

DISCUSSION PAPER SERIES

No. 10234

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Benjamin Chabot, Eric Ghysels
and Ravi Jagannathan

FINANCIAL ECONOMICS



Centre for Economic Policy Research

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Discussion Paper No. 10234

November 2014

Submitted 29 October 2014

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801
www.cepr.org

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MOMENTUM TRADING, RETURN CHASING, AND PREDICTABLE CRASHES[†]

Abstract

We combine self-collected historical data from 1867 to 1907 with CRSP data from 1926 to 2012, to examine over 140 years of risk and return of one of the most popular mechanical trading strategies—momentum. We find that the momentum strategy has earned abnormally high risk-adjusted returns—a three factor alpha of 1 percent per month between 1927 and 2012 and 0.5 percent per month between 1867 and 1907—both statistically significantly different from zero. However, the momentum strategy also exposed investors to large losses (crashes) during both periods. Momentum crashes were predictable. Crashes were more likely when momentum had recently performed well (both eras), interest rates were relatively low (1867–1907), or momentum had recently outperformed the stock market (CRSP era) - times when borrowing or attracting return chasing “blind capital” would have been easier. We argue based on a stylized model and simulated outcomes from a richer model that a money manager who competes for funds from return-chasing investors and is compensated via fees that are convex in the amount of money managed and the return on that money has an incentive to remain invested in momentum even when the crash risk is known to be high.

JEL Classification: G1, G12 and G14

Keywords: limits-to-arbitrage and momentum

Benjamin Chabot ben.chabot@chi.frb.org
Federal Reserve Bank of Chicago

Eric Ghysels eghysels@unc.edu
University of North Carolina and CEPR

Ravi Jagannathan rjaganna@northwestern.edu
Kellogg School of Management and NBER

[†] The views expressed in this article are those of the author and do not necessarily reflect those of the Federal Reserve Bank of Chicago or Federal Reserve System.

Is there something hardwired in the trading of financial assets that endogenously creates major, albeit infrequent, crashes? We provide an affirmative answer as we take a new look at momentum strategies. These strategies—buying recent winners and selling recent losers—are some of the oldest stock-selection strategies still in practice and have generated abnormal returns for over 140 years.¹ By “new look” we mean (1) using an entirely new long historical data set and (2) using a new model.

There is indeed a growing concern among regulators and market participants that large inflows of capital into trading strategies—such as momentum—may contribute to market fragility. The fear is that the past success of trading may set the stage for future crashes. The fact that money managers employing momentum strategies suffer occasional dramatic losses suggests that these managers either cannot anticipate fragile market conditions or lack the incentives to take actions to minimize exposure to large losses. Using momentum, one of the oldest and most popular trading strategies, we show that times when large losses are more likely can be predicted by superior past performance of momentum. These are the times when “blind capital” will likely find momentum more attractive and regulators should be most vigilant.²

We combine self-collected historical data with existing data to document the returns to momentum investing in the CRSP-era United States and Victorian-era London. A consistently applied momentum strategy generated abnormal returns and predictable profit cycles across both periods. While the momentum strategy has historically generated high abnormal returns on average, the strategy is prone to periodic crashes. Thus, while investors could enjoy abnormal average returns by buying winners and selling losers, the momentum strategy exposed investors to large losses with some regularity. What is even more remarkable is the fact that the hazards of these crashes vary in a predictable way across both eras.

How can we rationalize such a persistent historical pattern across eras with arguably very

¹ To be more precise, at least since the time of David Ricardo, who advised, “cut short your losses, let your profits run,” the strategy of holding winners and selling losers has been a favorite of stock market advisors. Ricardo’s investment maxims—with which he made a fortune speculating on the London Stock Exchange—are quoted in James Grant’s 1838 book *The Great Metropolis, Vol II* (p.58). Nineteenth and early twentieth century investment manuals, such as *The Ticker and Investment Digest* and *The Banker’s Magazine*, often carried advice columns recommending momentum strategies and stock guides, such as Walter Bagehot’s *Investors Monthly Manual*, Henry Poor’s *Poor’s Manual of Investments*, *Moody’s Manuals*, and *The Commercial and Financial Chronicle*, all of which included statistical information on stock highs and lows over various horizons for readers who wished to use recent momentum to select stocks.

² “Walter Bagehot blamed crashes on what he called “blind capital”—“periods when credulous cash, ignoring risk, flooded into unwise investment” (*The Economist*, April 12, 2014, p.7).

different equity trading environments? There were neither hedge funds during the Victorian era, nor electronic trading, for example. What made momentum return patterns so similar? What explains the persistence of momentum profits? Why does a strategy as simple as buy winners and sell losers not become crowded with followers who bid away any excess returns? The fact that momentum strategies show so many similarities across two different eras implies that it is hardwired into the dynamics of equity returns. What remained constant across these two different eras? It is surely not related to trading costs, market structure, and the like, since none remained constant. We think the answer lies in the fact that the momentum strategy does require significant trading and therefore requires skill in executing trades at minimal cost. There is likely to be a separation between the investors with the skill to execute trades cheaply and investors with capital to devote to the momentum strategy. This *separation of brains from capital* can be overcome by professional managers endowed with trading skills offering their services to investors with capital in exchange for a percentage of the profits (in the latter part of the CRSP sample) or through leverage financed by risky borrowings at suitable interest rates. However, while the momentum strategy does generate high returns, it also exposes investors to infrequent but large losses. The severe losses associated with the momentum strategy makes it difficult for investors who use other people's money or trading leverage to drive momentum profits out of the market. This is the "limits to arbitrage" explanation of persistent anomalies of Shleifer and Visney (1997).

Our paper makes three contributions. First, we employ a self-collected data set of Victorian-era London stock returns to extend the Fama–French momentum portfolios back to 1867. We combine our new momentum portfolios with existing data to document that the momentum strategy has generated abnormal returns for over 140 years.

Second, we establish the fact that momentum strategy returns exhibit predictable cyclical behavior involving large losses that are similarly predictable across the Victorian and CRSP eras. Exploiting momentum involves leverage or the use of other people's money. If capital constraints prevent skilled investors from driving excess momentum returns to zero, we hypothesize that a measure of capital scarcity should predict the duration of momentum profit cycles. To test this formally, we introduce a new methodology based on modeling profit duration dynamics as a function of the risk-free rate, the past stock market return, and the past performance of the momentum strategy, which we interpret as a proxy for the scarcity of capital

available to skilled momentum traders. Consistent with models of leverage-induced crashes, we find strong statistical evidence that our proxy for capital available to momentum traders predicts sharp downturns in momentum profits.

Third, we show that the combination of return-chasing customers and fee structure creates incentives for money managers to stay invested in the momentum strategy even when the probability of a crash is high; this would apply to the institutional structure during the latter part of the data period covered by CRSP. To that end we develop a three-period theoretical model with two managers and two types of states of the economy that we can solve analytically to explain this phenomenon, and we use simulations to verify that the explanation remains valid in richer economies with many money managers, states of nature, and time periods. In addition, the investors in our model perfectly understand the behavior of managers, and still choose to let them manage their money. The simulated model—calibrated to mimic the aforementioned duration properties of momentum cycles—explains the apparent paradox that even though large momentum losses are predictable, sophisticated money managers may nonetheless choose to crowd into this strategy at times of elevated risk. Our money managers are compensated by collecting fees equal to a small percentage of assets under management and a larger percentage of profits above a high-water mark. These managers compete with each other for the blind capital of return-chasing customers. In our simulations calibrated with CRSP data, money managers who go to cash in periods of elevated crash risk are less profitable on average than managers who remain invested in the momentum strategy. While we do not model the behavior of momentum investors of the Victorian era who relied on borrowed funds to invest in momentum strategies, we conjecture that they too would have had little incentive to exit when crash probabilities became high.

The paper is organized as follows. First, we provide a brief discussion of the limits to arbitrage literature in Section 1. In Section 2 we introduce and describe the new data and document the similarities between momentum profits in the Victorian and CRSP eras. Our main results—that momentum profits exhibit predictable cycles: they stochastically vanish and reemerge—are presented in Section 3. We characterize this stochastic periodicity using a hazard model that successfully predicts transitions into momentum strategy bear markets as a function of the recent relative attractiveness of the momentum strategy. In Section 4 we provide a possible explanation for this phenomenon based on simulations of a stylized partial-equilibrium model

economy calibrated to the data. Section 6 concludes. Details about the unique data set can be found in the Appendix.

1. The Momentum Strategy and Limits to Arbitrage

We argue that periodic momentum losses act as a limit to arbitrage by making it difficult for sophisticated investors to consistently employ leverage with other people's money. In particular, "separation of brains from capital" can explain both the occasional large losses to the momentum strategy apparent in the historical time series and why momentum continued to be a profitable strategy for 140 years.

When an anomaly exists, but only a limited number of investors have both the capital and skill to devote to a trading strategy designed to exploit it, they may not have enough collective resources to drive the anomalous returns to zero. Typically, skilled investors will seek to expand their profitable positions either through trading leverage (short positions funding long positions) or by soliciting outside capital from less-skilled investors. However, in theoretical models such as Aiyagari and Gertler (1999), Gromb and Vayanos (2002), Geanakopolis (2003), Fostel and Geanakopolis (2008), Brunnermeier and Pedersen (2009), and Kondor (2009), leverage constraints can result in sudden reversals if idiosyncratic declines lower the value of collateral and force correlated liquidations. Fear of forced liquidations limits the leverage arbitrageurs are willing to employ and therefore the capital these arbitrageurs can devote to eliminating anomalies. Moreover, when arbitrageurs raise equity from uninformed outside investors, poor returns can result in contagious liquidations if outside investors interpret losses as evidence that they have a low-quality investment manager. In models such as Shleifer and Visney (1997), Liu and Longstaff (2004), and Acharya et al. (2008), idiosyncratic volatility combines with the fear of outside-investor flight to prevent arbitrageurs from devoting sufficient capital to high-alpha investments. These models suggest that apparently profitable investment opportunities will be left unexploited due to crash fears. In that case, an econometrician would find that positive alpha and occasional large losses of trading strategies go together.

