Two Centuries of Price Return Momentum

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Abstract

We assemble a monthly dataset of U.S. security prices between 1801 and 1926 and, both in and out of sample, test price-return momentum strategies discovered in the post-1927 data. The pre-1927 momentum profits remain positive and statistically significant. Additional time-series data strengthen the evidence that momentum is dynamically exposed to market risk, conditional on the sign and duration of the trailing market state. In the beginning of each market state, momentum's equity beta is opposite from the new market direction, generating a negative contribution to momentum profits around market turning points. A dynamically-hedged momentum strategy significantly outperforms the un-hedged strategy.

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The first two U.S. stocks traded in 1792 in New York. Over 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. Most current academic studies of U.S. security-level data begin in or after 1926, the year the CRSP database and the SBBI files began. However, the U.S. market had been active for 133 years before that time, providing an opportunity to test stock return characteristics in earlier history. The 19th and early 20th centuries are filled with economic growth, contractions, wars, monetary and currency regimes, macroeconomic shocks, bull and bear markets and market volatility of varying magnitudes, all providing a rich out-of-sample history. Limiting studies to the post-1925 period (often utilizing the same data set!) introduces a strong selection bias and does not capture the full distribution of possible outcomes.

For example, consider the case of price-return momentum: Before 2009, only following the Great Depression did the basic strategy of following winners and eschewing losers (via the traditional momentum definition) have a decade-long negative compounded return. Without the broader view afforded by the more extensive sample, such an occurrence might have been considered to be an anomalous outlier with the remaining part of the distribution of outcomes remaining the focus of study. As a result of a significant drawdown in the strategy in 2009, following a period of substantial economic distress, momentum experienced another significant period of underperformance, creating a ripple in investment portfolios that use 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 has and will continue to influence theory examining this powerful characteristic in returns. By extending our analysis of equity momentum to 1801, we create a more complete picture of the potential outcomes of momentum strategy returns, discovering *seven* additional negative decade-long periods before 1925.

The first contribution of this study is a creation of a monthly stock price and price-return dataset. In this dataset, three known 19th and early 20th century data sources are combined into one testable dataset from 1800 to 1927. Those data sources are from the International Center of Finance at Yale University (ICF), the Inter-University Consortium for Political and Social Research (ICPSR), and Global Financial Data (GFD). Between 1800 and 1927, the merged dataset contains an average of 272 securities with price-return data per month (10 and 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 to add to the existing momentum literature by extending tests to the new data. We find 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-1927 period. From 1801 to 1926, the equally-weighted top third of stocks sorted on price momentum out-performed the bottom third by 0.28% per month on average (t-stat 2.7), compared to 0.58% per month (t-stat 3.6) for the 1927-2012 period. Linking the two periods together generates a 212-year history of momentum returns, averaging approximately 0.4% per month (t-stat 5.7).

As observed in the studies of the 20th century data for the traditional expressions of the strategies, momentum profits are highly variable over time, giving rise both to rational and limits to arbitrage explanations of the evident premia, although Geczy, Musto and Reed (GMR 2002) demonstrate that at least one class of constraint imparted by short-selling frictions seems not to impact momentum strategy premia. 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 momentum effect is not a product of data-mining but is persistent and has significant variation over time.

The third contribution of this study is to link the fundamental momentum strategy's market exposure to the market state duration. We find strong evidence that momentum's beta is positively exposed to the duration of both positive and negative market states. The longer a given market state persists, the stronger the momentum portfolio beta historically exposure becomes. Analyzing the longer time frame is especially useful for these time-series tests, as the sample size is more than doubled.

Using a 10-month return definition of a market state, we identify 116 discrete states in the full sample, with 69 of them in the pre-1927 period. We find strong evidence that momentum's beta is dynamic not only across up and down market states alike, but also within a given market state. In the first year of a given up or down market state, momentum's market exposure on average generates a negative contribution to the strategy's returns, while the non-market ("alpha") component of momentum's return is significantly positive during this time. In market states that last longer than one year, momentum's beta becomes a positive contributor to returns, while alpha contribution gradually declines. As a result, over the course of a market state, momentum's positive return drivers transform from a stock-specific effect to a combination of common-risk and stock-specific components.

We find that both industry-neutral and industry-level momentum strategies are statistically significant. Additionally, we find that individual macroeconomic variables do not explain momentum. However, the market states, which arguably encompass and lead the macroeconomic data, do significantly affect the nature of momentum profits, even as alphas remain significant.

The rest of the paper is organized as follows: Section I describes the pre-1927 data assembly process; Section II uses the early security data to test the price-return momentum effect; and Section III provides a decomposition of momentum profits into common and stock-specific components. Section IV concludes.

I. Early Security Returns Data

A series of academic efforts extended aggregate stock market returns back to 1792, the recognized inception of the U.S. stock market. While some of these studies work with already created indices (Schwert (1990), Siegel (1992), Shiller (2000), Wilson, Jones (2000)), others assemble individual security prices into datasets from which aggregate level returns are computed (Cowles (1939), Goetzmann, Ibbotson, Peng (GIP 2001), Sylla, Wilson, Wright (SWW 2006), Global Financial Data). While the original stock-level Cowles Foundation data files seem to have been lost[1], the other datasets are preserved; however, they vary both in the specific securities and the time periods they cover.

Return estimation and index construction methodologies also vary among studies. For example, Schwert (1990) uses spliced index data from Cole and Smith (1935); Macaulay (1938); Cowles (1939); and Dow Jones (1975). As a result, his index is equally-weighted before 1862, value-weighted from 1863 to 1885, and price-weighted between 1885 and 1925. GIP (2001) use price-weighted index construction over 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 (GIP (2001)) versus an average of high and low prices within the month (Cowles (1939), GFD).

[1] According to William Goetzmann (2008), email correspondence.

Our 1800-1926 dataset of security prices (hereafter Merged) and industry classifications is assembled from three sources: International Center of Finance at Yale (ICF); Inter-University Consortium for Political and Social Research (ICPSR); and Global Financial Data (GFD). Details of the data sources and our merging procedures are described in Appendix I. Table I contains summary statistics.

The number of securities with monthly return data grows from 10 in January 1800 to 781 in December 1926. The initial 9 out of 10 companies in January 1800 are financials with one manufacturing company (see Appendix II). For the majority of the period, the number of securities grows steadily, with the exception of the Civil War period in the early/mid 1860s, when a large drop in coverage takes place. This drop is also witnessed by GIP (2001) and is due to newspapers dropping coverage of many traded securities. After reaching a maximum of 415 securities in July 1853, the number first slowly and then rapidly drops to a minimum of 53 in January 1866. From then on it slowly grows, crossing 400 in May 1899.

Industry mappings in this study are used to estimate industry-neutral and industry-level momentum. Industry mappings for the Merged dataset are 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 firms in each group. From 52 GFD Industries, 6 IFC Sectors and 4 ICPSR sectors, we aggregate to 11 final groupings: Mining, Food, Retail, Chemical, Petroleum, Materials, Manufacturing, Transportation, 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 towards railroad and transportation companies (see Appendix II). Over the course of the 19th century, more industries emerge, reaching a required level of three by 1806, a figure necessary for the industry momentum computation.

The smallest sector by number of firms is Chemical with an average of 4 stocks over the pre-1927 period. The largest is Transportation with an average of 69 stocks. It is important to highlight that the average numbers stated above include many months in which a sector has 0 securities. For example, the Chemical sector has an average of 11.3 stocks, during the months when at least one Chemical company is present. This is an important feature for industry-neutral momentum portfolios, which become more robust as the number of securities increases in each industry. Nevertheless, there are clearly some months during which the number of securities in any given industry can dip to the low of three, the minimum required for an intra-industry momentum computation, making the results of that industry-neutral momentum less reliable during those months.

For the post-1927 period, we rely on the Center for Research in Security Prices (CRSP) database of security prices. The same market and momentum return computation methodology is applied to the CRSP data as it is to the Merged data. The CRSP price data begin on December 31, 1925 with 503 securities growing to 540 by December 31, 1926. The Merged dataset has 781 securities with one month return on December 31, 1926. Hence it appears that the Merged dataset is noticeably larger than the initial CRSP security list. However, in this study, we do not link the Merged securities data set to CRSP securities directly. Because the last month of Merged momentum return is on December 1926 and the first month of CRSP price momentum return is on January 1927, we splice the two time-series together to create an uninterrupted momentum history. In the equally-weighted universe returns during the overlapping 12 months of 1926, we see a correlation of 97.2% between the CRSP and Merged returns. For industry momentum computations during the CRSP period, we use 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, as the largest sector in both datasets is manufacturing with 127 CRSP and 169 Merged securities.

II. The Price Momentum Premium

A. Background

Like its highly examined in-sample performance, the out-of-sample record of momentum in equity returns has been exceptional. A positive gross premium has been seen in the data after its published discovery in the U.S. market (e.g., Jegadeesh, Titman (1993)), in the international markets (Rouwenhorst (1997)), market indices (Asness, Liew, Stevens (1997)), tactical asset allocation (Faber (2013)), currencies (Bhojraj, Swaminathan (2006)), and commodities (Gorton, Hayashi, Rouwenhorst (2012)). A recently updated study of both value and momentum effects "Everywhere" traces the power of the effect across the globe (Asness, Moskowitz, Pedersen (2012)). The momentum effect has also been confirmed in the 19th-century British and Russian stock prices (Chabot, Ghysels, Jagannathan (CGJ 2009) and Goetzmann and Huang (GH 2015)) and in two centuries of multi-asset trend following Lempérière et al. (2014).

Since Jegadeesh and Titman (1993), a large body of research attempts to isolate a risk-based explanation for the effect, in line with market efficiency. The following recent studies provide the roadmap for our discussion: Kotari, Shanken (KS 1992); Moskowitz, Grinblatt, (MG 1999); Grundy, Martin (GM 2001); Chordia, Shivakumar (CS 2002), Griffin, Ji, Martin (GJM 2003); Cooper, Gutierrez, Hameed (CGH 2004), Siganos, Chelley-Steeley, (SCS 2006), Liu, Lu

(LL 2008), Asem, Tian (AT 2010), Stivers, Sun (SS 2012), and Daniel and Moskowitz (DM 2014).

These studies investigate whether momentum profits are driven by industry effects (MG 1999); variation of expected returns (GM 2001); factor-level versus stock-specific momentum (GM 2001); macroeconomic factors (CS 2002, GJM 2003, LL 2008); or market states (CGH 2004, SCS 2006, SS 2012). The later studies conclude that industry momentum is a separate effect from stock-level momentum and find that market state is a better proxy for risk than macroeconomic variables.

