NBER WORKING PAPER SERIES

PRICE MOMENTUM IN STOCKS:
INSIGHTS FROM VICTORIAN AGE DATA

Benjamin Chabot
Eric Ghysels
Ravi Jagannathan

Working Paper 14500
http://www.nber.org/papers/w14500

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2008

We thank Nick Barberis, Jennifer Conrad, Gautam Kaul, Jegadeesh Narasimhan, Lu Zhang, and seminar participants at the University of Michigan for helpful comments. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Price Momentum In Stocks: Insights From Victorian Age Data
Benjamin Chabot, Eric Ghysels, and Ravi Jagannathan
NBER Working Paper No. 14500
November 2008
JEL No. G1,G12,G14

ABSTRACT

We find that price momentum in stocks was a pervasive phenomenon during the Victorian age (1866-1907) as well. Momentum strategy profits have little systematic risk even at business cycle frequencies; disappear periodically only to reappear later; exhibit long run reversal; and are higher following up markets, suggesting limited availability of arbitrage capital relative to opportunities during those times. Since there were no capital gains taxes during the Victorian age, the long run reversal of momentum profits must have a fundamental component, that is unrelated to tax based trading, identified by Grinblatt and Moskowitz (2004) using CRSP era data.

Benjamin Chabot
238 Lorch Hall
University of Michigan
Department of Economics
611 Tappan Street
Ann Arbor, MI 48109-1220
and NBER
remy@umich.edu

Eric Ghysels
Department of Economics
University of North Carolina-Chapel Hill
Gardner Hall, CB 3305
Chapel Hill, NC 27599-3305
eghysels@unc.edu

Ravi Jagannathan
J.L. Kellogg Graduate School of Management
2001 Sheridan Road
Leverone/Anderson Complex
Evanston, IL 60208-2001
and NBER
rjaganna@northwestern.edu

1 Introduction

The existence of relative price momentum in stocks, that past winners continue to win and past losers continue to lose, is generally viewed as a serious challenge to the "efficient markets hypothesis". Therefore, it is not surprising that a large literature has evolved trying to explain the momentum phenomenon - i.e., why momentum strategies appear to earn large positive abnormal returns on average.

When a strategy as simple as buying past winners and selling past losers produces an *almost free lunch,* i.e., high returns on average with little or no systematic risk, we are left with several possibilities.

First, for most of the CRSP era, investors may not have been aware of the existence of the almost free lunch but given the attention in the academic and trade literature it has received, investors will likely arbitrage away any future momentum profits. This is unlikely to be the case. Momentum returns declined in the first few years of the 21^{st} century presumably due to activities of hedge funds and other sophisticated investors who invested large amounts of capital to capture profits from momentum like strategies. However, momentum strategies have again become profitable since 2006. Indeed, momentum profits appear to feature periodic cycles. Figure 1 plots the time series of the Fama-French momentum factor returns from January 1946 to May 2008 and the momentum factor returns during the Victorian era - based on a new hand-collected data set introduced in this paper and described in detail later. When we compare the Post-War data with the Victorian era we observe the same cyclical pattern as well as momentum profits with roughly the same range of monthly gains/losses - between 4 % and - 3%. The similarities are striking: Post-War momentum profits as measured by the one year moving average of past Winners minus past Losers returns exhibited 26 negative episodes (i.e., vanished) with an average duration of 4.1 months per episode. During the period January 1867 to December 1907, momentum returns exhibited 31 negative episodes with an average duration of 3.8 months per episode [1] We would not expect to see this pattern of vanishing and reemerging momentum profits if momentum existed only because investors did not know about it.[2] Instead, the time-series of CRSP and historical era momentum profits resembles other rule-based trading strategies subject to the

[1]Griffin, Ji and Martin (2004) have documented similar periodic declines in other nations as well.

[2]Figure 1 involves a one-year centered moving average. Hence, the moving average scheme produces some induced temporal dependence. As will be discussed shortly, the temporal dependence in momentum profits goes beyond that induced by smoothing.

limits of arbitrage (see e.g. Shleifer and Vishny (1997)) - high average returns with enough periodic declines to prevent sophisticated leveraged investors from capturing profits without risk. For example, the decline in the profitability of momentum strategies at the beginning of this century appears to resemble periodic down cycles that have characterized momentum strategy profitability throughout the CRSP era.[3]

Second, the almost free lunch may not exist. That is, the apparent high returns may be a spurious artifact of the data mining that is unlikely to show up in future data. While a number of studies document the existence of price momentum in stocks in the United States and other countries, almost all of these studies use data from the same post World War II period and hence their findings cannot be viewed as being entirely independent of each other. We examine the returns on stocks listed on the London Stock Exchange during the Victorian era and find evidence the momentum existed outside of the CRSP era as well, thereby ruling out such a possibility.

Third, the lunch may not be free. Momentum strategies may generate high returns on average but expose investors to low returns during severe economic contractions. Such business cycle risks may not be discernable by looking at the Post-War CRSP era data alone. If momentum portfolios expose investors to occasional severe real risks at business cycle frequencies we may need to observe returns in more than the handful of relatively benign Post-War cycles before these risks become apparent. Historical Victorian age data helps us evaluate this hypothesis by observing momentum returns across several business cycles of varying levels of severity. Recessions were both more frequent and more severe during our Victorian era sample period. The NBER business cycle chronology includes 10 troughs during the 42 years between 1866 and 1907 compared to 10 troughs in the 63 years since World War II.[4] The cycles were more severe as well. The standard deviation of annual per capita GDP growth was 4.5 % between 1866 and 1907 and 3 % between 1946 and 2007 (see Johnston and Williamson (2008)).

Finally, the lunch may be due to taxes, and vanish when tax laws change. For example, Grinblatt and Moskowitz (2004) examine the extent to which tax motivated trading can account for some of the momentum phenomenon. They find that the long run reversal of momentum profits - i.e., the tendency of past Winners to lose relative to past Losers over

[3] Gatev, Goetzmann and Rouwenhorst (2006) note that pairs trading - like momentum trading - features periodic breaks as well. Hence, momentum trading; pairs trading; and the like – i.e. certain rules of forming portfolios and liquidating portfolios – appear to work with random periodic breaks.

[4] We should mention that the NBER business cycle chronology is for the U.S. Since the U.K. and U.S. business activities were highly correlated, we use the NBER Chronology.

36 to 60 months after portfolio formation - is largely confined to January, suggesting a link to tax effects. It is difficult to untangle tax and behavioral explanations of momentum using modern data. The British did not recognize capital gains as taxable income during our sample period. Our finding that the time series pattern in momentum profits seen in the post World War II data is also present during the Victorian age does not rule out an accentuating role for modern tax motivated trading but it does suggest that price momentum in stocks has a fundamental component that is unrelated to tax related trading activities of investors.

Stock Price Momentum during the Victorian Age: Cyclicality with Market States

To the extent decision making biases are hardwired into the human psyche, we should expect to find price momentum in stocks even during the second industrial revolution. The London market during the Victorian age was, by today's standards a primitive market with high execution costs, limited liquidity and very elementary computational power to sustain complex trading strategies. Even today's emerging markets may look quite advanced in comparison to 19^{th} century London, at least the know-how of trading and financial theory have made big leaps forward compared to what was available more than 100 years ago. Hence, if we do not find relative price momentum in stocks during the Victorian age, that would cast doubt upon the behavioral explanations that rely on the psychology of decision making.

We use a new hand-collected data set of the London Stock Exchange.[5] The new data set consists of the closing prices, dividends and shares outstanding of 1,808 stocks (equity) listed in London between 1866 and 1907. These stocks represent virtually every stock traded on the London Stock Exchange during this period. The fact that the London Stock Exchange was the most important market at the time, and that the U.K. was riding high on the waves of the second industrial revolution makes this a particularly interesting era to study as we cover a period of prosperity, expansion and the harbinger of twentieth century capitalism and financial markets.

[5] Historical data have been used before to assess some of the salient empirical stylized facts of asset returns. Most of these studies have focused on issues such as long term predictability, see e.g. for NYSE from 1815 to 1925, as discussed in Goetzmann (1993) and Goetzmann, Ibbotson and Peng (2001) or the Brussels stock exchange as discussed in Annaert and Van Hyfte (2006).

The existence of price momentum during the Victorian age will not by itself rule out any one class of theories, but does eliminate the possibility that price momentum may be an artifact of data mining. Furthermore, to the extent that existing theories place out of sample restrictions on historical data, we can use our 19^{th} century sample to evaluate competing hypotheses. We find both statistically and economically significant momentum effects – short run reversal, medium term continuation, and long run reversal in past winners minus past losers portfolio returns – and the order of magnitude is quite similar to that of the widely documented end of 20^{th} century evidence. However, we do not find a particularly strong relationship between momentum profits and firm size and we do not find a distinct January effect in our data.

Cooper, Gutierrez and Hameed (2004) (hereafter CGH) note that the theory of DHS can be extended to predict differences in momentum profits across states of the market, like bull and bear markets, as aggregate overconfidence should be greater following market gains. The HS model is also based on initial underreaction to information and subsequent overreaction, which eventually leads to stock price reversal in the long run. Hence, CGH test whether momentum profits depend on market states. They find strong evidence that CRSP era momentum profits depend on the state of the market, as predicted. Chordia and Sivakumar (2002) [CS] show that macroeconomic instruments commonly used for measuring macroeconomic conditions can explain a large portion of momentum profits. CS argue that intertemporal variations in the macroeconomic risk factors are the main sources of momentum profits. CGH overturn the CS results by examining the data in a different way. We find that similar patterns hold during the Victorian era as well, providing support of CGH's findings.

An important defining characteristic of momentum profits we find is that momentum profits are pro-cyclical with market states - momentum profits are high following high long run (36 months) market returns and low following low long run market returns – providing support of CGH's. However, momentum profits are unrelated to economic expansion and contraction cycles - and so the high returns to momentum strategies are difficult to reconcile as being compensation for macroeconomic risk according to standard economic theory. That suggests that "smart money, " i.e., the capital available to arbitrageurs, is in limited supply r*elative to available investment opportunities created by "dumb money,"* i.e., capital available to investors whose behavior is subject to behavioral biases documented in the literature. It would appear that the limits of arbitrage discussed in Shleifer and Vishny (1997) may be particularly binding following up markets, an empirical regularity in the data spanning over 100 years.

A Brief Review of the Momentum Literature

In what follows we provide a selective survey of the literature, emphasizing only the findings relevant for the analysis in the current paper.[6]

Although several early empirical studies of the efficient market hypothesis examined relative strength strategies, there was little consensus regarding the profitability of such strategies. Levy (1967) claimed that buying stocks when their prices are substantially higher than their 27 weeks moving average resulted in superior profits. Jensen and Bennington (1970) challenged this claim by showing that Levy's trading rules did no better than buy and hold strategies suggesting that Levy's findings could be subject to a data mining bias. In contrast, Fisher Black (1973) found that Value Line rankings that relied, among other things, on relative strength (of the stocks in the industry relative to the composite stock index) had value. Grinblatt and Titman (1989) found that mutual fund managers exhibited a tendency to buy past winners – their buy decisions appeared to rely on the existence of price momentum. Lehmann (1990) used a clever portfolio strategy to exploit short run reversal and showed that it is an economically interesting phenomenon. Lo and MacKinlay (1990) examined the sources of momentum profits by analyzing Lehmann's (1990) portfolio strategy.[7]

Jegadeesh and Titman (1993) designed a clever trading strategy that we follow in this paper. Jegadeesh and Titman's (1993) strategy relied on relative price momentum that was well defined and has been replicated by other researchers.[8] A vast number of studies have confirmed the Jegadeesh and Titman (1993) finding using data from markets in a number of countries – United States, Europe, and emerging economies (see e.g. Rouwenhorst (1998)).[9] Using a sample from 1973 until February 2008, Asness et al. (2008) study (value and) momentum in five major asset classes: (i) stock selection within four major countries, (ii) country equity index selection, (iii) government bond selection, (iv) currency selection, and (v) commodities. They provide ubiquitous evidence on the excess return

[6] For a recent comprehensive survey of the literature, see e.g. Jegadeesh and Titman (2005).

