THREE ESSAYS ON STOCK MARKET SEASONALITY

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
College of Management

Georgia Institute of Technology
December 2008

THREE ESSAYS ON STOCK MARKET SEASONALITY

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To My Wife Ji-Hyun and My Son Hyun-Woo

ACKNOWLEDGEMENTS

I would like to thank my dissertation advisor, Cheol Eun, for his guidance and support. I am grateful to the other committee members, Narayanan Jayaraman, Suzanne Lee, Qinghai Wang, and Rehim Kilic, for their helpful comments and willingness to help out. I want to thank Jonathan Clarke for his advice and support in many aspects. I am greatly indebted to Tuugi Chuluun for being such a good friend and making this lengthy journey interesting. I also want to thank my fellow PhD students for their encouragement.

I would like to express my gratitude to my wife, Ji-Hyun Kim, for her constant support, encouragement, and love. Any success that I have achieved is only because of her. I want to thank my son, Hyun-Woo, for coming to this world and making me refreshed every time I got tired. Finally I want to gratefully acknowledge my parents who always pray for me. With all my heart, I dedicate this dissertation to my family.

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SUMMARY

In chapter 1, we examine seasonality in returns to style portfolios, which serve as important benchmarks for asset allocation, and investigate its implications for investment. In doing so, we consider monthly returns on the style portfolios classified by six size/book-to-market sorting and six size/prior-return sorting over the sample period 1927 - 2006. The key findings are: first, as is well documented in the literature, small-cap oriented portfolios are subject to the January effect, but also to the ‘negative’ September and October effects. Second, cross-style return dispersion exhibits a seasonal pattern of its own (it is largest in January and smallest in August), suggesting possibly profitable trading strategies. Third, our seasonal strategies indeed yield significant profits, as high as about 18.7 % per annum. This profit is mostly attributable to the seasonal autocorrelation in style returns. Lastly, we find substantial seasonal patterns in style returns not only in the U.S. but also in other major stock markets – Germany, Japan, and the U.K. Our seasonal style rotation strategy yields economically and statistically significant profits in all of these stock markets.

In chapter 2, we examine the abnormal, negative stock returns in September which have received little attention from academic researchers. We find that in most of the 18 developed stock markets the mean return in September is negative and in 15 countries it is significantly lower than the unconditional monthly mean return. This September effect has not weakened in the recent period. Further, the examinations of the various style portfolios in the US market show that the September effect is the most pervasive anomalous phenomenon that is not affected by size, book-to-market ratio, past

performance, or industry. Our finding suggests that the forward looking nature of stock prices combined with the negative economic growth in the last quarter causes the September effect. Especially in the fall season when most investors become more risk averse, the stock prices reflect the future economic growth more than the rest of the year. Our investment strategy based on the September effect yields a higher mean return and a lower standard deviation than the buy-and-hold strategy.

In chapter 3, we establish the presence of seasonality in the cash flows to the U.S. domestic mutual funds. January is the month with the highest net cash flows to equity funds and December is the month with the lowest net cash flows. The large net flows in January are attributed to the increased purchases, and the small net flows in December are due to the increased redemptions. Thus, the turn-of-the-year period is the time when most mutual fund investors make their investment decisions. We offer the possible sources for the seasonality in mutual funds flows.

CHAPTER 1

SEASONALITY IN STYLE RETURNS

1.1 Introduction

Investors group assets into different classes based on some similar attributes among them. For example, stocks can be categorized into broad classes such as small versus large stocks, value versus growth stocks, prior winners versus losers, or categorized by different industry sectors. The asset classes are called "styles" and the process allocating money among styles is called "style investing" (See, Barberis and Shleifer (2003)). Sometimes investors must consider styles because portfolio allocation among different styles is required by law. For instance, a pension sponsor must follow systematic rules of asset allocation imposed by the Employee Retirement Income Security Act. Even when it is not required, as Barberis and Shleifer (2003) argue, it would be human nature to classify objects with the benefit of simplifying problems of choice. Recently, Peng and Xiong (2006) show that investors tend to process more market and sector-wide information than firm-specific information, because attention is a scarce resource and an enormous amount of new information comes into the market at lightning speeds.

