Financial Analysts Journal
Volume 72 • Number 5
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Two Centuries of Price-Return Momentum

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Having created a monthly dataset of US security prices between 1801 and 1926, we conduct out-of-sample tests of price-return momentum strategies that have been implemented in the post-1925 datasets. The additional time-series data strengthen the evidence that price momentum is dynamically exposed to market risk, conditional on the sign and duration of the trailing market state. On average, in the beginning of positive market states, momentum's equity beta is opposite to the new market direction, which generates a negative contribution to momentum profits around market turning points. A dynamically hedged momentum strategy significantly outperforms the unhedged strategy.

Most current academic studies of US security-level data begin in or after 1926, the year the CRSP database and the SBBI files began.[1] The US market was active for 133 years before that time, however, which provides an opportunity to test stock return characteristics in earlier market history.

The first two US stocks traded in New York City in 1792. During the following two decades, the equity market developed rapidly. By the end of 1810, 72 traded securities existed, and by the end of the 1830s, the number had risen to more than 300. The 19th and early 20th centuries brought economic growth, contractions, wars, changes in monetary and currency regimes, macroeconomic shocks, bull and bear markets, and market volatility of varying magnitudes—all providing a rich out-of-sample territory for testing strategies used in the post-1925 period. This point is important because limiting studies to the post-1925 period (often using the same dataset!) introduces a strong selection bias into a study and does not capture the full distribution of possible outcomes.

For example, consider the case of price-return momentum in the post-1925 period: Before 2009, the basic strategy of following winners and eschewing losers (via the traditional momentum definition) had a decade-long negative compounded return only following the Great Depression of the 1930s. Without the broader view afforded by a more extensive sample, such an occurrence might be considered an anomalous outlier, leaving the remaining part of the distribution of outcomes as the focus of study. Because of a significant drawdown in the momentum strategy in 2009, however, following a period of substantial economic distress, momentum experienced another significant period of underperformance, creating a ripple in investment portfolios that used this strategy. The most recent underperformance raised practical questions about the "anomalous outlier" assumption and what the actual distribution of momentum profits is, which by their nature have influenced and will continue to influence theory about this powerful characteristic in returns. By extending our analysis of equity momentum returns to 1801, we have created a more complete picture of the potential outcomes of momentum strategy returns. In doing so, we discovered *seven* additional decade-long negative periods before the Great Depression.

The first contribution of this study is the creation of a monthly stock price and return dataset. In this dataset, three known 19th- and early 20th-century data sources are combined into one testable dataset from 1800 to 1927. For the period between 1800 and 1927, the merged dataset contains an average of 272 securities with price-return data per month (10 at the beginning of the sample and 781 at the end of the sample), making it robust for security-level studies.

The second contribution of this study is the addition to the existing momentum literature via extending price-return tests to the new data. As observed in studies of the 20th-century data for traditional versions of momentum strategies, momentum profits

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Editor's note: This article was reviewed and accepted by Executive Editor Stephen J. Brown.

Authors' note: We make frequent use of factor models that include momentum (the topic of this article) in our asset management, consulting, and other activities at Forefront Analytics and GKFO.

are highly variable over time.[2] Nevertheless, over the long run, the strategy would have generated significant market outperformance in a different century than the one in which it was discovered and tested. Our study adds to the evidence that the momentum effect is not a product of data mining but is persistent and has significant variations over time.

The third contribution of this study is the development of a link between the fundamental momentum strategy's market exposure and market state duration. Market states significantly affect the nature of momentum profits in the extended sample.

Early Security Returns Data

A series of academic efforts extended aggregate stock market returns back to 1792, the recognized inception of the US stock market. Some of these studies worked with already-created indexes (Schwert 1990; Siegel 1992; Shiller 2000; Wilson and Jones 2002), whereas others assembled individual security prices into datasets from which aggregate-level returns could be computed (Cowles 1939; Goetzmann, Ibbotson, and Peng 2001; Sylla, Wilson, and Wright 2006; Global Financial Data [GFD]). Although the original stock-level Cowles Foundation data files seem to have been lost,[3] the other datasets have been preserved. They vary, however, in the specific securities and the time periods they cover.

Among the studies, return estimation and index construction methodologies also vary. For example, Schwert (1990) used spliced index data from Cole and Frickey (1928), Macaulay (1938), Cowles (1939), and Dow Jones (1972). As a result, his index was equally weighted before 1862, value weighted from 1863 to 1885, and price weighted between 1885 and 1925. Goetzmann et al. (2001) used a price-weighted index construction for the entire period to avoid the large bid–ask bounce effect in the 19th-century prices that especially affects equally weighted index and portfolio returns. Another difference between approaches is the use of month-end data (Goetzmann et al. 2001) versus an average of high and low prices within the month (Cowles 1939 and the GFD data).

Our 1800–1926 dataset of security prices (hereafter called the "merged dataset") and industry classifications was assembled from three sources: the International Center for Finance at Yale (ICF), Inter-University Consortium for Political and Social Research (ICPSR), and GFD. Details of the data sources and our merging procedures are given in Appendix A. **Table 1** contains summary statistics.

The number of securities with monthly return data grew from 10 in January 1800 to 781 in December 1926. Nine of the initial ten companies in January 1800 were financials, and one was a manufacturing company (see Appendix B). For most of the period, the number of securities grew steadily. The exception was the Civil War period—the early to mid-1860s—when a large drop in coverage took place. This drop, also noted by Goetzmann et al. (2001), was the result of newspapers dropping coverage of many traded securities. After reaching a maximum of 415 securities in July 1853, the number first slowly and then rapidly dropped to a minimum of 53 in January 1866. From then on, it slowly grew again, crossing 400 in May 1899.

We used industry mappings in this study to estimate industry-neutral and industry-level momentum. Industry mappings for the merged dataset were derived from the industry assignments in the individual datasets and aggregated to a level that was granular enough to capture industry differences while maintaining a large enough number of companies in each group. From 52 GFD industries, 6 IFC sectors, and 4 ICPSR sectors, we aggregated stocks to 11 final groupings: mining, food, retail, chemical, petroleum, materials, manufacturing, transportation,

Table 1. Descriptive Statistics for the Datasets

Data Source	Period	Avg. Monthly Return	Avg. Monthly Std. Dev.	Total # of Unique Securities	Avg. # of Securities with One-Month Return	Avg. # of Securities with One-Month Return & Momentum	Total # of Observations with One-Month Return	Total # of Observations with One-Month Return & Momentum
ICPSR[a]	1800–1862	0.09%	2.19%	1,167	139	114	103,684	84,148
GFD[b]	1825–1925	0.29	3.38	3,992	250	205	305,574	248,736
IFC[c]	1815–1925	0.38	4.85	671	46	32	57,871	41,925
Merged[d]	1800–1926	0.28	3.11	4,709	272	224	413,922	338,989
CRSP	1926–2012	0.98	7.35	29,542	3,667	3,356	3,828,692	3,462,990

[a]Inter-University Consortium for Political and Social Research (www.icpsr.umich.edu/icpsrweb/ICPSR/studies/4053). A corresponding paper describing the data collection process and results is Sylla et al. (2006).
[b]Global Financial Data (www.globalfinancialdata.com/Databases/HistoricalStockData.html).
[c]International Center of Finance at Yale University (http://icf.som.yale.edu/old-new-york-stock-exchange-1815-1925). A corresponding paper describing the data collection process and results is Goetzmann et al. (2001).
[d]Merged dataset of ICPSR, GFD, and IFC for 1800–1926.

utilities, financial, and other. Industry data are available from the beginning of the dataset, but in the first half of the 19th century, there is a high concentration in financial companies, which during the second half of the 19th century shifts toward railroad and transportation companies (see Appendix B). Over the course of the 19th century, more industries emerged, reaching a required level of three by 1806, a figure necessary for the industry momentum computation.

The smallest sector in the 1801–1926 period by number of companies was the chemical sector, with an average of four stocks over the pre-1927 period. The largest was transportation, with an average of 69 stocks. It is important to highlight that the average numbers include many months in which a sector had zero securities. For example, the chemical sector had an average of 11.3 stocks during the months when at least one chemical company was present. This is an important feature for industry-neutral momentum portfolios, which became more robust as the number of securities increased in each industry. Nevertheless, in some months, the number of securities in any given industry clearly could dip to a low of three, the minimum required for an intra-industry momentum computation, making the results of an industry-neutral momentum strategy less reliable during those months.

For the post-1927 period, we relied on the CRSP database of security prices. The same market and momentum return computation methodology was applied to the CRSP data as to the merged data. The CRSP price data begin on 31 December 1925 with 503 securities and grow to 540 by 31 December 1926. The merged dataset has 781 securities that had at least a one-month return on 31 December 1926. Hence, the merged dataset is noticeably larger than the initial CRSP security list. In this study, however, we did not link the merged dataset to CRSP securities directly. Because the last month of the merged momentum return was December 1926 and the first month of the CRSP price momentum return was January 1927, we spliced the two time series together to create an uninterrupted momentum history. In the equally weighted returns during the overlapping 12 months of 1926, the result was a correlation of 97.2% between the CRSP and merged returns. For industry-level momentum computations during the CRSP period, we used the 10 broadest CRSP sector classifications to match the number of industries in the early data. The industry breakdown on December 1926 confirms dataset similarity; the largest sector in both datasets was manufacturing, with 127 CRSP and 169 merged securities.

The Price Momentum Premium

Like its highly examined in-sample performance, the out-of-sample record of momentum in equity returns has been exceptional. A positive and economically and statistically significant gross premium appears in the data after its published discovery in the US market (e.g., Jegadeesh and Titman 1993), in international markets (Rouwenhorst 1998), market indexes (Asness, Liew, and Stevens 1997), active mutual funds (Carhart 1997), tactical asset allocation (Faber 2013), currencies (Bhojraj and Swaminathan 2006), and commodities (Gorton, Hayashi, and Rouwenhorst 2013). A recently updated study of both the value and the momentum effects (Asness, Moskowitz, and Pedersen 2013) traces the power of the momentum effect around the globe. The momentum effect has also been confirmed in 19th-century British and Russian stock prices (Chabot, Ghysels, and Jagannathan 2008; Goetzmann and Huang 2015) and in two centuries of multiasset trend following by Lempérière, Deremble, Seager, Potters, and Bouchaud (2014).

Related Research. Since at least the work by Jegadeesh and Titman (1993, 2001) and Chan, Jegadeesh, and Lakonishok (1996), a large body of research has attempted to isolate a risk-based or a regularities-based explanation for the momentum effect. Risk-based explanations are generally in line with market efficiency. The following studies provide the road map for our discussion: Jacobs and Levy (1988); Kothari and Shanken (1992); Conrad and Kaul (1998); Moskowitz and Grinblatt (1999); Grundy and Martin (2001); Chordia and Shivakumar (2002); Griffin, Ji, and Martin (2003); Cooper, Gutierrez, and Hameed (2004); Siganos and Chelley-Steeley (2006); Liu and Zhang (2008); Asem and Tian (2010); Stivers and Sun (2010, 2013); and Daniel and Moskowitz (2014).

These studies investigated whether momentum profits are driven by regularities or anomalies in returns (Jacobs and Levy 1988), by industry effects (Moskowitz and Grinblatt 1999), by variation of expected returns (Conrad and Kaul 1998; Grundy and Martin 2001), by factor-level versus stock-specific momentum (Grundy and Martin 2001), by macroeconomic factors (Chordia and Shivakumar 2002; Griffin et al. 2003; Liu and Zhang 2008), or by market state (Cooper et al. 2004; Siganos and Chelley-Steeley 2006; Stivers and Sun 2010, 2013). The latter studies concluded that industry momentum is a separate effect from stock-level momentum and found that market state is a better proxy for risk than are macroeconomic variables.

The connection between momentum portfolio beta loadings and the factor realization over portfolio formation periods was studied by Kothari and Shanken (1992) and Jegadeesh and Titman (1993), more formally by Grundy and Martin (2001), and recently by Blitz, Huij, and Martens (2011). Grundy and Martin explored the question analytically and found empirically that the momentum spread portfolio is loaded with high-beta stocks during a bull market and negative-beta stocks during a bear market.

A number of subsequent studies analyzed the connection between market states and momentum profits. Cooper et al. (2004) observed that momentum returns following an up market are higher than those following a down market. Siganos and Chelley-Steeley (2006) found that momentum profits are stronger after lagging poor market returns, where the longer the duration of the poor market, the stronger the momentum returns realized. Daniel and Moskowitz (2014) explored momentum crashes and concluded that the crashes follow periods of volatile and negative market returns. Finally, Asem and Tian (2010) and Stivers and Sun (2010, 2013) observed that momentum returns are stronger in a given state and weaker during state transitions.