Khandani and Lo (2007) and Mitchell et al. (2007) document recent examples of shocks that interact with leverage and capital constraints to generate forced liquidations and sudden reversals in otherwise high-return, low-systematic-risk strategies, such as long-short quant funds

and convertible arbitrage funds. Ambastha and Ben Dor (2010) observed the same pattern for the Long Barclays Alternatives Replicators, a particular hedge-fund index clone. Hedge-fund clones rely on price momentum to some extent, and Ben Dor, Jagannathan, Meier, and Xu (2011) find that an index of six hedge-fund clones exhibits the same pattern. Financial crises are times when banks and other intermediaries withdraw funding that is otherwise available to arbitrageurs, and Daniel and Moskowitz (2011) document a similar breakdown in performance in momentum strategies during the financial crisis. Elavia and Kim (2011) provide an explanation for a closely related phenomenon based on how investors perceive risk and make decisions, and Daniel, Jagannathan, and Kim (2011) make use of this pattern to identify hidden turbulent market conditions. More on point, Daniel and Moskowitz (2011) document that infrequent crashes skew returns from momentum strategies across numerous asset classes. These momentum crashes are the necessary ingredient to limit arbitrage with other people's money.

We argue that the 140-year time series of momentum returns exhibit the classic characteristics of an anomaly protected by the “limits to arbitrage.” To test this formally, we introduce a new methodology based on modeling profit duration dynamics as a function of the risk-free rate, the past stock market return, and the past performance of the momentum strategy, which we interpret as a proxy for the scarcity of capital devoted to momentum strategies. If capital constraints limit arbitrage, we would expect a measure of capital scarcity to predict the duration of momentum profit cycles. We find strong evidence supporting this explanation of momentum cycles.

We make use of our extended time series of momentum profits to identify states in which the hazard of loss is high. A simple proxy for the amount of capital devoted to momentum trades—the past relative performance of the momentum strategy—predicts the duration of momentum profit cycles in both the CRSP-era United States and 1866–1907 London. We hypothesize that markets always have noise traders who buy and sell for idiosyncratic liquidity reasons or are subject to the biases in the literature. Profit opportunities from a simple momentum trading rule should depend on the relative supply of capital available to sophisticated and noise traders. Noise traders slow the adjustment of prices to new information and create opportunities for momentum traders. When capital constraints on sophisticated traders are relaxed, many sophisticated traders crowd into the momentum strategy and drive away the future profits, thus ending the cycle. When capital is scarce, however, sophisticated traders are unable

to obtain the firepower to eliminate momentum profit opportunities. Time periods where investment capital is plentiful are also periods in which sophisticated traders find it easy to attract capital and expand their positions. Momentum profits are therefore most likely to persist in periods where capital available to sophisticated momentum traders is in short supply relative to noise traders. This is the familiar story of skilled but capital-constrained traders. When investment capital is plentiful, the entry of sophisticated leveraged traders can quickly exhaust the profits from mechanical trading rules. As profits are exhausted and sophisticated traders post losses with more regularity, these losses interact with leverage and capital constraints to force the exit of sophisticated traders, and the profit opportunities return.

Any cycle-based test of a trading strategy requires a large sample of observed cycles and a test based on the availability of arbitrage capital is best evaluated with a long time series rather than a cross-country comparison of momentum cycles. With increasing globalization, arbitrageurs in one country can easily exploit profitable trading opportunities in other countries. Globalization therefore makes it difficult to form country-specific measures of arbitrage capital, since capital can easily move across national borders and draws into question whether cross-country cycles are independent observations. We therefore focus on the largest stock markets and establish the robustness of our findings by examining an extremely long time series. We use CRSP-era US stock market data and Victorian-era London stock market returns to test our hypothesis.

2. Stock Price Momentum during CRSP and Victorian Eras: Abnormal Returns and Cyclical Profits

We use a hand-collected data set of the London Stock Exchange.³ Our data set consists of the closing prices, dividends, and shares outstanding of 1,808 stocks listed in London between 1866 and 1907. These data include virtually every stock traded on the

³ Pre-CRSP-era historical data have been used before to assess some of the salient empirical features of asset returns. Schwert (1989) uses 1857–1986 U.S. stock return data to investigate the cause of stock volatility. Schwert (1990) analyzes the relation between stock returns and real economic activity with 1889–1988 U.S. stock data. Goetzmann (1993), Goetzmann, Ibbotson, and Peng (2001) and Annaert and Van Hyfte (2006) study long-term predictability in London since 1695, the NYSE between 1815 to 1925, and the 19th century Brussels stock exchange, respectively.

London Stock Exchange during this period. In some ways the Victorian capital markets are an ideal laboratory to study momentum theories. The pre-WWI London Stock Exchange had no capital gains tax distortions, and it was remarkably easy to retail investors to short shares and form leveraged long–short portfolios.⁴

We consider two measures of returns from momentum strategies. The first is the return an investor would receive from holding the Fama–French momentum factor portfolio.⁵ The second, which we call the FF7030 portfolio, is computed from the Fama–French decile portfolios formed monthly on momentum. The FF7030 portfolio is the return an investor would receive from buying a value-weighted combination of the three Fama–French decile momentum portfolios with prior returns above the 70th percentile and shorting a value-weighted combination of the three portfolios with prior returns below the 30th percentile.⁶

Table 1 reports the average, standard deviation and skew of momentum portfolio returns in the United States between 1927 and 2012 and London between 1867 and 1907. Momentum strategies generated positive returns with remarkably similar Sharp ratios across both eras, but the CRSP-era NYSE momentum portfolios generated higher average returns along with more variance and skewness.

CRSP-era momentum is a well-known anomaly. The CRSP-era Fama–French momentum factor and 7030 portfolio returns cannot be explained by their exposure to the Fama–French market, small minus big (SMB), and the high book-to-market minus low book-to-market (HML) risk factors. Were momentum returns always abnormal? Table 1 also reports the coefficients from a regression of momentum portfolio returns on two three-factor models:

⁴ The LSE used fortnightly clearing that minimized the costs of forming long–short portfolios. On the day before settlement, the LSE clearing house ran a netting operation where shorts who did not want to deliver shares could be matched with longs who did not wish to take delivery. Supply and demand was equated by the “contango” or “backwardation” rate—the repo rate paid by longs and shorts to carry their position for another 14 days. Thus, shorting involved none of the search frictions modeled in papers such as Duffie et al. (2002). See *Rates of Interest on Collateral Call Loans* 66th 2nd session Congress Senate Doc 262 for a description of shorting on the Victorian LSE and a comparison to practice on the NYSE.

⁵ The momentum factor portfolio is formed monthly by sorting stocks at time t into one of six value-weighted portfolios formed on size and month $t-12$ to $t-1$ return. The six portfolios are the intersections of two portfolios formed on size and three portfolios formed on prior return. The monthly size breakpoint is the median NYSE market equity. The prior return breakpoints are the 30th and 70th percentiles. The momentum factor portfolio is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios,

⁶ All Fama–French portfolios are taken from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$R_{mom,t} = \alpha + \beta_{(mkt)}\{R_{mkt} - R_f\}_t + \beta_{(SMB)}\{R_{SMB}\}_t + \beta_{(HML)}\{R_{HML}\}_t + \varepsilon_t \quad (1)$$

$$R_{mom,t} = \alpha + \beta_{(mkt)}\{R_{mkt} - R_f\}_t + \beta_{(Size)}\{R_{Size}\}_t + \beta_{(divyield)}\{R_{divyield}\}_t + \varepsilon_t \quad (2)$$

The first model (1) is the familiar Fama–French three-factor model, where the SMB size factor and the HML value factor are both formed from double sorts that require accounting-book value. Unfortunately, accounting data are either unavailable or unreliable for most stocks trading in London before 1907. We therefore estimate a second three-factor model (2) with size and value factors formed on variables observable in the pre-1907 London market. Our size factor (Size) is a monthly small-minus-big portfolio formed by buying a value-weighted portfolio of all stocks with a market value below the median and shorting a value-weighted portfolio of all stocks with a market value above the median. Our value factor (Divyield) is a monthly high-minus-low portfolio formed on dividend yield. We form this value factor by sorting stocks each June based on the same criteria that Fama and French use to construct portfolios formed on dividend yield. Fama and French assign stocks to one of four portfolios based on dividend yield (no dividend, bottom 30%, middle 40%, top 30%). Our high-minus-low dividend yield portfolio is the monthly return on the top 30% of dividend-yielding stocks minus the return on the stocks that paid no dividends.

Table I reports the regression coefficient from monthly time-series regressions of momentum strategy returns on the factors in (1) and (2) for the CRSP-era United States and (2) for the pre-1907 London stocks. The monthly CRSP-era momentum factor alpha is 101 basis points in both specifications (1) and (2), and the monthly CRSP-era FF7030 alpha is 88 and 89 basis points, respectively. The similarity of alphas across specifications (1) and (2) reassure us that our alternative size and value factors capture the risks spanned by the traditional Fama–French SMB and HML factors.

The momentum strategy generated positive alpha in pre-1907 London as well. An investor who held the Fama–French momentum factor or the FF7030 portfolio would have enjoyed 28-day alphas of 52 and 49 basis points, respectively. The pre-1907 alphas are only 55% as large as the CRSP-era alphas, but the momentum strategy generated strongly statistically significant abnormal returns.

While the momentum strategy generated comparable Sharp ratios and statistically significant alphas across both sample periods, the Victorian-era momentum returns were less negatively skewed. Presumably, the limited role of delegated portfolio management during the Victorian era diminished the crash risk due to contagious investor liquidations. However, the ease with which Victorian retail investors could finance long–short positions in the stock lending market suggests the risk of crashes due to binding leverage constraints discussed earlier remained.

