff (2016). They find that out-of-sample performance decay of several anomalies increases due to post-publication arbitrage.[3] To rule out the arbitrage hypothesis

[2] These worries hold yet while many of the factors have been studied in international markets. For example, although the value factor is significant in European and Asian stock markets, size and momentum yield very mixed results (see Fama and French, 1998, 2012, 2017). Further, international markets are not independent of the U.S., as stock markets and its cross-sectional return patterns are integrated globally to a large degree (e.g. Griffin, Yi and Martin, 2003, Asness, Moskowitz and Pedersen, 2013).

[3] McLean and Pontiff (2016) find a post-publication performance decay of 58% over on average 13 years of post-publication data, which they attribute to arbitrage trading. In contrast, they find a much smaller decay in the post-sample period that is *prior* to publication of the results, although their out-of-sample period is short (on average 5 years), thereby limiting the power of their tests.

effectively, the most powerful way for independent out-of-sample test is to go backwards in time. Interestingly, the period before the start date of the Center for Research in Security Prices (CRSP) dataset (i.e., 1926) provides a unique opportunity. This 'pre-CRSP' period was a period of strong economic growth and rapid industrial developments, with stock markets playing a pivotal role. The available sample period spans a sizeable 61 years (1866-1926), which is comparable to the length used in many existing CRSP-based studies.[4] Consequently, conducting tests in the pre-CRSP era provides a powerful ground for independent out-of-sample tests, while at the same time negating the arbitrage hypothesis for factor decay, since investors at that time could not have traded on insights from future research.

To this end, we construct a novel database covering the 3,269 stocks traded on the U.S. exchanges between January 1866 and December 1926. The database consists of stock prices, dividend yields, and market capitalization values. To the best of our knowledge, we are the first to create an extensive dataset for this period that also includes market capitalization. This is imperative as a historical abundance of small capitalization stocks over the pre-CRSP era could render findings economically less important.[5] We apply a wide range of data quality filters to the pre-CRSP dataset to ensure good data quality, external validity, and sufficient economic importance.

[4] The first empirical tests of the Capital Asset Pricing Model (CAPM) by Black, Jensen, Scholes (1972) and Fama and MacBeth (1973) used a sample period of about 40-years. In the years that followed, the main asset pricing findings were that beta is not significantly related to return, whereas other factors such as dividend yield (Litzenberger and Ramaswamy,1979) and firm size (Banz, 1981) are related to return. These studies relied on samples of 500 to 1,000 NYSE-listed stocks over a 40 to 50 years sample periods. In their seminal paper, Fama and French (1992) use a sample period covering 28.5 years of data (1963-1990), and since most studies to the cross-section of stock returns span the post-1963 CRSP sample period.

[5] Amongst others, Fama and French (2008), Hou, Xue, and Zhang (2020), and Novy-Marx and Velikov (2022) show that many equity anomalies fail in the post-1963 sample when the smallest stocks are excluded.

The study focuses on equity factors previously studied that can reliably be constructed over the pre-CRSP sample. This procedure yields 37 variables across the following factor groups: low-risk (including market beta), firm size, value, price momentum, short-term reversal, long-term reversal, and seasonality. Importantly, across the study we test dividend yield as proxy for value – in the 19th century dividends were seen as the common valuation technique for stocks (e.g., Dowrie and Fuller, 1950, Poitras, 2010) – as the absence of comprehensive and cross-sectional comparable income and balance sheet data records in the pre-CRSP era prevents the inclusion of other value, as well as quality-related factors (such as profitability or investments), into our analysis.[6]

We start our analysis with Fama-MacBeth (1973) regressions and univariate portfolio sorts, both of which we value-weight to prevent an undue impact of smaller stocks. In line with CRSP sample evidence by Black, Jensen and Scholes and Fama-MacBeth, we find that market beta is not priced in the cross-section and the CAPM on average fails to explain asset prices: low-beta stocks have positive alpha and high-beta stocks have negative alpha over the 1866-1926 sample. Further, value, momentum, and seasonality carry significant cross-sectional premia. By contrast, size and long-term reversal have no significant return spread in portfolio sorts, while short-term reversal is only significant in Fama-MacBeth regressions.

Next, we build 'Fama-French style' market-neutral factor portfolios, double-sorted on size and a factor characteristic.[7] As size is known to interact strongly with other characteristics (e.g., Fama and French, 1992, 2012, and Israel and Moskowitz,

[6] Accordingly, our evidence establishes a value premium based on dividend yield but does not imply that the results necessarily extend to alternative value measures, such as book-to-market or earnings-to-price.
[7] Akin to Frazzini and Pedersen (2014) we lever beta-sorted portfolios to be market-neutral.

2013) and our historical sample includes sufficient coverage on market capitalization, we are able to control for interactions with size. The main findings are summarized in Figure 2. We find economically substantial and statistically significant premia (as reflected in CAPM alphas) for value, momentum, low-risk, and seasonality but insignificance of the other factor premia. Additional extensive robustness tests confirm that value, momentum, low-risk, and seasonality remain significant across testing choices.

INSERT FIGURE 2 HERE

Next, we assess the impact of data snooping on the observed factor premia. Comparing outcomes from the pre-CRSP and CRSP periods provides a natural way to assess the extent to which data snooping concerns may influence reported results, while abstracting from the competing hypothesis that factor decay reflects arbitrage activity. Prior work shows that data snooping can mechanically inflate in-sample returns and reduce estimated covariances, thereby overstating statistical significance (Linnainmaa and Roberts, 2018, McLean and Pontiff, 2016). We find that out-of-sample decay of stock factor premia is relatively small and statistically insignificant, with factor premia averaging 4.0% in the pre-CRSP sample and 4.7% during the CRSP sample period. Further, when distinguishing post-publication decay from decay attributable to data snooping over our 159-year sample, we find no statistically significant evidence of data-snooping-driven decay. Additionally, we find no evidence for changes in factor correlations. Interestingly, these findings align in size with a 26% out-of-sample decay observed by McLean and Pontiff (2016) over

5-years of post- sample periods yet diverge from Linnainmaa and Roberts (2018)'s findings on accounting-based anomalies for the 1938-1963 period. The absence of significant out-of-sample decay supports the conclusion that the value, momentum, low-risk, and seasonality factors are not a result of data snooping. Overall, we conclude that these factors stand out as persuasive empirical equity factors in out-of-sample analysis.

Finally, we explore several features of the early sample period to provide insights into economic explanations of stock factor premia. The 1866-1926 period is interesting for several reasons. First, it is characterized by large macroeconomic shocks and market fluctuations, enriching the traditional CRSP sample with additional market and business cycles, allowing for deep-sample insights into macroeconomic risk explanations. Second, delegated asset management was notably absent over this period (Rouwenhorst, 2004), hence providing a natural test on the impact of delegated management or benchmarks as a limit to arbitrage. Third, the period allows for an insightful examination of momentum's relation with crash risk, as highlighted by Daniel and Moskowitz (2016), given that crashes are infrequent yet critical events. Fourth, we explore more general downside risk explanations of stock factors, in spirit of Bawa and Lindenberg (1977). Our findings reveal that factor premia generally bear no significant relation to common macroeconomic factors nor the delegated management hypothesis. While momentum is exposed to crash risk, the equity factor premia are hard to align with downside risk explanations.

This study contributes to several additional strands of the asset pricing literature. First, we add to the body of empirical asset pricing studies utilizing deep

historical samples. Davis, Fama and French (2000) are the first to examine the value premium in the early CRSP period (1929–1963). More recent work studies individual factors before 1926. Geczy and Samonov (2016) document a momentum premium in the U.S. prior to 1926, but their dataset lacks dividends and market capitalization, which are important given the historical prevalence of small-cap stocks.[8] Goetzmann and Huang (2018) find similar evidence in the imperial Russia stock market from 1865 to 1914 but rely on equal-weighted returns due to missing share data. In contrast, we examine multiple characteristics, apply value-weighting, and incorporate both the capital appreciation and distribution component of returns.[9] Related work studies specific factors in historical markets, such as size and value in the U.K between 1870 and 1913 (Grossman and Shore, 2006). In a broader context, long-run studies document aggregate equity premia over extended horizons back to 1800 or even 1629 (e.g., Siegel, 1992, Goetzmann, 1993, Golez and Koudijs, 2018).

Most closely related, Baltussen, Swinkels and Van Vliet (2021) study global factor premia out-of-sample across equity, bond, currency, and commodity markets stretching back to 1800. They find a strong and consistent presence of the majority of global factor premia such as value, momentum, low-risk, and seasonality in 217 years of data. However, they do not study the cross-section of U.S. stock returns but rather focus on factors across global markets, which are largely uncorrelated with

[8] Dividends were historically a major source of return, on average accounting for 51% of the average stock return and 81% of the value-weighted returns.

[9] Other studies examine the out-of-sample performance of accounting-based variables over the early CRSP sample. Linnainmaa and Roberts (2018) show value, profitability, and investment factors are absent over the early CRSP period (i.e., 1926-1963), while Wahal (2019) finds a sizable profitability premium between 1940 and 1963 but an insignificant investment factor premium.

ours. Consequently, their findings complement ours, albeit on an independent set of assets.

In addition, several studies examine the role of data mining on equity factor premia and question the significance of many stock anomalies in replication studies and after applying multiple hypotheses testing corrections (Harvey, Liu, and Zhu, 2016, Hou, Xue, and Zhang, 2020, Chordia, Goyal, and Saretto, 2020). In contrast, Jensen, Kelly, and Pedersen (2023) challenge the view that the factor literature is dominated by spurious findings, showing that most factors can be replicated, cluster into a small number of underlying themes, and remain economically meaningful out-of-sample across a large international dataset. Complementing this evidence, we show that many of these return patterns were already present in the pre-CRSP era – an independent and extensive out-of-sample period that, by construction, is unaffected by post-publication arbitrage – thereby providing independent, long-horizon validation of the persistent presence of prominent equity factors; value, momentum, low-risk, and seasonality.

The remainder of this paper is structured as follows. Section II describes the history of the U.S. equity market and the novel database of U.S. stock prices between 1866 and 1926. Section III analyses the cross-section of stock returns via Fama-MacBeth regressions and portfolio sorts. Section IV analyses the out-of-sample decay of factor premia. Section V discusses historical investability. Section VI examines insights into economic mechanisms. Section VII concludes. The Online Appendix provides extensive detail on the sample construction, data quality, historical investability, and presents a series of additional results.

II. The 'pre-CRSP' U.S. stock dataset: 1866 – 1926

The 1866-1926 period was characterized by strong economic growth and industrial developments, laying the foundations of the U.S. becoming the leading economic power in the world. Demand and supply of stock financing grew rapidly resulting in the U.S. stock market experiencing rapid growth. By the early 20th century, the stock market was large relative to the size of the U.S. economy, with a (New York) stock market capitalization to GDP ratio of 174%, similar to the level observed in 2015 (Neal, 2016). Stocks traded across various exchanges, most notably the New York Stock Exchange (NYSE) and the New York Curb (the predecessor of the AMEX). Most of the trading activity took place on the NYSE, followed by the NY Curb and regional exchanges (mainly Boston and Philadelphia) (Brown et al., 2008, O'Sullivan, 2007). Total annual shares trading volume rose from about 100 million in 1885, to 150 million in 1900, to 250 million in 1915, to 1,151 million shares in 1930. Over two-thirds of trading volume originated from the NYSE, followed by the New York Curb (about 20%), and regional exchanges (about 10% of total). For more detail on the history of the U.S. equity market, we refer to Online Appendix A.

In order to construct a reliable and historically extensive sample we compile the pre-CRSP dataset from several sources. The sample spans the period from January 1866 through December 1926 and is at the monthly frequency, containing stock prices, dividend yields, shares outstanding, and market capitalizations for all major stocks traded on the NYSE, NY Curb, regional exchanges, and on Over-The-Counter (OTC) markets. We use Global Financial Data (GFD) and the Commercial and Financial Chronicle (CFC, the source used to build the CRSP sample as of 1926). The CFC was a well-read financial newspaper containing daily information

on stock prices and other characteristics, and the GFD stock database has an extensive informational coverage of stocks traded in the U.S. across the NYSE, NY Curb, and regional exchanges, as well as OTC markets. We use GFD as our main source, the prices which we validate against the CFC, and we complement data on the number of shares outstanding with hand-collected from the CFC (GFD did historically not always include reliable information on shares outstanding). The CFC dates to 1865, implying our start date of 1866 for this study. Importantly, the sample includes delisted stocks and as such is believed to be free of a survivorship bias. Our dataset construction and verification procedure are described in extensive detail in Online Appendix A. Tables A.3 to A.5 and Figures A.3 to A.5 in the Online Appendix summarize the stocks included in our sample, the return series, market capitalization, dividend characteristics, as well as the industry and exchange compositions.[10] We combine this data with post-1926 data on equity factor returns from CRSP and Kenneth French's website in Section IV. Further, we source risk-free rates before 1926 from GFD and Jeremy Siegel's database. However, because short-term interest rates before the establishment of the FED in 1914 likely embed meaningful credit risk, we focus throughout the paper on total returns rather than excess returns to improve comparability across periods.

Even though we (and the data vendors) have paid close attention to data quality, the deep historical data tends to be of lesser quality compared to the more recent data, as digital archives and strong requirements on data processes did not exist. Instead, data was typically maintained by exchanges, statistical agencies,

[10] A notable result in these tables is the relatively small number of stocks (less than 50) in our cross-section during the first years of our sample period. This makes it more difficult to detect the existence of factor premia as the variation around the average is likely greater due to limited diversification benefits in the factor portfolios.

newspapers, and investor annuals, often in manual writing. Potential data quality issues that could be at work include (manual) misprints and other measurement errors, but also the use of old data, the use of time-averaged prices over a month (often average of the lowest and highest monthly prices), and the timing of dividends sometimes being unknown but assigned at quarter or year ends.

Lesser data quality could influence our tests in a number of ways. On the one hand it could create random measurement errors in our data, thereby biasing our results towards the null hypothesis that a return factor does not exist. On the other hand, if biases in the data correlate with factor premia, they could create spurious results. For example, Schwert (1990) shows that the use of the average of high and low prices over a month generates an artificial AR(1) process in the return series. Further, measurement errors could cause prices to be spuriously inflated, trigger potential reversal (value) profits.

To construct a high-quality dataset, we have taken the following steps. First, we have checked and corrected each data series for potential data errors as outlined in detail in the Online Appendix, Section A. Second, we have verified (with 100% success) a random sample of dividends and stock prices from GFD versus CFC data, and corporate events versus CFC, Poor's Railroad Manual, and McQuarrie (2021). Third, we construct market indices which we compare against the GFD U.S. stock indices and indices constructed by Schwert (1990) and Goetzmann, Ibbotson, and Peng (2001) (see Table A.3 and Figure A.3 in the Online Appendix). Fourth, we compare the market value distributions of our sample in 1926 versus the CRSP sample (see Figure A.4 in the Online Appendix). Fifth, we apply a number of

conservative screens on our data series and remove data points when they do not pass these screens.

These screens include (i) a 'zero return screen' – leaving out data series with more than one zero or missing price return observations in the past 12 months, (ii) a 'return interpolation screen' – leaving out identical returns in consecutive months, and (iii) a 'stale return screen' – leaving out observation which do not have nine or more differentiating returns over the past 12 months. The first screen filters for data historically available at a non-monthly frequency and reduced liquidity, as assets with lower liquidity or no trades are more likely to have zero-returns. Lesmond, Ogden, and Trzcinka (1999) show that the number of periods with zero-returns is an efficient proxy for liquidity. The second screen filters an unlikely return pattern, exactly identical consecutive monthly returns, which indicate return interpolation. The third screen filters returns which are not updated at the monthly frequency. To this end, we remove an asset at each point in time when over the past 12-months there are less than nine unique monthly returns when rounded to five basis points. We have simulated that such a pattern is unlikely under a normal distribution and the empirical stock return distribution in our universe.[11] Further, we always skip a month between the momentum signal and investing, which removes possible spurious autocorrelation at the monthly frequency.

Please note that these screens mitigate data quality concerns and allow us to select reliable, better tradable data points. Importantly, we implement all data-

[11] More specifically, we have randomly drawn 10,000 observations (with replacement) from the normal distribution with mean and volatility equal to the equal-weighted or value-weighted average stock return over our sample period (see Online Appendix, Table A.1), or from the empirical 1926-2019 CRSP market return distribution, and examined the occurrence of this screen. Under these simulations this screen is triggered for less than 0.5% of the observations.

quality screens using only information available at the time of portfolio formation. Thus, the screens are strictly ex ante and do not use information realized during the subsequent holding period. We believe these screens to be of primary importance but emphasize that they could potentially bias factor premium estimates downwards if they remove correct data points.[12]

Table 1, Panel A provides an overview of the sample, while Online Appendix A, Tables A.4 and A.5 show further detail on the sample composition. Overall, we have 222,025 unique firm-month observations included in the pre-CRSP sample. Our cross-section starts with 43 stocks in 1866 and ends with 827 stocks in 1926.[13] Note that the latter number is higher than the sample of CRSP stocks (482 in January 1926) as CRSP only includes NYSE-listed stocks before 1962 (see also McQuarrie, 2009), thereby missing a substantial number of (mostly smaller capitalization) stocks from the NY Curb, regional exchanges, and OTC markets. In total, our sample includes 3,269 unique stocks between 1866 and 1926, showing that also delisted firms are included in the sample.

INSERT TABLE 1 HERE

Further, we classify the stocks into five sectors: (i) financials (mostly bank stocks), (ii) infrastructure (mostly railroad stocks), (iii) energy/mining, (iv) utilities, and (v) industrials & miscellaneous stocks. Infrastructure stocks accounted for

[12] We have also examined how data quality screens affect the CRSP universe and find they have a slight impact on the earliest years of the sample. The data quality screens exclude 9.0% of stock observations from CRSP over the period 1927-1930 (we start in 1927 as we need 12-months of observations to apply our screens), which compares drops to 5.2% over the 1926-1962 period, after which the impact becomes more marginal.

[13] Online Appendix Table B.5 compares the number of stocks in our sample with the Cowles and Goetzmann, Ibbotson, and Peng (2001) datasets. The comparison highlights the substantially broader coverage of our dataset, which extends beyond a subset of NYSE-listed firms and materially increases both the number and diversity of firms included in our cross-sectional analysis.

approximately 80% of the market capitalization between 1866 and about 1890, after which energy/mining, and industrial stocks gained in importance through a series of new issue booms, becoming of similar importance in terms of market capitalization as infrastructure, see Online Appendix A – Table A.4. Banks had a large number of listings, but many traded infrequently and had lower market caps. For example, our sample has over 42 stocks in the banking industry in 1896, but they only contributed to 9% of the total market capitalization.

Table 1, Panel B presents (annualized) summary statistics on individual stock returns in our sample. The time-series statistics are computed by first value-weighing returns per month for each firm and then averaging per decade. The value-weighted market index shows an average annual total return of 8.48% and volatility of 11.25% in this period (this compares with an average return of 11.45% and 18.44% volatility of over the period 1927-2024).[14] Further, dividends represent 63% of the average stock return, similar to the findings of Acheson, Hickson, Turner, and Ye (2009) for United Kingdom and United States stock markets in the 19th century. For comparison, in the CRSP sample, the dividend returns contributed to 32% of the total returns.

III. The cross-section of stock returns: 1866 and 1926

Next, we utilize our novel database and examine the cross-section of stock returns over the 1866-1926 period.

[14] Note that volatility was significantly lower over the pre-CRSP period, as also shown by Goetzmann, Ibbotson, and Peng (2001), Danielsson, Valenzuela, and Zer (2018), and Baltussen, Swinkels and Van Vliet (2021). A potential reason is a higher importance of dividends as compared to capital appreciation returns, but we leave an exact examination into the drivers of time-variation in volatility between pre-CRSP and CRSP samples for future research.

A. Anomaly variables

In our study we focus on equity factors that are well-documented in the literature and can reliably be constructed over the pre-CRSP sample. To this end, we (i) construct all variables computed in Jensen, Kelly, and Pedersen (2023) that build on monthly or lower frequency data and can be constructed using the data availability of the CFC and GFD sources outlined in the previous section, and (ii) add return seasonality as defined by Keloharju, Linnainmaa, and Nyberg, (2016). This selection process results in 37 anomaly variables that we cluster in the following seven factor groups, in line with the classification in Jensen, Kelly and Pedersen (2023); low-risk, size, value, price momentum, short-term reversal, long-term reversal, and seasonality. We measure each variable by following as closely as possible the common definition in the literature and outline all definitions in Appendix A. For each group, we focus on the most commonly studied variable in the main body of the paper, and show results of additional variables in Online Appendix B.

Important to note is that this excludes characteristics that require accounting data – such as book-to-market, profitability, or investments – because financial statement data lack consistent coverage and comparability in the U.S. prior to 1926 (Cohen, Polk, and Vuolteenaho, 2003, Linnainmaa and Roberts, 2018, Wahal, 2019).[15] With earnings and book values not widely available, we measure value using dividend yield, defined as dividends over the past 12 months divided by price.

[15] U.S. firms listed on the NYSE were not required to publish audited financial statements until 1932. Standardization of financial statements increased following the establishment of the SEC in 1934, and specific prescriptions regarding the content and format of financial reports was established by the Committee on Accounting Practices in 1939 and Regulation S-X in 1940. Cohen, Polk, and Vuolteenaho (2003) study the historical SEC enforcement records and conclude that post-1936 accounting data is of sufficiently high quality to employ in empirical analysis, while Wahal (2019) concludes that income statement data are of usable quality from 1938 onward and book value and total assets data from 1926.

Dividends are widely available throughout the pre-CRSP period. In the 19th century dividends were widespread, closely linked to earnings (Braggion and Moore, 2011), and widely regarded as the primary valuation metric for equities (Dowrie and Fuller, 1950, Poitras, 2010).[16]

B. Fama-MacBeth regressions

We start our analysis by estimating monthly Fama and MacBeth (1973) regressions to estimate premia associated with the above stock characteristics without a need to specify portfolio breakpoints or other degrees of freedom. We value-weight each stock-month observation to prevent our results from being skewed to smaller stocks, especially the many small bank stocks present historically. Moreover, value-weighting is shown to be an effective procedure to mitigate the upward biases in regression estimates arising from noise in stock prices (Asparouhova, Bessembinder, and Kalcheva, 2013). Table 2 contains the results, with average slopes multiplied by 100.

INSERT TABLE 2 HERE

[16] For example, Fama and French (1998) use dividend yield, amongst others, when testing the global value premium. We have verified that, in the post-1926 period, value strategies based on dividend yield are highly correlated with those based on book-to-market and earnings-to-price, although the average value premium based on dividend yield is weaker than the premiums based on these alternative value measures. Accordingly, our pre-CRSP results based on dividend yield do not necessarily extend to these alternative value measures.

First, we find a flat relationship between market beta and return, with a slope coefficient close to zero (0.01, t-statistic = 0.16). In other words, the CAPM fails in the cross-section of stock returns over the pre-CRSP sample, similar to the findings of amongst others Fama and French (1992) over a more recent sample. We also observe for size no significant relationship between (log) market capitalization and returns (slope = 0.03, t-statistic = 1.05).[17] Further, dividend yield (our historical measure for value) carries a positive slope (4.38, t-statistic = 3.52), in direction similar to the results of book-to-market ratio over the CRSP sample period (e.g., Fama and French, 1992). Momentum has a significantly positive slope (0.93, t-statistic = 3.42), again akin to recent sample results. Short-term reversal has a negative and insignificant slope (-1.02, t-statistic = -1.14), which becomes significant in a multivariate setting (-4.05, t-statistic = -4.26) as shown in the last column of Table 2. Long-term reversal has no significant relationship with future returns (0.09, t-statistic = 0.96), while seasonality has a strong positive relationship (3.12, t-statistic = 3.06).

[17] Note that these results could be driven by using value weights in the regressions. When using equal weights, we observe a univariate slope that is insignificant (-0.03, t-statistic = -0.57), but a slope in multivariate regressions that is negative and marginally significant (-0.09, t-statistic = -1.86), see Online Appendix Table B.1.

C. Univariate portfolio sorts

Next, we examine the performance of value-weighted univariate portfolios. At the end of every month, we form quintile portfolios that are rebalanced monthly, as our data series are updated at the end of every month (unlike for example post-1926 accounting data, which is typically available at the annual or quarterly frequency). We form quintile portfolios to balance the spread in characteristics across portfolios and the number of stocks within each portfolio. Note that in the first years of our sample we have 40 to 50 stocks in the cross-section, increasing to over 800 in the last years of our sample. In the robustness section we also consider tercile and decile portfolios, although we like to stress that especially the latter have sizable idiosyncratic risks in the earlier years of our sample. For value we group all non-positive[18] dividend stocks in one portfolio and distribute the remaining stocks equally across the other portfolios in case the breakpoint of the first portfolio equals zero. Table 3 shows the (annualized) excess returns, as well as intercepts and slopes from the CAPM model for each portfolio, as well as for the top minus bottom portfolios.

INSERT TABLE 3 HERE

[18] Note that several stocks historically exhibit negative dividends, see Online Appendix A for more detail. In particular several companies engaged in 'assessments', which are effectively reverse dividends whereby companies called for additional capital upon its shareholders to cover the difference between par value and subscribed (i.e., nominal) capital.

The results generally confirm the Fama-MacBeth regression results. The beta-sorted portfolios carry similar average excess returns, with high beta portfolios not significantly outperforming low beta portfolios (t-statistic = -0.21). Consequently, CAPM alphas are significantly positive for low beta portfolios and significantly negative for high beta portfolios, resulting in a -9.00 % (annualized) alpha of the high-minus-low beta portfolio (t-statistic = -5.11). Size-sorted portfolios reveal an insignificant return spread (t-statistic = 0.53). High value stocks significantly outperform low value stocks by 5.60% per annum (t-statistic = 2.48). As non-dividend paying firms typically have more volatile stocks with high market betas (see Fama and French, 1993, for similar effect over the more recent period)[19], the CAPM alpha increases to 10.20% (t-statistic = 5.83). Similarly, winner stocks outperform loser stocks by 8.40% per annum (t-statistic = 3.13). As losers typically had a higher beta than winners, the resulting CAPM alpha is 11.17% (t-statistic = 4.37). Further, we observe insignificant return spreads for short-term and long-term reversal sorted portfolios, while past seasonal winners outperform seasonal losers by 5.07% per annum (t-statistic = 2.94).

D. 2x3 factor portfolios

The above analysis reveals significant differences in the cross-section of stock returns based on characteristics. Next, we follow Fama and French (1993) and construct standard 2x3 portfolios sorted on size and a characteristic. To construct the 2x3 portfolios, every month all stocks in our database are classified as either

[19] Zero and negative dividend paying stocks have a beta of 1.99 compared to 0.99 for high dividend stocks over the pre-CRSP sample period. For comparison, Fama and French (1993) report a beta of 1.45 for zero-dividend firms and 0.73 for the quintile of firms that pay the highest dividends over the post-1963 CRSP sample period.

large or small, using the median cross-sectional market capitalization as breakpoint.[20] Next stocks are sorted on their characteristic within both size groups and split in three portfolios (Low, Medium, High) based on the 30% and 70% percentiles. High always refers to the favorable characteristic (i.e., low beta, high dividend yield, high momentum, low past 1-month or 60-months return, high past seasonal returns). The exception for this formation is for value, as at most points in time at least 30% of the smaller capitalization stocks have a 0% dividend yield, see Online Appendix A, Figure A.5. In these cases, stocks with a non-positive dividend yield are assigned to the Low portfolio. The remainder of the stocks are then assigned to the Medium and High portfolios, based on the 50% percentile of the stocks that have a dividend yield above 0%.[21] The final factor is created by taking a fifty-fifty long position in large-cap and small-cap High stocks, combined with a fifty-fifty short position in large-cap and small-cap Low stocks. Note that the above procedure differs from Fama and French (1993) by replacing independent sorts by dependent sorts, as the former sometimes produces empty portfolios, especially in the earlier part of our sample. Soebhag, Van Vliet and Verwijmeren (2024) show a limited impact of this choice over the CRSP sample.

