Abstract Of:

212 Years of Price Momentum

(The World's Longest Backtest: 1801–2012)

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Submitted for Review to the

National Association of Active Investment Managers (NAAIM)

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By

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The first two U.S. stocks traded in 1792 in New York. Over the following decades, the securities market developed rapidly. By the end of 1810, 72 traded securities existed, and by the end of the 1830s the number was more than 300. To our knowledge, all current academic studies of U.S. security-level data begin in 1926, the year the CRSP database began. The U.S. market had been active for 133 years before that time, providing an opportunity to test stock-level studies in earlier history. The 19th and early 20th centuries are filled with expansions, recessions, wars, panics, manias, and crashes, all providing a rich out-of-sample history. Limiting studies to the post-1925 period introduces a strong selection bias and does not capture the full distribution of possible outcomes.

We use the additional century to study the case of price momentum: Before 2009, only following the Great Depression did the strategy have a decade-long negative compounded return. Such an occurrence was considered to be an outlier and the remaining part of the distribution was understood as normal. Since 2009, coming out of the second-worst U.S. financial collapse, momentum has experienced another decade-long underperformance, creating a large ripple in investment portfolios that use this strategy. The repeated underperformance raised practical questions about the outlier conclusion and what the actual distribution of momentum profits is. By extending the momentum data back to

1801, we create a more complete picture of the potential outcomes of momentum profits, discovering seven additional negative decade-long periods prior to 1925.

The first contribution of this study is a creation of a monthly stock price dataset. In this dataset, three known 19^{th} and early 20^{th} century data sources are combined into one testable dataset from 1800 to 1927. Between 1800 and 1927, the merged dataset contains an average of 272 securities per month, making it robust for security-level studies.

The second contribution of this study is to add to the existing price momentum literature by extending the momentum tests to the new data. Our study finds that in the pre-1927 data, the momentum effect remains statistically significant and is 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 (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 0.4% per month (t-stat 5.7).

As observed in the studies of the 20^{th} century data, momentum profits are highly variable over time, giving rise to the limits-of-arbitrage explanation. Nevertheless, over the long run, the trend-following 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 highly variable overtime.

The third contribution of this study is to link momentum's beta exposure to the market state duration. We find strong evidence that momentum 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 exposure becomes. Analyzing the longer history is especially useful for the time-series tests, as the sample size is more than doubled.

We find strong evidence that momentum beta is dynamic not only across both up and down market states, but also within a given market state. In the first year of a given up or down market state, momentum's beta exposure generates a negative contribution to the momentum returns, while momentum's alpha exposure 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 transforms from a purely stock-specific strategy to a combination of common-risk and stock-specific strategy.

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I. Early Security Returns Data

A series of academic efforts extended aggregate stock market returns back to 1792, the 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 (2001), Sylla, Wilson, Wright (2006), Global Financial Data)[1].

Our 1800-1926 dataset of security prices (hereafter Merged) and industry classifications is created from three sources: International Center of Finance at Yale (ICF); Inter-University Consortium for Political and Social Research (ICPSR); and Global Financial Data (GFD) – [Table I]. 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. 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.

[1] Cowles, Alfred, 1939, Common stock indices, Principia Press, Bloomington.
Schwert, G. William, 1990, Index of U.S. stock prices From 1802 to 1897, *Journal of Business* 63,
Shiller, Robert, 2000, Irrational Exuberance, Princeton University Press.
Siegel, Jeremy, J., 1992, The Equity Premium: Stock and bond returns since 1802, *FAJ48*
Wilson, Jack, W., and Jones, Charles, P., 2000, An analysis of the S&P 500 Index and Cowles extensions: price indexes and stock returns, 1870 - 1999, University of North Carolina, working paper.

Industry mappings for the Merged dataset are derived from the industry assignments in the individual datasets and aggregated to the 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 ICPST sectors, 11 final industry groupings are derived: Mining, Food, Retail, Chemical, Petroleum, Materials, Manufacturing, Transportation, Utilities, Financial, and Other. Industry mappings in this study are used to estimate industry-neutral and industry-level momentum.