The current study further explores the connection between market states and momentum via the dynamic relationship between momentum beta and market state duration. Characterizing the duration of a market state allowed us to track the evolution of momentum beta and alpha across and within market states, thereby nesting much previous research. We found that state duration is importantly related to the factor loadings of the momentum portfolio, which in turn affects the size and direction of momentum profits in and across market states.

Empirical Results. Our measure of price-return momentum was defined as a stock's simple price change from $t-12$ to $t-2$. We skipped two months for the De Bondt and Thaler (1985) reversal effect, which appears to last approximately two months, on average, in the early history (as we explain later in the article). Every month in the research sample, we assigned each stock to one of three portfolios on the basis of its prior 10-month price change. Stocks with the highest momentum were assigned to the winner (W) portfolio, and stocks with the lowest momentum were assigned to the loser (L) portfolio. We rebalanced the portfolios monthly and computed a one-month-forward equally weighted return of each portfolio. Excess returns were derived by subtracting the market return, which is the equally weighted return of all stocks, from the momentum portfolio return. We observed the returns to this strategy for the period between 28 February 1801 and 31 December 2012. To compute the market returns, we used the equally weighted method of price-only returns because we did not have reliable shares outstanding or dividend information. Dividend data that accompany the ICF dataset are available only annually from 1826 to 1871 for 255 companies. ICPSR does not provide dividend data, and GFD is still gathering that information. For these reasons, we could not compute total returns for individual securities and the momentum effect. We believe, however, that price returns reflect information sufficiently for the purposes of extending the momentum studies. In addition, dividends and company payouts have varied systematically over time with changes in taxes and legal regimes as well as changes in preferences, although dividend volatility certainly has tended to be swamped by price-change volatility.

One way of thinking about our focus on the capital gains portion of total returns is that it assumes that the dividends of the winners roughly offset the dividends of the losers. We tested this assumption in several ways. First, using the post-1927 CRSP dataset, we confirmed that the momentum strategy based on price-only data for both the momentum signal and the return computation generates W and L portfolios with the same average dividend yield (2.97% for winners and 2.90% for losers). In particular, we computed dividend yields as in Fama and French (1988) by taking the 12-month difference between total return and price return as reported in the CRSP database. Second, we measured the total return of this price-only momentum strategy and confirmed that the W – L spread remained the same as the one measured when price-only returns were used (58 bps per month versus 57 bps per month between January 1927 and December 2012). Finally, we used the annual IFC dividend data between 1826 and 1871, which is available only for a small subset of our merged dataset, and computed the average dividend yield for the winner and loser portfolios generated from the merged dataset price-only data. We found the average dividend yield of the winner portfolio to be 7.35% and of the loser portfolio to be 5.95%.

The values in our final tests need to be viewed with caution because many months did not have any dividend information, since not all the stocks in the winner and loser portfolios in any given month might have had dividend values in the IFC dividend dataset. Nevertheless, these findings support our assumption that, when formed on the basis of price-return momentum, winner portfolios do not have lower dividend yields than loser portfolios. Hence, our W – L portfolio returns were not likely to be positively biased because of the omission of dividends.

As **Table 2** shows, in the 1801–1926 period, the arithmetic average monthly excess return of the W portfolio was 0.18%, of the L portfolio was –0.10%, and of the W – L portfolio was 0.28%. In the 1927–2012 period, the W portfolio average monthly excess return was 0.34%, the L portfolio's was –0.24%, and the W – L portfolio's return was 0.58%. For the period of 1801–2012, the W – L return was 0.40%, the W portfolio excess return was 0.25%, and the L portfolio excess return was –0.16%. **Figure 1** illustrates the cumulative returns to the three strategies for the total period.

The previously untested pre-1927 data confirm the significance of the momentum premium in 19th- and early 20th-century US stocks. The combined history creates the longest known US stock-level

Table 2. Momentum Profits by Time Periods

Period	Monthly Excess Return			t-Statistics			Data Source
	Winners	Losers	W – L	Winners	Losers	W – L	
31 Jan 1801–31 May 1862	0.13%	–0.12%	0.25%	1.9	–1.4	1.8	ICPSR
31 Jan 1826–31 Dec 1926	0.18	–0.07	0.25	3.0*	–1.1	2.1*	GFD
31 Jan 1816–31 Dec 1925	0.24	–0.10	0.34	2.7*	–0.9	1.9	IFC
31 Jan 1801–31 Dec 1926	0.18	–0.10	0.28	3.5*	–1.7	2.7*	Merged
31 Jan 1927–31 Dec 2012	0.34	–0.24	0.58	4.5*	–2.8*	3.6*	CRSP
31 Jan 1801–31 Dec 2012	0.25	–0.16	0.40	5.7*	–3.2*	4.5*	Merged + CRSP

Notes: For each month t, the price-return momentum strategy used top and bottom thirds of P_{t-2} to P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, were equally weighted and rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the equally weighted market return. Market return is defined as the equally weighted average return of all stocks.

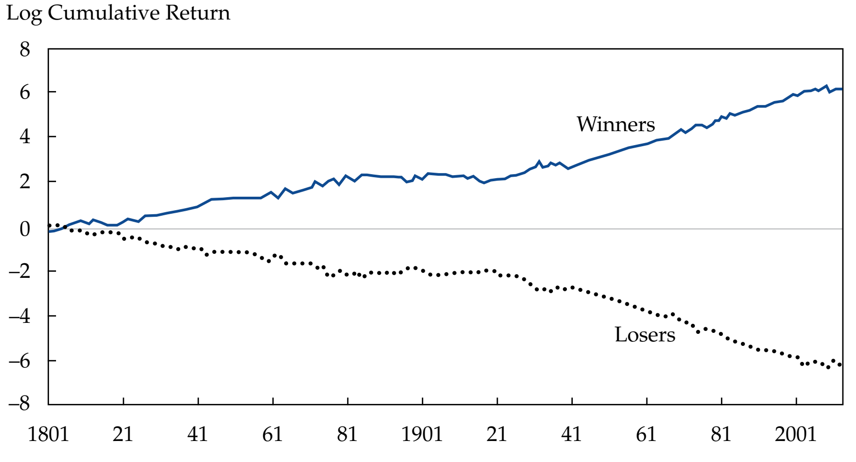
*Significant at the 5% level.

backtest of 212 years (or 2,543 months of momentum observations). The size of the effect is stronger in the post-1927 period, but it is economically and statistically significant in both subperiods. Moreover, we observed positive average W – L momentum returns in individual pre-1927 datasets. Using ICPSR data only, we found the W – L spread to be 0.25% per month for the 1801–1862 period; for GFD data only, the W – L spread is 0.25% for the 1826–1926 period; and for IFC data alone, the W – L spread is 0.34% for the 1816–1925 period. The momentum effect apparently was present in each of the three datasets for different (albeit overlapping) coverage periods and sample sizes.

The overlapping period across the three datasets ranged from 1826 to 1862. In this period, the W – L monthly spreads were found to be ICPSR, 0.17%; GFD, 0.38%; and ICF, 0.44%. The merged dataset over this period generated an average 0.33% W – L spread. This overlapping period reveals the increased robustness achieved by merging the three datasets. Between 1826 and 1862, ICPSR had a monthly average of 158 securities with return data, GFD had 107 such securities, and ICF had 15. The merged dataset resulted in a monthly average of 212 testable securities, with about 71 stocks total in the W and L portfolios. As expected, the greatest synergy among the datasets occurred during this overlapping period, which is when such synergy is most important because of the generally lower quality of data in the early and mid-19th century.

As mentioned previously, momentum premium profits were lower during the pre-1927 period, as was the equity premium. These results appear consistent with Goetzmann and Huang (2015), who observed a strong increase in momentum profits in the Russian stocks after 1893, which they attributed to the increased ease of speculation. Without a theoretical model linking

Figure 1. Cumulative Returns to Momentum Winner and Loser Portfolios, 1801–2012



Notes: This figure shows cumulative log scale excess returns of winner and loser portfolios. For each month t, the price-return momentum strategy uses top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, are equally weighted and rebalanced monthly. Excess return is defined as the return to the momentum portfolio minus the market return.

the size of the momentum premiums to the size of the equity premiums, we cannot assess whether this correlation is meaningful. Some commonality does appear to characterize the increase of both in the 20th century, however, which (judging from prior studies) was then unconditionally lower, on average, in the latter part of the period. In addition, as observed by Grundy and Martin (2001) and Chabot et al. (2008), significant time variations in momentum payoffs occurred. As **Table 3** shows, in the pre-CRSP history, the 10-year annualized return is negative in three decades (1890: –0.6%; 1900: –2.1%; and 1920: –1.2%). **Figure 2** and **Figure 3** show that on a 10-year rolling basis, seven negative periods occurred for the momentum strategy. These 10-year drawdowns were significant, and it is likely that any levered investor in the momentum strategy would have experienced a margin call during these periods. In the rest of the early history, 10-year profitability varied between 0% and 15.3% per year.

In the recent decade of negative momentum performance (from January 2002 to December 2012), the annualized geometric W – L return shown in Table 3 is –2.1%, which is less anomalous within the longer historical time frame of our study than it might appear if viewed unconditionally. The pre-1927 data capture a more complete distribution of momentum profits than what has been observed since 1927. Even though extended history by itself does not prove or disprove whether the momentum effect, viewed as an anomaly, has been arbitraged out by the large amount of capital deployed in this strategy over the past two decades, it does provide evidence that such periods of extended underperformance have occurred in the past. A "limits-to-arbitrage" hypothesis proposed by Shleifer and Vishny (1997) might imply that momentum profits are too risky to be fully arbitraged, suggesting that the latest period of underperformance will eventually give way to positive momentum returns. A "pure anomaly" theory might suggest that momentum profits have now been arbitraged away.

An important side issue, also noted by Grundy and Martin (2001), is that the turnover of the base momentum portfolios is high—in the pre-1927 period, averaging 27.6% and 27.5% per month, respectively, per each winner and loser side. Of course, in such a raw, unconstrained, and non-optimized form, 19th-century trading costs (or the trading costs in any century!) would probably eat away the stated profits. Furthermore, shorting was not widely possible during the 19th century. Note, however, that factor-mimicking

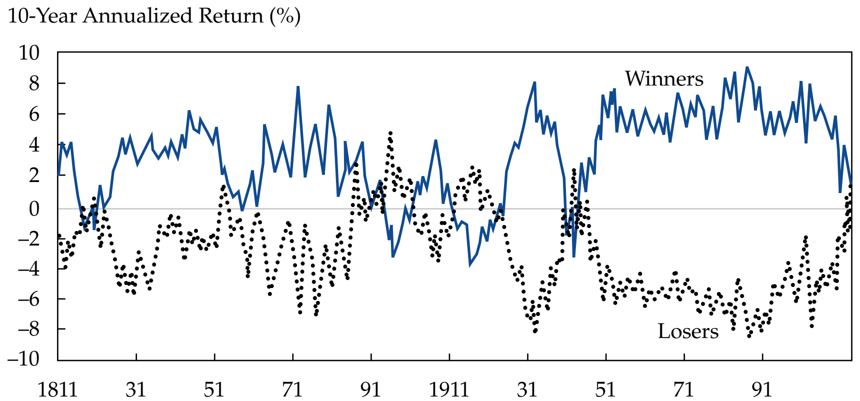
Table 3. Momentum Profits by Decade

Decade End	Average Excess Return		W – L	W – L	Market
	Winners	Losers	Arithmetic	Geometric	Geometric
1810	2.3%	–2.4%	4.4%	3.8%	3.76%
1820	0.4	–1.6	2.0	0.5	1.08
1830	3.0	–3.8	6.7	6.1	2.08
1840	3.5	–0.9	4.4	3.9	1.15
1850	4.9	–2.6	7.5	6.5	3.52
1860	0.9	–1.3	2.3	0.8	–1.96
1870	4.4	–4.0	8.4	6.1	10.20
1880	5.1	–4.5	9.7	6.3	6.49
1890	0.1	0.7	–0.6*	–2.6*	0.34
1900	–0.7	1.3	–2.0*	–4.0*	5.26
1910	0.9	–1.5	2.4	1.4	3.06
1920	–1.2	0.0	–1.2*	–2.5*	–2.10
1930	6.8	–7.1	13.9	12.2	–0.65
1940	0.3	–0.1	0.4	–17.7*	7.88
1950	6.8	–4.5	11.4	9.7	14.13
1960	5.9	–5.8	11.7	10.6	9.19
1970	6.0	–5.6	11.6	9.9	9.15
1980	7.6	–6.4	14.0	11.3	13.29
1990	5.3	–7.8	13.1	12.9	4.66
2000	5.8	–3.5	9.3	6.8	15.35
2010	2.7	–1.0	3.7	–3.4*	10.24
Average	3.4%	–3.0%	6.3%	3.8%	5.5%
2002–2012 (last decade)	1.9%	0.4%	1.4%	–2.1%*	10.2%

Notes: See notes to Table 2. Excess returns by decade are annualized 10-year returns, ending at period-end date.