The SMB factor is subsequently constructed by taking the difference, every month, between the simple average of the three small portfolios and the simple average of the three big portfolios across the value sorts (in spirit to Fama and French, 1993, who use book-to-market sorted portfolios). Further, we lever the top-

[20] Note that we deviate here from the common practice in the asset pricing literature by not NYSE-only based breakpoints, as stocks traded significantly on multiple exchanges, including regional exchanges and the Curb, see Section III and Online Appendix A, Table A.5.

[21] When the 30th percentile of dividend yield is zero, the low-value portfolio includes a large fraction of firms with non-positive dividends, which tend to exhibit high market betas. To address this, we also re-estimate the value premium restricting the sample to dividend-paying stocks. The resulting CAPM alpha remains economically large and statistically significant (3.11%, t-statistic = 3.34), indicating robustness to this construction.

bottom beta portfolio in order to make it market-neutral by levering the long (low beta) leg up and the short (high beta) leg down to a market beta of 1.[22] For simplicity, market betas are estimated full-sample against the market portfolio, but we like to stress that results do not change materially when we use ex-ante estimated betas using a 36-months rolling-window instead. We floor estimated betas at 0.5 and capped at 2.0 to limit the effect of estimation noise.[23] The 30-day T-bill rate is taken as borrowing and savings rate. This beta-adjustment is in spirit of Frazzini and Pedersen's (2014) Betting-Against-Beta (BAB) factor, while at the same time we mitigate the issue raised by Novy-Marx and Velikov (2022) that the size of the BAB stock factor premium is heavily influenced by a large weight to micro-cap stocks.[24]

INSERT TABLE 4 HERE

[22] Note that especially value and momentum also have strong beta differences across the long and short legs, as loser stocks and zero-dividend payers have substantially larger betas. Although these beta spreads are stronger over the 1866-1926 sample compared to the post-1926 sample, we choose to follow common practice and do not lever these factors to hedge out beta exposures.

[23] We have verified that this choice does not alter our conclusions.

[24] Novy-Marx and Velikov (2022) argue that the weighting scheme in Frazzini and Pedersen (2014) can overweight micro-cap stocks due to its similarity to equal weighting, an effect further amplified by leveraging the low-beta portfolio. Our use of 2×3 sorted value-weighted portfolios substantially reduces this concern and limits the influence of micro-cap stocks on the estimated BETA premium. In addition, we have verified that our results are robust to alternative portfolio constructions, including specifications that avoid leveraging the low-beta portfolio by instead buying market exposure to achieve a zero-beta position.

Table 4 shows the excess returns, volatilities, t-statistics, CAPM alphas and betas, and t-statistics of the CAPM alphas for the 2x3 sorted portfolios. Figure B.2 (B.1) in the Online Appendix shows the cumulative return (10-year rolling return) of each long-short factor series. The naming convention for the portfolios follows Fama and French, with BETA representing the market-neutral low-beta minus high-beta portfolio.

The results generally confirm the results of the Fama-MacBeth regressions and univariate portfolio sorts.

- SMB shows an insignificant and negative factor premium of -0.53% per annum (t-statistic = -0.55). Hence, the size factor does not have a significantly positive average return pre-1926.[25]
- Value (HML) shows an significant premium of 5.00% per annum (t-statistic = 2.78), and as the low dividend stocks have substantially higher betas (the HML beta spread is -0.91, driven especially by small non-dividend payers), the CAPM alpha equals 9.16% per annum, highly significant with a t-statistic of 7.41.
- Momentum (UMD) shows a sizable and significant average premium of 7.15% per annum (t-statistic = 3.58). When controlling for the higher beta on loser stocks (most notably of the small stocks), this spread increases to 9.41% per annum (t-statistic = 5.00).
- Short-term reversal shows an insignificant factor premium of 2.55% per annum (t-statistic = 1.43).

- BETA shows a sizable and significant premium of 7.04% per annum (t-statistic = 4.66), as low beta stocks offer a similar return as high beta stocks, and hence higher beta-corrected returns.[26]
- Long-term reversal shows an insignificant factor premium of 0.18% per annum (t-statistic = 0.09).
- Seasonality factor returns are strongly positive return with an average value of 6.87% per annum (t-statistic = 5.45).

The above results generally show up in both small cap stocks and large stocks. Interestingly, several studies reveal that average returns on factor portfolios tend to be larger in the small-cap space than in the large-cap space (e.g., Fama and French, 1992, 1993, 2012, 2015, Israel and Moskowitz, 2013). In line with this evidence, we find a higher factor premium amongst small-cap stocks for all but the BETA factor, with average premiums being higher between 2% to 3%.

[25] Hou and van Dijk (2019) show that changes in profitability of small versus large stocks explain the (dis)appearance of the size premium over time. Since we lack data on profitability, we cannot corroborate this conjecture over our sample.

[26] Note that the beta of the BETA portfolio is negative (-0.33), which we can attribute to the use of bounding estimated betas between 0.5 and 2.0 to prevent over-leveraging to relatively extreme beta estimates, and indicating that our procedure for levering the low and high beta portfolio is on the conservative side.

E. Robustness to methodological variations, data filters, and variable definitions

Next, we examine the robustness of the above portfolio sort findings for common variation in the sorting or portfolio construction procedure. Robustness of portfolio sort results across testing choices is an additional manner to limit the influence of p-hacking. We consider the following additional variations: univariate sorted tercile or decile portfolios, 2x5 size-characteristic sorted portfolios, or 2x3 size-characteristic sorted portfolios that are either equally weighted or sector-neutral by ranking on the sorting variables within each sector. Panel A of Table 5 summarizes the results by means of the top-bottom return spreads and panel B shows CAPM alphas (note that we now also lever the univariate sorted beta long-short portfolios towards market neutrality).

INSERT TABLE 5 HERE

Overall, we find similar results as in Tables 3 and 4. The value factor premium is sizable in univariate sorts and when controlling for beta exposures, while momentum and BETA are sizable and significant across all variations. Noteworthy exceptions are a significant but negative size premium in returns spreads and CAPM alphas in tercile (but not decile) sorts, and a significant short-term reversal premium in more extreme portfolios (decile or 2x5 sorted portfolios), equally weighted portfolios, or sector-neutral portfolios.

Online Appendix Tables B.2 and B.3 examine additional variables and alternative specifications of the main characteristics. The results are broadly consistent with the baseline findings, with several noteworthy observations. First,

the size effect is not present when measured using firm age, consistent with the results based on market capitalization. More broadly, we do not find evidence of a size premium in our baseline regressions, portfolio sorts, or robustness tests, consistent with the results of Davis, Fama, and French (2000) and Linnainmaa and Roberts (2018), who also fail to detect a significant size premium in the early CRSP period (1926-1963).[27] Second, momentum remains statistically significant across lookback windows ranging from three to twelve months, and is robust to alternative constructions, including price-only returns (excluding dividends) over horizons of six months or longer, firm-specific (residual) momentum, and price-to-high measures. Third, low-risk factor returns are also significant when constructed using total return volatility, downside beta, residual volatility, and correlation-based measures. Finally, seasonal return continuation effects are generally robust across specifications, and (in line with the effect) absent in the non-annual lag specification.[28]

F. Spanning tests

Next, we run spanning regressions of each 2x3 long-short factor portfolio on all other factors to examine factor redundancy. Table 6 shows the results. SMB has a small and insignificant intercept (0.20%, t-statistic = 0.14), akin to the Fama-MacBeth regression results and portfolio sorts. HML has a significantly positive

[27] Importantly, the early CRSP sample (1926–1963) is limited to NYSE-listed firms, whose listing standards favored larger, more established companies and therefore restricted the representation of genuinely small firms.
[28] Historically, dividend payment dates were not always precisely recorded and were sometimes assigned to fixed quarter- or year-end dates. Because the seasonality signal relies on returns in the same calendar month across years, such artificial clustering could mechanically induce seasonality patterns. Moreover, part of the documented seasonality effect is known to originate from dividend seasonality. To address these concerns, we re-estimate seasonality using price returns only. The resulting CAPM alpha remains economically large and statistically significant (3.62%, t-statistic = 2.89).

intercept (5.49%, t-statistic = 5.05), with especially a significant negative correlation to the market (as seen above), SMB and LT reversal, but positive correlation with UMD and BETA (as high dividend stocks typically also have lower beta). UMD has a significantly positive intercept (4.94%, t-statistic = 2.63), while being negatively (positively) correlated to market, size and ST reversal (value and BETA) factors, generally in line with CRSP sample behavior.[29] ST reversal has a marginally significant positive spanning alpha (3.35%, t-statistic = 1.86), indicating some limited complementarity to the other factors. The same holds for LT reversal, which has a significant spanning alpha (4.80%, t-statistic = 2.65) after controlling for its overlap with especially value. BETA has a significantly positive intercept (4.04%, t-statistic = 3.15), despite significant positive correlation to all other factors except short-term reversal. Finally, seasonality has strong non-redundant factor returns (5.71%, t-statistic = 4.26). Overall, we find momentum, value, (low-)BETA, LT reversal, and seasonality to be non-redundant asset pricing factors.

INSERT TABLE 6 HERE

[29] The positive correlation between value (i.e. dividends) and momentum is due to the high historical relevance of dividends in returns, and hence the momentum measure.

IV. Out-of-sample decay

Several studies reveal evidence of substantial out-of-sample decay of stock factor premia. McLean and Pontiff (2016) show that the performance of trading strategies declines after the publication of research papers that document their discovery. Linnainmaa and Roberts (2018) consider the performance of accounting-based equity anomalies in the period before and after discovery and find substantially weaker out-of-sample performance for both subsamples. This raises the question how the estimated premia over the post-1926 CRSP-era compared to premia over the 1866-1926 pre-CRSP sample? To study out-of-sample decay, we measure the performance of the 2x3 sorted high-low portfolios over the 1866-1926 'pre-CRSP' and 1927-2024 'CRSP' sample periods and examine returns spreads and CAPM alphas. To this end, we reconstruct the 2x3 value-weighted portfolios over the CRSP era.[30] Table 7 contains the resulting average top-bottom returns spreads (Panel A) and CAPM alphas (Panel B) of the individual factors and their equally weighted average, while Figure 2 in the introduction depicts the results.

INSERT TABLE 7 HERE

Return spreads and CAPM alphas are generally of similar size over the pre-CRSP and CRSP samples, and do not differ significantly for most characteristic-sorted portfolios. The exceptions are (i) SMB and ST reversal having a significantly lower return spread and CAPM alpha over the 1866-1926 period, and (ii) HML

[30] Factor premia over the CRSP 1927-2024 sample are similar in sign and of about equal size when using the portfolios as published on Kenneth French's data library, with size, dividend, momentum, short-term reversal, and long-term reversal average return spreads differing by 31, 25, 43, 30, and 60 bps per annum, respectively. Note that the most important difference with Kenneth French is the use of dependent sorts in our calculations (instead of independent sorts).

having a significantly larger return spread and CAPM alpha. One explanation for a short-term reversal premium is liquidity provision (e.g., Nagel, 2012), which is seemingly at odds with this finding given the higher illiquidity over the pre-CRSP sample.[31] SMB and LT reversal have insignificant CAPM alphas over both periods, while HML, UMD, BETA, and seasonality all have significant CAPM alphas over both periods.

Next, we examine the average effect across factors. Overall, we find no significant evidence of a pre-sample decay in stock factor performance. Return spreads (CAPM alphas) average 4.04% (4.86%) over the pre-CRSP sample and 4.66% (4.76%) over the CRSP sample period, differing by an insignificant -0.62% (0.10%). Panel regressions confirm these results. These findings compare to an average 26% out-of-sample decay in equity anomaly profits observed by McLean and Pontiff (2016) over 5-years of post-sample periods[32], but contrast with the results of Linnainmaa and Roberts (2018) who find a more significant performance decay in several accounting-based anomalies over the 1938-1963 period. Baltussen, Swinkels and Van Vliet (2021) observe no significant out-of-sample decay for global factor premia over 150 years of out-of-sample data.

A challenge in interpreting factor performance decay is that both arbitrage and data snooping predict weaker out-of-sample returns. Interestingly, the period before the start date of the CRSP dataset (i.e., 1926) provides a useful setting, as it negates the arbitrage hypothesis for factor decay – investors during this period

[31] An alternative explanation is the presence of indexed investors (Baltussen, Da and Van Bekkum, 2019), investors less prominent during the pre-CRSP sample.

[32] By contrast, they find a post-publication performance decay of 58% over on average 13 years of post-publication data, which they attribute to arbitrage trading. Jacobs and Muller (2020) find that the United States is the only country with a reliable post-publication decline, while the effect is generally not present in international markets. Further, Jensen, Kelly, and Pedersen (2023) argue that the observed post-publication decline in anomaly profits could be a statistical artifact of multiple sequential tests from the same data generating process.

could not have traded on insights from subsequent academic research. We can identify four primary periods: (i) the original in-sample period (as reflected in Figure 1), (ii) the subsequent 'post-publication period' (on average 32.7 years of length)[33], (iii) the pre-sample period over the CRSP sample before the in-sample period (on average 17.9 years of length), and (iv) the 1866-1926 'pre-CRSP' sample period (on average 61 years of length). All periods may reflect the influence of data snooping, while only the post-publication period can plausibly reflect performance decay associated with arbitrage activity.

To estimate the size of both effects we regress the factor returns on a dummy variable for the out-of-sample periods and a dummy for the post-publication sample period and show both coefficients relative to the in-sample period. The results of this exercise are as follows. The out-of-sample dummy variable (reflecting an estimate of the impact of data snooping) is significantly negative for the CAPM alpha of ST reversal and LT reversal, while the post-publication effect is significantly negative for the CAPM alpha of BETA, but insignificant for all other factor premiums. Across all seven factor portfolios the estimated data snooping decay effect (estimate via panel regressions) equals an insignificant -0.32%, and the effect of post-publication decay equals a significant -2.95%.

To maximize testing power, we also compute the full sample (1866-2024) results, as presented in the last rows of Panel A and Panel B of Table 7. These results confirm the results above, with an insignificant CAPM alpha on SMB of 0.55% (t-statistic = 0.74) and LT reversal (0.53%, t-statistic = 0.52), and significant

[33] McLean and Pontiff (2016) argue there is a difference in decay post the initial sample period but before publication, and post-publication. We have verified that changing the period to post-publication does not materially impact results.

CAPM alphas varying between 4.96% (t-statistic = 5.08) for ST reversal and 9.92% (t-statistic = 8.51) for UMD. On average, factor premia are sizable and highly significant (4.96% CAPM alpha, t-statistic = 15.27).

Finally, we examine the correlations of the stock factor premia amongst each other over the pre-CRSP and CRSP sample, as data mining could affect the entire return process, including the correlations amongst anomalies. McLean and Pontiff (2016) and Linnainmaa and Roberts (2018) show that correlations amongst anomalies tend to increase out-of-sample (being either on the 'post-discovery' sample of an anomaly or on the 'pre-discovery' sample). To this end, we run panel regressions, following McLean and Pontiff (2016) and Linnainmaa and Roberts (2018), of factor returns on a constant, the market factor, the average return on all other factor series, and interact these regressors with either a dummy for the pre-CRSP sample period, or dummies for the out-of-sample periods and post-publication periods. The results reveal that the dummy coefficients are relatively small (0.09 and 0.24, respectively) and not significantly different from zero (t-statistic = 0.46 and 0.93, respectively), and hence that the studied stock factor premia do not have different correlation structures out-of-sample. Overall, we find no significant evidence in the out-of-sample decay in stock factor premia across 159 years of data once controlling for post-publication decay. We conclude that the equity factors value, momentum, low-risk, and seasonality are unlikely caused by data snooping.

V. Investment frictions and historical investability of equity factors

Our results show that equity factor premia persist over 61 years of independent out-of-sample data. A natural question is whether these premia reflect investment frictions? While standard asset pricing models assume frictionless markets, investors face leverage constraints, short-selling restrictions, and transaction costs, particularly for stock-level factors requiring trading in less liquid securities (e.g., Korajczyk and Sadka, 2004, Avramov, Chordia and Goyal, 2006).

Although frictions are often presumed to have been higher in the 19th century, available evidence suggests that trading was active and not prohibitively costly. As summarized in Online Appendix A, U.S. markets were well developed, with active trading – including shorting – and transaction costs broadly comparable to later periods (e.g., Brown et al., 2008). Jones (2002) reports bid-ask spreads of about 0.5% since 1900, not much different from CRSP-era estimates up to round 1980, and higher turnover on NYSE stocks between 1900 and 1926 than in 2000.

That said, our results do not imply that factor premia were easily exploitable. We do not study implementation issues such as turnover, trading costs, or limits to arbitrage. Prior work shows that implementation costs can be reduced through portfolio design (Novy-Marx and Velikov, 2015), and even investors with limited access could benefit from factor signals, for example by adjusting the timing of trades. A full assessment of net returns after costs is left for future research.

A related point worth noting is that the pre-CRSP market differs materially from the modern CRSP-era market in terms of breadth, sector composition, and institutional structure. In particular, relatively few stocks traded on exchanges

during the 19th century, and markets were heavily dominated by infrastructure firms, whereas market breadth increased substantially over the 20th century. Historical comparisons should therefore be interpreted with appropriate caution, although the persistence of several major factor premia across these markedly different environments remains informative.

VI. Economic explanations

We document robust evidence for the pricing of key equity characteristics in the pre-CRSP sample, providing 61 years of independent out-of-sample validation. A natural next question is what drives these returns? While a complete explanation is beyond the scope of this paper, the pre-CRSP setting offers a unique opportunity to shed light on their economic origins. We therefore examine time-series variation in factor premia since 1866 and evaluate the roles of macroeconomic risk, delegated asset management, crash risk, and downside risk.

A. Macroeconomic risks

The 1866-1926 period is characterized by large macroeconomic shocks and market fluctuations, providing out-of-sample insights into macroeconomic risk explanations of stock factor premia. Asness, Moskowitz and Pedersen (2013) link value and momentum premia to macroeconomic risks, while Griffin, Ji, and Martin (2003) find no such relation for momentum. Following Griffin, Ji, and Martin (2003), we examine exposures to, and unconditional pricing of, macroeconomic factors in the spirit of Chen, Roll and Ross (1986). Specifically, we construct the standard Chen, Roll and Ross (1986) factors – log changes in industrial production (MP; led by 1 month), term spread (UTS), changes in expected inflation (DEI), and unexpected

inflation (UI) – using monthly data.[34] We regress factor returns on these variables to obtain loadings and intercepts. The sample begins in February 1875 due to data availability of historical U.S. inflation data at the monthly frequency. Table 8 reports results for the pre-CRSP (1875–1926), CRSP (1927–2024), and full (1875–2024) samples.

INSERT TABLE 8 HERE

If factor premia are driven by macroeconomic risk, returns should load significantly on these factors. Instead, macroeconomic variables are generally insignificant, inconsistent across subsamples, or exhibit wrong signs. Moreover, intercepts remain positive, highly significant, and comparable in magnitude to raw returns (reported in the column "Actual"), indicating limited explanatory power of macroeconomic risks over 159 years.

Next, we assess whether macroeconomic risk premia explain factor returns using the Fama and MacBeth (1973) approach with factor portfolios as test assets. Combining estimated loadings and premia, we decompose returns into predicted and unexplained components. If macro factors fully explain returns, the unexplained component should not differ from zero. Instead, we find no significant macroeconomic premia, and factor returns remain similar in magnitude and significance after controlling for macroeconomic exposures.[35] Overall, macroeconomic risks do not materially explain stock factor premia.

[34] We collect our data from the FRED database (https://fred.stlouisfed.org/), and before existence of each series in FRED spline with data from Baltussen, Swinkels and Van Vliet (2021). Akin to Griffin, Ji, and Martin (2003), we omit the default premium, as its historical data availability is limited.

[35] An alternative approach to assessing the role of macroeconomic risks is to divide the sample in 'good' and 'bad states' and evaluate factor returns across these states. Online Appendix Table B.4. reports results for two state

B. The role of delegated management

Vayanos and Woolley (2013) propose a model in which momentum and value premia arise from delegated asset management and fund flows. Investors allocate capital based on past performance, generating persistent flows that lead to underreaction and momentum, and eventually push prices away from fundamentals, giving rise to a value premium. Further, delegated asset management can lead to sub-optimal capital allocation, due to misalignment of interest between asset owner and asset manager, flattening the risk-return trade-off, giving rise to a low-risk premium (Baker, Bradley and Wurgler, 2011)

Delegated management was notably absent in the pre-CRSP period, with only a limited number of (primarily closed-end) equity mutual funds available to U.S. investors before 1926. presence of significant value, momentum, and low-risk premia in this setting therefore challenges explanations that rely solely on delegated management structures.[36]

C. Crash risk and Momentum

Several studies argue that momentum is exposed to extreme downside risk (Barroso and Santa-Clara, 2015, Daniel and Moskowitz, 2016), suggesting that its premium may reflect compensation for infrequent crashes or a peso problem. In contrast, Goetzmann and Huang (2018) show that momentum crashes are absent

indicators: recessions versus expansion and 12-month equity bear versus equity bull markets. Overall, factor premia vary only modestly across economic states.

[36] Note that this finding does not preclude delegated management to drive part of value, momentum, and low-risk factor returns over the CRSP sample.

out-of-sample in imperial Russia. The pre-CRSP sample provides 61 years of independent out-of-sample evidence for U.S. stocks.

To examine momentum crashes, we first analyze the distribution of monthly momentum returns. Panel A of Online Appendix Table B.5 shows the results for the pre-CRSP, CRSP and combined sample periods. Momentum exhibits negative skewness and excess kurtosis in the 1927–2024 period, and to a lesser extent in the pre-CRSP sample. However, the minimum return remains large (–27.65%), indicating that momentum is also subject to substantial crash risk before 1926. Consistent with Daniel and Moskowitz (2016), we further find that momentum behaves like a short call option on the market, particularly following multi-year drawdowns. Panel B confirms this pattern by regressing UMD returns on a past 2-years bear market indicator, the market, its interaction, and its interaction with a contemporaneous up-market indicator. Momentum exhibits significantly negative betas after bear markets and performs poorly during subsequent market rebounds, with similar coefficients across the pre-CRSP and CRSP samples.

Finally, we examine volatility-scaled momentum following Barroso and Santa-Clara (2015). Panel C shows that scaling by past 12-month volatility improves Sharpe ratios, consistent with CRSP-era evidence, but does not materially reduce crash risk in the pre-CRSP period. Overall, these results suggest that crashes are an inherent feature of momentum but are unlikely to explain its existence.[37]

[37] In addition, because institutional features such as delegated asset management were largely absent in the pre-CRSP period, these results suggest that such features are unlikely to be the primary drivers of momentum crashes.

D. Downside risk

A large literature examines whether stock factor premia compensate investors for downside risk. We assess this hypothesis using the Downside Risk CAPM (DR CAPM) of Hogan and Warren (1974) and Bawa and Lindenberg (1977), which extends the mean-variance framework to settings with non-normal returns and investor aversion to downside risk. In this framework, assets with higher downside betas command higher expected returns.

A key challenge in testing downside risk is the limited number of extreme negative market observations. For example, Lettau, Maggiori, and Weber (2014) identify only 55 months with equity market returns below -1 standard deviation in their 1974–2010 sample. In contrast, our 159-year sample contains 186 such observations, allowing for more precise estimation, including deeper left-tail events. We estimate downside betas using alternative thresholds: zero ('zero'), -1 standard deviation ('1 sigma'), and -2 standard deviations ('2 sigma').[38]

Table B.6 in the Online Appendix reports CAPM and DR CAPM results. Downside betas are similar to standard betas, with differences of at most 0.23. Consequently, DR CAPM alphas differ little from CAPM alphas (mostly 1.05%), and all persistent factor premia remain economically large and statistically significant. Overall, downside risk does not materially explain stock factor premia over 159 years of data.

[38] We define downside beta as: $\beta_{down,i} = \frac{E[R_m R_i | R_m \leq threshold]}{E[R_m^2 | R_m \leq threshold]}$.

VII. Conclusion

We examine the cross-section of stock returns out-of-sample using a newly constructed database of 3,269 U.S. stocks from 1866 to 1926. Results from this pre-CRSP period largely confirm CRSP-era findings: the relation between market beta and returns is flat, while momentum, value, low-risk, and seasonality premia are economically large and statistically significant. In contrast, we find no significant size, short-term reversal, or long-term reversal premia. Extending the analysis across the pre-CRSP and CRSP periods, we also find little evidence that factor premia decay out of sample due to data snooping. Overall, these findings indicate that equity factor premia are robust empirical regularities that persist out-of-sample. Finally, leveraging 159 years of data, we show that time variation in factor premia is difficult to reconcile with explanations based on macroeconomic risk, delegated management, crash risk, or downside risk.

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Appendix A: Variable definitions

- Market (1). We construct the market factor by value-weighting all stock returns by month and subtracting the proxy for the risk-free rate.

- Size (2). We define size as the (log) total market capitalization of a firm (Banz, 1981). Within the size theme we also use firm age, defined as age of the firms in months as in Jiang, Lee, and Zhang (2005).

- Value (1). We define value as the dividend yield over the past year (i.e., dividends over the past 12 months divided by price).

- Momentum (12). We measure momentum by the total return of a stock between months t − 12 and t − 2, as in Jegadeesh and Titman (1993). Following Jegadeesh and Titman (1993) we also various horizons measuring the total return of a stock between months t − 3 and t − 2, between months t − 6 and t − 2, and between months t – 9 and t – 2. We also create momentum between months t – 12 and t – 7 as in Novy-Marx, (2012). These five horizons are also replicated using price returns instead of total returns, resulting in five price momentum signals. Next, we calculate Residual Momentum as in Blitz et al. (2011), with a slight alteration as we only use the market factor for our residualization as Fama French factors are not available for this period. As a last variable within the Momentum theme, we use Price-To-High (PTH) as in Huang (2009) by dividing last month's price by the highest price over the past 12 months.

- Short-term reversal (2). We define short-term reversal by the past 1-month return, following Jegadeesh (1991), and create a short-term reversal based on price returns.

- Low-risk (5). We construct the beta via a regression of a stock's return on the market's excess return over the past 36 months (minimum of 12). We construct volatility by calculating the standard deviation of returns over the past 36 months (minimum of 12). Downside beta is calculated as in Ang, Chen, and Xing (2006), 60 months correlation as in Asness, Gormsen, and Pedersen (2020), and lastly residual volatility as in Ali, Hwang & Trombley (2003).

- Long-term reversal (2). We measured long-term reversal by the total return of a stock between months t − 60 and t − 13, as in De Bondt and Thaler (1985). A price long-term reversal variable is created over the same horizon.