2.1 Dating Momentum Bull and Bear Markets

The momentum returns across both eras can be characterized by abnormally high returns punctuated by occasional steep but predictable losses. To show this, we first date momentum bull and bear markets via the Lunde and Timmermann (2004) algorithm. Bull (Bear) markets are colloquially defined as a long-term upward (downward) trend in prices with inconsequential interruptions. Lunde and Timmermann (2004) formalize this intuition with a dating algorithm, which we briefly describe next.⁷

Assume time is measured at discrete intervals and the price of the portfolio of interest at the end of time t is P_t . Let I_t be a bull market indicator equal to 1 if we are in the bull state at time t and 0 otherwise. Let λ_1 be a scalar defining the threshold of stock price movements that trigger a switch from a bear to a bull market and λ_2 the threshold of stock price movements that trigger a switch from a bull to a bear market. Suppose that at time t_0 the portfolio is in a bull market at a local maximum ($I_{t_0} = 1$). Set $P_{t_0}^{max} = P_{t_0}$, where P_{t_0} is the value of the portfolio at time t_0 . Let τ_{max} and τ_{min} be stopping-time variables defined by

$$\begin{aligned}\tau_{max}(P_{t_0}^{max}, t_0 | I_{t_0} = 1) &= \inf\{t_0 + \tau: P_{t_0+\tau} \geq P_{t_0}^{max}\}, \\ \tau_{min}(P_{t_0}^{max}, t_0, \lambda_2 | I_{t_0} = 1) &= \inf\{t_0 + \tau: P_{t_0+\tau} < (1 - \lambda_2)P_{t_0}^{max}\}.\end{aligned}\quad (3)$$

⁷ This description is taken from Lunde and Timmermann (2004, p. 254–255).

The $\min(\tau_{max}, \tau_{min})$ is the first time the price crosses one of two barriers $\{P_{t_0}^{max}, (1 - \lambda_2)P_{t_0}^{max}\}$. If $\tau_{max} < \tau_{min}$, then we have a new local max. Update the current bull market state by setting I_t equal to 1 when t is in the interval t_{0+1} to $t_{0+\tau_{max}}$ and $P_{t_{0+\tau_{max}}}^{max} = P_{t_{0+\tau_{max}}}$ and continue with the new local max.

Conversely, if $\tau_{min} < \tau_{max}$, the price has declined by a sufficient amount to switch from a bull to a bear market that has prevailed since t_0 . Set I_t equal to 0 when t is in the interval t_{0+1} to $t_{0+\tau_{min}}$ and define $P_{t_{0+\tau_{min}}}^{min} = P_{t_{0+\tau_{min}}}$. If the starting point at t_0 is a bear market, then the stopping times are defined as

$$\begin{aligned} \tau_{min}(P_{t_0}^{min}, t_0 | I_{t_0} = 0) &= \inf\{t_0 + \tau: P_{t_0+\tau} \leq P_{t_0}^{min}\}, \\ \tau_{max}(P_{t_0}^{min}, t_0, \lambda_1 | I_{t_0} = 0) &= \inf\{t_0 + \tau: P_{t_0+\tau} > (1 + \lambda_1)P_{t_0}^{min}\}. \end{aligned} \quad (4)$$

This algorithm partitions the momentum return time series into bull or bear markets (i.e., $I_t = 0$ or $I_t = 1$ for all t). We consider symmetric thresholds ($\lambda_1 = \lambda_2$) for transitions between bull and bear markets. There is no consensus on what the thresholds should be. Exceedingly large thresholds will result in few transitions between bull and bear market states and are likely to diminish the power of our hazard model analysis. On the other hand, if we set the thresholds too small, we run the risk of labeling small fluctuations, which may be inconsequential to the decision making of momentum traders. We weigh these trade-offs and decide to choose symmetric 5% and 10% transition thresholds. We think these thresholds are large enough to affect the behavior of momentum investors who often employ leverage and are therefore sensitive to even small drawdowns while remaining small enough to generate a number of cycles in the data.

Table 2 reports the frequency, duration, and average cumulative loss from momentum strategy bear markets during both the CRSP and Pre-1907 eras. The CRSP-era momentum factor and the FF7030 portfolios suffered bear market declines of at least 5% 63 and 68 times, respectively, between 1927 and 2012. Bear markets of at least 5% occurred approximately every 15–16 months, and the average cumulative loss was 13.6% and 14.8%, respectively!

Given the absence of the delegated portfolio managers in the Pre-1907 era, we should

expect crashes to be less severe and less frequent. In fact, bear markets in momentum were both less frequent and more benign before 1907. While the momentum factor and 7030 portfolios suffered bear market declines of at least 5% every 16 or 15 months, respectively, during the CRSP era, these same strategies suffered bear markets every 28 or 25 months during the pre-1907 era. When bear markets did occur, both the speed and magnitude of declines were smaller.

The past 150 years illustrate that there is clearly more to momentum returns than large alphas. Although the momentum strategy generated high abnormal returns on average, the strategy has exposed momentum traders to brief but sharp declines. Cyclicity is consistent with many behavioral and rational explanations of momentum. Cooper, Gutierrez, and Hameed (2004) note that the theory of Daniel, Hirshleifer, and Subrahmanyam (1997) predicts differences in momentum profits across states of the market. Momentum cycles may also reflect changing risk over the business cycle. Chordia and Sivakumar (2002) show that macroeconomic instruments commonly used for measuring macroeconomic conditions can explain a large portion of momentum profits. Moskowitz, Ooi, and Pedersen (2012) find that momentum across many markets is consistent with initial under-reaction and the trading behavior of speculators, while Asness, Moskowitz, and Pedersen (2013) find that momentum across many markets can be partially explained by liquidity and long-run consumption risks.

While we are not the first to notice cyclicity in momentum returns, one of our contributions is to introduce a hazard model that successfully captures the time-varying likelihood of momentum downturns.

3. Predictable Momentum Cycles

If capital constraints prevent skilled investors from driving excess momentum returns to zero, we speculate that a measure of capital scarcity should predict the duration of momentum profit cycles. To test this formally, we introduce a new methodology based on modeling profit duration dynamics as a function of the risk-free rate, the past stock market return, and the past performance of the momentum strategy, which we interpret as a proxy for the scarcity of capital available to skilled managers employing momentum strategies.

Fund managers find it easier to attract new assets when their past performance is

strong.⁸ Likewise, self-leveraged investors have more money to invest when their strategy has performed well in the past. The past return of the momentum strategy is therefore likely to contain information about how crowded the momentum trade is. Money crowding into the momentum strategy is likely to both reduce any future returns attributable to slow moving capital and increase the probability that a negative shock will result in a large decline as more leveraged investors are forced to liquidate and rush for the exit.

If capital constraints do limit arbitrage, we would expect a measure of capital scarcity to predict the duration of momentum profit cycles. We model the hazard of the momentum strategy transitioning from a bull to a bear market and find strong evidence that our proxy for capital available to momentum traders predicts momentum cycles.

3.1 The Discrete Time Hazard Model

We model the hazard of a transition from a momentum strategy bull market to a bear market. We start with the assumption that the data are generated with a continuous time process with a proportional hazard

$$h(t, \mathbf{X}) = h_0(t)e^{\beta' \mathbf{X}}. \quad (5)$$

$h_0(t) = \gamma \rho t^{\rho-1}$ is the baseline Weibull hazard, where t is the age of the bull market and \mathbf{X} are covariates that shift the hazard relative to the baseline. The Weibull specification allows for duration dependence in the baseline hazard. If $\rho > 1$, the baseline hazard increases as the bull market ages; if $\rho < 1$, the baseline hazard decreased as the bull ages; and if $\rho = 1$, the baseline hazard becomes the exponential model with constant hazard.

When the data are generated by (5), Prentice and Gloeckler (1978) derive the discrete time hazard with time-varying covariates. The probability that a bull market ends at time t is Pr_t :

$$Pr_t = 1 - e^{-h_t e^{\beta' \mathbf{X}_t}} \quad (6)$$

⁸ Agarwal, Daniel, and Naik (2009) and Fung, Hsieh, Naik, and Ramadorai (2008) have documented the AUM Flow-Performance Relationship with individual hedge funds and funds of funds, respectively.

where $h_t = e^{\alpha+(\rho-1)\ln(t)}$ is the Weibull baseline hazard.

Let d_t be a dummy variable equal to 1 if the bull market ends at time t and 0 otherwise. The discrete time log-likelihood function is⁹

$$\ln L = \sum_{t=1}^{T_{bull}} d_t \ln\left(\frac{Pr_t}{1-Pr_t}\right) + \sum_{t=1}^{T_{bull}} \ln(1 - Pr_t), \quad (7)$$

where T_{bull} is the number of time periods at risk (the number of time periods in bull markets).

We estimate (7) via maximum likelihood with three covariates in \mathbf{X}_t . Our first covariate—the level of the time t risk-free rate—captures the opportunity cost of capital. Our second and third covariates are the cumulative return on the momentum portfolio and the value-weighted market portfolio from time $(t-12)$ to $(t-1)$ —which captures the performance of the momentum strategy relative to the market over the past year.

3.2 Empirical Findings

The estimated hazard model coefficients are reported in Table 3. Holding the past return on the market fixed, high past returns on the momentum strategy increase the odds of the onset of a bear market in momentum in both the NYSE CRSP and Pre-1907 London data. On the other hand, holding the past momentum return fixed, higher past returns on the market lower the odds of entering a bear market in momentum during the CRSP era, but increase the odds of entering a bear market in the Victorian era, and statistically significantly so for the 7030 momentum strategy. Again, this is consistent with the institutional differences across the two eras. In the Victorian era, when delegated portfolio management was not in vogue, individual investors engaging in momentum trading financed their positions by pledging their financial assets as collateral. An increase in the level of the stock market would increase collateral values, thereby reducing the odds of crashes induced by forced selling to meet collateral calls. In contrast, during the CRSP era, when professional money management became more prevalent, superior past stock market

⁹ See Allison (1982)

performance would decrease the relative attractiveness of investing in momentum strategies to owners of money, especially return-chasing blind capital. Consequently, momentum strategies were likely to be less crowded following superior stock market performance.¹⁰

High levels of the risk-free rate decreased the odds of a bear market in momentum during the Victorian era but had no effect on bear market odds in the CRSP sample. Again, this is consistent with institutional differences. In the Victorian era, absent the availability of other peoples' money, a momentum trader could only deploy large amounts of money through margin borrowing.¹¹ An increase in the level of the risk-free rate raised the cost of margin borrowing, which would make the momentum strategy funded by margin borrowing less attractive and consequently less crowded.

The hazard models do an excellent job fitting the data. Momentum bear markets can be forecasted with surprising precision. Figure 1 plots the receiver-operating-characteristic (ROC) curve for the full model estimated with the CRSP-era data and the Fama–French momentum factor.¹² In our context, the hazard model generates a time-varying probability of transitioning to a bear market. A money manager who wishes to avoid bear markets could select a discrimination threshold above which he will exit momentum and move into cash.