Table I[2]
Descriptive Statistics for the Datasets

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%	1,167	139	114	103,684	84,148
GFD[2]	1825:1926	0.29%	3.38%	3,992	250	205	305,574	248,736
IFC[3]	1815:1925	0.38%	4.85%	671	46	32	57,871	41,925
MERGED[4]	1800:1926	0.28%	3.11%	4,709	272	224	413,922	338,989
CRSP[5]	1926:2012	0.98%	7.35%	29,542	3,667	3,356	3,828,692	3,462,990

[2] The ICF dataset was created for and described in detail in "A New Historical Database for the NYSE 1815 to 1925: Performance and Predictability" (Goetzmann, Ibbotson, Peng (2000)). The ICPSR dataset was created for "Price Quotations in Early United States Securities Markets, 1790-1860" (Sylla, Wilson, Wright (2002)). 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 1926. For the post-1927 period, we rely on the Center for Research in Security Prices (CRSP) database of security prices. Additionally, we download the macroeconomic data from Global Financial Data and Measuring Worth websites.

II. The Price Momentum Anomaly

A. Background

Since the discovery of the momentum anomaly (JT 1993), a large body of research attempts to isolate a risk-based explanation for the effect, inline 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)[3].

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 agree that industry momentum is a separate effect from stock-level

[3] Griffin, John, M., Ji, Susan, and Martin, Spencer, J., 2003, Momentum investing and business cycle risks", *JOF 58*.
Grundy, Bruce, and Martin, Spencer, J., 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14.
Jegadeesh, Narasimhan, and Titman, Sheridan, 1993, Returns to buying winners and selling losers", *Journal of Finance* 48.
Siganos, Antonios, and Chelley-Steeley, Patricia, 2006, Momentum profits following bull and bear markets, *Journal of AM 6.*
Stivers, Chris, and Sun, Licheng, 2012, Cross-sectional return dispersion and time-variation in value and momentum premiums, *Journal of Financial and Quantitative Analysis* 45.
Kang, Qiang and Li, Canlin, 2004, Understanding the sources of momentum profits: stock-specific component versus common-factor component, *EFA 2004 Maastricht* meetings paper No. 3629.
Kothari, S. P. and Shanken, Jay, 1992, Stock return variation and expected dividends", *Journal of Financial Economics* 31.

momentum and find that market state is a better proxy for risk than macroeconomic variables.

By far, the most insightful observations by KS (1992), JT (1993), more formally by GM (2001), and recently Blitz, Huij, Martens (2011) explore the connection between momentum portfolio beta loading and the factor realization over the portfolio formation period. GM (2001) proves analytically and demonstrates empirically that the momentum portfolio is loaded with high beta stocks during the bull market and negative beta stocks during the bear market.

This has led to a growing number of studies analyzing the connection between market states and momentum profits. CGH (2004) observes 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 to describe the poor market, the stronger the momentum returns realized. Daniel (2011) explores 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[4].

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[4] Asem, Ebenezer, and Gloria Tian, 2010, Market dynamics and momentum profits, *Journal of Financial and Quantitative Analysis* 45.
Chordia, Tarun, and Shivakumar, Lakshmanan, 2002, Momentum, business cycle, and time varying expected returns, *JOF 5*7.
Cooper, Michael, Gutierrez, Roberto, and Hameed, Allaudeen, 2004, Market states and momentum, *JOF* 59.

This study further explores the connection between market states and momentum via the dynamic relationship between momentum beta and the market state duration. Adding a duration concept to the market state definition allows us to track evolution of momentum beta and alpha both across and within market states. We find that state duration critically determines the factor loading of the momentum portfolio, which in turn affects the size and direction of momentum profits within and across market states.

B. Empirical Results

Momentum is defined as the stock's price change from t – 12 to t – 2, skipping the 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 average return of all stocks form the momentum portfolio return. Returns to this strategy are observed between February 28, 1801 and December 31, 2012.