- Seasonality (12). We construct seasonality following Keloharju, Linnainmaa, and Nyberg (2016) by averaging returns over annual lags from year t-1 to t-20, requiring a minimum of one year of observations. In similar fashion, we create seasonality non-annual by averaging returns over non-annual lags from year t-1 to t-20. We extend the set of annual and non-annual seasonality variables with the horizons from Heston & Sadka (2008), which require full coverage for the period specified. There horizons are year t − 1, year t − 2 until t − 5, year t − 6 until t − 10, year t − 11 until t − 15, and year t − 16 until t − 20.

Figures

Figure 1: Equity factor premia: in-sample and subsequent out-of-sample samples.

The figure shows t-statistics of CAPM alphas for the size, value, momentum, short-term reversal, beta, long-term reversal, and seasonality factors over original 'in-sample CRSP' periods and subsequent 'out-of-sample CRSP' periods. The dotted line represents the traditional 5% significance level cutoffs. Factors are constructed from top-bottom portfolios from 2x3 size-characteristic-based portfolios. Definitions and in-sample periods generally follow the original studies: Banz, 1981, and Fama and French, 1992; Basu, 1977, and Fama and French, 1992; Jegadeesh and Titman, 1993; Lehmann, 1990, and Jegadeesh, 1990; Black, Jensen, and Scholes, 1972; De Bondt and Thaler, 1985; Heston and Sadka, 2008 and Keloharju, Linnainmaa, and Nyberg, 2016. The in-sample periods are 1926-1990 for size, 1957-1990 for value, 1965-1989 for momentum, 1934-1987 for short-term reversal, 1931-1990 for beta, 1931-1982 for long-term reversal, and 1963-2011 for seasonality. The out-of-sample periods spans the period after till the end of 2024. Performance is measured on a monthly frequency.

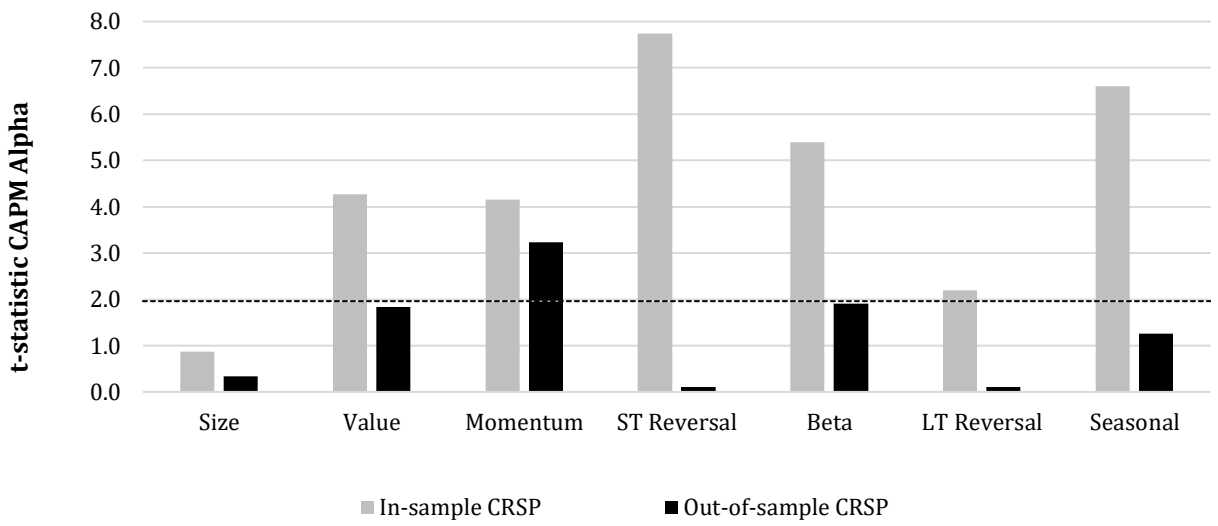
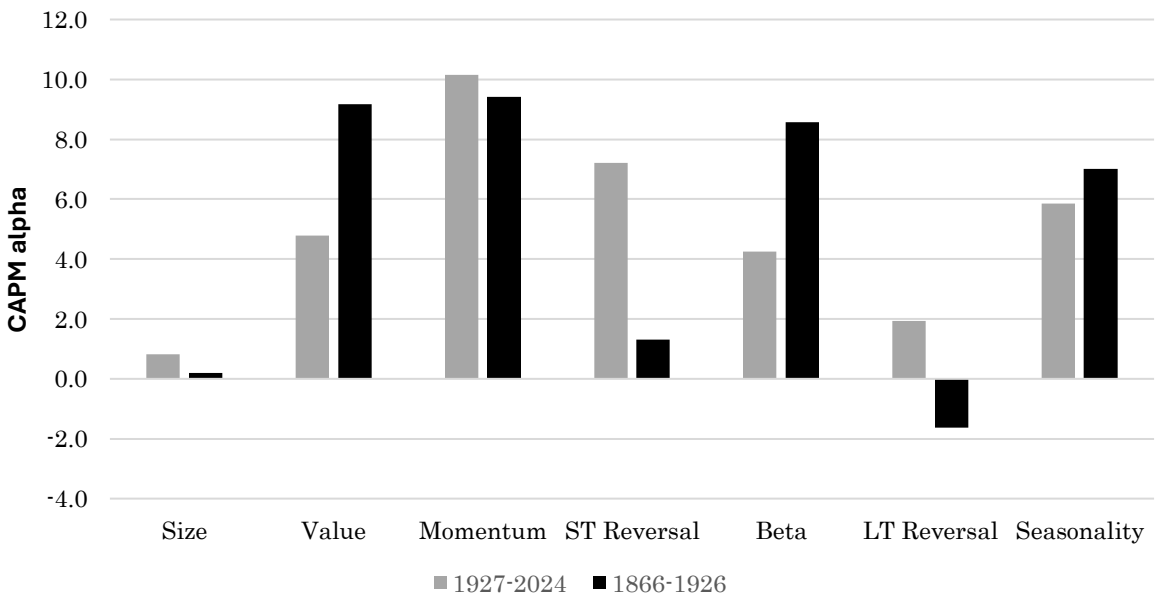


Figure 2: Equity factor premia: pre-CRSP and CRSP samples.

The figure shows the average CAPM alphas for the size, value, momentum, short-term reversal, beta, long-term reversal, and seasonality factors for the pre-CRSP and full CRSP samples. Factors are constructed from top-bottom portfolios from 2x3 size-characteristic-based portfolios. The pre-CRSP sample starts in January 1866 and ends December 1926. The CRSP sample runs between January 1927, except for long-term reversal which starts in 1931, the starting date of UMD, and December 2024. Performance is measured on a monthly frequency.



Tables

Table 1: The U.S. stock database – 1866-1926

The table reports descriptive statistics of our sample. Panel A reports the statistics of our sample composition. The panel reports the number of stocks included in the cross-section ("Nr. of Stocks") and the total market value of all stocks in the cross-section ("MV of stocks ($mln). Panel B reports summary statistics for the return distribution. It presents the sample averages of the value-weighted (annualized) total return, price return and dividend return, as well as the cross-sectional standard deviation ("CS std. deviation"), and 25th, 50th, and 75th percentiles of monthly total returns. The bottom row shows the grand average over our total sample. Statistics are shown per start of every 10-year period in our sample and over our full sample period. The sample runs from January 1866 to December 1926 and is at the monthly frequency.

Panel A: Sample composition

Year	Nr. of stocks	MV of stocks ($mln)
1866	43	299
1876	70	586
1886	241	1,795
1896	217	2,226
1906	329	8,091
1916	478	15,348
1926	827	37,820
1866-1926	3,269	

Panel B: Return distribution

Year	Total return	Price return	Dividend return	CS std. deviation	25-th percentile	50-th percentile	75-th percentile
1866-1869	7.11	0.37	6.73	6.51	-2.40	0.56	3.38
1870s	9.51	3.10	6.42	9.14	-2.65	0.40	3.33
1880s	6.24	1.52	4.73	12.40	-3.29	0.43	3.99
1890s	8.17	3.44	4.73	10.50	-3.15	0.32	3.90
1900s	9.97	5.41	4.56	9.05	-3.04	0.30	4.03
1910s	6.61	1.04	5.57	8.77	-3.08	0.13	3.45
1920-1926	11.99	6.54	5.45	10.74	-4.20	0.23	4.85
1866-1926	8.48	3.15	5.33	9.83	-3.13	0.32	3.84

Table 2: Fama-MacBeth regression results

This table presents coefficient estimates from monthly Fama-MacBeth (1973) regressions of returns between month *t* and *t+1* against a constant and a series of stock characteristics, as described in Section III. Stock characteristics are measured at the end of month *t* over our sample period from January 1866 to December 1926. We report slope coefficients (multiplied by 100) with standard t-statistics in parentheses, the R^2 of the regressions ("R^2"), and the number of observations ("No. of obs."). Observations are value-weighted. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5	6	7	8
Constant	0.71***	0.62***	0.48***	0.61***	0.59***	0.64***	0.67***	0.31*
t	(10.17)	(3.80)	(2.75)	(5.52)	(5.38)	(5.08)	(5.65)	(1.75)
Beta	0.01							0.05
t	(0.16)							(0.48)
ln(Size)		0.03						-0.04
t		(1.05)						(-1.04)
Value			4.38***					5.08***
t			(3.52)					(4.34)
Momentum				0.93***				0.63**
t				(3.43)				(2.34)
ST Reversal					-1.02			-4.05***
t					(-1.14)			(-4.26)
LT Reversal						0.09		0.07
t						(0.96)		(0.82)
Seasonality							3.12***	5.23***
t							(3.06)	(3.93)
R2	0.1	0.02	0.04	0.05	0.05	0.05	0.03	0.32
No. of Obs.	219,615	222,025	200,318	200,318	220,134	123,834	220,199	111,901

Table 3: Portfolio sorts

The table reports average returns on univariate portfolios sorted by various stock characteristics, as described in Section III. Each month we sort stocks in ascending order into quintile portfolios ("Q1," "Q2," "Q3," "Q4," and "Q5) based on one stock characteristic and compute returns over the subsequent month. Portfolios are value-weighted. The table presents average annualized returns (Panel A), CAPM alphas (Panel B), and market betas (Panel C) for each portfolio, as well as the difference between the high portfolio and the low portfolio ("Q5–Q1'). The sample runs from January 1866 to December 1926 and is at the monthly frequency. Numbers in parentheses indicate standard t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, which we present only for high-low portfolios.

Panel A: Return

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Size	7.49	6.02	8.76	8.24	8.65	1.16
t	(2.79)	(3.40)	(5.28)	(5.03)	(6.04)	(0.53)
Value	5.94	3.91	8.81	8.36	11.55	5.60**
t	(1.85)	(1.47)	(6.93)	(6.82)	(7.19)	(2.48)
Momentum	4.44	6.24	8.41	10.05	12.84	8.40***
t	(1.42)	(3.45)	(6.56)	(7.06)	(6.15)	(3.13)
ST Reversal	10.29	8.60	7.48	9.48	6.54	-3.75
t	(3.81)	(5.33)	(6.12)	(6.35)	(3.09)	(-1.56)
Beta	8.06	8.94	8.98	7.42	7.39	-0.67
t	(10.31)	(9.44)	(6.68)	(3.39)	(2.21)	(-0.21)
LT Reversal	7.18	7.24	8.67	8.56	8.87	1.69
t	(2.26)	(3.99)	(6.37)	(6.00)	(4.36)	(0.65)
Seasonality	6.08	5.47	8.24	11.09	11.15	5.07***
t	(2.59)	(3.70)	(6.46)	(7.23)	(5.45)	(2.94)

Panel B: CAPM alpha

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Size	-1.82	-2.42	0.15	-0.53	0.25	2.07
t	(-0.87)	(-2.28)	(0.20)	(-0.89)	(1.09)	(0.94)
Value	-7.11	-7.09	1.35	0.91	3.09	10.20***
t	(-4.95)	(-4.86)	(2.21)	(1.77)	(4.20)	(5.83)
Momentum	-7.68	-2.68	0.77	2.17	3.49	11.17***
t	(-4.35)	(-2.99)	(1.50)	(3.18)	(2.91)	(4.37)
ST Reversal	-0.71	0.20	0.08	1.41	-2.88	-2.17
t	(-0.46)	(0.25)	(0.15)	(1.96)	(-2.34)	(-0.91)
Beta	2.87	2.83	1.22	-3.01	-6.13	-9.00***
t	(4.24)	(4.33)	(2.11)	(-3.89)	(-4.27)	(-5.11)
LT Reversal	-4.63	-1.46	0.91	0.68	-0.48	4.15*
t	(-2.33)	(-1.43)	(1.46)	(0.99)	(-0.44)	(1.66)
Seasonality	-4.29	-2.69	0.63	2.77	1.60	5.88***
t	(-3.62)	(-4.25)	(1.22)	(4.20)	(1.56)	(3.43)

Panel C: CAPM beta

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Size	1.18	0.99	1.03	1.06	0.98	-0.20
Value	1.99	1.55	0.78	0.77	0.99	-1.00
Momentum	1.79	1.10	0.82	0.87	1.19	-0.60
ST Reversal	1.55	0.98	0.76	0.91	1.20	-0.35
Beta	0.28	0.48	0.84	1.42	2.10	1.81
LT Reversal	1.72	1.05	0.84	0.87	1.19	-0.54
Seasonality	1.41	0.93	0.81	0.96	1.23	-0.18

Table 4: 2x3 sorted portfolios

The table reports average returns on 2x3 sorted portfolios sorted by size and various stock characteristics, as described in Section III. Every anomaly is constructed as an HML-like factor by sorting stocks first into six portfolios by size and the stock characteristic at the end of every month. The sorts use the 50th percentile breakpoint on market capitalization, and subsequently the 30th and 70th percentile breakpoints on the stock characteristic. The return on the stock factor is the average return on the two high portfolios minus that on the two low portfolios, with the "BETA" factor being ex-ante corrected for expected market beta. "SMB" is computed by averaging across the small or large size-value sorted portfolios. The high and low labels are chosen based on the 'CRSP-era' studies so that the stocks in the high portfolio earn higher returns than those in the low portfolios. Portfolios are value-weighted. Panel A presents average annualized returns ("Return"), standard deviation of returns ("Vol."), and the t-statistic of the average return ("*t*"). Panel B reports CAPM alphas ("Alpha"), beta ("Beta"), and the t-statistic of the CAPM alpha ("*t (alpha)*"). The sample runs from January 1866 to December 1926 and is at the monthly frequency. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, which we present only for returns spreads and CAPM alphas of the high-low portfolios.

Panel A: Return

Return					Vol.					*t*				
Size														
	L	M	H	Total		L	M	H	Total		L	M	H	Total
Small	5.15	7.82	11.54	8.17	Small	23.50	9.53	10.62	12.78	Small	1.71	6.41	8.49	4.99
Big	6.96	8.58	10.57	8.70	Big	20.01	9.07	11.83	12.67	Big	2.72	7.39	6.97	5.37
SMB	-1.81	-0.76	0.97	-0.53	SMB	14.23	8.43	10.21	7.60	SMB	-0.99	-0.70	0.74	-0.55
Value														
	L	M	H	HML		L	M	H	HML		L	M	H	HML
Small	5.15	7.82	11.54	6.39***	Small	23.50	9.53	10.62	18.57	Small	1.71	6.41	8.49	2.69
Large	6.96	8.58	10.57	3.61**	Large	20.01	9.07	11.83	13.43	Large	2.72	7.39	6.97	2.10
Total	6.05	8.20	11.05	5.00***	Total	20.64	8.29	10.02	14.01	Total	2.29	7.73	8.62	2.78
Momentum														
	D	M	U	UMD		D	M	U	UMD		D	M	U	UMD
Small	3.41	6.97	11.71	8.30***	Small	25.84	12.01	15.54	21.57	Small	1.03	4.53	5.88	3.00
Large	5.65	8.80	11.66	6.00***	Large	16.85	9.66	13.81	13.89	Large	2.62	7.11	6.59	3.38
Total	4.53	7.88	11.68	7.15***	Total	20.05	10.06	13.62	15.61	Total	1.77	6.12	6.70	3.58
ST Reversal														
	LR	M	HR	ST_Rev		LR	M	HR	ST_Rev		LR	M	HR	ST_Rev
Small	9.42	6.58	5.34	4.09*	Small	21.84	11.16	17.86	19.22	Small	3.37	4.60	2.33	1.66
Large	9.17	8.67	8.16	1.01	Large	15.52	9.89	13.86	13.11	Large	4.62	6.85	4.60	0.60
Total	9.30	7.58	6.75	2.55	Total	17.48	9.69	14.68	13.87	Total	4.15	6.11	3.59	1.43
BETA														
	LB	M	HB	BETA		LB	M	HB	BETA		LB	M	HB	BETA
Small	7.69	7.05	5.48	6.84***	Small	7.63	13.07	27.58	15.37	Small	7.87	4.21	1.55	3.47
Large	8.61	9.01	7.82	7.25***	Large	6.29	10.43	21.51	12.30	Large	10.69	6.75	2.84	4.60
Total	8.15	8.03	6.65	7.05***	Total	6.04	10.84	23.54	11.81	Total	10.54	5.78	2.21	4.66

Panel A continued:

Return

LT Reversal

	LR	M	HR	LT_Rev
Small	11.36	9.91	9.71	1.65
Large	7.73	7.64	9.01	-1.29
Total	9.54	8.78	9.36	0.18

Seasonality

	LV	M	HV	SEAS
Small	2.16	7.36	10.25	8.08***
Large	5.89	8.43	11.56	5.67***
Total	4.03	7.89	10.90	6.87***

Vol.

	LR	M	HR	LT_Rev
Small	26.73	16.43	15.34	23.71
Large	14.86	10.19	13.39	11.88
Total	19.56	12.32	13.19	15.32

	LV	M	HV	SEAS
Small	19.27	10.36	18.58	15.33
Large	13.49	10.34	13.61	9.04
Total	15.33	9.42	15.03	9.85

t

	LR	M	HR	LT_Rev
Small	3.32	4.71	4.94	0.54
Large	4.06	5.85	5.26	-0.85
Total	3.81	5.57	5.54	0.09

	LV	M	HV	SEAS
Small	0.88	5.55	4.31	4.12
Large	3.41	6.37	6.63	4.90
Total	2.05	6.55	5.67	5.45

Panel B:

Alpha

Size

	L	M	H	Total
Small	-6.79	1.60	4.88	-0.10
Big	-4.41	1.25	2.24	-0.31
SMB	-2.38	0.35	2.64**	0.20

Value

	L	M	H	HML
Small	-6.79	1.60	4.88	11.67***
Large	-4.41	1.25	2.24	6.66***
Total	-5.60	1.43	3.56	9.16***

Beta

	L	M	H	Total
Small	1.75	0.51	0.60	0.95
Big	1.63	0.75	0.97	1.12
SMB	0.12	-0.24	-0.36	-0.16

	L	M	H	HML
Small	1.75	0.51	0.60	-1.15
Large	1.63	0.75	0.97	-0.66
Total	1.69	0.63	0.78	-0.91

t(alpha)

	L	M	H	Total
Small	-4.12	1.62	4.62	-0.12
Big	-4.28	2.90	3.69	-1.37
SMB	-1.30	0.34	2.19	0.21

	L	M	H	HML
Small	-4.12	1.62	4.62	6.80
Large	-4.28	2.90	3.69	4.63
Total	-5.45	2.54	5.79	7.41

Panel B continued:

Alpha

Momentum

	D	M	U	UMD
Small	-8.33	-0.59	3.36	11.69***
Large	-4.28	1.17	2.85	7.14***
Total	-6.31	0.29	3.11	9.41***

ST Reversal

	LR	M	HR	ST_Rev
Small	-1.32	-0.51	-3.60	2.28
Large	-0.32	0.95	-0.64	0.32
Total	-0.82	0.26	-2.12	1.30

BETA

	LB	M	HB	BETA
Small	2.45	-0.84	-8.03	8.74***
Large	2.99	1.07	-4.34	8.39***
Total	2.72	0.12	-6.19	8.57***

LT Reversal

	LR	M	HR	LT_Rev
Small	-0.47	0.76	1.16	-1.62
Large	-1.32	-0.01	0.32	-1.63
Total	-0.89	0.37	0.74	-1.63

Seasonality

	LV	M	HV	SEAS
Small	-7.80	0.31	0.57	8.37***
Large	-3.09	0.56	2.55	5.64***
Total	-5.45	0.43	1.56	7.01***

Beta

	D	M	U	UMD
Small	1.71	0.80	0.97	-0.74
Large	1.32	0.81	1.07	-0.25
Total	1.51	0.81	1.02	-0.49

	LR	M	HR	ST_Rev
Small	1.49	0.73	1.10	0.39
Large	1.22	0.83	1.07	0.15
Total	1.35	0.78	1.08	0.27

	LB	M	HB	BETA
Small	0.29	0.87	2.09	-0.41
Large	0.38	0.88	1.80	-0.25
Total	0.34	0.88	1.95	-0.33

	LR	M	HR	LT_Rev
Small	1.73	1.15	1.01	0.71
Large	1.12	0.82	1.05	0.08
Total	1.43	0.98	1.03	0.39

	LV	M	HV	SEAS
Small	1.32	0.69	1.26	-0.06
Large	1.11	0.87	1.12	0.01
Total	1.22	0.78	1.19	-0.03

t(alpha)

	D	M	U	UMD
Small	-3.74	-0.57	2.35	4.55
Large	-4.13	2.94	3.27	4.06
Total	-4.61	0.52	3.28	5.00

	LR	M	HR	ST_Rev
Small	-0.73	-0.52	-2.16	0.95
Large	-0.34	2.33	-0.72	0.19
Total	-0.74	0.49	-2.01	0.75

	LB	M	HB	BETA
Small	2.75	-0.75	-4.36	4.62
Large	4.93	2.57	-4.66	5.43
Total	4.43	0.20	-5.60	5.93

	LR	M	HR	LT_Rev
Small	-0.20	0.58	0.88	-0.56
Large	-1.31	-0.01	0.38	-1.07
Total	-0.62	0.53	0.91	-0.86

	LV	M	HV	SEAS
Small	-4.94	0.35	0.37	4.24
Large	-4.69	1.25	3.73	4.84
Total	-6.10	0.96	1.75	5.52

Table 5: Robustness tests

The table summarizes the robustness test results to methodological variations of equity characteristic portfolio sorts, as described in Section III. We consider the following methodological variations: quintile portfolios ("Quintile"), as in Table 3, tercile portfolios ("Tercile"), decile portfolios ("Decile"), 2x3 size-characteristic sorted portfolios ("2x3"), as in Table 4, 2x5 size-characteristic sorted portfolios based on every 20th percentile breakpoint ("2x5"), equally-weighted 2x3 portfolios ("Equal-weighted"), and sector-neutral portfolio that construct 2x3 portfolios by first standardizing each characteristic within industries ("Sector-neutral"). The table presents average annualized returns (Panel A), and CAPM alphas (Panel B) of the high-low for each characteristic-sorted portfolio. Portfolios are value-weighted except for the row labelled "Equal-weighted". The sample runs from January 1866 to December 1926 and is at the monthly frequency. Numbers in parentheses indicate standard t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

Panel A: Return spread

	Size	Value	Momentum	ST_Rev	BETA	LT_Rev	Seas
Quintile	-1.16	5.60**	8.40***	3.75	6.68***	-1.69	5.07***
t	(-0.53)	(2.48)	(3.13)	(1.56)	(3.73)	(-0.65)	(2.94)
Tercile	-2.79**	5.64***	5.95***	1.65	6.48***	-1.15	6.07***
t	(-2.03)	(2.82)	(3.07)	(0.96)	(4.30)	(-0.64)	(5.28)
Decile	3.79	6.02**	9.79***	8.40**	6.34**	-1.83	5.86***
t	(0.93)	(2.35)	(2.69)	(2.39)	(2.38)	(-0.47)	(2.10)
2X3	-0.53	5.00***	7.15***	2.55	7.05***	0.18	6.87***
t	(-0.55)	(2.78)	(3.58)	(1.43)	(4.66)	(0.09)	(5.45)
2X5	0.49	5.35***	9.00***	5.28**	5.99***	0.63	8.42***
t	(0.58)	(4.34)	(3.53)	(2.25)	(3.43)	(0.25)	(5.18)
Equal weighted	0.43	4.20**	7.05***	6.56***	6.68***	1.19	6.55***
t	(0.37)	(1.99)	(3.29)	(3.23)	(4.05)	(0.53)	(4.26)
Sector neutral	1.25	3.32*	6.18***	3.47**	6.29***	1.84	5.02***
t	(1.54)	(1.93)	(3.55)	(2.14)	(4.57)	(1.10)	(4.32)

Panel B: CAPM alpha

	Size	Value	Momentum	ST_Rev	BETA	LT_Rev	Seas
Quintile	-2.07	10.20***	11.17***	2.17	8.66***	-4.15*	5.88***
t	(-0.94)	(5.83)	(4.37)	(0.91)	(5.13)	(-1.66)	(3.43)
Tercile	-3.02**	10.23***	7.78***	0.64	7.85***	-2.72	6.25***
t	(-2.18)	(7.33)	(4.18)	(0.38)	(5.39)	(-1.56)	(5.40)
Decile	2.14	10.04***	12.71***	6.37*	8.06***	-5.55	7.32***
t	(0.53)	(4.48)	(3.59)	(1.73)	(3.07)	(-1.48)	(2.63)
2X3	0.20	9.16***	9.41***	1.30	8.56***	-1.63	7.01***
t	(0.21)	(7.41)	(5.00)	(0.75)	(5.92)	(-0.86)	(5.52)
2X5	1.75**	5.06***	11.58***	3.75	7.89***	-1.36	8.76***
t	(2.37)	(4.09)	(4.76)	(1.62)	(4.77)	(-0.55)	(5.37)
Equal weighted	1.09	8.93***	9.51***	5.26***	8.14***	-1.32	6.79***
t	(0.94)	(5.87)	(4.72)	(2.62)	(5.10)	(-0.63)	(4.39)
Sector neutral	1.51*	7.25***	8.03***	2.39	6.52***	0.28	5.26***
t	(1.86)	(6.02)	(4.84)	(1.50)	(4.70)	(0.18)	(4.51)

Table 6: Spanning regressions

The table summarizes the results of spanning tests for each 2x3 size-characteristic sorted high-low factor return series on all other factor return series. We also include the value-weighted market factor ("Mkt-rf"). The stock characteristics are described in Section III. Portfolios are value-weighted. The sample runs from January 1866 to December 1926 and is at the monthly frequency. Shown are slope coefficients and intercepts (annualized and expressed in percentages) with standard t-statistics in parentheses, the R^2 of the regressions ("R^2"), and residual standard errors from each spanning regression ("s(e)"). Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