KS (1992), JT (1993), more formally by GM (2001), and recently Blitz, Huij, Martens (2011) explore the connection between momentum portfolio beta loadings and the factor realization over portfolio formation periods. GM (2001) explore analytically and find empirically that the momentum spread portfolio is loaded with high beta stocks during the bull market and negative beta stocks during the bear market.

A number of subsequent studies analyze the connection between market states and momentum profits. CGH (2004) observe that momentum returns following an up market are higher than following the down market. SCS (2006) finds that momentum profits are stronger after lagging poor market returns, where the longer the duration of a poor market, the stronger the momentum returns realized. DM (2014) explore momentum crashes and concludes that they follow periods of volatile and negative market returns. Finally, AT (2012) and SS (2012) observe that momentum returns are stronger within a given state and are weaker during state transitions.

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

B. Empirical Results

As in many studies, our measure of price return momentum is defined as a stock's simple price return from t – 12 to t – 2, skipping the DeBondt and Thaler (DT 1985) reversal effect. Every month in the research sample, each stock each stock is assigned to one of three portfolios based on prior 10-month price change. Stocks with the highest momentum are assigned to the Winner (W) portfolio, and stocks with the lowest momentum are assigned to the Loser (L) portfolio. The portfolios are rebalanced monthly, and a one-month forward equally-weighted return of each portfolio is computed. Excess returns are derived by subtracting the market return, which is the equally-weighted return of all stocks, form the momentum portfolio return. Returns to this strategy are observed between February 28, 1801 and December 31, 2012. To compute the market returns we use the equally-weighted method of price-only returns, because we do 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. This makes impossible at this stage any attempt to compute total returns for individual securities and the momentum effect. However, we believe that price returns reflect information sufficiently for the purposes of extending the momentum studies. In addition, as is well known, dividends and firm payouts have varied systematically over time with changes in tax and legal regimes as well as changes in preferences, although certainly dividend volatility has tended to be swamped by price change volatility. One way of thinking about our focus on the capital gain portion of total returns is that it might assume that the dividends of the Winners roughly offset the dividends of the Losers. We test our assumption in several ways. First, using the post-1927 CRSP dataset we confirm that the momentum strategy that is based on price only data for both momentum signal and the return computation generates Winner and Loser portfolios with the same average dividend yield (2.97% for Winners and 2.90% for Losers). In particular, we compute dividend yields as in Fama and French (1988), by taking the twelve month difference between total return (RET) and price return (RETX) as reported in the CRSP database. Second, we measure the total return of this price only momentum strategy and confirm that the Winner-Looser spread remains the same as the one measured using price only returns (58 bps per month vs 57 bps per month between January 1927 and December 2012). Finally, we use the annual IFC dividend data between 1826 and 1871, which is available only for a small subset of our Merged dataset and compute the average dividend yield for the Winner and Loser portfolios generated from the Merged dataset using price only data. We find the average dividend yield of the Winner portfolio to be 7.35% and Loser 5.95%. In our final tests, these values need to be viewed with caution as many months do not have any dividend information since all the stocks in the Winner or Looser portfolio in any given month might not have a dividend value in the IFC dividend dataset. Nevertheless, these findings support our assumption that, when formed based on price return momentum, Winner portfolios do not have a lower dividend yields than Losers. Hence, our Winner minus Looser portfolios returns are not likely to be positively biased due to omissions of dividends.

During the 1801-1926 period, the average monthly excess return of the W portfolio is 0.18% (t-stat 3.5), the L portfolio is -0.10% (t-stat -1.7), and the W-L portfolio is 0.28% (t-stat 2.7). During the 1927-2012 period, the W portfolio average monthly excess return is 0.34% (t-stat 4.5), L portfolio -0.24% (t-stat -2.8), and the W-L return is 0.58% (t-stat 3.6). In Table II and Figure I, we show that during the entire period from 1801-2012, the W-L return is 0.40% (t-stat 4.5), the W portfolio excess return is 0.25% (t-stat 5.7) and the L portfolio excess return is -0.16% (t-stat -3.2).

The previously untested pre-1927 data confirm the significance of the momentum premium among 19^{th-} and early 20^{th}-century U.S. stocks. The combined history creates the longest known U.S. stock-level backtest of 212 years (or 2,543 months of momentum observations). The size of the effect is stronger in the post-1927 period, yet it remains both economically and statistically significant in both sub-periods. Moreover, we observe positive average W-L momentum returns in individual pre-1927 datasets as well. Using ICPSR data only, the W-L spread is 0.25% per month (t-stat 1.8) for the 1801-1862 period, using GFD data only, the W-L spread is 0.25% (t-stat 2.1) for the 1826-1926 period, and using IFC data the W-L spread is 0.34% (t-stat 1.9) for 1816-1925 period. The momentum effect apparently is present in each of the three different datasets for different (albeit overlapping) coverage periods and sample sizes.

The overlapping period across the three datasets ranges from 1826 to 1862. In this period the W-L monthly spreads are: ICPSR +0.17%, GFD +0.38%, and ICF +0.44%. The Merged dataset over this period generates and average 0.33% W-L spread. This overlapping period reveals the increased robustness effect achieved by merging the three datasets. Between 1826 and 1862, ICPSR has a monthly average of 158 securities with return data, GFD has 107 such securities, and ICF has 15. The merged dataset results in the 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 appears 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 above, momentum premium profits are lower during the pre-1927 period as is the equity premium. These results appear consistent with GH (2015), who observe a strong increase in momentum profits in the Russian Stocks after 1893, which they attribute to the increase ease of speculation. Without a theoretical model linking the size of the momentum premia to the size of the equity premia, we cannot access whether this correlation is meaningful, yet there does appear to be some commonality in the increase of both during the 20th century, which appears unconditionally lower on average in the latter part period, judging from prior studies. In addition, as observed by GM (2001) and CGJ (2009), significant time variation to momentum payoffs occurs. During the pre-CRSP history, 10-year annualized return is negative in three decades (1890: -0.6%, 1900: -2.1%, and 1920: -1.2%). Figure III shows that, on a 10-year rolling basis, there are seven negative periods. These are significant 10-year drawdowns and it is highly likely that any levered investor in the momentum strategy would have experienced a margin call during these periods. During the rest of the early history, 10-year profitability varied between 0% and 15.3% per year.

During the recent decade of negative momentum performance (from January 2002 to December 2012) the annualized W-L spread is -2.1%, which appears less anomalous within the longer historical timeframe of our study than it might 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 into this strategy over the last two decades, it does provide evidence that such periods of extended underperformance have occurred in the past. A limits to arbitrage hypothesis, stating that momentum profits are too risky to be fully arbitraged, would suggest that the latest period of underperformance would eventually give way to positive momentum returns once again, while a pure anomaly theory might suggest that momentum profits have now been arbitraged away.

As an important side note and as noted by GM (2001), the turnover of the base momentum portfolios is very high, in the pre-1927 period averaging 27.6% and 27.5% per month per each Winner and Loser side respectively. Of course, in such raw, unconstrained and non-optimized form, 19th century trading costs (or the trading costs of any century!) would likely eat away the stated profits. Furthermore, shorting was not widely possible during the 19th century. On the other hand, it is important to emphasize that factor-mimicking portfolios (or anomaly tracking portfolios) do not need to be tradeable for them to be useful to 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 its practical tradability, our understanding of the existence and features of the momentum effect is deepened with the extended history.

The January effect is in the same negative direction before 1927 as it is after, as described by Schwert (1990). In the 1801-1926 period, average W-L spread during the month of January is -0.1%, while it is 0.3% during non-January months, although the January t-statistic is not significant (t-stat 0.32) during the early period. In Table VI, we report that the post-1927 period the W-L January return is -3.3% (t-stat -6.0) and non-January spread is 0.9% (t-stat 7.2). 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 and 2002) document a decline in the magnitude of the January effect.

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

Confirming existing long-term reversal studies (such as DT (1985) and JT (1995)), momentum profits experience a significant reversal within eight months of portfolio formation. The power of this mean reversion effect is strong since it is apparent and we measure a non-overlapping future one-month performance of the W-L strategy. So, for example, in month 11 after portfolio formation, the W-L return in the pre-1927 period is -0.31% with a t-stat of -3.1, and in the post-1927 period, it is -0.78% with a t-stat of -5.8. The negative returns persist for up to five years after portfolio formation.

Another well-known effect, that of short-term reversal (Jagadeesh (1990)) is also present in the pre-1927 history. We observe that both P_t / P_{t-1} and P_{t-1} / P_{t-2} months experience reversals during the entire sample we study, but the P_{t-1} / P_{t-2} reversal is statistically significant only during the pre-1927 history, perhaps due to liquidity or mark-to-market effects. As a result we require that our momentum formation period ends on month *t-2*. In the pre-1927 data, Long-Short portfolio based on month P_t / P_{t-1} reversal averages is 0.22% per month (t-stat 2.1) and P_{t-1} / P_{t-2} reversal averages 0.82% (t-stat 7.3). In the post-1927 history, the corresponding results are 1.4% (t-stat 10.9) for P_t / P_{t-1} and 0.14% (t-stat 1.3) for P_{t-1} / P_{t-2}. In Table IV, we show that the combined P_t / P_{t-2} reversal effect averages 0.8% (t-stat 7.7) in the pre-1927 history and 1.1% (t-stat 8.1) in the post-1927.

One strong and unexpected pattern which deserves further exploration outside the current examination that emerges in the pre-1927 data related to the cumulative behavior of the P_t / P_{t-1} price reversal factor. For the first 64 years from 1801 to 1865 the average 1m reversal return is 1.7% and for the following 62 years, from 1866 to 1926, the average reversal return is -1.3%, shown in Figure IV. This dynamic is puzzling. At the same time, the P_{t-2} / P_{t-1} month reversal is extremely strong in the pre-1927 data and then is practically flat in the post-1927 data. It is possible that some distortion is caused by the data collection methods of the pre-1927 prices. In addition, it is possible that the patterns documented in previous studies on the reversal effect are simply sample-dependent. As we note earlier, pre-1927 price returns are rarely based on precise month-end prices, but rather either an average of min and max prices achieved during the previous month or the available end of week price closest to month end. Of course, there does arise a distinct possibility that just as medium term momentum can experience very long periods of underperformance, so can the price reversal effect.