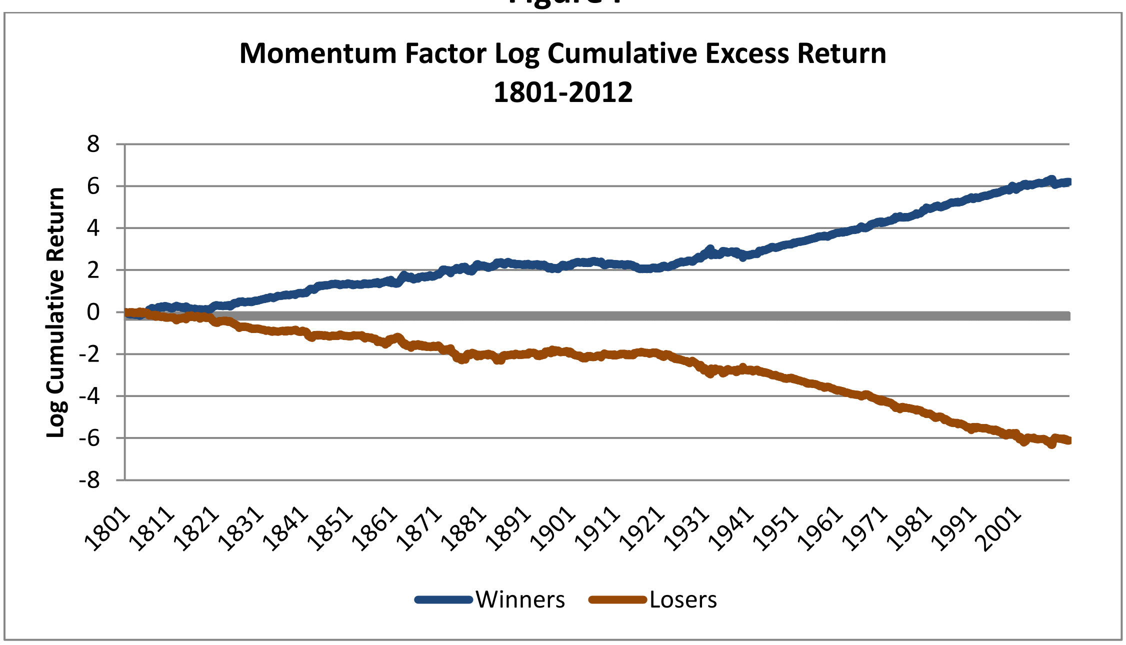
Daniel, Kent D., 2011, Momentum crashes, *Columbia Business School Research Paper No. 11-03*.
Fama, Eugene, and French, Kenneth, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51.

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 entire period from 1801-2012, W-L return is 0.40% (t-stat 4.5) - [Table II, Figure I].

Table II
Momentum Profits by Time Periods

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

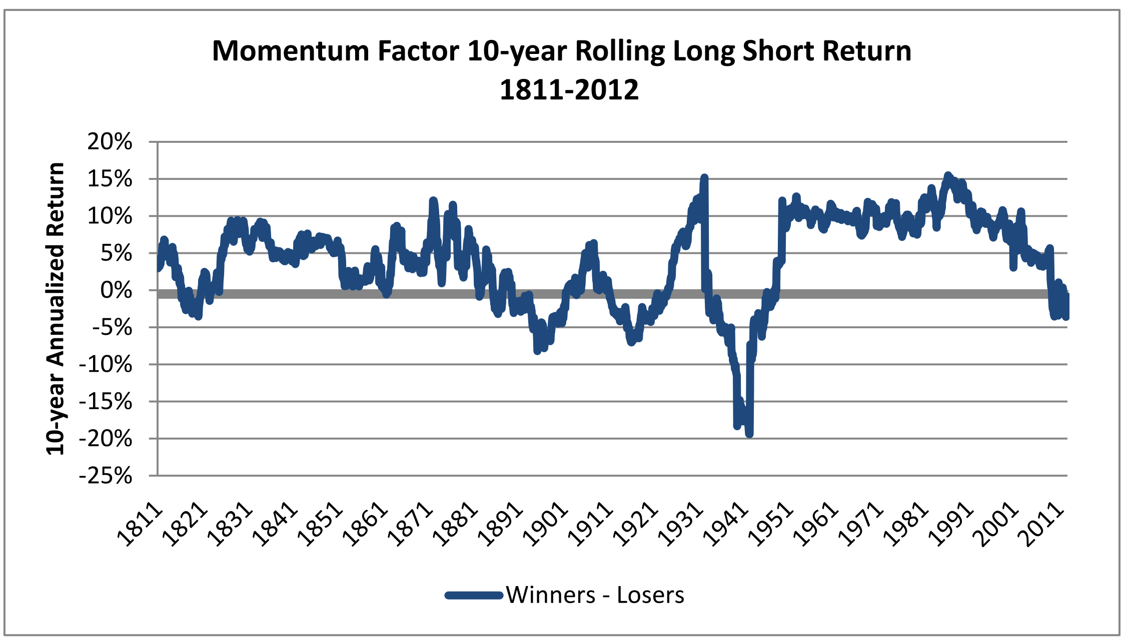
Figure I



The previously untested pre-1927 data confirms the significance of the momentum anomaly in the 19th and early 20th century U.S. stocks. The combined history creates the longest known U.S. stock-level backtest of 212 years. The size of the anomaly is stronger in the post-1927 period, yet it remains significant in both sub-periods. The merged dataset results in the monthly average of 212 testable securities, with about 71 stocks in the W and L portfolios.

There is a significant time variation to momentum payoffs occurs. During the pre-CRSP history, there are seven negative 10-year periods - [Figure II]. Any levered investor in the momentum strategy would have experienced a margin call during these periods[5]. During the recent decade of negative momentum performance (from January 2002 to December 2012) the annualized W-L spread is -2.1%, which is consistent within a longer historical timeframe.