	Mkt-rf	**SMB**	**HML**	**UMD**	**ST_Rev**	**BETA**	**LT_Rev**	**Seas**
Intercept (ann.)	6.71***	0.20	5.49***	4.94***	3.35*	4.04***	4.80***	5.71***
t	(6.91)	(0.14)	(5.05)	(2.63)	(1.86)	(3.15)	(2.65)	(4.26)
Mkt-rf		-3.17***	-8.98***	-2.92***	2.71***	2.52***	-2.58***	0.71
t		(-8.08)	(-24.80)	(-3.50)	(3.40)	(4.43)	(-3.20)	(1.18)
SMB	-3.76***		-3.21***	-4.13***	-0.58	6.89***	-0.58	0.19
t	(-8.08)		(-6.16)	(-4.58)	(-0.66)	(12.03)	(-0.66)	(0.29)
HML	-7.37***	-2.22***		2.10***	1.40*	4.47***	-7.60***	1.01*
t	(-24.80)	(-6.14)		(2.77)	(1.93)	(9.03)	(-11.20)	(1.85)
UMD	-0.82***	-0.98***	0.72***		-2.11***	1.46***	-0.13	0.85***
t	(-3.50)	(-4.58)	(2.77)		(-5.04)	(4.84)	(-0.30)	(2.67)
ST_Rev	0.83***	-0.15	0.53*	-2.30***		-1.33***	-0.44	0.34
t	(3.40)	(-0.66)	(1.93)	(-5.04)		(-4.23)	(-0.99)	(1.01)
BETA	1.51***	3.48***	3.26***	3.10***	-2.60***		-1.23**	-0.18
t	(4.43)	(12.03)	(9.03)	(4.84)	(-4.23)		(-1.97)	(-0.38)
LT_Rev	-0.78***	-0.15	-2.80***	-0.14	-0.44	-0.62**		0.39
t	(-3.20)	(-0.66)	(-11.20)	(-0.30)	(-0.99)	(-1.97)		(1.18)
Seas	0.39	0.09	0.36*	1.65***	0.60	-0.16	0.70	
t	(1.18)	(0.29)	(1.85)	(2.67)	(1.01)	(-0.38)	(1.18)	
R2	0.59	0.23	0.67	0.24	0.11	0.37	0.26	0.05
s(e)	2.09	1.92	2.31	3.94	3.77	2.70	3.80	2.83

Table 7: Out-of-sample decay

The table reports the results of out-of-sample decay tests for stock factor portfolios. Factors are constructed from top-bottom portfolios from 2x3 size-characteristic-based portfolios. We include the value-weighted market factor ("Mkt-rf"), the stock characteristic-based factors described in Section III, and the equally weighted average over the stock factor portfolios ("Average"). We estimate average (annualized) returns (Panel A) and CAPM alphas (Panel B) separately over the pre-CRSP ("1866-1926") and CRSP ("1927-2024") samples, and examine their difference, their out-of-sample effect, and their post-publication effect. The pre-CRSP sample starts in January 1866 and ends December 1926. The CRSP sample runs from January 1927 till December 2024. Out-of-sample and post-publication periods follow Figure 1. The final columns shows the result of panel regression combining all factor series. The rows labelled "1866-2024" present full sample results. Data is at the monthly frequency. Numbers in parentheses indicate standard t-values, while panel regressions use double (date/factor) cluster-corrected standard errors. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

	SMB	HML	UMD	ST_Rev	BETA	LT_Rev	Seas	Average	Panel
Panel A: Return spread									
1866-1926	-0.53	5.00***	7.15***	2.55	7.05***	0.18	6.87***	4.04***	
t	(-0.42)	(2.75)	(3.57)	(1.57)	(5.50)	(0.11)	(6.57)	(7.28)	
1927-2024	2.55***	0.76	7.82***	8.39***	4.26***	2.98**	5.86***	4.66***	
t	(2.53)	(0.53)	(4.95)	(6.58)	(4.21)	(2.22)	(7.10)	(10.64)	
Difference	-3.08*	4.24*	-0.67	-5.85***	2.79*	-2.79	1.02	-0.62	-0.63
t	(-1.90)	(1.83)	(-0.26)	(-2.84)	(1.71)	(-1.31)	(0.76)	(-0.88)	(-0.48)
Out-of-sample effect	-3.10*	-1.09	-2.30	-7.82***	0.99	-4.72*	0.76		-1.78
t	(-1.74)	(-0.38)	(-0.66)	(-3.40)	(0.55)	(-1.93)	(0.53)		(-1.29)
Post-publication effect	0.18	-0.28	-0.15	-0.09	-0.35	0.03	-0.30		-2.18***
t	(1.00)	(-1.18)	(-0.59)	(-0.40)	(-1.98)	(0.16)	(-1.48)		(-2.64)
1866-2024	1.37*	2.38**	7.57***	6.15***	5.33***	1.88*	6.25***	4.42***	
t	(1.73)	(2.12)	(6.09)	(6.13)	(6.71)	(1.80)	(9.64)	(12.87)	
Panel B: CAPM alpha									
1866-1926	0.20	9.16***	9.41***	1.30	8.56***	-1.63	7.01***	4.86***	
t	(0.17)	(6.79)	(5.00)	(0.83)	(6.87)	(-1.01)	(6.70)	(9.62)	
1927-2024	0.76	4.83***	10.24***	7.24***	4.28***	1.93	5.84***	4.76***	
t	(0.80)	(4.54)	(6.89)	(5.83)	(4.35)	(1.49)	(7.08)	(11.94)	
Difference	-0.56	4.33**	-0.83	-5.94***	4.28***	-3.56*	1.17	0.10	-0.18
t	(-0.36)	(2.52)	(-0.35)	(-2.96)	(2.70)	(-1.72)	(0.87)	(0.15)	(-0.12)
Out-of-sample effect	-0.75	1.00	-1.02	-7.83***	2.39	-5.53**	0.85		-0.32
t	(-0.45)	(0.47)	(-0.31)	(-3.50)	(1.37)	(-2.34)	(0.59)		(-0.21)
Post-publication effect	-0.63	-3.29	-1.81	-1.13	-5.59***	1.11	-3.66		-2.95***
t	(-0.31)	(-1.55)	(-0.63)	(-0.45)	(-2.71)	(0.44)	(-1.52)		(-4.54)
1866-2024	0.55	6.49***	9.92***	4.96***	5.92***	0.53	6.29***	4.96***	
t	(0.74)	(7.76)	(8.51)	(5.08)	(7.66)	(0.52)	(9.71)	(15.27)	

Table 8: Macroeconomic risk and factor returns

The table summarizes the explanatory power of macroeconomic risk for stock factor returns using methods outlined in Griffin, Ji, and Martin (2003). We regress the benchmark-adjusted returns of each stock factor on the following macroeconomic variables of Chen, Roll and Ross (1986): industrial production growth (MP), term premium (UTS), change in expected inflation (DEI), and unexpected inflation (UI). The coefficients and annualized intercept ("Interc. (ann.)") of the regression are shown in the table. We combine the resulting loadings against macroeconomic risks with estimates of risk premia of these risks (estimated using Fama and MacBeth on the 2x3 sorted individual and factor portfolios) to get the predicted return originating from an unconditional macroeconomic risk model ("Pred"). The table further contains the historical average annual return ("Act.") and the differences with predicted returns (i.e., the unexplained return; "Diff."). We estimate results separately over the pre-CRSP and CRSP samples. The pre-CRSP sample starts in February 1875 and ends December 1926. The CRSP sample runs from January 1927 till December 2024. The combined sample runs from February 1875 till December 2024. Both samples are at the monthly frequency. Numbers in bold are significant at the 5% level, while parentheses indicate standard t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

Factor	Period	MP	UTS	DEI	UI	Interc. (ann.)	t	Act.	Pred.	Diff.	t
SMB	1875-1926	**-0.02**	-0.15	-5.91	**2.16**	1.51	(1.39)	0.32	-0.24	0.32	(1.52)
	1927-2024	0.00	**0.25**	0.37	-0.35	-3.68**	(-2.06)	0.72	1.33	-0.66***	(-3.70)
	1875-2024	0.00	**0.14**	0.21	0.42	-0.59	(-0.57)	0.79	0.34	-0.52	(0.11)
HML	1875-1926	0.02	0.27	3.95	-0.92	8.65***	(5.97)	7.20	0.40	3.17***	(5.97)
	1927-2024	0.01	0.03	**-5.17**	0.85	4.44**	(2.34)	4.32	1.15	3.62***	(3.49)
	1875-2024	0.01	-0.04	**-4.56**	0.75	6.67***	(5.78)	7.46	0.37	6.69***	(3.98)
UMD	1875-1926	-0.01	0.14	7.96	-1.76	9.27***	(4.13)	4.25	0.70	2.70***	(3.40)
	1927-2024	**0.03**	-0.15	3.10	-0.81	11.40***	(4.52)	6.86	2.13	4.66***	(4.54)
	1875-2024	0.02	-0.05	3.57	**-1.32**	9.17***	(5.70)	8.05	0.95	6.64***	(7.48)
ST_Rev	1875-1926	0.02	-0.07	-0.79	-2.21	-0.33	(-0.16)	0.45	-0.26	0.51	(0.72)
	1927-2024	-0.02	**0.17**	-1.10	0.20	4.99**	(2.55)	6.25	-1.23	6.45***	(6.40)
	1875-2024	-0.01	**0.21**	-1.65	-0.94	2.62**	(1.96)	5.02	-0.34	5.38**	(2.48)
BETA	1875-1926	-0.02	0.35	-3.52	1.77	10.01***	(5.85)	5.87	1.30	4.64***	(4.84)
	1927-2024	0.01	0.10	**-3.57**	0.23	2.40	(1.61)	4.87	1.51	1.79	(0.73)
	1875-2024	0.00	0.00	**-3.43**	**1.13**	6.14***	(5.81)	7.55	1.07	5.71***	(5.44)
LT_Rev	1875-1926	0.00	-0.26	-6.00	0.43	-1.45	(-0.63)	-0.73	-0.63	-0.10	(0.19)
	1927-2024	**0.03**	0.13	**-4.82**	0.01	-1.62	(-0.81)	1.70	1.64	-0.89***	(-6.04)
	1875-2024	**0.02**	0.12	**-4.65**	-0.17	-1.56	(-1.11)	0.68	0.72	-1.57***	(-5.98)
Seas	1875-1926	0.00	0.14	4.84	-1.18	7.47***	(5.05)	5.63	0.51	3.10***	(4.68)
	1927-2024	-0.01	-0.03	1.91	0.16	6.71***	(5.67)	8.36	-1.69	6.38***	(13.14)
	1875-2024	-0.01	-0.04	1.77	-0.21	6.98***	(8.01)	9.88	-0.44	11.07***	(13.15)

Online Appendix

In the main text we have analyzed factor premia in cross-section of U.S. stocks over a unique, novel sample between 1866 and 1926. In this Online Appendix we describe our dataset and the history of the U.S. stock market in more detail in Section A, including the cross-sectional dataset construction procedure and additional summary statistics and present results on the robustness in Section B.

Online Appendix A: The pre-CRSP (1866-1926) sample

A. A brief history of the U.S. equity market

One of the first form of organized trading in U.S. stocks date to 1792, when the origins were laid for the New York Stock Exchange (NYSE) by 21 brokers and 3 firms agreed to maintain exclusive dealings and minimum commissions. This "Buttonwood Agreement" eventually evolved 25 years later in the NYSE. Soon, the first railroad stock was listed in New York (1830) and within two decades the exchange became predominantly a market for railroad securities (Garvy, 1944), where also banks stocks were well-represented. By the end of 1838, over 300 stocks were trading in the United States. The NYSE grew rapidly and had an annual business in excess of three billion dollars in 1867. In 1869, the NYSE merged with the Open and Gold Boards and became the dominant exchange for trading stocks in New York and one the three leading exchanges in the world (Davis and Neal, 1998). Memberships now became tradable, and aspiring members could purchase seats from retiring members. Besides on the NYSE, stocks traded on the New York Curb, which later became named the American Stock Exchange (AMEX), and several regional exchanges.[39]

As the U.S. economy developed, demand for and supply of stock financing grew rapidly, with the U.S. stock market experiencing rapid growth between the early 1880s and late 1920s. Neal (2016) shows that in the early 20th century the New York stock market was large relative to the size of the U.S. economy, with a stock market capitalization to GDP ratio of 174%, about similar levels as observed in 2015. Most of the trading activity took place on the NYSE, followed by the NY Curb

[39] The Curb market represents the market outside of general market operations. Trading took place outside the exchanges, on the street curb.

(the predecessor of the AMEX) and regional exchanges (mainly Boston and Philadelphia) (Brown et al., 2008, O'Sullivan, 2007). Total annual share trading volume rose from about 100 million in 1885, to 150 million in 1900, to 250 million in 1915, to 1,151 million shares in 1930. Over two-thirds of trading volume originated from the NYSE, followed by the New York Curb (about 20%), and regional exchanges (about 10% of total). In dollars, trading volume on the U.S. exchanges was $26.5 billion in 1920 and $49.5 billion in 1926 (O'Sullivan, 2007).

The 19th and 20th century markets shared many important behavioral and institutional characteristics (Harrison, 1998, Koudijs, 2016). Traded equities could quite readily be bought or sold across exchanges via stock dealer firms, traded via derivatives and options, could be bought on margin, and an active market existed for shorting stocks with well-known short speculators (see for example Gibson, 1906, Brown et al., 2008, Poitras, 2012). Major technological innovations such as the telegraph in 1844, the transatlantic cable (1866), the introduction of the ticker tape (1867), the availability of local telephone lines (1878), and direct phone links via cables around 1890 facilitated the growth in the depth and breadth of NYSE trading activity (Poitras, 2012, Fohlin, 2016). These innovations gave rise to a liquid and active secondary market for stocks and other securities, like corporate bonds (Giesecke et al., 2011). With the introduction of the transatlantic cable and ticker tape, price quotations were quite instantly known from coast to coast and on the other side of the Atlantic (Garvy, 1944, Hoag, 2006). Hoag (2006) notes that historical markets priced securities so well that transatlantic steamship crossing times can be recovered from stock prices. In the second half of the 19th century, the increased communication networks were utilized by several firms for arbitrage as

prices on different exchanges were rapidly known, and increased brokerage and market making activities due to enhanced market liquidity. Investors had access to a wide range of reputable sources of information such as the Commercial and Financial Chronicle, newspapers, and monthly bulletin of all recorded prices on major exchanges and quarterly or semi-annual supplements which listed all the major companies and gave detailed information on securities issued by them (Giesecke et al., 2011). A sizable industry of financial analysts provided assessments of assets and financial markets, while also investment advice developed quickly and was not dissimilar to what we observe today (e.g., Lowenfeld, 1909).

Further, trading costs in the 19th century seem not very much different from 20th. Brown et al. (2008) shows trading costs were limited for many stocks. The median bid-ask spread for NYSE stocks remained fairly constant between 1885 and 1926 at 2.0% for most of the period, but the higher-volume stocks and NYSE stocks that also traded at other exchanges had about a quarter of these costs, or even often traded at the minimum tick of 1/8th. Jones (2002) reports spread estimates for Dow Jones stocks of about 0.5% since 1900, not much different from CRSP-era estimates up to round 1980, and annual share turnover on NYSE stocks being higher between 1900 and 1926 than in 2000. Fohlin (2016) reports that in the decade prior to World War I, quoted spreads at the NYSE averaged about 2%, but the median spread was 86 basis points, and a quarter of trades took place with spreads less than 36 basis points.[40]

[40] Related, Gehrig and Fohlin (2006) find low trading costs in the German stock market, a major stock market in the 19th and 20th century, among a nearly comprehensive set of stocks trading in Berlin for four benchmark years (1880, 1890, 1900, and 1910). Koudijs (2016) finds that trading costs in the 1770s and 1780s Dutch stock market were substantially lower than over recent decades.

Stock ownership was spread over many investors with stock data being well available. Market participants in early U.S. stock market mostly were wealthy individuals, but also banks[41], insurance companies, retail investors, investment trusts, and arbitrage players. In the 19th century, stock ownership was largely dominated by the rich. However, stock ownership expanded rapidly as of around 1900 from the rich to the less rich, making the middle class an important factor. Warshow (1924) and Means (1930) estimated that the number of stockholders grew from 4.4 million in 1900, to 8.6 million by 1917, to 18 million by 1928, driven by amongst other entrepreneurs and large trusts unloading their stock upon the public, financial education campaigns teaching the less wealthy to save and invest, and larger incomes of the wage-earning classes. Broad market indices were introduced around 1885 when Charles Dow began publishing a daily index of actively traded, large capitalization stocks, with the Commercial and Financial Chronicle (and later Wall Street Journal) being a well-read financial newspaper containing daily information on stock prices, volumes, and other characteristics.

B. Dataset construction

We have compiled our data from several sources in order to obtain a reliable and historically extensive dataset. Our sample covers 61 years of data on monthly stock prices, dividend yields and market capitalizations for all major stocks traded on the NYSE, NY Curb and regional exchanges. The sample spans the period from January 1866 through December 1926 and is at the monthly frequency. We build our dataset from the Commercial and Financial Chronicle (CFC, the source also used to build the CRSP sample as of 1926) and Global Financial Data (GFD), which

[41] For example, O'Sullivan (2007) reports $781 million of bank security holdings in utility and industrial companies in 1920.

we combine with risk-free rates from Jeremy Siegel's website. Note that we choose to overlap our sample partly with CRSP over 1926, as characteristics like momentum and beta require at least one year of data, and as such are not tested in CRSP over 1926. Below we further outline the data sources and the construction of each series we use in detail.

1. Data sources and items

We collect dates, company identifiers, company names, monthly stock prices, dividends, price returns and monthly total returns from GFD, all adjusted for stock splits. GFD handles splits, dividends and stock dividends by adjusting the total and price return series with the relevant multipliers, which we have verified by also calculating returns ourselves for a random subset of 100 stocks. We calculate dividend yields by subtracting the monthly price return from the monthly total return, also to capture negative dividends. One important note to make is that several companies engaged in 'assessments'. These are reverse dividends in which companies called for capital upon its shareholders to pay for the difference between par and nominal amounts. The GFD stock database has an extensive coverage of historical stocks traded in the U.S. across the NYSE and regional exchanges, as well as stocks traded in the Over-The-Counter (OTC) markets and includes delisted stocks. As such it is relatively free of a survivorship bias or an exchange bias (i.e., focusing on a specific exchange, while historically many exchanges varied in importance). GFD has covered United States stock prices from 1791 till date. As a downside, this database did not include number of shares outstanding.

We manually collect shares outstanding from the CFC, the first national business newspaper in the United States, which we complement with data from

GFD. The CFC was a weekly newspaper founded in 1865 representing the industrial and commercial interest of the United States. The Fraser library has published a digital archive of this newspaper online, with articles from July 1st, 1865, to August 23, 1962, implying our start date of 1866 for this study. These articles contain company names, prices, dividends, par value outstanding, and size of par value, both for stocks and bonds. We retrieve par value outstanding and size of par value from the CFC. Figures A.1 and A.2 show pages of the CFC in 1865 and 1925. Note that the first few years, December 1925 - January 1928, of the monthly stock data from the Center for Research in Securities Prices (CRSP) database were also gathered from the Commercial and Financial Chronicles' Bank and Quotation Section and Public Utility Compendium. The following 33 years (February 1928 - December 1960) were assembled from an expansion of this section, the Bank and Quotation Record. From CFC we collect par value outstanding and par value of a share via the following procedure.

To keep data collection efficient, we apply the following procedure. We start by collecting the CFC data in five-year periods of e.g., 1865, 1870, ..., 1925. If data items differ in value between five-year periods, we continue by also collecting the data items for every year in between. The main assumption behind this methodology is as follows: if the number of shares outstanding in year 1 is equal to the number of shares outstanding in year 6, every value in between is likely to have the value found at year 1 and the same and interpolated accordingly. We have performed 100 random checks to verify this methodology, with a 100% success rate, confirming the efficacy of the above approach. Most of the interpolation is done for stocks in the banking industry, as most banks did not have frequent changes in their number of

shares outstanding. The data on shares outstanding per year has been compared with past and future values at the time of entry and with data from GFD. The companies' shares outstanding are calculated as the amount of par value outstanding divided by the par value of a share. Consistent with the construction of the CRSP database, this procedure (including data from GFD) does not adjust market capitalizations for free float, and we follow this convention throughout our analysis. Most shares were issued at a par value of 100 dollars before 1926, with however several stocks breaking up of their par-values into 50, 25, 10, 5 and even 1 dollar shares post World War I. Table A.1 shows an example of the data-collection procedure.

Table A.1: Data collection example

This table displays how entries have been added to create the data set of number of shares outstanding for the period 1866-1926. "Found as" contains the name of the company as found in the CFC, "Industry" refers to the industry the company belongs to, and columns 1869 through 1874 show the number of shares outstanding. The "Company" and "Found as" names are abbreviated, for example Continental (NY) was Continental national bank of New York (NY).

Company	Found as	Industry	1869	1870	1871	1872	1873	1874
Continental (NY)	Continental	Bank	20,000	20,000	20,000	20,000		
NY NH Railroad	NY and NH	RR	90,000	90,000	90,000			
Penn Coal Co.	Pennsylvania Coal	Misc		64,000	80,000	80,000	80,000	80,000
Morris & Essex RR Co.	Morris and Essex	RR	157,602	157,602	273,344	273,965	280,162	283,309
Sw Rr Georgia	SW (Georgia)	RR		39,399	38,773	38,773	38,773	

2. Data quality

The deep historical data tends to be of lesser quality compared to the more recent data, as digital archives and strong requirements on data processes did not exist. Instead, data was maintained typically by exchanges, statistical agencies, newspapers and investor annuals, often in manual writing. Potential data quality issues that could be at work include:

- Misprints and other measurement errors. This could cause prices to be spuriously inflated, trigger potential value profits.
- Reported prices in our databases are not necessarily transaction prices, but bid prices, ask prices, average prices of the day or month, or average of daily or monthly high and low prices. The use of bid or ask prices creates artificial short-term reversal effects, while the use of average prices over a month creates an artificial AR(1) process (see Working, 1960, Schwert, 1990). Working (1960) shows that such time averaging does not induce autocorrelation beyond a one-month horizon, and therefore does not preclude testing for momentum effects, provided that one skips a month between the end of the formation period and the beginning of the holding period.
- Missing data, which have sometimes been solved by interpolating, or padding, prices or returns known at a lower frequency to the monthly frequency.
- The timing of equity dividends was not always known historically. As a solution, to construct return series, they have sometimes been distributed to fixed points over the year, often year ends. For equities this can result in high returns during 'assigned dividend' months, while returns may be artificially low on the actual ex-dividend months (as prices may drop to reflect the dividend payment). This could generate spurious seasonality in stock returns.

3. Data selection

We applied several data filters on the database to focus on common stocks that are economically comparable and interesting to be used in factor research. First, we filter all securities in the GFD database by excluding every instrument that does not

have “United States” as home country. This filter excludes many international stocks. Second, we exclude all instruments that do not have “United States Dollar” as currency. Third, we remove every instrument that is not a *common* stock (noteworthy is that the word stock was historically also used for debt claims, common stocks refer to equity claims), and remove bonds, real estate investment trusts (REITs), American depositary receipts (ADRs), certificates, preferred stocks and other financial instruments. Fourth, we require each stock to have at least 12 monthly return observations. As data collection is a very labor-intensive process, we applied data filters one to four before collecting the number of shares outstanding. Fifth, we apply the zero-return screen, return interpolation screen, and stale return screen described in Section II. These screens reduce the impact of data issues such as missing monthly data, reduced liquidity or non-tradability (‘zero return screen’), the possibility that prices or returns known at a lower frequency have been interpolated to the monthly frequency (‘return interpolation screen’), and the possibility that returns are stale or update infrequently (‘stale return screen’). Sixth, we require stock to have shares outstanding (and hence market capitalization) available over the previous year-end. Table A.2 shows the exclusion criteria in greater detail. Finally, we drop NYSE stock observations for the period July 1914 – December 1914 from our sample and for our data quality screens, as the NYSE was closed for over this period due to World War I.

Table A.2: Sample exclusion criteria

This table outlines the filters we have applied to the Global Financial Data stock data set.

Exclusion Criteria	Description
1. Domestic stocks only	If one financial instrument is not from the United States, it is excluded from the sample.
2. Domestic currency only	If one financial instrument is denominated in a currency other than United States dollar, it is excluded from the sample.
3. Common stocks only	If one financial instrument is not a common stock, it is excluded from the sample. Instruments excluded are: American depositary receipts (ADRs), corporate bonds, exchange traded funds (ETFs), government bonds, municipal bonds, preferred stocks, preferred convertibles, preferred trusts, real estate investment trusts (REITs), rights, scrips, state bonds, units, and warrants.
4. Minimum observations per stock	If one stock has less than 12 monthly return observations, it is excluded from the sample.
5. Qualified stocks only	Zero return screen, return interpolation screen and stale return screen
6. Stocks with Market capitalization only	If one stock does not have market capitalization, it is excluded from the sample.

Using the filters described above, we collect 56,424 yearly number of shares outstanding observations from the CFC for 4,321 common stocks.

4. Data verification procedure

We have taken the following steps to check the quality of each data series and clean for obvious measurement errors. First, we have randomly checked 100 observations in GFD against prices and dividends reported in the CFC. Similarly, we have verified the GFD data against 126 matched listings in the International Center for Finance at Yale database.[42] These checks all verified the GFD data. Second, we have manually verified extreme returns (>100%, <-50%), dividends, and changes from year to year in number of shares outstanding, and when due to a data error corrected. We have checked changes from year to year in number of shares outstanding. For example, if the value of shares outstanding in 1870

[42] International Center of Finance at Yale University (http://icf.som.yale.edu/old-new-york-stock-exchange-1815-1925).

divided by the value in 1869 is equal to 0.1, or 10, there was a high chance a zero to many or a zero to few was added to the value in 1870. These values were checked again in the data sources and when erroneous replaced with the correct value. Third, we have compared the number of stocks, overall, per exchange and per sector with other sources, like O'Sullivan (2007) and Michie (2006) and found them to be roughly in line. Fourth, we have compared GFD against CRSP over the post-1926 sample in terms of number of firms and average returns, causing us to apply data quality filter six described above. Fifth, we checked each series on gaps, the level and dynamics in the first- and second-order autocorrelations. Finally, we built an industry classification starting from GFD subgroups: Financials (Finance & real estate), Energy/Mining (Materials & Energy), Industrials & Other (all other), Infrastructure (Transports), and Utilities. Subsequently, we have manually checked company names against classifications in CFC, and when available descriptions of company practices. This verification led us to reclassify several companies compared to GFD.[43]

5. Corporate events

Historical stock returns can be materially affected by corporate events such as assessments, cash dividends, stock dividends, and rights issues. We explicitly verify and account for such events in constructing our historical return series. We primarily rely on the event treatment embedded in the GFD database, which documents corporate actions in the metadata associated with each security and adjusts return series where needed. To validate these adjustments, we cross-checked all assessments, stock dividends, and rights issues reported in Appendix C of McQuarrie (2021) against GFD and, where discrepancies arose, against contemporaneous sources including the Commercial and Financial Chronicle (CFC) and Poor's Railroad Manuals. In addition, we worked directly with GFD to review potential anomalies and corporate-event treatment in a number of historical series.

[43] More specifically, 12 stocks were reclassified from Infrastructure to Industrial & Other, two stocks were reclassified from Financials to Industrials & Other, and one stock was reclassified from Industrials & Other to Infrastructure. We follow the classification of GFD in case of conglomerates and firms changing industries over time.

Cash dividends are incorporated directly through total return calculations. Stock dividends are handled by adjusting the number of shares held and incorporating in total returns. In rights offering, existing shareholders receive the right to purchase additional shares at a subscription price below market value and therefore receive an economically valuable claim. GFD computes the implied value of these rights using the Theoretical Ex-Rights Price (TERP) – as in CRSP – and incorporates this into the return calculation. Assessments are essentially reverse dividends in which companies called for capital upon its shareholders to pay for the difference between par and nominal amounts. Around the date of assessment the additional capital needs to be embed in return calculations, which we do following GFD by treating the capital call (i.e., assessment) as an additional cash contribution required from shareholders – thus essentially treating assessments as negative dividends.