III. Sources of Momentum Profits

A. Industry-Neutral Momentum

We first examine whether industry momentum explains stock-level momentum and, like previous studies, find 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 above, we test an industry-neutral momentum portfolio by ranking each stock within its industry based on its 10-month price change. We then combine the top third of ranked stocks from each industry into a Winner portfolio and the bottom third into a Loser portfolio. Rebalancing monthly, we find that between 1801 and 1927 the industry-neutral average monthly

W-L return is 0.21% (t-stat 2.2), compared to the raw 0.28% (t-stat 2.7), reported in Table V. We then construct an industry momentum portfolio by identifying the three industries out of the ten with the highest and three 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 is 0.3% (t-stat 1.9) on average. For the full history between 1801 and 2012, the average industry momentum return spread is 0.34% (t-stat 3.2) and average industry-neutral momentum spread is 0.33% (t-stat 4.0).

We also test the industry momentum strategy without skipping the reversal months and discover stronger results in both periods, pointing to the fact that industries do not experience the stock-level reversal effect, again as documented previously. Between 1801 and 1926, 10-month industry momentum -- without skipping the reversal effect -- generates 0.35% per month on average (t-stat 2.2), and between 1927 and 2012 the return to this strategy is 0.61% per month (t-stat 5.7). For the full history from 1801 to 2012, the 10-month industry momentum without skipping the reversal effect generates 0.46% (t-stat 4.4) on average. Consistent with GM (2001) and many others, Figure V shows that pre-1927 data confirm that industries have a momentum of their own, which does not explain away the stock-level momentum.

B. Common vs. Stock-Specific Momentum

Following the GM (2001) methodology, we test 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 decompose momentum returns into stock-specific momentum and factor momentum by regressing individual stock returns (priced-based) on a dummy variable and the market return

$$r_{i,t} = a_0 * D_t + a_1 * (1\text{-}D_t) + B_i * r_{ma,t} + e_i, \quad (1)$$

where $D_t = 1$ during the momentum formation months (t-12:t-2) and 0 elsewhere (t-13:t-60); $r_{i,t}$ is the month *t* stock-level return; $r_{ma,t}$ is the month *t* market return, which is defined as the equally-weighted price return of all the stocks with available data in that month. We construct a stock-specific momentum strategy using a_0 as the ranking input (10-month stock-specific momentum)[2], and the factor-related return momentum strategy uses $B_{i,t} * r_{ma,t:[t-12:t-2]}$ as the ranking input. Table VI reports the results. Confirming GM (2001), we find that the stock-specific momentum effect is positive and significant. Between 1801 and 1927, the average stock-specific W-L portfolio spread is 0.22% per month (t-stat 2.3), and for the 1927-2012 period it is 0.7% per month (t-stat 6.9).

The common factor momentum component is also positive in both periods. For the entire period, the common factor momentum spread is 0.25% (t-stat 2.1) per month, on average. The common factor momentum is more significant in the early history with a spread of 0.31% per month on average (t-stat 2.2). Importantly, the longer history makes it clear that both the stock-specific and common factor momentum components are priced. As our further results will demonstrate, the premium of these factors arises at different points of a given market state, with the stock-specific momentum payoff more dominant at the early stages of a market state, while the common-factor component is more dominant at later stages.

[2] 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, Martens (2011). Both specifications produce very similar, statistically significant positive results before and after 1927.

C. Beta Variation of Momentum Portfolios

While many studies attempt to explain performance of momentum with individual macroeconomic variables (for example CS 2002, GJM 2003, LL 2008), 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 (CGH 2004, SCS 2006, DM 2014, SS 2012). Because the momentum factor becomes riskier the longer a "market state" lasts, when the economic conditions change, the strong beta exposure at the worst possible time significantly harms momentum profits.

Unreported in this paper, we test whether common macroeconomic indicators explain momentum profits and concur with CGH (2003) that no single macroeconomic variable explains momentum profits. We test change in expected inflation (DEI); unexpected inflation (UI); term-premium (UTS); growth of industrial production (YP); default-premium (URP); consumption growth (CG); where CG is proxied by wage growth; commodity price growth (CG); FX $ versus pound exchange (FX); and residual market (RES) computed by regressing the macro variables from the market return and using the residual as a factor. Only the UTS factor is found to be significant in the post-1927 period. For these tests, macroeconomic data was obtained from the Global Financial Data and Measuring Worth websites. These results suggest that it is unlikely that momentum is subsumed by the Chen, Roll and Ross (1986) factors.

GM (2001) provide analytical evidence and estimate the empirical demonstration of the variation of momentum beta exposure as a function of the trailing market return. When the market has been positive during the momentum formation period, our momentum spread portfolio's beta is positive, and it is negative following negative market return. Even 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 experienced a strong rally.

Because market state and momentum definitions vary across studies, results in the literature are difficult to compare. For example, GM (2001) define up and down states as the 6-month trailing equally-weighted total return of the market above / below one standard deviation around the full sample average return. On the other hand, CGH (2004) define market states via the sign of the 36-month trailing value-weighted total return of the CRSP index. Alternatively, SS (2012) define market states based on a peak-to-trough ex-post value-weighted total return in excess of +/- 15%. Finally, DM (2014) define a "market state" as the value-weighted 2-year return of all CRSP stocks. While CGH (2004) conclude that momentum returns are positive only following up markets, SS (2012) conclude that momentum returns are positive within a given market state, either up or down, and negative during transitions. DM (2014) conclude that momentum crashes occur during market reversals that follow negative market states with high volatility.

We use a market state definition that matches our momentum portfolio formation definition. In the current study, the momentum formation period covers 10 trailing months (skipping the reversal months), and 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 use 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 market state with the momentum portfolio, while 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 formation period (t-12:t-2) and a duration variable that measures the number of consecutive months in a given state.

We first construct a one-factor version of GM (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

$$r_{mo,t} = a_{mo} + B_{moDOWN} * D_{tDOWN} * r_{ma,t} + B_{moUP} * D_{tUP}\ r_{ma,t} + e_{mo,t}, \tag{3}$$

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 bearing in mind possible attenuation bias.

In Table VII, we confirm that before 1927, as estimated in the manner described above, the average beta of the momentum W-L portfolio is negative (-0.26, t-stat -8.0), while the alphas are significantly positive at 0.36% on average (t-stat 3.5). We also confirm that in an up market, momentum beta is on average positive (0.31 t-stat 7.9) and in the down market it is negative (-0.91 t-stat -21.9). For the 1927-2012 period, the average W-L beta is -0.34 (t-stat -17.7). The magnitude of the beta variation is about twice as large in the pre-1927 period as in the post-1927. For the entire period 1801-2012, W-L momentum beta is -0.32 (t-stat -20.2).

In the pre-1927 period, the negative beta is a result of the L portfolio having an estimated average beta of 1.27 vs. the W portfolio average beta of 1.01. In the down markets in the period, the W portfolio beta drops to an estimated 0.7 and the estimated L beta rises to 1.6. The reverse occurs in the up markets wherein W portfolio beta rises to 1.3 and L beta drops to 0.98. Since the level of beta in the momentum portfolio is analytically linked to recent market performance, it is unsurprising to find in the pre-CRSP data results similar to those of GM (2001) using the CRSP data. Nevertheless, it is fascinating how powerful the beta variation of a momentum portfolio is.

DM (2014) take these results a step further and look at the optionality of the momentum portfolio payoffs by observing that the Winner minus Loser portfolio beta during contemporaneous up market months that follow an extended trailing bear market state is significantly more negative than the average beta, and more negative than the betas following negative and positive markets. We also extend these results to the pre-1927 data and draw similar conclusions.

Specifically, we first confirm their findings by looking at the twenty most negative W-L monthly returns in the early history. We observe a similar pattern in which the months with most negative W-L portfolio returns, on average, have been followed by negative average market returns and are accompanied by a contemporaneously positive market return. For example, in Table VIII.A we show that between 1801 and 1926, the average monthly W-L return during the twenty most negative months has been -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 DM (2014), we estimate the following regression:

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

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

We confirm the statistically significant negative b_u coefficient of -0.53 for the full sample (t-stat -10.6), and -0.92 for the 1801-1926 sample (t-stat -7.8) and – 0.68 for the CRSP sample (t-stat -11.2), which, according to DM (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. During the months when the contemporaneous market return is negative, the estimate of W-L portfolio beta is -0.41(b_o+b_b) (-0.47 during 1801-1926), but when the contemporaneous market return is positive, the beta drops significantly to -0.94 (b_o+b_b + $b_{b,U}$) (-1.37 during 1801-1926 period). We confirm their empirics without taking a firm stand on their interpretation.

Therefore, prior studies that document 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, because beta exposure that induces raw momentum profits to correlate with market states. Depending on the definition of the market state, the observed correlations between momentum and market states will be different, but the root of the correlation is the beta of the stocks inside the momentum portfolios, and hence once measured, the momentum portfolio beta can explain the direction of market state correlation with momentum profits.

We further investigate this connection between market state and momentum beta exposure by focusing on the duration of the realized market state and its effect on the momentum portfolio beta exposure. We find strong evidence that momentum beta is dynamic not only across 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 define a state duration variable by summing the number of consecutive positive / negative market states until the state changes. This variable provides additional visibility into the momentum portfolio dynamic over the course of a market state. We compute the exposure of momentum beta to the market state duration in the following way: First, a 10-month rolling momentum beta is obtained by regressing monthly momentum returns ($r_{mo,t}$) on a constant and equally-weighted market return ($r_{ma,t}$).

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

Next, calculated $B_{mo,t}$ are regressed on the market state duration variable:

$$B_{mo,t} = a_b + Coef_b * Duration_t + e_{b,t}, \quad (6)$$

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

In this explanatory model, we find a strong dependence of momentum beta on market state duration. We estimate the full period coefficient to be 0.02 (t-stat 19.3); the up state estimate is 0.03 (t-stat 19.8), and down state estimate is 0.04 (t-stat 11.5). Hence, the higher the market state duration variable, the stronger the momentum portfolio beta becomes, as can be seen in Table IX and Figure VI. In the pre-1927 period, the up state coefficient estimate is 0.05 (t-stat 17.0) vs. the post-1927 period up state point estimate of 0.02 (t-stat 17.4). The pre-1927 down coefficient is estimated to be 0.05 (t-stat 8.9) and the post-1927 period down estimate is 0.03 (t-stat 10.4). This confirms our prior observations that momentum beta variability is higher in the pre-1927 period.