Partition the data sample into crash months (denoted by C) and no crash months (denoted by NC). If a crash occurs while the money manager is in cash, the model has correctly predicted that bear. Let c^* denote the number of crash months that occur when the manager is in cash. Define the true positive rate as $\frac{c^*}{C}$. Similarly, let nc^* denote the number of months when the manager is in cash and no crash occurs. Then the false positive rate is $\frac{nc^*}{NC}$.

Consider an extremely careful manager who chooses a very low discrimination threshold such that he is always in cash. All crashes will occur when this manager is in

¹⁰ See Agarwal et al. (2009) and Fung et al. (2008) for the effect of relative performance on investment flows.

¹¹ It was exceptionally easy for a Victorian-era retail investor to lever long–short portfolios with margin loans. See Chapter 17 in Duguid (1902) and Chiswell (1902, p. 11–18) for descriptions of the rules and practice of short selling with margin on the London Stock Exchange.

¹² The ROC curve is a common tool used in engineering, medicine, and machine learning for measuring the accuracy of diagnostic models of rare events. See Swets (1988).

cash, and consequently the true positive rate $\frac{c^*}{C}$ equals 1. However, by choosing such a low threshold, the manager will also be in cash every time a crash does not occur, and the false positive rate $\frac{nc^*}{NC}$ will also be 1. As the manager increases the discrimination threshold, both the false positive and true positive rates will decline. The ROC curve plots the trade-off between the true positive and false positive rates as the money manager varies the discrimination threshold above which he will exit the momentum strategy.

The area under the ROC curve (AUC) is a summary statistic of the model's goodness of fit. A model that can successfully predict every transition from bull to bear with no false positives will have an AUC of 1, while a model with no ability to forecast will have an AUC of .5.¹³ Our hazard model is estimated to fit within sample, so even if the underlying data are generated from i.i.d. returns selected at random with no predictability, the estimated AUC will be greater than .5. To evaluate the predictability in a time series of data and a given model, one can bootstrap the AUC by generating data series via random draws with no memory and fit the model to each to compute the distribution of AUCs under the null of no predictability. Using this bootstrap procedure, we find that momentum return bear markets are predictably different from random at the 1% significance level in all specifications.

In addition to the probability of transitioning to a bear market increasing with past momentum returns, the return to investing in momentum *conditional on remaining in a bull market* also increases with past momentum return.

In Table 4 we select only the realized momentum strategy returns where the momentum portfolio was purchased in a bull market (return realized at time t if $t-1$ is a bull state). We partition this data into decile bins based on the percentile rank of momentum strategy returns from time $(t-12)$ to $(t-1)$. Therefore, the 1st decile is the one-month return one would receive if they invested in the momentum strategy when the average return of momentum over the past year was in the lowest 10% of all bull market states, and the 10th decile is the one-month return one would receive if they invested in the momentum strategy when the average return of momentum over the past year was in the highest 10% of all bull market

¹³ For example, the ROC for the naïve model that each month assigns the same probability of transitioning from bull to bear will have two points, (0,0) and (1,1) and the area under the line connecting these points will be .5. . .

states.

Conditional on past momentum return deciles, Table 4 reports the probability of transitioning to a bear market, the annualized sharp ratio of the one-month return, and the one-month momentum strategy return conditional on remaining in a bull market or transitioning to a bear market. In the CRSP era, the probability of transitioning to a bear market increases dramatically and the sharp ratio for remaining invested in the momentum strategy declines when the past year's momentum strategy return enters the top decile.

4. *Why Money Managers Stay Invested when Crash Risk Is Elevated*

The hazard model coefficients and areas under ROC curves imply that bear markets in momentum are predictable based on the past performance of the momentum strategy. The probability of a bear market in momentum increases significantly when the momentum strategy has performed well over the past year. This is consistent with market folk wisdom. The “crowded trade” is common jargon amongst practitioners for a strategy that performed well in the past but has attracted so much money that it is now unprofitable and risky. Nonetheless, skilled money managers crowd into strategies that have generated recent success.¹⁴

Why do skilled money managers not exit the momentum strategy when the probability of a bear market is high? Two factors diminish the incentives for fund managers to attempt to strategically enter and exit the momentum strategy. First, fund managers are often compensated with incentive fees equal to a portion of profits above a high-water mark and solicit funds from return-chasing investors. The momentum strategy is most likely to transition into a bear market when past returns are high. This is exactly the time when a fund manager is most able to attract more funds and likely to have a high proportion of his assets under management above the high-water mark. The risk-shifting convex payout structure of incentive fees can combine with the return-chasing behavior of future investors to provide incentives for fund managers who have a *finite horizon* to remain in a crowded momentum strategy.¹⁵ Secondly, as we discussed earlier,

¹⁴ See Pedersen (2009) for a theoretical overview and example of crowded trades and subsequent crashes. Fung et al. (2008) document the performance–flow relationship in funds of hedge funds and find that capital inflows to funds that have over-performed in the recent past attenuates the ability of past alpha-producing funds to continue to deliver market-beating returns.

¹⁵ Many authors have claimed that the fee structure of hedge funds creates an incentive for excess risks. For instance, see the models of Carpenter (2000) or Goetzmann, Ingersol, and Ross (2003).

the return to investing in momentum *conditional on remaining in a bull market* increases with past momentum return as well. Therefore, a manager who exited momentum when past returns were high would avoid the risk of being invested in momentum during a bear market but would also forgo abnormally high returns should the bull market in momentum persist.

In the remainder of this section, we first illustrate the effects of the convex compensation structure and return-chasing investors on rational fund managers' behavior using a parsimonious two-period game-theoretic model. We then, explore the profitability of various managers' strategies in a richer setting via a simulation that reflects the conditional return dynamics documented Table 4.

4.1 *An Illustrative Model of Fund Managers' Behavior*

Why would a sophisticated money manager remain invested in momentum when the probability of a large decline is high? In this section we present a parsimonious model that illustrates how risk-shifting convex incentive fees and return-chasing investors can combine to provide incentives for fund managers to remain invested in momentum even when the probability of a crash is high.

The model consists of two time periods, two investors, and two fund managers who can allocate funds between cash and the momentum strategy with the following return dynamics.

Returns:

Each period, the gross momentum return can take one of two values, $R_{up} > 1$ or $R_{down} < 1$. We model the predictability of momentum returns as a two-state Markov process where the states are unobservable to investors but observed by skilled fund managers before making investment decisions. The probability of R_{up} is p_{UG} in the good state and p_{UB} in the bad state with $p_{UG} > p_{UB}$. The probability of transitioning between states is governed by a 2x2 Markov transition matrix with the $(i,j)^{th}$ element $\pi_{i,j}$ equal to the probability of transitioning from state i to state j .

Investors:

Each of the two investors has \$1 of saving each period. Investors can allocate this saving between cash with a risk-free unit gross return or deposit it with one or both fund managers who can invest in the risky momentum strategy. In the first period, investors have no signal about the managers' skills and choose to divide all their period 1 savings equally between the two fund managers. In period 2, investors' *return-chasing behavior* manifests itself in two ways. First, any investment in momentum will be allocated to the fund manager(s) who performed best in period 1. Second, investors allocate all of their period 2 savings to the best-performing fund manager(s) if the momentum strategy generated positive returns in period 1 and a smaller amount ($f < 1$) of their period 2 savings to the fund managers if the momentum strategy generated negative returns in period 1. We further assume that the flow f is sufficiently small such that $(R_{\text{down}} + f) * R_{\text{up}} < (1 + f)$.

Investor behavior results in the following aggregate cash flows to fund managers based on their period 1 performance. In period 1, \$2 is split equally between the fund managers. If momentum earns a positive return in period 1, an additional \$2 is allocated to the fund manager with the best period 1 performance or split equally if both managers enjoyed the same return in period 1. If momentum earns a negative return in period 1, however, $\$2 * f$ is allocated to the fund manager with the best period 1 performance or split equally if both managers enjoyed the same return in period 1.

The fund managers provide investors with access to the momentum strategy via the following contract. Managers take deposits from investors in each period. For analytical convenience, we only allow contracts where any money given to a manager is committed until the end of period 2. At the end of period 2, managers subtract a management fee equal to a proportion $\delta \in [0, 1]$ of investment profits and return the remaining money to investors. Due to our assumption that $(R_{\text{down}} + f) * R_{\text{up}} < (1 + f)$, fees will be zero unless the managers' returns are weakly positive in both time periods.

Fund Managers' Decisions:

Each period fund managers decide whether to invest their assets under management in cash or the momentum strategy. The fund managers' skills enable them to observe the state

before choosing how to allocate funds between momentum and cash. Managers are risk neutral and maximize their expected management fee taking investors' *return-chasing behavior* and the strategy of the other manager as given. Let fee_1 denote the management fee of the first fund manager.

Period 2 Strategies:

There are 16 states of nature at the beginning of period 2. The states are characterized by what each of the two managers chooses (to invest in momentum or cash), the realization of the period 1 return on momentum (up or down), and the state going into period 2 (good or bad)—i.e., $2^4 = 16$. Without loss of generality, consider the strategies available to manager 1 at the beginning of period 2 in each of the 16 states. If manager 1 did not invest at the beginning of period 1 (8 of the 16 states), investing at the beginning of period 2 dominates not investing. To see this, note that when the manager does not invest at the beginning of period 2, he will get no fees at the end of period 2. Investing gives positive fees with positive probability. So, for 8 of the states the strategy is to invest regardless of what the other manager chooses to do. Suppose manager 1 had invested in momentum at the beginning of period 1 and the return on momentum was down (4 of the remaining 8 states). Given our assumption that $(R_{down}+f)*R_{up} < (1+f)$, the manager will get no fees regardless of his period 2 investment decision. Suppose manager 1 had invested in momentum at the beginning of period 1 and the return on momentum was up (the remaining 4 states). Then manager 1 will have $R_{up} + 1$ or $R_{up}+2$ assets under management depending upon manager 2's investment decision at the beginning of period 1. Suppose the state is bad at the beginning of period 2. Then manager 1 will always invest if $[(R_{up}+1)R_{up-2}]*P_{UB} > (R_{up}-1)$. We limit our parameter space to values of R_{up} and P_{UB} such that $[(R_{up}+1)R_{up-2}]*P_{UB} > (R_{up}-1)$. Since $P_{UG} > P_{UB}$, manager 1 will always choose to invest regardless of the state at the beginning of period 2. To summarize, manager 1 will always invest in momentum at the beginning of period 2. He will only be paid a fee if the momentum strategy has a high return R_{up} in period 2. We have therefore shown that at the beginning of period 2, both managers will remain invested in momentum.

