Review of Finance (2013) 0: 1–17

Advance Access publication:

# Implied Price Risk and Momentum Strategy*

Hongwei Chuang[1], Hwai-Chung Ho[1,2]
[1] *Institute of Statistical Science, Academia Sinica;* [2] *Department of Finance, National Taiwan University*

**Abstract.** Examining the properties of stock returns has long been a central topic in finance. Most quantitative analyses conducted by academic researchers and practitioners focus only on the return distribution. However, the return distribution itself hardly helps to determine whether the price of a winner stock picked by using the momentum strategy reaches the level where the risk incurred from the falling of prices is imminent. Therefore, we construct an implied price risk index to quantify the downside risk of a stock and use it to manage the tail risk of the momentum strategy. The empirical results demonstrate that our modified strategy can not only achieve significant improvement on the overall performance, but also substantially reduce the drastic losses suffered from the 2008 global recession.We also establish the connection between the implied price risk index and the cross-sectional return differences based on the well-known three factors, the market beta, the firm size and the book-to-market ratio.

*JEL Classification:* G11, G12, G14

## 1. Introduction

Momentum strategies, also known as relative strength strategies, are prevalent among traders. The momentum effect has been confirmed in financial assets such as commodity and currency,[1] and in the financial markets of several countries.[2] The profits made cannot be explained away simply by stating that high-performance stocks are riskier, or by arguing

*The paper originally appeared under the title "Price Risk and Momentum Crash." We thank Shing-Yang Hu, Hsiaw-Chan Yeh, Keh-Luh Wang, Meng-Feng Yen, Pei-Yu Yang, and seminar participants at Academia Sinica, National Taiwan University, National Chung Hsing University, and Shin Kong Investment Trust Co., Ltd. for their helpful comments and suggestions. We are especially grateful to the Co-Editor, Bernard Dumas, and an anonymous referee for their valuable comments. This research is supported by the National Science Council (NSC-100-2118-M-001-007-MY2) in Taiwan.

[1] The momentum effect is emphasized in Jegadeesh and Titman (1993) and is found to be persistent in other financial assets. Okunev and White (2003) report the effect in currencies, Erb and Harvey (2006) in commodities, and Moskowitz, Ooi and Pedersen (2012) in the exchange traded futures contracts.

[2] Rouwenhorst (1998, 1999) finds evidence of the momentum effect in both developed and emerging stock markets.

that the trading cost will eat up all the profits. Rather, these stocks should be considered potentially profitable.

Attempts have been made to interpret the evidence and identify the source of profit. Lakonishok, Shleifer, Thaler and Vishny (1991) and Lakonishok, Shleifer and Vishny (1992) provide an explanation related to the "window dressing." That is, when fund managers are asked to prepare for clients regular progress reports on their portfolios, they tend to demonstrate their skills by keeping shares that are rising and selling those that are falling. This behavioral tendency is further encouraged by the common practice of fund selection in the business. Fund managers who have recently outperformed the market can attract more capital flows from their sponsors. These fund managers will then invest more in the winner stocks they hold, giving the momentum an extra boost. More properties have been observed on the stocks that exhibit the momentum effect. Lee and Swaminathan (2000) consider trading volume to be a factor in the momentum effect. Grundy and Martin (2001) attribute the profits of the momentum strategy to the firm's specific component of returns. George and Hwang (2004) report that a large portion of momentum profits can be obtained by using the 52-week high price. Other characteristics such as high market-to-book ratios (Daniel and Titman (1999)), small size and low analyst coverage (Hong, Lim and Stein (2000)), and high analyst forecast dispersion (Zhang (2006)) have also been shown to exist in stocks with elevated momentum profits. These characteristics, as argued by Bandarchuk and Hilscher (2010), can be explained through the concept of information uncertainty suggested in Zhang (2006).

Buying the under-priced assets and selling those that are over-priced is one of the principle goals in financial investment. However, determining the price that should be executed is difficult. Although literature on the momentum strategy is vast, the issue on assessing whether a stock is running out of momentum to reach its peak remains mostly untouched. The lack of attention is perhaps due to that the quantitative investment analysis conducted by academic researchers and practitioners has been mainly focused on the distribution of returns, despite the limited information it contains about how investors anticipate the future trend of the price. As a result, investors hardly have sufficient information to determine whether the price of a winner stock has exceeded its equilibrium to such a level that the risk incurred from the falling of prices is imminent. We call this kind of risk "price risk." Two real examples will be used to illustrate the concept of price risk in Section 2. An implied price risk (IPR) index that is concerned with serving as a proxy variable to measure the downside risk of a stock is introduced in Equation (5). The statistical thinking behind the IPR is to treat the index value of each stock as the empirical quantile of an observation sampled from an approximately standard normal distribution.

One application of our IPR is to help identify those stocks that are less likely overpriced and have more momentum left to sustain their trends given a pool of winner stocks. Chordia and Shivakumar (2002) reveal that the profits of the momentum strategy exhibit a strong variation in the business cycle. Their study shows that from January 1930 to December 2009 the momentum strategy earns a 14.70% annualized return during expansions and loses 8.70% during recessions. Cooper, Gutierrez and Hameed (2004) examine the variation of average returns to the US equity momentum strategies. They find that in the "UP" states, which are defined by the lagged three-year return of the market, the historical mean of returns of an equally weighted momentum strategy is 0.93% per month. In the "DOWN" states, the historical mean of returns of an equally weighted momentum strategy is -0.37% per month. Kelsey, Kozhan and Pang (2011) examine the asymmetric profitability of the momentum trading strategy. The different reactions of past winners and past losers to market uncertainty create asymmetric patterns in price continuations. Kelsey, Kozhan and Pang (2011) show that momentum is more likely to continue for downward trends in a highly uncertain market. Daniel and Moskowitz (2011) argue that the losses of momentum portfolio are due to the highly skewed returns of the momentum strategies. In extremely bad conditions, the past losers of the momentum strategy usually have a very high premium. The strong gains that come along with the market recovery lead to a "momentum crash." Therefore, investors who implemented the momentum strategy would experience strings of negative returns especially after a market collapse. As shown in Section 3, the momentum investor lost 39.52% in the US stock market at the turning-point occurrence in 2009. The 1930s, 1975, 2000, and 2003 were similarly bad years. In Section 3, we use the IPR to modify the momentum strategy and propose a new trading strategy, the IPR-momentum strategy. We apply the IPR-momentum strategy to the US stock market from January 1930 to December 2010. The empirical results indicate that buying the winners with low IPR and selling the losers with high IPR yield a return of 2.09% per month and an annualized Sharpe ratio of 0.8587. The IPR-modified strategy greatly improves the overall performance of the momentum strategy. In the Appendix, we propose a dynamic information diffusion price model attempting to give an explanation of the significant improvement made by the IPR-momentum strategy. According to the model, when the cumulative proportion of information diffused increases, the stock price will rise in a upward trend, which in turn results that the IPR value becomes large. Because the variable of the model that measures the cumulative proportion of information diffused among investors is hardly observable, we use the IPR as a proxy for the variable.

To verify that the premium of our strategy does not come from the value investing strategy, the relationship between the value investing strategy and the momentum strategy is examined in Section 4. We investigate the correlations among the returns of the momentum strategy, value investing strategy, and the IPR-momentum strategy. We find the IPR-momentum strategy is nearly orthogonal to the value investing strategy. Therefore, we conclude that the premiums of our strategy does not come from the value investing strategy because if the two strategies are similar, then their portfolios should share many common stocks such that their portfolio returns exhibit a positive correlation. Furthermore, separate period from January 2000 to December 2010, the compound returns of the momentum strategy and the IPR-momentum strategy are 36.16% and 109.04% respectively. The winner-loser criterion for stock selection appears to be ineffective after 2000. Therefore, we propose another trading strategy in Section 4, the IPR strategy, which sorts the stocks based only on their IPR values. The empirical results shown in Figure 9 indicate that the compound returns of the momentum strategy, S&P 500 index, IPR-momentum strategy, Risk-free, and the IPR strategy are 36.16%, 85.60%, 109.04%, 131.25% , and 133.15%, respectively, from January 2000 to December 2010. The IPR strategy produces returns that are better and more stable than those derived from the two momentum-type strategies, especially in the 2008 to 2010 financial crisis.

The anomaly derived from the momentum effect poses a fundamental challenge to one of the tenets in financial theory, which is the efficient market hypothesis (Fama (1970), Fama and French (1988)). The efficient market hypothesis in its weak form definition states that past price movements should not provide any guide to future price changes, which clearly disapproves of the trading strategy that prefers past winners over past losers. In other words, an efficient market means that it is a wasteful attempt trying to time the trades of buying and selling stocks because everything one can possibly know about the stocks is already reflected in the price. Although the challenge is still far from settled, the criticism on the efficient market hypothesis has been prompted from time to time by empirical evidence. In Section 5, we investigate the relationship between the IPR and the common factors, the market beta, the firm size, and the **B/M** ratio. The main finding is that the returns of the factor-based portfolios with low IPR are greater than those with high IPR, regardless of the factor being the market beta, the firm size, or the **B/M** ratio.

The rest of the paper is organized as follows. We first propose the IPR index and follow it with an illustration of price risk by using two examples in Section 2. We then describe the momentum crash and propose a modified strategy, the IPR-momentum strategy, in Section 3. The relationship between the value investing strategy and the IPR-momentum strategy is shown in Section 4. Section 5 connects the IPR index and the cross-sectional return differences. Section 6 concludes.

## 2. Implied Price Risk and Dot-com bubble

A financial crisis usually starts with a burst of economic bubbles when the price rises to a relative high status. For example, when the Dot-com bubble burst, the technology **NASDAQ** composite index lost 66% of its value, plunging from the peak of 5048 in March 10, 2000 to the 1720 in April 2, 2001. To examine the price status of a stock on a uniform scale, in this section, we first introduce a quantitative measure, namely, the "implied price risk" (IPR) index. We use two firms to demonstrate the relationship between the price risk and the IPR. To further strengthen the link between the price level and the returns, we use the **NASDAQ** data to carry out a portfolio analysis during the Dot-com bubble.

### 2.1 IPR index

Let $Y_j$ be the stock's discrete-time price process with initial price $y_0$ and define $\beta_j(y) = P(Y_j \geq y)$ as the tail probability for $Y_j$ exceeding level $y$. A simple standardization gives

$$\beta_j(y) = P\left(\frac{\ln(Y_j/y_0) - j\cdot\mu}{\sqrt{j\cdot\sigma^2}} \geq \frac{\ln(y/y_0) - j\cdot\mu}{\sqrt{j\cdot\sigma^2}}\right), \tag{1}$$

which implies, for suitable $\mu$ and $\sigma^2$,

$$\beta_j(y) \approx 1 - \Phi\left(\frac{\ln(y/y_0) - j\cdot\mu}{\sqrt{j\cdot\sigma^2}}\right), \tag{2}$$

according to the central limit theorem. Suppose for a particular path observed the price at time $j$ is $y_j$, and we want to estimate $\beta_j(y_j)$. Using the preceding expression, we can approximate $\beta_j(y_j)$ by

$$\beta_j(y_j) \approx 1 - \Phi\left(\frac{\ln(y_j/y_0) - j\cdot\mu}{\sqrt{j\cdot\sigma^2}}\right). \tag{3}$$

Given that $1 - \Phi\left(\frac{\ln(y_j/y_0)-j\cdot\mu}{\sqrt{j\cdot\sigma^2}}\right)$ is an approximated value of the probability of the event in which the price will go above the current level $y_j$, $\Phi\left(\frac{\ln(y_j/y_0)-j\cdot\mu}{\sqrt{j\cdot\sigma^2}}\right)$ would be a natural measure for assessing the downside risk of the price, that is, the greater the measure value the riskier the price level. From the statistical viewpoint, the implied price risk measure

$$\Phi\left(\frac{\ln(y_j/y_0) - j \cdot \mu}{\sqrt{j \cdot \sigma^2}}\right) \tag{4}$$

can be treated as the empirical quantile of an observation, $(\ln(y_j/y_0) - j \cdot \mu)/\sqrt{j \cdot \sigma^2}$, which is sampled from an approximately standard normal distribution.

Based on Equation (4), we use weekly returns to calculate the IPR value by plugging the proper estimates of $\mu$ and $\sigma^2$ in the following empirical studies. We define the

$$\mathrm{IPR}_t^j = \Phi\left(\frac{\ln\left(\frac{p_{(t-1)^*}}{p_{(t-1)^*-j}}\right) - j \times \hat{\mu}_t}{\sqrt{j \times \hat{\sigma}_t^2}}\right). \tag{5}$$

In Equation (5), $t$ is the index for month and $j$ represents the weekly lag; $(t-1)^*$ signifies the last week of the month $t-1$, and $(t-1)^* - j$ the $j$ weeks backward from the week $(t-1)^*$; $\hat{\mu}_t$ and $\hat{\sigma}_t^2$ are estimates of $\mu_t$ and $\sigma_t^2$ respectively using the weekly returns of the past three years starting from the $t$-th month. $j$ equals $13, 26, 39$, and $52$. $\mathrm{IPR}_t^j$ can be viewed to serve as a proxy measure of the relative price strength to its long-term equilibrium level.

## 2.2 Exxon and Cisco

To investigate the properties of the IPR proposed in the previous section, we use two companies, Exxon and Cisco, to examine their price trends and $\mathrm{IPR}^{13}$ values during the Dot-com bubble period in 2000. The price trends and $\mathrm{IPR}^{13}$ values are plotted in Figure 1.

<Insert Figure 1 here>

In Figure 1, the left panel shows the price trend and IPR for Exxon and the right panel is for Cisco. The yellow lines represent the day that **NASDAQ** reaches to a climax, March 10, 2000 during the Dot-com bubble period.