*Significant at the 5% level.

Figure 2. Ten-Year Annualized Returns to Momentum Winner and Loser Portfolios, 1801–2012



Notes: This figure shows the 10-year rolling excess returns of winner and loser portfolios. For each month t, the price-return momentum strategy uses top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, are equally weighted and rebalanced monthly. Excess return is defined as the return to the momentum portfolio minus the market return.

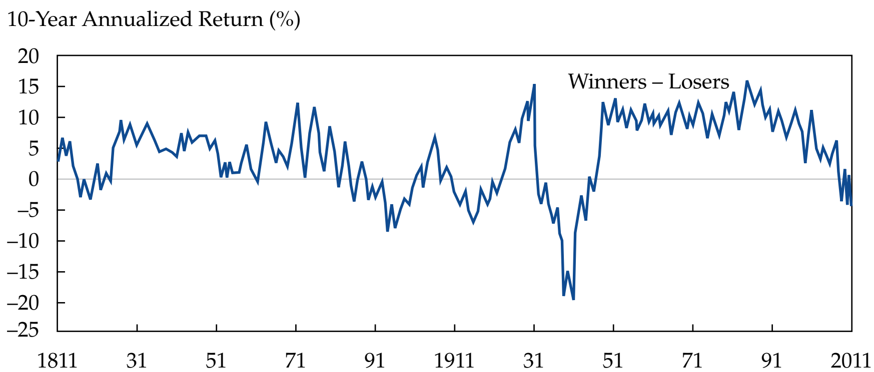
portfolios (or anomaly-tracking portfolios) do not need to be tradable to be useful for investors in numerous ways. Moreover, a long-only version with a reasonable turnover constraint certainly might have been used in a realistic scenario even in early history. Regardless of the momentum effect's practical tradability, our understanding of the existence and features of the effect is deepened with the extended history.

In **Table 4**, we show a similar term structure of momentum profits after the formation month in the pre-1927 era as in the post-1927 era, as documented in previous studies. On average, between 1801 and 1926, momentum profits accumulated up to the fourth month after portfolio formation and in the post-1927 period, up to the fifth month. Returns are statistically significant for the first and second months in both periods.

Confirming existing long-term reversal studies—such as De Bondt and Thaler (1985); Lakonishok, Shleifer, and Vishny (1994); and Jegadeesh and Titman (1995)—we found that momentum profits experience a significant reversal within eight months of portfolio formation. The power of this mean reversion is strong; it is apparent when we measure the nonoverlapping future one-month performance of the W – L strategy. For example, Table 4 shows that in month 11 after portfolio formation, the W – L return in the pre-1927 period was –0.31% with a t-statistic of –3.1, and in the post-1927 period, it was –0.78% with a t-statistic of –5.8. The negative returns persisted for up to five years after portfolio formation.

Another well-known effect, that of short-term reversal in momentum (Jegadeesh 1990), is also present in the pre-1927 history. **Table 5** provides the returns to the long–short periods. As Table 5 shows, we observed reversals in both month P_t/P_{t-1} and month P_{t-1}/P_{t-2} for the entire sample we studied, but the P_{t-1}/P_{t-2} reversal is statistically significant only during the pre-1927 history, perhaps because of liquidity or mark-to-market effects. As a result, we

Figure 3. Ten-Year Annualized Returns to Momentum W – L Portfolio, 1801–2012



Notes: This figure shows 10-year rolling returns of (W – L) portfolios. For each month t, the price-return momentum strategy uses top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, are equally weighted and rebalanced monthly.

Table 4. Term Structure of Momentum Profits

	Average Excess Return per Month			t-Statistic		
Month	Winners	Losers	W – L	Winners	Losers	W – L
1801–1926						
$t-1$	0.18%	–0.10%	0.28%	3.5*	–1.7	2.7*
$t-2$	0.17	–0.12	0.30	3.4*	–2.1*	2.9*
$t-3$	0.12	–0.03	0.14	2.1*	–0.5	1.3
$t-4$	0.16	–0.03	0.18	2.9*	–0.5	1.7
$t-5$	–0.03	0.06	–0.09	–0.6	1.0	–0.9
$t-6$	0.05	0.02	0.03	1.0	0.3	0.3
$t-7$	0.16	–0.07	0.24	3.1*	–1.3	2.3*
$t-8$	0.04	0.01	0.03	0.8	0.3	0.3
$t-9$	–0.01	0.08	–0.10	–0.3	1.5	–1.0
$t-10$	–0.01	0.05	–0.07	–0.2	0.9	–0.7
$t-11$	–0.13	0.18	–0.31	–2.5*	3.2*	–3.1*
$t-12$	–0.09	0.11	–0.19	–1.6	1.8	–1.9
$t-13$	0.03	0.02	0.01	0.6	0.3	0.1
$t-14$	–0.01	0.05	–0.06	–0.1	1.0	–0.6
$t-15$	0.05	0.02	0.03	0.8	0.3	0.3
$t-16$	0.01	0.09	–0.08	0.2	1.5	–0.7
$t-17$	–0.09	0.18	–0.26	–1.7	3.1*	–2.6*
$t-18$	–0.07	0.16	–0.23	–1.4	2.7*	–2.3*
$t-19$	–0.06	0.13	–0.20	–1.3	2.3*	–2.0
$t-20$	–0.03	0.12	–0.14	–0.5	2.1*	–1.5
$t-21$	0.02	0.10	–0.08	0.4	1.8	–0.8
$t-22$	–0.07	0.15	–0.21	–1.3	2.7*	–2.2*
$t-23$	–0.08	0.14	–0.21	–1.5	2.5*	–2.2*
$t-24$	–0.08	0.14	–0.22	–1.6	2.5*	–2.2*
$t-25$	–0.01	0.12	–0.13	–0.2	2.1*	–1.3
$t-26$	0.04	0.06	–0.02	0.8	1.1	–0.2
$t-27$	0.05	0.03	0.02	1.0	0.5	0.2
$t-28$	0.04	0.05	–0.01	0.8	1.0	–0.1
$t-29$	–0.02	0.08	–0.10	–0.4	1.4	–1.0
$t-30$	–0.01	0.15	–0.16	–0.3	2.6*	–1.7
$t-31$	–0.03	0.09	–0.13	–0.6	1.7	–1.3
$t-32$	0.07	0.02	0.05	1.3	0.3	0.5
$t-33$	–0.05	0.15	–0.20	–0.9	2.7*	–2.0*
$t-34$	–0.01	0.12	–0.14	–0.3	2.2*	–1.4
$t-35$	–0.08	0.09	–0.18	–1.5	1.7	–1.8
$t-36$	–0.01	0.11	–0.13	–0.2	2.0*	–1.3
1927–2012						
$t-1$	0.34%	–0.24%	0.58%	4.5*	–2.8*	3.6*
$t-2$	0.24	–0.15	0.39	3.3*	–1.7	2.5*
$t-3$	0.18	–0.08	0.26	2.4*	–1.0	1.7
$t-4$	0.17	–0.05	0.21	2.5*	–0.6	1.5
$t-5$	0.09	0.00	0.09	1.4	0.0	0.7
$t-6$	0.01	0.07	–0.06	0.2	1.0	–0.5
$t-7$	–0.01	0.11	–0.12	–0.1	1.5	–0.9
$t-8$	–0.10	0.20	–0.31	–1.7	2.8*	–2.3*
$t-9$	–0.15	0.24	–0.39	–2.4*	3.4*	–3.0*
$t-10$	–0.23	0.33	–0.56	–3.6*	4.4*	–4.2*
$t-11$	–0.34	0.44	–0.78	–5.3*	5.8*	–5.8*

(continued)

Table 4. Term Structure of Momentum Profits (continued)

	Average Excess Return per Month			*t*-Statistic		
Month	Winners	Losers	W – L	Winners	Losers	W – L
$t-12$	–0.33%	0.41%	–0.74%	–5.2*	5.5*	–5.5*
$t-13$	–0.21	0.29	–0.50	–3.1*	3.9*	–3.6*
$t-14$	–0.23	0.31	–0.55	–3.5*	4.2*	–4.0*
$t-15$	–0.21	0.31	–0.52	–3.3*	4.3*	–3.9*
$t-16$	–0.22	0.31	–0.53	–3.5*	4.3*	–4.0*
$t-17$	–0.24	0.31	–0.55	–3.7*	4.5*	–4.3*
$t-18$	–0.22	0.29	–0.50	–3.5*	4.0*	–3.9*
$t-19$	–0.17	0.25	–0.42	–2.7*	3.7*	–3.3*
$t-20$	–0.17	0.24	–0.42	–3.1*	3.8*	–3.6*
$t-21$	–0.18	0.27	–0.44	–3.2*	4.1*	–3.8*
$t-22$	–0.15	0.23	–0.38	–2.9*	3.8*	–3.5*
$t-23$	–0.23	0.32	–0.55	–4.3*	5.2*	–5.0*
$t-24$	–0.18	0.30	–0.48	–3.4*	4.8*	–4.3*
$t-25$	–0.08	0.18	–0.25	–1.4	3.0*	–2.3*
$t-26$	–0.06	0.19	–0.25	–1.2	3.1*	–2.3*
$t-27$	–0.12	0.22	–0.33	–2.1*	3.6*	–3.0*
$t-28$	–0.09	0.21	–0.29	–1.7	3.4*	–2.7*
$t-29$	–0.13	0.23	–0.36	–2.6*	4.0*	–3.5*
$t-30$	–0.11	0.23	–0.34	–2.3*	4.0*	–3.4*
$t-31$	–0.06	0.18	–0.24	–1.4	3.2*	–2.5*
$t-32$	–0.08	0.19	–0.27	–1.8	3.3*	–2.8*
$t-33$	–0.07	0.17	–0.24	–1.5	3.1*	–2.5*
$t-34$	–0.07	0.18	–0.25	–1.5	3.3*	–2.6*
$t-35$	–0.13	0.25	–0.37	–2.7*	4.5*	–3.9*
$t-36$	–0.11	0.24	–0.35	–2.6*	4.4*	–3.8*

Notes: For each month t, the price-return momentum strategy used top and bottom thirds of P_{t-2} to P_{t-12} to designate winners and losers. Average excess returns and t-statistics were computed for the nonoverlapping month t after portfolio formation. Returns for the momentum portfolio and the market were equally weighted.

*Significant at the 5% level.

Table 5. Short-Term Reversals: Returns to Long–Short Portfolios

	Average Long–Short Return per Month			*t*-Statistic		
Period	P_t/P_{t-1}	P_{t-1}/P_{t-2}	P_t/P_{t-2}	P_t/P_{t-1}	P_{t-1}/P_{t-2}	P_t/P_{t-2}
1801–1926	0.22%	0.82%	0.38%	2.1*	7.7*	4.2*
1927–2012	1.38	0.14	1.12	10.9*	1.3	8.1*
1801–2012	0.69	0.28	0.94	8.5*	4.1*	11.1*

Notes: For each month t, the price-reversal strategy used top and bottom thirds of P_t/P_{t-1} (one-month reversal), P_{t-1}/P_{t-2} (one-month reversal skipping one month, $t-1$), and P_t/P_{t-2} (two-month reversal) to designate winners and losers. Returns were equally weighted and rebalanced monthly. Returns in the table are for the long–short (W – L) portfolios.

*Significant at the 5% level.

required that our momentum-formation period end on month $t-2$. As **Table 6** shows, in the pre-1927 data, a long–short portfolio based on the month P_t/P_{t-1} reversal averaged a return of 0.22% per month and the P_{t-1}/P_{t-2} reversal averaged 0.82%. In the post-1927 history, the corresponding results are 1.4% for P_t to P_{t-1} and 0.14% for P_{t-1} to P_{t-2}. The combined P_t/P_{t-2} reversal effect averaged 0.8% in the pre-1927 history and 1.1% in the post-1927 period.