Figure II



[5] These are significant drawdowns that support CGJ (2009) limits to the arbitrage explanation of momentum profits. Chabot, Benjamin, Eric, Ghysels, and Jagannathan, Ravi, 2009, Price momentum in stocks: insights from Victorian age, NBER. Shleifer, Andre, and Vishny, Robert, W. 1997, The limits of arbitrage, *Journal of Finance* 52.

III. Sources of Momentum Profits

A. Industry-Neutral Momentum

We first examine if industry momentum explains stock level momentum and 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 we test an industry-neutral momentum portfolio by ranking each stock within its industry on its 10-month price change. 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) - [Table III]. 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). The resulting W-L return of the monthly rebalanced industry portfolio in the pre-1927 history is 0.3% (t-stat 1.9). Consistent with GM (2001) and many others, pre-1927 data confirms that industries have a momentum of their own, which does not explain away the stock level momentum - [Table III, Figure III][6].

[6] Moskowitz, Tobias J., and Grinblatt, Mark, 1999, Do industries explain momentum?, *Journal of Finance* 54.

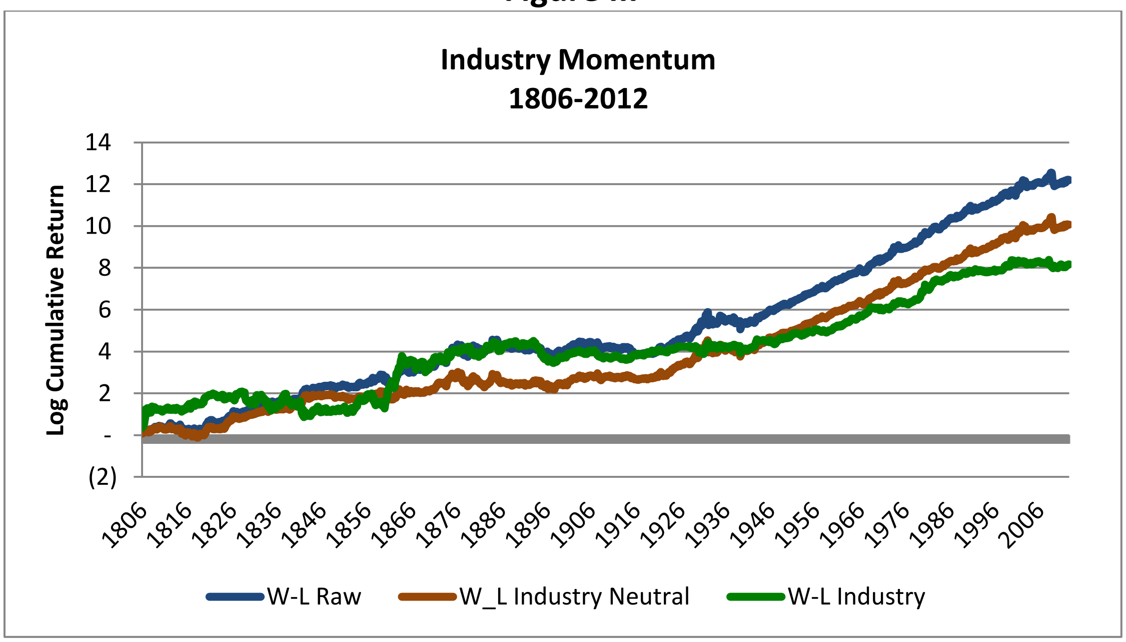
Table III
Momentum Profits for Individual Stocks and Industries

A. *1806-1926*	W-L		Industry Neutral W-L		Industry W-L		Industry W-L (w/o reversal)	
	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
Wi-Lo	0.28%	**2.7**	0.21%	**2.2**	0.31%	**1.9**	0.35%	**2.2**

B. *1927-2012*	W-L		Industry Neutral W-L		Industry W-L		Industry W-L (w/o reversal)	
	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
Wi-Lo	0.58%	**3.6**	0.51%	**3.5**	0.38%	**3.5**	0.61%	**5.7**

C. *1801-2012*	W-L		Industry Neutral W-L		Industry W-L		Industry W-L (w/o reversal)	
	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
Wi-Lo	0.40%	**4.5**	0.33%	**4.0**	0.34%	**3.2**	0.46%	**4.4**

Figure III



B. Common vs. Stock-Specific Momentum

Following the GM (2001) methodology, we test whether the stock-specific momentum is the significant driver of the W-L portfolio. 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 stock return on a dummy variable and the market return

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

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. 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 - [Table IV]. 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)[7].