The figure clearly show that the stock price of Cisco rose from \$9.20 to \$65.66, which is about 7.13 times more for the stock price from January 1, 1998 to March 10, 2000. In the same period, the stock price of Exxon rose from \$22.06 to \$28.90, which is only about 1.31 times. Therefore, we can expect the downside risk of Cisco's price will be higher than that of Exxon's price on March 10, 2000. Applying our IPR to measure the downside risk of Cisco and Exxon, we plot their $\mathrm{IPR}^{13}_{Exxon}$ and $\mathrm{IPR}^{13}_{Cisco}$ in the bottom panel of Figure 1. Indeed, we find that the IPR value of Cisco on March 10, 2000 is 0.70, which is relatively higher than the 0.22 IPR value of Exxon.

## 2.3 Price Risk and Dot-com bubble

The IPR index aims to identify those stocks with more momentum left to sustain their trends by measuring stocks on a uniform scale. Based on our findings in the previous section, we further examine the properties of the IPR in forming the portfolio. When we consider forming a portfolio, it is necessary to take the price risk of each stocks into account. Therefore, we apply the IPR to form a low price-risk portfolio and compare its performance of those portfolios with high price-risk during the Dot-com bubble period.

Data for our study comes from the **CRSP** weekly and monthly files. We are only concerned with the dataset that consists of all **NASDAQ** stock markets from March 15, 1997 to September 15, 2000. Stocks with prices below $1 are excluded during the formation period to reduce the microstructure effect associated with low-price stocks. The sample contains 2160 stocks. We rank the stocks based on their corresponding $\text{IPR}_t^{13}$ on March 15, 2000 and group these stocks into 10 portfolios (labeled I1 to I10 from low to high). After forming the portfolios, we track their buy-and-hold cumulative returns in the following six months. The results are shown in Table 1.

<Insert Table 1 here>

According to Table 1, the one-month portfolio return of I1 portfolio and the I10 portfolio is 7.18% and -32.27% respectively. For the six-months cumulative return, the I1 portfolio is 13.86% and the I10 portfolio is 31.92%. The performance of the low price-risk portfolio is clearly better than those with high IPR.

## 3. Momentum Crash and IPR-Momentum Strategy

Recently, Daniel and Moskowitz (2011) have pointed out some disadvantages of implementing the momentum strategy and called it "momentum crash." Although Daniel, Jagannathan and Kim (2012) and Barroso and Santa-Clara (2012) have provided some methodologies to prevent such a crash, in this section, we propose an IPR-momentum strategy to adjust the momentum strategy based on our empirical results in Section 2. In the following, we first review the momentum strategy over the long period from January 1930 to December 2010.

### 3.1 Data and Portfolio Formation

Data for our study mainly comes from the **CRSP** monthly files. The dataset consists of all domestic primary stocks listed in the New York Stock Exchange (**NYSE**), American Stock Exchange (**AMEX**), and **NASDAQ** stock markets from January 1929 to December 2010. We utilize the returns only on common shares with a 10 or 11 **CRSP** share code. Close-end funds, Real Estate Investment Trust, unit trusts, American Depository Receipts, and foreign stocks are excluded from the analysis. We also exclude stocks with prices below $1 during the formation period to reduce the microstructure effect associated with low-price stocks.

Following most of the literature, we rank the stocks based on their past 12-month returns excluding the most recent month. This momentum definition is currently most broadly used and readily available through the PR1YR factor of Carhart (1997). The momentum strategy typically disentangles the intermediate horizon momentum effect from the short reversal effect documented by Jegadeesh (1993) and Lehmann (1990). We assign stocks that meet the data criteria mentioned above into 10 equally weighted portfolios at the end day of each formation month (i.e., sort them into 10 decile portfolios labeled P1 to P10 according to their cumulative returns in the ranking period). Ten percent of firms with the highest ranking period returns are grouped into portfolio P10, which is the "[W]inner"-decile portfolio, and those with the lowest ranking period returns are grouped into portfolio P1, which is the "[L]oser"-decile portfolio. The return on a zero investment "Winner-Minus-Loser" (WML) portfolio is the difference between the returns on the Winner-decile portfolio and the Loser-decile portfolio in each period. Each portfolio is held for one month following the formation month.

The monthly returns of the decile portfolios are based on the equally weighted returns.[3] Decile membership does not change in a month, except for the case of delisting. We also consider the overlapping portfolio approach, which is a strategy that holds a series of portfolios selected in the current month and the previous month. The baseline market return is the S&P 500 index, which is also available in **CRSP**. The risk-free rate we use is downloaded from the data library of Kenneth R. French.[4]

### 3.2 Performance of the Momentum Strategy

Table 2 presents the statistical characteristics of the decile portfolios' monthly returns from January 1930 to December 2010. For all portfolios, Mean, Std, Skew, Kurt, and SR denote the full-period realized mean, standard deviation, skewness, kurtosis, and Sharpe ratio, respectively. Only Sharpe ratios are annualized, all the others are monthly. The average monthly return of the Winner portfolio is 1.63%, and for the Loser portfolio, it is 0.69%. A market neutral strategy that buys the top 10%, the Winner portfolio, and sells the bottom 10%, the Loser portfolio, produces a profit of 0.94% per month. The results are in line with those documented in literature.

<Insert Table 2 here>

The skewness of the Loser portfolio and the Winner portfolio is 2.3866 and 1.0294 respectively. The former is more than twice that of the latter. The Loser portfolios are considerably more positively skewed than the Winner portfolios, yielding the large negative skewness -2.7992 of the WML portfolio. The kurtosis of the WML portfolio is 22.7026, which is also quite large.

<Insert Figure 2 here>

Figure 2 presents the compound returns[5] for investing $1 initially in (1) the risk-free asset, (2) the S&P 500 index, and (3) the WML portfolio, which is the zero-investment portfolio, respectively, from January 1930 to December 2010. On the right side of the plot, we show the final dollar values for each of the three portfolios: $448.73 for WML, $58.63 for the S&P 500 index, and $17.78 for the risk-free asset. The momentum strategy does earn a significantly higher return.

### 3.3 Crashes of the Momentum Strategy

The momentum strategy appears to have lost its profitability in recent years. In Figure 3, we plot the compound returns for investments in the risk-free asset, the S&P 500 index, and the WML portfolio from January 2000 to December 2010.

---

[3] We also check the results based on value-weighted returns. The findings are similar.

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

[5] The compound return on an implementable strategy is based on an investment at time 0 and fully reinvested at each subsequent time point. During the investment period, no cash is put in or taken out. $R(t,T)$ denotes the compound return between time $t$ to $T$, $R(t,T) = \prod_{s=t+1}^{T}(1+R_s)$, where $R_s$ is the s-period portfolio return.

<Insert Figure 3 here>

The WML portfolio suffered a nearly 64% loss at the end of 2010. In fact, it lost 1.46% per annum from January 2000 to December 2010. The large losses of the WML portfolio occurred in the first half of 2009, especially in March, April, and May where the losses were 18.22%, 39.52%, and 14.29%, respectively. The poor under-performance takes place when the market rebounds from the bottom. We further present the 10 worst-month returns of the WML strategy from January 1930 to December 2010 in Table 3, which also gives the contemporaneous monthly returns of the S&P 500 index.

<Insert Table 3 here>

Similar to the aforementioned losses in 2009, these worst-month returns usually occur when the market recovers gradually from a dramatic downturn. In July and August 1932, for example, the S&P 500 index was up 37.70% and 37.54%, but the WML portfolio lost 62.18 % and 56.90% respectively. The loss is due to the momentum strategy reversal in which the Loser portfolios significantly outperform the Winner portfolios. Their returns for the same two months are 77.76% and 100.08% for the former and 15.58% and 43.18 % for the latter. Daniel and Moskowitz (2011) characterize the strong momentum reversals as a momentum crash, which is caused by the large negative skewness of the WML portfolio. Momentum crashes not only occur on the short side of the portfolio, that is, the Loser portfolio, but are also clustered, as shown in Figure 4. The strong performance of the losers may span multiple months.

<Insert Figure 4 here>

### 3.4 IPR-Momentum Strategy

In this section, we use the IPR as defined in Equation (5) to construct a trading strategy, the IPR-momentum strategy, and apply it to the **CRSP** dataset. All the stocks examined satisfy the same criteria prescribed in Section 3.1. In each formation month $t$, we form the portfolios by independently sorting all eligible stocks by their own previous cumulative monthly returns and $j$-week IPRs, $\mathrm{IPR}_t^j$. That is, the stocks are first assigned into one of the 10 portfolios based on their cumulative returns over the previous 12 months with the most recent month excluded, exactly the same way as described in Section 3.1. The top 10% of firms with the highest ranking period returns are filed in portfolio P10, the "[W]inner" decile portfolio. Conversely, the bottom 10% of firms with the lowest ranking period returns are in portfolio P1, the "[L]oser" decile portfolio. Meanwhile, all the stocks are independently assigned into one of the three equal-size portfolios, labeled as [L]ow, [M]iddle, or [H]igh, and sorted by the IPR value of each individual stock during the same period.

The two separate rankings produce 30 different combinations of price-risk modified momentum portfolios. "WL-LH" is defined as the monthly portfolio return of the "[W]inners with [L]ow IPR minus that of the [L]osers with [H]igh IPR." Returns on zero investment of WL-LH portfolios are the difference between the equally-weighted returns of WL and LH portfolios. Our focus is on the returns of one-month forward WL-LH portfolios. In the sequel, the strategy introduced above is called the IPR-momentum strategy.

### 3.5 Performance of the IPR-Momentum Strategy

The empirical returns of the WL-LH portfolios are shown in Table 4.

<Insert Table 4 here>

From Table 4, we find that the WL-LH portfolio returns decrease as the weekly lag, $j$, of IPR increases. When $j = 13$ (or one-quarter), the monthly average return of the WL-LH portfolio is 2.09%, which is equal to a 28.15% annual return. For $j = 26$ (or two-quarter), the monthly average return of the WL-LH portfolio is 1.47%, or 19.10% annually. When $j = 39$ (or three-quarter) and 52 (or four-quarter), the monthly average returns of the WL-LH portfolio are only 0.78% and 0.48% respectively. The fact that our LH (short-side) portfolio has -0.20% monthly average return with one-quarter IPR is worth pointing out. To evaluate the performance of portfolios, annualized Sharpe ratios are presented in Table 5.

<Insert Table 5 here>

The Sharpe ratio of WL-LH is 0.8587 for one-quarter IPR, 0.4316 for two-quarter IPR, 0.1421 for three-quarter IPR, and 0.0454 for four-quarter IPR. Compared to the momentum strategy (0.3310 in Table 2), the performance of the WL-LH one-quarter portfolio is twice greater than that of the momentum strategy. For the rest of this section, the empirical analysis concentrates on the one-quarter (or $j = 13$) case. Figure 5 plots the monthly portfolio returns of the IPR-momentum strategy from January 1930 to December 2010.

<Insert Figure 5 here>

We find that the IPR-momentum strategy does perform better than the momentum strategy shown in Figure 4. In addition, the WL-LH portfolio returns are more stable than the returns of momentum portfolio. Nevertheless, we also recognize the imperfection of our strategy in its inability to avoid a huge loss of -80.00% in July 1932, -85.33% in September 1939, and -41.17% in April 2009. These jump events weaken the performance of both the momentum strategy and our approach. A remedy for the shortcoming is proposed in Section 4.2.

A further plot on the compound returns of the two momentum-type strategies from January 1930 to December 2010 is presented in Figure 6, which shows that the profits made by the WL-LH and WML portfolios are $7,068,859.27 and $448.73, respectively.

<Insert Figure 6 here>

Regarding the performance after 2000, the compound returns are plotted in Figure 7 for both the momentum strategy and the IPR-momentum strategy from January 2000 to December 2010. Results show that WML lost about 64% in December 2010 with the initial investment in January 2000. In contrast, the IPR-momentum strategy earned 9.04% in the same period.

<Insert Figure 7 here>

By comparing the results of Figures 7 and 3, we see that the IPR-momentum strategy performs better than the S&P 500 index after 2000. For the same period, however, both of the two momentum-type strategies did worse than investing in the risk-free asset.

In Section 4.2 below, we further propose another trading strategy to improve the two momentum-type strategies.

## 4. Value Investing Premiums and IPR Strategy

### 4.1 Value Investing Premiums

Asness, Moskowitz and Pedersen (2009) study the relationships between the value investing strategy and the momentum strategy, and conclude that the returns of the two strategies are negatively correlated. To verify that our premium does not come from the value investing strategy, we adopt their approach to calculate the correlations among the returns of the momentum strategy, value investing strategy, and the IPR-momentum strategy. The rationale is simple. If two strategies are similar in the sense that the portfolios formed share many common component stocks, then their portfolio returns should exhibit a positive correlation. The data consist of all non-financial firms in (a) the **NYSE**, the **AMEX**, and the **NASDAQ** return files from **CRSP**, and (b) the merged **COMPUSTAT** annual accounting data from 1962 to 2010. We follow the same procedures as described in Sections 3.1 and 3.4 to excute the momentum strategy and the IPR-momentum strategy respectively, and label the former as "Momentum" and latter as "IPR-Momentum." For the value investing strategy, we sort stocks according to their book-to-market (**B/M**) ratios,[6] then implement a long-short (essentially market neutral) portfolio strategy by buying the top 10% high **B/M** ratios portfolio and selling the bottom 10% low **B/M** ratio portfolio. We also form the value investing portfolios with four different holding periods, one month, one year, three years and five years, which are labeled "Value-1M," "Value-1Y," "Value-3Y," and "Value-5Y," respectively. All portfolio returns are monthly and equally weighted. The correlation matrix among the different strategies is shown in Table 6, with the long-short value investing strategy in the top panel and the long only value investing strategy in the bottom.