The duration variable helps refine GM (2001), who only capture the average betas following up and down market states. Our study shows that the dynamics of momentum's conditional market exposure is dependent on the duration of the market state and that only after the market state duration lengthens does momentum beta actually take on those signs and that in the beginning of each state, momentum's beta actually has appeared opposite from the new market direction.

D. Alpha and Beta Contribution

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 opposite of the market direction, hence historically generating a negative drag on momentum performance. During that time period, the momentum strategy spread portfolio has started by being long the winners from the last market state and short the last state's losers, which have the opposite beta tilt from 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 persists, 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 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 look at the average alpha and beta components of momentum portfolio return as a function of the market state duration. For every month *t*, we calculate momentum alpha as the difference between raw momentum return and the CAPM 10-month rolling beta multiplied by the market return for that month, acknowledging that in this one-factor context, the estimated "alpha" likely embeds numerous effects. The beta contribution is 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 X and Figure VII show that in the overall history, average monthly momentum returns within the first year of all market states is 0.4% (t-stat 4.1) vs. 0.3% (t-stat 2.2) in the subsequent market state months. The estimated eta contribution is -0.4% (t-stat -4.7) in the first year, and +0.1% (t-stat 0.1) in the subsequent market state months, and the “alpha” contribution is significantly positive in the first year (0.8%, t-stat 6.8) and positive, yet not significant, in the subsequent months (0.2%, t-stat 1.6). As market state continues and momentum portfolio beta changes with market direction, the contribution from the beta component switches from significantly negative to slightly positive, while the alpha portion declines from significantly positive to insignificantly positive. As a result, over a 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 upcoming state reversal.

Breaking down the sample into up and down market states, a similar pattern can be seen. For example, we estimate the alpha contribution in first 12 months of an up state to be 1.2%, while the beta contribution is -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%, while beta contributes -0.2%. In the subsequent months, alpha contribution drops to -0.2%, while beta contribution remains at -0.2%.

The reason that the beta contribution in the first 12 months compared to subsequent months is asymmetric between up and down states is because the momentum beta at the end of an average down state tends to be negative at an estimated -0.34 (t-stat -3.5), while it is near zero and insignificant at 0.02 (t-stat 0.2) at the end of the average up state. This occurs because the volatility of the market in down states is larger, leading to large absolute beta. Therefore, the estimated average beta following the average down markets is highly negative, while following average duration up markets it is approximately 0. This is the reason why the first 12 months of a new up state historically have experienced a large negative beta contribution, while the first 12 months of a down state have not.

Our findings provide the support for the argument in SS (2012) that momentum is higher within a market state than across states, due to the dynamic nature of momentum's beta. Our findings also support CGH (2004) in that momentum portfolio returns have been stronger following positive market states than negative. However, we point out that this occurs mainly due to negative market states that last longer than a year. Momentum historically has experienced significant negative returns on average due to 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 DM (2014) who show that momentum strategy has failed especially following negative trailing markets accompanied by a positive contemporaneous market return. Our explanation is closest in nature to DM (2014), who also attributes the momentum underperformance to the beta exposure of the strategy, especially the short portfolio.

E. Dynamically-Hedged Strategy

To account for the dynamic variation of momentum's beta, we test the following ex-ante hedging strategy. If the market state has just changed according to our simple rule, we hedge 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 state – accounting for the beta asymmetry between up and down states. At month 10 for up and month 7 for down, the hedge is turned off, and we allow for the beta contribution to add to momentum returns. We select the 10 month and 7 month thresholds because they roughly correspond to the typical duration levels at which the average beta contribution of the momentum portfolio aligns with the direction of the market state. Perhaps due to higher volatility and lower initial beta, it takes several months less for the down market beta contribution to turn positive than for the up markets on average. For robustness, we test different threshold points, and the results, not shown, demonstrate a consistent improvement over the un-hedged strategy. For example, a 10/10 hedging rule compared to a 10/7 is only one basis point lower over the full timeframe.

Table XI reports that during the full sample, the dynamically-hedged strategy generates a large increase in performance (albeit gross of transactions costs) in the up states from an average of 0.6% per month (t-stat 6.9) to 0.9% per month (t-stat 8.7), and in the down states, on average from 0.1% (t-stat 0.4) per month to 0.2% per month (t-stat 1.3). Between 1801 and 2012, the average monthly dynamically-hedged Long/Short return increases to 0.7% (t-stat 6.8) from the raw momentum return of 0.4% (t-stat 4.5). Figure VIII plots the cumulative returns to the hedged and the raw momentum strategy. Of practical significance to investors utilizing momentum signals is the fact that the hedged momentum strategy significantly outperforms the raw momentum strategy during the periods with large market reversals such as the last ten years. Ostensibly by dynamically moderating momentum portfolio market risk, the hedged strategy is implicitly capturing the remaining market level momentum effect resulting in a significant risk / return improvement for the overall strategy.

We also attempt to compare our hedging methodology to the ones proposed by DM (2014) and Barroso and Santa-Clara (BS, 2014). The main difficulty in such comparisons lies in the absence of daily return data for the pre-1927, which significantly inhibits the accuracy of the necessary volatility forecasts. We use 10 month rolling return standard deviation as a very crude estimate of expected volatility of momentum portfolios and replicate both the constant Sharpe ratio strategy proposed by BS (2014) and the dynamic Sharpe ratio proposed by DM (2014). BS (2014) create 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. Every month during our sample we solve for the BS (2014) momentum portfolio weight as follows:

$$W_{BS,t} = 12\% / \sigma_{\mu o,\tau} \tag{7}$$

where $\sigma_{\mu o,\tau}$, in our simplified version, is defined as 10 month rolling standard deviation of Winner-Loser portfolio returns during the momentum portfolio formation months.

DM (2014) create a dynamic Sharpe ratio hedged momentum strategy by using a forecast of expected W-L return ($E(r_{mo})$) based on estimates from:

$$r_{mo,t} = y_o + y_b * D_t + y_s * \sigma^2 (r_{ma,t}) + y_{int} * D_t * \sigma^2 (r_{ma,t}) + e_{b,t} \tag{8}$$

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 is negative and 0 otherwise, σ^2 is the 10 month rolling variance of market returns during the momentum portfolio formation months, and $r_{ma,t}$ is the market return. We solve for the DM (2014) momentum portfolio weight ($W_{DM,t}$) as:

$$W_{DM,t} = (1/2*\lambda)* E(r_{mo,t}) / \sigma_{\mu o,\tau}^2 \tag{9}$$

where $E(r_{mo,t})$ is the expected momentum portfolio return based on estimates from (8), σ_τ^2 is defined as 10 month rolling variance of Winner-Loser portfolio returns during the momentum portfolio formation months, and λ is a constant term that scales portfolio volatility, which is set to match DM (2014) choice of realized volatility of 19% in the post-1927 timeframe.

Table XI contains the results. While we confirm that in the post-1927 timeframe both dynamic and constant Sharpe hedging approaches, even with our crude estimate of volatility, result in significant improvements over the raw momentum strategy, this is not the case in the pre-1927 history. Specifically, the average monthly W-L spread for the dynamic Sharpe ratio strategy is on average 1.3% between 1927 and 2012 (t-stat 7.7) compared to the 0.6% (t-stat 3.65) for the raw momentum. Yet, in the pre-1927 data, the same strategy averages 0.2% per month (t-sat 2.5), slightly lower than the 0.3% (t-stat 2.7) for the raw momentum. The constant Sharpe ratio strategy also adds significant value in the post-1927 period, averaging 1.1% (t-stat 6.6), while it delivers no noticeable improvement in the in the pre-1927, averaging 0.3% (t-stat 2.8). In the post-1927 timeframe, dynamic Sharpe hedging outperforms both constant Sharpe and our proposed method; however during the earlier history, the method proposed in this paper performs the best.

These out-of-sample tests of recently established hedging strategies on the post-1927 data raise important questions about stability and robustness of such approaches. As mentioned earlier, the frequency of momentum drawdowns is much larger in the pre-1927 data resulting is a more complete distribution of momentum crashes than previously considered. More importantly, we demonstrate that the dynamic nature of momentum portfolio beta is the fundamental driver of the underperformance, the influence of which grows with the duration of a given market state. Our proposed hedging strategy directly takes this 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 are heavily reliant on the sustained negative correlation between the realized momentum volatility and the future momentum payoffs. In the post-1927 data, the correlation between realized volatility and future month momentum return has been -4.2%, while in the pre-1927 data is it only -0.83%. Specifically, the two largest post-1927 momentum drawdowns followed very extreme and volatile market conditions of the Great Depression of the 1930's and the Financial Crisis of 2008. Sharpe ratio focused hedging strategies protect well against such occurrences because during these events, strong increases in trailing volatility were predictive of the upcoming momentum crashes due to the upcoming strong market reversals. Yet, as shown above, the nature of the relationship between volatility spikes and upcoming market reversals appears to be different in the 19th century. Deeper investigation of these relationships provide a research opportunity for future studies.

IV. Conclusion

We initiate out-of-sample research of the 19^{th-} and early 20th-century US stock-level data by creating a dataset starting in 1801 and ranging through 1926, making possible both in and out of sample tests of momentum strategies. Testing of the traditional equity price return momentum strategy is extended to the new data and its effect is found to be significant since the beginning of the 19th century. Using the longer time-series, a robust connection is observed between momentum spread portfolios betas, alphas and the duration of up and down market states. The longer each state continues, the more market exposure contributes to momentum returns. The momentum effect becomes riskier the longer a market state lasts, 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.

Appendix I
Data Collection

The ICF dataset was created for and described in detail in "A New Historical Database for the NYSE 1815 to 1925: Performance and Predictability" (GIP (2001)). A total of 671 NYSE stocks is covered 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 month-return observations occurs.

The ICPSR dataset was created for "Price Quotations in Early United States Securities Markets, 1790-1860" (SWW 2006). We filter out any preferred, fixed income, or international securities, resulting in a total of 1,167 common U.S. stocks covered between January 1800 and May 1862. Prices were manually collected from archived newspapers of the time for nine U.S. exchanges: New York, Boston, Philadelphia, Baltimore, Charleston, New Orleans, Richmond, Norfolk, and Alexandria. Within any given month, price frequency ranges from daily to monthly. To convert ICPSR data to a monthly frequency, we allow for a look-back window of one month minus a day. Hence, if a security price is missing during the month-end date, we look back for the last available price during the same calendar month. This significantly improves data coverage for stocks whose prices are available only in the weeks not coinciding with month-end. Sometimes an ask price would be supplied in addition to the bid price, in which case we would average the two. As a result, a total of 103,684 unique month-return observations is recorded.