A strong and unexpected pattern that deserves further exploration outside the current study emerged in the pre-1927 data. It is related to the cumulative behavior of the P_t/P_{t-1} price reversal. In **Figure 4**, we show the cumulative return to price-reversal strategies. For the first 64 years, from 1801 to 1865, the average one-month reversal return was 1.7%; for the following 62 years, from 1866 to 1926, the average reversal return was –1.3%. This dynamic is puzzling. The P_{t-2}/P_{t-1}

Table 6. Momentum Profits for Industry-Neutral Portfolios and Portfolios Based on Industries, by Period

					Industry W – L			
	Raw W – L		Industry-Neutral W – L		Skipping Reversal Months		Without Skipping	
Period	Mean	*t*-Stat.	Mean	*t*-Stat.	Mean	*t*-Stat.	Mean	*t*-Stat.
1806–1926	0.3%	2.7*	0.2%	2.2*	0.3%	1.9	0.3%	2.2*
1927–2012	0.6	3.6*	0.5	3.5*	0.4	3.5*	0.6	5.7*
1801–2012	0.4	4.5*	0.3	4.0*	0.3	3.2*	0.5	4.4*

Notes: For each month t, the price-return momentum strategy consisted of the top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, were equally weighted and rebalanced monthly. Market return is defined as the equally weighted average return of all stocks. Excess return is defined as return to the momentum portfolio minus the market return. The "Industry-Neutral" column reports the raw profits of the industry-neutral momentum strategy, for which stocks were sorted on the basis of their past 10-month return within each industry. The top third of stocks from each industry were grouped to form the winner portfolio, and the bottom third of stocks from each industry formed the loser portfolio. The "Industry" column reports average monthly profits of momentum strategies of industries, where industries were sorted on the basis of their past 10-month raw returns with and without skipping the two reversal months and a zero investment strategy was followed that was long the three highest-past-return industries and short the three lowest. Positions were held constant for one month, and the strategy was recomputed monthly.

*Significant at the 5% level.

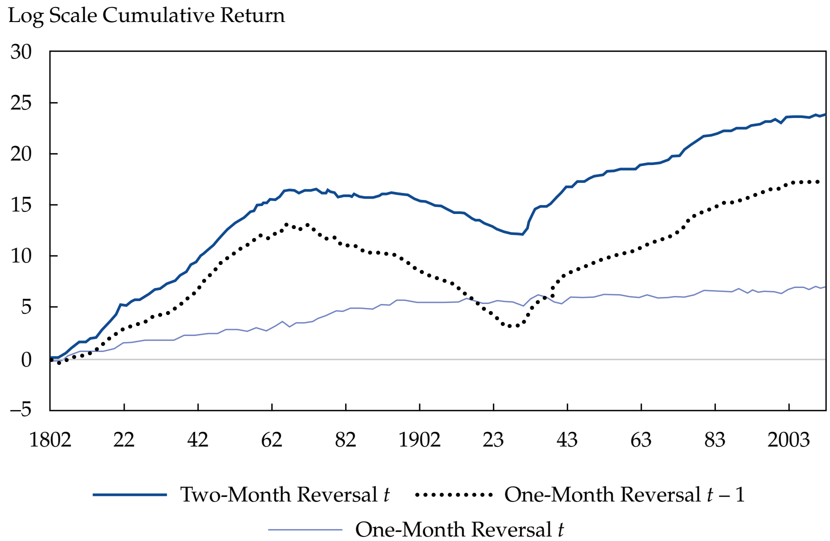
month reversal is extremely strong in the pre-1927 data and then is practically flat in the post-1927 data. Possibly, some distortion has been caused by the data collection methods of the pre-1927 prices. In addition, the patterns of the reversal effect documented in previous studies may simply be sample dependent. As we noted previously, pre-1927 price returns were rarely based on precise month-end prices but, rather, were either an average of minimum and maximum prices achieved during the previous month or the available end-of-week price closest to month end. Of course, there is a distinct possibility that just as medium-term momentum can experience long periods of underperformance, so can the price-reversal effect.

Sources of Momentum Profits

We also used our extended dataset to investigate the sources of momentum profits, including the presence of industry momentum, market momentum versus stock-specific momentum, macroeconomic factors, and importantly, market states and dynamic beta exposure of momentum portfolios. Consistent with prior literature, we found that market states have the relatively largest economic impact on momentum profits.

Industry-Neutral Momentum. We first examined whether industry momentum explains stock-level momentum and found, as did previous studies,

Figure 4. Average Cumulative One- and Two-Month P_t/P_{t-1} Price Return, 1802–2012



Notes: For each month t, the price-reversal strategies use top and bottom thirds of P_t/P_{t-1} (one-month reversal t), P_{t-1}/P_{t-2} (one-month reversal t – 1), and P_t/P_{t-2} (two-month reversal t) to designate winners and losers. Returns are equally weighted and rebalanced monthly. Excess return is defined as the return to the reversal portfolio minus the market return.

that it does not. As in the post-1927 period, industry momentum is a separate and significant effect in the pre-1927 data.

Using the constructed industry classifications discussed previously, we tested an industry-neutral momentum portfolio by ranking each stock within its industry based on its 10-month price change. We then combined the top third of ranked stocks from each industry into a winner portfolio and the bottom third into a loser portfolio. Rebalancing monthly, we found that between 1801 and 1927, the industry-neutral average monthly W – L return was 0.21%, compared with the raw 0.28% reported in Table 6. We then constructed an industry momentum portfolio by identifying the 3 industries out of the 10 with the highest and 3 with the lowest 10-month trailing returns (skipping the reversal months as usual). The resulting W – L return of the monthly rebalanced industry portfolio in the pre-1927 history was 0.3%, on average. For the full history between 1801 and 2012, the average industry momentum return spread is 0.34% and the average industry-neutral momentum spread is 0.33%. **Table 7** reports momentum results within each industry. We also tested the industry momentum strategy without skipping the reversal months and discovered stronger results in both periods, which points to the fact that industries do not experience the stock-level reversal effect, as documented previously. Between 1801 and 1926, as Table 6 shows, 10-month industry momentum—without skipping the reversal effect—generated 0.35% per month on average, and between 1927 and 2012, the return to this strategy was 0.61% per month. For the full history from 1801 to 2012, the 10-month industry momentum without skipping the reversal effect generated a 0.46%, on average, return. Consistent with Grundy and Martin (2001) and many others, the **Figure 5** pre-1927 data confirm that industries have a momentum of their own that does not explain away the stock-level momentum.

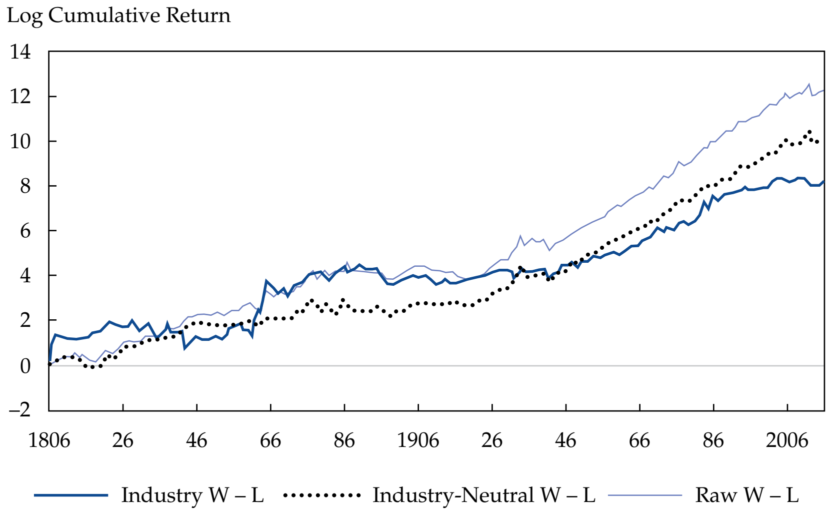
Table 7. Momentum Results for Each Industry, 1806–1926

Industry	Avg. # Stocks	# Stocks on 31 Dec 1925	W – L Mean	W – L *t*-Stat.
Mining	16	25	0.2%	0.4
Food	9	101	0.7	1.8
Retail	10	84	0.5	2.1*
Chemical	4	38	0.5	1.3
Petroleum	9	98	–0.1	–0.3
Materials	9	67	0.4	0.9
Manufacturing	17	155	0.5	2.0*
Transportation	64	89	0.1	0.7
Utilities	14	43	0.0	0.2
Financial	52	65	0.3	2.0*
Other	8	2	0.1	0.5

Note: See notes to Table 6.

*Significant at the 5% level.

Figure 5. Momentum Effect for Industry-Neutral Portfolios and Portfolios Based on Industries, 1806–2012



Notes: For each month t, the price-return momentum strategy uses top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, are equally weighted and rebalanced monthly. Excess return is defined as the return to the momentum portfolio minus the market return. The industry-neutral portfolios represent the raw profits of the industry-neutral momentum-sorted winners-minus-losers portfolio, where stocks are sorted based on their past 10-month return within each industry. The top third of stocks from each industry form the winner portfolio, and the bottom third of stocks from each industry form the loser portfolio. The industry portfolios represent average monthly profits of momentum strategies of industries, where industries are sorted on their past 10-month raw return, skipping the reversal months. A zero investment strategy is formed that is long the three highest-past-return industries and short the three lowest, holding positions constant for one month and recomputing the strategy monthly.

Common-Factor vs. Stock-Specific Momentum. Following the Grundy and Martin (2001) methodology, we also tested whether stock-specific momentum is the significant driver of the W – L portfolio and also whether industry- and security-specific effects behave differently through the evolution of the market state. Using a 60-month rolling regression (requiring a minimum of 37 months of data), we decomposed momentum returns into stock-specific momentum and factor momentum by regressing individual stock returns (price based) on a dummy variable and the market return:

$$r_{i,t} = a_0 D_t + a_1 \left(1 - D_t\right) + B_i \left(r_{ma,t}\right) + e_i, \tag{1}$$

where $D_t = 1$ during the momentum-formation months ($t-12$ to $t-2$) and 0 elsewhere ($t-13$ to $t-60$); $r_{i,t}$ is the month t stock-level return; $r_{ma,t}$ is the month t market return, defined as the equally weighted price return of all the stocks with available data in that month. We constructed a stock-specific momentum strategy by using a_0 as the ranking input (10-month stock-specific momentum),[4] and the factor-related return momentum strategy used $B_{i't}\,(r_{ma,t:[t-12:t-2]})$ as the ranking input. The last columns in Table 7 report the results. Confirming the findings of Grundy and Martin, we found the stock-specific momentum effect to be positive and significant. Between 1801 and 1927, the average stock-specific W – L portfolio spread was 0.22% per month, and for the 1927–2012 period, it was 0.7% per month.

As **Table 8** shows, the common-factor momentum, which captures the effect of market-level momentum inside the W – L returns, is also positive in both periods. For the entire period, the common-factor momentum spread is 0.25% per month, on average. The common-factor momentum was more significant in the early history, with a spread of 0.31% per month, on average. An important point is that the longer history makes it clear that both the stock-specific and common-factor momentum components are priced. As our additional results will demonstrate, the premium on these factors arises at different points in a given market state, with the stock-specific momentum payoff more dominant in the early stages of a market state.

The January effect worked in the same negative direction before 1927 as it did after that date, as described by Schwert (1990) and Sadka (2002), among others. As Table 8 shows, in the 1801–1926 period, the average W – L spread during the month of January was –0.1%, but it was 0.3% during non-January months, although the January t-statistic is not significant during the early period. In the post-1927 period, the W – L January return is –3.3% and the non-January spread is 0.9%. Because the January equity return is negative in both periods, longer history does imply that the effect is less likely to be a random aspect of 20th-century data, although, again, Schwert (1990, 2002) documented a decline in the magnitude of the January effect.