[7] See Jegadeesh and Titman (2005) for a comprehensive survey of the momentum literature.

[8] Jegadeesh (1990) showed short term reversal and medium term continuation in returns in the cross section using regression methods.

[9] Chui, Titman, and Wei (2007) note that Korea, Japan, and Taiwan are exceptions.

to value and momentum, extending the existing evidence to government bonds, currencies and commodities. The consensus appears to be that there is reversal in the short run – i.e., past *Winners* lose relative to past *Losers* during the first month following portfolio formation; continuation during the intermediate term – i.e., past *Winners* continue to win relative to past *Losers* during the 2 to 12 months following portfolio formation; and long run reversal - i.e., past *Winners* lose relative to past *Losers* over 36 to 60 months following portfolio formation. The evidence is stronger for short term reversal and intermediate term continuation. Korajczyk and Sadka (2004) show that momentum profits cannot be explained away by transactions costs. Given their estimates of visible and invisible transactions costs, find that the abnormal returns to some of the momentum strategies disappear only after about $ 5 billion of money chases them.

A variety of explanations are offered for these relations. They range from data issues, such as microstructure and data snooping biases (Boudoukh et al. (1994), Conrad and Kaul (1989), Lo and MacKinlay (1988), to rational risk-based explanations (Conrad and Kaul (1998) Berk et al. (1999), Chordia and Shivakumar (2002), Bansal et al. (2002), to irrational behavioral stories (DeBondt and Thaler (1985, 1987) Jegadeesh and Titman (1993), Daniel et al. (1998), Barberis et al. (1998), Hong and Stein (1999), Hong et al. (2000), Lee and Swaminathan (2000), Grinblatt and Han (2002), among others.

Several theories have been advanced to explain this phenomenon. They can be put into two classes: those that rely on investor psychology affecting stock prices and others that rely on the changing nature of real investment options available to firms. Daniel, Hirshleifer, and Subrahmanyam (1997) (henceforth DHS), Barberis, Shleifer and Vishny (1998) (henceforth BSV), Hong and Stein (1999) (hereafter HS) and Grinblatt and Han (2005) (henceforth GH)are some of the notable papers falling in the former class. DHS assume overconfidence and self attribution - leads to momentum from overreaction that subsequently corrects resulting in reversal. BSV assume conservatism and extrapolation on the part of investors and show that will lead to continuation in the intermediate term and reversal in the long run. Hong and Stein assume slow information diffusion and positive feedback trading and show it can lead to momentum and subsequent reversal. GH argue that the tendency of some investors to hold on to their losing stocks, driven by prospect theory" of Kahneman and Tversky (1979) "and mental accounting" of Thaler (1980) can lead to slower diffusion of information and price momentum in stocks. The commonality among all these models is they all rely on biases in how investors process information.

Berk, Green and Naik (1999) (BGN), Carlson, Fisher and Giammarino (2004), Johnson (2002), Chen and Zhang (2007), and Sagi and Seasholes (2007) fall in the latter class. BGN pioneered the latter line of thinking by showing that when firms make optimal investment choices, their assets and investment options change in a predictable way affecting their life cycle risk characteristics and that can also cause price momentum in stocks.

Rest of the paper

The remainder of the paper is organized as follows. We start in section 2 with details of the historical data set we collected. In section 3 we discuss the empirical findings regarding momentum. Section 4 reports some measures of trading costs for the London market. Section 5 studies the dependence of momentum profits on market states, while Section 6 examines the dependence of momentum profits on the state of the economy. Section 7 analyzes the term structure of momentum profits, and Section 8 concludes the paper.

2 The London Stock Market Data: 1866-1907

This study makes use of a new data set consisting of the closing prices, dividends and shares outstanding of 1,808 stocks (equity) listed in London between 1866 and 1907, compiled by the authors from late 19^{th} and early 20^{th} Century financial publications. As can be seen from Figure 2, the number of stocks we use to form momentum portfolios, varies from 126 in 1866 to 1074 in 1907. The number of stocks declines from 985 in 1903 to 544 in 1904, due to a number of industries vanishing from the quotation list, only to reappear in 1905.

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 was sampled every 28-days rather then the more traditional end of month observations, due to the 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, British, Commonwealth and foreign railroads and concludes with commercial securities organized by industry (banks, breweries, canals & docks, insurance, iron coal & steel, gas, mining, shipping, spinning, waterworks, tea, land, financial & 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* published weekly economic statistics and a "Stock Market Prices Current" throughout our period of study. The *Economist*'s price list included only the largest and most active securities listed in London. Since the coverage was sparse, we only employ the *Economist* to fill in data that was missing from the *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 was 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 19^{th} Century the difference between debt and equity was seldom obvious. The 19^{th} 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 19^{th} 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 at which time 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 allow 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.*[10]. 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+1} is the net dividend payments and capital calls (if any) that occurred

[10]The IMM is available online at `http://som.yale.edu/imm/html/index.shtml`

between time t and $t+1$. Capital calls are a form of reverse dividend common to 19^{th} Century stock exchanges.

Many 19^{th} 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.[11] To compute holding period returns, we treat capital calls as a negative dividend paid at the beginning of the holding period.

Data Limitations

Historical data provides both a new laboratory to evaluate theories as well as a unique set of challenges. Missing observations are far more common in historical data. There are three types of missing data. Firstly, there are securities that vanish because the company goes out of business. Secondly, there are securities that are not quoted for a period and then re-appear without explanation. Finally, there are dates when the newspapers omit an entire industry from the price lists.

The first case is the well known problem of survivorship bias. Securities do not vanish from the price list at random. Instead, the companies with poor returns and low stock prices are far more likely to go bankrupt and vanish. Two characteristics of our data mitigate the potential survivorship bias. To begin with, very few securities simply "vanish". When a security disappears from our price list we generally observe its decline to zero (or negative) price before it is removed from the list. When a security vanishes we make every attempt to discover what happened to the company and compute the final holding period return. If

[11] We only include stocks with positive values in the analysis that follows.

the security vanished due to reorganization, liquidation or merger, the IMM often lists the details and we correct the last return to reflect these events.

The second and third cases of missing data are more troublesome. These are cases of securities that do not go out of business, but are merely omitted from the price list on a given day. If prices are missing completely at random, the analysis that follows can easily be altered to accommodate the missing observations. If the probability of observing a given return is correlated with the value of that return, however, the missing values will bias our estimates.

In the computations to follow, we form our momentum portfolios using actual prices available to Victorian era investors. We base all buy and sell decisions on actual price data. Once a portfolio is formed, however, we compute its post-formation return from observable prices if possible and interpolate data if necessary.

When necessary, we replace missing prices with interpolated data via the following algorithm. If a security vanishes from the quotation list we look ahead to the next date that a quotation is available. If the security reappears N-periods in the future, we compute the N-period gross return and convert it to a 1-period return by taking the gross return to the (1/N)th power. We replace all missing 1-period returns with this interpolated return. For example, if a security's price is last observed at time t and reappears 20% higher at time t+5 we replace the missing values at time t+1 to t+5 with $(1.2)^{(1/5)}$. When computing multiperiod returns we assume all dividends are paid at the end of the period.

If a stock vanishes and does not reappear for one year we set its return to -99.99 %. Setting all extinct stocks to -99.99 % return surely understates the true return. However, the nature of the conclusions we obtain do not change if we relax our assumptions by either ignoring the extinction (don't set the last return to -99.99%) or ignoring all missing data by assuming it is missing at random and computing results from observable data only. Setting extinct stocks to -99.99% obviously lowers gross returns but the relative comparisons of portfolios sorted by size or momentum are robust to the treatment of missing data - as will be discussed in detail later.

Finally, it should be noted that we do not have enough industries during the Victorian age, which prevents us from examining the importance of industry momentum identified by Grinblatt and Moskowitz (1999).

3 Intermediate Term Momentum in Stock Prices

The structure of this section follows that of Jegadeesh and Titman (1993), henceforth referred to as JT. It is worth recalling the trading strategies considered by JT. The main motivation is the premise that if stock prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist. Therefore strategies examined by JT, consider selecting stocks based on their returns over the past 1 through 4 quarters. To increase the power of the tests, the strategies include portfolios with overlapping holding periods. Therefore, in any given month t, the strategies hold a series of portfolios that are selected in the current month as well as in the previous K - 1 months, where K is the holding period.[12] Specifically, a strategy that selects stocks on the basis of returns over the past J months and holds them for K months is referred to as a J-month/K-month strategy. It is constructed as follows: At the beginning of each month t the securities are ranked in ascending order on the basis of their returns in the past J months. Based on these rankings, JT grouped stocks into deciles and formed a value-weighted portfolio of stocks within each decile. Since the number of stocks available to us during the Victorian age is smaller, we will work with a coarser grid, namely top, middle and bottom thirds - or small, medium and large. The top portfolio is called the "losers"and the bottom is called the "winners". In each month t, the strategy buys the winner portfolio and sells the loser portfolio, holding this position for K months.[13]

Let us recall that JT used constructed momentum portfolio returns over the 1965 to 1989 period using data from the CRSP daily returns file. All stocks with available returns data in the J months preceding the portfolio formation date are included in the sample from which the buy and sell portfolios are constructed. Table 1, similar to Table I in JT, reports the average returns of the different buy and sell portfolios as well as the zero-cost, winners minus losers, portfolios constructed using our data set. JT have a larger set of 32 strategies, while our selection strategy is constrained by the smaller set of stocks and less frequent trading. JT find that the returns of all the zero-cost portfolios are positive and statistically significant except for the 3-month/3-month strategy. Our historical results reported in Table 1 are the same. The weakest case is the 3/3 strategy, which is not statistically significant.

[12] As noted at the beginning of section 2, we considered 28-day periods as months in our calculations. Moreover, when considering a year, i.e. $K = 12$ months in JT, we used 13 28-day periods.

[13] As mentioned earlier, if a stock, included in a momentum portfolio, vanishes from the database when the portfolio is formed, but does not reappear at any future point in time, we remove it. When a stock does reappear at a latter time, we interpolate its price in computing the return on the momentum portfolio.

The most successful zero-cost strategy in JT is the J=12/K=3 months strategy which yields 1.31 % per month. Our most profitable strategies are also of the same type (J=13/K=3 and J=9/K=6 being quite similar) although they yield only .5 % per month. Moreover, the 9-month formation period produces returns of about .5 % per month regardless of the holding period. This is to be expected since we use a coarser partition of stocks based on past returns (tertile instead of decile as in JT). While the order of magnitude of monthly returns is less than half that reported in the JT paper, the statistical significance is about the same.