The GFD dataset was acquired for this study from Global Financial Data. There are 3,992 common stocks covered in the dataset between January 1825 and December 1925, and another 94 unique firms during 1926. Due to 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. A total of 305,574 unique month-return observations is noted.

We merge the three datasets creating the Merged dataset by using company names and correlation of prices, since there is no other common security identifier among the three datasets. Naming conventions among the three datasets vary greatly in terms of abbreviations, articles, order of words etc., so a simple name comparison without price correlations is not sufficient. Since GFD database is the largest, we use all available GFD data as a starting point and supplement it with unique data from ICF and ICPSR sources. We follow the following procedure. First, for each ICF security, a list of GFD securities is generated with which they have the highest price correlation. Next, a manual comparison of ICF's security names and the names in the generated list is conducted, and if there is a clear match of names, they are paired; otherwise, the ICF security is labeled as unique. Then the same procedure is performed for the ICPSR securities against the merged GFD and ICF dataset. All ICPSR securities are assigned to a list labeled "unique" or "already included" in the GFD-ICF dataset.

We identify 222 unique securities in the ICF and an additional 401 unique securities in ICPSR datasets that were additive to the GFD dataset, resulting in a total of 4,709 unique securities in the merged dataset. Importantly, in addition to forming a larger set of unique securities, the Merged dataset fills in missing data for the GFD individual securities, creating a richer dataset. To accomplish this, we look for any missing month-end prices from the GFD dataset in the other two sources, and use the additional data if it is available. The merged dataset also results in an extended coverage period from January 1800 to December 1926. The only interruption of the Merged data is during the first two months of World War I in 1914. A total of 413,922 unique month-return observations appears in the merged dataset.

Inspection of the price data for potential outliers reveals that many stocks experience either a one month price outlier or a multi-month shift to a new scale of prices and then returns to the original scale. According to GIP (2001), jumps of these magnitudes are due to 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, there is a reasonable chance of data entry mistakes across the three datasets. Another source of large price changes is liquidation dividends, which were common at the time. According to GIP (2001), liquidation dividends were not due to bankruptcies but rather loss of charters and orderly business closures. In these cases, negative price returns would be at least partially offset by the dividend payments. Finally, according to GIP (2001), there were no splits in their sample, hence price jumps are unlikely to occur because of stock splits. To account for the outlier effects, we winsorize outlier returns at a 50% cutoff by setting returns which are 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 -50% level, we conservatively account for the liquidation dividend situations. Our momentum results are robust to different winsorization boundaries (+/- 75%, +/-100%); however the returns generated for the Universe as a whole are most consistent with the published results using the 50% winsorization rule.[3] Specifically, the wider the boundaries become, the higher the universe return and standard deviation becomes, showing the impact of erroneously recorded price jumps.

[3] For the overlapping period from 1815 to 1925, we closely match the average universe price-only 50% winsorized returns from our study (0.28% - Table I), with the results by Schwert (0.21%), GIP (0.19%), and SWW (0.22%) for the same period. While, for example, with 100% winsor boundary, the calculated average universe return becomes 0.46%, much larger due to erroneous data.

Appendix II
Initial 10 Companies on January 1800

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

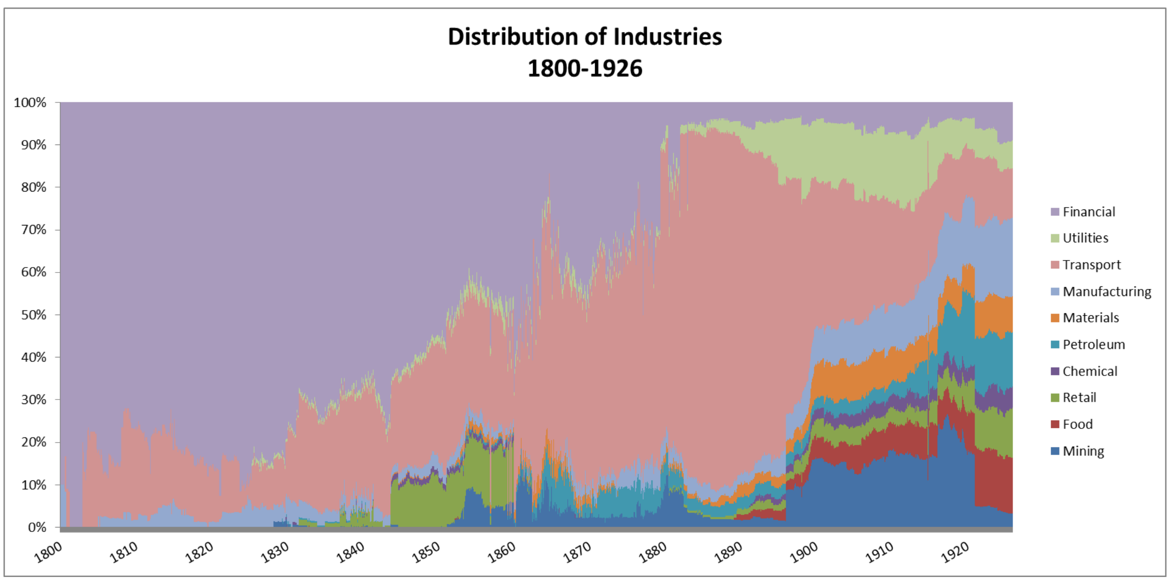

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Table I
Descriptive Statistics for the Datasets

The following datasources have been combined into one dataset of monthly security prices:

1. The Inter-University Consortium for Political and Social research (http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/4053) - Corresponding paper describing data collection process and results is by Sylla, Richard E., Wilson, Jack, Wright, Robert E. "Price Quotations in Early U.S. Securities Markets, 1790-1860: Description of the Data Set" (November 17, 2006).
2. Global Financial Data (http://www.globalfinancialdata.com/Databases/HistoricalStockData.html)
3. International Center of Finance at Yale University (http://icf.som.yale.edu/old-new-york-stock-exchange-1815-1925) - Corresponding paper describing data collection process and results is by Goetzmann, William N., Ibbotson, Roger G. and Peng, Liang, "A New Historical Database For The NYSE 1815 To 1925: Performance And Predictability" (2001).
4. Merged dataset of ICPSR, GFD and IFC from 1800-1926.
5. The Center for Research in Security Prices (http://www.crsp.com/)

Data Source	Period	Average Monthly Return	Average Monthly Stdev	Total # of unique securities	Average # securities with 1-month Return	Average # securities with 1-month Return & Momentum	Total # of observations with 1-month Return	Total # of observations with 1 -month Return & Momentum
ICPSR[1]	1800:1862	0.09%	2.19%	1167	139	114	103684	84148
GFD[2]	1825:1925	0.29%	3.38%	3992	250	205	305574	248736
IFC[3]	1815:1925	0.38%	4.85%	671	46	32	57871	41925
MERGED[4]	1800:1926	0.28%	3.11%	4709	272	224	413922	338989
CRSP[5]	1926:2012	0.98%	7.35%	29542	3667	3356	3828692	3462990

Table II
Momentum Profits by Time Periods

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the equally-weighted market return. Market is defined as the equally-weighted average return of all stocks. Excess returns by decade are annualized 10-year return, ending at period end date.

A.

Period	Monthly Excess Returns			t-stat			Data Source
	Winners	Losers	W-L	Winners	Losers	W-L	
01/31/1801 - 05/31/1862	0.13%	-0.12%	0.25%	1.9	-1.4	1.8	ICPSR
01/31/1826 - 12/31/1926	0.18%	-0.07%	0.25%	**3.0**	-1.1	**2.1**	GFD
01/31/1816 - 12/31/1925	0.24%	-0.10%	0.34%	**2.7**	-0.9	1.9	IFC
01/31/1801 - 12/31/1926	0.18%	-0.10%	0.28%	**3.5**	-1.7	**2.7**	Merged
01/31/1927 - 12/31/2012	0.34%	-0.24%	0.58%	**4.5**	**-2.8**	**3.6**	CRSP
01/31/1801 - 12/31/2012	0.25%	-0.16%	0.40%	**5.7**	**-3.2**	**4.5**	Merged+CRSP

B.

Decade End	Excess Return by Decade			Price Return
	Winners	Losers	W-L	Market
1810	2.3%	-2.4%	4.4%	3.76%
1820	0.4%	-1.6%	2.0%	1.08%
1830	3.0%	-3.8%	6.7%	2.08%
1840	3.5%	-0.9%	4.4%	1.15%
1850	4.9%	-2.6%	7.5%	3.52%
1860	0.9%	-1.3%	2.3%	-1.96%
1870	4.4%	-4.0%	8.4%	10.20%
1880	5.1%	-4.5%	9.7%	6.49%
1890	0.1%	0.7%	**-0.6%**	0.34%
1900	-0.7%	1.3%	**-2.0%**	5.26%
1910	0.9%	-1.5%	2.4%	3.06%
1920	-1.2%	0.0%	**-1.2%**	-2.10%
1930	6.8%	-7.1%	13.9%	-0.65%
1940	0.3%	-0.1%	0.4%	7.88%
1950	6.8%	-4.5%	11.4%	14.13%
1960	5.9%	-5.8%	11.7%	9.19%
1970	6.0%	-5.6%	11.6%	9.15%
1980	7.6%	-6.4%	14.0%	13.29%
1990	5.3%	-7.8%	13.1%	4.66%
2000	5.8%	-3.5%	9.3%	15.35%
2010	2.7%	-1.0%	3.7%	10.24%
Average	3.4%	-3.0%	6.3%	5.5%

Table III
Term Structure of Momentum Profits

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 {W and L}. Average excess returns and t-statistics are compute for the non-overlapping month *t*, after portfolio formation. Returns for the momentum portfolio and the market are equally-weighted.

A. 1801:1926

	Average Excess Return per Month			t-stat		
Month	Winners	Losers	W-L	Winners	Losers	W-L
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

B. 1927:2012

	Average Excess Return per Month			t-stat		
Month	Winners	Losers	W-L	Winners	Losers	W-L
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**
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**

Table IV
Short Term Reversals

For each month *t*, the price reversal strategies use top and bottom thirds of $P_t/P_{t-1,}$ (1m reversal t); $P_{t-1}/P_{t-2,}$ (1m reversal skipping 1 month t-1); and P_t/P_{t-2} (2m reversal t) to designate winners and losers {W and L}. Returns are equally-weighted, rebalanced monthly. Returns in the table are for the Long Short {W-L} portfolios.