<Insert Table 6 here>

According to Table 6, the IPR-momentum strategy is nearly orthogonal to the value investing strategy. The moderately positive correlation between the momentum strategy and the adjusted momentum strategy is expected because the latter is based on and intended to improve the former. To implement the momentum strategy, the issue of central importance is to have an idea of whether or not the stock is running out of momentum to reach its peak. The IPR we propose aims to measure on a uniform scale the amount of information diffusion for each individual stock during the momentum trend, and to identify those stocks with more momentum left to sustain the trend.[7] Hence, the premium of our strategy is generated not from the value investing stocks, but from those past winners with

[6] The **B/M** ratio is constructed by following Fama and French (1992). We also use other value investing variables for robustness check. The empirical results are similar.

[7] In the Appendix, we use a dynamic information diffusion model to give an economic explanation of the improvement brought by the IPR-momentum strategy. In that model, the cumulative proportion of information among investors could affect the stock price. If the amount of cumulative information among investors becomes large, the stock price will also rise. Because the value of the IPR is positively correlated with the price increase, the

good news traveling slowly. The statistical idea of the IPR is to measure the empirical quantile for stock prices within a certain time frame. The large IPR of a stock means that the current price level of the stock is high relative to its recent historical prices, which indicates that this stock has a larger probability to soon exhaust its momentum compared to others.

### 4.2 IPR Strategy

Hwang and Rubesam (2008) and Daniel and Moskowitz (2011) have also shown that the profits of the momentum strategy fell away after 2000. As demonstrated in Figure 3, the momentum strategy suffered a considerable loss of 64% from January 2000 to December 2010 when the S&P 500 only posted a 14% negative return. During the same period, the momentum effect not only lost its thrust, but also created an adverse effect of momentum crashes. The cause for the strategy's poor performance appears to be the frequent relatively high price level of the stocks picked by the winner-loser classification, which is unlikely to sustain the upward trend in the following month. To improve the momentum strategy, the foremost issue that needs to be dealt with is refining the stock selection by avoiding those firms with high risk of being over-priced.

Both the momentum strategy and the IPR-momentum strategy are vulnerable to drastic changes in the market conditions. As pointed out in Section 3, the two strategies report huge losses upon the occurrence of jump events from January 2000 to December 2010. During the periods when the momentum effect diminishes as a result of the market crashes interrupting the price continuation, the winner-loser classification of stocks may no longer be an effective criterion for producing strong returns. A natural remedy for the shortcoming is to sort stocks solely by the IPR.

In this section, stocks are sorted according to their IPR values only. The portfolio taking a long position on decile 1 and a short position on decile 10 is labeled as IPR-10g.[8] The monthly returns of the portfolios are shown in Figure 8. The largest loss of IPR-10g is -45.60% in February 2000 and the second-largest loss is -24.61% in December 1999. We find that the returns of the investing portfolio are more stable over time.

<Insert Figure 8 here>

With regard to whether IPR-10g can avoid those huge losses during the financial crisis period, especially from 2000 to 2010, we plot the compound returns of the three different strategies, IPR-10g, WML, and WL-LH, in Figure 9. At the end of 2010, the IPR-10g eventually earns 32.47%, which is better than WL-LH's 13.25% and WML's -63.84%. Figure 9 also indicates that the IPR strategy not only produces returns that are better and more stable than those derived from the two momentum-type strategies, but also performs better than investing in the risk-free asset especially in the 2008 to 2010 financial crisis.

<Insert Figure 9 here>

IPR can be viewed as a proxy measure for the amount of information diffused, and thus motivates its use in the IPR-momentum strategy described in Section 3.4.

[8] We are indebted to an anonymous referee for the suggestion of applying the IPR strategy to a separate period from January 2000 to December 2010.

We further consider the compound returns of the momentum strategy (labeled with "WML"), our IPR-momentum strategy (labeled "WL-LH"), and the IPR strategy (labeled "IPR-10g") from January 1930 to December 2010 as shown in Figure 10. Despite its more stable returns, the IPR-10g profits only $4,223, which is still far less than that of WL-LH.

<Insert Figure 10 here>

### 4.3 Robustness check

For robustness check, we sort all firms that meet the data requirements into 10-decile portfolios, labeled PR1 to PR10, based on their IPR values for different weekly lags of $j$ equal to 13, 26, 39, and 52. The top 10% of firms with the highest ranking period price risk are grouped into portfolio PR10, that is, the [H]igh-decile portfolio, and the bottom 10% of firms with the lowest ranking period price risk are grouped into portfolio PR1, that is, the [L]ow-decile portfolio. The return on a zero investment Low-Minus-High (LMH) portfolio is the difference of the return on the Low to the return on the High portfolio in each period. The monthly return of the decile portfolios is based on the equal-weighted return. We focus on the monthly return of extreme low price risk and high price risk portfolios in the next $K$ months ($K$=1, 3, 6, 9, and 12). Table 7 presents the monthly return of the IPR-momentum decile portfolios for the different ($j$, $K$)'s.

<Insert Table 7 here>

With the holding period of one month, the returns of portfolios with low price risk are higher than those of portfolios with high price risk except for $j$=52. The trend reverses across the table if the portfolios are held for more than three months.

In Table 7, the results for the 13 weeks may imply that the source of short-term reversal is due to the IPR. We further verify the relationship between the IPR and short-term reversal in Table 8.

<Insert Table 8 here>

At the end of every month of 1963 to 2010, we sort the stocks by their previous month's IPR (labeled I1 to I10 from low to high) and independently sort the stocks by their previous month's return (labeled R1 to R10 from low to high). These stocks are grouped into 100 portfolios. We track the returns of the 100 portfolios in the following one month. The average portfolio returns are shown in Table 8. For those short-term losers (like R1, R2, and R3), we find that the short-term reversal is strong even we control for IPR. However, for those short-term winners (like R9 and R10), the IPR effect is not negligible. The IPR effect and the short-term reversal effect are mixing for those stocks whose previous-month returns are moderate.

## 5. Price Risk and Cross-Sectional Returns

It has been shown that average stock returns are related to some firm characteristics (Fama and French (1996)). The most well-known model is the three-factor model (Fama and French (1992, 1993)),

$$E(R_i) - R_f = b_i[E(R_M) - R_f] + s_i E(SMB) + h_i E(HML), \tag{6}$$

which offers a good description for the returns on portfolios formed by size and **B/M** ratio. The model denotes the risk-return relation of the expected return on a portfolio in excess of the risk-free rate $E(R_i) - R_f$ to three factors: (i) $E(R_M) - R_f$ is the excess return on a broad market portfolio; (ii) $SMB$ is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks; and (iii) $HML$ is the difference between the return on a portfolio of high **B/M** ratio stocks and the return on a portfolio of low **B/M** ratio stocks. Furthermore, Fama and French (1995) show that weak firms with persistently low earnings tend to have high **B/M** ratio and positive slopes on HML, and strong firms with persistently high earnings have low **B/M** ratio and negative slopes on HML.

In order to connect IPR to cross-sectional return differences, we examine the performance of the IPR portfolios that combines with the three factors proposed in Equation (6). The stocks analyzed here have the same conditions as described in Section 3.1. The accounting variables are obtained from **COMPUSTAT**. For the data availability, we follow previous researches only using those accounting variables which start from 1963. At every end of the month from 1963 to 2010, we first sort the stocks according to their **NYSE**-beta-based groups (labeled B1 to B10 from low to high), **NYSE**-size-based groups (labeled S1 to S10 from small to big), and **NYSE-B/M**[9]-based groups (labeled R1 to R10 from low to high). We further independently sort the stocks according to their IPR values and group them into three levels: low, medium and high (labeled L, M and H). The one-month holding returns of the 30 portfolios for each factor are shown in Table 9 where all the portfolio returns are equally-weighted.

<Insert Table 9 here>

In each of the three panels in Table 9, the average returns of the ten factor-grouped portfolios exhibit a trend. The trend is increasing for both the market beta factor from B1 to B10 and the **B/M** ratio factor from R1 to R10, and decreasing for the firm size factor from S1 to S10. The tendency is consistent with the findings reported in the literature. The more interesting feature of Table 9 is that in the three panels, the returns of the factor-based portfolios with low IPR (i.e., labeled L) are greater than those with high IPR (i.e., labeled H), regardless of the factor being the market beta, the firm size or the **B/M** ratio. This clear patten together with the similar results presented in Table 4 indicates that the IPR is closely related to the cross-sectional return differences.

## 6. Conclusions

We propose a quantitative index, the IPR, to assess the risk of being over-priced and set it as the downside risk of a stock. Our empirical results show the two-fold advantage of the IPR. First, from 1930 to 2010, the IPR-momentum strategy performs significantly better than the momentum strategy by incorporating the IPR to refine the stock selection. Second, for the separate period from 2000 to 2010 when the IPR-momentum strategy only produces mild improvements, the strategy that is based on the IPR alone reduces the impact of jump events and results in returns that are greater and more stable than those of the two momentum-type strategies.

[9] Here, we follow the definition of Daniel and Titman (2006) to measure the book equity (BE).

Given the anomaly achieved by the IPR-momentum strategy, the source of its returns will normally be associated with some other established strategies such as the value investing strategy. By showing that the returns of the two strategies under consideration are uncorrelated, we clarify that the premium generated by the IPR-momentum strategy does not come from the value investing strategy. We attribute the higher profits of the IPR-momentum strategy to its use of the IPR to identify those stocks with slow traveling of good news. The issue of whether the two nearly orthogonal strategies [cf. Table 6 and Asness, Moskowitz and Pedersen (2009)] can be simultaneously improved by a certain mixture of these strategy is worthy of further investigation. Exploring potential applications of the IPR-momentum strategy or the IPR alone in other financial markets and, more broadly, in the portfolio management of different asset classes combined is also interesting.

Furthermore, we investigate the relationship between the IPR and the cross-sectional return differences. The empirical evidence shows that the returns of the factor-based portfolios with low IPR are greater than those with high IPR, regardless of the factor being the market beta, the firm size, or the **B/M** ratio. This return pattern across all the factor-based portfolios gives rise to the question of whether the IPR could be verified as a component of the systematic risk, which we will examine in another paper. Further on future research, although the IPR is a normalized measure according to the finding of Figure 1, it would be interesting to measure the downside risk in conjunction with the variance of individual stocks using the variable IPR$\times$variance (or standard deviation). One can also propose a price equilibrium model to precisely describe the risk or to explore the price risk in different financial assets and markets.

## Appendix

Market is a place where people make trades based on how they interpret the information available on the product in terms of price. Investors as a whole perceive and digest news about a stock differently when the market conditions change. To incorporate the market reality, the price model proposed below treats the information diffusion as a time-varying process,[10] and assumes that the information of future earning shocks is dynamically distributed across all the investors.

The formulation of our model is as follows: (i) $k$ (predetermined) future earning shocks come to influence the price one shock at a time; (ii) Each of these shocks, $\epsilon_{t+1}, \ldots, \epsilon_{t+k}$, is indexed by the time point when it becomes entirely public $k$ periods after the shock begins to affect the price[11]; and (iii) For each future earning shock $\epsilon_{t+i}$ defined in (ii), two random processes, $h_{t+i,\ell}$ and $z_{t+i,\ell}$, characterize the dynamics of the information diffusion. $h_{t+i,\ell}$ denotes the diffusion rate by which the remaining information of $\epsilon_{t+i}$ is instantaneously reflected into the current price at time $t+i-k+\ell$; the value of $h_{t+i,\ell}$ belongs to $(0, 1]$. $z_{t+i,\ell}$ represents the cumulative fraction of future earning shock $\epsilon_{t+i}$ that has been priced

[10] Shive (2010) uses an epidemic model to describe investors' trading behavior in which the influence between investors is like the spread of a disease. Ozsoylev, Walden, Yavuz, and Bildik (2011) also support the view of dynamic information diffusion from the perspective of investor networks.

[11] For example, the shock $\epsilon_{t+i}$ enters the market at $t+i-k$ and its information is fully revealed at $t+i$.

in up to time $t+i-k+\ell$, and is defined by the following relation with $h_{t+i,\ell}$:

$$z_{t+i,\ell} = \begin{cases} h_{t+i,0} & ,\ell = 0; \\ z_{t+i,\ell-1} + h_{t+i,\ell}(1 - z_{t+i,\ell-1}) & ,\ell = 1, \ldots, k-i \end{cases} \tag{A1}$$

The instantaneous rate $h_{t+i,\ell}$ is required to be a measurable function with respect to the information field generated by the prices up to time $t+i-k+\ell-1$, so that it can be used to design an investment strategy. Notably, $z_{t+i,\ell}$'s defined in Equation (A1) satisfy the necessary constraints that $1 \geq z_{t+i,\ell+1} \geq z_{t+i,\ell} > 0$. $z_{t+i,\ell}$ can be viewed as the $\ell$-periods cumulative proportion of investors who have received information of future earning shock $\epsilon_{t+i}$.