Beta Variation in Momentum Portfolios. Many studies have attempted to explain performance of momentum by using individual macroeconomic variables (e.g., Chordia and Shivakumar 2002; Griffin et al. 2003; Liu and Zhang 2008), but we believe that market information, including market states and volatilities, can be used to proxy better for macroeconomic effects if shocks to conditions are priced (Cooper et al. 2004; Siganos and Chelley-Steeley

Table 8. Stock-Specific vs. Common-Factor Momentum by Period

	W – L Spread			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy		
Parameter	Overall	Jan.	Non-Jan.	Overall	Jan.	Non-Jan.	Overall	Jan.	Non-Jan.
1801–1926									
Mean (%)	0.3	–0.1	0.3	0.2	–0.4	0.3	0.3	0.3	0.3
Std. dev. (%)	4.0	4.7	3.9	3.7	3.5	3.7	5.4	5.6	5.4
t-Statistic	2.7*	–0.3	3.0*	2.3*	–1.4	2.8*	2.2*	0.6	2.1*
1927–2012									
Mean (%)	0.6	–3.3	0.9	0.7	–2.2	0.9	0.2	0.4	0.1
Std. dev. (%)	5.1	6.2	4.9	3.1	4.1	2.8	6.2	8.5	6.0
t-Statistic	4.4*	–6.0*	7.2*	6.9*	–4.9*	10.0*	0.8	0.5	0.6
1801–2012									
Mean (%)	0.4	–1.4	0.6	0.4	–1.1	0.5	0.2	0.4	0.2
Std. dev (%)	4.5	5.6	4.4	3.5	3.8	3.4	5.8	6.9	5.6
t-Statistic	4.5*	–3.7*	6.3*	5.8*	–4.3*	7.6*	2.1*	0.8	2.0*

Note: For each month t, the one-factor model given in Equation 1 was estimated for all stocks i in the database with returns for at least 37 months within a 60-month rolling window.

*Significant at the 5% level.

2006; Daniel and Moskowitz 2014; Stivers and Sun 2013). Because the momentum factor becomes riskier the longer a market state lasts, when economic conditions change, the strong beta exposure at the worst possible time significantly harms momentum profits.

Unreported in this article, we tested whether common macroeconomic indicators explain momentum profits. We tested change in expected inflation, unexpected inflation, the term premium, growth of industrial production, the default premium, consumption growth (proxied by wage growth), commodity price growth, foreign exchange of the dollar versus the British pound, and a residual market factor (computed by regressing the macro variables from the market return and using the residual as a factor).[5] We concur with Cooper et al. (2004) that no single macroeconomic variable explains momentum profits. Only the term premium factor was found to be significant in the post-1927 period. These results suggest that momentum is unlikely to be subsumed by the Chen, Roll, and Ross (1986) and Fama–French (1989) factors.

Grundy and Martin (2001) provided analytical evidence of momentum beta exposure as a function of the trailing market return and estimated the empirical demonstration of the variation of momentum beta exposure as a function of that return. When the market was positive during the formation period for the momentum portfolio, our momentum spread portfolio's beta was positive, and it was negative following negative market returns. Though obvious, this critical characteristic is often a misunderstood dynamic risk property of the momentum portfolios used throughout our sample. A recent realization of this risk occurred in 2009, when the momentum beta loading was significantly negative while the market was experiencing a strong rally.

Because definitions of market state and momentum vary among studies, results in the literature are difficult to compare. For example, Grundy and Martin (2001), on the one hand, defined up and down states as the six-month trailing equally weighted total return of the market above/below one standard deviation around the full sample average return. On the other hand, Cooper et al. (2004) defined market states via the sign of the 36-month trailing value-weighted total return of the CRSP Index. Stivers and Sun (2013) defined market states based on a peak-to-trough *ex post* value-weighted total return in excess of ±15%. Finally, Daniel and Moskowitz (2014) defined a market state as the value-weighted two-year return of all CRSP stocks. Although Cooper et al. concluded that momentum returns are positive only following up markets, Stivers and Sun concluded that momentum returns are positive within a given market state, either up or down, and negative during transitions. Daniel and Moskowitz concluded that momentum crashes occur during market reversals that follow negative market states with high volatility.

We used a market state definition that matches the definition of our momentum portfolio formation. In the current study, the momentum-formation period covered 10 trailing months (skipping the reversal months), so the market state definition uses the same 10 months. Instead of making the trailing periods longer—and, as a result, misaligning the formation periods—we used a state duration variable to describe the length of a market state. Our comprehensive definition of a market state has two parts: the sign of the market return during momentum portfolio formation and the number of consecutive months of that market return sign. The first part aligns a market state with the momentum portfolio, and the second captures the concept of state duration. Hence, in this study, market state is defined as an equally weighted price-only return of the market over the momentum portfolio–formation period ($t - 12$ to $t - 2$) and a duration variable that measures the number of consecutive months in a given state.

We first constructed a one-factor version of the Grundy and Martin (2001) test adapted to our definition of momentum portfolio and market states, sequentially estimating the following two regressions:

$$r_{mo,t} = a_{mo} + B_{mo}(D_t)(r_{ma,t}) + e_{mo,t} \tag{2}$$

and

$$\begin{aligned} r_{mo,t} = a_{mo} &+ B_{moDOWN}(D_{tDOWN})(r_{ma,t}) \\ &+ B_{moUP}(D_{tUP})(r_{ma,t}) + e_{mo,t}, \end{aligned} \tag{3}$$

where dummy variable D_t (DOWN, UP) is 1 if the cumulative performance of the market over months $t - 12$ to $t - 2$ is (negative, positive) and a possible attenuation bias is borne in mind.

In **Table 9**, we confirm that before 1927, as estimated in the manner described, the average beta of the momentum W – L portfolio is negative (–0.26), whereas the alphas are significantly positive at 0.36%, on average. We also confirm that in an up market, momentum beta is, on average, positive (0.31) and in the down market, it is negative (–0.91). For the 1927–2012 period, the average W – L beta is –0.34. The magnitude of the beta variation is about twice as large in the pre-1927 period as in the post-1927 period. For the entire 1801–2012 period, the W – L momentum beta is negative, –0.32.

In the pre-1927 period, the negative beta is a result of the loser portfolio having an estimated average beta of 1.27 whereas the winner portfolio has an average beta of 1.01. For the down markets in the period, the winner portfolio beta drops to an estimated 0.7 and the estimated loser beta rises to 1.6. The reverse occurs in the up markets, wherein winner portfolio beta rises to 1.3 and the loser beta drops to 0.98. Because the

Table 9. Relationship between Investment-Period Factor Exposure and Formation-Period Factor Realization

	W – L Momentum Strategy			Winners			Losers		
Parameter	Estimate	S.E.	*t*-Statistic	Estimate	S.E.	*t*-Statistic	Estimate	S.E.	*t*-Statistic
1801–1926									
Intercept (Eq. 2)	0.36%	0.10%	3.5*	0.12%	0.05%	2.2*	–0.24%	0.06%	–4.0*
Beta	–0.26	0.03	–8.0*	1.01	0.02	58.9*	1.27	0.02	66.1*
Intercept (Eq. 3)	0.17%	0.09%	1.9	0.03%	0.05%	0.7*	–0.14%	0.06%	–2.5*
Beta down	–0.91	0.04	–21.8*	0.70	0.02	30.9*	1.61	0.03	62.6*
Beta up	0.31	0.04	7.9*	1.29	0.02	61.3*	0.98	0.02	40.9*
1927–2012									
Intercept (Eq. 2)	0.92%	0.14%	6.5*	0.50%	0.07%	7.2*	–0.42%	0.07%	5.6*
Beta	–0.34	0.02	–17.7*	0.87	0.01	92.9*	1.21	0.01	120.2*
Intercept (Eq. 3)	0.79%	0.12%	6.8*	0.44%	0.06%	7.9*	–0.36%	0.06%	–5.5*
Beta down	–0.69	0.02	–30.9*	0.68	0.01	64.4*	1.37	0.01	110.6*
Beta up	0.00	0.02	–0.1	1.05	0.01	102.1*	1.05	0.01	87.2*
1801–2012									
Intercept (Eq. 2)	0.59%	0.08%	7.0*	0.28%	0.04%	6.6*	–0.31%	0.05%	–6.5*
Beta	–0.32	0.02	–20.2*	0.90	0.01	111.3*	1.22	0.01	137.9*
Intercept (Eq. 3)	0.46%	0.07%	6.3*	0.22%	0.04%	5.8*	–0.24%	0.04%	–5.7*
Beta down	–0.73	0.02	–37.5*	0.69	0.01	68.5*	1.42	0.01	123.6*
Beta up	0.07	0.02	3.6*	1.10	0.01	114.0*	1.04	0.01	93.6*

Notes: S.E. = standard error. For each month t, the price-return momentum strategy used the top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns, $r_{mo,t}$, and market returns, $r_{ma,t}$, were equally weighted and rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the market return, defined as the equally weighted average return of all stocks. The table shows the results of the regressions given in Equations 2 and 3.

*Significant at the 5% level.

level of beta in the momentum portfolio is analytically linked to recent market performance, it is not surprising to find in the pre-CRSP data results similar to those Grundy and Martin (2001) found using the CRSP data. Nevertheless, it is fascinating how powerful the beta variation of a momentum portfolio is.

Daniel and Moskowitz (2014) took these results a step further and examined the optionality of the momentum portfolio payoffs by observing that the W – L portfolio beta during contemporaneous up-market months that followed an extended trailing bear market was significantly more negative than the average beta—and more negative than the betas following negative and positive markets. We also extended these results to the pre-1927 data and drew similar conclusions.

Specifically, we first confirmed their findings by looking at the 20 most negative W – L monthly returns in the early history. We observed a similar pattern in which the months with the most negative W – L portfolio returns, on average, were followed by negative average market returns and were accompanied by a contemporaneously positive market return. For example, in **Table 10**, we show that between 1801 and 1926, the average monthly W – L return during the 20 most negative months was –14.3%, which was preceded by the market return of –6.3% during the momentum-formation months and accompanied by the contemporaneous market return of +5%.

Next, in the spirit of Daniel and Moskowitz (2014), we estimated the following regression:

$$r_{mo,t} = a_0 + a_b(D_t) + b_0(r_{ma,t}) + b_b(D_t)(r_{ma,t}) + b_{b,u}(D_t)(D_{upmonth,t})(r_{ma,t}) + e_{b,t}, \quad (4)$$

where the dependent variable is the W – L portfolio and the independent variables are a constant; an indicator for the market state D_t (which was 1 if the cumulative performance of the market over months $t-12$ to $t-2$ was negative and 0 otherwise); the market return, $r_{ma,t}$; and a contemporaneous up-market indicator, $D_{upmonth,t}$ (which was 1 if the contemporaneous market return was positive and 0 otherwise).

We confirm in Table 10 the statistically significant negative $b_{b,u}$ coefficient of –0.53 for the full sample, –0.92 for the 1801–1926 sample, and –0.68 for the CRSP sample, which, according to Daniel and Moskowitz (2014), indicates the presence of optionality in the momentum portfolios. Specifically, their interpretation is that in bear markets, the momentum portfolio is, in effect, short a call option on the market. For the months when the contemporaneous market return was negative, the estimate of the W – L

Table 10. Momentum Return during Crashes

	W – L	$Market_t$	$Market_{t-2 \text{ to } t-12}$
1801–1926			
Top 20 most negative months	–14.3%	5.0%	–6.3%
Average	0.29	0.28	3.40
1927–2012			
Top 20 most negative months	–22.4	23.1	–26.1
Average	0.58	0.99	10.9

	Market-Timing Regressions					
Parameter	a_0	a_b	b_0	b_b	$b_{b,u}$	R^2_{adj}
1801–1926						
Estimate	0.23%	0.95%	0.31	–0.77	–0.92	29.22%
S.E.	0.12	0.23	0.04	0.08	0.12	
t-Statistic	2.0*	4.2*	7.9*	–9.6*	–7.8*	
1927–2012						
Estimate	0.88%	1.73%	0.00	–0.26	–0.68	53.90%
S.E.	0.13	0.29	0.02	0.05	0.06	
t-Statistic	6.6*	5.9*	–0.2	–5.5*	–11.2*	
1801–2012						
Estimate	0.56%	0.70%	0.06	–0.47	–0.53	38.76%
S.E.	0.09	0.17	0.02	0.04	0.05	
t-Statistic	6.2*	4.1*	3.5*	–11.7*	–10.6*	

Notes: Momentum returns and market returns were equally weighted and rebalanced monthly. The top 20 most negative months correspond to the months when the W – L portfolio experienced the most negative returns. The table shows the results of the regression given in Equation 4.

*Significant at the 5% level.

portfolio beta is –0.41, $b_0 + b_b$ (–0.47 for 1801–1926), but when the contemporaneous market return was positive, the beta drops significantly to –0.94, $b_0 + b_b + b_{b,u}$ (and –1.37 for the 1801–1926 period). We confirm their empirics without taking a firm stand on their interpretation.

Therefore, prior studies that documented connections between market states and momentum performance could be explained by first observing the beta of the momentum portfolio within and across a market state. The reason is that beta exposure induces raw momentum profits to correlate with market states. Depending on the definition of the market state, the observed correlations between momentum and market state will be different, but the root of the correlation is the beta of the stocks inside the momentum portfolios; hence, the momentum portfolio beta, once measured, can explain the direction of market state correlation with momentum profits.