To assess whether momentum strategy profits are abnormally high, it is necessary to examine their exposure to systematic risk. We follow the JT approach in focusing all our remaining analysis on the 6-month/6-month strategy, and thus in the rest of this paper the length of a period is 6 months. This has the advantage that we are dealing with equally spaced return observations, which makes the analysis of factor models and temporal dependence easier.

Table 2 reports estimates of the two most common indicators of systematic risk, the post-ranking betas of the 6-month/6-month relative strength portfolios and the average capitalizations of the stocks in these portfolios. The table is similar to Table 2 in JT, except for the fact that we have less entries due to the smaller set of strategies considered. We find, (similar to JT) that the beta of the zero-cost winners minus losers portfolio is negative (we find a beta of -0.02, whereas JT have a beta of -0.08), since the beta of the portfolio of past losers is higher than that of the portfolio of past winners. The average capitalizations of the stocks in the different portfolios show that the highest and the lowest past returns portfolios consist of smaller than average stocks, with the stocks in the losers portfolios being smaller than the stocks in the winners portfolio. This evidence is consistent with JT, suggesting positive risk adjusted returns on average, for the momentum portfolio.

Next, we examine the profitability of the 6-month/6-month strategy within subsamples stratified on the basis of firm size. Size is sorted in lower, middle and highest thirds. Panel A of Table 3 reports average returns and Jensen's CAPM alphas, and Panel B reports CAPM regressions augmented with a NBER Business Cycle dummy.[14]

[14] Consensus U.K. business cycle dates are not available for this time period. Therefore, we use NBER business cycle dates as proxies for the trans-Atlantic business cycle. However, there is considerable evidence that the U.S. and U.K business cycle was correlated during the Victorian era. U.S. and U.K. industrial production and per capita GDP had correlations of .22 and .25 respectively. Historical consumption data is unavailable but average U.K. household earnings grew at a rate of 1.55 % in years without NBER contractions and 1 % in years with an NBER contraction. See Officer (2008 a,b).

We note in Panel A of Table 3 that all the CAPM alphas are negative. A robustness check reported in Table 4 shows that this is due to our treatment of missing data. Recall that we set the last monthly return to -99.99 % whenever a firm vanishes from our sample after portfolio formation. This grossly understates the actual returns. In Table 4 we compute returns under the alternative assumption that firms leave the database at random and do not set the last monthly return to -99.99%. This alternative method ignores the survivorship issue, as is done in JT. Under the alternative treatment of missing data half the portfolios have positive alphas and half have negative alphas - as is found with modern era data. Thus we can be confident that the negative CAPM alphas are due to our treatment of missing data.

As JT note, measuring relative strength profits on size-based subsamples allows us to examine whether the profitability of the strategy is confined to any particular subsample of stocks. This analysis also provides additional evidence about the source of the observed relative strength profits. Table 3 presents the average returns of the 6-month/6-month strategy for each of the subsamples. The results we report are in line with JT. They indicate that the observed abnormal returns are of approximately the same magnitude when the strategies are implemented on the various subsamples of stocks as when they are implemented on the entire sample. Unlike JT we do not find a particularly strong relationship with firm size. For the zero-cost, winners minus losers portfolio, JT find that the subsample with the largest firms generates lower abnormal returns than the other two subsamples. In Table 3 we find a large return for the medium-sized category, although the large firms in our sample still create the lowest return for the zero-cost, winners minus losers portfolio. When we control for the business cycle, we obtain similar findings, as discussed later. These findings indicate that the relative strength profits are not primarily due to the cross-sectional differences in the systematic risk of the stocks in the sample.

Likewise, Table 6 reports the average returns of the zero-cost portfolio in January versus the rest of the year. JT note that following Roll (1983), there are reasons to expect that the relative strength strategies will not be successful in the month of January. They find that relative strength strategy loses about 7 % on average in each January but achieves positive abnormal returns in each of the other months. We do not find such seasonal patterns, namely the month of January does not yield negative returns in our sample. Moreover, according to statistical tests reported in Table 6 there is, with a few minor exceptions, basically no difference between January and the other months of the year. Our findings essentially confirm the Roll (1983) story. With no capital gain taxes in our time period we do not expect a January effect, as predicted by Roll (1983).

To conclude, we examine again whether our choice of missing data treatment alter the results of the paper. In Table 5 we report the results we obtain for size-sorted average monthly returns and t-statistics for buy minus sell portfolios under our treatment of missing data and results we would obtain if we relaxed our assumptions by either ignoring the extinction (don't set the last return to -99.99%) or ignoring all missing data by assuming it is missing completely at random (MCAR) and computing results from observable data only. Setting extinct stocks to -99.99% obviously lowers gross returns but the relative comparisons of portfolios sorted by size or momentum are robust to the treatment of missing data. The t-stats are significant under all treatments of missing data. The results in Table 5 show that our decision to replace missing with -99.99% is in fact the most conservative. Moreover, the probability that a firm vanishes appears to be largely independent of past returns. While the actual magnitude of winner and loser alphas depend on the treatment of missing data the alpha generated from a long winner short loser portfolio is robust to assumptions about missing firm returns.

4 Trading Costs

In Tables 7 and 8 we turn our attention to transaction costs. It is indeed worth investigating how costly it would be to sustain a momentum strategy. Lesmond, Schill and Zhou (2004) examine the profitability of momentum trading strategies and find that those stocks that generate large momentum returns are precisely the stocks with high trading costs. Along similar lines, Korajczyk and Sadka (2004) test whether momentum strategies remain profitable after considering market frictions induced by trading. Both studies use data, such as intraday data, which is not available in our historical period. We therefore use a simpler approach to gauge the importance of trading costs associated with momentum portfolios.

Table 8 provides data on average bid-ask spreads and average prices of stocks in each of the portfolio categories, whereas Table 7 displays the transition probabilities pertaining to portfolio turnover. Regarding the latter, each cell in the matrix contains the proportion of times that a stock in a given portfolio at time t lands in a given portfolio at time $t + 1$. With respect to trading costs we are most interested in the diagonal values which tell us the proportion of times a stock remains in the same portfolio during a new formation. The persistence of stock assignment is generally in the 30-35 % range, which is fairly high compared to current momentum strategies (see e.g. Conrad and Kaul (1998)).

Table 8 also reports the value-weighted bid-ask spread as a percentage of the midpoint for all stocks that are assigned to each portfolio at each date. For example, when the Large Buy portfolio's spread is .02, it means that the value-weighted average bid-ask spread of all stocks purchased or sold from the Large Buy portfolio was 2 % of the midpoint of their bid-ask price. To get an idea of transaction costs, it should be noted that the average bid-ask spread of the Large Buy portfolio was .02. We know that only 1/6 of the portfolio is replaced each period so dividing by 6 .02/6 = .0033. This is the average per period transaction cost if one paid the full bid-ask spread and bought and sold every stock in the new and old portfolios. However, some of the stocks in the new portfolio were also in the portfolio we formed 6 months ago. From the transition matrix in Table 6 we see that on average 32 % of the stocks in the Large Buy portfolio at any time are also in the same portfolio 6 months later. We would therefore only have to turn over 68 % of the stocks. Multiply .0033 by .68 to get the final back of the envelope estimate of bid-ask costs of roughly 23 basis points per period. This turns out to be the lowest cost. For the other portfolios the costs can be as high as 229 basis points (Small Loser). Hence, these rough measures show that trading costs are high, at least as much as they are in recent history, which makes the profits of momentum not realizable except possibly to those who were making a market in those stocks.

5 Market States and Momentum

Cooper, Gutierrez and Hameed (2004) note that the theory of DHS can be extended to predict differences in momentum profits across states of the market, like bull and bear markets, as aggregate overconfidence should be greater following market gains (DHS and Gervais and Odean (2001)). With overconfidence higher following market increases, overreactions will be stronger following up markets, generating greater momentum in the short run. The HS model is also based on initial underreaction to information and subsequent overreaction, which eventually leads to stock price reversal in the long run.

In Table 9 we report the evidence of momentum and market states in our sample. For each month, between 1929 and 1995, CGH define the state of the market as *Up* (*Down*) if the markets trailing three-year return is positive (negative) on that date. They compare the returns of momentum portfolios formed during *Up* and *Down* markets and conclude that momentum was largely an up market phenomenon during the CRSP era. The London market index was seldom down in the 3-year windows during our historical sample period. We therefore take a slightly different definition of up and down markets. By CGH′s definition, 85 % of their observed market states were UP markets. We define Victorian market states as follows *Up* = market index return over the past 3 years in the top 85 % of sample returns, and *Down* = market index return over the past 3 years in the bottom 15 % of sample returns. We include a panel in Table 9 that contains the CRSP era results with the our sorting method over CGH′s sample years, because CGH sort stocks into deciles while we sort into terciles. The choice of tercile sorts instead of deciles, weakens the relationship between market state and momentum in the CRSP era but the difference between UP and DOWN market states, remains.

Average profits and risk adjusted returns by market state are computed by taking the profits of each zero-cost momentum portfolio (winner minus loser terciles) for each formation date and averaging across all formation dates that qualify for a particular market state. The average monthly profit of the momentum portfolio formed at time t is:

$$AvgRET_t = [\sum_{k=t+1}^{t+6} r_k]/6 \tag{5.1}$$

where r_k is the return of the 6-6 winner minus loser momentum portfolio formed at time t. We follow CGH and also report the average CAPM alpha across market states. The CAPM alpha of the momentum portfolio formed at time t is:

$$\alpha_t = [\sum_{k=t+1}^{t+6} r_k - \widehat{\beta}_t(r_{m,k} - r_{f,k})]/6 \tag{5.2}$$

where $\widehat{\beta}_t$ is the OLS estimator of a CAPM regression, using data from $t+1$ to $t+6$.

Table 9 reports the mean monthly profits and mean CAPM alphas by market state. The *Up* market average monthly profit is computed by taking the average of all $AvgRET_t$ for formation time t that corresponds to an *Up* market state. *Down* market results are computed in the same manner. Since the average returns are computed from overlapping holding periods, all t-stats are computed with the Newey and West (1987) HAC procedure using 5 lags.

CGH find that momentum profits depend on the state of the market, as predicted. From 1929 to 1995, the mean monthly momentum profit following positive market returns is 0.93 % in their sample, whereas the mean profit following negative market returns is - 0.37 %. The up-market momentum reverses in the long run.

In Table 9 for the 6/6 winner minus loser portfolio, we find that the average monthly return following an *Up* market is 40 bp per month in the CRSP sample, and 38 bp per month in our sample. The corresponding numbers following a *Down* market are -28 bp per month and 15 bp per month respectively. Clearly, momentum profits are higher following *Up* markets than *Down* markets in our sample just like in the CRSP sample, using our rule for classifying *Up* and *Down* markets. While the difference is statistically significant in the CRSP sample, it is not significant in our sample. We also find similar patterns for Jensen's alpha.