Period	Average Long-Short Return per Month			t-stat		
	Pt/Pt-1	Pt-1/Pt-2	Pt/Pt-2	Pt/Pt-1	Pt-1/Pt-2	Pt/Pt-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**

Table V
Momentum Profits for Individual Stocks and Industries

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Market 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. Industry Neutral column reports 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. Top third of stocks from each industry are grouped to form the Winner portfolio and bottom third of stocks from each industry form the Loser portfolio. Industry reports average monthly profits of momentum strategies of industries, where industries are sorted on their past 10-month raw returns with and without skipping the two reversal months and 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 re-computing the strategy monthly. Table B reports momentum results within each industry.

A.

	W-L		Industry Neutral W-L		Industry W-L		Industry W-L (w/o reversal)	
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**

B.

1806 - 1926		# of Stocks on	W-L		Code
Industry	Ave # of Stocks	12/31/1925	Mean	(t-stat)	
Mining	16	25	0.2%	0.4	11
Food	9	101	0.7%	1.8	12
Retail	10	84	0.5%	**2.1**	13
Chemical	4	38	0.5%	1.3	14
Petroleum	9	98	-0.1%	-0.3	15
Materials	9	67	0.4%	0.9	16
Manufacturing	17	155	0.5%	**2.0**	17
Transport	64	89	0.1%	0.7	18
Utilities	14	43	0.0%	0.2	19
Financial	52	65	0.3%	**2.0**	20
Other	8	2	0.1%	0.5	21

Table VI
Stock-Specific vs. Common Factor Momentum

For each month t, the following one-factor model is estimated for all stocks i in the database with returns for at least 37 months within a 60-month rolling window, $r_{i,t} = a_0 * D_t + a_1 * (1-D_t) + B_i * r_{ma,t} + e_i$, where $D_t = 1$ during the momentum formation months (t-12:t-2) and 0 elsewhere (t-13: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 average return of all stocks. Stock-specific momentum strategy uses a_0 as the ranking input (10-month stock-specific momentum), and the factor-related return momentum strategy uses $B_{i,t} * r_{ma,t:[t-12:t-2]}$ as the ranking input.

A.

1801 - 1926	W-L Momentum Strategy			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy		
Parameter	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
mean (%)	0.3%	-0.1%	0.3%	0.2%	-0.4%	0.3%	0.3%	0.3%	0.3%
s.d. (%)	4.0%	4.7%	3.9%	3.7%	3.5%	3.7%	5.4%	5.6%	5.4%
(t-stat)	**2.7**	-0.3	**3.0**	**2.3**	-1.4	**2.8**	**2.2**	0.6	**2.1**

B.

1927 - 2012	W-L Momentum Strategy			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy		
Parameter	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
mean (%)	0.6%	-3.3%	0.9%	0.7%	-2.2%	0.9%	0.2%	0.4%	0.1%
s.d. (%)	5.1%	6.2%	4.9%	3.1%	4.1%	2.8%	6.2%	8.5%	6.0%
(t-stat)	**4.4**	**-6.0**	**7.2**	**6.9**	**-4.9**	**10.0**	0.8	0.5	0.6

C.

1801 - 2012	W-L Momentum Strategy			Stock-Specific Return Momentum Strategy			Factor-Related Return Momentum Strategy		
Parameter	Overall	January	NonJan	Overall	January	NonJan	Overall	January	NonJan
mean (%)	0.4%	-1.4%	0.6%	0.4%	-1.1%	0.5%	0.2%	0.4%	0.2%
s.d. (%)	4.5%	5.6%	4.4%	3.5%	3.8%	3.4%	5.8%	6.9%	5.6%
(t-stat)	**4.5**	**-3.7**	**6.3**	**5.8**	**-4.3**	**7.6**	**2.1**	0.8	**2.0**

Table VII
Relation Between Investment Period Factor Exposure and Formation Period Factor Realizations

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, 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. Table below shows the results of the following two regressions, where momentum portfolio beta is estimated for all months, up market months and down market months. $r_{mo,t} = a_{mo} + B_{mo} * D_t * r_{ma,t} + e_{mo,t}$, and $r_{mo,t} = a_{mo} + B_{moDOWN} * D_{tDOWN} * r_{ma,t} + B_{moUP} * D_{tUP}\ r_{ma,t} + e_{mo,t}$, 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}.

A.

1801 - 1926	W-L			Winners			Losers		
Parameter	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)
Intercept	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	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**

B.

1927 - 2012	W-L			Winners			Losers		
Parameter	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)
Intercept	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	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**

C.

1801 - 2012	W-L			Winners			Losers		
Parameter	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)	Estimate	S.E.	(t-stat)
Intercept	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	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**

Table VIII
Momentum Crashes Regression

Momentum returns {W-L} $r_{mo,t}$ and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Top 20 most negative months correspond to the months when the W-L portfolio experienced the most negative returns. Table shows the results of the following regression:

$$r_{mo,t} = a_o + a_b * D_t + b_0 * r_{ma,t} + b_b * D_t * r_{ma,t} + b_{b,u} * D_t * D_{upmonth,t} * r_{ma,t} + e_{b,t}$$

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

A.

Momentum Crashes				
		W-L	Market $_t$	Market $_{t-2:t-12}$
Top 20 most negative months	1801-1926	-14.3%	5.0%	-6.3%
Average	1801-1926	0.29%	0.28%	3.40%
Top 20 most negative months	1927-2012	-22.4%	23.1%	-26.1%
Average	1927-2012	0.58%	0.99%	10.9%

B.

1801 - 1926	Market Timing Regressions					
Parameter	a_0	a_b	b_o	b_b	$b_{b,U}$	R^2_{adj}
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	
tstat	**2.0**	**4.2**	**7.9**	**-9.6**	**-7.8**	

C.

1927 - 2012	Market Timing Regressions					
Parameter	a_0	a_b	b_o	b_b	$b_{b,U}$	R^2_{adj}
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	
tstat	**6.6**	**5.9**	-0.2	**-5.5**	**-11.2**	

D.

1801 - 2012	Market Timing Regressions					
Parameter	a_0	a_b	b_o	b_b	$b_{b,U}$	R^2_{adj}
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	
tstat	**6.2**	**4.1**	**3.5**	**-11.7**	**-10.6**	

Table IX
Momentum Beta Variation and Market State Duration

Table shows the results of the following regression: $B_{mo,t} = a_b + Coef_b * \text{Duration}_t + e_{b,t}$, where $B_{mo,t}$ is computed from 10-month rolling regression of momentum returns onto the market returns, defined as the equally-weighted average return of all stocks, during the momentum formation months {t-12:t-2}: $r_{mo,t} = a_{mo} + B_{mo} * r_{ma,t} + e_{mo,t}$; Duration is the number of the consecutive months in a given state; Market state is defined as the sign of the market return for the months {t-12: t-2}, same as momentum portfolio formation. Standard Errors (*S.E.*) are Newey-West adjusted.

A.

1801 - 1926	UP		Down		Overall	
Parameter	$Coef_{up}$	intercept	$Coef_{dn}$	intercept	Coef	intercept
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
tstat	**7.2**	**-8.9**	**4.2**	-0.6	**9.1**	**-10.9**

B.

1927 - 2012	UP		Down		Overall	
Parameter	$Coef_{up}$	intercept	$Coef_{dn}$	intercept	Coef	intercept
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
tstat	**6.9**	**-7.1**	**5.1**	1.1	**9.1**	**-8.4**

C.

1801 - 2012	UP		Down		Overall	
Parameter	$Coef_{up}$	intercept	$Coef_{dn}$	intercept	Coef	intercept
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
tstat	**6.4**	**-8.4**	**5.1**	-0.3	**11.4**	**-12.0**

Table X
Alpha and Beta Contribution and Market State Duration

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 12 months. 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, defined as the equally-weighted average return of all stocks, $r_{mm,t}$ is the month *t* {W-L} momentum return. Our results show an evolution of the source of momentum profits over the course of a market state.

A.

1801 - 1926	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
UP_State	0.4%	0.3%	0.4%	0.8%	0.0%	0.5%	-0.4%	0.3%	-0.1%
tstat	**2.9**	1.6	**3.2**	**4.4**	-0.1	**3.4**	**-3.3**	1.9	-0.9
DN_State	0.1%	0.2%	0.1%	0.2%	0.5%	0.3%	-0.1%	-0.3%	-0.1%
tstat	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%
tstat	**2.3**	1.6	**2.8**	**3.9**	0.7	**3.7**	**-3.0**	1.0	-1.5

B.

1927 - 2012	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
UP_State	0.9%	0.9%	0.9%	1.7%	0.8%	1.3%	-0.8%	0.1%	-0.4%
tstat	**4.7**	**4.8**	**6.7**	**6.1**	**3.6**	**7.0**	**-3.2**	0.7	**-2.6**
DN_State	0.4%	-1.9%	0.0%	0.7%	-1.9%	0.2%	-0.3%	-0.1%	-0.2%
tstat	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%
tstat	**3.6**	1.5	**3.6**	**5.6**	1.5	**5.5**	**-3.6**	0.3	**-2.8**

C.

1801 - 2012	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
UP_State	0.6%	0.6%	0.6%	1.2%	0.4%	0.8%	-0.6%	0.2%	-0.2%
tstat	**5.3**	**4.4**	**6.8**	**7.4**	**2.4**	**7.3**	**-4.4**	2.0	**-2.6**
DN_State	0.2%	-0.4%	0.1%	0.4%	-0.2%	0.3%	-0.2%	-0.2%	-0.2%
tstat	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%
tstat	**4.1**	**2.2**	**4.5**	**6.8**	1.6	**6.5**	**-4.7**	0.9	**-3.1**

Table XI
Dynamically-Hedged Momentum Returns

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Dynamically-hedged Geczy-Samonov (GS 2015) profits are computed as follows. Factor loadings are estimated from regression 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 is 1 of the state $Duration_{t-1}$ is <11 months for up markets and <8 months for down markets; else $H_t = 0$.

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

BS(2014) constant Sharpe ratio hedged momentum strategy uses a forecast of volatility, $\sigma_{\mu o,\tau}^2$ in our simplified version defined as 12-month rolling variance of W-L returns, and targets a volatility level of 12%, solving for momentum portfolio $W_{BS},_t = 12\% / \sigma_{\mu o,\tau}$.