Table IV
Stock-Specific vs. Common Factor Momentum

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%	0.31%	0.32%	0.31%
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%	0.15%	0.45%	0.13%
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 (%)	0.40%	-1.43%	0.57%	0.41%	-1.15%	0.55%	0.25%	0.37%	0.23%
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**

[7] Confirming GM (2001), we find that stock-specific momentum is positive and significant. 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. Blitz, David, Huij Joop, and Martens, Martin, 2011, Residual momentum, *Journal of Empirical Finance* 18, 506-521.

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). The common factor momentum is more significant in the early history with a spread of 0.31% (t-stat 2.2). Importantly, the longer history makes it clear that both the stock-specific and common factor momentum are priced. As our further results will demonstrate, the pricing of these factors occurs 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.

C. Beta Variation of Momentum Portfolios

Many studies argue that market states are a better proxy for macro-economic variables, as the market is seen as a timelier leading indicator[8]. We concur with this observation and suggest that because 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. In our view, one of the most significant contributions of GM

[8] 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.

(2001) is the analytical proof and 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, momentum portfolio's beta is positive, and it is negative following negative market return. Even though obvious, it is often a misunderstood dynamic risk property of the momentum portfolios. The recent observation of this risk occurred in 2009 when the momentum beta loading was negative and the market experienced a strong rally.

We use a market state definition that matches the momentum portfolio formation definition. 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 (duration variable). The first part aligns market state with the momentum portfolio, while the second captures the concept of state duration.

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

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

and

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

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}.

We confirm that before 1927, average beta of momentum W-L portfolio is negative (-0.26, t-stat -8.0), while the alphas are significantly positive 0.36% (t-stat 3.5) - [Table V]. We also confirm that in an up market, momentum beta is 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, 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). It is fascinating how powerful the beta variation of a momentum portfolio is.

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

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**

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. The longer each state persists, the stronger the beta becomes.

A state duration variable is created by summing the number of consecutive positive / negative market states until the state changes. This variable provides additional visibility into momentum portfolio dynamic over the course of a market state. We compute the exposure of momentum beta to 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 ($r_{ma,t}$).

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

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

$$B_{mo,t} = a_b + Coef_b * \text{Duration}_t + e_{b,t}, \tag{6}$$

where Duration is the length of the consecutive months in a given state. Duration is positive during 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 between momentum beta and market state duration. Full period coefficient is 0.02 (t-stat 19.3). Up state coefficient is 0.03 (t-stat 19.8), and down state coefficient is 0.04 (t-stat 11.5). Hence, the higher the market state duration variable, the stronger the momentum portfolio beta becomes - [Table VI, Figure IV].

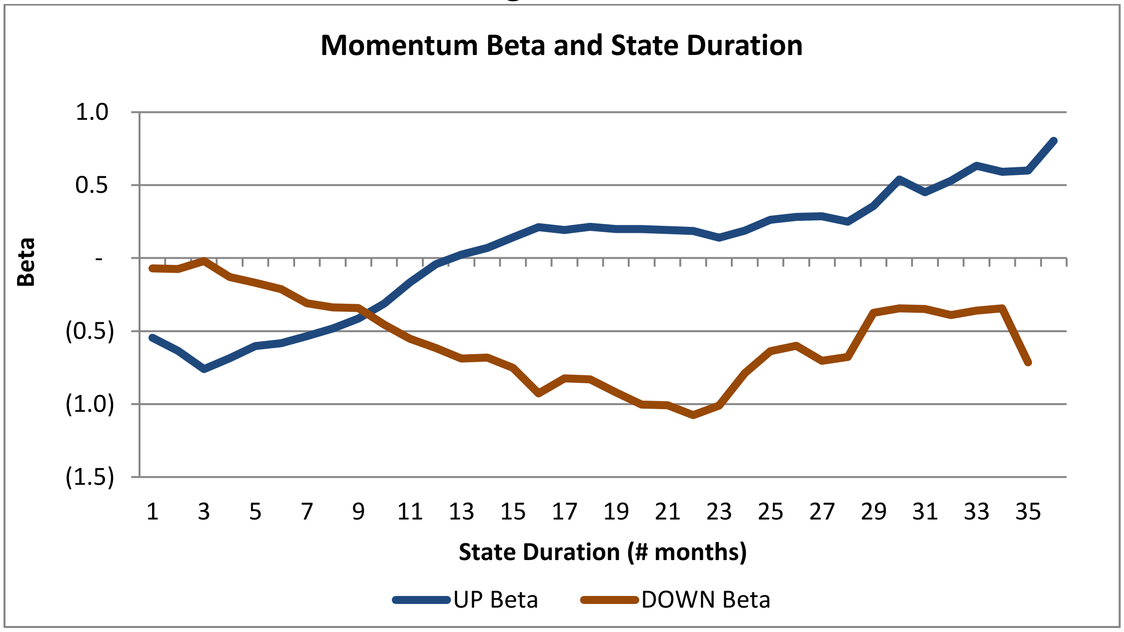
Table VI
Momentum Beta Variation and Market State Duration