Next we examine whether commonly used macroeconomic instruments for measuring market conditions can explain a large portion of momentum profits, following the methods used in CGH. Following Chordia and Sivakumar (2002) we construct a factor model for expected returns:

$$r_t = a + b_1 Mkt_t + b_2 Divyld_t + b_3 Term_t + b_4 Default_t \tag{5.3}$$

where the return on the 6-6 momentum portfolio (i.e., Winner minus Loser monthly rate of return) is projected onto $Divyld_t$: lagged dividend yield on the market index, $Term_t$: lagged term spread [yield on British consol - yield on 30-day bankbill], and $Default_t$: lagged default spread [yield on risky bonds (portfolio of British RR bonds) - yield on British consol].[15]

We use two methods to evaluate the ability of the factors to explain momentum profits. In Panel A of Table 10 we report the slope coefficients, the test statistic for the hypothesis that $b_2 = b_3 = b_4 = 0$ and the proportion of variation collectively explained by the $Divyld$, $Term$ and $Default$ factors. The latter is obtained via the R^2 of the CAPM residuals regressed on $Divyld$, $Term$ and $Default$. For most 6-6 momentum portfolios we can soundly reject the null, that the betas on the macroeconomic factors are collectively equal to zero. It should be noted that CS use a 3 factor model with no market index. We add the market index for the regression that reports factor loadings and proportion of extra variation explained by CS's 3 factors (panel A of Table 10). In Panel B of Table 10 we sort on CS's three factors model

[15] We computed the yields on the British consol and British railroad bonds from quotations in the Course of the Exchange. The yield on 30-day bank bills was collected from *The Economist*.

(no market index). However, the proportion of variation explained by the macro factors is extremely small. Collectively the macro factors explain less than 3 % of the time series variation in portfolio returns and in the case of the largest stocks less than 0.3 %.

CGH employ a clever double sort methodology to illustrate the relative influence of momentum and factor premium on portfolio returns. For each stock and time period, they compute the factor loadings via an OLS regression over the trailing 60 months. With time t beta estimates in hand, they compute the expected return of each stock over the future 6 months given current betas and actual future realizations of the factors. They then sort stocks into portfolios based on momentum and factor model expected return. This is equivalent to the double sorts we report in our Table 3, using factor model expected returns in place of size. We form historical portfolios via this method and report the results in Panel B of Table 10. We see that Winner minus Loser portfolios within each of the three predicted return categories earn positive returns on average; the average returns are statistically (t=3.75) and economically (54 bp per month) significant within the high predicted returns group. Further, within the Loser and Middle groups, stocks with high predicted returns earn lower returns than stocks with low expected returns, and they are jointly significantly different from zero. Hence, the findings with Victorian era data, support the results of CGH, although our evidence appears somewhat weaker.

6 Business Cycles and Momentum Profits

During the Victorian age there were at least as many business cycles as in the current CRSP data; and the depressions of those days have been characterized as more severe.[16] We therefore examine how momentum profits are related to business conditions (expansions and contractions; as well as past stock market returns). To do so we turn our attention now to Tables 11 and 12. In Table 11 we report the results of the regression:

$$r = a + b_1 * (Mkt) + b_2 * (GDP)$$

where r is the return on buy portfolio minus the return on sell portfolio and GDP is the demeaned real per capita GDP growth. We examine this regression for small, medium and large stocks. In none of the cases do we observe any significantly positive exposure of the

[16]There were 10 NBER recessions between 1866 and 1907 and 10 between 1946 and the present.

momentum profits to GDP growth rate risk; in fact the point estimates of the slope coefficient for GDP growth rate is negative for all size classes.

To complement this, we also report in Table 12 a correlation matrix for the following variables: real per capita GDP growth, buy-sell portfolio annual returns for small, medium and large stocks, the average cross-sectional monthly stock return standard deviation, market excess returns and UK short and long-term rates obtained from Ordinary Funds. The correlations are computed using annual data. The first column of Table 12 shows that the annual returns of the buy-sell portfolio for small stocks features very negative correlations with GDP growth (around 30 %), as well as the excess market returns and the long term rate. The medium-sized firms feature similar negative correlations except for the long rate which is positively correlated with buy-sell portfolio annual returns for medium firms (more than 35 %). Finally, the Buy-sell portfolio annual returns for large firms also show negative correlation with GDP growth, although the correlation monotonically declines with the size of the firms.

7 Term structure of momentum returns

Momentum profits can occur for a variety of reasons even from the perspective of some one who subscribes to the behavioral point of view. For example, if momentum profits are entirely due to slow diffusion of information, then the positive abnormal returns should decay over time to zero. On the other hand, if momentum profits are due to delayed overreaction, momentum profits will likely reverse in sign before decaying down to zero over time. We therefore examine the term structure of the profits to the various momentum portfolios in this section.

We report in Table 13 the average monthly excess return on the momentum portfolios during each of the five years following portfolio formation, after skipping a month.[17] The loser portfolios' returns almost double from year 1 to year 5. In contrast, the winner portfolios' returns come down somewhat by year 5. Therefore the difference, i.e., the winner minus loser

[17] It is important to note that the results in Table 13 are computed from all available time periods. This means the sample periods vary by column. For example the portfolio return in year 2 after formation is computed by looking at the buy-sell portfolio 14-26 months after formation, so our first "year 2" observation is July 1867-June 1868. Our first "year 5" observation doesn't begin until July 1871, however. Therefore the Year 2 column has more observations than the Year 5 column. This is also why the various columns do not add up.

momentum portfolio returns becomes negative in years 4 and 5, and marginally significant. As can be seen from Figure 4, a dollar invested in the 6 month Winner portfolio can be expected to grow steadily over time to 1.15 dollars in 5 years; and a dollar invested in the 6 month Loser portfolio can be expected to decline to 0.99 dollars after 19 months before rising to 1.08 dollars at the end of 5 years. The difference between the value of a dollar invested in each of the Winner and the Loser portfolios peaked at 7.7 cents on average by the end of the 3rd year before narrowing down to 6.1 cents at the end of 5 years (see Figure 5). So, while the evidence of long run reversal exists, it is not as dramatic as that reported in Jegadeesh and Titman (2001)we can reject the hypothesis that momentum returns in years 2 to 5 are the same as that during year 1, in favor of the alternative that they are smaller at conventional levels of significance.

Since our historical data is sampled every 28-days, therefore one year is 13 "months". We wish to test the null hypothesis that the winner minus looser (WML) portfolio exhibits no momentum or reversal. We begin by forming a $T \times N$ matrix X where the $(t-th, n-th)$ element is equal to the month t annual return on the WML portfolio formed n years earlier. Let $X(t,n)$ be the holding period return from month $(t-12)$ to month t on the WML portfolio formed $n \times 13$ "months"earlier. Under the null hypothesis that WML returns are independent of time since formation, each column of X should have the same expectation. We test this hypothesis by subtracting the year 1 WML return from the year 2, 3, 4 and 5 returns to form a new $\tilde{X}$ matrix, such that $\tilde{X}(t,n) \equiv (X(t,n+1)$ - $X(t,1))$. Therefore $\tilde{X}(t,n)$ measures the difference between the holding period return from month $(t-12)$ to month t on the WML portfolio formed $(n+1)$ years earlier and the WML portfolio formed 1 year earlier. Under the null hypothesis of no momentum or reversal $\tilde{X}(t,n)$ should have expectation zero. Table 14 reports the mean return of the WML portfolio 1 through 5 years after formation. We test of the null that $E[\tilde{X}(t,n)] = 0 \ \forall \ t$ and n. via a Wald test.[18] The results in Table 14 show strong rejections of the null that average monthly returns are equal in years 1 through 5. It is interesting to note the pattern of mean returns: 0.0034 after one year, 0.0016, 0.0006 after two and three years and finally -0.0006 and -0.0015 after years four and five. This reaffirms the finding of short run reversal, medium term continuation, and long run reversal in past winners minus past losers portfolio returns.

The lower panel of the Table shows some pairwise test results and we note that year 1 is

[18]More specifically, consider: $g = (\sum_t[\tilde{X}(t,1)]/T, \ldots, \sum_t[\tilde{X}(t,4)]/T)$, then the test statistic is $W = gCov(g)^{-1}g$, where under the null $W \sim \chi^2(4)$, asymptotically. Since the elements of $\tilde{X}$ are serially correlated, we use a HAC estimator for $Cov(g)$ using Newey-West with 13 lags.

significantly different from all other years. The average monthly returns after 2 and 3 years appear to have the same mean, and so do years 3 and 4 as well as 4 and 5.

It should be noted that the above test may be biased by missing data. In particular, when an asset vanishes from our data set we set its return to -99.9% at the time of extinction and replace missing data with interpolated data when possible. However, we verified that the momentum in years 1 and 2 and reversal in years 4 and 5 are robust to missing data treatment, and we find indeed they are.[19]

8 Conclusion

We use a new hand-collected data set of the London Stock Exchange which consists of the closing prices, dividends and shares outstanding of 1,808 stocks (equity) listed between 1866 and 1907. By today's standard, the market was very primitive - and therefore presented an interesting case to examine price momentum.

We replicate the trading strategy designed by Jegadeesh and Titman (1993) and find compelling evidence for short term reversal, intermediate term continuation and long run reversal in momentum profits. We also find that momentum profits are higher following up markets when compared to down markets. Further, momentum profits do not appear to be compensation for economy wide systematic risk, captured by the standard CAPM or macroeconomic factor models. Momentum profits are higher during economic contractions, a pattern that is different from the post World War II period. That poses a challenge rational models of investor behavior that have been proposed in the literature as an explanation of the momentum phenomenon. Also, 0ur finding of price momentum during the Victorian age eliminates the possibility that price momentum may be an artifact of data mining.

We find that momentum profits are low following three year down markets and high following three year up markets. That is the systematic pattern across data spanning several centuries. The defining characteristics of momentum – its cyclicality – is not related to aggregate

[19]We did this as follows. If survival rates differ across buy and sell portfolios this may bias our reversal tests. We evaluate the effect of missing data on the results in two ways. First we simply compute the probability of extinction. If the probability of extinction is independent of past return the momentum results should be robust to our choice of missing data treatment. We find survival probabilities that a stock remains in the data set, n-months after formation, for buy and sell portfolios. The difference between survival rates in buy and sell portfolios is very small. We also computed the event time returns of WML portfolios under our treatment of missing data and an alternative treatment that simply ignores securities that vanish.

consumption or GDP numbers, but what happens to the stock market. The theoretical literature emphasizes the role of "dumb money" and "limits of arbitrage" in explaining price momentum in stocks. Our findings suggest that "dumb money" may be abundant relative to "smart money" following up markets, and regulators interested in the stability of financial system may have to be especially watchful during up markets, lest the "dumb money" effect takes over and exerts major influence over economic activities.

Finally, our finding that price momentum in stocks during the Victorian age when there was no capital gains taxation suggests that the long run reversal of momentum profits must have a fundamental component identified by Grinblatt and Moskowitz (2004) using CRSP era data, that is unrelated to tax-based trading.

References

[1] Annaert, J. and W. Van Hyfte, 2006, Long-horizon mean reversion for the Brussels Stock Exchange: evidence for the 19th century, Discussion Paper, Ghent University.

[2] Asness, C., T. Moskowitz and L. Pedersen, 2008, Value and Momentum Everywhere, Discussion Paper, Chicago and NYU.

[3] Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307 - 343.

[4] Berk, Jonathan, Richard Green and V. Naik, 1999, Optimal Investment, Growth Options and Security Returns, *Journal of Finance*, 54, 1553 – 1608.