Much of academic literature has shown that certain styles outperform other styles in the long run[1]. In particular, small-cap (value) stocks outperformed large-cap (growth)

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[1] See, for example, Banz (1981), Fama and French (1992), Jegadeesh and Titman (1993), La Porta (1996), Daniel and Titman (1997), Barber and Lyon (1997), Carhart (1997), and Lewellen (1999).

stocks historically. However, the relative performance between these styles is not stable over time. Chan, Karceski, and Lakonishok (2000), for example, show that large-cap (growth) stocks outperform small-cap (value) stocks in 13 years (8 years) out of their 29 year sample period from 1970 to 1998. Style based strategy can produce long periods of poor performance. Thus, style rotation strategy, switching from one style to another, could generate additional returns when we can forecast the relative performance between styles.

In this study, we examine seasonal patterns in the cross-section of expected returns on twelve style portfolios. Instead of focusing on the returns on style index or mutual funds, we focus on the returns on the style portfolios classified by six size/book-to-market sorting and six size/prior-return sorting. We do so for three reasons. First, we need a substantially long sample period to test the seasonal pattern. While the style indexes used in the previous studies, such as Wilshire Style Index, are available only from the mid-1970's, we investigate the style returns over 80 years. Mutual fund style classification also has the same problem of the short available sample period. Second, our seasonal strategy requires monthly portfolio rebalancing so it is critical to make the style of the portfolio to be persistent while mutual funds could deviate from their stated style objects. Third, the characteristics of those twelve style portfolios are comparable to the commonly used Morningstar style classification and those portfolios are likely to have seasonal patterns as suggested by previous studies.

We find that style returns exhibit substantial variations across calendar months. For example, over the sample period of January 1927 to December 2006, in January the mean return of the Small/Down portfolio is 6.2 percent and that of the Big/Up portfolio is only 1.3 percent. However, in March the mean return of the Small/Down portfolio is 0.03 percent and that of the Big/Up portfolio is 1.26 percent. Our finding is consistent with previous literature on seasonality in stock returns which suggests the outperformance of some style against another in a specific calendar month. For example, Keim (1983), Reinganum (1983), and Roll (1983) find that small-cap stocks outperform large-cap stocks in January. Branch (1977) and Dyl (1977) suggest that tax-loss selling creates a downward price pressure on loser stocks in December and a price rebound in January. Lakonishok, Shleifer, Thaler, and Vishny (1991) find that pension funds dump prior loser stocks at the end of every quarter. However, these studies explored only the turn-of-the-year period or the end of each quarter.[2] Our finding shows that the seasonal pattern of style returns is not limited to January or the end of each quarter. Small stocks perform poorly in October and the Big/Value portfolio beat the market in April and July. Unexpectedly, our seasonality test of style portfolio returns reveals that all twelve style portfolios perform poorly in September. This is the most pervasive seasonal regularity in the stock market.

We also propose a style rotation strategy using the seasonal pattern among style returns. We take the long positions of styles with good performance in a specific calendar month and the short positions of styles that have done poorly in the same calendar month. For example, we rank the twelve style portfolios according to their average returns during the previous five Januaries to construct a zero investment portfolio for the next January.

[2] To our knowledge, the only academic study to explore the general seasonal variation across stock returns is Heston and Sadka (2008). They find that stocks tend to have relatively high (or low) returns every year in the same calendar month.

We repeat this for each of twelve calendar months. Our strategy is different from the style rotation strategies that have been employed by the previous literature.[3] The focus of this study is not to explain or predict the relative style performance but to utilize the seasonal patterns in the style returns that we observe. The strategy yields profits across all calendar months. Specifically, the mean profit in January alone is 4.5 percent. Overall, our seasonal strategy yields economically and statistically significant profits of 18.7 percent per year.