As an illustration of an assessment, consider the 1895 reorganization of the Atchison, Topeka & Santa Fe Railroad Company. The CFC in its April 13, 1895, issue describes the foreclosure process and formation of a successor company, the Atchison, Topeka & Santa Fe Railway Company, with existing shareholders required to pay a $10 assessment in various installments to participate in the reorganization in which the properties acquired at foreclosure sale on December 10, 1895, vest in a new company, the Atchison, Topeka & Santa Fe Railway Co. Upon payment of the assessment, shareholders in the old company received equal shares in the new company. We follow GFD who implements the following installment schedule after publication of the plan: $4 on June 10th, 1895, $3 on July 20th, 1895, and $3 on September 19th, 1895. The worked example below shows the resulting assessment-adjusted total returns.

Atchison, Topeka & Santa Fe: Assessment-adjusted return calculation in 1895

Month	Price	Price return	Assessment installment	Assessment-adjusted return
Mar. 1895	6.875	71.88%	-	71.88%
Apr. 1895	5.625	-18.18%	-	-18.18%
May. 1895	7.875	40.00%	-	40.00%
Jun. 1895	9.625	22.22%	$4	22.22%
Jul. 1895	15.75	63.64%	$3	15.59%
Aug. 1895	20.25	28.57%	-	1.08%
Sep. 1895	22.25	9.88%	$3	9.88%
Oct. 1895	18.375	-17.42%	-	-27.23%
Nov. 1895	17.25	-6.12%	-	-6.12%
Dec. 1895	14.75	-14.49%	-	-14.49%

Overall, we identify 86 assessment events across 54 firms between 1865 and 1926, with approximately 70% associated with mining firms and the remainder concentrated among railroads, especially during the railroad build-out period and the 1890s restructuring wave.

6. Survivorship and delisting biases

To the best of our knowledge, our sample free if survivorship bias because it does not condition inclusion on subsequent survival, and our sample includes delisted stocks. Delisting returns are a separate potential concern, however, because the last observed price fail to capture subsequent investor losses. For example, the CRSP database contained a delisting bias for many years before it was detected and cleaned by Shumway (1997). This bias was most severe among small risky stocks, thus leading to an overestimation of the size premium (Shumway and Warther, 1999). A possible delisting bias in general overstates the returns of risky assets thus leading to a potential underestimation of the BETA premium in particular. We believe this to be of limited concern. First, we have stocks entering and

exiting the sample over time but have stocks that experience bankruptcy being maintained in the sample for several years. We apply data filter five to manage these observations. Second, our approach of using value-weights limits the potential impact of a delisting bias. Third, Shumway (1997) documents substantial losses following performance-related delistings and proposes a −30% return when the actual delisting return is unavailable. Because our historical sources do not reliably identify the reason for each disappearance, we have also applied a conservative additional −30% return to every stock that disappears from the sample, resulting in largely similar numbers.

7. Other studies to U.S. stock prices pre-1926

We are not the first to use historic data of the United States stock exchanges before 1926, but to our knowledge we are the first to use market capitalizations throughout our sample period in constructing factor portfolios and use the Commercial and Financial Chronicle (CFC) as a data source. Other studies have mainly used different sources. Goetzmann, Ibbotson, and Peng (2001) use The New York Shipping List, The New York Herald, and The New York Times and collect end of month equity prices and combine these with semi-annual dividend announcements of The New York Commercial, The Banker's Magazine, The New York Times, and The New York Herald. Their collected data have a few gaps, 1822, part of 1848, 1849, and 1866, all of 1867, January 1868 and July 1914 to December 1914. Golez and Koudijs (2018) use the data of Cowles III et al. (1938) for the period 1871-1925.[44] Unfortunately, the original Cowles data were lost and only the monthly indices remain. Schwert (1990) spliced the monthly stock returns of Smith and Cole (1935), Macaulay (1938), and Cowles III et al. (1938) and created a monthly stock return index from 1802 to 1925.[45] Geczy and Samonov (2016) use a combination of GFD, the International Center for

[44] The monthly Cowles indices are available at: https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/historical-cowles.

[45] The monthly index of William Schwert is available at: http://schwert.ssb.rochester.edu/mstock.htm.

Finance at Yale (ICF), and Inter-University Consortium for Political and Social Research (ICPSR) databases to study price momentum in U.S. stock markets between 1800 and 1925. However, their sample lacks dividend and market capitalization data, implying they have to rely on equal-weighted price returns and are consequently plagued by the abundance of small caps and banks historically. None of the previously discussed studies can consistently use market capitalization values to weight their market indices or construct factor portfolios.

8. Summary statistics

First, we present summary statistics of the value-weighted and equal-weighted market returns between 1866 and 1926, as shown in Table A.3. Shown are the average (annualized) return and volatility by decade and over the full 1866-1926 period. We compare these with other available U.S. equity return series from Schwert (1990), which was value-weighted between 1863 and 1885 and price-weighted thereafter, and Goetzmann, Ibbotson and Peng (2001), which was price-weighted over the entire sample but excludes dividends. As both series end in 1925, we append the series over 1926 with the constructed market returns from our database. Figure A.3 depicts the resulting series. We find that U.S. stock returns are generally of comparable magnitudes across our and the Schwert series, while the Goetzmann et al. series lag by about the average dividend yield in our sample. The average yearly value-weighted total return of the early sample was 8.48% and dividends contributed to 63% of this return, the average yearly value-weighted dividend return was 5.33%. Furthermore, we compare our market returns with the CRSP sample between 1927 and 2024, again finding similar statistics. Noteworthy is that in the CRSP sample, dividends contributed less than 1/3rd to the total returns, showing that the structure of total returns of investments changed over the 19th and 20th century.

Second, we summarize the distribution of the key variables in our final dataset. Figure A.4 compares the U.S. stock market capitalization distribution (by plotting the time-series average of the monthly cross-sectional distribution statistics) of the stocks in our sample with the CRSP sample, finding overall similarly distributed market capitalizations. Figure A.5 depicts the number of dividend payers versus zero-dividend versus negative-dividend stocks, split per small (market capitalization below median) and large (market capitalization above median) stocks. Figure A.6 shows the 20th, 50th, and 80th percentiles of key characteristics at each point in time.

Third, we report details on our dataset composition. Tables A.4 and A.5 show the number of stocks and the cross-sectional composition of market capitalizations per sector or exchange, respectively. Key sectors were infrastructure stocks (especially railroads), industrials, mining, and utilities (for example, telephone and telegraph stocks). Railroads were the most important stocks in terms of market capitalization for the first 30 years of our sample (see also Garvy, 1944). This started changing around 1890 when also industrial stocks and mining stocks started dominating stock exchanges (see also Garvy,1944). In the early 1860s, mining securities made their appearances on the stock markets, these included oil, copper, and gold mining stocks (Garvy, 1944). Banks became very prominent in the lists of U.S. stocks traded in the early part of the 20th century (see also Goetzman, Ibbotson and Peng, 2001). As of the 1890s, the number of banks increased considerably. However, for the most part of our sample (up to the 1920s) bank stocks were not widely traded and represent relatively low market capitalizations, which has been attributed to their double liability characteristic (i.e. stockholders of a failing bank could lose not only the amount they had spent in purchasing the shares but could also be assessed an amount up to the par value of the shares they owned) and their relatively low dividend payments (O'Sullivan, 2007)[46]. For

[46] See for example, Michie (2006, p. 104): "*bank and insurance stocks …. These did not generate sufficient turnover to justify space on the trading floor and the attention of members, and so were also traded outside on the street or curb market.*"

example, our sample has a large number of stocks in the banking industry after 1896, but they constituted less than 10% of the total market capitalization. Note that when creating an equal-weighted index, the index return will largely be driven by the (historically less important) banking industry.

Regional exchanges gained in importance mainly as of the 1890s and presented a sizable fraction of market capitalization (increasing from 11% in 1866 to 25% in 1926). The New York Curb market (the predecessor of the AMEX) gained importance as of the mid-1920s (close to the start of CRSP) presented a small fraction of the market capitalizations (3% in 1926). The NYSE had conservative listing requirements, precluding it from admitting issuers other than the largest and most well-established companies and, at that time, such companies in the United States tended to be railroads (O'Sullivan, 2007). Outside of the NYSE many small, and typically more thinly traded securities were listed on the New York Curb and regional exchanges, mostly banks (financials) and textile companies (industrials). By the 1880s, the NYSE was largely an exchange for railroad stocks, with the most actively traded stocks on the NYSE being generally railroads or Western Union (Brown et al., 2008, see also Goetzmann Ibbotson and Peng, 2001). Ten years later, railroads continued to dominate the ranks of NYSE stocks but energy/mining stocks, industrial and utility stocks had grown considerably in importance. Most of the utility companies that were added to the Exchange in the period 1886–1895 were traction companies, telephone, telegraph and cable companies, and electric and gas companies. Similarly, OTC stocks – after applying our data quality screens – represent on average over 10% of the listings but a smaller percentage (4%) of market capitalizations.[47]

Finally, Table A.5 compares the number of stocks in our sample with the Cowles (1939; as reported by Jones and Wilson, 2002) and Goetzmann, Ibbotson, and Peng (2001)

[47] GFD and CFC contain data on more OTC stocks, but most fail our data quality filters, as they were typically small and thinly traded, with more opaque stock structures and governance. O'Sullivan (2007) reports that the OTC market in stocks accounted for about $2,5 (3,5) billion in trading volume in 1920 (1926), or 6% (7%) of the value of exchange sales in that year.

NYSE-only datasets. The comparison highlights the substantially broader coverage of our dataset – on average 303 stocks compared to less than 100 in both NYSE-only datasets. This expanded universe materially increases both the number and diversity of firms and is important for our cross-sectional analysis, as the more limited coverage of earlier datasets could constrain their ability to test size, value, and other factor premia.

Figure A.1: Example Commercial and Financial Chronicle 1865

860 THE CHRONICLE. [December 30, 1865.

RAILROAD, CANAL, AND MISCELLANEOUS STOCK LIST.

Companies.	Stock out-standing.	Dividend. Periods.	Last p'd.	Market. Bid.	Askd
Railroad.					
Albany and Susquehanna...100	1,347,192				
Alleghany Valley...50	1,947,600				
Alton and St. Louis...100	800,000	Quarterly.	Jan ..1¾	92	
Atlantic & Great Western, N. Y.100	919,153				
do do Pa..100	2,500,000				
do do Ohio.100	5,000,000				
Baltimore and Ohio...100	13,188,903	April and Oct	Oct...4	111½	115
Washington Branch...100	1,650,000	April and Oct	Oct...5	127	
Bellefontaine Line...100	4,434,250	Feb. and Aug	Aug..3		
Belvidere, Delaware...100	997,112				
Berkshire...100	600,000	Quarterly.	Oct...1¾		
Blossburg and Corning...50	250,000	June & Dec.	Dec. .2½		
Boston, Hartford and Erie...100	8,500,000			11¾	13
Boston and Lowell...500	1,830,000	June & Dec.	Dec..3½	94	95
Boston and Maine...100	4,076,974	Jan. and July	Jan ..4	118½	120
Boston and Providence...100	3,160,000	Jan. and July	Jan ..5	125	126
Boston and Worcester...100	4,500,000	Jan. and July	Jan ..4½	130	132
Brooklyn Central...100	492,150				
Brooklyn City...10	1,000,000	Feb. and Aug	Aug..3½	180	
Brooklyn City and Newtown...100	366,000				
Buffalo, New York, and Erie...100	850,000	Jan. and July	July..3½		
Buffalo and State Line...100	2,200,000	Feb. & Aug.	Aug..5		190
Burlington and Missouri River.100	1,000,000				
Camden and Amboy...100	6,472,400	Jan. and July	Jan...5	125½	126
Camden and Atlantic...50	378,455				
do do preferred..50	682,600				
Cape od...60	681,665	Jan. and July	July..3½		
Catawissa...50	1,150,000			43	48½
o preferred...50	2,200,000	Feb. & Aug.	Aug..3½	72	75
Central of New Jersey...100	5,600,000	Quarterly.	Oct...2½	118	120
Central Ohio...					
Cheshire (preferred)...100	2,085,925			48	49
Chester Valley...50	871,900			102	104¼
Chicago and Alton...100	1,783,100	Feb. & Aug.	Aug..3½	104½	105
do preferred...100	2,425,200	Feb and Aug.	Aug..3½		109
Chicago Burlington and Quincy.100	8,376,510	May & Nov.	N.5c.20s	113½	114
Chicago and Great Eastern...100					
Chicago, Iowa and Nebraska...100	1,000,000				
Chicago and Milwaukee...100	2,250,000			53	
Chicago and Northwestern...100	13,160,927			35½	35¾
do do pref..100	12,994,719	June & Dec.	June..3½	61¾	61½
Chicago and Rock Island...100	6,000,000	April and Oct	Oct...5	107¼	107¾
Cincinnati and Chicago Air Line100	1,106,125				
Cincinnati, Hamilton & Dayton.100	3,000,000	May and Nov.	Nov..5	98	100
Cincinnati and Zanesville...100	2,000,000			12	
Cleveland, Columbus, & Cincin.100	6,000,000	Feb. and Aug	Aug..5		125
Cleveland, Painesville & Ashta.100	4,000,000	Jan. and July	Jan		
Cleveland and Pittsburg...50	5,253,625	Jan. and July	Jan.'66 4	82½	82⅝
Cleveland and Toledo...50	4,654,800	April and Oct	Oct...5	113	113¼
Columbus & Indianapolis Cent.100					125
Columbus and Xenia...100	1,490,800	Jan. and July	July..5		
Concord...50	1,500,000	Jan. and July	July..3½	121	
Concord and Portsmouth...100	250,000	Jan. and July	July..3½	126	
Coney Island and Brooklyn...100	500,000				
Connecticut and Passumpsic...100	392,900				
do do pref.100	1,255,200	Jan. and July	July..3	74	
Connecticut River...100	1,591,100	Jan. and July	July..4	103½	
Covington and Lexington...100	1,582,169				
Dayton and Michigan...100	2,316,705			20	
Delaware...50	406,132	Jan. and July	July..3		
Delaware, Lacka., & Western..50	6,832,950	Jan. and July	Jan...3	165	170
Des Moines Valley...100	1,550,000				
Detroit and Milwaukee...100	952,350				
do do pref....100	1,500,000				
Dubuque and Sioux City...100	1,751,577				
do do pref....100	1,982,180				
Eastern, (Mass)...100	3,155,000	Jan. and July	Jan.. 3	99¾	100
Eighth Avenue, N. Y...100	1,000,000	Quarterly.	Oct		
Elmira, Jefferson, & Canandagua100	500,000	Feb. and Aug	Aug..2½		
Elmira and Williamsport...50	500,000	Jan. and July	Jan..2½	52	53
do do pref...50	500,000	Jan. and July	Jan..3½	82	86
Erie...100	16,400,100	Feb. & Aug.	Aug..4	95⅞	96
do preferred...100	8,535,700	Feb. & Aug.	Aug..3½	85½	87
Erie and Northeast...50	400,000	Feb. & Aug.	Aug..5		
Fitchburg...100	3,540,000	Jan. and July	July..3	106	
Forty-sec'd St. & Grand St. F'y.100	750,000	April and Oct	Oct 5..		
Hannibal and St. Joseph...100	1,900,000			30	
do do pref...100	5,253,836				
Hartford and New Haven...100	2,350,000	Quarterly.	Oct ..3		
Housatonic...100	820,000				
do preferred...100	1,180,000	Jan. and July	July..4		
Hudson River...100	6,218,042	April and Oct	Oct...4	108¾	109⅛
Huntingdon and Broad Top...50	617,500				
do do pref. 50	190,750	Jan. and July	July..3½		
Illinois Central...100	22,888,900	Feb. and Aug	Au5.&10s	131½	132½
Indianapolis and Cincinnati...50	1,499,900	April and Oct	Oct...4	99	

Companies.	Stock out-standing.	Dividend. Periods.	Last p'd.	Market. Bid.	Askd
New York and Boston Air Line.100	788,047				
New York Central...100	34,386,000	Feb. and Aug	Aug..3	96⅜	96½
New York and Harlem...50	5,085,050				
do preferred...50	1,500,000	Jan. and July	Jan..4		
Niagara Bridge & Canandaigua.100	1,000,000	Jan. and July	Jan...3		
New York and New Haven...100	2,980,839	Quarterly.	Jan...4	114½	115
New York Providence & Boston100	1,508,000	Quarterly.	Jan...3	122½	125
Ninth Avenue...100	795,360				
Northern of New Hampshire...100	3,068,400	June and Dec	Dec 4	83½	90
Northern Central...50	3,344,800	Quarterly.	Nov 2	88	90
North Pennsylvania...50	3,150,150			61	62
Norwich and Worcester...100	2,338,600	Jan. and July	July..4		100
Ogdensburg & L. Champlain...100	3,077,000			41	42
Ohio and Mississippi...100	21,250,000			28⅜	28½
do preferred..100	2,979,000	January.	Jan ..7	70	
Old Colony and Newport...100	3,609,600	Jan. and July	Jan...4	100	100
Oswego and Syracuse...50	482,400	Feb. and Aug	Aug..4		
Panama (and Steamship)...100	7,000,000	Quarterly.	Jan ..6	235	40
Peninsula...100					
Pennsylvania...50	20,000,000	May and Nov	May..5	113½	113¾
Philadelphia and BaltimoreCent100	218,100				
Philadelphia and Erie...50	5,013,054			60¾	61
Philadelphia and Reading...50	20,072,323		De.'65-10	106⅜	106⅞
Phila., Germant'n, & Norrist'n. 50	1,358,100	Apr. and Oct	Oct. .4	106½	106¾
Phila., Wilmington & Baltimore 50	8,657,300	Apr. and Oct	Oct ..5	119	120
Pittsburg and Connellsville...50	1,770,414				
Pittsburg, Ft. Wayne & Chicago100	8,181,126	Quarterly.	Jan...2½	105¾	106
Portland, Saco, and Portsmouth100	1,500,000	Jan. and July	July..4	94	100
Providence and Worcester...100	1,700,000	Jan. and July	July..4½		
Racine and Mississippi...100					
Raritan and Delaware Bay...100	2,360,700				
Reading and Columbia...50	501,890				
Rensselaer and Saratoga...50	800,000	Jan. and July	July..4		
Rome, Watertown & Ogdensb'g100	1,774,175	Jan. and July	Jan...5		
Rutland and Burlington...100	2,223,376				
St. Louis, Alton, & Terre Haute100	2,300,000			39	43
do do pref.100	1,700,000	Annually.	May..7	70	
Sandusky, Dayton, and Cincin..100	2,989,090				
do do pref.100	354,866	Feb. and Aug	Aug..3		
Sandusky, Mansfield & Newark100	862,571				
Schuylkill Valley...50	576,000	Jan. and July	July..5		
Second Avenue (N. Y.)...100	650,000	Apr. and Oct		66	
Shamokin Valley & Pottsville..50	869,450	Feb. and Aug	Aug..3		70
Sixth Avenue (N. Y.)...100	750,000	Quarterly.		130	136
Syracuse, Binghamton & N. Y.100	1,200,130				
Terre Haute and Richmond...50	1,900,150	Jan. and July	Jan...6		
Third Avenue (N. Y.)...100	1,170,000	Quarterly.	Oct		
Toledo, Peoria, and Warsaw...100	1,700,000				
do do 1st pref.100	1,700,000				
do do 2d pref.100	1,000,000				
Toledo, Wabash and Western..50	2,442,350	June and Dec	June.3	42	45
do do preferred. 50	984,700	June and Dec	Dec. .3½		65
Tioga...100	125,000	Jan. and July	July..3½		
Troy and Boston...100	607,111				
Troy and Greenbush...100	274,400	June and Dec	Dec ..3		
Utica and Black River...100	811,560	Jan. and July	Jan ..4		
Vermont and Canada...100	2,860,000	June and Dec	Dec ..4	94	95
Vermont and Massachusetts...100	2,214,225		Jan...2	43	44
Warren...50	1,408,300	Jan. and July	Jan...3	93½	95
Westchester and Philadelphia..50	684,036				
Western (Mass)...100	5,665,000	Jan. and July	Jan...4	137½	140
Worcester and Nashua...83⅓	1,141,000	Jan. and July	July..3	100	
Wrightsville, York & Gettysb'g 50	317,050	Jan. and July	July..1		
Canal.					
Chesapeake and Delaware...25	1,343,563				
Chesapeake and Ohio...25	8,228,595				
Delaware Division...50	1,633,350	Feb. and Aug	Aug..3	62	63
Delaware and Hudson...100	10,000,000	Feb. and Aug	Aug.10	144	146
Delaware Junction (Pa.)...100	398,910				
Delaware and Raritan...100		Jan. and July	Jan...5		
Lancaster and Susquehanna...50	200,000				
Lehigh Navigation...50	4,282,950	May and Nov	Nov..5	109	110¼
Monongahela Navigation...50	726,800				
Morris (consolidated)...100	1,025,000	Feb. and Aug	Feb..6	82	83
do preferred...100	1,175,000	Feb. and Aug	Feb..5	120	121
North Branch...50	138,086				121
Schuylkill Navigation (consol.). 50	1,908,207			53	54
do preferred. 50	2,888,805	Feb. and Aug	Aug..3½	66	67
Susquehanna and Tide-Water..50	2,050,070			18	20
Union...50	2,750,000			2	5
do preferred...50				40	42
West Branch and Susquehanna.100	1,000,000	Jan. and July	July..5		
Wyoming Valley...50	700,000	May & No	Nov. 4	112	116
Miscellaneous.					
American Coal...25	1,500,000	Feb. and Aug	Aug..4		72
American Telegraph...100			10		
Ashburton Coal...50					

Figure A.2: Example Commercial and Financial Chronicle 1925

NEW JERSEY—(Concluded)

	Capital.	Surplus & Profits.	Gross Deposits.	Par.	Bid.	Ask.
Long Branch—	$	$	$		Per	share
Citizens' Nat Bank	100,000	240,000	2,450,000	100	325	-----
Long Branch Bkg Co	150,000	187,557	2,429,316	50	200	220
Morristown—					Per	share.
First National Bank	200,000	373,678	5,013,494	100	l240	-----
National Iron Bank	200,000	214,482	5,289,541	50	l100	-----
American Trust Co	150,000	122,157	1,750,549	100	l140	-----
Morristown Trust Co	600,000	1,049,371	8,733,592	100	l275	-----
Mt. Holly—					Per	share.
Mt Holly Nat Bank	100,000	88,822	773,171	25	38	40
Union Nat Bank	100,000	216,386	1,387,085	50	135	150
Farmers' Trust Co	200,000	133,290	1,053,445	100	120	125
Mt Holly S D & Tr	100,000	179,324	709,007	100	135	150
Newark—						
American Nat Bank	500,000	1,095,436	15,598,126	100	425	-----
Broad & Market N B	200,000	550,196	8,235,724	100	425	-----
Cit N Bk & Tr Co	200,000	118,763	1,232,336	100	160	-----
Lincoln Nat Bank	600,000	159,331	1,622,704	100	220	-----
Mer & Mfrs N Bk	1,350,000	2,061,854	14,572,182	100	320	-----
Mutual Bk of Rosev.	200,000	223,517	2,331,492	100	190	-----
Nat Newark & Essex Banking Co	2,500,000	1,630,707	32,634,935	100	280	-----
National State Bank	500,000	1,057,126	6,228,152	100	375	-----
North Ward Nat Bk	400,000	976,368	12,162,245	109	450	-----
City Trust Co	300,000	408,656	4,778,671	100	330	-----
Clinton Trust Co	400,000	465,188	7,692,076	100	315	-----
Federal Trust Co	2,500,000	1,851,032	23,339,292	100	410	-----
Fidelity Union Tr Co	5,250,000	5,209,189	76,248,383	100	525	-----
Ironbound Trust Co	500,000	779,117	13,832,704	100	500	-----
Liberty Trust Co	200,000	122,369	2,298,251	100	160	-----
Newark Trust Co	200,000	107,800	2,140,510	100	300	-----
So Side N B & T Co	200,000	g56,000	415,000	100	150	-----
Springfield Av Tr Co	200,000	427,755	7,593,437	100	400	-----
Vailsburg Trust Co	200,000	90,797	1,765,874	100	210	-----
Washington Trust Co	300,000	421,851	3,714,821	100	320	-----
Weequahic Trust Co	200,000	178,109	2,238,323	100	300	-----
West Side Trust Co	600,000	785,673	8,343,189	100	475	-----
New Brunswick					Per	share
Cits Nat Bk of N Br	250,000	g50,000	1,246,714	100	125	-----
Nat Bank of N J	500,000	1,003,631	12,808,754	100	325	350
Peoples Nat Bank	200,000	297,387	3,795,505	100	290	300
Middlesex TG&T Co	100,000	121,000	2,200,000	100	175	195
New Brunsw Tr Co	300,000	396,738	5,187,486	100	270	-----
North & West Hudson—						
First Nat Bk, Town of Union	150,000	g65,998	3,728,014	100	160	-----
First N Bk, West NY	100,000	g149,721	3,967,428	100	160	-----
Commonw'lth Tr Co	600,000	g629,160	7,621,753	100	300	-----
Guttenberg B & T Co	100,000	g135,409	3,992,625	100	350	-----
Weehawken Tr Co	600,000	g200,000	8,639,737	100	175	-----
Highland Trust Co	300,000	g191,962	4,832,712	100	240	-----
Passaic—					Per	share
Merchants Bank	100,000	125,907	1,897,899	100	------	240
Passaic N Bk&Tr Co	1,500,000	2,091,996	22,994,385	100	------	225
City Trust Co	200,000	257,832	4,213,134	100	------	-----
Hobart Trust Co	300,000	343,226	3,854,754	100	450	-----
People's Bk & Tr Co	400,000	972,476	9,110,413	100	375	400
Service Trust Co	400,000	260,000	1,500,000	100	------	180
Paterson—					Per	share
First National Bank	600,000	813,394	8,301,216	100	415	-----
Paterson Nat Bank	1,200,000	1,118,580	14,835,058	100	280	290
Second Nat Bank	750,000	999,992	12,166,076	50	225	-----
Nat Bank of Amer	500,000	332,129	3,709,408	100	200	205
Paterson Sav Inst	1,000,000	1,621,300	23,854,500	25	145	160
Citizens' Trust Co	500,000	714,699	9,569,369	100	360	-----
Franklin Trust Co	150,000	410,035	3,226,369	100	360	-----
Hamilton Trust Co	600,000	556,135	10,871,482	100	300	-----
U S Trust Co	350,000	1,390,651	18,496,652	100	580	-----
Plainfield—						
City National Bank	150,000	347,043	6,699,691	100	------	l200
First National Bank	200,000	339,265	5,881,270	100	------	l230
Plainfield Trust Co	609,300	857,954	12,986,123	100	------	l225
State Trust Co	100,000	159,368	3,301,619	100	190	-----
Trenton—						
Broad St Nat Bank	250,000	953,085	10,330,515	100	400	-----
Capital City Tr Co	150,000	g140,676	1,228,624	100	200	-----
First National Bank	500,000	1,233,438	9,248,718	100	350	-----
Hanover Trust Co	200,000	167,454	3,354,419	100	200	-----
Mechanics' Nat Bk	1,000,000	1,655,157	17,593,422	50	260	-----
Trenton Banking Co	750,000	1,288,408	13,784,727	50	175	-----
Colonial Trust Co	100,000	188,382	3,587,887	100	225	-----
Mercer Trust Co	200,000	500,731	5,595,772	100	275	-----
Trenton Trust Co	750,000	1,132,009	10,902,440	100	225	-----
Wilbur Trust Co	100,000	50,495	1,641,538	100	165	-----

NEW YORK—(Continued).