[5] Black, Fischer, 1973, Yest, Virgina, There is Hope: Tests of the Value Line Ranking System, *Financial Analyst Journal*, 29, 10 – 14.

[6] Brav, A., and J. B. Heaton, 2002, Competing Theories of Financial Anomalies, *Review of Financial Studies* 15, 575 – 606

[7] Carhart, M. M., 1997, On persistence in mutual fund performance, *Journal of Finance*, 52, 57 - 82.

[8] Carlson, M., Fisher, A., Giammarino, R., 2004, Corporate investment and asset price dynamics: implications for the cross-section of returns, *Journal of Finance* 59, 2577 - 2603.

[9] Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681 - 1713.

[10] Chen, Long and Lu Zhang, 2007, Neoclassical Factors, *Working Paper*, Ross School of Business, University of Michigan.

[11] Chui, Andy C. W., Sheridan Titman, and K. C. John Wei, 2007, Individualism and Momentum around the World, Working paper, University of Texas.

[12] Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985 – 1019

[13] Conrad, Jennifer, and Gautam Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11, 489 - 519.

[14] Cooper, Michael. J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345 – 1365.

[15] Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839 - 1886.

[16] Daniel, Kent, M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1217 – 1218.

[17] Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Financial Economics* 51, 55 - 84.

[18] Frazzini, Andrea, 2006, The disposition effect and under-reaction to news, *Journal of Finance*

[19] Gatev, Evan, William Goetzmann and Geert Rouwenhorst, 2006, Pairs Trading: Performance of a Relative-Value Arbitrage Rule, *Review of Financial Studies,* 19, 797 – 827.

[20] Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies* 14, 1 - 27.

[21] Goetzmann, William, 1993, Patterns in Three Centuries of Stock Market Prices, *Journal of Business*, 66, 249 – 270.

[22] Goetzmann, W., R.G. Ibbotson, and L. Peng, 2001, A New Historical Database for the NYSE 1815 to 1925: Performance and Predictability, *Journal of Financial Markets*, 4, 1 – 32.

[23] Griffin, John, M., Xiuqing Ji, and J. Spencer Martin, 2005, Global momentum strategies: A portfolio perspective, *Journal of Portfolio Management*, 31, 23 – 29

[24] Grinblatt, Mark, and Bing Han, 2005, Prospect Theory, Mential Accounting, and Momentum, *Journal of Financial Economics,* 78, 311 – 149.

[25] Grinblatt, Mark, and Matti Keloharju, 2001, What makes investor trade? *Journal of Finance* 56, 589 – 616.

[26] Grinblatt, Mark, and Tobias Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249 – 1290.

[27] Grinblatt, Mark, and Tobias Moskowitz, 2004, Predicting stock price movements from past returns: the role of consistency and tax-loss selling , *Journal of Financial Economics*, 71, 541 - 579.

[28] Grinblatt, Mark, and Sheridan Titman, 1989, Mutual Fund Performance: An Analysis of Quarterly Portfolio Holdings, *Journal of Business* 62, 393 – 416..

[29] Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29 – 78.

[30] Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265 - 295.

[31] Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143 - 2184.

[32] Hou, Kewei, 2001, Information diffusion and asymmetric cross-autocorrelations in stock returns, Working Paper, The Ohio State University.

[33] Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881 – 898.

[34] Jegadeesh, Narasimhan and Sheridan Titman, 1991, Short horizon return reversals and the bid-ask spread, Working paper UCLA.

[35] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65 - 91.

[36] Jegadeesh, Narasimhan, and Sheridan Titman, 1995, Overreaction, delayed reaction, and contrarian profits, *Review of Financial Studies* 8, 973 - 993.

[37] Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699 – 720.

[38] Jegadeesh, Narasimhan, and Sheridan Titman, 2002, Cross-sectional and time-series determinants of momentum returns, *Review of Financial Studies* 15, 143 – 158.

[39] Jegadeesh, Narasimhan, and Sheridan Titman, 2005, Momentum: A review, in *Advances in Behavioral Finance II*, Ed. Richard Thaler, Princeton University Press, NJ.

[40] Jensen, Michael and George Bennington, 1970, Random walks and technical theories: Some additional evidence, *Journal of Finance* 25, 469 – 482.

[41] Johnston, Louis D. and Samuel H. Williamson, 2008, What Was the U.S. GDP Then? *Measuring Worth*.

[42] Korajczyk, Robert A. and Ronnie Sadka, 2004, Are Momentum Profits Robust to Trading Costs?, *Journal of Finance* 59, 1039 – 1082.

[43] Lakonishok, J., R. Shleifer, and R. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541 – 1578.

[44] Lesmond, David, Michael Schill and Chungsheng Zhou, 2004, The Illusory Nature of Momentum Profits, *Journal of Financial Economics*, 71, 349 – 380.

[45] Levy, Robert, 1967, Relative strength as a criterion for investment selection, *Journal of Finance*, 22, 595 – 610.

[46] Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market-overreaction? *Review of Financial Studies* 3, 175 - 208.

[47] Newey, W., and K. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55, 703-708.

[48] Officer, Lawrence H., 2008a, What Was the U.K. GDP Then?" *Measuring Worth*.

[49] Officer, Lawrence H., 2008b, Five Ways to Compute the Relative Value of a UK Pound Amount, 1830 to Present, *Measuring Worth*.

[50] Rouwenhorst, K. Geert, 1998, International momentum strategies, Journal of Finance 53, 267284.

[51] Roll, Richard, 1983, Vas ist Das? *Journal of Portfolio Management*, 18 – 28.

[52] Sagi, Jacob S., and Mark S. Seasholes (2007), Firm-Specific Attributes and the Cross-Section of Momentum, *Journal of Financial Economics* 84, 389434.

[53] Shleifer, A. and Vishny, R.W. (1997), The Limits of Arbitrage, *Journal of Finance*, 52, 35–56.

[54] Thomas and Hwang, The 52 week high and momentum investing, *Journal of Finance*

Table 1: Returns of Relative Strength Portfolios - Short horizons

The relative strength portfolios are formed on J-month lagged returns and held for K months. The values of J and K for the different strategies are indicated in the first column and row respectively. The stocks are ranked in ascending order on the basis of J-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. t-statistics are between parentheses. As noted at the beginning of section 2, we considered 28-day periods as months in our calculations. Moreover, when considering a year, i.e. $K = 12$ in Jegadeesh and Titman, we used 13 28-day periods.

J		K =	3	6	9	1 YR
3	Buy		0.0001	0.0016	0.0019	0.0023
			(0.002)	(1.4428)	(1.8167)	(2.4009)
3	Sell		0.0000	-0.0003	0.0000	0.0001
			(0.0001)	(-0.2643)	(0.0389)	(0.1415)
3	Buy-sell		0.0001	0.0019	0.0018	0.0022
			(0.0019)	(1.8938)	(2.1452)	(3.0538)
6	Buy		0.0018	0.0026	0.0030	0.0032
			(1.5419)	(2.306)	(2.8644)	(3.267)
6	Sell		-0.0008	-0.0008	-0.0007	0.0000
			(-0.6585)	(-0.6817)	(-0.6093)	(-0.0161)
6	Buy-sell		0.0027	0.0034	0.0038	0.0032
			(2.0877)	(2.9693)	(3.6612)	(3.6469)
9	Buy		0.0026	0.0035	0.0034	0.0034
			(2.119)	(3.061)	(3.2159)	(3.4521)
9	Sell		-0.0023	-0.0019	-0.0013	-0.0006
			(-1.3453)	(-1.2881)	(-0.983)	(-0.4663)
9	Buy-sell		0.0049	0.0054	0.0048	0.0040
			(2.8105)	(3.7652)	(3.7538)	(3.7212)
13	Buy		0.0032	0.0034	0.0034	0.0033
			(2.8363)	(3.1544)	(3.2221)	(3.3945)
13	Sell		-0.0023	-0.0014	-0.0007	-0.0001
			(-1.3502)	(-0.9738)	(-0.4948)	(-0.054)
13	Buy-sell		0.0055	0.0048	0.0040	0.0034
			(3.3047)	(3.4207)	(3.2261)	(3.0743)

Table 2: Betas and Market Capitalization of Relative Strength Portfolios

The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. The remaining are assigned in the middle portfolio.

	Beta	Market Cap (Million Pounds)
Buy	1.1711	13.369
Middle 1/3	0.735	19.409
Sell	1.1947	12.437
Buy-Sell	-0.0236	

Table 3: Monthly Returns of Size-based and Beta-based Relative Strength Portfolios

The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio and A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. The remaining are assigned in the middle portfolio. Average monthly returns and excess returns of these portfolios and the returns of the relative strength portfolios formed using size-based and beta-based subsamples of securities are reported here. Size is sorted in lower, middle and highest thirds. Panel A reports average returns and Jensen's CAPM alphas. Panel B reports CAPM regressions augmented with a NBER Business Cycle dummy.

Panel A

Size-sorted Average returns and t-stats

	All	Small	Medium	Large
Past Returns				
Sell	-0.0008	-0.0019	-0.0019	-0.0007
	(-0.6817)	(-1.01)	(-1.4414)	(-0.5188)
Middle	0.0020	-0.0018	0.0006	0.0021
	(3.0078)	(-1.042)	(0.4981)	(3.13)
Buy	0.0026	0.0014	0.0034	0.0024
	(2.306)	(0.7968)	(2.7908)	(2.0136)
Buy-Sell	0.0034	0.0033	0.0053	0.0031
	(2.9693)	(2.713)	(6.0779)	(2.4098)

Excess returns (Jensen's CAPM alphas)

	All	Small	Medium	Large
Past Returns				
Sell	-0.0075	-0.0071	-0.0074	-0.0075
	(-8.1057)	(-3.7656)	(-6.241)	(-7.486)
Middle	-0.0029	-0.0052	-0.0032	-0.0029
	(-6.6399)	(-2.8756)	(-2.6764)	(-6.6667)
Buy	-0.004	-0.0028	-0.0013	-0.0044
	(-5.0428)	(-1.5862)	(-1.1498)	(-4.9347)
Buy-Sell	0.0035	0.0043	0.0061	0.0031
	(2.9840)	(3.4295)	(6.8496)	(2.3639)

Table continued on next page ...

Table 3 Continued

Panel B

Jensen alphas with Market and NBER Business Cycle Dummy

	All	Small	Medium	Large	All	Small	Medium	Large
	Jensen alphas				Beta on NBER Business Cycle Dummy (Dummy=1 if recession)			
Past Returns								
Sell	-0.0074	-0.0058	-0.0048	-0.0077	-0.0004	-0.0025	-0.0052	0.0003
	(-5.6204)	(-2.2076)	(-2.8974)	(-5.4264)	(-0.1968)	(-0.6662)	(-2.2123)	(0.1533)
Middle	-0.0028	-0.0037	-0.0019	-0.0028	-0.0003	-0.0029	-0.0025	-0.0002
	(-4.4469)	(-1.4656)	(-1.1618)	(-4.5684)	(-0.3852)	(-0.8222)	(-1.0538)	(-0.2391)
Buy	-0.0041	-0.001	-0.0002	-0.0046	0.0002	-0.0036	-0.0023	0.0004
	(-3.6934)	(-0.3983)	(-0.1022)	(-3.6858)	(0.1573)	(-1.0369)	(-1.0167)	(0.2553)
Buy-Sell	0.0032	0.0048	0.0047	0.0031	6.08E-04	-0.0011	0.0028	1.44E-04
	(1.9362)	(2.7614)	(3.7368)	(1.6406)	(0.2613)	(-0.4610)	(1.6222)	(0.0551)

Table 4: Sensitivity to treatment of exit firms - CAPM Alphas

In this table we relax the assumption that extinct stocks have -99.99 % return. The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio and A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. The remaining are assigned in the middle portfolio. Average monthly returns and excess returns of these portfolios and the returns of the relative strength portfolios formed using size-based and beta-based subsamples of securities are reported here. Size is sorted in lower, middle and highest thirds.