We further investigated this connection between market state and the momentum portfolio's beta exposure by focusing on the duration of the realized market state and its effect on the momentum portfolio's beta exposure. We found strong evidence that momentum beta is dynamic not only in up and down market states but also within a given market state. Momentum beta is positively exposed to the duration of both positive and negative states. Moreover, the longer each state persists, the stronger the beta becomes.

We defined a state duration variable by summing the number of consecutive positive/negative market state months until the state changed. This variable provides additional visibility into the momentum portfolio dynamic over the course of a market state. We computed the exposure of the momentum beta to the market state duration in the following way: First, we obtained a 10-month rolling momentum beta by regressing monthly momentum returns, $r_{mo,t}$, on a constant and equally weighted market return, $r_{ma,t}$:

$$r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}. \tag{5}$$

Next, we regressed $B_{mo,t}$ on the market state's duration variable:

$$B_{mo,t} = a_b + \text{Coef}_b(\text{Duration}_t) + e_{b,t}, \tag{6}$$

where Duration is the length of the consecutive months in a given state. Duration is positive during up-market states and negative during down-market states. For example, if the market state is positive for two months in a row, Duration is set to 2.

In this explanatory model, we found a strong dependence of momentum beta on market state duration. As **Table 11** shows, we estimated the full period's coefficient to be 0.02; the up-state estimate is 0.03, and the down-state estimate is 0.04. Hence, the higher the market state's duration variable, the stronger the momentum portfolio beta becomes, as can be seen in **Figure 6**. Table 11 shows that in the pre-1927 period, the up-state coefficient estimate is 0.05 versus the post-1927 period up-state point estimate of 0.02. The pre-1927 down coefficient is estimated to be 0.05, and the post-1927 period down estimate is 0.03. These results confirm our prior observations that momentum beta variability was higher in the pre-1927 period.

The duration variable helps refine the results of Grundy and Martin (2001), who captured only the average betas following up and down states. Our study shows that the dynamics of momentum's conditional market exposure are dependent on the duration of the market state and that only after the market state's duration lengthens does momentum beta actually take on those signs; in the beginning of each state, momentum's beta actually appears to have been opposite to the new market direction.

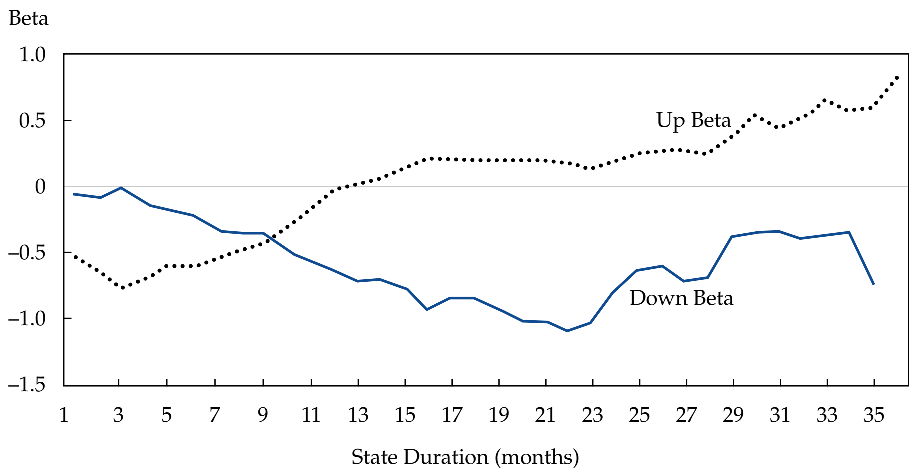
Alpha and Beta Contributions. The dynamic nature of beta over the course of a market state provides the following insights. In the first year of a new market state, momentum beta has tended to be

Table 11. Momentum Beta Variation and Market State Duration

	Up		Down		Overall	
Parameter	$Coef_{up}$	Intercept	$Coef_{dn}$	Intercept	Coef	Intercept
1801–1926						
Estimate	0.05%	–0.86%	0.05%	–0.07%	0.03%	–0.41%
S.E.	0.01	0.10	0.01	0.11	0.00	0.04
t-Statistic	7.2*	–8.9*	4.2*	–0.6	9.1*	–10.9*
1927–2012						
Estimate	0.02%	–0.41%	0.03%	0.08%	0.01%	–0.22%
S.E.	0.00	0.06	0.01	0.07	0.00	0.03
t-Statistic	6.9*	–7.1*	5.1*	1.1	9.1*	–8.4*
1801–2012						
Estimate	0.03%	–0.58%	0.04%	–0.02%	0.02%	–0.34%
S.E.	0.00	0.07	0.01	0.08	0.00	0.03
t-Statistic	6.4*	–8.4*	5.1*	–0.3	11.4*	–12.0*

Notes: The table shows the results of the regression in Equation 6. Standard errors were Newey–West adjusted.
*Significant at the 5% level.

Figure 6. Momentum Beta during Up and Down States



Notes: This figure shows the average beta per market state duration. Results are derived from the following regression: $B_{mo,t} = a_b + \text{Coef}_b$ $(\text{Duration}_t) + e_{b,t}$, where $B_{mo,t}$ is computed from a 10-month rolling regression of momentum returns on the market returns ending at month $t - 2$: $r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}$; Duration is the number of consecutive months in a given state; market state is defined as the sign of the market return for the months ($t - 12$ to $t - 2$), the same period used for momentum portfolio formation.

opposite to the market direction—thus, historically, generating a negative drag on momentum performance. In that time period, the momentum spread portfolio started by being long the winners from the last market state and short the last state's losers, which have the opposite beta tilt to the new market direction. In our analysis, in the second year and beyond, momentum beta generally has taken on the sign of the market direction and has added to momentum returns. The longer a market state persisted, the higher the beta and the more such exposure contributed, on average, to momentum strategy returns. This effect may explain, at least in part, why both the stock-specific and common-factor momentum components appear to be separately priced. It also explains why momentum has underperformed after the market reverses direction, albeit in a very specific manner.

To measure this effect, we looked at the average alpha and beta components of momentum portfolio returns as a function of the market state's duration. For every month t, we calculated momentum alpha as the difference between raw momentum return and the CAPM 10-month rolling beta multiplied by the market return for that month, which acknowledges that in this one-factor context, the estimated "alpha" probably embeds numerous effects. The beta contribution was derived by subtracting the alpha contribution from momentum raw returns. Our results show a striking evolution of the source of momentum profits over the course of a market state.

Table 12 shows that in the overall history, average monthly momentum returns within the first year of all market states were 0.4% versus 0.3% in the subsequent market state months. The estimated beta contribution is –0.4% in the first year and +0.1% in the subsequent market state months, and the "alpha" contribution is significantly positive in the first year (0.8%) and positive, yet not significant, in the subsequent months (0.2%). As the market state continues and the momentum portfolio beta changes with market direction, the

Table 12. Alpha and Beta Contribution and Market State Duration

	W – L			Alpha Contribution			Beta Contribution		
Parameter	D:1–12	D–>12	All D	D:1–12	D–>12	All D	D:1–12	D–>12	All D
1801–1926									
Up state	0.4%	0.3%	0.4%	0.8%	0.0%	0.5%	–0.4%	0.3%	–0.1%
t-Statistic	2.9*	1.6	3.2*	4.4*	–0.1	3.4*	–3.3*	1.9	–0.9
Down state	0.1%	0.2%	0.1%	0.2%	0.5%	0.3%	–0.1%	–0.3%	–0.1%
t-Statistic	0.6	0.5	0.8	1.1	1.5	1.7	–0.9	–0.8	–1.3
All states	0.3%	0.3%	0.3%	0.5%	0.1%	0.4%	–0.3%	0.2%	–0.1%
t-Statistic	2.3*	1.6	2.8*	3.9*	0.7	3.7*	–3.0*	1.0	–1.5
1927–2012									
Up state	0.9%	0.9%	0.9%	1.7%	0.8%	1.3%	–0.8%	0.1%	–0.4%
t-Statistic	4.7*	4.8*	6.7*	6.1*	3.6*	7.0*	–3.2*	0.7	–2.6*
Down state	0.4%	–1.9%	0.0%	0.7%	–1.9%	0.2%	–0.3%	–0.1%	–0.2%
t-Statistic	1.1	–1.3	–0.1	1.9	–2.1*	0.6	–1.7	–0.1	–1.1
All states	0.7%	0.4%	0.6%	1.3%	0.4%	0.9%	–0.6%	0.1%	–0.3%
t-Statistic	3.6*	1.5	3.6*	5.6*	1.5	5.5*	–3.6*	0.3	–2.8*
1801–2012									
Up state	0.6%	0.6%	0.6%	1.2%	0.4%	0.8%	–0.6%	0.2%	–0.2%
t-Statistic	5.3*	4.4*	6.8*	7.4*	2.4*	7.3*	–4.4*	2.0	–2.6*
Down state	0.2%	–0.4%	0.1%	0.4%	–0.2%	0.3%	–0.2%	–0.2%	–0.2%
t-Statistic	1.2	–0.8	0.5	2.2	0.6*	1.6	–1.8	–0.6	–1.7
All states	0.4%	0.3%	0.4%	0.8%	0.2%	0.6%	–0.4%	0.1%	–0.2%
t-Statistic	4.1*	2.2*	4.5*	6.8*	1.6	6.5*	–4.7*	0.9	–3.1*

Notes: The table shows the decomposition of momentum profits into alpha and beta components as a function of market state duration. Average monthly alpha and beta contributions to the momentum portfolio return are shown for the market state durations less than or equal to 12 months and greater than 12 months. For every month t, we calculated momentum alpha as the difference between the momentum raw return and the beta portion of the return, $B_{mo}(r_{ma,t})$, where beta was computed from the 10-month rolling CAPM regression ending at $t - 2$: $r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}$, where $r_{ma,t}$ is the month t market return, defined as the equally weighted average return of all stocks, and $r_{mo,t}$ is the month t (W – L) momentum return.

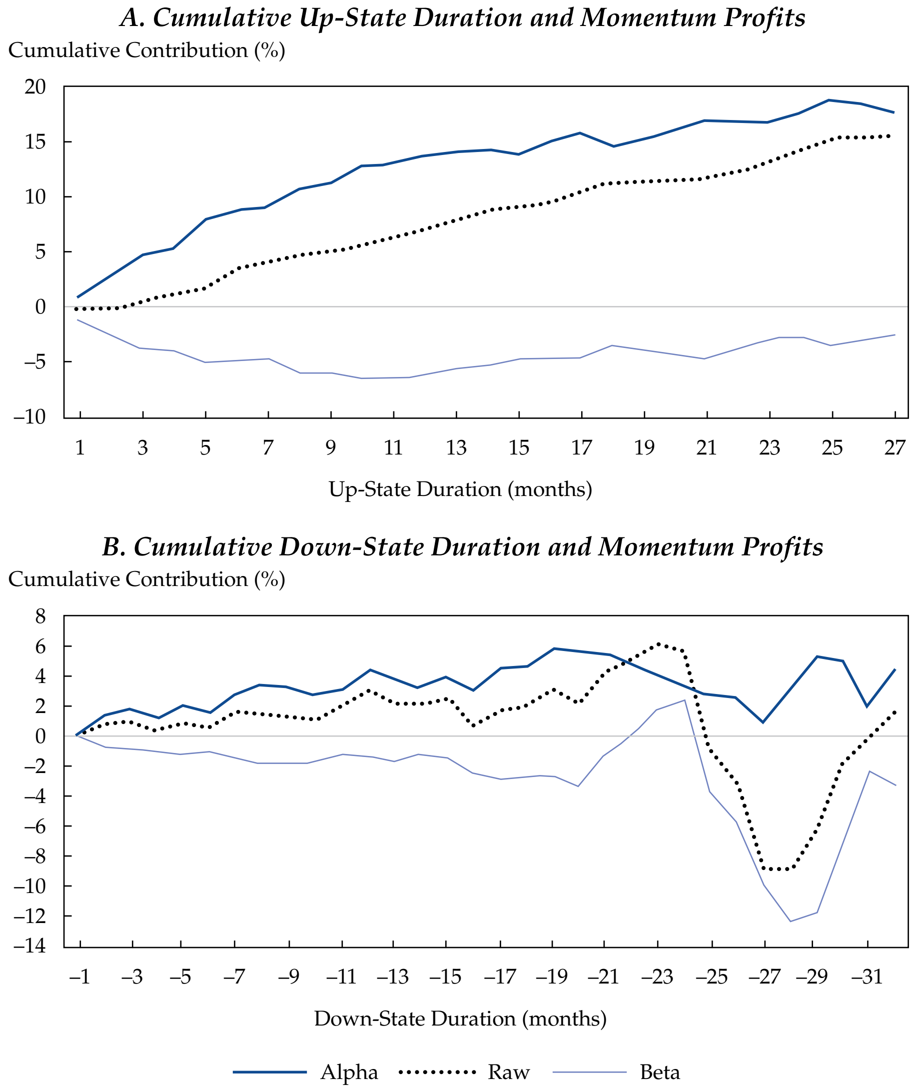
*Significant at the 5% level.

contribution from the beta component switches from significantly negative to slightly positive, whereas the alpha portion declines from significantly positive to insignificantly positive. As a result, over the course of a market state, there is an increased contribution in market exposure via a combination of increasing beta and the conditional chance (eventuality) of an upcoming state reversal. **Figure 7** illustrates cumulative up-state and down-state duration and momentum profits.