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	0.00	0.05	0.01	0.05	0.00	0.02
tstat	**17.0**	**(18.7)**	**8.9**	**(1.3)**	**15.1**	**(18.2)**

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	0.02	0.00	0.03	0.00	0.01
tstat	**17.4**	**(18.2)**	**10.4**	**2.6**	**14.9**	**(15.6)**

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	0.03	0.00	0.04	0.00	0.01
tstat	**19.8**	**(21.9)**	**11.5**	**(0.6)**	**19.3**	**(22.8)**

Figure IV



Duration variable helps refine GM (2001), who only capture the average betas following up and down market states. Our study shows that only after the market state has been occurring for some time does momentum beta actually take on those signs, and that in the beginning of each state, momentum beta is actually 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 will be opposite from the market direction, hence generating a negative drag on momentum performance. During the first year of a market state, momentum portfolio starts by being long last state's winners and short last state's losers, which have the opposite beta tilt from the new market direction. In the second year and beyond, momentum beta takes on the sign of the market direction and begins to add to momentum returns. The longer a market state persists, the higher the beta and the more such exposure contributes to the momentum portfolio return. This effect explains why both the stock specific and factor momentum components are priced. It also explains why momentum underperforms after the market reverses direction.

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 - [Table VII, Figure V]. 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. 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 VII
Alpha and Beta Contribution and Market State Duration

A. *1801-2916*	*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%	-0.25%	0.15%	-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%	-0.58%	0.06%	-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%	-0.38%	0.11%	-0.2%
tstat	**4.1**	**2.2**	**4.5**	**6.8**	1.6	**6.5**	**(4.7)**	0.9	**(3.1)**

Figure V.A

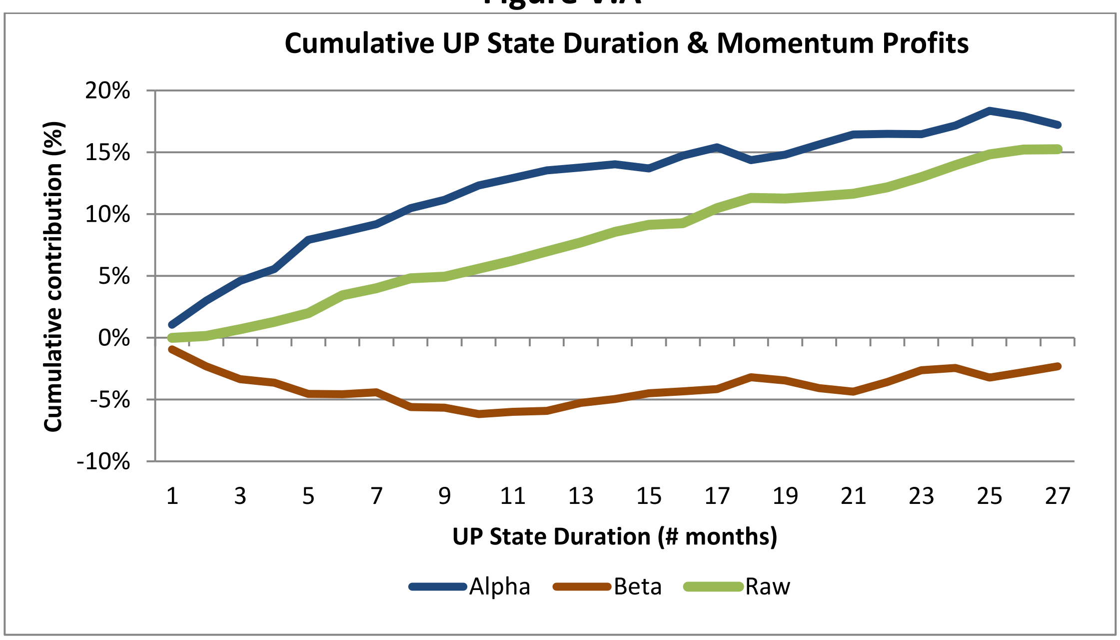
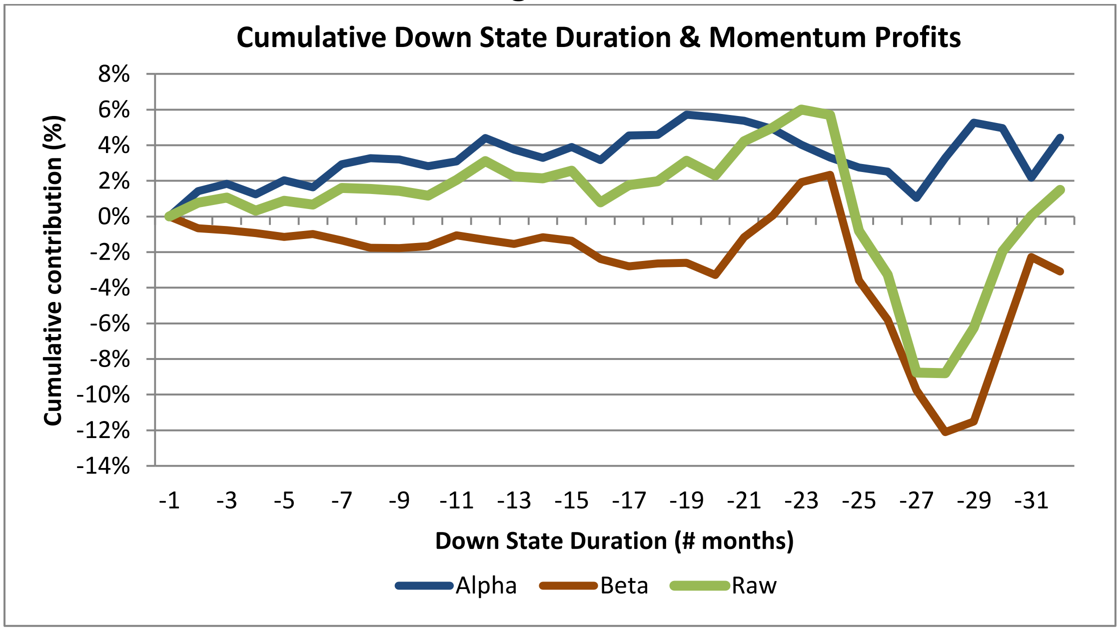