Now consider the decision rule of manager 1 at the beginning of period 1. Given that the optimal strategy during period 2 is to always invest in momentum, the expected management fee

conditional on the period 1 state and period 1 investment decision of manager 2 can be written as follows.

Given: Bad State ($st_1 = \text{bad}$) in period 1, Manager 2 holds cash in period 1.

Expected fee of Manager 1 to investing in momentum in period 1:

$$E[\text{fee}_1 \mid \text{mom, cash, } st_1 = \text{bad}] = [p_{UB} * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})] * [(R_{up}^2 + 2R_{up} - 3)\delta]. \quad (8a)$$

Expected fee of Manager 1 to holding cash in period 1:

$$E[\text{fee}_1 \mid \text{cash, cash, } st_1 = \text{bad}] = \{[p_{UB} * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})] * [(2R_{up} - 2)\delta]\} + \{(1 - p_{UB}) * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})\} * [(R_{up} + fR_{up} - 1 - f)\delta]. \quad (8b)$$

Given: Bad State ($st_1 = \text{bad}$) in period 1, Manager 2 invests in momentum in period 1.

Expected fee of Manager 1 when investing in momentum in period 1:

$$E[\text{fee}_1 \mid \text{mom, mom, } st_1 = \text{bad}] = [p_{UB} * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})] * [(R_{up}^2 + R_{up} - 2)\delta]. \quad (8c)^{16}$$

Expected fee of Manager 1 to holding cash in period 1:

$$E[\text{fee}_1 \mid \text{cash, mom, } st_1 = \text{bad}] = \{[p_{UB} * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})] * [(R_{up} - 1)\delta]\} + \{(1 - p_{UB}) * (\pi_{B,B} * p_{UB} + \pi_{B,G} * p_{UG})\} * [(R_{up} + 2fR_{up} - 1 - 2f)\delta]. \quad (8d)$$

Given: Good State ($st_1 = \text{good}$) in period 1, Manager 2 holds cash in period 1.

Expected fee of Manager 1 when investing in momentum in period 1:

$$E[\text{fee}_1 \mid \text{mom, cash, } st_1 = \text{Good}] = [p_{UG} * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})] * [(R_{up}^2 + 2R_{up} - 3)\delta]. \quad (8e)$$

Expected fee of Manager 1 when holding cash in period 1:

$$E[\text{fee}_1 \mid \text{cash, cash, } st_1 = \text{Good}] = \{[p_{UG} * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})] * [(2R_{up} - 2)\delta]\} + \{(1 - p_{UG}) * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})\} * [(R_{up} + fR_{up} - 1 - f)\delta]. \quad (8f)$$

¹⁶ Note that (8c) implicitly assumes that the case where R_{down} in period 1 is followed by R_{up} in period 2 yields zero fees, which is only true if $(R_{\text{down}} + f)R_{\text{up}} - (1 + f) < 0$, or equivalently, $R_{\text{down}}R_{\text{up}} < 1 - f(R_{\text{u}} - 1)$.

Given: Good State ($st_1 = \text{good}$) in period 1, Manager 2 invests in momentum in period 1.

Expected fee of Manager 1 when investing in momentum in period 1:

$$E[\text{fee}_1 | \text{mom, mom, } st_1 = \text{Good}] = [p_{UG} * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})] * [(R_{up}^2 + R_{up} - 2)\delta]. \quad (8g)$$

Expected fee of Manager 1 when holding cash in period 1:

$$E[\text{fee}_1 | \text{cash, mom, } st_1 = \text{Good}] = \{[p_{UG} * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})] * [(R_{up} - 1)\delta]\} + \\ \{[(1 - p_{UG}) * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})] * [(R_{up} + 2fR_{up} - 1 - 2f)\delta]\}. \quad (8h)$$

We are interested in showing that for reasonable parameter values, an equilibrium with the following properties exists: (A) If investors could directly invest in momentum after observing the state, they would prefer to hold cash in the bad state. (B) Despite their ability to observe the state, all fund managers choose to remain invested in momentum when period 1 is a bad state. (C) Investors who use the steady state probabilities implied by the Markov transition probability matrix to compute expected values prefer to allocate funds to managers rather than hold cash even though they know that managers will always remain invested in momentum. In addition, previously discussed parameter restrictions include (D) $p_{UB} > \frac{R_{up} - 1}{(1 + R_{up})R_{up} - 2}$ and (E) $R_{down}R_{up} < 1 - f(R_{up} - 1)$.

A) Implies $p_{UB}R_{up} + (1 - p_{UB})R_{down} < 1$

B) Implies (8a) > (8b) and (8c) > (8d), which also automatically ensures (8e) > (8f) and (8g) > (8h)

C) Implies $p_G E[m | st_1 = \text{good}] + p_B E[m | st_1 = \text{bad}] > 0$

Where:

$\mathbf{P} = [p_G \ p_B]$ is the row vector of steady-state probabilities that satisfy $\mathbf{P}\mathbf{\Pi} = \mathbf{P}$ for the matrix of transition probabilities $\mathbf{\Pi}$;

and m is the money returned to an investor at the end of period 2, in excess of what was invested;

$$\begin{aligned}
E[m|st_1 = good] &= pUUG * [(R_{up}^2 + R_{up} - 2) * (1 - \delta)] + pUDG * [R_{up}R_{down} + R_{down} - 2] \\
&+ pDUG * [R_{down}R_{up} + fR_{up} - 1 - f] + pDDG * [R_{down}R_{down} + fR_{down} - 1 - f]; \\
E[m|st_1 = bad] &= pUUB * [(R_{up}^2 + R_{up} - 2) * (1 - \delta)] + pUDB * [R_{up}R_{down} + R_{down} - 2] \\
&+ pDUB * [R_{down}R_{up} + fR_{up} - 1 - f] + pDDB * [R_{down}R_{down} + fR_{down} - 1 - f];
\end{aligned}$$

where $pUUG = [p_{UG} * (\pi_{G,B} * p_{UB} + \pi_{G,G} * p_{UG})]$ is the probability of drawing two up returns conditional on the good state in period 1, and $pUDG, pDUG, pDDG, pUUB, pUDB, pDUB, pDDB$ are similarly defined.

For reasonable parameter values ($R_{up}=1.02, R_{down}=0.75, P_{UG}=0.99, f=0.5, \delta = 0.2$, and $\pi_{i,j}=0.5$ for all i and j), Figure 3 plots manager 1's profits as a function of his period 1 investment choice and the crash probability ($1-p_{UB}$) when the first period is a bad state and manager 2 holds cash. The fund manager is indifferent between investing in momentum or holding cash at the break-even value of P_{UB} equal to $.426$. As long as the probability of a crash in the bad state is less than $(1-.426)$, manager 1 will prefer to respond to manager 2's decision to hold cash in the bad state by investing in momentum. It can be verified that manager 1 will prefer to respond to manager 2's decision to be in momentum in the bad state by investing in momentum under these conditions.

In Table 5, we confirm that all equilibrium conditions exist for a reasonable choice of a 10% crash probability in the bad state (i.e., $p_{UB} = 0.9$). When $p_{UG} = 0.99$ and $p_{UB} = 0.9$, $R_{up} = 1.02, R_{down} = 0.75, \delta = 0.2, f = 0.5$, and $\pi_{ij} = 0.5$ for all i and j , $p_{UUB} = 0.8505$ and $p_{DUB} = 0.0945$. Table 5 summarizes and confirms that all equilibrium conditions are met.

Table 5:
Equilibrium conditions of the 2-player game

Condition	Expression	Value
(A)	$p_{UB}R_{up} + (1 - p_{UB})R_{down} < 1$	0.993<1
(B1) (8a)>(8b)	$p_{UUB}[(R_{up}^2 + 2R_{up} - 3)\delta] >$ $p_{UUB}(2R_{up} - 2)\delta + p_{DUB}(R_{up} + fR_{up} - 1 - f)\delta$	0.0137>0.0077
(B2) (8c)>(8d)	$p_{UUB}[(R_{up}^2 + R_{up} - 2)\delta] >$ $p_{UUB} * [(R_{up} - 1)\delta] + p_{DUB}[(R_{up} + 2fR_{up} - 1 - 2f)\delta]$	0.0103>0.0042
(C)	$p_G E[m st_1 = good] + p_B E[m st_1 = bad] > 0$	0.0045>0
(D)	$p_{UB} > \frac{R_{up} - 1}{(1 + R_{up})R_{up} - 2}$	0.90>0.33
(E)	$R_{down}R_{up} < 1 - f(R_u - 1)$	0.765<0.99

4.2 Profit Simulations with CRSP-Era Data

The example above explains in a simple two-period, two-player game setting the apparent paradox that even though large momentum losses are predictable, sophisticated money managers may nonetheless crowd into the momentum strategy at times of elevated risk. The actual dynamics of conditional momentum returns and predictable crashes and investor return-chasing behavior is too complex for a multiplayer, multi-period game. Instead, we use the CRSP data to calibrate a simulation of the profits managers could expect to earn by following momentum timing strategies when the number of time periods and competing funds are large. Our simulations suggest that managers who aggressively remain invested in momentum even when the likelihood of a crash is high outperform managers who attempt to time the momentum strategy.

4.2.1 Fees and Assets under Management

Our simulations model the profits of money managers who are compensated by collecting

a monthly management fee equal to $2/12$ ths of a percent of assets under management and a quarterly performance fee of 20% of profits above a high-water mark. These managers compete with each other to manage the investment funds of return-chasing customers who reallocate their investments each month by withdrawing 1% of assets under management (AUM) from the managers in the bottom quartile of performance over the past year and invest an equal portion of these funds with the managers in the top quartile of performance over the past year. In addition to the monthly reallocation, investors devote new funds or withdraw existing funds from the momentum strategy each month based on the relative performance of the momentum strategy. We assume these new deposits or withdrawals are equal to 20% of the difference between the return on the momentum strategy and the return on the value-weighted market portfolio over the past year. Therefore, if the momentum strategy outperformed the market by 10% over the past year, investors would invest new funds equal to 2% of existing assets under management. Likewise, if the momentum strategy underperformed by 10%, investors would withdraw 2% of assets under management. We assume new investment is divided equally amongst the funds in the top quartile of performance over the past year and all funds are subject to withdrawals when the momentum strategy underperforms.