If we assume the ultimate value of this liquidating dividend for an asset can be written as

$$D_T = D_0 + \sum_{j=0}^{T} \epsilon_j, \tag{A2}$$

where all the $\epsilon_j$'s are independent and normally distributed with zero mean and an identical variance $\lambda^2$. Each $\epsilon_j$ represents the future earning information shock about the risky asset that gradually diffuses into the current value of the asset. The investors are all constant absolute risk aversion (CARA) with the same risk-aversion parameter $\psi^*$ and live until the terminal date $T$. They can be viewed as a class of fully rational arbitragers. The risk-free interest rate is zero and the supply of the asset is fixed at $Q$. The price at time $t$ is then given by

$$p_t = D_t + \{z_{t+1,k-1}\epsilon_{t+1} + z_{t+2,k-2}\epsilon_{t+2} + \ldots + z_{t+k,0}\epsilon_{t+k}\} - \gamma^* Q \tag{A3}$$

where $\gamma^*$ is also a function of investors' risk aversion and the variance of $\epsilon$'s. The equilibrium price of Equation (A3) could be found under the restriction of the covariance-stationary equilibrium (Hong and Stein (1999)).

With regard to the economic interpretation of our dynamic innovation diffusion model, we recall Equation (A3). Let $\mathfrak{D}_t = D_t - \gamma^* Q$ and $\mathfrak{R}_t = z_{t+1,k-1}\epsilon_{t+1} + z_{t+2,k-2}\epsilon_{t+2} + \ldots + z_{t+k,0}\epsilon_{t+k}$. We further assume that the price $p_t$ has been centered to the price $p_0$ on an earlier initial date so that $p_t$ is allowed to be negative in a descending trend. Equation (A3) can be rewritten as

$$p_t = \mathfrak{D}_t + \mathfrak{R}_t. \tag{A4}$$

For simplicity, we only consider the case in which only one future innovation in $\mathfrak{R}_t$ exists, which is of one-period with $k = 1$, that is,

$$p_t = \mathfrak{D}_t + z_t \epsilon_{t+1}. \tag{A5}$$

Equation (A5) can also be written as

$$\epsilon_{t+1} = (p_t - \mathfrak{D}_t)/z_t. \tag{A6}$$

Our goal is to base the preceding equation on the information available at time $t$ to choose the stock whose unobservable innovation $\epsilon_{t+1}$ is of the desired sign and has a large absolute value. One should note that $z_t$ represents the cumulative proportion of the next period's innovation $\epsilon_{t+1}$ that has been reflected into the current price. Hence, a low value of $z_t$ means a small portion of the innovation $\epsilon_{t+1}$ is reflected into the current price $p_t$.

For two given winner stocks having the same price $p_t$ and $\mathfrak{D}_t$ at time $t$, we can conclude from Equation (A6) that the one with the smaller $z_t$ has a greater probability of carrying a larger innovation $\epsilon_{t+1}$ at $t+1$ than the other is not difficult. In other words, the smaller the $z_t$ value, the higher the probability that further good news will be revealed in the following period. The same criterion, however, could not be applied to the loser stocks, because Equation (A6) indicates that a smaller $z_t$ gives $\epsilon_{t+1}$ a greater probability to become positive. In the comparison of loser stocks, our strategy chooses those having a large $z_t$. The choice aims to ensure that the succeeding innovation $\epsilon_{t+1}$ of the stock selected or equivalently $p_t - \mathfrak{D}_t$ in Equation (A6) is more likely to be negative, although the tendency of the absolute value $|\epsilon_{t+1}|$ to be large is uncertain. This outcome perhaps explains why our modified momentum strategy presented in Section 3.5 brings a greater improvement in the winner stocks than in loser ones.

## References


Asness, C.S., Moskowitz, T.J. and Pedersen, L.H. (2009) Value and momentum everywhere, *NBER Working Paper*

Bandarchuk, P. and Hilscher, J. (2012) Sources of momentum profits: Evidence on the irrelevance of characteristics, *Review of Finance* **doi: 10.1093/rof/rfr036**

Barroso, P. and Santa-Clara, P. (2012) Managing the risk of momentum, *Available at SSRN 2041429*

Carhart, M. (1997) On persistence in mutual fund performance, *Journal of Finance* **52**, 57–82.

Chan, L., N. Jegadeesh, and J. Lakonishok (1996) Momentum strategies, *Journal of Finance* **51**, 1681–1714.

Chordia, T., and L. Shivakumar (2002) Momentum, business cycle, and time-varying expected returns, *Journal of Finance* **57**, 985–1019.

Cooper, M., R. Gutierrez, and A. Hameed (2004) Market states and momentum, *Journal of Finance* **59**, 1345–1365.

Daniel, K., and T. Moskowitz (2011) Market crashes, *University of Columbia working paper*

Daniel, K. and Jagannathan, R. and Kim, S. (2012) Tail risk in momentum strategy returns, *National Bureau of Economic Research*

Daniel, K. and Titman, S. (1999) Market efficiency in an irrational world, *Financial Analysts Journal* **55**, 28–44.

Daniel, K. and Titman, S. (2006) Market reactions to tangible and intangible information, *Journal of Finance* **61**, 1605–1643.

Erb, C., and C. Harvey (2006) The strategic and tactical value of commodity futures, *Financial Analysts Journal* **62**, 69–97.

Fama, E. (1970) Efficient capital markets: A review of theory and empirical work, *Journal of Finance* **25**, 383–417.

Fama, E., and K. French (1988) Permanent and temporary components of stock prices, *The Journal of Political Economy* **96**, 246–273.

Fama, E., and K. French (1992) The cross-sectional of expected stock returns, *Journal of Finance* **47**, 427–465.

Fama, E., and K. French (1993) Common risk factors in the returns on stocks and bounds, *Journal of Financial Economics* **33**, 3–56.

Fama, E., and K. French (1995) Size and book-to-market factors in earnings and returns, *Journal of Finance* **50**, 131–155.
Fama, E., and K. French (1996) Multifactor explanations of asset pricing anomalies, *Journal of Finance* **51**, 55–84.
George, T.J. and Hwang, C.Y. (2004) The 52-week high and momentum investing, *Journal of Finance* **59**, 2145–2176.
Grundy, B.D. and Martin, J.S. (2001) Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* **14**, 29–78.
Hong, H., T. Lim, and J. Stein (2000) Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* **55**, 265–295.
Hong, H., and J. Stein (1999) A unified theory of underreaction, momentum trading and overreaction in financial markets, *Journal of Finance* **54**, 2143–2184.
Hwang, S. and A. Rubesam (2008) The disappearance of momentum, *Working paper*
Jegadeesh, N. (1990) Evidence of predictable behavior of security returns, *Journal of Finance* **45**, 881–898.
Jegadeesh, N., and S. Titman (1993) Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* **48**, 65–91.
Jegadeesh, N., and S. Titman (2001) Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* **56**, 699–720.
Kelsey, D. and Kozhan, R. and Pang, W. (2011) Asymmetric momentum effects under uncertainty, *Review of Finance* **15**, 603–631.
Lakonishok, J. and Shleifer, A. and Thaler, R.H. and Vishny, R.W. (1991) Window dressing by pension fund managers, *American Economic Review, papers and Proceedings* **81**, 227–231.
Lakonishok, J. and Shleifer, A. and Vishny, R.W. (1992) The impact of institutional trading on stock prices, *Journal of Financial Economics* **32**, 23–43.
Lee, C. and Swaminathan, B. (2000) Price momentum and trading volume, *Journal of Finance* **55**, 2017–2069.
Lehmann, B. (1990) Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* **105**, 1–28.
Moskowitz, T. and Ooi, Y.H. and Pedersen, L.H. (2012) Time series momentum, *Journal of Financial Economics* **104**, 228–250.
Okunev, J., and D. White (2003) Do momentum-based strategies still work in foreign currency markets?, *Journal of Financial and Quantitative Analysis* **38**, 425–447.
Ozsoylev, H. and Walden, J. and Yavuz, M.D. and Bildik, R. (2011) Investor networks in the stock market, *Working paper*
Rouwenhorst, K. (1998) International momentum strategies, *Journal of Finance* **53**, 267–284.
Rouwenhorst, K. (1999) Local return factors and turnover in emerging stock markets, *Journal of Finance* **54**, 1439–1464.
Shive, S. (2010) An epidemic model of investor behavior, *Journal of Financial and Quantitative Analysis* **45**, 169–198.
Zhang, X. (2006) Information uncertainty and stock returns, *Journal of Finance* **61**, 105–137.