The possible source of the profit from our strategy is seasonal autocorrelation in style returns (predictability component) or cross-sectional variation (dispersion component) in style returns (see, Lo and MacKinlay (1990) and Conrad and Kaul (1998)). The decomposition of the profit shows that the main source of the profit is the predictability component. The predictability component explains more than 90 percent of the profit in every calendar month. Therefore, the seasonal patterns among style returns have significant power to forecast future relative style performance, which seems to be inconsistent with the efficient market hypothesis.

Lastly, we find substantial seasonal patterns in style returns not only in the U.S. but also in other major stock markets – Germany, Japan, and the U.K. The outperformance of Small portfolios in January is strong across all major stock markets, but this size effect is reversed in December. Most styles have been either the best or the worst performing style in some month, in some country. For example, the Small/Value

[3] Barberis and Shleifer (2003) proposed the style-level momentum and value strategies. Levis and Liodakis (1999), Asness, Friedman, Krail, and Liew (2000), Lucas, Dijk, and Kloek (2002), and Wang (2005) proposed models to predict relative style performance using macro-economic variables.

portfolio is the best performing style in February and April in Germany but it is the worst performing style in November in the U.K. Surprisingly, September is the worst month for most of the style portfolios in all countries. All twelve style portfolios in Germany yield negative mean September returns. Our seasonal style rotation strategy yields economically and statistically significant profits in all the major stock markets. The strategy yields 11.1 % in Germany, 11.4 % in Japan, 17.9 % in the U.K., and 16.2 % in the U.S. per year over 1987 – 2006.

The rest of this paper proceeds as follows. Section 2 describes the style portfolio construction and seasonal patterns in their returns. Section 3 reports the seasonality test results of style portfolio returns, while section 4 describes the style rotation strategy to exploit this seasonality. Section 5 examines a seasonal pattern in style portfolio returns in the major stock markets and the performance of the style rotation strategy. Finally, section 6 concludes.

1.2 Style Portfolio Returns by Month

To study the seasonality in style returns, we use monthly returns on six size/book-to-market sorted portfolios and six size/prior-return sorted portfolios[4] over the sample period of January 1927 – December 2006. At the end of each June, firms are sorted independently along size and book-to-market ratios to construct Small, Big, Value, Neutral, and Growth portfolios. The median NYSE market equity is the size breakpoint and the 30th and 70th NYSE book-to-market percentiles are the book-to-market

[4] We thank Kenneth French for making the data available. The data on the style portfolios are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