Figure V.B



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. Beta 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. Alpha contribution is significantly positive in the first year (0.8%, t-stat 6.8) and positive but 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, momentum return increases with state duration, but there is also an increase in systematic risk via a combination of increasing beta and the conditional probability of state upcoming reversal.

Breaking down the sample into up and down market states, a similar pattern can be seen. For example, alpha contribution in first 12 months of an up state is 1.2%, while the beta contribution is -.6%. In the subsequent months of an up state, alpha contribution declines to 0.4% while beta contribution rises to 0.2%. In the 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 vs. subsequent months is asymmetric between up and down states is because the momentum beta at the end of an average down state is -0.34 (t-stat 3.5), while it is insignificant 0.02 (t-stat 0.2) at the end of the average up state. This occurs because the volatility of the down states is larger leading to large absolute beta. Therefore, the expected average beta following the average down markets is highly negative, while following average duration up markets it is insignificant from 0. This is the reason why the first 12 months of a new up state experience a large negative beta contribution, while the first 12 months of a down state do not.

Our findings provide the support for the argument in SS (2012) that momentum is higher within a state than across states. This is due to the dynamic nature of momentum's beta. When a new state starts, the duration variable resets to zero, and the beta of the momentum portfolio starts a new cycle of adjusting to the new state. During this adjustment period of one year, beta's negative contribution to momentum portfolio makes returns during state transitions lower than during state continuations.

Our findings support CGH (2004) in that momentum returns are stronger following the positive market states than negative. However, we point out that this occurs mainly due to the negative market states that last longer than a year. Momentum experiences significant negative returns due to the negative beta exposure caused by lasting bear markets such as 1930s and 2000s. In market states under one year, momentum profits remain positive.

Finally, our findings concur with Daniel (2011) who shows that momentum strategy fails following volatile negative markets. Our explanation is closest in nature to Daniel, who also attributes the momentum underperformance to the beta exposure of the strategy, especially the short portfolio. Unlike Daniel, we do find a feasible hedging strategy.

E. Dynamically Hedged strategy

To account for the dynamic variation of momentum's beta, we test the following feasible ex-ante hedging strategy. If the market state has just changed, 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. This strategy is implicitly capturing the market level momentum effect expressed via the momentum portfolios which creates a significant risk / return improvement for the overall strategy.