# Figures

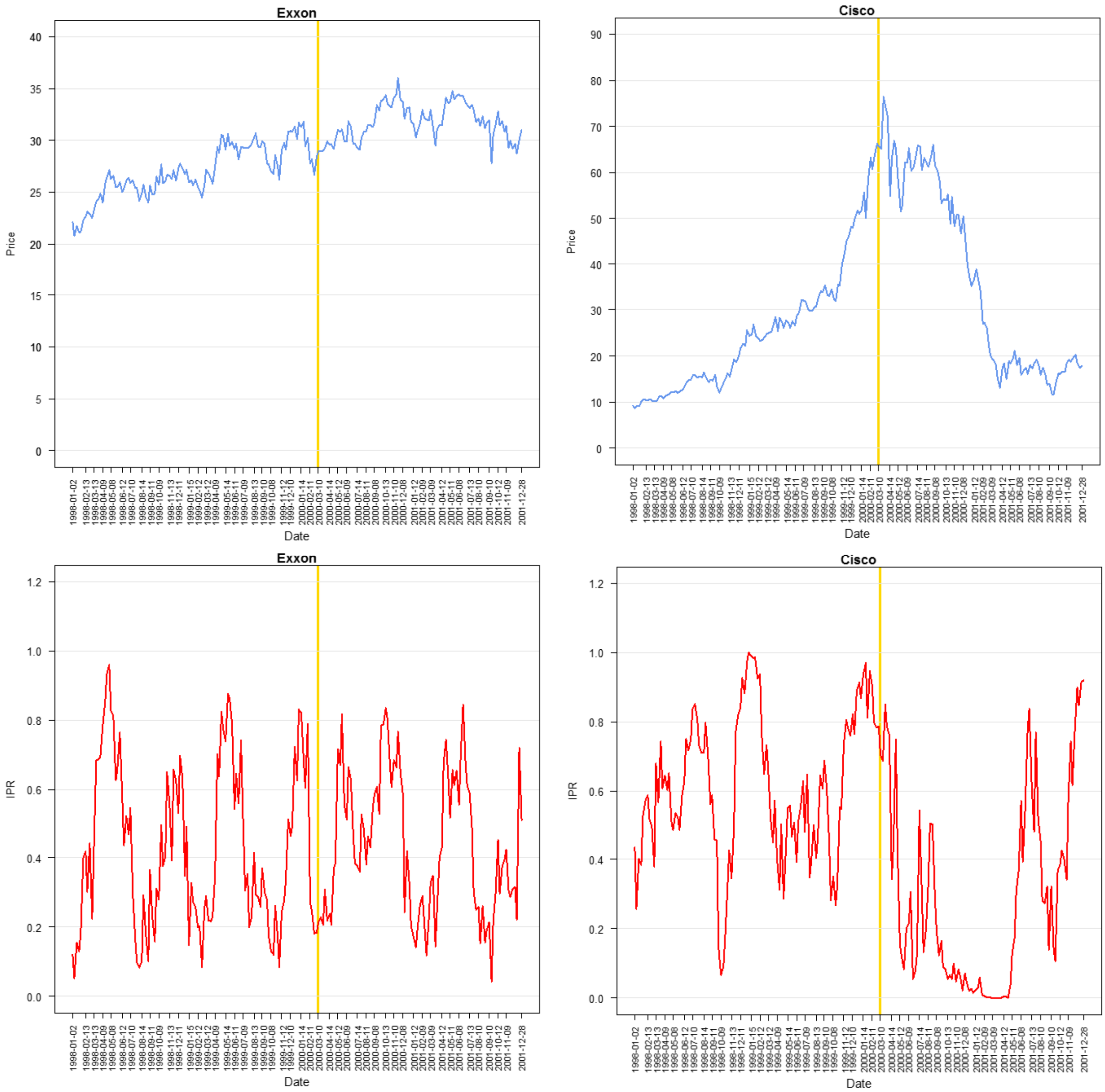


**Figure 1:** Price and IPR values of Exxon and Cisco during the Dot-com bubble

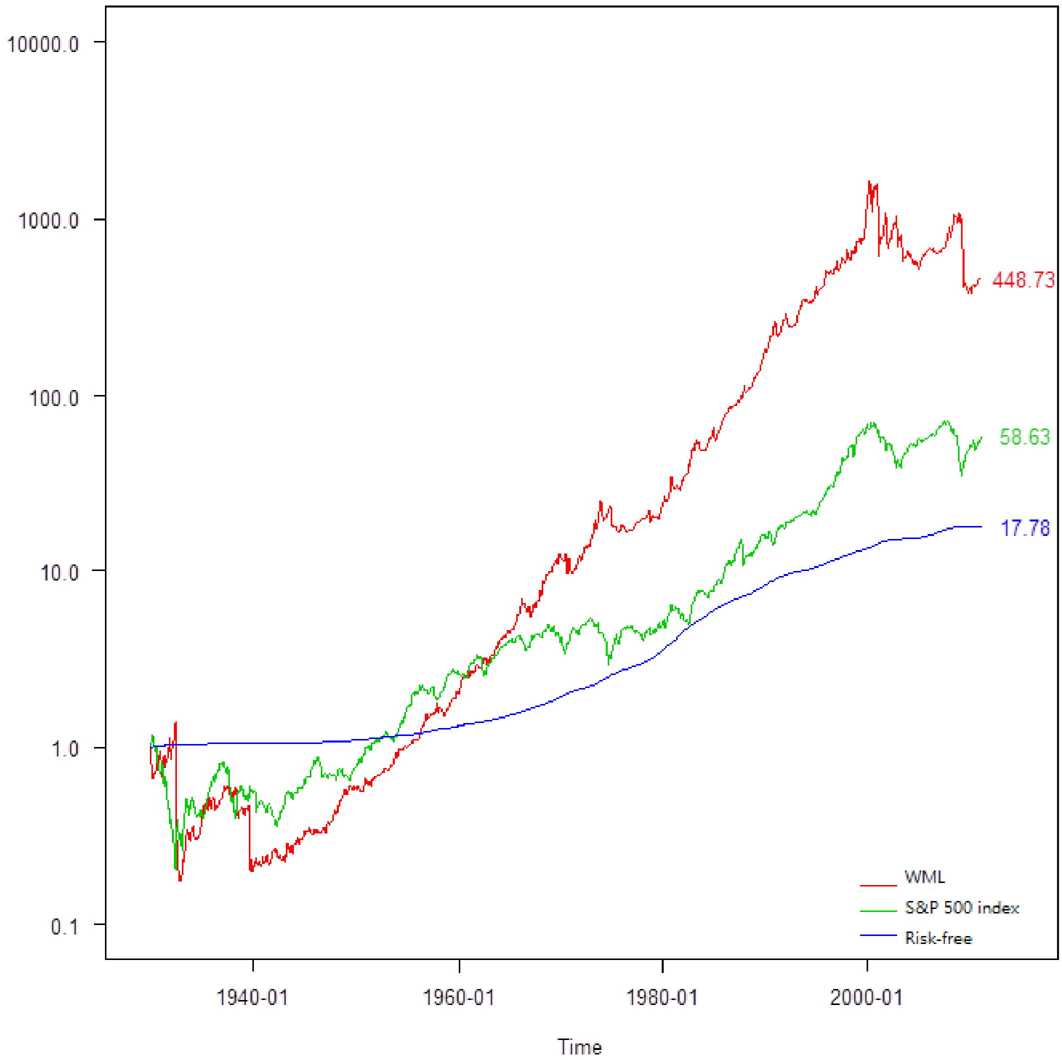


**Figure 2:** Compound returns of WML, S&P 500 index, and Risk-free, January 1930 to December 2010

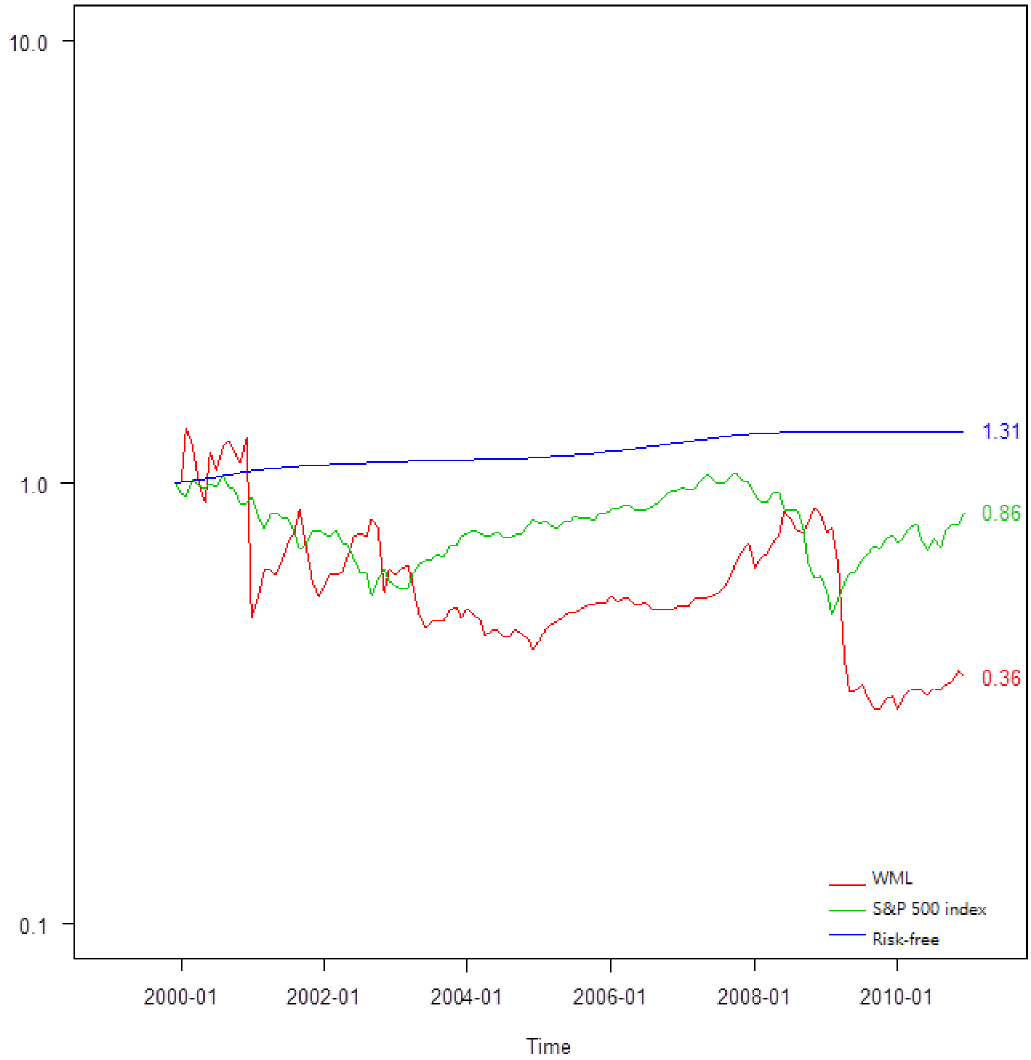


**Figure 3:** Compound returns of WML, S&P 500 index, and Risk-free, January 2000 to December 2010

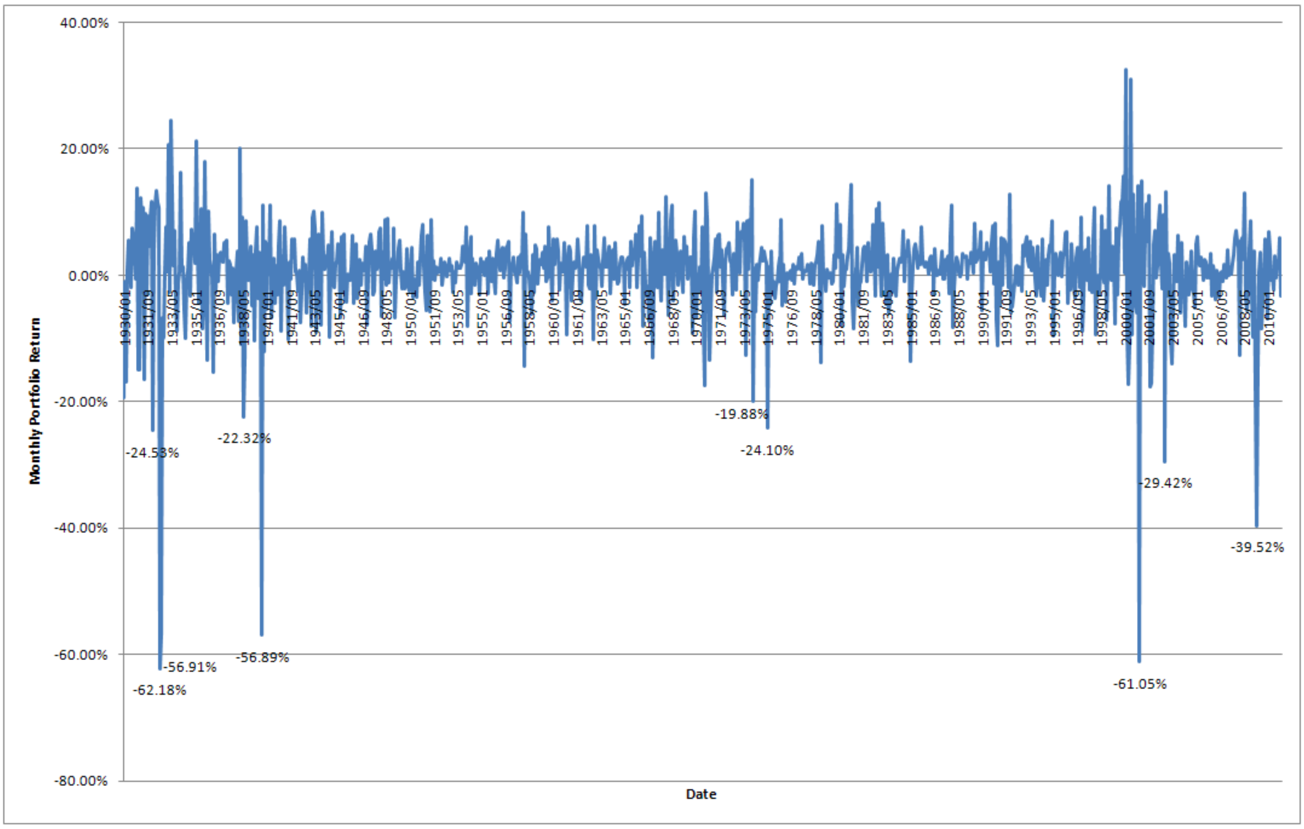


**Figure 4:** Performance of the momentum portfolios, January 1930 to December 2010

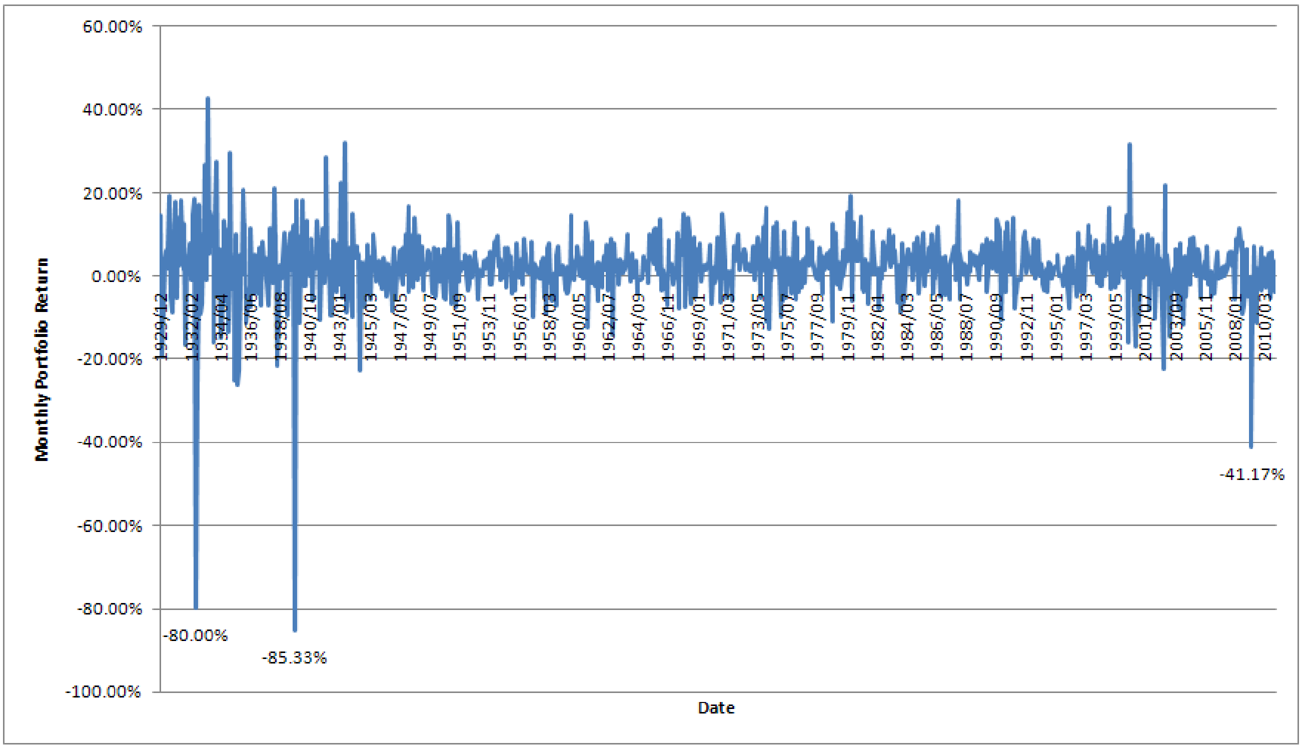


**Figure 5:** Performance of the IPR-Momentum portfolios, January 1930 to December 2010

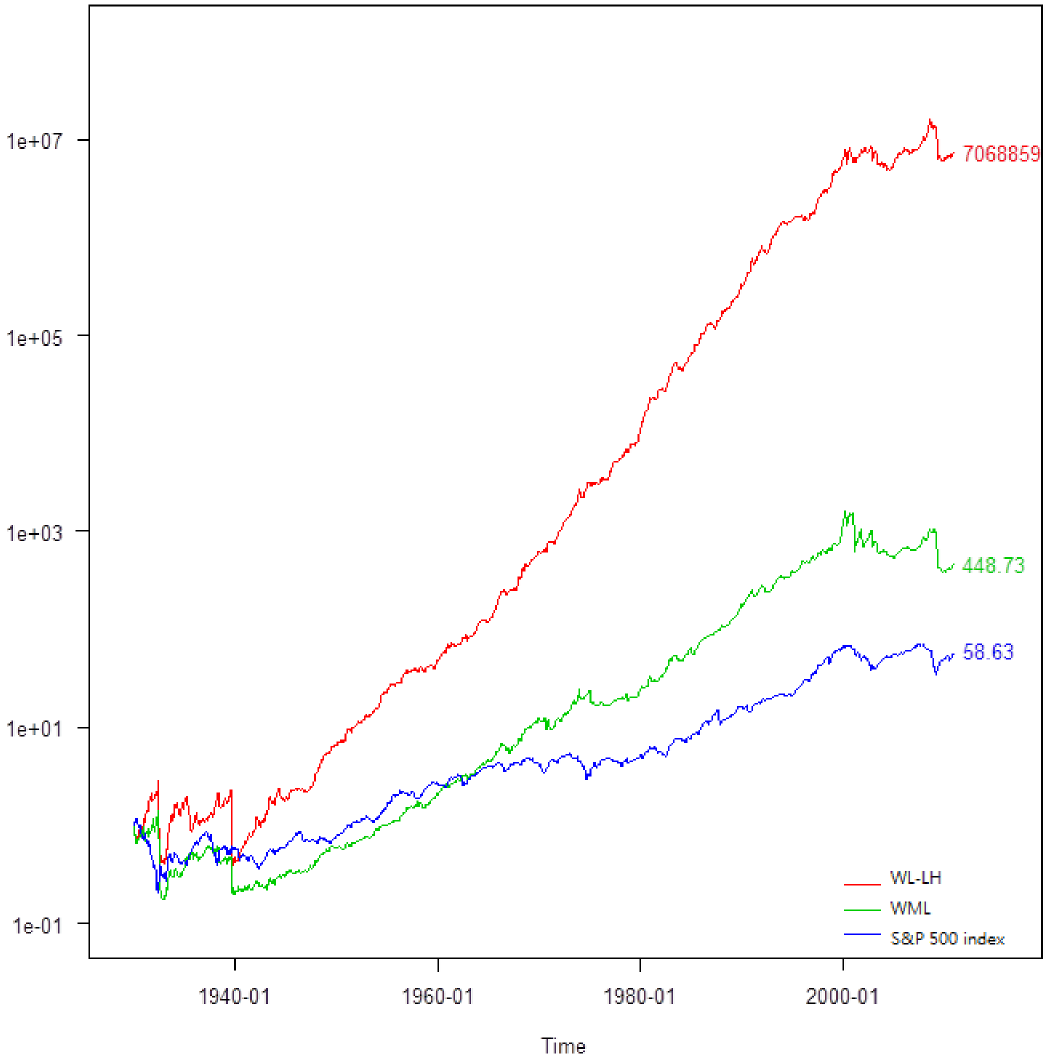


**Figure 6:** Compound returns of WML, WL-LH, and the S&P 500 index, January 1930 to December 2010

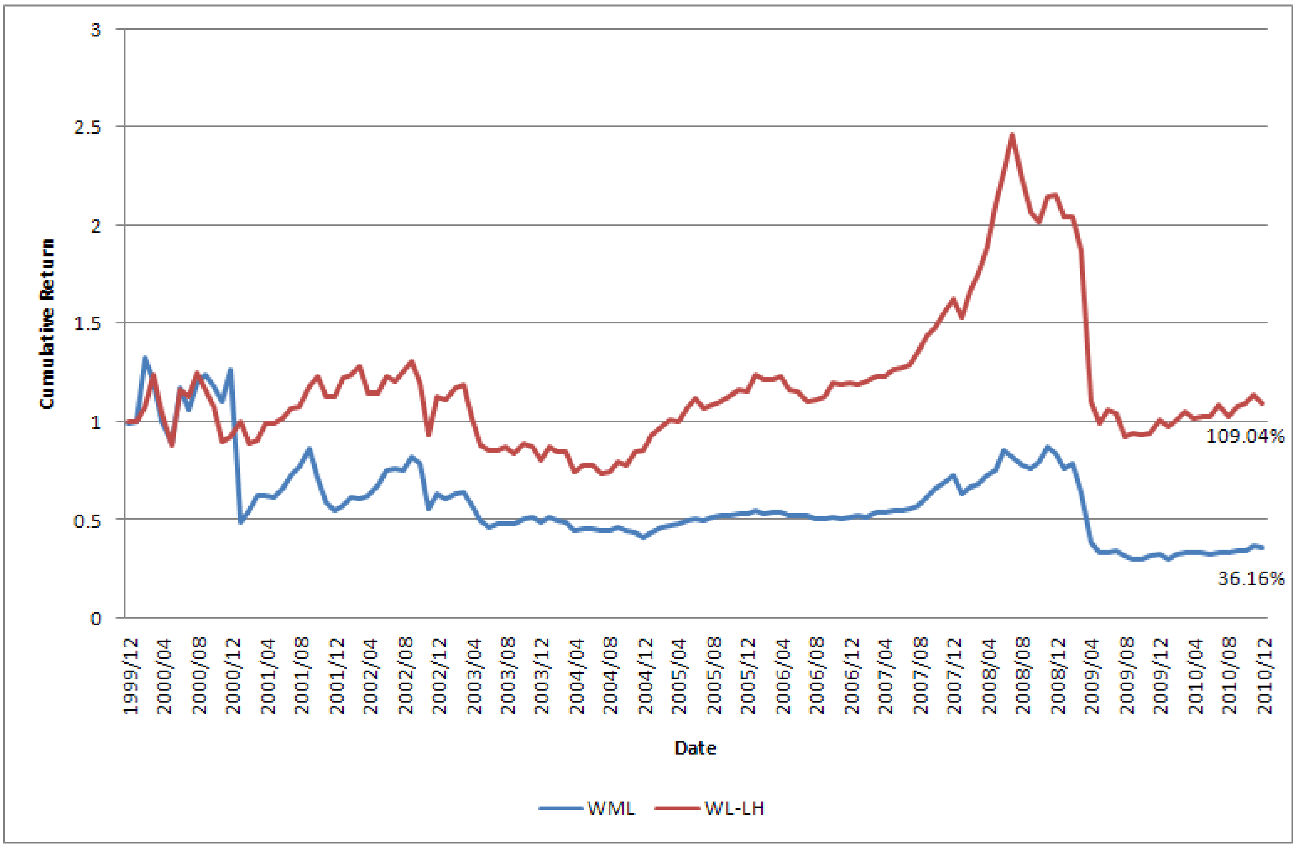


**Figure 7:** Compound returns of WML and WL-LH, January 2000 to December 2010

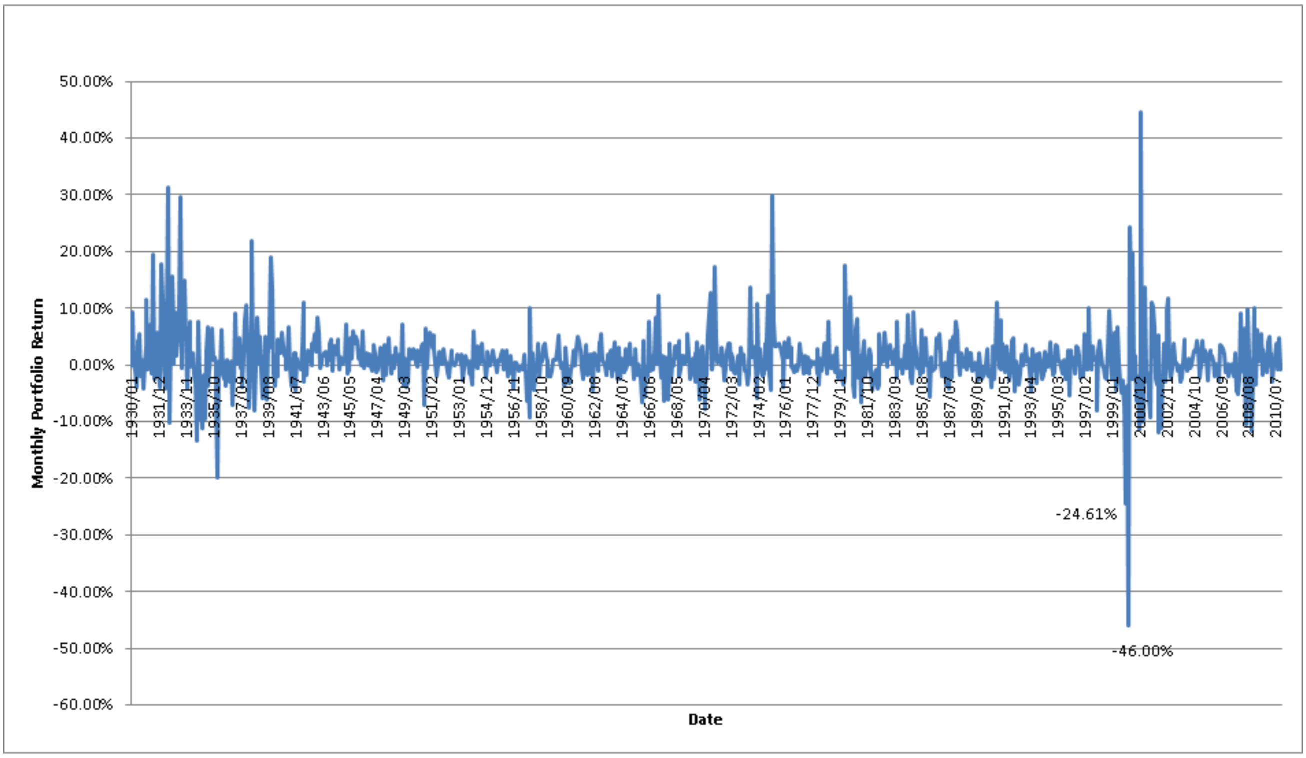


**Figure 8:** Performance of the IPR portfolios, January 1930 to December 2010

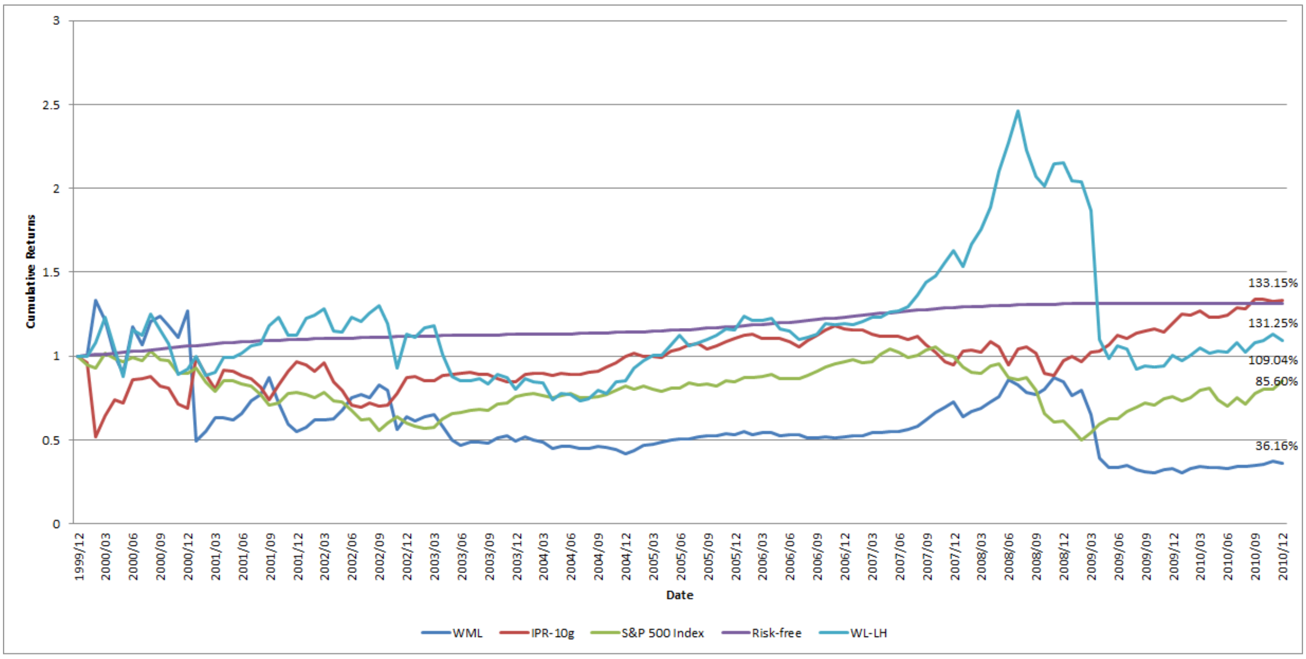


**Figure 9:** Compound returns of WML, IPR-10g, S&P 500 index, Risk-free and WL-LH, January 2000 to December 2010

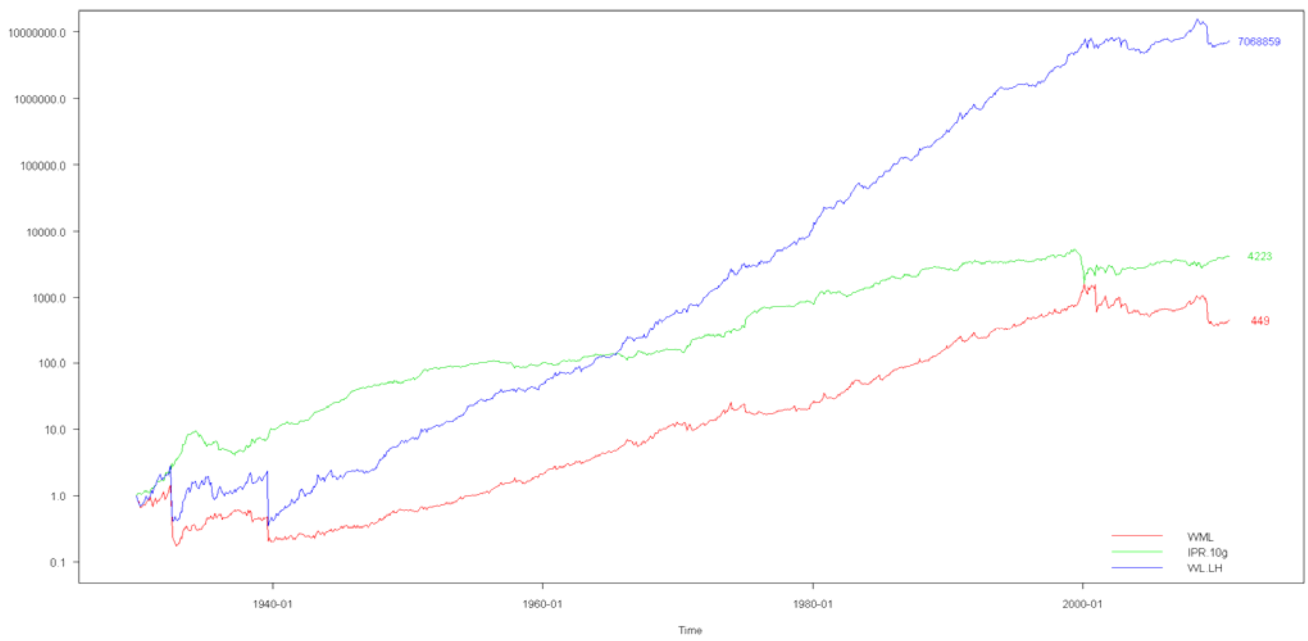


**Figure 10:** Compound returns of WML, WL-LH, and IPR-10g, January 1930 to December 2010

## Tables

**Table 1:** Price Risk and **NASDAQ** Stocks, March 15, 2000 to September 15, 2000

| IPR | 1 Month | 2 Months | 3 Months | 4 Months | 5 Months | 6 Months | n |
|---|---|---|---|---|---|---|---|
| I1 | 0.0718 | 0.0425 | 0.0786 | 0.0737 | 0.0939 | 0.1386 | 217 |
| I2 | 0.0324 | -0.0096 | 0.0062 | 0.0168 | 0.0263 | 0.0592 | 226 |
| I3 | 0.0191 | -0.0231 | -0.0041 | 0.0075 | 0.0010 | 0.0270 | 221 |
| I4 | -0.0140 | -0.0722 | -0.0603 | -0.0377 | -0.0319 | 0.0248 | 220 |
| I5 | -0.0566 | -0.1158 | -0.0948 | -0.0897 | -0.1137 | -0.0675 | 216 |
| I6 | -0.0673 | -0.1517 | -0.1498 | -0.1291 | -0.1529 | -0.1206 | 212 |
| I7 | -0.1255 | -0.2036 | -0.1935 | -0.1600 | -0.1792 | -0.1521 | 209 |
| I8 | -0.1851 | -0.2959 | -0.2583 | -0.2224 | -0.2785 | -0.2323 | 212 |
| I9 | -0.2239 | -0.3403 | -0.2782 | -0.2427 | -0.3251 | -0.2579 | 212 |
| I10 | -0.3227 | -0.4514 | -0.3861 | -0.3256 | -0.3803 | -0.3192 | 215 |

This table reports the IPR portfolio returns during the Dot-com bubble. Data for our study comes from the **CRSP** weekly and monthly files. We only concerns the dataset which consists of all **NASDAQ** stock markets during the period from March 15, 1997 to September 15, 2000. Those stocks with price below $1 are excluded during the formation period to reduce the microstructure effect associated with low-price stocks. The sample contains 2160 stocks. We rank the stocks based on their corresponding $\mathrm{IPR}_t^{13}$ as defined in Equation (5) on the day of March 15, 2000 and group the stocks into 10 portfolios (labeled with I1 to I10 from low to high). After forming these portfolios, we track their buy-and-hold cumulative returns in the following one month to six months.

**Table 2:** Statistics of the momentum portfolios, January 1930 to December 2010

| Portfolios | Mean | Std | Skew | Kurt | SR |
|---|---|---|---|---|---|
| P1 (Past Losers) | 0.69% | 0.1067 | 2.3866 | 17.9023 | 0.1291 |
| P2 | 0.82% | 0.0819 | 1.6241 | 14.4532 | 0.2254 |
| P3 | 1.01% | 0.0781 | 2.1760 | 20.5349 | 0.3265 |
| P4 | 1.06% | 0.0719 | 1.5558 | 15.7259 | 0.3822 |
| P5 | 1.15% | 0.0690 | 1.1678 | 13.2865 | 0.4464 |
| P6 | 1.20% | 0.0663 | 0.9465 | 12.3870 | 0.4955 |
| P7 | 1.28% | 0.0645 | 0.4184 | 7.8186 | 0.5589 |
| P8 | 1.41% | 0.0676 | 0.6713 | 9.8730 | 0.6060 |
| P9 | 1.54% | 0.0718 | 0.3366 | 6.9300 | 0.6398 |
| P10 (Past Winners) | 1.63% | 0.0870 | 1.0294 | 13.4764 | 0.5702 |