Breaking down the sample into up-market and down-market states allows us to see similar momentum patterns in the market states. For example, as Table 12 shows, we estimated alpha contribution in the first 12 months of an up state to be 1.2% in the entire sample and beta contribution to be –0.6%. In the subsequent months of an up state, the estimated alpha contribution declines to 0.4% while the beta contribution rises to 0.2%. In down markets, during the first 12 months, alpha contributes 0.4% and beta contributes –0.2%. In the subsequent months, the alpha contribution drops to –0.2% whereas the beta contribution remains at –0.2%.

The reason beta contribution is asymmetrical between up and down states in the first 12 months, compared with subsequent months, is that the momentum beta at the first month of the up state tends to be negative, at an estimated –0.55, whereas it is near zero and insignificant at –0.07 at the beginning of the average down state (as shown in Figure 6). The reason is that the volatility of the market in down states is larger than in up states, leading to large absolute

Figure 7. Cumulative Up-State and Down-State Duration and Momentum Profits



Notes: This figure shows the cumulative contributions of the alpha and beta components of momentum profits as a function of the market state duration. For every month t, we calculate momentum alpha as the difference between momentum raw return and the beta portion of the return $B_{mo}(r_{ma,t})$, where beta is computed using the 10-month rolling CAPM regression ending at $t-2$: $r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}$, where $r_{ma,t}$ is the month t market return and $r_{mo,t}$ is the month t (W – L) momentum return. Average alpha and beta returns are then compounded over the state duration, showing the total contribution per state duration.

betas. Therefore, the estimated average beta following average-duration down markets is highly negative, whereas following average-duration up markets, it is approximately zero. For this reason, the first 12 months of a new up state have historically experienced a large negative beta contribution whereas the first 12 months of a down state have not.

Our findings provide support for the argument in Stivers and Sun (2010, 2013) that momentum is higher within a market state than across states, as a result of the dynamic nature of momentum's beta. Our findings also support Cooper et al. (2004) in that momentum portfolio returns have been stronger following positive market states than following negative states. Note, however, that this behavior is mainly a result of negative market states that last longer than a year. Momentum has historically experienced significant negative returns, on average, because of its negative beta exposure associated with lasting bear markets during such times as the 1930s and 2000s. In market states under one year, momentum profits have been positive, on average. Finally, our findings are consistent with Daniel and Moskowitz (2014), who showed that the momentum strategy has failed following negative trailing markets accompanied by a positive contemporaneous market return. Our explanation is closest in nature to that provided by Daniel and Moskowitz (2014), who also attributed the momentum underperformance to the beta exposure of the strategy, especially the short portfolio.

A Dynamically Hedged Strategy. To account for the dynamic variation of momentum's beta, we tested the following *ex ante* hedging strategy. If the market state has just changed according to our simple rule, we hedged out the beta exposure of the momentum portfolio for the first 10 months of the new up-market state and the first 7 months of the new down-market state—accounting for the beta asymmetry between up and down states. We selected the 10-month and 7-month thresholds because they roughly correspond to the typical duration levels at which the average beta contribution to the momentum portfolio aligns with the direction of the market state. Perhaps because of higher volatility and lower initial beta, it takes several fewer months, on average, for the down-market beta contribution to turn positive than for the up-market contribution. At Month 10 for up and Month 7 for down states, we turned the hedge off and allowed the beta contribution to add to momentum returns.

For robustness, we tested various threshold points, and the results, not shown here, demonstrated a consistent improvement over the unhedged strategy. For example, a 10/10 hedging rule compared with a 10/7 was only 1 bp lower over the full time frame.

Table 13 reports that for the full sample, the dynamically hedged strategy generated a large increase in performance (albeit gross of transaction costs). In the up states, return went from an average of 0.6% per month to 0.9% per month, and in the down states, it went, on average, from 0.1% per month to 0.2% per month. Between 1801 and 2012, the average monthly dynamically hedged long–short return increased to 0.7% from the raw momentum return of 0.4%. **Figure 8** plots the cumulative returns to the dynamically hedged strategy and the raw momentum strategies. Of practical significance to investors using momentum signals is the fact that the hedged momentum strategy significantly outperformed the raw momentum strategy during the periods with large market reversals, such as the past 10 years. Ostensibly, by dynamically moderating momentum portfolio market risk, the hedged strategy is implicitly capturing the remaining market-level momentum, resulting in a significant risk–return improvement for the overall strategy.

We also attempted to compare our hedging methodology with the ones proposed by Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2014). The main difficulty in such comparisons is the absence of daily return data for the pre-1927 period, which significantly inhibits the accuracy of the necessary volatility forecasts. We used 10-month rolling return standard deviation as a crude estimate of expected volatility of momentum portfolios and replicated both the constant Sharpe ratio strategy proposed by Barroso and Santa-Clara and the dynamic Sharpe ratio proposed by Daniel and Moskowitz. Barroso and Santa-Clara created a constant Sharpe ratio–hedged strategy with 12% target volatility by allocating some capital, $W_{BS,t}$, to the raw momentum portfolio and the rest, $1 - W_{BS,t}$, to cash. For every month during our sample period, we solved for the Barroso and Santa-Clara momentum portfolio weight as follows:

$$W_{BS,t} = \frac{12\%}{\sigma_{\mu 0,\tau}}, \quad (7)$$

where $\sigma_{\mu 0,\tau}$, in our simplified version, is the 10-month rolling standard deviation of W – L portfolio returns during the portfolio-formation months.

Daniel and Moskowitz (2014) created a dynamic Sharpe ratio–hedged momentum strategy by using a forecast of expected W – L return, $E(r_{mo})$, based on estimates from the following equation:

$$\begin{aligned} r_{mo,t} = {} & y_0 + y_b(D_t) + y_s\sigma^2\left(r_{ma,t}\right) \\ & + y_{int}(D_t)\sigma^2\left(r_{ma,t}\right) + e_{b,t}, \end{aligned} \quad (8)$$

where D_t is an indicator for the market state (1 if the cumulative performance of the market over months $t-12$ to $t-2$ was negative and 0 otherwise), σ^2 is the

Table 13. Dynamically Hedged Momentum Returns

	Raw Data	Geczy and Samonov[a]	Daniel and Moskowitz[b]	Barroso and Santa-Clara[c]
1802–1926				
Average	0.3%	0.5%	0.2%	0.3%
Standard deviation	4.0%	4.4%	3.1%	4.3%
t-Statistic	2.72*	4.36*	2.53*	2.79*
1926–2012				
Average	0.6%	0.9%	1.3%	1.1%
Standard deviation	5.1%	5.7%	5.5%	5.2%
t-Statistic	3.65*	5.17*	7.72*	6.57*
1800–2012				
Average	0.4%	0.7%	0.7%	0.6%
Standard deviation	4.5%	5.0%	4.3%	4.7%
t-Statistic	4.51*	6.75*	7.75*	6.60*

Notes: For each month t, the price-return momentum strategy used the top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns, $r_{mo,t}$, and market returns, $r_{ma,t}$, were equally weighted and rebalanced monthly.

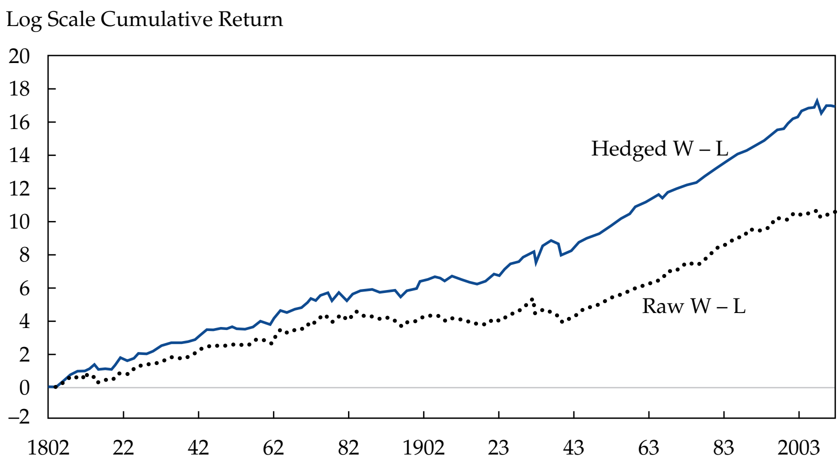
[a]In our study, we used a dynamically hedged strategy and calculated profits as follows. Factor loadings were estimated from the 10-month rolling CAPM regression ending at $t-2$: $r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}$. The hedge profit for month t, $r_{hedge,t} = r_{mo,t} - H_t(B_{mo,t-1})(r_{ma,t})$, where $H_t = 1$ if the state Duration$_{t-1}$ was < 11 months for up markets and < 8 months for down markets; otherwise, $H_t = 0$.

[b]The Daniel and Moskowitz (2014) hedged momentum strategy uses a forecast of expected W – L return, $E(r_{mo,t})$, based on the estimates of $r_{mo,t} = y_0 + y_b(D_t) + y_s[\sigma^2(r_{ma,t})] + y_{int}\,[D_t\,\sigma^2(r_{ma,t})] + e_{b,t}$, and a forecast of variance $\sigma_{\mu 0,\tau}{}^2$, which in our simplified version was defined as the 12-month rolling variance of W – L returns, to estimate the momentum portfolio weight, $W_{DM,t} = [(1/2)(\lambda)E(r_{mo,t})]/\sigma_{\mu 0,\tau}{}^2$, where D_t is 1 if the cumulative performance of the market over months $t-12$ to $t-2$ was negative and 0 otherwise and λ was calibrated to match the Daniel–Moskowitz choice of realized volatility of 19% between 1927 and 2012.

[c]The Barroso and Santa-Clara (2014) momentum strategy uses a constant Sharpe ratio–hedged forecast of volatility, $\sigma_{\mu 0,\tau}{}^2$; in our simplified version, it was defined as the 12-month rolling variance of W – L returns and targeted a volatility level of 12%, solving for the momentum portfolio $W_{BS,t} = 12\%/\sigma_{\mu 0,\tau}$.

*Significant at the 5% level.

Figure 8. Cumulative Returns to the Hedged and Raw Momentum Strategies, 1802–2012



Notes: This figure shows the cumulative difference between the winner and loser log cumulative excess returns of dynamically hedged and raw momentum strategies. For each month t, the price-return momentum strategy uses top and bottom thirds of P_{t-2}/P_{t-12} to designate winners and losers. Momentum returns (W – L), $r_{mo,t}$, and market returns, $r_{ma,t}$, are equally weighted and rebalanced monthly. Dynamically hedged profits are computed as follows: Factor loadings are estimated from a 10-month rolling CAPM regression ending at $t-2$: $r_{mo,t} = a_{mo} + B_{mo}(r_{ma,t}) + e_{mo,t}$. The hedge profit for month t is $r_{hedge,t} = r_{mo,t} - H_t(B_{mo,t-1})(r_{ma,t})$, where H_t is 1 if the state Duration$_{t-1}$ is < 11 months for up markets and < 8 months for down markets and 0 otherwise.

10-month rolling variance of market returns during the portfolio-formation months, and $r_{ma,t}$ is the market return. We solved for the Daniel and Moskowitz momentum portfolio weight, $W_{DM,t}$, as

$$W_{DM,t} = (1/2)(\lambda)\left[\frac{E(r_{mo,t})}{\sigma^2_{\mu 0,\tau}}\right], \tag{9}$$

where $E(r_{mo,t})$ is the expected momentum portfolio return based on estimates from Equation 8, σ_τ^2 is defined as the 10-month rolling variance of W – L portfolio returns during the portfolio-formation months, and λ is a constant term that scales portfolio volatility, which was set to match the Daniel–Moskowitz choice of realized volatility of 19% in the post-1927 time frame.