Exit firms set at -99.99 %

	Small	Medium	Large
Sell	-0.0071	-0.0074	-0.0075
	(-3.7656)	(-6.241)	(-7.486)
Middle	-0.0052	-0.0032	-0.0029
	(-2.8756)	(-2.6764)	(-6.6667)
Buy	-0.0028	-0.0013	-0.0044
	(-1.5862)	(-1.1498)	(-4.9347)
Buy-Sell	0.0043	0.0061	0.0031
	(3.4295)	(6.8496)	(2.3639)

Exit firms not set at -99.99 %

	Small	Medium	Large
Sell	-0.0014	-0.0034	-0.0048
	(-1.3781)	(-5.0422)	(-8.3276)
Middle	0.0012	0.0008	-0.0010
	(2.1281)	(2.1064)	(-3.8416)
Buy	0.0024	0.0025	-0.0011
	(2.4802)	(4.6837)	(-2.3061)
Buy-Sell	0.00380	0.0059	0.0037
	(3.7387)	(8.2087)	(4.2804)

Table 5: Sensitivity to treatment of exit firms - Average returns

We relaxed our assumptions by either ignoring the extinction (don't set the last return to -99.99%) or ignoring all missing data by assuming it is missing completely at random (MCAR) and computing results from observable data only. The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio and A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. The remaining are assigned in the middle portfolio. Average monthly returns and excess returns of these portfolios and the returns of the relative strength portfolios formed using size-based and beta-based subsamples of securities are reported here. Size is sorted in lower, middle and highest thirds.

Size	MCAR	Not set at -99.99 %	Set at -99.99 %
	Size-sorted Average monthly returns and t-stats Buy - Sell		
Small	0.0031	0.0028	0.0033
	(3.0173)	(2.8179)	(2.7130)
Medium	0.0049	0.0049	0.0053
	(6.6676)	(6.8329)	(6.0779)
Large	0.0034	0.0034	0.0031
	(3.9647)	(4.0896)	(2.4098)
	Excess returns (Jensen's CAPM alphas) Buy - Sell		
Small	0.0040	0.0037	0.0043
	(4.0116)	(3.7387)	(3.4295)
Medium	0.0058	0.0059	0.0061
	(8.1034)	(8.2087)	(6.8496)
Large	0.0037	0.0037	0.0031
	(4.0850)	(4.2804)	(2.3639)

Table 6: Monthly Returns on Size-based Relative Strength Portfolio by Calendar Months

The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. Returns are 28-day, not monthly. January returns are coded as the first 28-day return entirely in the new year.

Month	All	Small	Med	Large
		Panel A		
		Return on 6-6 portfolios: Losers		
Jan	0.0020	0.0080	0.0039	0.0017
Feb-Dec	-0.0010	-0.0027	-0.0022	-0.0008
p-val for t-test of equality with Jan	0.53	0.14	0.22	0.61
		Return on 6-6 portfolios: Middle		
Jan	0.0103	0.0096	0.0094	0.0105
Feb-Dec	0.0014	-0.0029	-0.0001	0.0015
p-val for t-test of equality with Jan	0.00	0.07	0.04	0.00
		Return on 6-6 portfolios: Winners		
Jan	0.0082	0.0087	0.0132	0.0076
Feb-Dec	0.0024	0.0008	0.0027	0.0023
p-val for t-test of equality with Jan	0.17	0.25	0.03	0.24
		Panel B: Return on Winner - Loser Portfolio		
Jan	0.0063	0.0005	0.0095	0.006
	(2.3922)	(0.177)	(4.3477)	(2.0312)
Feb-Dec	0.0032	0.0035	0.005	0.0029
	(2.5891)	(2.7262)	(5.3517)	(2.0833)
		t-test Ho: Jan = Feb through Dec		
p-value	0.4694	0.5089	0.17	0.513

Table 7: Momentum Portfolio Turnover: Transition Probability Matrix

The turnover of the relative strength portfolios is measured via a transition probability matrix for the K=6/J=6 strategy. The diagonal elements are of most interest as they reveal what fraction of stocks remain in the portfolio.

			Portfolio at time t								
	Size		Small	Med	Large	Small	Med	Large	Small	Med	Large
		Momentum	Sell	Sell	Sell	Med	Med	Med	Buy	Buy	Buy
	Small	Sell	0.345	0.051	0.000	0.282	0.023	0.000	0.322	0.033	0.000
	Med	Sell	0.008	0.296	0.032	0.008	0.207	0.014	0.010	0.232	0.019
Probability	Large	Sell	0.000	0.009	0.306	0.001	0.007	0.211	0.000	0.008	0.243
of being in	Small	Med	0.202	0.008	0.000	0.281	0.009	0.000	0.212	0.009	0.000
Portfolio at	Med	Med	0.011	0.224	0.009	0.018	0.354	0.012	0.013	0.276	0.012
time t+6	Large	Med	0.000	0.017	0.310	0.000	0.026	0.452	0.000	0.014	0.336
	Small	Buy	0.282	0.006	0.000	0.256	0.005	0.000	0.301	0.005	0.000
	Med	Buy	0.039	0.279	0.005	0.036	0.263	0.005	0.045	0.308	0.006
	Large	Buy	0.000	0.031	0.279	0.000	0.027	0.246	0.000	0.035	0.321
	No Price at t+6		0.113	0.079	0.058	0.119	0.079	0.059	0.096	0.078	0.062

Table 8: Bid-Ask Spread Statistics

The relative strength portfolios are formed on a 6-month lagged returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. Value weighted average of the Bid-Ask spread of each security that is added or removed from the portfolio at time t, where Bid-Ask Spread = (Ask-Bid)/[average(bid,ask)]

Small Sell	Med Sell	Large Sell	Small Mid	Med Mid	Large Mid	Small Buy	Med Buy	Large Buy
				Prob of remaining in portfolio				
0.345	0.296	0.306	0.281	0.354	0.452	0.301	0.308	0.321
				Bid-ask spread of those traded				
0.21	0.09	0.03	0.14	0.06	0.02	0.15	0.07	0.02
				Percentage of "new" stocks in new portfolio				
0.655	0.704	0.694	0.719	0.646	0.548	0.699	0.692	0.679
				Per period Bid-ask cost trading cost				
0.0229	0.0106	0.0035	0.0168	0.0065	0.0018	0.0175	0.0081	0.0023
				Per period costs in basis points				
229	106	35	168	65	18	175	81	23

Table 9: Momentum Profits and Market States

The Table reports evidence on market states and momentum profit similar to CGH (2004). At the beginning of each month t, all stocks are allocated into deciles based on their lagged six-month returns (from $t-5$ to $t-1$, skipping month t). Down, Avg and Up markets were defined as follows Up = market index return over past 3 years in top 1/3 of sample Avg = market index return over past 3 years in middle 1/3 of sample Down = market index return over past 3 years in Bottom 1/3 of sample. Profits of the momentum portfolios (winner minus loser deciles) are cumulated across holding period months $t+1$ to $t+6$. Reported below are the mean monthly profits and CAPM alphas.

	CRSP Data 1929-1995	London Data 1869-1907
Monthly returns following 36 month UP-Markets (85 % of observed states)		
Mean Ret.	0.004	0.0038
	(3.800)	(4.4555)
CAPM alpha	0.0053	0.0039
	(4.8913)	(4.5414)
Monthly returns following 36 month Down-Markets (15 % of observed states)		
Mean Ret.	-0.0028	0.0015
	(-1.1061)	(0.7713)
CAPM alpha	-0.0002	0.0016
	(-0.0971)	(0.8158)
Test for equality Up-Down = 0		
t-stat Mean Ret.	2.5055	1.0474
tstat: CAPM alpha	2.0031	1.0403

Table 10: Factor-Model Predicted Monthly Returns and Momentum

All stocks are first sorted each month t into quintiles based on their six-month ($t-5$ to t) predicted returns from the four-factor model:

$$(r - r_f) = a + b_1 Mkt + b_2(Divyld) + b_3(Term) + b_4(Default)$$

where excess return on market portfolio, Divyld: lagged dividend yield on market index, Term: lagged term spread (yield on British consol - yield on 30day bankbill), and Default: lagged default yield (yield on risky bonds (brit RR) - yield on British consol). This table employs the nonoverlapping-return method used by CS (2002). Panel B reports sorts based on predicted returns of the four factor model.

Panel A

	Small Sell	Med Sell	Large Sell	Small Mid	Med Mid	Large Mid	Small Buy	Med Buy	Large Buy
b_2	0.2964	-0.1459	0.174	0.0688	0.1374	-0.0584	0.018	0.0676	0.0562
	(0.8799)	(-0.6828)	(0.9542)	(0.2115)	(0.6439)	(-0.7423)	(0.0568)	(0.3213)	(0.3479)
b_3	0.3009	0.1767	-0.2143	0.4298	0.1904	0.1913	0.1549	0.3812	-0.0572
	(0.6824)	(0.6315)	(-0.8977)	(1.0088)	0.6817	1.8565	0.3722	1.3838	-0.2707
b_4	0.5088	0.3196	0.0919	0.2999	0.3726	0.0705	0.4165	0.2669	-0.0412
	(3.0051)	(2.9753)	(1.0031)	(1.8330)	(3.4753)	(1.7812)	(2.6067)	(2.5231)	(-0.5078)
F-stat: b2=b3=b4=0	4.3343	3.75	0.5343	2.1365	5.1524	2.9292	2.6002	4.0728	0.1689
p-val F	0.005	0.011	0.659	0.0947	0.0016	0.0332	0.0515	0.0071	0.9174
R^2 of CAPM regression resid. on Divyld Term Default	0.0241	0.0209	0.003	0.012	0.0285	0.0164	0.0146	0.0227	0.001

Panel B

Chordia and Shivakumar (2002) predicted returns sort

Momentum Sorts:		Sell	Med	Buy	Buy-Sell
	$E[R]$ low	0.001	0.0028	0.0031	0.0021
		(0.6279)	(3.4371)	(2.1358)	(1.2509)
Factor sorts:	$E[R]$ med	0.001	0.0026	0.002	0.001
		(1.0013)	(3.9661)	(1.9003)	(0.9976)
	$E[R]$ high	-0.0015	0.0013	0.0039	0.0054
		(-0.9799)	(1.4754)	(3.0703)	(3.7516)
	high-low	-0.0025	-0.0015	0.0008	
		(-1.6382)	(-1.7748)	(0.5686)	

Table 11: Momentum Profits and the Economy

The Table reports evidence on momentum profits and the state of the economy, in particular the results of the regression:

$$r = a + b_1 * (Mkt) + b_2 * (GDP)$$

where r is annual the return on the 6-6 buy portfolio minus the return on the 6-6 sell portfolio and GDP is the demeaned real per capita GDP growth. Note that in this table we examine annual returns - not monthly - as GDP is only available at an annual frequency.