These realistic assumptions—that funds have a fee structure of 2–20 with high-water marks, and investors chase returns by depositing more money in top-performing funds when their track record is good and withdrawing funds from underperforming funds and strategies—create incentives for money managers to stay invested in the momentum strategy even when the probability of a crash is high. The intuition is simple: the very time that crash risk is high is also the time when a high proportion of AUM is likely to be above high-water marks and a large inflow of new assets awaits any manager who outperforms his peers in the immediate future.

4.2.2 Simulated Returns

We simulate 25 years of returns to match the conditional returns and bear market-transition probabilities of the CRSP-era Fama–French momentum factor portfolio previously reported in Table 4. Specifically, we simulate returns by drawing from an 11-state Markov chain, with states 1–10 corresponding to the 10 bull market states in Table 4 and state 11 corresponding to the bear markets. We calibrate the Markov transition matrix to match the sample transition

probabilities in the CRSP data.

We form a time series of returns via the following algorithm:

- 1) Begin by selecting a bull market state at random, and draw one monthly momentum and market return pair at random from the sample returns of the selected state.
- 2) Draw a state at random to transition to, where the probability of transitioning to the next state is determined by the Markov transition matrix calibrated to the CRSP data.
- 3) If the draw results in another bull state, select a random momentum and market return from the sample returns of the selected state and return to 2) to draw a new state.
- 4) If the draw is a bear state, select an entire sequence of momentum and market returns from the 63 bear markets in the CRSP data (we choose the entire sequence to assure that once one transitions to a bear market, the momentum strategy will lose at least 5%). Once the bear market is complete, draw a new bull state at random from the Markov transition probabilities.
- 5) Let this process run for 100 years and select the last 25 years for analysis.
- 6) Repeat steps 1–5 5,000 times to generate 5000 times series of simulated returns.

4.2.3 Profits as a Function of Risk-Taking

We wish to show that in our simulations calibrated with CRSP data, money managers who go to cash in periods of elevated crash risk are less profitable on average than managers who remain invested in the momentum strategy. Of course, due to the tournament nature of return-chasing investors, profits depend on the behavior of other fund managers.

We model the behavior of fund managers by assigning each a risk threshold based on the past momentum return percentile beyond which they exit momentum and place their funds in cash earning the risk-free rate. For example, a type 80 manager would invest in the momentum strategy if the past year's momentum return were at or below the 80th percentile of all 1-year lagged returns, while a type 99 manager would not exit momentum until the 1-year lagged return exceeded 99% of all sample returns.

The profits of a given type depend on the distribution of types he is competing against. To summarize the riskiness of the distribution of types in a parsimonious manner, we assign a proportion α of managers to the 70–80 interval at random and a proportion $(1-\alpha)$ of managers to

the 90–100 interval at random. Thus, if $\alpha = .1$, 10% of the managers will be conservative types assigned a uniform random integer between 70 and 80, and 90% will be aggressive types assigned a uniform random integer type between 90 and 100.

We run 5000 simulations of 100 competing fund managers who begin with the same initial assets under management. Table 6 reports the average profits of managers as a proportion of the average profit of the most aggressive, type-100 manager. The more aggressive managers are more profitable on average. For example, in the economy where 90% of the managers are conservative types ($\alpha=.9$), the conservative fund managers earn average profits that range from 27.7% to 68.2% of the profits of a manager who is always invested. The conservative fund managers underperform by an even worse margin in an economy with more aggressive competitors. In the economy where only 10% of the managers are conservative types ($\alpha=.1$), the conservative fund managers earn meager average profits that range from 9.64% to 37.6% of the profits of a manager who is always invested.

The aggressive type of fund manager earns higher average profits across all values of α . These simulations suggest that a profit-maximizing manager who took other managers' behavior, momentum returns, and crash probabilities as given would choose a very high threshold of past return beyond which he would exit momentum and hold cash.

5. *Conclusion*

Using unique historical data on stock returns spanning 140 years, we examine the returns on one of the most popular mechanical trading strategies—momentum. We confirm that momentum investors have enjoyed large abnormal risk-adjusted returns. However, the strategy also incurs infrequent very large losses.

These losses are more likely to occur during periods when capital is easily available to investors employing the momentum strategy with other people's money. In Victorian London, momentum investors could leverage via margin loans collateralized by the value of their portfolio, and momentum crashes were more likely to occur following large momentum strategy gains and periods of easy availability of margin leverage as evidenced by low interest rates. In the CRSP era, when many momentum investors access other people's money through active funds established to invest in momentum, crashes are more likely to occur when the recent

performance of momentum has compared well with the overall stock market. These are times when momentum fund managers are likely to find it easy to access the blind capital of return-chasing investors.

In light of the fact that momentum crashes are predictable, why do professional money managers not take steps to avoid momentum crashes? The times when the hazard of momentum crashes is high are exactly the times when a momentum fund manager will have a strong recent performance and find it easy to attract funds from return-chasing investors. We show that even sophisticated money managers may rationally crowd into momentum strategies at times of elevated risk. We argue based on both a stylized model and simulated outcomes from a richer model that a money manager who competes for funds from return-chasing investors and is compensated via fees that are convex in the amount of money managed and the return on that money has an incentive to remain in a crowded momentum trade even when the hazard of large losses is high.

Our findings suggest that regulators who wish to monitor the buildup of crash risk in the financial sector should pay particular attention to strategies that become crowded by inflows of blind capital following recent success.

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Appendices

The London Stock Market Data: 1866–1907

The closing bid and ask prices were collected from the quotation list of *The Money Market Review*, a weekly financial paper published in London between 1860 and 1908. Published on Saturdays, *The Money Market Review* reprinted H.H. Wetenhall's official quotation list of the previous Friday's closing prices. These were the official prices published by the Committee of the Stock Exchange under the name "Course of the Exchange." The data were sampled every 28 days, rather than the more traditional end-of-month observations, due to the newspaper's weekly publication schedule.

The official list was organized by industry and asset type. The list begins with British government debt, then lists foreign government debt and British, Commonwealth, and foreign railroads, and concludes with commercial securities organized by industry (banks, breweries, canals and docks, insurance, iron, coal and steel, gas, mining, shipping, spinning, waterworks, tea, land, financial and investment trusts, and miscellaneous securities). *The Money Market Review's* list is not complete. Some industries do not appear on certain dates, and, within industries, individual stocks may have no price for one or more dates. When possible, we filled in the missing price data with *The Economist's* "Stock Market Prices Current." *The Economist's* price list included only the largest and most active securities listed in London. Since its coverage was sparse, we only employ the *Economist* to fill in data that were missing from *The Money Market Review*. If a section of the official list was omitted from a given *Money Market Review*, we attempted to replace the missing data with quotes from the *Economist*.

The data set contains 610,421 bid and ask prices. To minimize entry time and assure quality, the data were double entered by undergraduate research assistants. As a consequence of our data-entry strategy, a stock must appear on the official list for at least one January before it is included in the data set.

The official lists did not differentiate between equity and debt. Today, one would assume that an economist and trained historian would have no problem distinguishing a stock from a bond, but in the 19th century the difference between debt and equity was seldom obvious. The 19th century English publications generally referred to both debt and equity claims as "stocks." A careful examination of the claims each class of shareholder enjoyed usually allowed us to determine if a given security was a debt or equity claim. When selecting which securities to include in our data set, we excluded all securities with fixed interest rates, a face value to be returned at a maturity date, or other obvious characteristics of bonds.

In general, London securities were divided into the following types of asset classes: "stocks," "shares," "ordinary," "common," "limited," "deferred," "preference," "debenture" and "convertible" shares. Whether, the name of the share corresponded to what a modern investor would consider equity depended upon the type of company in question. We looked at each potential security and excluded every security with characteristics similar to modern-day debt. "Common," "limited," and "ordinary" shares were almost always the residual claimants and therefore correspond to modern-day equity. "Stock," on the other hand, was the name given to 19th century bonds! "Preference," "debenture," and "convertible" shares were also excluded, while "deferred" shares generally referred to debt offerings with one notable exception—the investment trusts. Many investment trusts issued only three types of shares: "preference," "debenture," and "deferred." Debenture and preference shares had a fixed dividend rate and often had a maturity date when the nominal amount (face value) of the share would be returned. Deferred shares in investment trusts, on the other hand, were generally the residual claimant to all income in excess of the debenture and preference obligations. We include the deferred shares of investment trusts in our data, provided the trust has no ordinary shares and the deferred shares satisfy our conditions of no maturity date and no cap on dividends.

For each January, a list of all securities was compiled, meeting our definition of equity. This list of security names and copies of the subsequent year's quotation lists were distributed to research assistants. To eliminate typos, each date was double entered by different research assistants and then compared. Therefore, to appear in the data set, a stock had to appear on the official quotation list for at least one January.

In addition to the closing prices, we collected dividend payments and shares outstanding for each security. These allowed us to compute market values and 28-day holding period returns that accurately reflect dividend payments and stock splits. In total, the data set consists of 610,421 bid and ask prices and 39,090 dividend payments. The dividend payments were collected from the security lists of *The Investor's Monthly Manual*.¹⁷ The *Investor's Monthly Manual* (IMM) published the monthly closing price, shares outstanding, and last four dividends of each security, listed on the London Stock Exchange. We use the IMM to collect dividend and share histories for each security that appears in our data set. Like *The Money Market Review*, certain securities vanish from the IMM and reappear at a later date without explanation.

Capital Calls and Returns

We use the price and dividend data to compute the 28-day holding period return for each consecutive price observation. The 28-day holding period gross return is defined as $(P_{t+1} + d_{t+1})/P_t$, where P_{t+1} and P_t are the average of the bid and ask prices at time $t + 1$ and t , respectively, and d_t is the net dividend payments and capital calls (if any) that occurred between time t and $t + 1$. Capital calls are a form of reverse dividend common to 19th century stock exchanges.