	Capital.	Surplus & Profits.	Gross Deposits.	Par.	Bid.	Ask.
Buffalo—	$	$	$		Per	share
Liberty Bank	2,500,000	4,172,662	53,230,170	100	335	-----
Manuf'rs & Trad Nat	2,000,000	2,711,852	53,624,419	100	400	-----
People's Bank	1,000,000	1,167,735	25,598,859	100	270	-----
Com-So Side N Bk	550,000	431,334	11,609,081	100	240	-----
Buffalo Trust Co	2,500,000	3,482,175	55,854,318	100	440	450
Fidelity Trust Co	1,000,000	1,943,231	30,291,213	100	400	-----
Marine Trust Co	11,250,000	13,355,072	141,680,375	100	335	370
Elmira—					Per	share
Merchants' Nat Bk	250,000	253,582	3,150,691	100	225	-----
Second Nat Bank	400,000	914,874	8,185,544	100	305	-----
Chemung Can T Co	600,000	958,674	8,871,829	100	275	-----
New York City—	*Deposits N*	*ew York Ci*	*ty banks are*	*repo*	*rted ne*	*t and*
are of date Nov.	28 1925.	*Surplus an*	*d profits are*	*of da*	*te Sept.*	28 '25
for National and	*Nov* 14 19	*'25 for Stat*	*e banks. A*	*divi*	*dend r*	*ecord*
of banks and trust	*companies*	*in New Yo*	*rk City and*	*Broo*	*klyn m*	*ay be*
found in our "Rai	*lway and I*	*ndustrial"*	*Section, pag*	*e244*	.	
	$	$			Per	share
Amalg Bank of N Y	200,000	151,278	d5,536,715	----	------	------
Amer Ex-Pac Nat Bk	7,500,000	12,625,380	143,608,000	100	475	485
Amer Union Bank	1,200,000	429,509	d8,595,046	100	205	220
Bank of America	6,500,000	5,223,884	93,623,000	100	335	-----
Bank of Europe	450,000	488,199	d10,322,203	100	------	------
Bank of Manhat Co	10,000,000	14,732,900	154,488,000	50	225	230
Bank of U S	4,000,000	2,683,238	d68,214,064	100	285	295
Bank of Wash Hgts	200,000	604,380	9,067,000	100	725	-----
Berardini State Bank	150,000	783,788	d1,022,806	----	------	------
Bowery Nat Bank	250,000	928,200	5,229,000	100	850	950
Broadway Cent Bank	300,000	205,234	d6,235,910	100	245	-----
Bronx Borough Bank	150,000	727,172	7,547,266	100	675	-----
Bronx National Bank	300,000	252,000	a7,098,600	100	350	450
Bryant Park Bank	200,000	213,389	d2,462,989	100	210	230
Capitol Nat Bank	2,000,000	890,000	a20,075,600	100	215	225
Chase National Bank	20,000,000	29,008,050	392,103,000	100	563	568
Cent Mercantile Bk	1,500,000	1,105,009	d21,161,726	100	330	-----
Chatham Phenix Nat Bk & Tr Co	13,500,000	13,231,500	215,828,000	100	358	363
Chelsea Exch Bank	1,500,000	722,764	d16,094,510	100	215	225
Chemical Nat Bank	4,500,000	17,597,100	120,279,000	100	710	725
Coal & Iron Nat Bk	1,500,000	1,755,003	18,208,000	100	345	355
Colonial Bank	1,200,000	2,787,800	32,770,000	100	550	------
Commonwealth Bank	600,000	1,089,659	13,677,000	100	355	370
Continental Bank	1,000,000	1,161,388	7,185,000	100	250	-----
Corn Exchange Bank	10,000,000	14,558,000	204,424,000	100	570	580
Cosmopolitan Bank	400,000	226,844	d8,887,671	100	190	-----
Eastern Exch Bank	100,000	28,450	d1,341,582	----	------	------
East River Nat Bank	2,500,000	2,375,200	43,992,000	100	355	370
Federation Bk of N Y	750,000	842,724	d11,484,828	----	------	------
Fifth Avenue Bank	500,000	2,905,364	25,288,000	100	2350	------
First National Bank	10,000,000	71,199,679	222,732,000	100	2950	3000
Franklin Nat Bank	800,000	483,371	a4,877,214	----	160	170
Garfield Nat Bank	1,000,000	1,766,100	19,129,000	100	380	-----
Gimbel Bros Bank	100,000	106,600	e1,114,600	----	------	------
Grace Nat Bk of N Y	1,000,000	1,798,200	10,462,000	100	270	-----
Greenwich Bank	1,000,000	2,594,680	24,689,000	100	425	-----
Hamilton Nat Bank	1,000,000	350,000	a9,378,000	100	218	225
Hanover Nat Bank	5,000,000	25,443,000	110,082,000	100	1100	1120
Harriman Nat Bank	1,000,000	1,326,500	a39,540,500	100	480	490
Internat Union Bank	250,000	208,391	d3,547,414	----	------	------
Lebanon Nat Bank	250,000	80,400	a1,185,600	----	------	------
Liberty Nat Bank	1,500,000	662,900	a7,901,400	----	------	------
Longacre Bank	200,000	102,088	d4,853,153	----	------	------
Madison State Bank	200,000	47,177	d2,303,606	----	------	------
Mech & Met Nat Bk	10,000,000	17,380,479	183,668,000	100	418	425
Mutual Bank	500,000	764,600	e15,706,600	100	465	-----
Nat American Bank	1,000,000	603,700	a8,025,600	100	175	185
Nat Butch & Drov	1,000,000	863,400	a9,204,100	25	170	180
Nat Bk of Commerce	25,000,000	40,021,600	327,280,000	100	365	370
National City Bank	50,000,000	63,149,175	726,665,000	100	585	595
National Park Bank	10,000,000	24,375,400	137,807,000	100	505	515
New Netherland Bk	600,000	372,538	d13,319,761	100	270	280
Penn Exchange Bank	200,000	55,061	d2,327,328	100	124	134
Peoples Comm'l Bk	100,000	57,393	d2,437,114	100	------	------
Port Morris Bank	100,000	100,422	d2,514,698	----	200	-----
Prisco State Bank	150,000	69,200	e1,543,500	----	------	------
Public Nat Bank	4,000,000	6,702,700	a104636 000	100	625	650
Seaboard Nat Bank	5,000,000	8,558,441	125,096,000	100	690	710
Seventh Nat Bk	k1,000,000	88,100	a4,664,200	100	170	180
Standard Bank	200,000	243,987	d5,423,897	100	480	500
State Bank	3,500,000	5,867,562	105,076,000	100	775	825
Trade Bank of N Y	500,000	241,085	d2,909,827	----	145	155
United Nat Bk in NY	1,000,000	571,500	a11,209,300	----	210	225
World Exch Bank	100,000	42,400	e1,227,500	----	------	------
Trust Co. returns da	*te Nov.* 14	1925				
American Trust Co	4,000,000	3,009,770	45,120,502	100	------	------
Anglo South Am Tr	1,000,000	584,061	9,264,075	----	------	------
Banca Com It Tr Co	1,000,000	584,332	8,999,515	----	------	------
Banco di Sicilia Tr Co	500,000	15,133	1,681,798	----	------	------
Bank of N Y & Tr Co	4,000,000	12,867,853	71,844,790	100	625	635
Bankers Trust Co	20,000,000	30 391,589	372,277,384	100	573	578
Bronx County Tr Co	825,000	420,741	11,471,796	100	230	255
Brotherhood Locom Eng Co-Op Tr Co	700,000	259,958	6,062,628	----	------	------

Figure A.3: U.S. stock market returns: 1866-1926.

The figure shows the cumulative value of a one-dollar investment from 1866 through 1926 in the U.S. stock market. Shown are the value-weighted ('VW') or equal-weighted ('EW') cumulative U.S. market stock return as constructed in this paper ("Market"), the index of Schwert (1990; "Schwert") and the index of Goetzmann et al. (2001; "Goetzmann et al."). The y-axis is on a logarithmic scale.

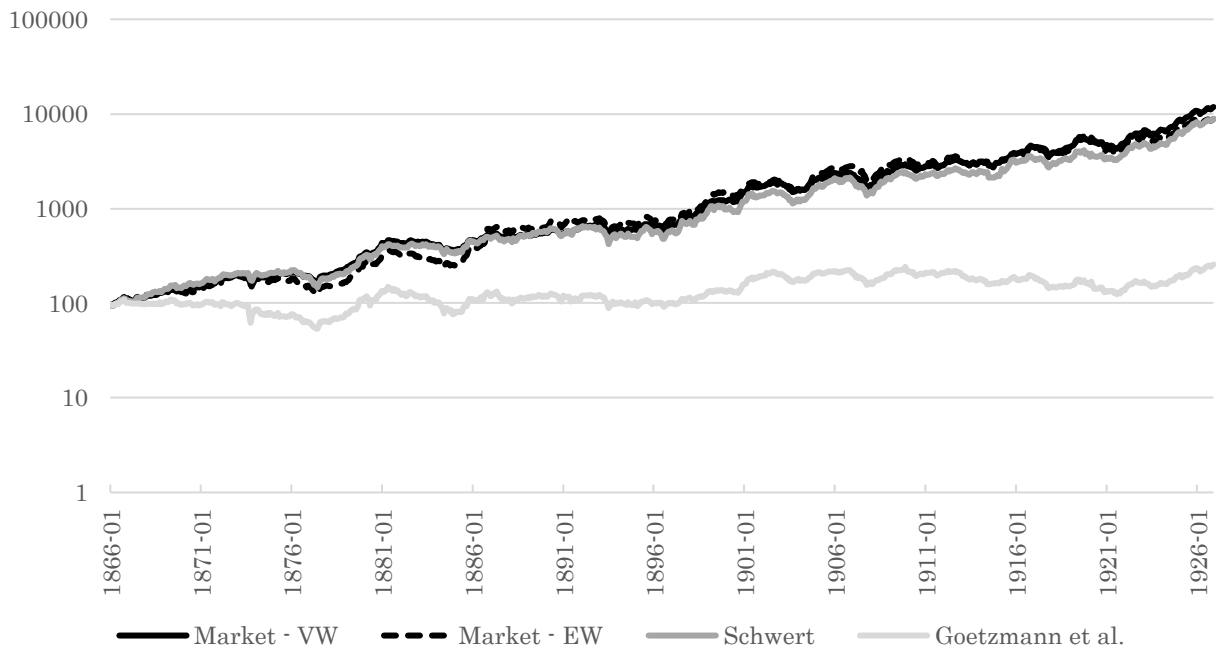


Figure A.4: Distribution of market capitalization of U.S. stocks: 1866-1926 versus 1927-2024.

The figure shows the time-series average of the monthly cross-sectional distribution of (the natural logarithm of) stocks' market capitalizations for our sample (1866-1926; 'Pre-CRSP') and the CRSP sample (1927-2024; 'CRSP').

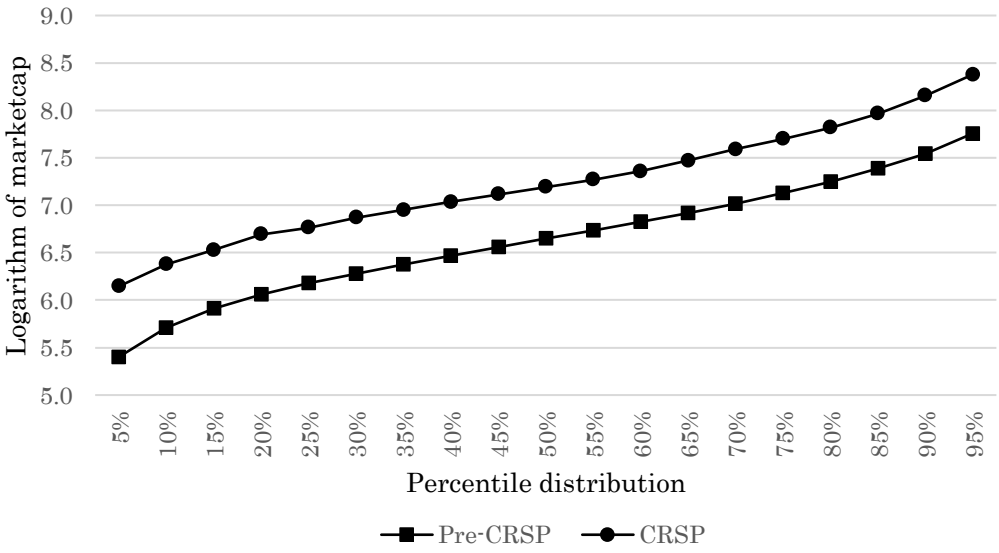


Figure A.5: Distribution of dividend-paying stocks: 1866-1926.

The figure shows per month in our sample the number of dividend payers versus zero-dividend versus negative dividend stock, split per small (market capitalization below median) and large (market capitalization above median) stocks. The sample runs from 1866 till 1926.

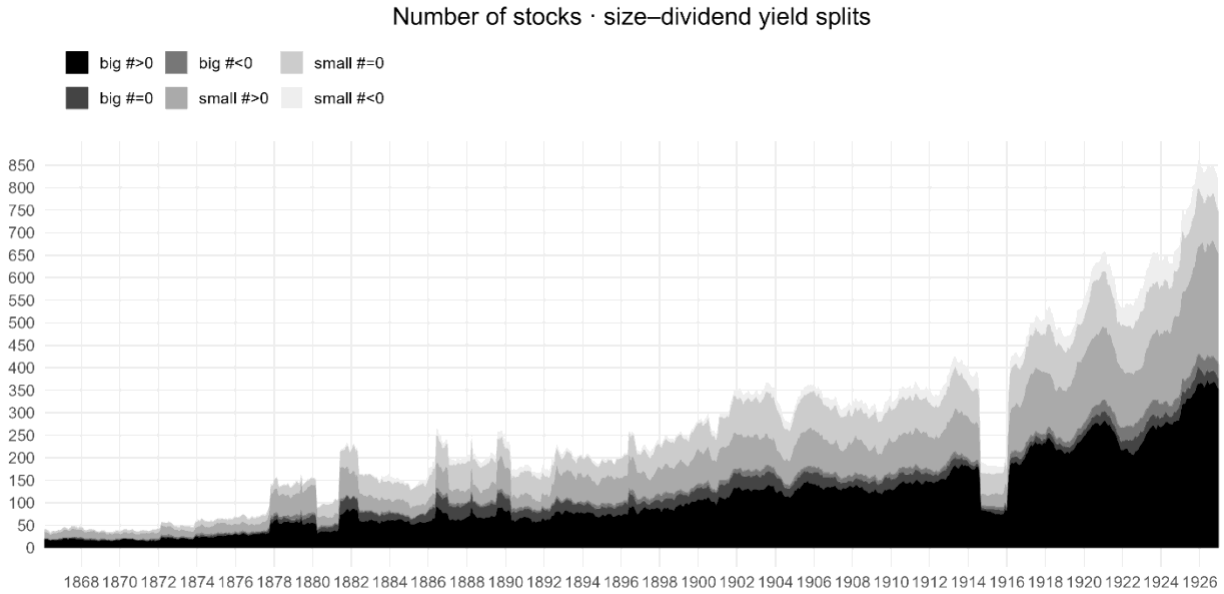


Figure A.6: Cross-sectional distribution of characteristic variables: 1866-2024.

The figure shows per month in our sample the 20th (bottom black line), 50th (grey line), and 80th (top black line) percentiles for several key characteristics. The sample runs from 1866 till 2024, with the dotted vertical line indicating the pre-CRSP versus CRSP sample cutoff date.

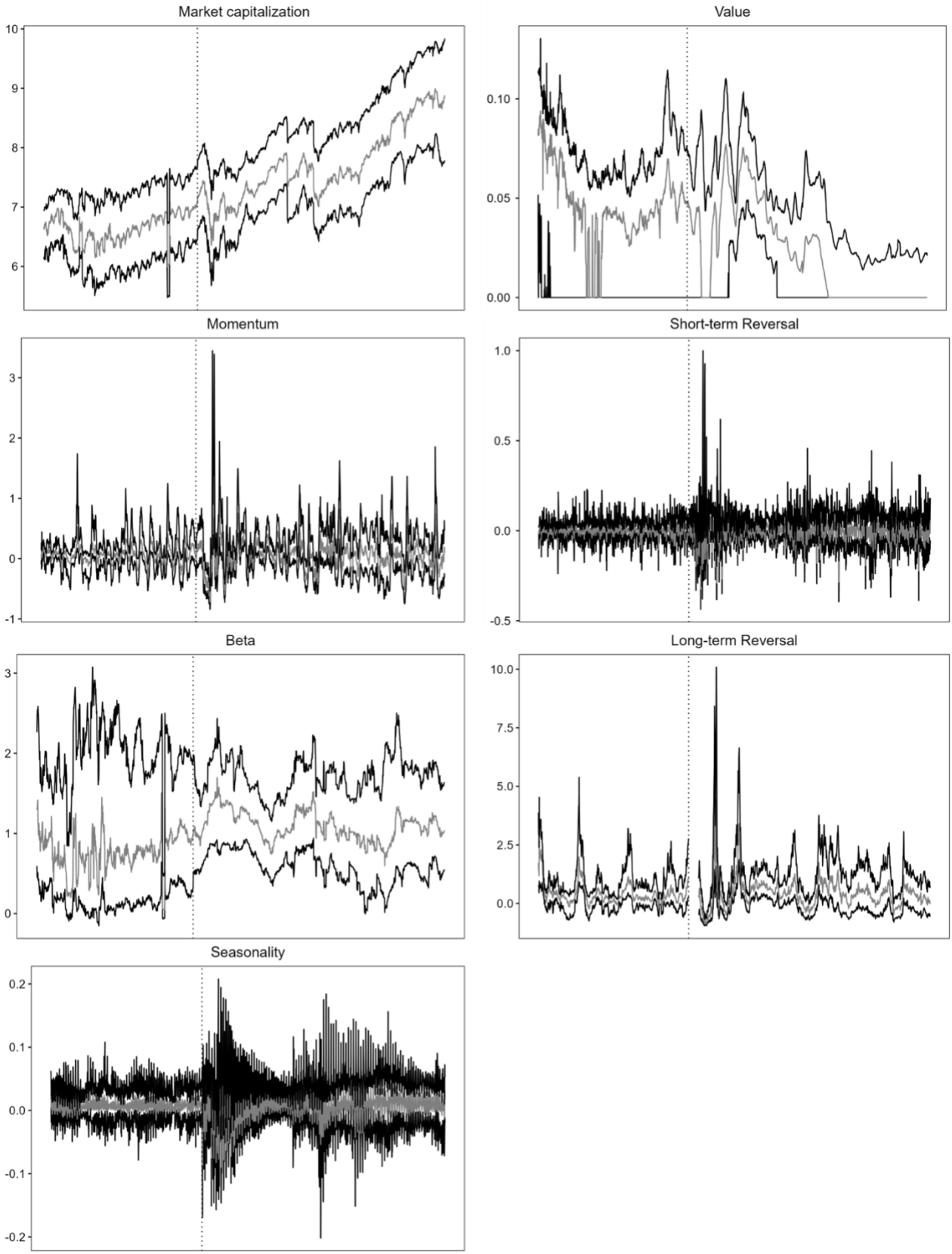


Table A.3: Sample summary statistics

The table summarizes the return series we use in our sample. Shown are the average annualized total return and volatility ('Std. deviation') of the value-weighted ('VW') or equal-weighted ('EW') market index as constructed in this paper, the equally weighted index of Schwert (1990), and the price-weighted index of the price appreciation (i.e., excluding dividends) on NYSE stocks of Goetzmann et al. (2001). Results are shown per calendar decade and over our full sample period (1866-1926). The last row shows the results over the CRSP sample period (1927-2024) based on the value-weighted market index from CRSP.

	Our sample - VW		Our sample - EW		Schwert (1990)		Goetzmann, Ibbotson and Peng (2001)	
Year	Average return	Std. deviation	Average return	Std. deviation	Average return	Std. deviation	Average return	Std. deviation
1866-1869	7.11	10.92	5.65	11.19	9.54	9.41	-0.59	7.77
1870s	9.51	11.17	7.76	13.54	8.03	11.91	2.49	16.74
1880s	6.24	11.06	10.71	15.54	7.38	13.22	2.14	16.20
1890s	8.17	11.05	8.98	13.58	6.91	17.87	2.03	13.13
1900s	9.97	12.31	9.75	12.49	10.39	15.25	6.63	10.69
1910s	6.61	10.26	5.45	11.57	5.49	13.40	-3.28	10.14
1920-1926	11.99	12.10	7.82	15.33	13.06	12.76	7.33	11.89
1866-1926	8.48	11.25	8.26	13.47	8.38	13.97	2.44	13.14
1927-2024	11.45	18.45						

Table A.4: Sample distribution: sectors

The table shows the number of unique stock observations included in our sample split per sector over all sectors combined ('Total'). Panel A shows the number of stocks in each sector, panel B shows the market capitalization composition (in millions of U.S. Dollars), and panel C shows the percentage of market capitalization of each sector with respect to the total market capitalization. Results are per December of the start year of every 10-year period and over the average over all months in our full sample period (1866-1926).

Panel A: Number of stocks

Year	Energy/Mining	Financials	Industrial & Other	Infrastructure	Utilities	Total
1866	4	7	3	28	1	43
1876	3	9	2	52	4	70
1886	38	66	8	114	15	241
1896	34	42	30	74	37	217
1906	92	41	67	88	41	329
1916	164	60	152	62	40	478
1926	220	108	366	68	65	827
Average	75	57	69	74	28	303

Panel B: MV distribution

Year	Energy/Mining	Financials	Industrial & Other	Infrastructure	Utilities	Total
1866	7	33	6	251	2	299
1876	5	48	6	518	10	586
1886	47	158	30	1,463	98	1,795
1896	325	206	254	1,152	288	2,226
1906	1,766	447	892	4,042	943	8,091
1916	5,551	965	3,344	4,072	1,415	15,348
1926	11,478	3,656	12,744	5,019	4,923	37,820
Average	1642	457	1,217	2,153	687	6,156

Panel C: MV distribution %

Year	Energy/Mining	Financials	Industrial & Other	Infrastructure	Utilities	Total
1866	2%	11%	2%	84%	1%	100%
1876	1%	8%	1%	88%	2%	100%
1886	3%	9%	2%	82%	5%	100%
1896	15%	9%	11%	52%	13%	100%
1906	22%	6%	11%	50%	12%	100%
1916	36%	6%	22%	27%	9%	100%
1926	30%	10%	34%	13%	13%	100%
Average	27%	7%	20%	35%	11%	100%

Table A.5: Sample distribution: exchanges

The table shows the number of unique stock observations included in our sample split per exchange (NYSE, Curb, or regional exchanges) and over all exchanges combined ('Total'). Panel A shows the number of stocks by exchange – including a comparison with the NYSE-only cross-sectional equity sample used by Cowles (1939) and Goetzmann et al. (2001), panel B shows the market capitalization composition (in millions of U.S. Dollars), and panel C shows the percentage of market capitalization by exchange with respect to the total market capitalization. * indicates the use of an end of previous year number. Results are per December of the start year of every 10-year period and over the average over all months in our full sample period (1866-1926).

Panel A: Number of stocks

Year	NYSE	Curb	Regional	OTC	Total	Cowles (1939)	Goetzmann et al. (2001)
1866	33	-	8	2	43	-	94
1876	49	-	20	1	70	45*	38
1886	135	-	86	20	241	73*	75
1896	106	3	64	44	217	88*	70
1906	152	7	124	46	329	131*	89
1916	233	39	161	45	478	186*	95
1926	486	38	248	55	827	-	86*
Average	96	150	12	45	303		-

Panel B: MV distribution

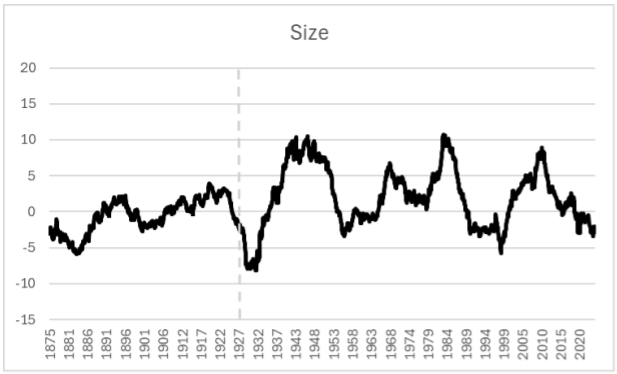
Year	NYSE	Curb	Regional	OTC	Total
1866	262	-	33	4	299
1876	502	-	84	0	586
1886	1479	-	270	47	1795
1896	1408	9	713	96	2226
1906	5736	41	2079	235	8091
1916	10942	353	3626	428	15348
1926	26046	1011	9515	1249	37820
Average	4308	130	1485	233	6156

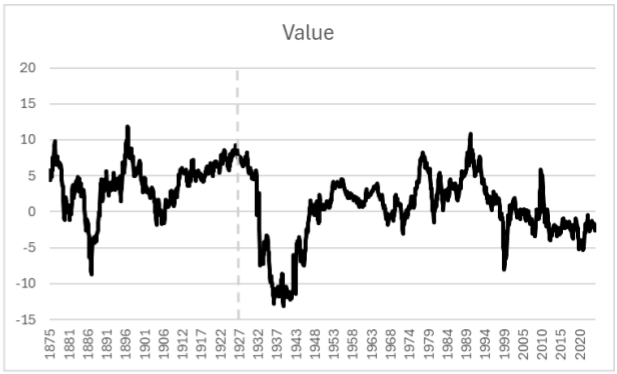
Panel C: MV distribution – %

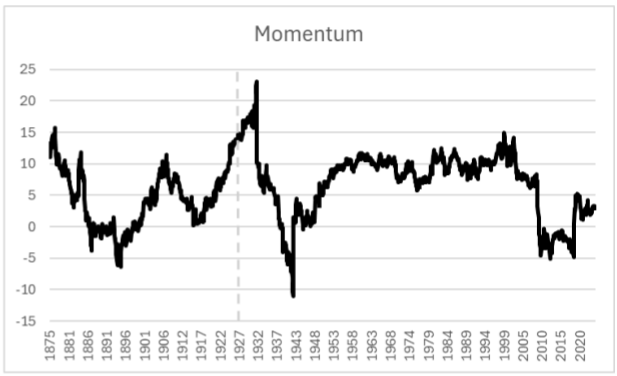
Year	NYSE	Curb	Regional	OTC	Total
1866	88%	-	11%	1%	100%
1876	86%	-	14%	0%	100%
1886	82%	-	15%	3%	100%
1896	63%	0%	32%	4%	100%
1906	71%	1%	26%	3%	100%
1916	71%	2%	24%	3%	100%
1926	69%	3%	25%	3%	100%
Average	70%	2%	24%	4%	100%

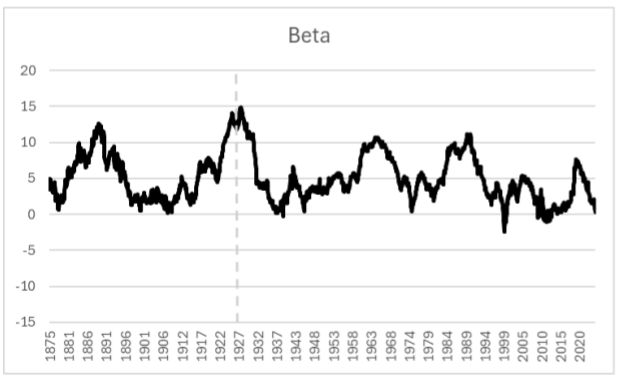
Online Appendix B: Additional results

Figure B.1: U.S. equity factor returns: 1866-2024. The figure shows rolling 10-year annualized performances from 1866 through 2024 for the size ('SMB'), value ('HML'), momentum ('UMD'), short-term reversal ('ST_Rev'), beta ('BETA'), long-term reversal ('LT_Rev'), and seasonality ('Seas') factors. Factors are constructed from top-bottom portfolios from 2x3 size-characteristic-based portfolios.