Size	a	b_1	b_2	Adj. R^2
Small	0.06100	-0.3510	-0.8704	0.10
	(3.4017)	(-1.6974)	(-1.2196)	
Med.	0.0780	-0.1771	-0.4754	0.03
	(5.9050)	(-1.1626)	(-0.9044)	
Large	0.0321	0.1554	-0.8030	0.01
	(2.3458)	(0.9833)	(-1.4718)	

Table 12: Correlations among series

The table displays full sample estimates of the correlations computed at an annual frequency between (1) returns on buy-sell small stock portfolio, (2) buy-sell medium portfolio, (3) buy-sell large stock portfolio, (4) average cross-sectional monthly standard deviation, (5) excess returns (Mkt - r_f, (6) growth real GDP, (7) short term rate (Ordinary funds), and (8) long term rate.

		Buy-sell small	Buy-sell med	Buy-sell large	Avg. cross-sect. monthly st. dev.	Mkt -r_f	Growth rgdp/pc	Short Term rate Ordinary funds	Long term rate
Buy-sell	small	1							
Buy-sell	med	0.02	1						
Buy-sell	large	0.14	0.10	1					
avg cross-sect	monthly st. dev.	0.17	0.12	0.15	1				
Mkt - r_f		-0.33	-0.24	0.08	0.09	1			
Growth	rgdp/pc	-0.28	-0.21	-0.19	-0.15	0.33	1		
Short term rate	Ordinary funds	0.16	0.00	0.13	-0.23	-0.41	-0.03	1	
Long term rate		-0.35	0.36	0.10	-0.05	0.02	-0.06	0.33	1

Table 13: Monthly Returns of Relative Strength Portfolios - Long horizons

The relative strength portfolios are formed on J-month lagged returns and held for K months. The values of J and K for the different strategies are indicated in the first column and row respectively. The stocks are ranked in ascending order on the basis of J-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio. t-statistics are between parentheses. As noted at the beginning of section 2, we considered 28-day periods as months in our calculations. Moreover, when considering a year, i.e. $K = 12$ in Jegadeesh and Titman, we used 13 28-day periods. It is important to note that the results are computed from all available time periods. This means the sample periods vary by column. For example the portfolio return in year 2 after formation is computed by looking at the buy-sell portfolio 14-26 months after formation, so our first "year 2" observation is July 1867-June 1868. Our first "year 5" observation doesn't begin until July 1871, however. Therefore the Year 2 column has more observations then the Year 5 column. This is also why the various columns do not add up.

J		Year 2	Year 3	Year 4	Year 5	Year 2-5	Year 3-5
3	Buy	0.0028	0.0028	0.0026	0.0019	0.0025	0.0024
		(3.4085)	(3.4459)	(3.2127)	(1.8392)	(3.133)	(2.9863)
3	Sell	0.0018	0.0024	0.0028	0.0031	0.0022	0.0027
		(1.9838)	(2.6039)	(3.1467)	(3.5481)	(2.4413)	(3.102)
3	Buy-sell	0.001	0.0004	-0.0002	-0.0013	0.0004	-0.0003
		(2.2551)	(0.8765)	(-0.4505)	(-1.6807)	(1.1792)	(-1.0119)
6	Buy	0.0032	0.0032	0.0026	0.002	0.0028	0.0027
		(3.90711)	(4.1021)	(3.071)	(2.20911)	(3.45531)	(3.3621)
6	Sell	0.0015	0.0022	0.0033	0.0034	0.0022	0.0029
		(1.4816)	(2.1186)	(3.3508)	(3.4622)	(2.2689)	(2.9919)
6	Buy-sell	0.0017	0.001	-0.0006	-0.0014	0.0006	-0.0002
		(2.6502)	(1.4971)	(-1.0493)	(-2.1428)	(1.1576)	(-0.3828)
9	Buy	0.0033	0.003	0.0022	0.0021	0.0026	0.0025
		(3.8523)	(3.5455)	(2.4311)	(2.285)	(3.1731)	(2.9911)
9	Sell	0.0016	0.0027	0.0035	0.0034	0.0025	0.0032
		(1.611)	(2.5483)	(3.4945)	(3.1871)	(2.5406)	(3.3295)
9	Buy-sell	0.0016	0.0003	-0.0014	-0.0013	0.0001	-0.0008
		(2.1863)	(0.3738)	(-1.8331)	(-1.6262)	(0.1324)	(-1.4513)
13	Buy	0.0035	0.0029	0.0018	0.0022	0.0026	0.0023
		(4.0243)	(3.439)	(1.8966)	(2.2931)	(3.164)	(2.6976)
13	Sell	0.0019	0.0027	0.004	0.0033	0.0029	0.0035
		(1.7501)	(2.5532)	(3.7176)	(2.8022)	(2.7927)	(3.4251)
13	Buy-sell	0.0016	0.0002	-0.0022	-0.0012	-0.0002	-0.0012
		(1.9642)	(0.2816)	(-2.4996)	(-1.1253)	(-0.3999)	(-1.9273)

Table 14: Reversal equality tests

We form a $T \times N$ matrix X where $X(t,n)$ is the holding period return from month $(t-12)$ to month t on the winner minus loser portfolio formed $n \times 13$ "months"earlier. Let $\tilde{X}(t,n) \equiv (X(t,n+1)$ - $X(t,1))$. The entries to the table report the mean return of the winner minus loser portfolios 1 through 5 years after formation. We test of the null that $E[\tilde{X}(t,n)] = 0 \; \forall \; t$ and n. via a Wald test $W = gCov(g)^{-1}g$, with $g = (\sum_t [\tilde{X}(t,1)]/T, \ldots, \sum_t [\tilde{X}(t,4)]/T)$, and $Cov(g)$ is estimated using the Newey-West procedure with 13 lags. The test statistic is under the null $W \sim \chi^2(4)$, asymptotically.

	Average monthly return in year N after formation				
N	1	2	3	4	5
	0.0034	0.0016	0.0006	-0.0006	-0.0015

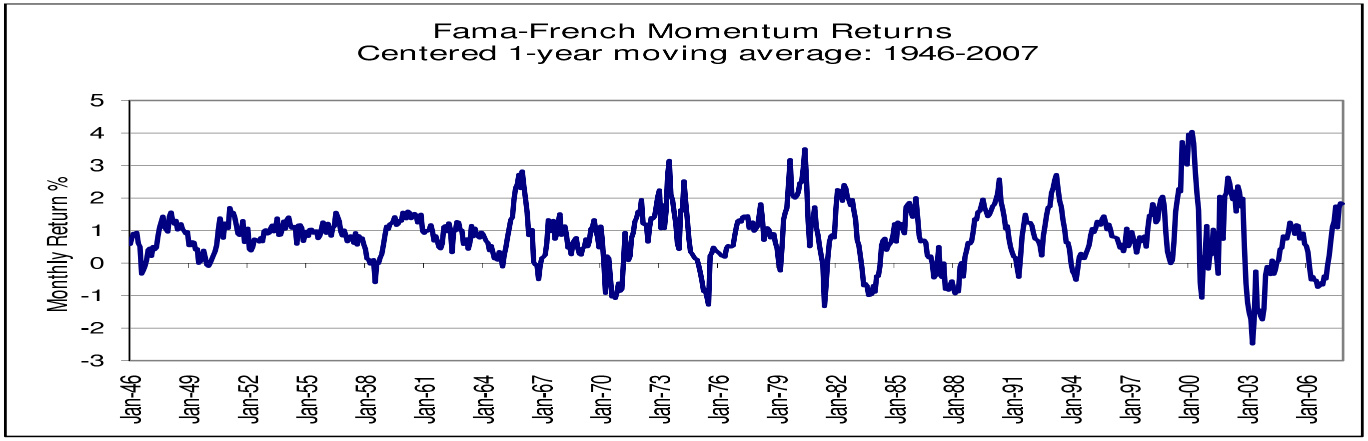
Wald test that average monthly return
is equal in years 1 through 5:
35.14 (p-val = 0.00)

P-values for Wald test that average
monthly return in N years after
formation = average monthly return J years
after formation for any N, J

N =	1	2	3	4	5
J =1	-				
J = 2	0.00	-			
J = 3	0.00	0.16	-		
J = 4	0.00	0.02	0.12	-	
J = 5	0.00	0.00	0.01	0.22	-

Figure 1: Momentum Profit Cycles

The figure displays the time series of the Fama-French momentum factor returns from January 1946 to May 2008 and the momentum factor returns during the Victorian era.



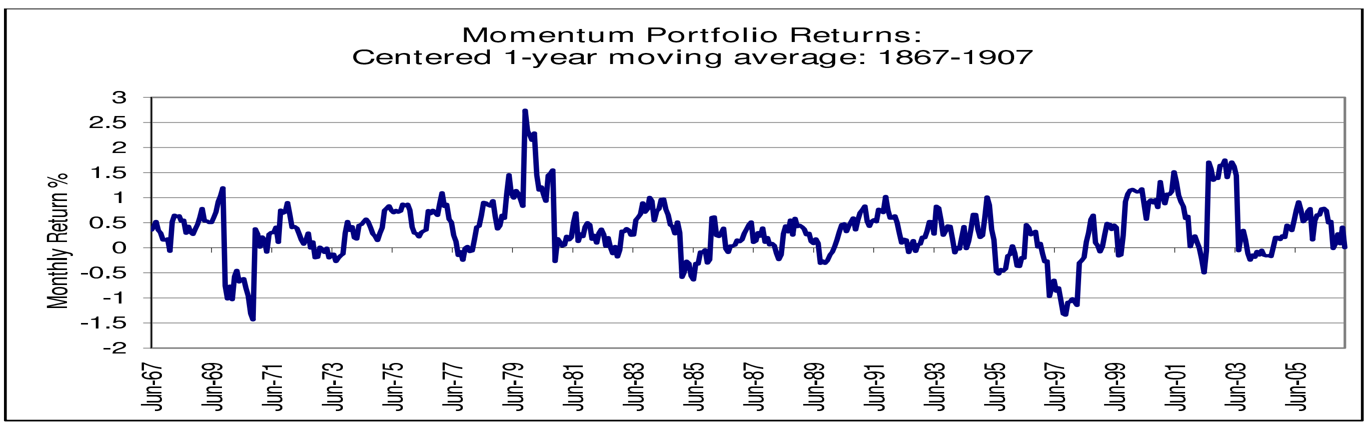


Figure 2: Number of Stocks in Portfolios

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.