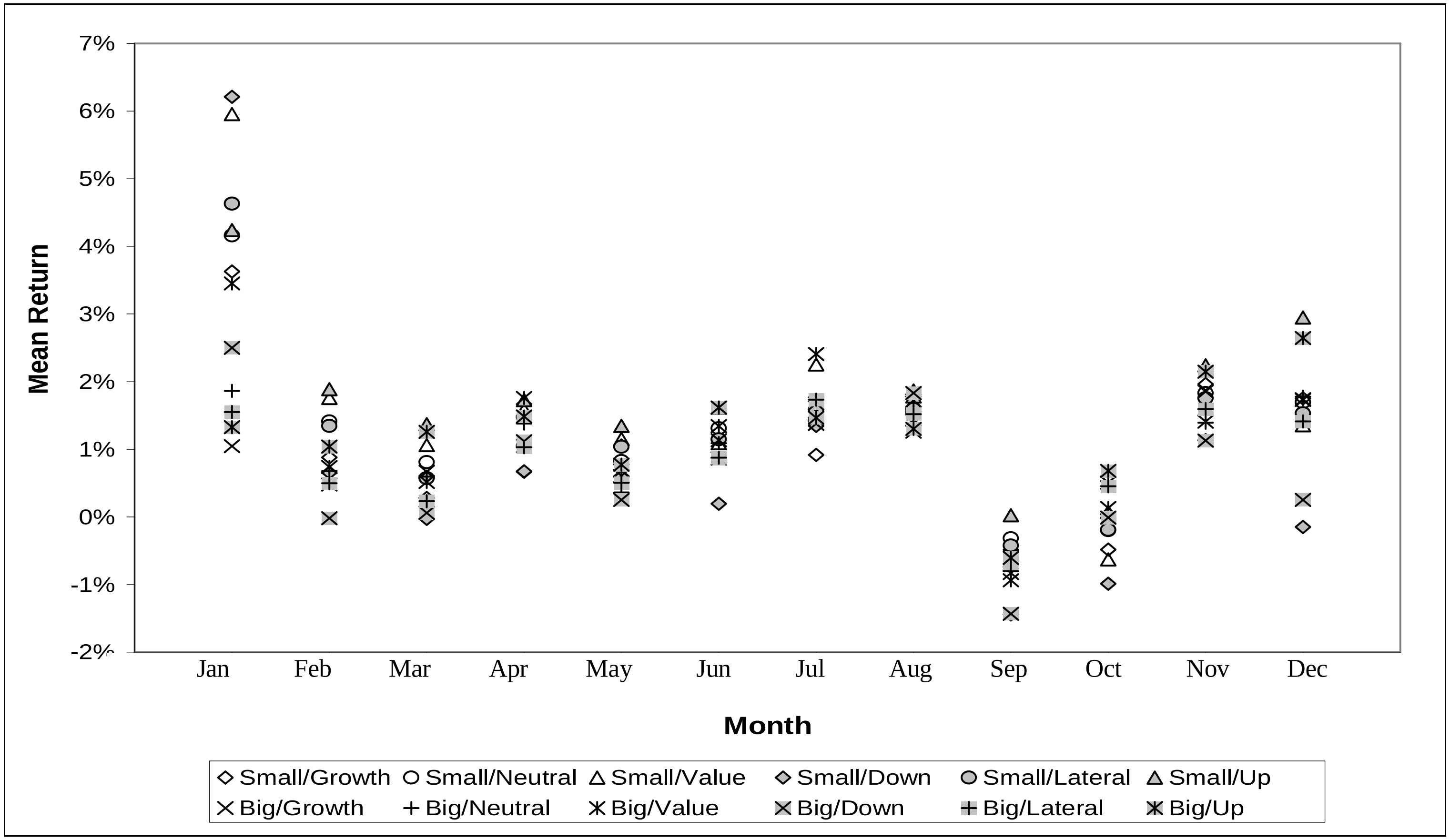
breakpoints. Thus the first six style portfolios used in this study are Small/Value, Small/Neutral, Small/Growth, Big/Value, Big/Neutral, and Big/Growth.

In addition, at the end of each month *t*, firms are sorted independently along size at month *t-1*, and prior returns over month *t-12* through *t-2* to construct Small, Big, Up, Lateral, and Down portfolios. The monthly size breakpoint is the median NYSE market equity and the monthly prior return breakpoints are 30^{th} and 70^{th} NYSE percentiles. Thus, the next six style portfolios used in this study are Small/Up, Small/Lateral, Small/Down, Big/Up, Big/Lateral, and Big/Down.

We compute the mean return by calendar month for each of the twelve style portfolios during our sample period January 1927 – December 2006. The results are presented in Table 1 and illustrated in Figure 1. Table 1 also provides the *t*-statistics from the paired *t*-test between each style portfolio return and the CRSP value weighted market return in parenthesis.