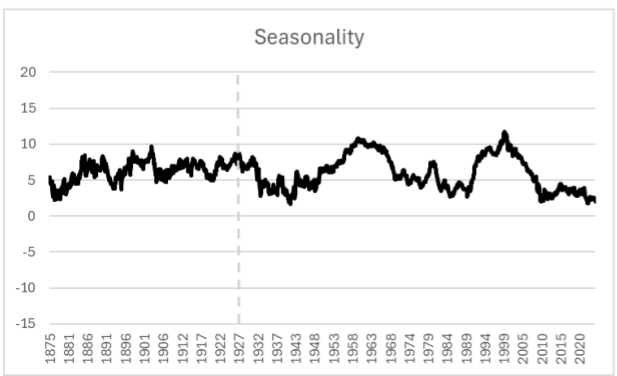


Figure B.2: U.S. equity factor returns: 1866-1926.

The figure shows the cumulative value of a one-dollar investment from 1866 through 1926 for the size ('SMB'), value ('HML'), momentum ('UMD'), short-term reversal ('ST_Rev'), beta ('BETA'), long-term reversal ('LT_Rev'), and seasonality ('Seas') factors. Factors are constructed from top-bottom portfolios from 2x3 size-characteristic-based portfolios. The y-axis is on a logarithmic scale.

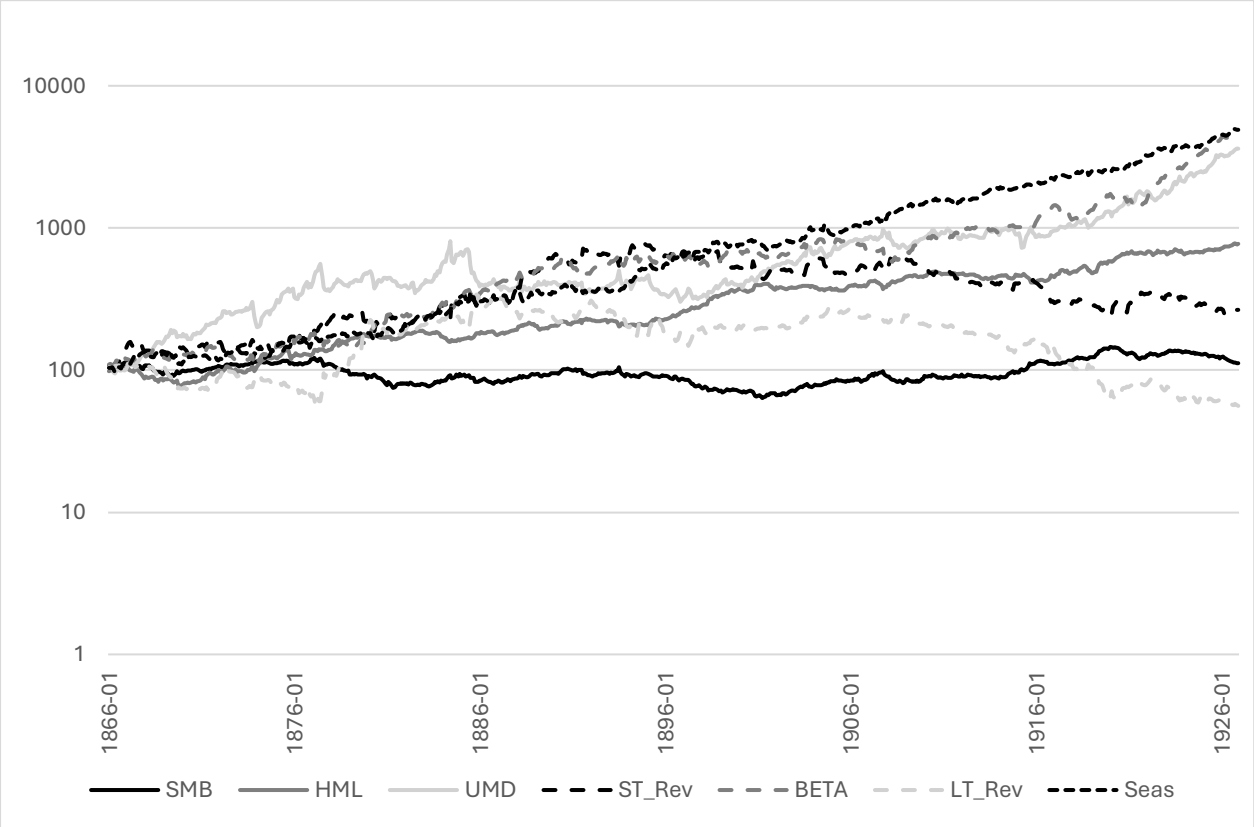


Table B.1: Fama-MacBeth regression results (equal-weighted)

This table presents coefficient estimates from monthly Fama-MacBeth (1973) regressions of returns between month *t* and *t+1* against a constant and a series of stock characteristics, as described in Section III. Stock characteristics are measured at the end of month *t* over our sample period from January 1866 to December 1926. We report slope coefficients (multiplied by 100) with standard t-statistics in parentheses, the R^2 of the regressions ("R^2"), and the number of observations ("No. of obs."). Observations are equal-weighted. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
constant	0.67***	0.66***	0.58***	0.68***	0.62***	0.75***	0.66***	0.47**
t	(6.88)	(3.57)	(3.01)	(4.81)	(4.59)	(4.60)	(4.64)	(2.26)
Beta	0.04							0.08
t	(0.49)							(0.78)
ln(Size)		-0.03						-0.09*
t		(-0.57)						(-1.86)
Value			3.35***					6.15***
t			(2.69)					(4.93)
Momentum				0.53**				0.08
t				(2.16)				(0.29)
ST Reversal					-4.19***			-6.09***
t					(-5.18)			(-6.42)
LT Reversal						-0.14		-0.05
t						(-1.02)		(-0.52)
Seasonality							3.54***	5.15***
t							(3.62)	(3.03)
R2	0.06	0.03	0.03	0.04	0.04	0.04	0.02	0.29
No. of Obs.	219,615	222,025	200,318	200,318	220,134	123,834	220,199	111,901

Table B.2: Portfolio sorts

The table reports average returns on univariate portfolios sorted by various stock characteristics, as described in Section III. Each month we sort stocks in ascending order into quintile portfolios ("Q1," "Q2," "Q3," "Q4," and "Q5) based on one stock characteristic and compute returns over the subsequent month. Portfolios are value-weighted. The table presents average annualized returns (Panel A), CAPM alphas (Panel B), as well as the difference between the high portfolio and the low portfolio ("Q5–Q1'). The sample runs from January 1866 to December 1926 and is at the monthly frequency. Numbers in parentheses indicate standard t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, which we present only for high-low portfolios.

Panel A: Return							Panel B: CAPM alpha					
	Q1	Q2	Q3	Q4	Q5	Q5-Q1	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Size	7.49	6.02	8.76	8.24	8.65	1.16	-1.82	-2.42	0.15	-0.53	0.25	2.07
t	(2.79)	(3.40)	(5.28)	(5.03)	(6.04)	(0.53)	(-0.87)	(-2.28)	(0.20)	(-0.89)	(1.09)	(0.94)
Age	7.62	10.28	8.47	9.42	7.15	-0.46	-2.43	0.27	-0.50	1.28	0.00	2.43*
t	(3.48)	(4.76)	(4.89)	(6.37)	(6.15)	(-0.29)	(-2.33)	(0.27)	(-0.74)	(1.97)	(0.00)	(1.84)
Value	5.94	3.91	8.81	8.36	11.55	5.60***	-7.11	-7.09	1.35	0.91	3.09	10.20***
t	(1.85)	(1.47)	(6.93)	(6.82)	(7.19)	(2.48)	(-4.95)	(-4.86)	(2.21)	(1.77)	(4.20)	(5.83)
Momentum	4.44	6.24	8.41	10.05	12.84	8.40***	-7.68	-2.68	0.77	2.17	3.49	11.17***
t	(1.42)	(3.45)	(6.56)	(7.06)	(6.15)	(3.13)	(-4.35)	(-2.99)	(1.50)	(3.18)	(2.91)	(4.37)
Momentum_3_1	7.74	7.40	8.69	9.89	9.00	1.26	-3.66	-1.21	1.10	2.14	-0.28	3.38
t	(2.71)	(4.37)	(6.85)	(7.00)	(4.44)	(0.52)	(-2.25)	(-1.45)	(2.12)	(2.92)	(-0.25)	(1.46)
Momentum 6_1	7.76	8.45	8.13	9.10	9.93	2.17	-4.14	-0.33	0.54	1.23	0.70	4.84**
t	(2.55)	(4.81)	(6.42)	(6.38)	(4.90)	(0.85)	(-2.38)	(-0.39)	(1.05)	(1.77)	(0.61)	(2.00)
Momentum 9_1	6.11	6.84	8.10	9.42	10.90	4.79*	-5.72	-2.01	0.40	1.57	1.60	7.32***
t	(2.01)	(3.79)	(6.20)	(6.57)	(5.32)	(1.82)	(-3.25)	(-2.18)	(0.75)	(2.17)	(1.38)	(2.90)
Momentum 12_7	4.09	7.43	8.10	8.92	12.84	8.75***	-7.23	-1.13	0.49	0.88	3.19	10.42***
t	(1.46)	(4.34)	(6.32)	(6.05)	(5.91)	(3.70)	(-4.61)	(-1.27)	(0.91)	(1.26)	(2.63)	(4.49)
Price Momentum	4.96	6.75	7.95	9.42	12.61	7.65***	-6.69	-2.06	0.31	1.51	3.07	9.75***
t	(1.65)	(3.81)	(6.15)	(6.51)	(5.83)	(2.87)	(-3.74)	(-2.34)	(0.57)	(2.11)	(2.45)	(3.76)
Price Mom 3_1	7.32	7.89	8.69	8.97	9.04	1.72	-3.80	-0.56	1.14	1.19	-0.40	3.40
t	(2.65)	(4.86)	(6.81)	(6.35)	(4.33)	(0.73)	(-2.38)	(-0.73)	(2.04)	(1.65)	(-0.34)	(1.48)
Price Mom 6_1	8.56	8.63	7.85	8.71	10.05	1.49	-3.24	0.18	0.18	0.83	0.64	3.89
t	(2.87)	(5.22)	(6.03)	(5.97)	(4.77)	(0.60)	(-1.95)	(0.22)	(0.33)	(1.10)	(0.53)	(1.62)
Price Mom 9_1	6.17	7.82	7.94	9.33	10.62	4.45*	-5.35	-0.87	0.32	1.34	1.26	6.61***
t	(2.10)	(4.45)	(6.21)	(6.19)	(5.11)	(1.73)	(-3.10)	(-0.96)	(0.61)	(1.69)	(1.07)	(2.65)
Price Mom 12_7	4.34	7.37	8.72	9.20	12.08	7.74***	-6.65	-1.19	1.13	1.19	2.31	8.96***
t	(1.62)	(4.36)	(6.74)	(6.29)	(5.53)	(3.43)	(-4.42)	(-1.40)	(1.95)	(1.71)	(1.95)	(4.00)
Residual Momentum (12-1)	4.53	7.97	7.62	9.53	11.97	7.44***	-6.06	-1.04	-0.53	1.95	4.30	10.35***
t	(1.88)	(4.52)	(5.07)	(7.13)	(8.56)	(3.99)	(-5.08)	(-1.41)	(-0.76)	(2.89)	(5.72)	(6.33)
Price-to-High	8.94	6.86	8.69	8.48	9.11	0.17	-4.58	-3.65	0.28	0.89	2.15	6.73***
t	(2.48)	(2.96)	(5.61)	(6.56)	(7.44)	(0.06)	(-2.33)	(-3.53)	(0.45)	(1.54)	(2.81)	(2.88)

Panel A: Return							Panel B: CAPM alpha					
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q5-Q1**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q5-Q1**
ST Reversal	10.29	8.60	7.48	9.48	6.54	-3.75	-0.71	0.20	0.08	1.41	-2.88	-2.17
t	(3.81)	(5.33)	(6.12)	(6.35)	(3.09)	(-1.56)	(-0.46)	0.25)	(0.15)	(1.96)	(-2.34)	(-0.91)
ST Reversal (price)	9.68	8.08	6.87	9.94	7.31	-2.37	-1.28	-0.25	-0.56	1.91	-2.19	-0.91
t	(3.61)	(5.11)	(5.58)	(6.74)	(3.37)	(-0.99)	(-0.85)	-0.33)	(-1.02)	(2.71)	(-1.71)	(-0.38)
Beta	8.06	8.94	8.98	7.42	7.39	-0.67	2.87	2.83	1.22	-3.01	-6.13	-9.00***
t	(10.31)	(9.44)	(6.68)	(3.39)	(2.21)	(-0.21)	(4.24)	(4.33)	(2.11)	(-3.89)	(-4.27)	(-5.11)
Vol	7.32	9.36	8.63	7.31	6.04	-1.28	1.43	1.67	-1.13	-4.69	-6.62	-8.05***
t	(9.47)	(7.20)	(4.40)	(2.59)	(1.79)	(-0.43)	(3.11)	(3.19)	(-1.66)	(-3.83)	(-3.38)	(-3.81)
Downside beta	7.72	7.97	9.07	8.30	8.35	0.63	0.95	1.56	1.42	-1.77	-4.04	-4.98***
t	(5.93)	(8.48)	(7.04)	(4.00)	(2.82)	(0.26)	(1.00)	(3.01)	(2.69)	(-2.41)	(-3.11)	(-2.84)
60m Correlation	8.21	8.94	8.09	9.12	7.96	-0.25	2.59	2.36	0.88	0.20	-1.63	-4.22***
t	(8.22)	(7.47)	(6.28)	(5.31)	(4.24)	(-0.14)	(3.05)	(2.74)	(1.14)	(0.29)	(-2.82)	(-3.46)
Residual Volatility	8.09	9.05	9.42	7.91	5.19	-2.90	1.44	1.11	-0.40	-3.00	-7.33	-8.77***
t	(8.30)	(6.58)	(4.68)	(3.22)	(1.49)	(-0.97)	(3.18)	(2.07)	(-0.51)	(-2.75)	(-3.32)	(-3.72)
LT Reversal	7.18	7.24	8.67	8.56	8.87	1.69	-4.63	-1.46	0.91	0.68	-0.48	4.15*
t	2.26	(3.99)	(6.37)	(6.00)	(4.36)	(0.65)	(-2.33)	(-1.43)	(1.46)	(0.99)	(-0.44)	(1.66)
Seasonality_1_20an	6.08	5.47	8.24	11.09	11.15	5.07***	-4.29	-2.69	0.63	2.77	1.60	5.88***
t	(2.59)	(3.70)	(6.46)	(7.23)	(5.45)	(2.94)	(-3.62)	(-4.25)	(1.22)	(4.20)	(1.56)	(3.43)
Seasonality_1_1an	6.38	6.70	7.93	9.76	10.92	4.53**	-3.94	-1.53	0.38	1.62	1.44	5.38***
t	(2.66)	(4.38)	(6.30)	(6.52)	(5.36)	(2.32)	(-3.00)	(-2.17)	(0.73)	(2.35)	(1.37)	(2.75)
Seasonality_2_5an	6.58	6.83	7.99	9.36	11.99	5.40***	-2.86	-0.82	0.54	1.33	2.45	5.31***
t	(3.23)	(5.07)	(6.34)	(6.28)	(5.85)	(3.24)	(-2.67)	(-1.26)	(0.91)	(1.80)	(2.35)	(3.16)
Seasonality_6_10an	7.06	6.16	7.19	9.41	10.50	3.43**	-1.91	-1.38	-0.04	1.90	1.69	3.59**
t	(3.72)	(4.55)	(5.52)	(6.84)	(5.53)	(2.07)	(-1.83)	(-1.89)	(-0.05)	(2.42)	(1.51)	(2.15)
Seasonality_11_15an	7.40	6.89	7.39	9.37	11.00	3.60**	-0.94	-0.47	0.03	1.97	2.82	3.76**
t	(4.18)	(4.94)	(5.24)	(6.81)	(6.41)	(2.26)	(-0.85)	(-0.54)	(0.03)	(2.37)	(2.63)	(2.35)
Seasonality_16_20an	5.29	6.64	8.96	8.99	10.14	4.85***	-2.89	-0.47	1.74	1.90	1.86	4.75***
t	(3.09)	(5.00)	(4.91)	(6.60)	(5.73)	(3.02)	(-2.70)	(-0.53)	(1.15)	(2.04)	(1.65)	(2.93)
Seasonality_1_20na	6.98	8.74	8.56	7.49	8.76	1.78	-3.31	0.94	0.71	-1.17	-0.84	2.47
t	(2.89)	(6.17)	(6.34)	(4.65)	(4.24)	(0.94)	(-2.46)	(1.31)	(1.33)	(-1.91)	(-0.81)	(1.31)
Seasonality_1_1na	6.60	6.89	8.32	9.01	11.27	4.67*	-4.83	-1.43	0.78	0.83	1.50	6.34**
t	(2.27)	(4.25)	(6.69)	(5.91)	(4.96)	(1.76)	(-2.84)	(-1.70)	(1.60)	(1.14)	(1.13)	(2.43)
Seasonality_2_5na	8.62	8.34	8.09	7.98	9.30	0.68	-1.13	0.91	0.58	-0.14	-0.43	0.70
t	(3.74)	(6.47)	(6.29)	(5.29)	(4.39)	(0.33)	(-0.80)	(1.38)	(0.95)	(-0.19)	(-0.40)	(0.34)
Seasonality_6_10na	6.53	7.68	8.11	8.98	7.31	0.78	-1.88	0.29	0.83	0.93	-1.69	0.19
t	(3.65)	(5.79)	(6.41)	(5.72)	(3.90)	(0.48)	(-1.71)	(0.38)	(1.20)	(1.06)	(-1.71)	(0.12)
Sesaonality 11_15na	8.69	7.99	7.45	9.35	8.50	-0.20	0.29	0.26	0.57	1.62	0.23	-0.07
t	(4.85)	(4.99)	(5.99)	(5.98)	(4.98)	(-0.12)	(0.26)	(0.25)	(0.69)	(1.61)	(0.22)	(-0.04)
Seasonality_16_20na	7.09	7.29	8.11	7.54	8.32	1.23	-0.90	0.31	1.31	-0.02	0.29	1.19
t	(4.10)	(4.50)	(6.49)	(5.14)	(4.77)	(0.71)	(-0.77)	(0.23)	(1.52)	(-0.02)	(0.24)	(0.68)

Table B.3: 2x3 sorted portfolios

The table reports average returns on 2x3 sorted portfolios sorted by size and various stock characteristics, as described in Section III. The return on the stock factor is the average return on the two high portfolios minus that on the two low portfolios, with "BETA" factor being ex-ante corrected for expected market beta. The high and low labels are chosen based on the 'CRSP-era' studies so that the stocks in the high portfolio earn higher returns than those in the low portfolios. Portfolios are value-weighted. Panel A presents average annualized excess returns ("Return"), standard deviation of returns ("Vol."), and the t-statistic of the average return ("*t*"). Panel B reports CAPM alphas ("Alpha"), beta ("Beta"), and the t-statistic of the CAPM alpha ("*t (alpha)*"). The sample runs from January 1866 to December 1926 and is at the monthly frequency. Numbers in parentheses indicate standard t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, which we present only for returns spreads and CAPM alphas of the high-low portfolios.

Panel A: Return

Size				
	L	M	H	Total
Small	5.15	7.82	11.54	8.17***
	(1.71)	(6.41)	(8.49)	(4.99)
Large	6.96	8.58	10.57	8.70***
	(2.72)	(7.39)	(6.97)	(5.37)
SMB	-1.81	-0.76	0.97	-0.53
	(-0.99)	(-0.70)	(0.74)	(-0.55)
Age				
	Young	Medium	Old	YMO
Total	8.91	9.16	7.36	1.56
	(4.29)	(5.64)	(5.94)	(1.16)
Value				
	L	M	H	HML
Small	5.15	7.82	11.54	6.39***
	(1.71)	(6.41)	(8.49)	(2.69)
Large	6.96	8.58	10.57	3.61**
	(2.72)	(7.39)	(6.97)	(2.10)
Total	6.05	8.20	11.05	5.00***
	(2.29)	(7.73)	(8.62)	(2.78)
Momentum				
	D	M	U	UMD
Small	3.41	6.97	11.71	8.30***
	(1.03)	(4.53)	(5.88)	(3.00)
Large	5.65	8.80	11.66	6.00***
	(2.62)	(7.11)	(6.59)	(3.38)
Total	4.53	7.88	11.68	7.15***
	(1.77)	(6.12)	(6.70)	(3.58)
Momentum_3_1				
Small	6.11	7.37	7.55	1.44
	(2.06)	(5.16)	(3.53)	(0.55)
Large	7.31	8.74	9.32	2.01
	(3.60)	(6.91)	(5.48)	(1.23)
Total	6.71	8.04	8.43	1.73
	(2.87)	(6.46)	(4.75)	(0.95)
Small	6.11	7.37	7.55	1.44

Panel B: CAPM alpha

Size				
	L	M	H	Total
Small	-6.79	1.60	4.88	-0.10
	(-4.12)	(1.62)	(4.62)	(-0.12)
Large	-4.41	1.25	2.24	-0.31
	(-4.28)	(2.90)	(3.69)	(-1.37)
SMB	-2.38	0.35	2.64	0.20
	(-1.30)	(0.34)	(2.19)	(0.21)
Age				
	Young	Medium	Old	YMO
Total	2.78	4.21	3.70	-0.92
	(3.58)	(8.87)	(7.95)	(-0.83)
Value				
	L	M	H	HML
Small	-6.79	1.60	4.88	11.67***
	(-4.12)	(1.62)	(4.62)	(6.80)
Large	-4.41	1.25	2.24	6.66***
	(-4.28)	(2.90)	(3.69)	(4.63)
Total	-5.60	1.43	3.56	9.16***
	(-5.45)	(2.54)	(5.79)	(7.41)
Momentum				
	D	M	U	UMD
Small	-8.33	-0.59	3.36	11.69***
	(-3.74)	(-0.57)	(2.35)	(4.55)
Large	-4.28	1.17	2.85	7.14***
	(-4.13)	(2.94)	(3.27)	(4.06)
Total	-6.31	0.29	3.11	9.41***
	(-4.61)	(0.52)	(3.28)	(5.00)
Momentum_3_1				
Small	-4.93	0.13	-1.04	3.89
	(-2.51)	(0.14)	(-0.67)	(1.54)
Large	-2.33	1.02	0.67	3.00*
	(-2.48)	(2.53)	(0.81)	(1.86)
Total	-3.63	0.60	-0.19	3.44*
	(-3.06)	(1.17)	(-0.19)	(1.96)
Small	-4.93	0.13	-1.04	3.89

Panel A: Return

Momentum 6_1

	D	M	U	UMD
Small	6.43	7.50	8.27	1.85
	(2.05)	(5.21)	(4.03)	(0.70)
Large	7.78	8.65	10.00	2.22
	(3.75)	(6.95)	(5.67)	(1.33)
Total	7.10	8.08	9.14	2.03
	(2.90)	(6.52)	(5.16)	(1.07)

Momentum 9_1

	D	M	U	UMD
Small	6.39	6.45	10.08	3.69
	(1.99)	(4.20)	(5.05)	(1.34)
Large	5.90	8.81	10.69	4.78***
	(2.82)	(7.03)	(6.03)	(2.73)
Total	6.15	7.63	10.38	4.24**
	(2.47)	(5.88)	(5.93)	(2.14)

Momentum 12_7

	D	M	U	UMD
Small	3.14	7.57	11.28	8.14***
	(1.05)	(4.80)	(5.42)	(3.29)
Large	5.79	8.88	11.04	5.24***
	(2.88)	(7.03)	(6.16)	(3.25)
Total	4.47	8.22	11.16	6.69***
	(1.89)	(6.24)	(6.21)	(3.75)

Price Momentum

	D	M	U	UMD
Small	3.84	7.40	10.42	6.58**
	(1.21)	(4.77)	(5.07)	(2.45)
Large	6.73	8.46	11.38	4.65***
	(3.23)	(6.83)	(6.28)	(2.65)
Total	5.28	7.93	10.90	5.62***
	(2.14)	(6.13)	(6.06)	(2.86)

Price Mom 3_1

	D	M	U	UMD
Small	6.75	7.67	6.42	-0.32
	(2.32)	(5.32)	(2.97)	(-0.13)
Large	7.61	8.86	9.12	1.51
	(3.79)	(6.94)	(5.32)	(0.91)
Total	7.18	8.14	7.77	0.59
	(3.12)	(6.51)	(4.33)	(0.33)

Price Mom 6_1

	D	M	U	UMD
Small	6.59	7.69	7.49	0.90
	(2.17)	(5.29)	(3.54)	(0.35)
Large	8.28	8.42	9.50	1.22
	(4.08)	(6.57)	(5.30)	(0.73)
Total	7.44	8.02	8.50	1.06
	(3.11)	(6.35)	(4.67)	(0.57)

Panel B: CAPM alpha

Momentum 6_1

	D	M	U	UMD
Small	-5.10	0.11	-0.09	5.01**
	(-2.51)	(0.11)	(-0.06)	(2.02)
Large	-1.98	1.02	1.20	3.18*
	(-2.05)	(2.45)	(1.38)	(1.92)
Total	-3.54	0.56	0.56	4.09**
	(-2.84)	(1.13)	(0.56)	(2.28)

Momentum 9_1

	D	M	U	UMD
Small	-5.06	-1.23	1.78	6.84***
	(-2.31)	(-1.26)	(1.23)	(2.65)
Large	-3.85	1.13	1.88	5.73***
	(-3.82)	(2.83)	(2.13)	(3.29)
Total	-4.45	-0.05	1.83	6.29***
	(-3.34)	(-0.10)	(1.89)	(3.34)

Momentum 12_7

	D	M	U	UMD
Small	-7.79	-0.10	2.57	10.36***
	(-3.79)	(-0.09)	(1.78)	(4.33)
Large	-3.78	1.16	2.10	5.87***
	(-4.02)	(2.88)	(2.49)	(3.64)
Total	-5.79	0.53	2.33	8.12***
	(-4.55)	(0.94)	(2.54)	(4.66)

Price Momentum

	D	M	U	UMD
Small	-7.48	-0.18	1.88	9.36***
	(-3.45)	(-0.18)	(1.29)	(3.65)
Large	-3.00	0.82	2.47	5.47***
	(-3.00)	(2.08)	(2.74)	(3.13)
Total	-5.24	0.32	2.17	7.42***
	(-3.90)	(0.57)	(2.23)	(3.92)

Price Mom 3_1

	D	M	U	UMD
Small	-4.06	0.56	-2.27	1.80
	(-2.08)	(0.59)	(-1.45)	(0.72)
Large	-1.96	1.14	0.47	2.42
	(-2.08)	(2.63)	(0.55)	(1.48)
Total	-3.01	0.86	-0.90	2.11
	(-2.53)	(1.70)	(-0.91)	(1.19)