Many 19th century companies issued shares with a nominal value known as the “amount.” The company typically did not require the shareholders to pay for the entire share at the time of issue. Instead, shares were issued with a “par” or “paid” value that was less than the nominal amount of the share. Dividends were based on the par value of the share and not the nominal amount. For example, if a company with a £100 share with £50 paid announced a 10% declared dividend, this would amount to £5 rather than £10.

The shareholder was legally obligated to pay the remaining capital (the difference between the nominal and paid amount) at the whim of the company. Thus, the company could “call” upon its shareholders to pay for the remaining value of their shares. This call was apparently binding, as the shares in many bankrupt companies with par values less than nominal amounts traded at negative values when the implicit short put option embedded in the shares was worth more than the company's equity.¹⁸ To compute holding period returns, we treat capital calls as a negative dividend paid at the beginning of the holding period.

¹⁷ The IMM is available online at <http://som.yale.edu/imm/html/index.shtml>

¹⁸ We only include stocks with positive values in the analysis that follows.

Figure 1: ROC Curve

The figure displays the ROC curve from the full hazard model estimated with CRSP-era data to predict bear markets in the Fama–French momentum factor portfolio returns

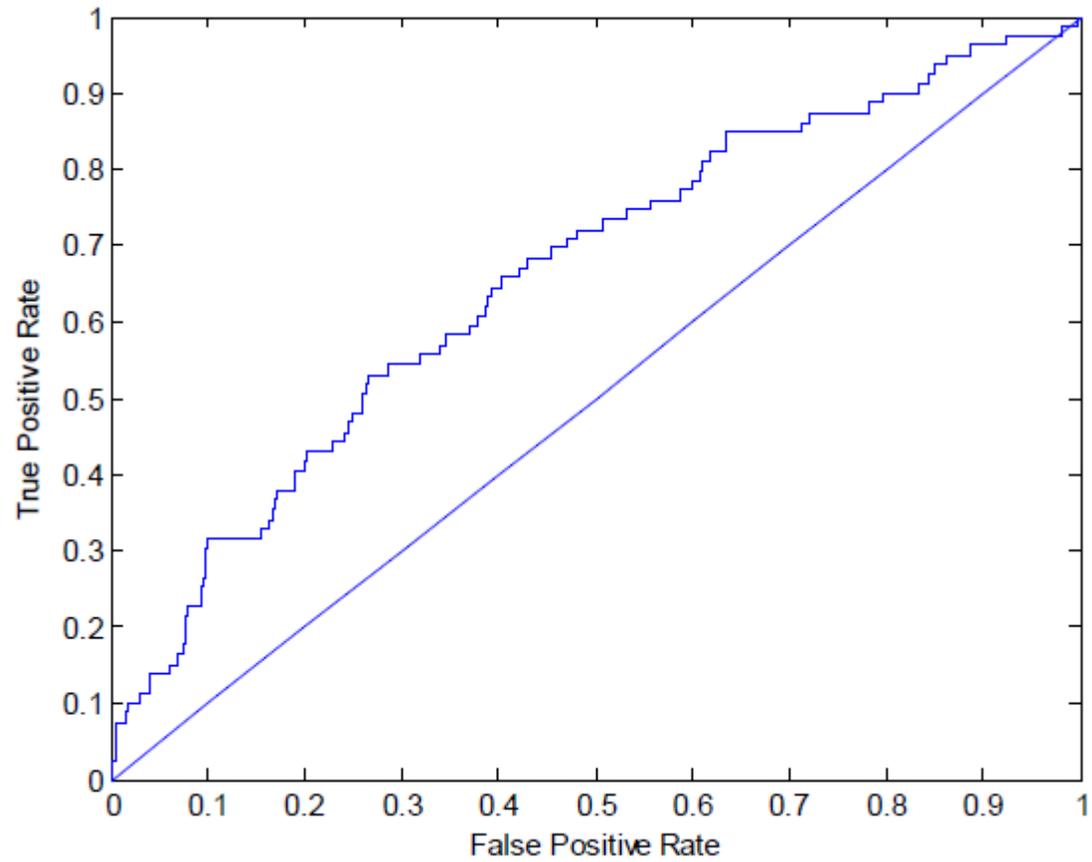


Figure 2: Number of Stocks in London Portfolios

This study makes use of a new data set of 1,808 stocks (equity) listed in London between 1866 and 1907. The plots display the number of stocks, which decline to 985 in 1903 and 544 in 1904, due to a number of industries vanishing from the quotation list, only to reappear in 1905.

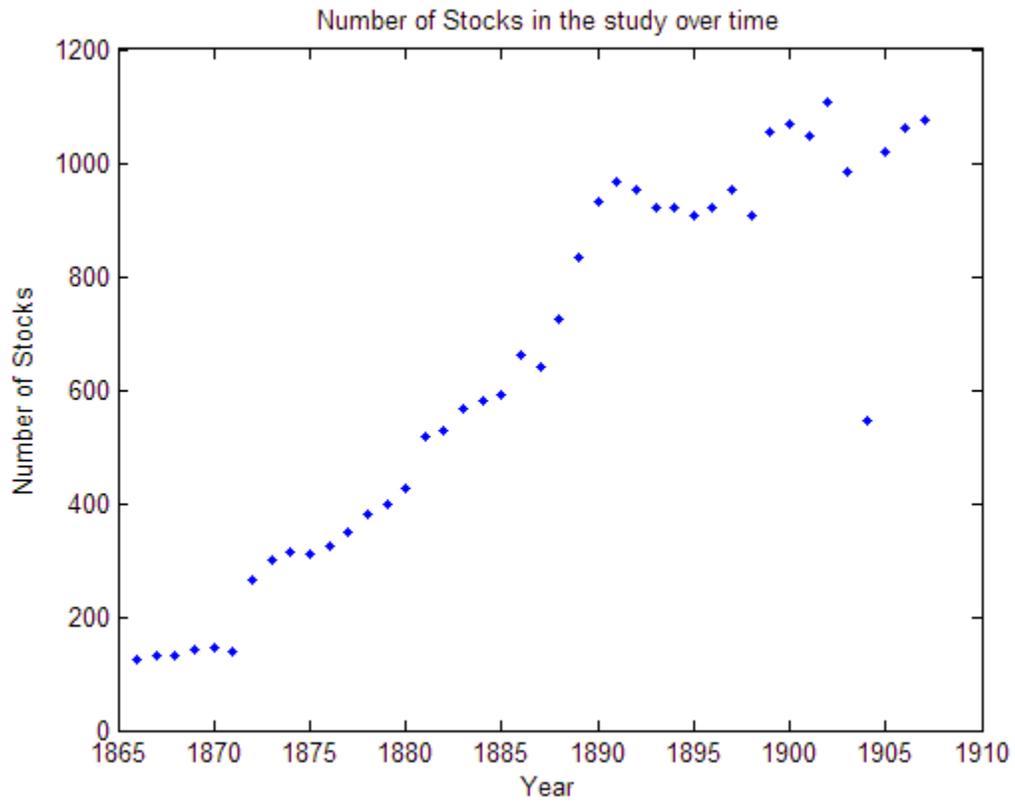


Figure 3: Manager 1's profits as a function of his period 1 investment choice

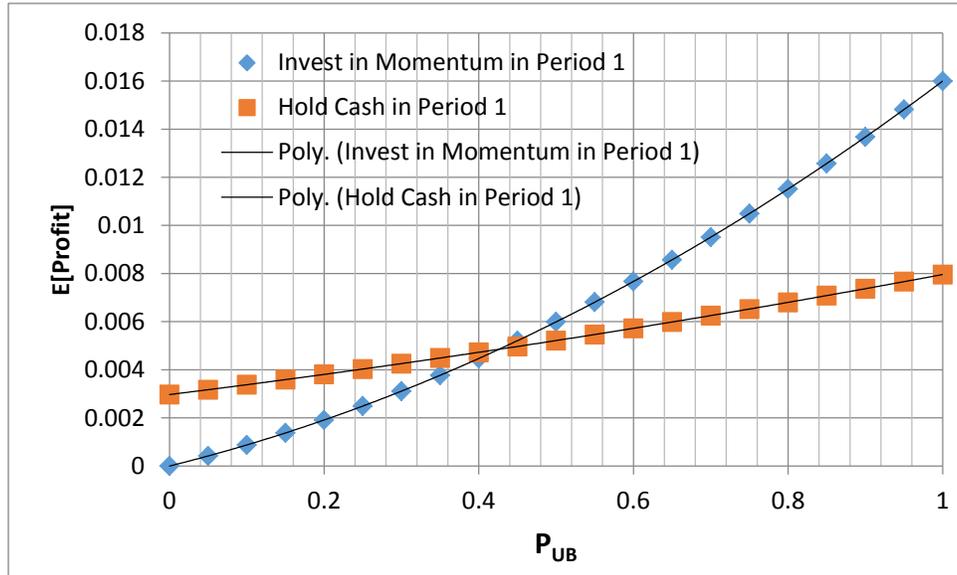


Table 1:
Summary Statistics and Regression Results

Momentum Portfolio:	CRSP FF MOM FACTOR	CRSP FF MOM FACTOR	CRSP FF 7030 MOM PORT	CRSP FF 7030 MOM PORT	London FF MOM FACTOR	London 7030 MOM PORT
Sample Dates:	JUL1927-DEC2012	JUL1927-DEC2012	JUL1927-DEC2012	JUL1927-DEC2012	JUL1867-DEC1907	JUL1867-DEC1907

Monthly Returns¹:

Mean	0.0069		0.0055		0.003	0.0027
St.Dev.	0.048		0.051		0.0224	0.026
Skewness	-3.03		-2.89		-1.55	-1.39
<u>Ann. Sharp Ratio:</u>	0.50		0.37		0.48	0.37

FF- 3 Factor Regression

α	0.0101 (0.001)***	0.0101 (0.001)***	0.0088 (0.001)***	0.0089 (0.002)***	0.0052 (.001)***	0.0049 (.001)***
$\beta_{(mkt)}$	-0.22 (0.027)***	-0.34 (0.03)***	-0.23 (0.029)***	-0.36 (0.033)***	-0.45 (0.071)***	-0.35 (0.079)***
β_{SMB}	-0.07 (0.043)*		-0.10 (0.047)**			
β_{HML}	-0.45 (0.039)***		-0.45 (0.042)***			
β_{Size}		-0.31 (0.031)***		-0.33 (0.034)***	-0.10 (0.05)**	-0.32 (0.056)***
$\beta_{divyield}$		-0.31 (0.033)***		-0.34 (0.036)***	-0.11 (0.028)***	-0.17 (0.031)***
R^2	0.22	0.22	0.21	0.22	.08	.12
N	1026	1026	1026	1026	529	529

1) CRSP returns are monthly. 1867-1907 returns are 28-day returns.