		Hedged Strategies			
		Raw	GS (2015)	DM (2014)	BS (2014)
1802-1926	*Average*	0.3%	0.5%	0.2%	0.3%
1802-1926	*Stdev*	4.0%	4.4%	3.1%	4.3%
1802-1926	*T-stat*	**2.72**	**4.36**	**2.53**	**2.79**
1926-2012	*Average*	0.6%	0.9%	1.3%	1.1%
1926-2012	*Stdev*	5.1%	5.7%	5.5%	5.2%
1926-2012	*T-stat*	**3.65**	**5.17**	**7.72**	**6.57**
1800-2012	*Average*	0.4%	0.7%	0.7%	0.6%
1800-2012	*Stdev*	4.5%	5.0%	4.3%	4.7%
1800-2012	*T-stat*	**4.51**	**6.75**	**7.75**	**6.60**

Figure I
Cumulative Momentum Portfolio Profits

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the market return.

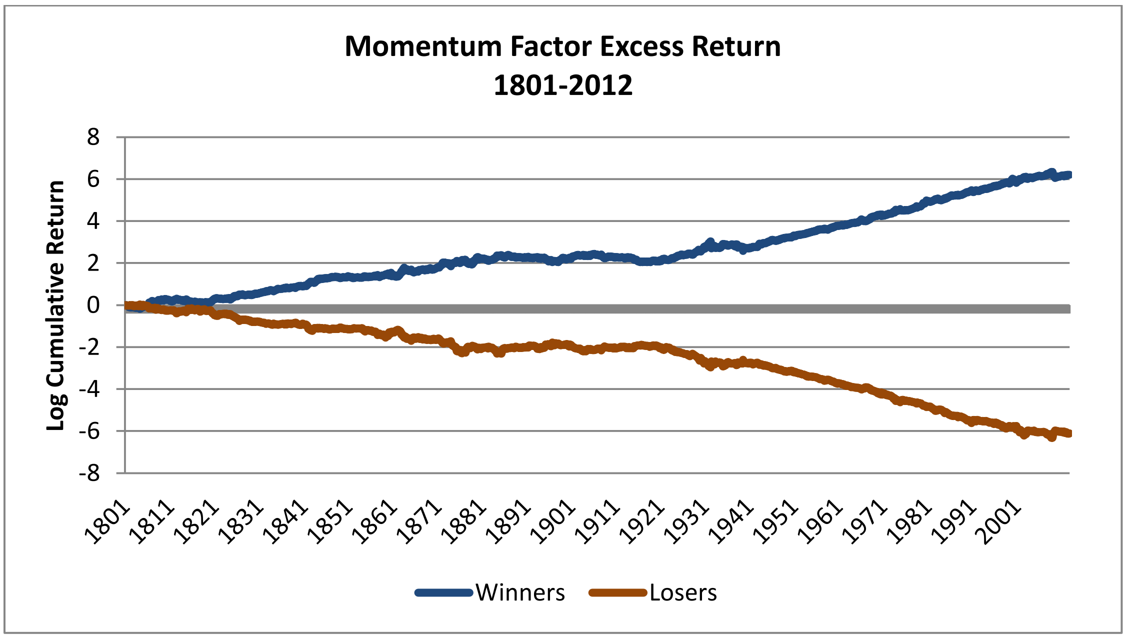


Figure II
10-Year Rolling Excess Returns

Figure shows 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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the market return.

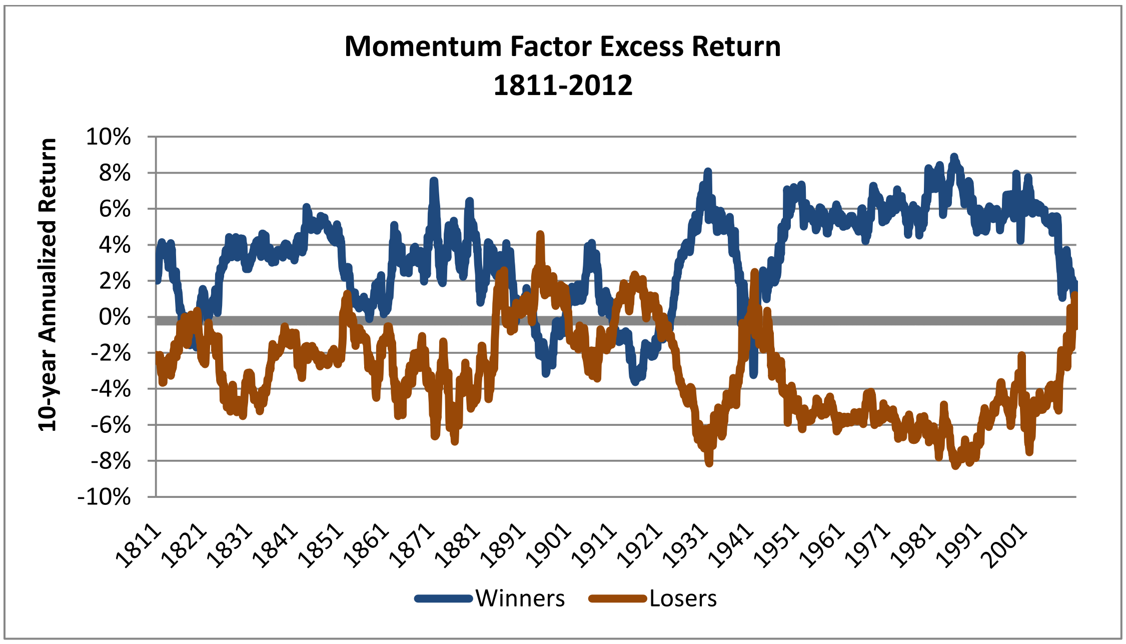


Figure III
10-Year Rolling W-L Returns

Figure shows 10-year rolling returns of {W-L} portfolio. 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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly.

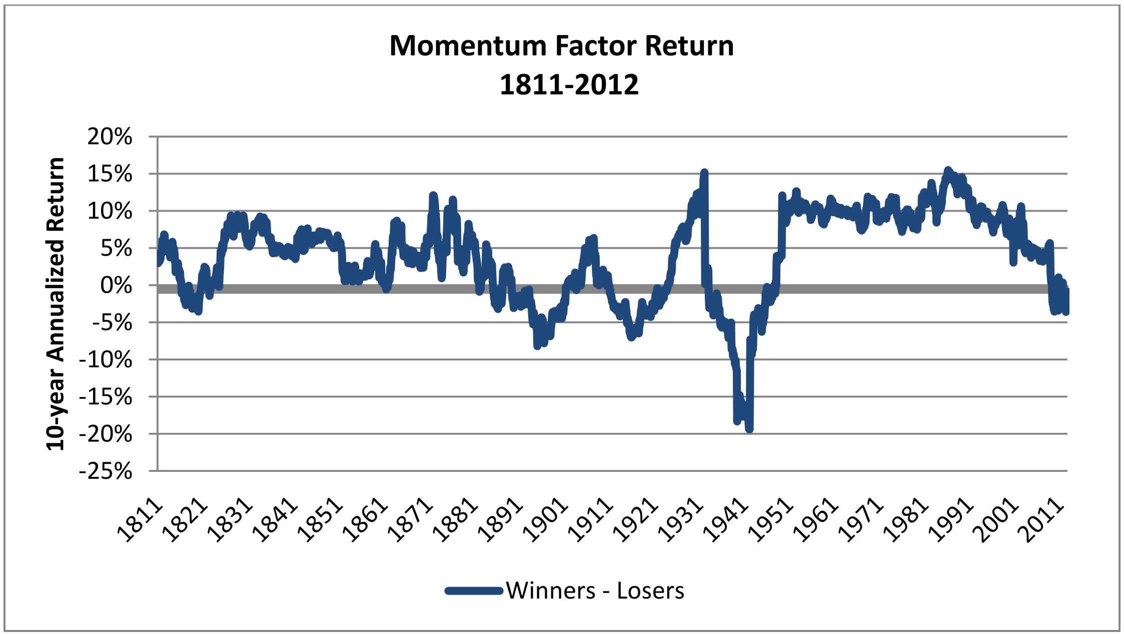


Figure IV
Short Term Reversals

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

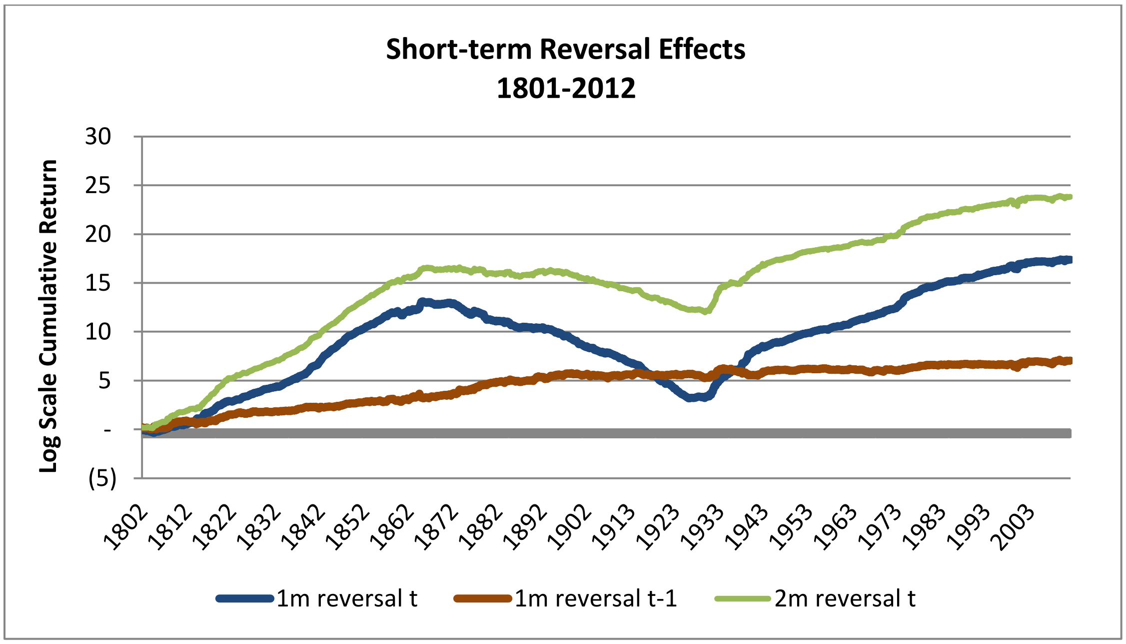


Figure V
Industry Momentum

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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Excess return is defined as return to the momentum portfolio minus the market return. Industry Neutral column reports 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. Top third of stocks from each industry are grouped to form the Winner portfolio and bottom third of stocks from each industry form the Loser portfolio. Industry reports average monthly profits of momentum strategies of industries, where industries are sorted on their past 10-month raw return, skipping the reversal months, and 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 re-computing the strategy monthly.