Price Mom 6_1

	D	M	U	UMD
Small	-4.72	0.37	-1.04	3.68
	(-2.39)	(0.39)	(-0.67)	(1.49)
Large	-1.33	0.68	0.66	1.99
	(-1.39)	(1.54)	(0.73)	(1.19)
Total	-3.03	0.54	-0.19	2.84
	(-2.49)	(1.04)	(-0.18)	(1.58)

Panel A: Return				
Price Mom 9_1				
	D	M	U	UMD
Small	6.07	7.08	9.18	3.11**
	(-1.65)	(-0.33)	(0.29)	(2.17)
Large	6.66	8.65	10.45	3.78**
	(-1.43)	(0.76)	(0.83)	(2.52)
Total	6.37	7.87	9.81	3.45***
	(-1.67)	(0.18)	(0.58)	(2.64)
Price Mom 12_7				
	D	M	U	UMD
Small	3.49	7.61	10.38	6.89***
	(1.19)	(4.90)	(4.75)	(2.74)
Large	6.25	8.70	10.87	4.63***
	(3.18)	(6.82)	(5.99)	(2.89)
Total	4.87	8.15	10.63	5.76***
	(2.11)	(6.21)	(5.71)	(3.22)
Residual Momentum (12-1)				
	D	M	U	UMD
Small	5.89	5.98	11.25	5.36**
	(2.15)	(3.29)	(8.51)	(2.37)
Large	5.86	8.95	11.11	5.25***
	(2.92)	(6.30)	(8.08)	(3.57)
Total	5.88	7.46	11.18	5.30***
	(2.65)	(4.95)	(9.24)	(3.36)
Price-to-High				
	L	M	H	HML
Small	9.61	3.39	9.60	-0.01
	(2.62)	(1.83)	(7.76)	(-0.00)
Large	7.01	8.15	8.97	1.96
	(2.81)	(5.60)	(7.46)	(1.01)
Total	8.31	5.39	9.28	0.98
	(2.88)	(3.54)	(8.40)	(0.42)
ST Reversal				
	LR	M	HR	ST_Rev
Small	9.42	6.58	5.34	4.09*
	(3.37)	(4.60)	(2.33)	(1.66)
Large	9.17	8.67	8.16	1.01
	(4.62)	(6.85)	(4.60)	(0.60)
Total	9.30	7.58	6.75	2.55
	(4.15)	(6.11)	(3.59)	(1.43)
ST Reversal (price)				
Small	9.35	6.91	5.31	4.04
	(3.40)	(4.79)	(2.29)	(1.64)
Large	8.77	7.80	9.21	-0.44
	(4.49)	(6.18)	(5.12)	(-0.26)
Total	9.06	7.30	7.26	1.80
	(4.12)	(5.85)	(3.81)	(1.02)
Small	9.35	6.91	5.31	4.04

Panel B: CAPM alpha				
Price Mom 9_1				
	D	M	U	UMD
Small	-5.17	-0.49	0.60	5.78**
	(-2.42)	(-0.51)	(0.41)	(2.27)
Large	-2.89	0.96	1.52	4.41**
	(-2.96)	(2.28)	(1.60)	(2.52)
Total	-4.03	0.23	1.06	5.10***
	(-3.10)	(0.44)	(1.06)	(2.72)
Price Mom 12_7				
	D	M	U	UMD
Small	-7.20	0.01	1.37	8.57***
	(-3.53)	(0.01)	(0.92)	(3.46)
Large	-3.15	0.97	1.85	5.01***
	(-3.36)	(2.25)	(2.18)	(3.11)
Total	-5.18	0.49	1.61	6.79***
	(-4.08)	(0.86)	(1.71)	(3.83)
Residual Momentum (12-1)				
	D	M	U	UMD
Small	-5.03	-2.41	4.57	9.60***
	(-3.09)	(-2.08)	(4.58)	(5.23)
Large	-3.83	0.83	3.38	7.21***
	(-4.47)	(1.63)	(5.02)	(5.37)
Total	-4.43	-0.79	3.97	8.41***
	(-4.69)	(-1.23)	(6.34)	(6.72)
Price-to-High				
	L	M	H	HML
Small	-3.25	-5.13	3.34	6.59***
	(-1.38)	(-4.36)	(3.35)	(2.63)
Large	-4.11	0.63	1.75	5.86***
	(-3.96)	(0.94)	(2.89)	(3.87)
Total	-3.68	-2.43	2.55	6.23***
	(-2.67)	(-3.61)	(3.87)	(3.70)
ST Reversal				
	LR	M	HR	ST_Rev
Small	-1.32	-0.51	-3.60	2.28
	(-0.73)	(-0.52)	(-2.16)	(0.95)
Large	-0.32	0.95	-0.64	0.32
	(-0.34)	(2.33)	(-0.72)	(0.19)
Total	-0.82	0.26	-2.12	1.30
	(-0.74)	(0.49)	(-2.01)	(0.75)
ST Reversal (price)				
Small	-1.25	-0.26	-3.70	2.45
	(-0.70)	(-0.26)	(-2.19)	(1.01)
Large	-0.61	0.09	0.30	-0.92
	(-0.67)	(0.22)	(0.34)	(-0.55)
Total	-0.93	-0.07	-1.70	0.77
	(-0.86)	(-0.13)	(-1.60)	(0.44)
Small	-1.25	-0.26	-3.70	2.45

Panel A: Return				
BETA				
	LB	M	HB	BETA
Small	7.69	7.05	5.48	6.84***
	(7.87)	(4.21)	(1.55)	(3.47)
Large	8.61	9.01	7.82	7.25***
	(10.69)	(6.75)	(2.84)	(4.60)
Total	8.15	8.03	6.65	7.05***
	(10.54)	(5.78)	(2.21)	(4.66)
Vol				
	LB	M	HB	VOL
Small	8.04	7.70	2.37	9.12***
	(9.97)	(3.41)	(0.63)	(4.38)
Large	7.64	9.56	8.14	5.13***
	(9.12)	(6.10)	(2.92)	(4.10)
Total	7.84	8.63	5.25	7.13***
	(11.03)	(4.78)	(1.74)	(5.31)
Downside beta				
	LB	M	HB	BETA_D
Small	6.21	7.71	6.26	2.83
	(4.13)	(5.19)	(2.03)	(1.25)
Large	8.05	8.75	8.52	4.64***
	(8.13)	(6.73)	(3.41)	(3.43)
Total	7.13	8.23	7.39	3.73**
	(6.47)	(6.41)	(2.76)	(2.54)
60m Correlation				
	LB	M	HB	60MCOR
Small	7.90	4.67	7.66	5.91***
	(7.28)	(2.80)	(2.59)	(2.97)
Large	8.88	8.93	8.09	6.54***
	(8.88)	(5.98)	(4.37)	(3.78)
Total	8.39	6.80	7.88	6.23***
	(9.20)	(4.72)	(3.42)	(4.07)
Residual Volatility				
	LB	M	HB	RESVOL
Small	8.12	8.78	4.02	8.38***
	(8.93)	(4.07)	(1.13)	(4.07)
Large	8.18	8.71	9.30	3.49***
	(8.06)	(5.59)	(3.65)	(3.13)
Total	8.15	8.75	6.66	5.93***
	(9.63)	(5.00)	(2.37)	(4.71)
LT Reversal				
	LR	M	HR	LT_Rev
Small	11.36	9.91	9.71	1.65
	(3.32)	(4.71)	(4.94)	(0.54)
Large	7.73	7.64	9.01	-1.29
	(4.06)	(5.85)	(5.26)	(-0.85)
Total	9.54	8.78	9.36	0.18
	(3.81)	(5.57)	(5.54)	(0.09)

Panel B: CAPM alpha				
BETA				
	LB	M	HB	BETA
Small	2.45	-0.84	-8.03	8.74***
	(2.75)	(-0.75)	(-4.36)	(4.62)
Large	2.99	1.07	-4.34	8.39***
	(4.93)	(2.57)	(-4.66)	(5.43)
Total	2.72	0.12	-6.19	8.57***
	(4.43)	(0.20)	(-5.60)	(5.93)
Vol				
	LB	M	HB	VOL
Small	2.92	-2.05	-10.16	11.25***
	(4.08)	(-1.56)	(-3.91)	(5.66)
Large	1.45	0.85	-4.01	5.14***
	(3.33)	(2.05)	(-3.91)	(4.08)
Total	2.19	-0.60	-7.09	8.19***
	(4.82)	(-0.89)	(-4.88)	(6.26)
Downside beta				
	LB	M	HB	BETA_D
Small	-0.28	0.24	-6.09	2.81
	(-0.22)	(0.25)	(-3.82)	(1.23)
Large	1.59	0.93	-2.88	4.62***
	(2.72)	(2.22)	(-3.50)	(3.40)
Total	0.65	0.59	-4.49	3.72**
	(0.87)	(1.13)	(-4.76)	(2.51)
60m Correlation				
	LB	M	HB	60MCOR
Small	2.33	-2.99	-4.46	7.15***
	(2.43)	(-2.50)	(-3.06)	(3.63)
Large	2.73	0.61	-1.41	6.61***
	(3.81)	(1.10)	(-2.49)	(3.80)
Total	2.53	-1.19	-2.94	6.88***
	(3.72)	(-1.80)	(-3.79)	(4.51)
Residual Volatility				
	LB	M	HB	RESVOL
Small	2.52	-0.81	-7.91	9.56***
	(3.40)	(-0.66)	(-3.12)	(4.69)
Large	1.38	0.09	-2.11	3.47***
	(3.08)	(0.19)	(-2.18)	(3.09)
Total	1.95	-0.36	-5.01	6.52***
	(4.41)	(-0.57)	(-3.55)	(5.19)
LT Reversal				
	LR	M	HR	LT_Rev
Small	-0.47	0.76	1.16	-1.62
	(-0.20)	(0.58)	(0.88)	(-0.56)
Large	-1.32	-0.01	0.32	-1.63
	(-1.31)	(-0.01)	(0.38)	(-1.07)
Total	-0.89	0.37	0.74	-1.63
	(-0.62)	(0.53)	(0.91)	(-0.86)

Panel A: Return

Seasonality

	L	M	H	HML
Small	2.16	7.36	10.25	8.08***
	(0.88)	(5.55)	(4.31)	(4.12)
Large	5.89	8.43	11.56	5.67***
	(3.41)	(6.37)	(6.63)	(4.90)
Total	4.03	7.89	10.90	6.87***
	(2.05)	(6.55)	(5.67)	(5.45)

Seasonality_1_1an

	L	M	H	HML
Small	3.58	6.33	10.15	6.57***
	(1.39)	(4.37)	(4.55)	(3.14)
Large	7.09	8.01	10.90	3.82***
	(3.85)	(6.20)	(6.23)	(2.62)
Total	5.33	7.10	10.52	5.19***
	(2.57)	(5.64)	(5.69)	(3.48)

Seasonality_2_5an

	L	M	H	HML
Small	5.77	8.31	12.33	6.56***
	(2.64)	(6.47)	(5.65)	(3.26)
Large	6.53	8.09	11.21	4.68***
	(3.96)	(6.35)	(6.53)	(3.77)
Total	6.15	8.20	11.77	5.62***
	(3.46)	(7.05)	(6.49)	(4.22)

Seasonality_6_10an

	L	M	H	HML
Small	7.40	7.16	13.20	5.80***
	(3.57)	(5.94)	(7.00)	(3.07)
Large	6.03	8.30	9.19	3.16**
	(3.68)	(6.46)	(5.68)	(2.38)
Total	6.72	7.73	11.19	4.48***
	(3.99)	(7.04)	(7.07)	(3.50)

Seasonality_11_15an

	L	M	H	HML
Small	9.25	6.93	12.63	3.38*
	(4.94)	(5.42)	(6.78)	(1.86)
Large	8.30	7.29	9.56	1.26
	(5.19)	(5.31)	(6.29)	(0.99)
Total	8.77	7.11	11.09	2.32*
	(5.70)	(6.21)	(7.28)	(1.91)

Seasonality_16_20an

	L	M	H	HML
Small	6.93	5.13	12.39	5.46***
	(3.93)	(4.01)	(6.81)	(2.78)
Large	5.84	8.18	9.37	3.53**
	(3.55)	(5.38)	(5.88)	(2.55)
Total	6.39	6.66	10.88	4.50***
	(4.35)	(5.79)	(7.37)	(3.60)

Panel B: CAPM alpha

Seasonality

	L	M	H	HML
Small	-7.80	0.31	0.57	8.37***
	(-4.94)	(0.35)	(0.37)	(4.24)
Large	-3.09	0.56	2.55	5.64***
	(-4.69)	(1.25)	(3.73)	(4.84)
Total	-5.45	0.43	1.56	7.01***
	(-6.10)	(0.96)	(1.75)	(5.52)

Seasonality_1_1an

	L	M	H	HML
Small	-6.70	-0.78	1.01	7.71***
	(-4.10)	(-0.79)	(0.67)	(3.72)
Large	-2.06	0.21	2.01	4.07***
	(-2.50)	(0.51)	(2.57)	(2.77)
Total	-4.38	-0.25	1.51	5.89***
	(-4.41)	(-0.47)	(1.63)	(3.96)

Seasonality_2_5an

	L	M	H	HML
Small	-3.26	1.43	3.16	6.42***
	(-2.20)	(1.61)	(2.20)	(3.17)
Large	-2.09	0.43	2.40	4.48***
	(-2.87)	(0.90)	(3.18)	(3.59)
Total	-2.67	0.93	2.78	5.45***
	(-3.03)	(1.92)	(3.23)	(4.07)

Seasonality_6_10an

	L	M	H	HML
Small	-0.86	0.70	3.77	3.31***
	(-1.25)	(0.62)	(5.03)	(6.28)
Large	-2.68	1.35	1.00	2.33***
	(-2.31)	(0.91)	(0.80)	(3.11)
Total	-2.05	1.45	3.68	3.64***
	(-1.78)	(0.76)	(2.91)	(4.69)

Seasonality_11_15an

	L	M	H	HML
Small	1.33	0.58	4.60	3.27*
	(0.95)	(0.57)	(3.41)	(1.79)
Large	0.25	-0.33	1.61	1.36
	(0.27)	(-0.45)	(1.92)	(1.06)
Total	0.79	0.13	3.11	2.32*
	(0.92)	(0.21)	(3.76)	(1.90)

Seasonality_16_20an

	L	M	H	HML
Small	-0.49	-0.71	4.88	5.37***
	(-0.35)	(-0.62)	(3.40)	(2.71)
Large	-2.12	0.88	1.46	3.58**
	(-2.02)	(0.81)	(1.48)	(2.57)
Total	-1.31	0.09	3.17	4.48***
	(-1.51)	(0.11)	(3.64)	(3.56)

Panel A: Return

Seasonality_1_20na

	L	M	H	LMH
Small	4.32	8.25	6.41	-2.10
	(1.82)	(5.60)	(2.58)	(-0.92)
Large	8.44	8.51	8.62	-0.18
	(5.04)	(6.29)	(4.79)	(-0.14)
Total	6.38	8.38	7.51	-1.14
	(3.39)	(6.40)	(3.85)	(-0.79)

Seasonality_1_1na

	L	M	H	LMH
Small	6.06	6.88	7.37	-1.31
	(2.09)	(4.87)	(3.32)	(-0.51)
Large	6.54	8.17	10.99	-4.45**
	(3.17)	(6.72)	(5.88)	(-2.48)
Total	6.30	7.53	9.18	-2.88
	(2.69)	(6.14)	(4.87)	(-1.49)

Seasonality_2_5na

	L	M	H	LMH
Small	10.17	7.95	8.99	1.19
	(4.53)	(5.88)	(4.08)	(0.54)
Large	9.29	7.60	8.84	0.45
	(5.42)	(6.01)	(5.01)	(0.32)
Total	9.73	7.78	8.91	0.82
	(5.36)	(6.55)	(4.89)	(0.55)

Seasonality_6_10na

	L	M	H	LMH
Small	11.73	7.34	8.93	2.80
	(6.36)	(5.70)	(4.43)	(1.56)
Large	6.43	8.42	8.21	-1.77
	(4.13)	(6.66)	(4.71)	(-1.30)
Total	9.08	7.88	8.57	0.51
	(5.95)	(7.02)	(5.02)	(0.42)

Sesaonality 11_15na

	L	M	H	LMH
Small	9.71	8.11	10.87	-1.16
	(4.90)	(6.58)	(5.91)	(-0.60)
Large	7.91	8.99	8.17	-0.25
	(4.73)	(6.69)	(5.03)	(-0.18)
Total	8.81	8.55	9.52	-0.71
	(5.44)	(7.61)	(6.25)	(-0.56)

Seasonality_16_20na

	L	M	H	LMH
Small	7.05	7.77	9.86	-2.81
	(4.34)	(6.75)	(5.35)	(-1.55)
Large	7.75	7.43	8.34	-0.58
	(3.97)	(5.74)	(5.29)	(-0.33)
Total	7.40	7.60	9.10	-1.69
	(4.78)	(7.34)	(6.11)	(-1.26)

Panel B: CAPM alpha

Seasonality_1_20na

	L	M	H	LMH
Small	-5.19	0.71	-2.94	-2.24
	(-3.24)	(0.76)	(-1.62)	(-0.98)
Large	-0.19	0.51	-0.59	0.40
	(-0.25)	(1.21)	(-0.86)	(0.31)
Total	-2.69	0.61	-1.77	-0.92
	(-2.80)	(1.24)	(-1.80)	(-0.64)

Seasonality_1_1na

	L	M	H	LMH
Small	-4.82	-0.43	-1.31	-3.51
	(-2.53)	(-0.46)	(-0.80)	(-1.39)
Large	-3.05	0.60	1.86	-4.92***
	(-2.96)	(1.55)	(2.07)	(-2.72)
Total	-3.94	0.09	0.28	-4.21**
	(-3.17)	(0.17)	(0.26)	(-2.21)

Seasonality_2_5na

	L	M	H	LMH
Small	1.19	0.87	0.09	1.10
	(0.75)	(0.95)	(0.06)	(0.49)
Large	0.77	-0.02	-0.20	0.98
	(0.84)	(-0.05)	(-0.28)	(0.69)
Total	0.98	0.43	-0.06	1.04
	(0.98)	(0.87)	(-0.06)	(0.69)

Seasonality_6_10na

	L	M	H	LMH
Small	3.83	0.73	0.08	3.75**
	(2.81)	(0.75)	(0.06)	(2.10)
Large	-1.66	1.02	-0.51	-1.16
	(-2.00)	(1.63)	(-0.58)	(-0.85)
Total	1.08	0.88	-0.21	1.29
	(1.30)	(1.56)	(-0.28)	(1.07)

Sesaonality 11_15na

	L	M	H	LMH
Small	1.70	1.72	2.98	-1.28
	(1.12)	(1.79)	(2.20)	(-0.66)
Large	-0.30	1.59	-0.01	-0.30
	(-0.31)	(2.05)	(-0.01)	(-0.21)
Total	0.70	1.65	1.49	-0.79
	(0.74)	(2.69)	(1.85)	(-0.62)

Seasonality_16_20na

	L	M	H	LMH
Small	-0.11	2.01	1.99	-2.10
	(-0.09)	(2.01)	(1.45)	(-1.16)
Large	-0.41	0.23	0.48	-0.89
	(-0.28)	(0.29)	(0.49)	(-0.49)
Total	-0.26	1.12	1.24	-1.49
	(-0.26)	(1.72)	(1.50)	(-1.10)

Table B.4: Stock factor returns in 'good' and 'bad' states

The table summarizes the historical performance of stock factors across 'good' and 'bad' states based on macroeconomic and market sub-periods. Sub-periods examined are at the annual frequency and include recession versus non-recession, and bear and bull equity markets. Shown are historical (annualized) market-adjusted returns per macroeconomic state for each stock factor. The column "Dif." contains the differential factor returns between bad and good states. We estimate results separately over the pre-CRSP, CRSP and combined samples. The pre-CRSP sample starts in January 1866 and ends December 1926. The CRSP sample runs from January 1927 till December 2024. The combined sample runs from January 1866 till December 2024. Both samples are at the monthly frequency. Numbers in parentheses indicate t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

		Recession/expansion				Bear/bull market			
		Rec.	Exp.	Diff.	*t*	Bear	Bull	Diff.	*t*
SMB	1866-1926	-2.15	2.64	-4.80**	(-2.55)	-2.53	1.44	3.98*	(1.95)
	1927-2024	4.17	0.10	4.07	(1.42)	1.12	0.61	-0.51	(-0.22)
	1866-2024	0.00	0.78	-0.78	(-0.48)	-0.33	0.93	1.25	(0.77)
HML	1866-1926	9.99	8.31	1.68	(0.68)	5.89	10.64	4.75*	(1.79)
	1927-2024	0.71	5.63	-4.92	(-1.63)	3.46	5.40	1.94	(0.79)
	1866-2024	6.83	6.35	0.48	(0.26)	4.43	7.39	2.96	(1.63)
UMD	1866-1926	9.00	9.84	-0.85	(-0.23)	3.98	11.87	7.89**	(1.96)
	1927-2024	1.66	11.91	-10.25**	(-2.54)	6.31	11.89	5.59	(1.71)
	1866-2024	6.50	11.36	-4.86*	(-1.90)	5.39	11.89	6.50**	(2.56)
ST_Rev	1866-1926	6.46	-4.02	10.48***	(3.04)	9.21	-2.28	-11.49***	(-3.09)
	1927-2024	15.38	5.65	9.73***	(3.11)	9.26	6.40	-2.86	(-1.13)
	1866-2024	9.50	3.06	6.43***	(3.01)	9.24	3.12	-6.13***	(-2.88)
BETA	1866-1926	5.88	11.33	-5.46*	(-1.90)	-2.49	13.56	16.06***	(5.28)
	1927-2024	-0.17	5.15	-5.32**	(-2.24)	2.16	5.17	3.01	(1.56)
	1866-2024	3.82	6.80	-2.98*	(-1.76)	0.32	8.35	8.03***	(4.79)
LT_Rev	1866-1926	-0.09	-3.22	3.13	(0.83)	1.60	-3.09	-4.69	(-1.16)
	1927-2024	4.63	1.46	3.17	(1.00)	7.16	-0.18	-7.33***	(-2.94)
	1866-2024	1.38	0.18	1.20	(0.54)	4.86	-1.30	-6.16***	(-2.79)
Seas	1866-1926	8.18	5.79	2.39	(0.95)	7.84	6.63	-1.21	(-0.44)
	1927-2024	7.04	5.61	1.44	(0.76)	5.08	6.16	1.08	(0.70)
	1866-2024	7.80	5.66	2.14	(1.51)	6.17	6.34	0.16	(0.12)

Table B.5: Momentum crashes

The table summarizes the results of momentum crash analyses. Panel A reports the return distribution of Momentum (UMD). Panel B reports the results of regression specification (3) of Daniel and Moskowitz (2016). Panel C reports the return distribution of Momentum volatility-scaled momentum (UMD*) of Barroso and Santa-Clara (2015). Returns ('Ret.') and Sharpe ratios ('SR') are annualized, other numbers (skewness; 'Skew.', kurtosis; 'Kurt.', minimum return; 'Min.') are monthly. 'Min.*' represent the minimum monthly return of UMD* scaled to the same volatility of UMD. We estimate results separately over the pre-CRSP, CRSP and combined samples. The pre-CRSP sample starts in January 1866 and ends December 1926. The CRSP sample runs from January 1927 till December 2024. The combined sample runs from January 1866 till December 2024. Both samples are at the monthly frequency. Numbers in parentheses indicate t-values. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level, respectively.

Panel A: Return distribution Momentum

		Ret. (%)	SR	Skew.	Kurt.	Min. (%)	Min*. (%)
UMD	1866-1926	7.20	0.46	-1.07	4.51	-27.65	-
	1927-2024	7.80	0.50	-2.95	25.51	-47.30	-
	1866-2024	7.56	0.48	-2.24	17.54	-47.30	-

Panel B: Market timing regression results Momentum

		α_0	α_B	β_0	β_B	$\beta_{B,U}$	R^2
UMD	1866-1926	0.88***	1.28***	-0.00	-1.21***	-0.58***	0.34
		(5.19)	(3.06)	(-0.09)	(-13.92	(-5.46)	
	1927-2024	0.85***	1.08***	0.02	-0.61***	-0.29***	0.30
		(6.78)	(2.85)	(0.86)	-14.39	(-6.61)	
	1866-2024	0.86***	0.61**	0.02	-0.71***	-0.27***	0.28
		(8.37)	(2.28)	(0.72)	(-18.32)	(-6.98)	

Panel C: Return distribution volatility-scaled Momentum

		Ret. (%)	SR	Skew.	Kurt.	Min. (%)	Min*. (%)
UMD*	1866-1926	7.56	0.57	0.57	16.20	-23.77	-27.77
	1927-2024	9.96	0.79	-0.87	6.54	-29.24	-36.59
	1866-2024	9.00	0.70	-0.26	10.79	-29.24	-35.62

Table B.6: Downside risk and stock factor returns

The table shows the beta and downside betas of the six stock factors returns. The downside beta is calculated versus the excess return of the equity market portfolio and uses three downside risk thresholds: zero, -1 standard deviation (1 sigma) and -2 standard deviation (2 sigma). The difference between regular CAPM beta (β) and downside beta (β^-) indicates the amount of additional downside risk. The annualized CAPM alpha (α) and downside risk CAPM alphas (α^-), both in percent with t-stats added. We estimate results over the combined pre-CRSP and CRSP samples at the monthly frequency. The combined sample runs from December 1866 till December 2024.

Factor	DR threshold	β–	β	β– – β	α	t-stat	α–	t-stat
SMB	zero	0.13	0.14	-0.012	0.73	(0.96)	0.78	(1.04)
	1 sigma	0.15	0.14	0.012	-	-	0.73	(0.97)
	2 sigma	0.18	0.14	0.043	-	-	0.73	(0.98)
HML	zero	-0.51	-0.57	0.062	6.36***	(7.51)	5.96***	(7.08)
	1 sigma	-0.46	-0.57	0.109	-	-	5.73***	(6.77)
	2 sigma	-0.39	-0.57	0.181	-	-	5.39***	(6.28)
UMD	zero	-0.20	-0.32	0.125	9.92***	(8.40)	9.09***	(7.60)
	1 sigma	-0.20	-0.32	0.125	-	-	9.14***	(7.66)
	2 sigma	-0.25	-0.32	0.074	-	-	9.79***	(8.24)
ST_Rev	zero	0.17	0.17	0.004	5.15***	(5.20)	5.05***	(5.07)
	1 sigma	0.18	0.17	0.009	-	-	4.83***	(4.83)
	2 sigma	0.14	0.17	-0.025	-	-	4.66***	(4.58)
BETA	zero	-0.02	-0.06	0.046	6.13***	(7.82)	5.83***	(7.44)
	1 sigma	0.03	-0.06	0.089	-	-	5.60***	(7.11)
	2 sigma	0.06	-0.06	0.124	-	-	5.56***	(7.04)
LT_Rev	zero	0.07	0.17	-0.104	0.49	(0.48)	0.06	(0.06)
	1 sigma	0.04	0.17	-0.134	-	-	0.69	(0.67)
	2 sigma	0.04	0.17	-0.138	-	-	1.10	(1.07)
Seas	zero	0.02	-0.01	0.023	6.43***	(9.80)	6.52***	(9.89)
	1 sigma	0.02	-0.01	0.025	-	-	6.50***	(9.86)
	2 sigma	-0.01	-0.01	-0.001	-	-	6.71***	(10.14)