| WML | 0.94% | 0.0701 | -2.7992 | 22.7026 | 0.3310 |

This table reports the statistics of the momentum portfolio returns from January 1930 to December 2010. All firms that meet the data requirements are included as described in Section 2.1. These firms are sorted into 10-decile portfolios by their past 12-month cumulative returns excluding the most recent one. The top 10% of firms, which form the "[W]inner"-decile portfolio, is labeled as P10, and the bottom 10% of firms, which form the "[L]oser"-decile portfolio, is labeled as P1. The return on a zero investment of "Winner-Minus-Loser" (WML) portfolio is the difference between the returns on the Winner-decile portfolio and those on the Loser-decile portfolio in each period. The holding duration for each portfolio is one month. The monthly portfolio returns are all equal-weighted. Mean, Std, Skew, Kurt, and SR denote the realized mean, standard deviation, skewness, kurtosis, and Sharpe ratio, respectively.

**Table 3:** The 10 worst-month WML portfolio returns

| Rank | Month | Past Loser | Past Winner | WML | S&P 500 index |
|---|---|---|---|---|---|
| 1 | 1932/07 | 77.76% | 15.58% | -62.18% | 37.70% |
| 2 | 2001/01 | 78.79% | 17.74% | -61.05% | 3.46% |
| 3 | 1932/08 | 100.08% | 43.18% | -56.91% | 37.54% |
| 4 | 1939/09 | 81.67% | 24.78% | -56.89% | 16.46% |
| 5 | 2009/04 | 48.12% | 8.61% | -39.52% | 9.39% |
| 6 | 2002/11 | 37.68% | 8.26% | -29.42% | 5.71% |
| 7 | 1932/01 | 29.66% | 5.14% | -24.53% | -13.86% |
| 8 | 1975/01 | 44.12% | 20.02% | -24.10% | 12.28% |
| 9 | 1938/06 | 38.84% | 16.52% | -22.32% | 24.70% |
| 10 | 1974/01 | 24.72% | 4.84% | -19.88% | -1.01% |

This table presents the equal-weighted returns of the 10 worst months of the WML strategy from January 1930 to December 2010. The last column lists the contemporaneous monthly returns of the S&P 500 index.

**Table 4:** Characteristics of IPR-momentum portfolios

| j-week IPR | | P1 (Losers) | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 (Winners) | WL-LH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13 | Low | 1.48% | 1.33% | 1.38% | 1.24% | 1.40% | 1.31% | 1.56% | 1.61% | 1.72% | 1.89% | |
| | | (0.1097) | (0.0883) | (0.0798) | (0.0743) | (0.0794) | (0.0712) | (0.0746) | (0.0742) | (0.0837) | (0.0956) | 2.09% |
| | Middle | 0.61% | 1.03% | 0.90% | 1.23% | 1.25% | 1.28% | 1.33% | 1.47% | 1.57% | 1.54% | |
| | | (0.1083) | (0.0861) | (0.0812) | (0.0860) | (0.0731) | (0.0679) | (0.0685) | (0.0702) | (0.0744) | (0.0825) | |
| | High | -0.20% | 0.25% | 0.65% | 0.56% | 0.69% | 0.85% | 1.07% | 1.16% | 1.28% | 1.40% | (0.0794) |
| | | (0.1054) | (0.0797) | (0.0808) | (0.0720) | (0.0678) | (0.0650) | (0.0641) | (0.0665) | (0.0700) | (0.0796) | |
| 26 | Low | 1.16% | 1.21% | 1.14% | 1.17% | 1.30% | 1.34% | 1.55% | 1.57% | 1.73% | 1.76% | |
| | | (0.1067) | (0.0901) | (0.0783) | (0.0751) | (0.0766) | (0.0715) | (0.0729) | (0.0793) | (0.0878) | (0.1049) | 1.47% |
| | Middle | 0.47% | 0.96% | 1.10% | 1.14% | 1.16% | 1.26% | 1.31% | 1.49% | 1.71% | 1.59% | |
| | | (0.1052) | (0.0853) | (0.0821) | (0.0780) | (0.0723) | (0.0713) | (0.0684) | (0.0687) | (0.0770) | (0.0870) | |
| | High | 0.30% | 0.46% | 0.61% | 0.67% | 0.84% | 0.95% | 1.06% | 1.20% | 1.28% | 1.58% | (0.0997) |
| | | (0.1286) | (0.0844) | (0.0794) | (0.0758) | (0.0677) | (0.0650) | (0.0645) | (0.0661) | (0.0686) | (0.0775) | |
| 39 | Low | 1.00% | 1.12% | 1.22% | 1.18% | 1.20% | 1.18% | 1.42% | 1.64% | 1.93% | 1.09% | |
| | | (0.1035) | (0.0843) | (0.0796) | (0.0748) | (0.0754) | (0.0714) | (0.0759) | (0.0892) | (0.1048) | (0.1008) | 0.78% |
| | Middle | 0.52% | 0.81% | 1.00% | 1.13% | 1.19% | 1.30% | 1.36% | 1.52% | 1.62% | 1.37% | |
| | | (0.1080) | (0.0847) | (0.0778) | (0.0755) | (0.0688) | (0.0716) | (0.0699) | (0.0684) | (0.0853) | (0.0917) | |