During the full sample, the dynamically hedged strategy generates a large increase in performance in the up states from 0.6% per month (t-stat 6.9) to 0.9% per month (t-stat 8.7), and in the down states, from 0.1% (t-stat 0.4) per month to 0.2% per month (t-stat 1.3) - [Table VIII, Figure VI]. 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 VI 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 raw momentum strategy during the periods with large market reversals such as the last ten years.

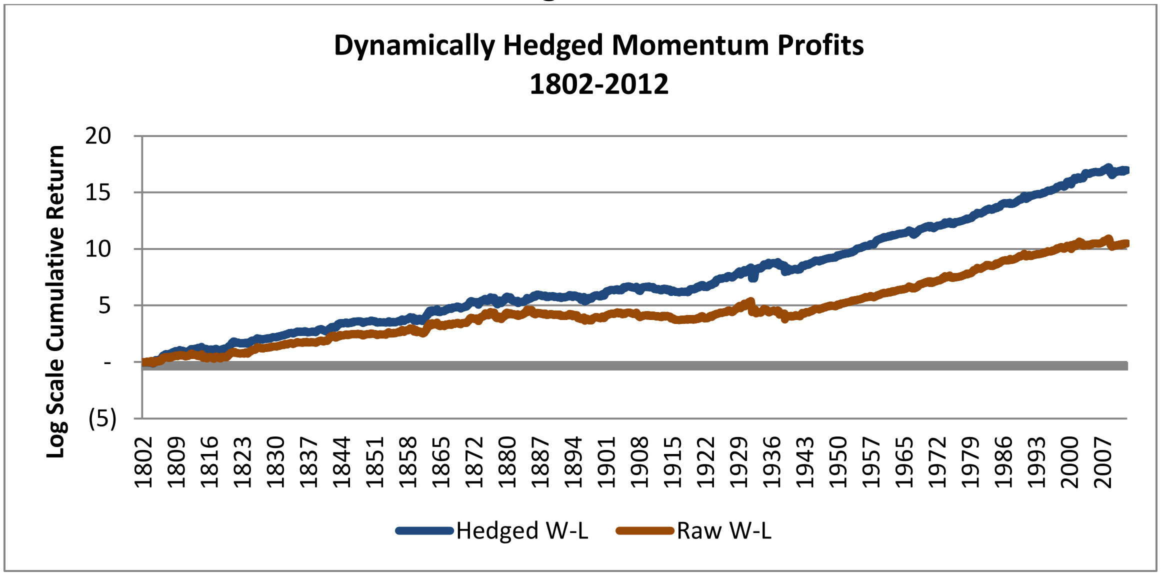
Table VIII
Dynamically Hedged Momentum Returns

A. *1801-1926*	W-L			Dynamic Hedge		
Parameter	**Average**	**S.E.**	**(t-stat)**	**Average**	**S.E.**	**(t-stat)**
UP	0.4%	3.5%	**3.3**	0.6%	4.0%	**4.6**
Down	0.1%	4.6%	0.7	0.3%	4.7%	1.5
Overall	0.3%	4.0%	**2.7**	0.5%	4.4%	**4.4**

B. *1927-2012*	W-L			Dynamic Hedge		
Parameter	**Average**	**S.E.**	**(t-stat)**	**Average**	**S.E.**	**(t-stat)**
UP	0.9%	3.5%	**6.7**	1.3%	4.4%	**7.7**
Down	0.0%	7.5%	(0.1)	0.1%	7.7%	0.4
Overall	0.6%	5.1%	**3.6**	0.9%	5.7%	**5.2**

C. *1801-2012*	W-L			Dynamic Hedge		
Parameter	**Average**	**S.E.**	**(t-stat)**	**Average**	**S.E.**	**(t-stat)**
UP	0.6%	3.5%	**6.9**	0.9%	4.2%	**8.7**
Down	0.1%	5.8%	0.4	0.2%	5.9%	1.3
Overall	0.4%	4.5%	**4.5**	0.7%	5.0%	**6.8**

Figure VI



IV. Conclusion

We initiate out-of-sample research of the 19th and early 20th century stock-level data by identifying three datasets that can be used for such studies, and creating a merged dataset that combines all three. Test of the price 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 portfolio beta, alpha and the duration of up and down market states. The longer each state continues, the higher the proportion that the beta exposure contributes to momentum returns. Therefore, the momentum factor becomes riskier the longer a market state lasts, and when the economic conditions change, the strong beta exposure significantly harms momentum profits. Dynamically hedging out beta in the early stages of a market state significantly improves the profitability of momentum strategy.[9]

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[9] **Remaining References**

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