As can be seen from Figure 1.1, style returns exhibit substantial seasonal variations across calendar months. Consistent with the well known January effect, which would be caused by the small firm effect or the tax-loss selling, returns tend to be high in January, especially for Small and Down portfolios. In January, the mean return of the Small/Growth (Small/Neutral, Small/Value) portfolio is 3.63% (4.16%, 5.96%) and that of the Small/Down (Small/Lateral, Small/Up) portfolio is 6.21% (4.63%, 4.24%). All of these returns are significantly higher than the CRSP value weighted market return at any conventional level. The mean January return of the Big/Down portfolio is 2.50% which is significantly greater than the market return at the 10% level. We also note that the mean return of the Value portfolio is high in January. Small/Value portfolio return is 5.96% and

Figure 1.1: Size/Book-to-Market and Size/Prior-Return Portfolio Returns by Month



We plot the monthly mean returns of the six size/book-to-market portfolios and the six size/prior-return portfolios by month. At the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The median NYSE market equity is the size breakpoint; the 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints; and the monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. Portfolio percentage returns are calculated by month. The analysis uses NYSE, AMEX, and NASDAQ-listed stocks for the period January 1927 through December 2006.

Big/Value portfolio return is 3.45%. They are significantly higher than the market return at the 1% level.

Consistent with the tax-loss selling hypothesis, the mean December return on the Down portfolio is low and that of the Up portfolios is high. The mean return of the Small/Down portfolio is -0.15% and that of the Big/Down portfolio is 0.25% in December. Meanwhile, the mean December return of the Small/Up portfolio is 2.95% and that of the Big/Up portfolio is 2.65%. Surprisingly, the mean returns are uniformly negative across all style portfolios in September with the exception of the Small/Up portfolio. Considering the mean September return of the Small/Up portfolio is marginally positive, September turns out to be the cruel month in terms of mean returns. Although major market crashes occurred most often in October, (e.g., October 19, 1987 and October 28-29, 1929), the negative September return across almost all style portfolios is somewhat puzzling.

Table 1.1 also shows how the relative returns among contrasting style portfolios (i.e., Small vs. Big, Value vs. Growth, and Up vs. Down) vary across calendar months. Controlling for the size, the Value portfolios have higher returns than the Growth portfolios in the first half of the year but the situation is reversed with the latter having a higher return than the former. In the case of Up vs. Down portfolios, the Small/Up portfolio has a higher return than the Small/Down portfolio in each month except January and the Big/Up portfolio has a higher return than the Big/Down portfolio in eight out of twelve months. Thus, Table 1.1 provides evidence of the substantial value premium and momentum premium and these style premiums are much stronger between Small portfolios than Big portfolios. The value premium between Small portfolios (Small/Value