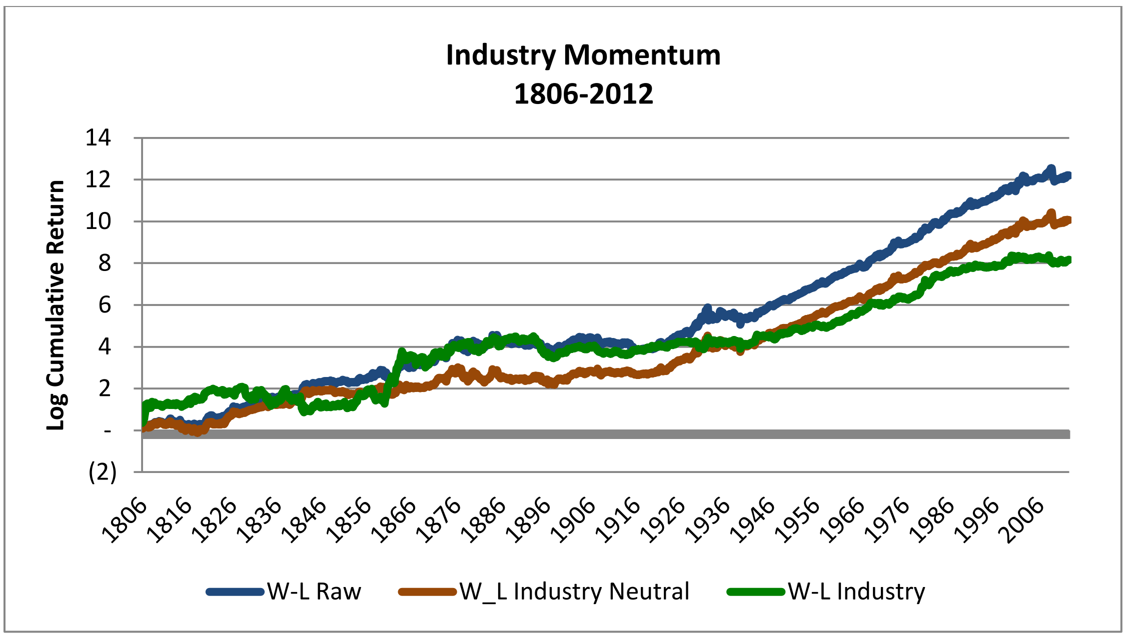


Figure VI
Momentum Beta Variation over Market State

Figure shows the average Beta per market state duration. Results are derived from the following regression: $B_{mo,t}$ = a_b + $Coef_b$* Duration$_t$ + $e_{b,t}$, where $B_{mo,t}$ is computed from 10-month rolling regression of momentum returns onto 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 the consecutive months in a given state; Market state is defined as the sign of the market return for the months {t-12: t-2}, same period as used for momentum portfolio formation.

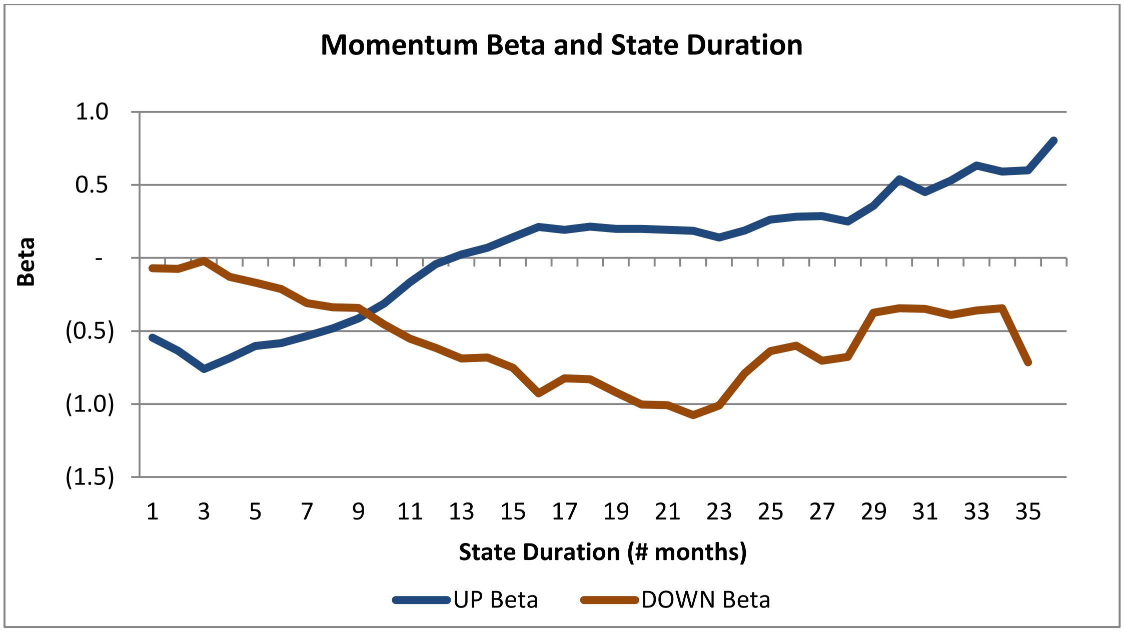
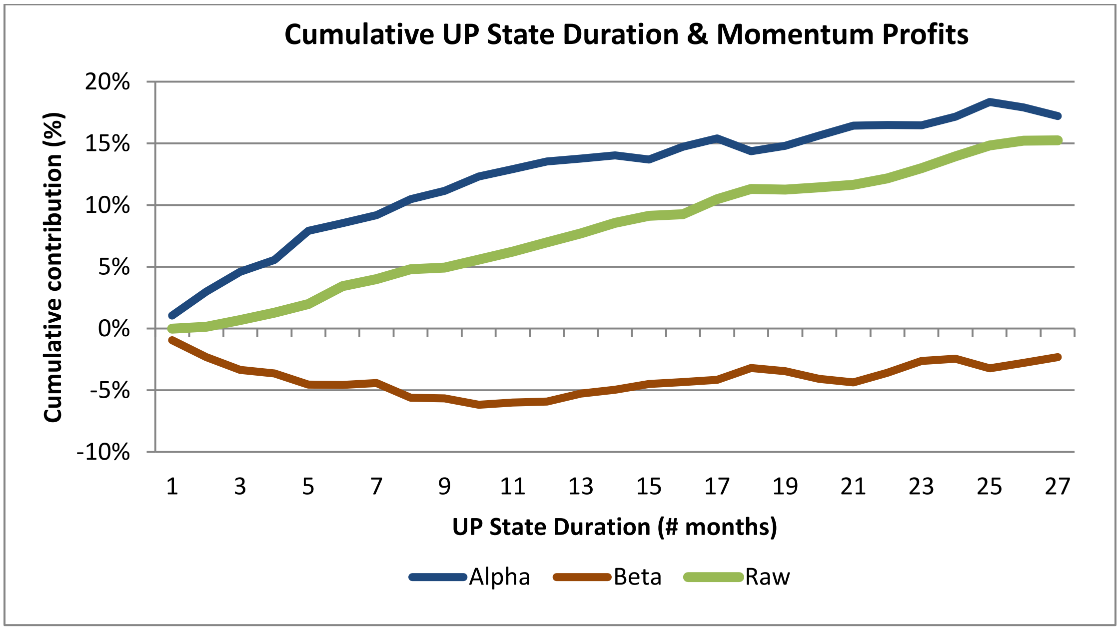


Figure VII
Alpha and Beta Contribution and Market State Duration

Graph shows the cumulative contributions of 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, $r_{mm,t}$ 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.



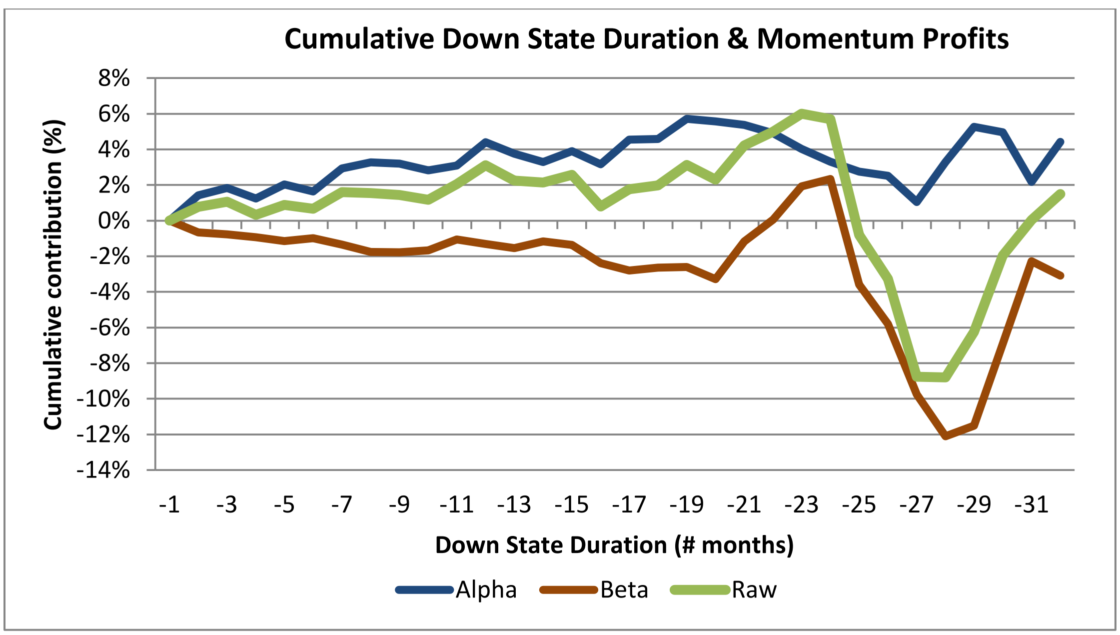


Figure VIII
Dynamically-Hedged Momentum Strategy

Figure shows the cumulative difference between the Winners and Losers 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 {W and L}. Momentum returns {W-L} $r_{mo,t}$, and market returns $r_{ma,t}$ are equally-weighted, rebalanced monthly. Dynamically-hedged profits are computed as follows. Factor loadings are estimated from regression 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 is 1 of the state $Duration_{t-1}$ is <11 months for up markets and <8 months for down markets; else $H_t = 0$.