| | High | 0.30% | 0.45% | 0.71% | 0.68% | 0.98% | 1.05% | 1.16% | 1.33% | 1.46% | 1.69% | (0.1236) |
| | | (0.1368) | (0.0983) | (0.0857) | (0.0808) | (0.0717) | (0.0652) | (0.0624) | (0.0680) | (0.0676) | (0.0744) | |
| 52 | Low | 0.87% | 1.03% | 1.03% | 0.99% | 1.11% | 1.07% | 1.13% | 1.31% | 1.27% | 0.45% | |
| | | (0.1029) | (0.0828) | (0.0741) | (0.0708) | (0.0743) | (0.0706) | (0.0722) | (0.0958) | (0.1127) | (0.1199) | 0.48% |
| | Middle | 0.57% | 0.96% | 1.03% | 1.18% | 1.25% | 1.27% | 1.40% | 1.54% | 2.18% | 1.09% | |
| | | (0.1131) | (0.0907) | (0.0811) | (0.0721) | (0.0734) | (0.0684) | (0.0752) | (0.0819) | (0.1878) | (0.1211) | |
| | High | -0.03% | 0.84% | 0.89% | 0.93% | 1.07% | 1.24% | 1.22% | 1.36% | 1.60% | 1.70% | (0.1397) |
| | | (0.1341) | (0.0969) | (0.0930) | (0.0790) | (0.0735) | (0.0693) | (0.0642) | (0.0654) | (0.0648) | (0.0780) | |

This table reports the monthly portfolio of the IPR-momentum strategy from January 1930 to December 2010. We construct the portfolios by assigning the stocks into one of the 10 portfolios based on their cumulative returns over the previous 12 months with the most recent month excluded, exactly the same way as described in Section 2. The top 10% of firms with the highest ranking period returns are labeled as portfolio P10, the "[W]inner" decile portfolio; the bottom 10% of firms with the lowest ranking period returns are assigned to portfolio P1, the "[L]oser" decile portfolio. Meanwhile, all the stocks are independently assigned into one of the three equal-size portfolios, labeled as [L]ow, [M]iddle, or [H]igh, according to their IPR values during the same period of time. The two separate rankings produce 30 different combinations of price-risk modified momentum portfolios. "WL-LH" is defined as the monthly equal-weight return of the "[W]inners with [L]ow IPR'' minus that of the "[L]osers with [H]igh IPR." Our focus is on the returns of one-month forward WL-LH portfolios. The variances are in the parentheses.

**Table 5:** Sharpe ratios for the IPR-momentum portfolios

| j-week IPR | | P1 (Losers) | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 (Winners) | WL-LH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 13 | Low | 0.4067 | 0.4374 | 0.4981 | 0.4621 | 0.5072 | 0.5248 | 0.6250 | 0.6583 | 0.6350 | 0.6243 | 0.8587 |
| | Middle | 0.1039 | 0.3131 | 0.2693 | 0.3996 | 0.4768 | 0.5321 | 0.5520 | 0.6151 | 0.6339 | 0.5591 | |
| | High | -0.1578 | -0.0153 | 0.1564 | 0.1341 | 0.2082 | 0.3072 | 0.4380 | 0.4727 | 0.5108 | 0.5063 | |
| 26 | Low | 0.2984 | 0.3761 | 0.3881 | 0.4218 | 0.4750 | 0.5407 | 0.6365 | 0.5934 | 0.6107 | 0.5204 | 0.4316 |
| | Middle | 0.0630 | 0.2825 | 0.3576 | 0.3944 | 0.4346 | 0.4971 | 0.5453 | 0.6425 | 0.6846 | 0.5491 | |
| | High | -0.0016 | 0.0737 | 0.1444 | 0.1787 | 0.2859 | 0.3634 | 0.4297 | 0.4941 | 0.5153 | 0.5977 | |
| 39 | Low | 0.2496 | 0.3566 | 0.4213 | 0.4313 | 0.4334 | 0.4547 | 0.5466 | 0.5610 | 0.5923 | 0.2829 | 0.1421 |
| | Middle | 0.0759 | 0.2182 | 0.3270 | 0.4004 | 0.4713 | 0.5141 | 0.5576 | 0.6564 | 0.5723 | 0.4254 | |
| | High | -0.0002 | 0.0592 | 0.1778 | 0.1730 | 0.3421 | 0.4190 | 0.5045 | 0.5525 | 0.6121 | 0.6275 | |
| 52 | Low | 0.2047 | 0.3228 | 0.3531 | 0.3508 | 0.3968 | 0.4008 | 0.4182 | 0.3868 | 0.3170 | 0.0476 | 0.0454 |
| | Middle | 0.0856 | 0.2666 | 0.3235 | 0.4446 | 0.4731 | 0.5198 | 0.5366 | 0.5561 | 0.3850 | 0.2423 | |
| | High | -0.0801 | 0.2031 | 0.2286 | 0.2894 | 0.3844 | 0.4896 | 0.5083 | 0.5514 | 0.6353 | 0.3750 | |

This table presents the Sharpe ratios of the IPR-momentum portfolios (j=13, 26, 39, and 52 weeks) from January 1930 to December 2010. The Sharpe ratios are calculated by monthly IPR-momentum portfolio returns.