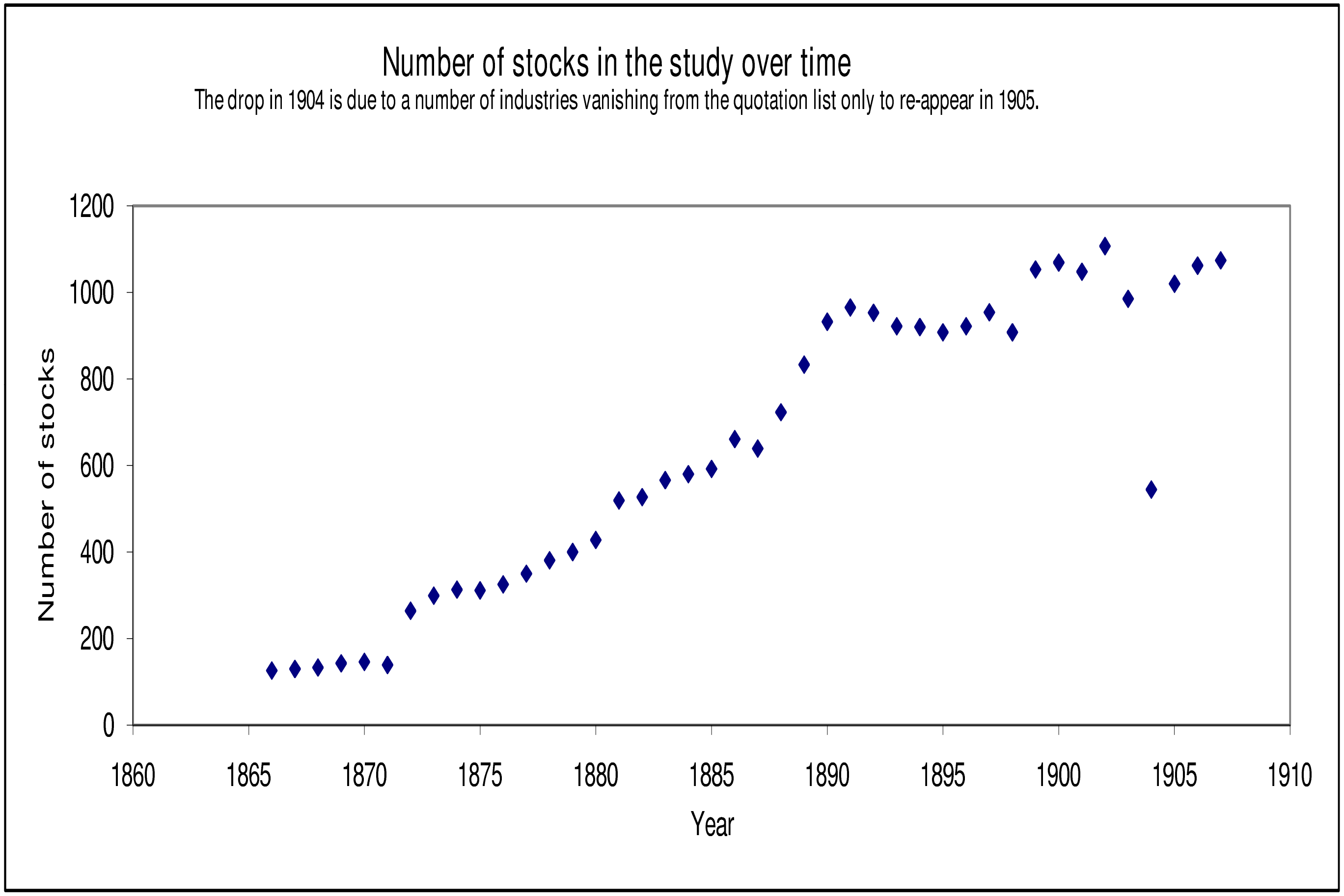


Figure 3: Five-Year Rolling Average Returns on Size-based Relative Strength Portfolios

We report the average monthly excess return on the momentum portfolios during each of the five years following portfolio formation, after skipping a month. The relative strength portfolios are formed on a 6-month lagged return and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. A value-weighted portfolio of stocks in the lowest 33rd percentile past return is the *sell* portfolio. A value-weighted portfolio of stocks in the highest 67th percentile past return decile is the *buy* portfolio.

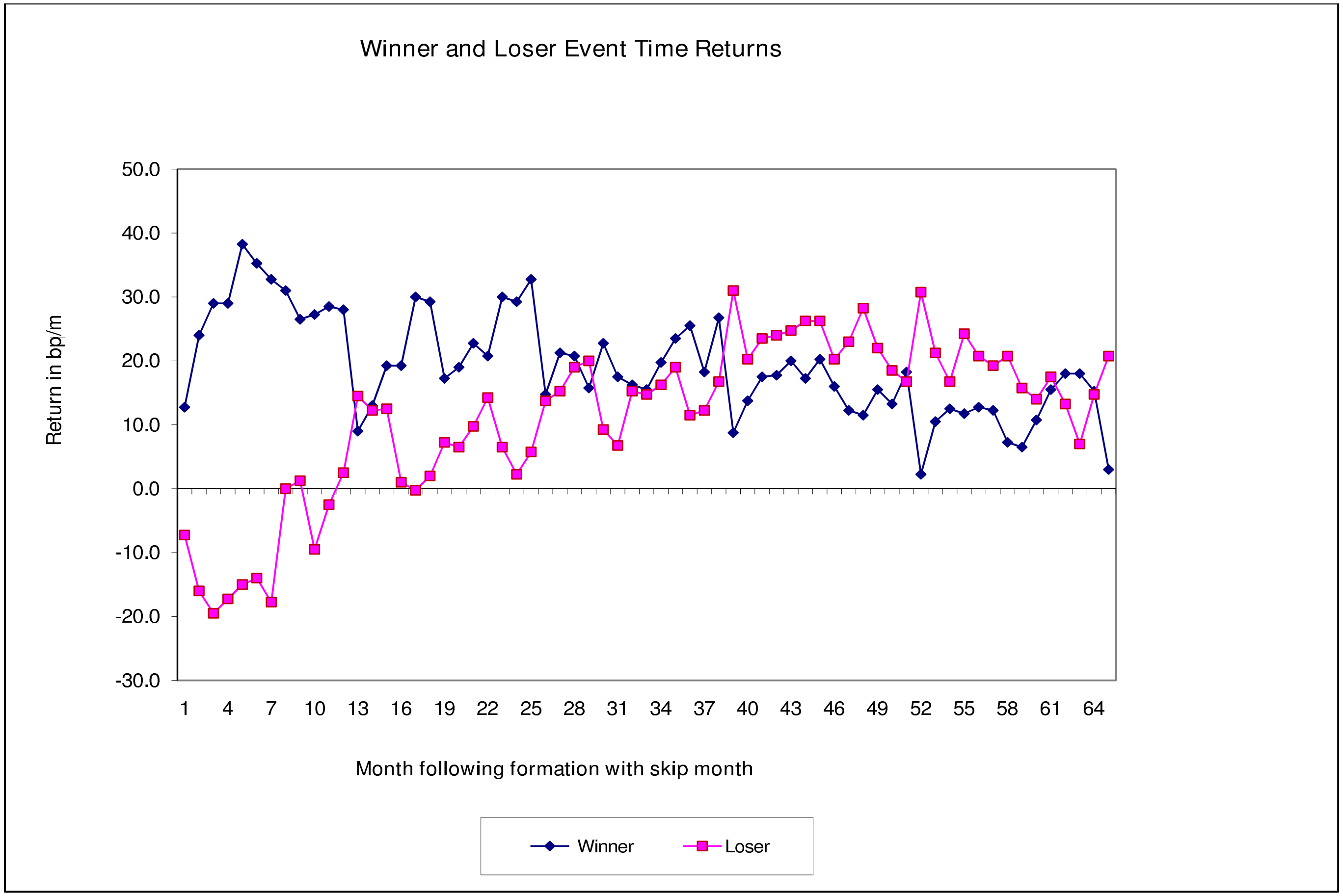


Figure 4: Winner and Looser Portfolio Investment

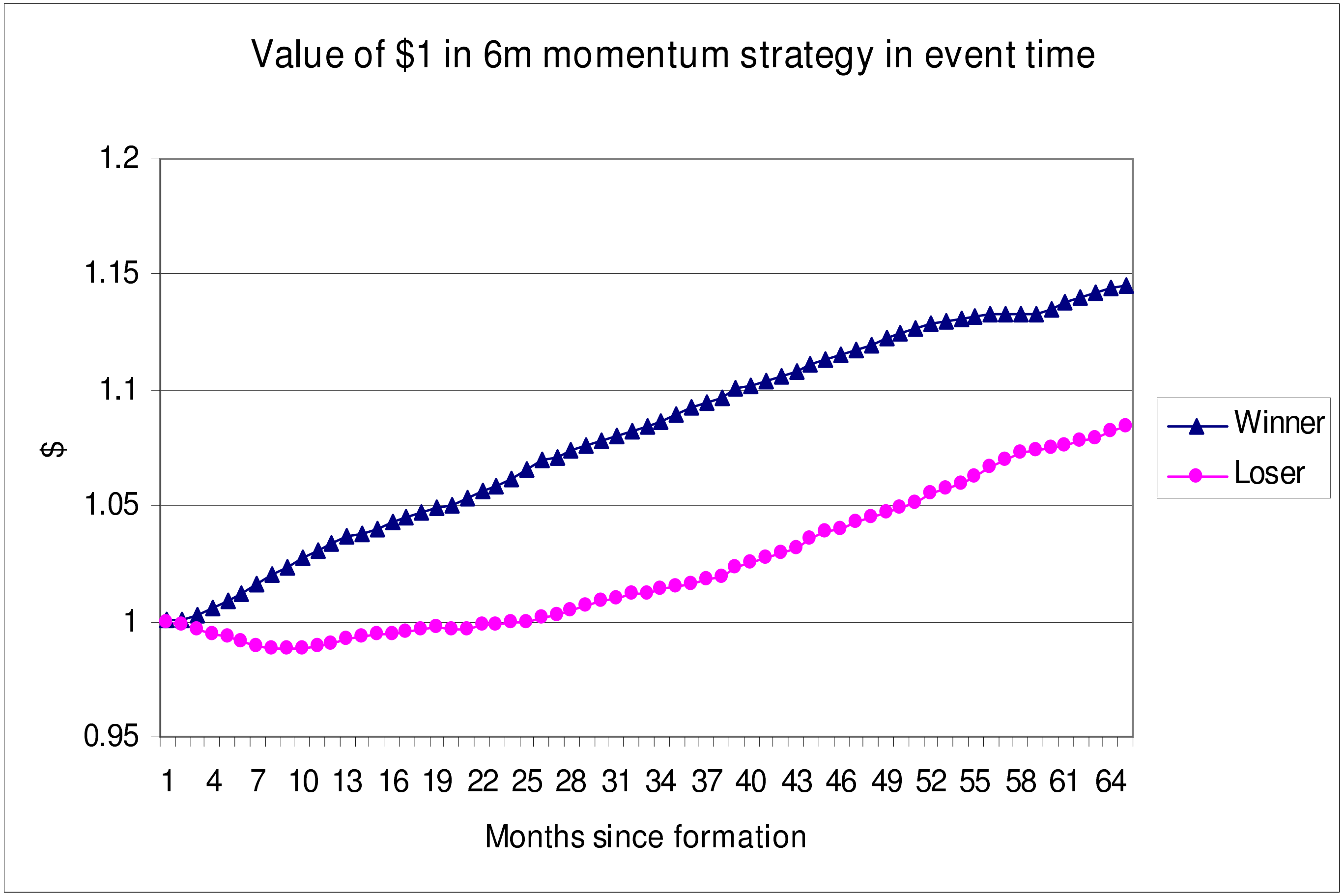


Figure 5: Winner Minus Looser Investment