Table 2:
Momentum Bear Markets

Momentum Portfolio:	CRSP FF MOM FACTOR	CRSP FF 7030 MOM PORT	London FF MOM FACTOR	London 7030 MOM PORT
Sample Dates:	JAN1927- DEC2012	JAN1927- DEC2012	JAN1867- DEC1907	JAN1867- DEC1907
<u>< -5% Bear Markets *</u>				
# of bear markets	63	68	19	21
average duration	3.7	4.9	7.3	7.9
average cumulative decline	13.6%	14.8%	10.2%	11.7%
<u><-10% Bear Markets *</u>				
# of bear markets	30	36	7	9
average duration	5.6	7.4	16.7	14.7
average cumulative decline	20.6%	21.6%	15.8%	16.9%
Monthly observations	1032	1032	548	548

* Bear markets are dated via the Lunde & Timmerman (2004) algorithm described in the text
 <-5% bear markets are declines of 5% or greater and <-10% bear markets are declines of 10% or greater.

Table 3:
Hazard Model Coefficients

Momentum Portfolio:	CRSP FF MOM FACTOR	CRSP FF MOM FACTOR	CRSP FF MOM FACTOR	CRSP FF MOM FACTOR	CRSP 7030 MOM PORT	CRSP 7030 MOM PORT	CRSP 7030 MOM PORT	CRSP 7030 MOM PORT
Sample Dates:	DEC1927- DEC2012	APR1930- DEC2012	DEC1927- DEC2012	MAR1931- DEC2012	DEC1927- DEC2012	MAY1928- DEC2012	DEC1927- DEC2012	MAR1931- DEC2012
Decline Necessary for Bear Market	5%	5%	10%	10%	5%	5%	10%	10%

Hazard Model
Coefficients

Constant	-3.09 (1.41)**	-3.52 (1.45)**	-8.52 (2.15)***	-9.27 (2.42)***	-2.50 (1.09)**	-2.41 (1.18)**	-8.02 (2.70)***	-10.05 (2.27)***
ρ		0.94 (0.12)		1.10 (0.17)		0.92 (0.11)		0.85 (0.16)
Rf_t	-2.48 (4.38)	-2.69 (4.43)	2.63 (6.21)	3.28 (6.47)	-2.65 (3.22)	-2.69 (5.20)	1.76 (9.96)	-0.13 (17.09)
$RET_{mkt(t-12) \rightarrow (t-1)}$	-1.96 (0.58)***	-1.63 (0.64)**	-1.81 (0.80)**	-1.81 (0.92)**	-1.71 (0.53)***	-1.69 (0.60)***	-1.57 (1.22)	-0.71 (0.89)
$RET_{mom(t-12) \rightarrow (t-1)}$	2.50 (0.92)***	2.70 (0.94)***	6.06 (1.39)***	6.4642 (1.56)***	1.96 (0.76)**	1.98 (0.73)***	5.76 (1.57)***	7.18 (1.46)***

Goodness of Fit

LogLik	-205.75	-202.19	-109.93	-105.99	-212.29	-209.37	-125.21	-117.98
AUC	0.68***	0.68***	0.80***	0.80***	0.65***	0.66***	0.76***	0.77***
# of Bear Markets	63	62	30	29	68	67	36	35
N (times at risk)	788	763	852	815	690	686	753	716

Table 3 cont.
Hazard Model Coefficients

Momentum Portfolio:	London FF MOM FACTOR	London FF MOM FACTOR	London FF MOM FACTOR	London FF MOM FACTOR	London 7030 MOM PORT	London 7030 MOM PORT	London 7030 MOM PORT	London 7030 MOM PORT
Sample Dates:	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907	DEC1867- DEC1907
Decline Necessary for Bear Market	5%	5%	10%	10%	5%	5%	10%	10%

Hazard Model
Coefficients

Constant	-12.6 (3.97)***	-13.42 (9.23)	-21.63 (7.14)***	-21.12 (10.27)**	-19.06 (5.39)***	-20.59 (5.58)***	-27.39 (7.93)***	-27.60 (8.16)***
ρ		0.85 (0.23)		0.87 (0.53)		0.69 (0.25)		1.10 (0.51)
Rf_t	-57.61 (12.23)***	-53.32 (11.26)***	-37.43 (9.55)***	-41.84 (43.62)	-81.72 (26.02)***	-74.40 (27.32)***	-33.93 (31.51)	-29.99 (34.32)
$RET_{mkt(t-12) \rightarrow (t-1)}$	2.42 (2.82)	2.72 (6.03)	7.62 (4.54)	7.39 (5.84)	6.91 (3.35)**	6.83 (3.33)**	13.56 (4.53)***	13.57 (4.55)***
$RET_{mom(t-12) \rightarrow (t-1)}$	7.74 (1.97)***	8.46 (3.31)**	9.26 (3.56)***	9.53 (4.83)**	9.74 (2.47)***	11.74 (3.01)***	8.693 (3.89)**	8.47 (4.05)**

Goodness of Fit

LogLik	-63.94	-63.75	-28.71	-28.68	-64.48	-63.72	-33.99	-33.97
AUC	0.78***	0.788***	0.77***	0.78***	0.79***	0.80***	0.76***	0.75***
# of Bear Markets	18	18	6	6	20	20	8	8
N (times at risk)	375	375	410	410	360	360	395	395

Table 4:

Transition probabilities and conditional returns

	CRSP		London		CRSP		London	
	MomFactor	CRSP FF7030	momFactor	FF7030	MomFactor	CRSP FF7030	momFactor	FF7030
Past 1-year								
Return Decile	<u>Prob of Transition to Bear¹</u>				<u>Annual Sharp Ratio</u>			
1	0.114	0.116	0.027	0.000	0.625	1.305	2.397	2.005
2	0.051	0.087	0.000	0.028	1.170	0.796	1.005	1.337
3	0.063	0.087	0.000	0.000	1.602	0.617	1.613	2.704
4	0.051	0.029	0.079	0.083	1.445	1.541	0.619	1.058
5	0.051	0.059	0.054	0.028	1.402	1.798	0.067	0.436
6	0.038	0.116	0.000	0.056	0.748	1.129	2.945	0.940
7	0.025	0.130	0.054	0.056	1.697	0.658	0.494	0.546
8	0.063	0.044	0.105	0.114	0.979	1.847	1.375	0.810
9	0.103	0.101	0.054	0.083	1.416	1.606	0.901	1.452
10	0.241	0.217	0.108	0.111	0.230	0.604	1.184	1.336
Past 1-year								
Return Decile	<u>E[R bull]*</u>				<u>E[R bear]**</u>			
1	0.017	0.026	0.012	0.009	-0.072	-0.064	-0.007	NA
2	0.022	0.020	0.003	0.009	-0.103	-0.077	NA	-0.025
3	0.014	0.017	0.007	0.013	-0.033	-0.085	NA	NA
4	0.014	0.016	0.006	0.009	-0.042	-0.053	-0.021	-0.028
5	0.015	0.021	0.007	0.011	-0.054	-0.036	-0.116	-0.212
6	0.016	0.019	0.015	0.007	-0.140	-0.045	NA	-0.025
7	0.016	0.014	0.004	0.004	-0.047	-0.041	-0.021	-0.018
8	0.014	0.021	0.012	0.009	-0.063	-0.057	-0.027	-0.026
9	0.023	0.027	0.007	0.014	-0.047	-0.048	-0.036	-0.037
10	0.039	0.037	0.015	0.017	-0.099	-0.079	-0.040	-0.040

1. Prob of transitioning to bear = the in-sample frequency of switching from a bull to bear market

* E[R|bull] = the in-sample average one month ahead return conditional on remaining in a bull market

** E[R|bear] = the in-sample average one month ahead return conditional on switching to a bear market

Table 6:
Average Profits by Fund Type as a Ratio of Type 100 profits

Fund Types*	$\alpha = .1$	$\alpha = .25$	$\alpha = .5$	$\alpha = .75$	$\alpha = .9$
70	0.1014	0.0714	0.2753	0.1237	0.503
71	0.0964	0.0655	0.2065	0.1406	0.4223
72	0.323	0.015	0.2516	0.1428	0.5439
73	0.0986	0.0545	0.237	0.1547	0.5092
74	0.2497	0.0504	0.2252	0.1418	0.4921
75	0.3137	0.0212	0.2281	0.1404	0.2772
76	0.376	0.0147	0.2981	0.1828	0.3574
77	0.1889	0.0394	0.3339	0.1486	0.3421
78	0.2507	0.0518	0.3332	0.1636	0.4565
79	0.3164	0.026	0.2806	0.177	0.4757
80	0.2579	0.0347	0.3163	0.2482	0.6824
90	0.339	0.066	0.448	0.5976	0.9934
91	0.3158	0.0684	0.4314	0.6936	0.7671
92	0.37	0.1196	0.5096	0.9032	0.7662
93	0.2717	0.0684	0.5228	1.0395	1.1228
94	0.3555	0.2626	0.6704	1.0834	1.0729
95	0.3509	0.8493	0.7123	0.8687	1.2765
96	0.9373	0.3723	0.7714	0.9315	0.7778
97	0.7038	0.5704	0.9502	0.891	1.7108
98	0.7999	1.0011	0.8584	0.9504	0.8761
99	1.349	1.3102	1.0362	1.0078	1.4583
100	1	1	1	1	1

* A fund of type k holds cash if the past-year momentum return exceeds the k-th percentile of all in-sample past year returns and otherwise follows the momentum strategy.

Each cell reports the average profit by fund types in the 5000 simulations as a ratio of type 100 average profits.

each simulation has 100 funds with α proportion of the fund types drawn uniformly from 70-80 interval and $(1-\alpha)$ drawn uniformly from the 90-100 interval