Table 13 shows that we confirmed the benefits found in the post-1927 time frame of both the dynamic and the constant Sharpe ratio–hedged approaches (even with our crude estimate of volatility). These approaches would have resulted in significant improvements over the raw momentum strategy. This result is not what we found, however, in the pre-1927 history. Specifically, the average monthly W – L spread for the dynamic Sharpe ratio strategy was, on average, 1.3% between 1927 and 2012, compared with the 0.6% for the raw momentum strategy. Yet in the pre-1927 data, the same strategy averaged 0.2% per month, slightly lower than the 0.3% for the raw momentum. The strategy based on a constant Sharpe ratio also added significant value in the post-1927 period, averaging 1.1%, but it delivered no noticeable improvement in the pre-1927 period, when it averaged 0.3%. In the post-1927 time frame, dynamic Sharpe hedging outperformed both the constant Sharpe strategy and our proposed approach, but during the earlier history, the hedging strategy proposed in this article performed the best.

These out-of-sample tests of recently established hedging strategies based on post-1927 data raise important questions about the stability and robustness of such approaches. As mentioned previously, the frequency of momentum drawdowns was much larger in the pre-1927 period than in later data, resulting in a more complete distribution of momentum crashes than previously considered. More importantly, we have demonstrated that the dynamic nature of momentum portfolio beta is the fundamental driver of the underperformance, and its influence grows with the duration of a given market state. Our proposed hedging strategy directly takes the importance of the market state into account and hedges the portfolio at market turning points. In the alternative hedging formulations, because the weight of the allocation to momentum varies inversely with realized momentum volatility, the strategies rely heavily on the sustained negative correlation between realized momentum volatility and future momentum payoffs. In the post-1927 data, the correlation between realized volatility and future-month momentum return has been –4.2%, whereas in the pre-1927 data, it was only –0.83%. Specifically, the two largest post-1927 momentum drawdowns followed extreme and volatile market conditions—the Great Depression of the 1930s and the financial crisis of 2008. Hedging strategies focused on Sharpe ratios protect well against such occurrences because during these events, strong increases in trailing volatility were predictive of the upcoming momentum crashes as a result of the upcoming strong market reversals. Yet, as we have shown, the nature of the relationship between volatility spikes and upcoming market reversals appears to have been different in the 19th century. Deeper investigation of these relationships is a research opportunity for future studies.

Conclusion

We initiated out-of-sample research of 19th- and early 20th-century US stock-level data by creating a dataset starting in 1801 and extending through 1926. This dataset made possible both in-sample and out-of-sample tests of momentum strategies. We extended testing of the traditional equity price-return momentum strategy to the pre-1927 data and found its effect to be significant since the beginning of the 19th century. We found that in the pre-1927 data, the mean return of the basic price-return momentum effect was statistically significant at about half that of the post-1926 period. From 1801 to 1926, the equally weighted top third of stocks sorted on price momentum outperformed the bottom third by 0.28% per month, on average, compared with 0.58% per month for the 1927–2012 period. Linking the two periods together generated a 212-year history of momentum returns, averaging approximately 0.4% per month.

We found both industry-neutral and industry-level momentum strategies to be statistically significant. Additionally, we found that individual macroeconomic variables do not explain momentum.

Analyzing the longer time frame was especially useful for time-series tests because the sample size was more than doubled. Using the longer time series, we observed a robust connection between momentum spread portfolio betas and alphas and the duration of up and down markets: The longer each state continued, the more market exposure contributed to momentum returns. The longer a market state lasts, therefore, the riskier the momentum strategy becomes, and when the market conditions change, the strong beta exposure significantly denudes momentum profits. Dynamically hedging out beta in the early stages of a market state significantly improves the profitability of the base momentum strategy.

We thank Cliff Asness, David Blitz, Mark Carhart, and Jay Shanken for comments and Eugene Fama, Kenneth French, William Goetzmann, Michael Halperin, Roger Ibbotson, Charles Jones, Liang Peng, and Bryan Taylor for data. We also thank Peter Cachion and our research assistants, Kseniya Demchenko and Kirill Samonov, as well as Global Financial Data, the International Center of Finance at Yale, the Inter-University Consortium for Political Social Research, and Wharton Research and Data Services.

Appendix A. Data Collection

The ICF dataset was created for and described in detail in Goetzmann et al. (2001). It covers a total of 671 NYSE stocks between January 1815 and December 1925. Month-end equity prices were manually collected at a monthly frequency from archived newspapers of the time. A total of 57,871 unique monthly return observations were recorded.

The ICPSR dataset was created for Sylla et al. (2006). Prices were manually collected from archived newspapers of the time for nine US exchanges: New York, Boston, Philadelphia, Baltimore, Charleston (South Carolina), New Orleans, and three in Virginia—Richmond, Norfolk, and Alexandria. Within any given month, price frequency ranged from daily to monthly. We filtered out any preferred, fixed-income, or international securities, resulting in a total of 1,167 common US stocks covered between January 1800 and May 1862. To convert ICPSR data to a monthly frequency, we allowed for a look-back window of one month minus a day. Hence, if a security price was missing during the month-end date, we looked back for the last available price during the same calendar month. This approach significantly improved data coverage for stocks whose prices were available only in the weeks not coinciding with month ends. Sometimes an asking price was supplied in addition to the bid price, in which case we averaged the two. As a result, we had available a total of 103,684 unique month-return observations.

The GFD dataset holds 3,992 common stocks between January 1825 and December 1925 and another 94 unique stocks for 1926. Because of the reporting format of the newspapers used for this data collection, month-end prices represent averages of the maximum and minimum prices reached during each calendar month. We had available from this source a total of 305,574 unique month-return observations.

We merged the three datasets to create the "merged" dataset by using company names and correlations of prices; no other security identifiers were common among the three datasets. Naming conventions among the three datasets vary greatly in terms of abbreviations, articles, order of words, and so on, so a simple name comparison without price correlations was not sufficient. Because the GFD database is the largest, we used all available GFD data as a starting point and supplemented them with unique data from the ICF and ICPSR sources. We followed this procedure: First, for each ICF security, we generated a list of GFD securities with which it had the highest price correlations. Next, we made a manual comparison of ICF security names and the names in the generated list, and if we found a clear match of names, we paired them; otherwise, we considered the ICF security to be unique. Then, we performed the same procedure for the ICPSR securities against the merged GFD and ICF dataset. All ICPSR securities were assigned to a list labeled "unique" or "already included" in the GFD–ICF dataset.

We identified 222 unique securities in the ICF dataset and an additional 401 unique securities in the ICPSR dataset that were added to the GFD dataset, resulting in a total of 4,709 unique securities in the merged dataset. An important point is that, in addition to enlarging the set of unique securities, the merged dataset filled in missing data for the GFD individual securities, creating a richer dataset. To fill in data, we looked for any missing month-end prices from the GFD dataset in the other two sources and used any additional data that were available. The merged dataset also resulted in an extended coverage period—from January 1800 to December 1926. The only interruption of the merged data occurs during the first two months of World War I in 1914. The merged dataset contains a total of 413,922 unique month-return observations.

Inspection of the price data for potential outliers revealed that many stocks experienced either a one-month price outlier or a multimonth shift to a new scale of prices and then returned to the original scale. According to Goetzmann et al. (2001), jumps of these magnitudes are caused by erroneous data either in the original newspaper source or in data compilation. Given the manual nature of price entry for these securities from archived newspapers into spreadsheets, data entry mistakes across the three datasets had a reasonable chance of occurring. Another source of large price changes was liquidation dividends, which were common at the time. According to Goetzmann et al., liquidation dividends were a result not of bankruptcies but, rather, of loss of charters and orderly business closures. In these cases, negative price returns were, at least partially, offset by the dividend payments. Finally, according to Goetzmann et al., no splits occurred in their sample, so price jumps were unlikely to have been caused by stock splits.

To account for the outlier effects, we Winsorized outlier returns at a 50% cutoff by setting returns that were outside the 50% range to 50%, resulting in about 1.6% of the sample being designated outliers. On the negative side, by Winsorizing negative returns at the –50% level, we conservatively accounted for the situations involving a liquidation dividend. Our momentum results are robust to various Winsorization boundaries (±75%, ±100%); however, the returns generated for the universe as a whole and the 50% Winsorization rule are most consistent with the published results.[6] Specifically, the wider the boundaries became, the higher the universe return and standard deviation became, which shows the impact of erroneously recorded price jumps.

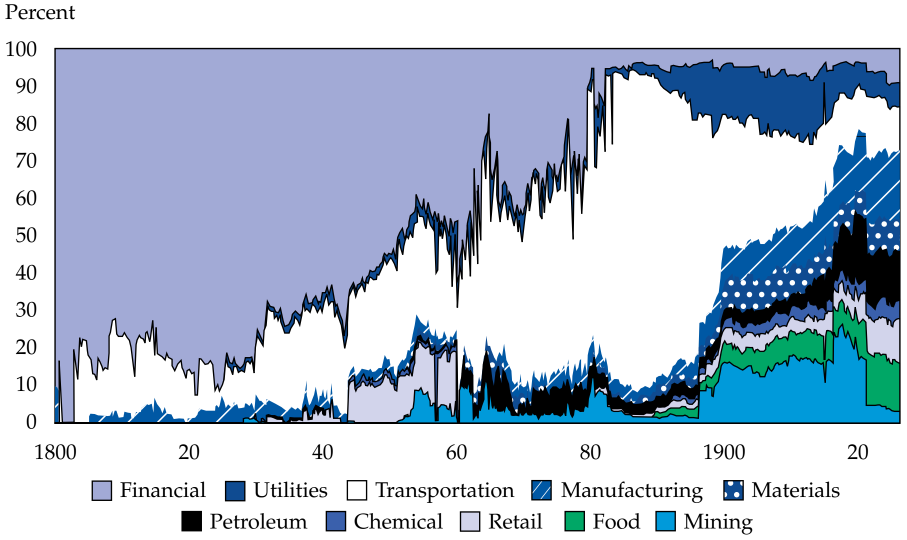
Appendix B. The Picture in the 19th and Mid-20th Centuries

This appendix provides in **Table B.1** a list of the first (mainly financial) firms with traded stocks as of 1800 and shows in **Figure B.1** the distribution of industries from 1800 to 1926.

Table B.1. Initial 10 Companies in January 1800

January 1800	Price ($)	Sector
Bank of North America	600	Finance
Bank of Pennsylvania	480	Finance
Bank of the State of New York	135	Finance
Bank of the United States	500	Finance
East India Co. of North America	100	Manufacturing
Insurance Co. of North America	10.5	Finance
Insurance Co. of Pennsylvania	488	Finance
Manhattan Bank Co.	113	Finance
New York Insurance Co.	113	Finance
Union Bank	118.75	Finance

Figure B.1. Distribution of Industries, 1800–1926



Notes

1. CRSP is the Center for Research in Security Prices; SBBI is a reference to *Stocks, Bonds, Bills, and Inflation*—a book, updated annually, originally prepared by Roger G. Ibbotson and Rex A. Sinquefield.
2. This result has given rise to both rational explanations and limits-to-arbitrage explanations of the premiums, although Geczy, Musto, and Reed (2002) demonstrated that at least one class of constraint imparted by short-selling frictions seems not to impact momentum strategy premiums.

3. According to email correspondence with William Goetzmann in 2008.
4. An alternative way to define stock-specific momentum is to use the residuals, e_i, from a simplified form of Equation 1, $r_{i,t} = a_0 + B_i\,(r_{ma,t}) + e_i$, to form a 10-month residual momentum as in Blitz, Huij, and Martens (2011). The specifications produced similar and statistically significant positive results before and after 1927.
5. For these tests, macroeconomic data were obtained from GFD (www.globalfinancialdata.com/index.html) and Measuring Worth (www.measuringworth.com/).
6. For the overlapping period from 1815 to 1925, we closely matched the average universe price-only 50% Winsorized returns from our study (0.28%, from Table 1) with the results of Schwert (1990), 0.21%; Goetzmann et al. (2001), 0.19%; and Sylla et al. (2006), 0.22%, for the same period. With a 100% Winsor boundary, however, the calculated average universe return became 0.46%, much larger than with the 50% boundary, because of erroneous data.

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