**Table 6:** Return correlations among the three strategies, momentum, value investing, and IPR-momentum

**Long-short value investing strategy:**

| | Momentum | IPR-Momentum | Value-1M | Value-1Y | Value-3Y | Value-5Y |
|---|---|---|---|---|---|---|
| Momentum | 1.0000 | | | | | |
| IPR | 0.6130 | 1.0000 | | | | |
| Value-1M | -0.0838 | -0.0593 | 1.0000 | | | |
| Value-1Y | -0.0262 | 0.0442 | 0.2109 | 1.0000 | | |
| Value-3Y | 0.0085 | -0.0023 | -0.0299 | -0.0848 | 1.0000 | |
| Value-5Y | 0.0450 | 0.0230 | 0.0186 | 0.0514 | 0.1382 | 1.0000 |

**Long value investing strategy:**

| | Momentum | IPR-Momentum | Value-1M | Value-1Y | Value-3Y | Value-5Y |
|---|---|---|---|---|---|---|
| Momentum | 1.0000 | | | | | |
| IPR | 0.6130 | 1.0000 | | | | |
| Value-1M | -0.0651 | -0.0325 | 1.0000 | | | |
| Value-1Y | -0.0251 | 0.0429 | 0.2219 | 1.0000 | | |
| Value-3Y | 0.0040 | 0.0001 | 0.0809 | 0.2485 | 1.0000 | |
| Value-5Y | -0.0014 | -0.0149 | 0.0734 | 0.2913 | 0.3484 | 1.0000 |

This table presents the return correlations among (a) the momentum strategy in Section 2.1, (b) value investing strategy [based on the book-to-market (B/M) ratio] in Section 5.3, and (c) the IPR-momentum strategy in Section 5.1. The data consist all non-financial firms in (a) the **NYSE**, the **AMEX**, and the **NASDAQ** return files from **CRSP** and (b) the merged **COMPUSTAT** annual accounting data over the period from 1962 to 2010. We implement a market neutral long-short portfolio strategy (i.e., forming a portfolio by buying top 10% high B/M ratios portfolio and selling bottom 10% low **B/M** ratio portfolio). We also form the value investing portfolios that start one month, one year, three years, or five years (labeled with "Value-1M," "Value-1Y," "Value-3Y," and "Value-5Y") backward. All portfolio returns are monthly and equally weighted. Long-short value investing strategy is on the top panel, and the long value investing strategy is on the bottom.

**Table 7:** Performance of the IPR portfolios for different (j, K)

| | | K-month holding period | | | | |
|---|---|---|---|---|---|---|
| j-week IPR | Portfolios | 1 | 3 | 6 | 9 | 12 |
| 13 | PR1(Low) | 1.66% | 3.43% | 5.64% | 8.22% | 10.92% |
| | | (0.0796) | (0.1629) | (0.2055) | (0.2403) | (0.2982) |
| | PR10(High) | 0.68% | 3.05% | 7.13% | 11.33% | 16.21% |
| | | (0.0675) | (0.1386) | (0.1932) | (0.2293) | (0.2983) |
| 26 | PR1(Low) | 1.36% | 2.97% | 4.85% | 6.87% | 10.05% |
| | | (0.0831) | (0.1628) | (0.2057) | (0.2467) | (0.3012) |
| | PR10(High) | 0.95% | 3.63% | 8.09% | 12.65% | 17.02% |
| | | (0.0683) | (0.1340) | (0.1915) | (0.2372) | (0.3006) |
| 39 | PR1(Low) | 1.23% | 2.80% | 4.17% | 6.50% | 9.96% |
| | | (0.0826) | (0.1704) | (0.2056) | (0.2462) | (0.3090) |
| | PR10(High) | 1.13% | 4.06% | 8.76% | 12.80% | 16.80% |
| | | (0.0692) | (0.1385) | (0.2037) | (0.2439) | (0.3008) |
| 52 | PR1(Low) | 0.90% | 2.20% | 4.00% | 6.64% | 10.21% |
| | | (0.0801) | (0.1576) | (0.2025) | (0.2447) | (0.3052) |
| | PR10(High) | 1.35% | 4.43% | 8.74% | 12.60% | 16.46% |
| | | (0.0699) | (0.1418) | (0.2093) | (0.2470) | (0.3120) |

This table presents the monthly equal-weight portfolio returns for the IPR strategy. The sample period is from January 1930 to December 2010. The stocks are sorted on a monthly basis into 10-decile portfolios based on their IPR values that are calculated using the returns of past j weeks, j=13, 26, 39, and 52. K denotes the monthly holding period, K=1, 3, 6, 9, and 12. The variances are in the parentheses.

**Table 8:** IPR and Short-term Reversal Effect

| | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 |
|---|---|---|---|---|---|---|---|---|---|---|
| I1 | 0.0253 | 0.0199 | 0.0158 | 0.0132 | 0.0126 | 0.0128 | 0.0074 | 0.0034 | -0.0031 | -0.0179 |
| | (0.0862 ) | (0.0689 ) | (0.0642 ) | (0.0634 ) | (0.0617 ) | (0.0669 ) | (0.0712 ) | (0.0811 ) | (0.0942 ) | (0.1197 ) |
| I2 | 0.0254 | 0.0178 | 0.0172 | 0.0140 | 0.0139 | 0.0124 | 0.0118 | 0.0102 | 0.0021 | -0.0107 |
| | (0.0844 ) | (0.0700 ) | (0.0619 ) | (0.0601 ) | (0.0579 ) | (0.0585 ) | (0.0606 ) | (0.0730 ) | (0.0738 ) | (0.0940 ) |
| I3 | 0.0235 | 0.0178 | 0.0164 | 0.0133 | 0.0135 | 0.0111 | 0.0118 | 0.0099 | 0.0045 | -0.0061 |
| | (0.0866 ) | (0.0684 ) | (0.0628 ) | (0.0568 ) | (0.0579 ) | (0.0567 ) | (0.0582 ) | (0.0605 ) | (0.0662 ) | (0.0918 ) |
| I4 | 0.0228 | 0.0182 | 0.0143 | 0.0133 | 0.0137 | 0.0131 | 0.0121 | 0.0107 | 0.0048 | -0.0051 |
| | (0.0849 ) | (0.0716 ) | (0.0635 ) | (0.0582 ) | (0.0537 ) | (0.0553 ) | (0.0549 ) | (0.0590 ) | (0.0655 ) | (0.0847 ) |
| I5 | 0.0230 | 0.0146 | 0.0135 | 0.0155 | 0.0133 | 0.0126 | 0.0116 | 0.0101 | 0.0065 | -0.0050 |
| | (0.0860 ) | (0.0707 ) | (0.0615 ) | (0.0578 ) | (0.0550 ) | (0.0543 ) | (0.0538 ) | (0.0577 ) | (0.0628 ) | (0.0765 ) |
| I6 | 0.0217 | 0.0176 | 0.0143 | 0.0145 | 0.0122 | 0.0130 | 0.0114 | 0.0108 | 0.0084 | 0.0016 |
| | (0.0903 ) | (0.0747 ) | (0.0641 ) | (0.0577 ) | (0.0548 ) | (0.0536 ) | (0.0521 ) | (0.0555 ) | (0.0590 ) | (0.0735 ) |
| I7 | 0.0228 | 0.0167 | 0.0144 | 0.0146 | 0.0125 | 0.0132 | 0.0111 | 0.0105 | 0.0084 | 0.0037 |
| | (0.0906 ) | (0.0722 ) | (0.0641 ) | (0.0595 ) | (0.0561 ) | (0.0541 ) | (0.0510 ) | (0.0527 ) | (0.0583 ) | (0.0684 ) |
| I8 | 0.0229 | 0.0166 | 0.0138 | 0.0123 | 0.0122 | 0.0117 | 0.0101 | 0.0099 | 0.0104 | 0.0047 |
| | (0.0959 ) | (0.0742 ) | (0.0640 ) | (0.0592 ) | (0.0567 ) | (0.0529 ) | (0.0514 ) | (0.0501 ) | (0.0562 ) | (0.0676 ) |
| I9 | 0.0228 | 0.0116 | 0.0117 | 0.0104 | 0.0141 | 0.0112 | 0.0107 | 0.0100 | 0.0098 | 0.0053 |
| | (0.1014 ) | (0.0801 ) | (0.0713 ) | (0.0609 ) | (0.0572 ) | (0.0526 ) | (0.0505 ) | (0.0517 ) | (0.0544 ) | (0.0656 ) |
| I10 | 0.0166 | 0.0110 | 0.0141 | 0.0122 | 0.0127 | 0.0121 | 0.0107 | 0.0098 | 0.0110 | 0.0084 |
| | (0.1168 ) | (0.0886 ) | (0.0780 ) | (0.0709 ) | (0.0597 ) | (0.0588 ) | (0.0535 ) | (0.0529 ) | (0.0536 ) | (0.0659 ) |

This table presents the relationship between IPR and short-term reversal effect. At the end of every month of 1963 to 2010, we sort the stocks by their previous month's IPR (labeled I1 to I10 from low to high) and independently sort the stocks by their previous month's return (labeled R1 to R10 from low to high). We track the one month holding returns of the 100 portfolios. The standard deviation are in the parentheses.

**Table 9:** IPR and Three Factor Portfolios

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| I | | | Beta | | | | | | | | | | |
| | | | B1 | B2 | B3 | B4 | B5 | B6 | B7 | B8 | B9 | B10 | Avg. |
| | IPR | L | 0.0117 | 0.0144 | 0.0140 | 0.0153 | 0.0163 | 0.0166 | 0.0155 | 0.0154 | 0.0157 | 0.0168 | 0.0152 |
| | | M | 0.0102 | 0.0114 | 0.0120 | 0.0117 | 0.0130 | 0.0143 | 0.0122 | 0.0114 | 0.0128 | 0.0118 | 0.0121 |
| | | H | 0.0078 | 0.0084 | 0.0087 | 0.0095 | 0.0102 | 0.0097 | 0.0108 | 0.0125 | 0.0115 | 0.0091 | 0.0098 |
| | | Avg. | 0.0099 | 0.0114 | 0.0116 | 0.0122 | 0.0132 | 0.0135 | 0.0128 | 0.0131 | 0.0133 | 0.0126 | |
| II | | | Size | | | | | | | | | | |
| | | | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | Avg. |
| | IPR | L | 0.0291 | 0.0197 | 0.0170 | 0.0161 | 0.0156 | 0.0155 | 0.0140 | 0.0130 | 0.0121 | 0.0109 | 0.0163 |
| | | M | 0.0220 | 0.0165 | 0.0158 | 0.0138 | 0.0139 | 0.0127 | 0.0125 | 0.0113 | 0.0107 | 0.0095 | 0.0139 |
| | | H | 0.0151 | 0.0146 | 0.0146 | 0.0157 | 0.0137 | 0.0134 | 0.0116 | 0.0101 | 0.0094 | 0.0079 | 0.0126 |
| | | Avg. | 0.0221 | 0.0169 | 0.0158 | 0.0152 | 0.0144 | 0.0139 | 0.0127 | 0.0115 | 0.0107 | 0.0094 | |
| III | | | B/M ratio | | | | | | | | | | |
| | | | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | Avg. |
| | IPR | L | 0.0134 | 0.0117 | 0.0121 | 0.0138 | 0.0148 | 0.0169 | 0.0177 | 0.0187 | 0.0217 | 0.0276 | 0.0168 |
| | | M | 0.0092 | 0.0103 | 0.0105 | 0.0109 | 0.0118 | 0.0131 | 0.0148 | 0.0155 | 0.0172 | 0.0231 | 0.0136 |
| | | H | 0.0114 | 0.0106 | 0.0119 | 0.0099 | 0.0112 | 0.0111 | 0.0114 | 0.0131 | 0.0149 | 0.0161 | 0.0122 |
| | | Avg. | 0.0113 | 0.0109 | 0.0115 | 0.0115 | 0.0126 | 0.0137 | 0.0146 | 0.0158 | 0.0179 | 0.0223 | |

This table presents the relationship between the IPR index and the cross-sectional returns based on the well-known three factors, the market beta, the firm size and the book-to-market ratio. At the end of every month of 1963 to 2010, we sort the stocks by their previous month's IPR (labeled L, M and H from low to high) and independently sort the stocks by their previous month's **NYSE**-based betas (labeled B1 to B10 from low to high), sizes (labeled S1 to S10 from small to big), and **B/M** ratios (labeled R1 to R10 from low to high). We track the one month holding portfolio returns of the 30 portfolios. All the portfolio returns are equally-weighted. Avg. denotes the average.