Table 1.1: Style Portfolio Returns by Month

This table reports the mean returns of the six size/book-to-market portfolios and the six size/prior-return portfolios by month. At the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The median NYSE market equity is the size breakpoint; the 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints; and the monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. Portfolio percentage returns are calculated by month. The last row (Market) reports the mean CRSP value weighted return by month. The *t*-statistics from the paired *t*-test between each style portfolio return and the CRSP value weighted return are reported in the parenthesis. The analysis uses NYSE, AMEX, and NASDAQ-listed stocks for the period January 1927 through December 2006. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Small/Growth	3.630 ***	0.879	0.279	0.669	1.056	0.874	0.916	1.347	-0.486	-0.485 **	1.965	1.752
	(4.88)	(0.59)	(-0.71)	(-1.25)	(0.80)	(-0.51)	(-1.33)	(-0.03)	(0.96)	(-2.04)	(0.80)	(-0.05)
Small/Neutral	4.163 ***	1.412 ***	0.811	1.471	0.826	1.311	1.425	1.544	-0.317	-0.195 *	1.832	1.696
	(6.14)	(2.77)	(0.87)	(1.01)	(0.51)	(0.74)	(-0.14)	(0.52)	(1.51)	(-1.81)	(0.68)	(-0.24)
Small/Value	5.955 ***	1.760 ***	1.063	1.587	1.152	1.091	2.255	1.870	-0.696	-0.628 ***	1.682	1.356
	(7.51)	(3.15)	(1.26)	(1.10)	(0.89)	(-0.01)	(1.54)	(0.74)	(0.28)	(-2.69)	(0.11)	(-0.97)
Big/Growth	1.047 ***	0.480	0.666	1.051	0.683	1.135	1.376	1.260	-0.831	0.506	1.853 *	1.731
	(-5.07)	(-1.15)	(0.84)	(-0.58)	(1.61)	(0.33)	(-0.59)	(-0.80)	(0.26)	(1.24)	(1.83)	(-0.30)
Big/Neutral	1.863	0.677	0.596	1.381	0.363	1.090	1.708	1.554	-0.806	0.529	1.393	1.777
	(0.49)	(0.29)	(0.17)	(1.06)	(-0.97)	(-0.03)	(0.97)	(0.85)	(0.34)	(1.01)	(-1.21)	(0.04)
Big/Value	3.452 ***	0.736	0.518	1.758 *	0.607	1.341	2.409 *	1.721	-0.938	0.133	1.410	1.739
	(4.35)	(0.33)	(-0.16)	(1.84)	(0.25)	(0.70)	(1.69)	(0.91)	(-0.19)	(-0.60)	(-0.65)	(-0.10)
Small/Down	6.212 ***	0.655	-0.031	0.673	0.602	0.196 *	1.347	1.509	-1.442	-0.987 ***	1.135	-0.149 ***
	(6.51)	(0.10)	(-1.64)	(-0.96)	(0.11)	(-1.94)	(-0.21)	(0.19)	(-0.83)	(-3.02)	(-1.08)	(-3.93)
Small/Lateral	4.632 ***	1.345 ***	0.574	1.049	1.035	1.148	1.589	1.596	-0.423	-0.191 *	1.756	1.532
	(6.48)	(2.91)	(0.03)	(-0.30)	(0.73)	(0.17)	(0.36)	(0.51)	(1.16)	(-1.98)	(0.41)	(-0.68)
Small/Up	4.241 ***	1.888 ***	1.371 **	1.726	1.346	1.613	1.509	1.781	0.024 ***	0.076	2.241 *	2.948 ***
	(5.61)	(3.13)	(2.14)	(1.58)	(1.29)	(1.27)	(0.11)	(1.25)	(2.77)	(-0.70)	(1.68)	(3.46)
Big/Down	2.501 *	-0.020 *	0.059	1.118	0.252	0.865	1.678	1.832	-1.432	-0.009	1.127	0.250 ***
	(1.88)	(-1.89)	(-1.63)	(-0.05)	(-0.72)	(-0.56)	(0.37)	(0.86)	(-1.45)	(-0.98)	(-1.62)	(-5.09)
Big/Lateral	1.550 *	0.498	0.234 **	1.029	0.504	0.876	1.734 *	1.518	-0.690	0.452	1.596	1.413 *
	(-1.90)	(-0.68)	(-2.17)	(-0.75)	(-0.11)	(-1.08)	(1.68)	(1.02)	(1.09)	(0.70)	(-0.28)	(-1.86)
Big/Up	1.328 *	1.039 **	1.258 ***	1.485	0.771	1.618 **	1.466	1.302	-0.605	0.682	2.148 *	2.647 ***
	(-1.95)	(2.27)	(4.10)	(1.42)	(1.59)	(2.55)	(-0.01)	(-0.23)	(1.20)	(1.64)	(1.87)	(4.22)
Market	1.783	0.617	0.565	1.136	0.518	1.095	1.469	1.362	-0.863	0.341	1.638	1.770

– Small/Growth) is 6.05% per year but the value premium between Big portfolios (Big/Value – Big/Growth) is only 3.93% per year. The difference of the momentum premium between the Small and the Big portfolios is much bigger than that of the value premium. The momentum premium between Small portfolios (Small/Up – Small/Down) is 11.04% per year but the momentum premium between Big portfolios (Big/Up – Big/Down) is only 6.92% per year.

The size premium is also prevalent across all book-to-market style portfolios and momentum style portfolios. The cumulative size premium between Up portfolios (Small/Up – Big/Up) is 5.63% per year and the Small/Up portfolio has a higher return than Big/Up portfolio in each month, except June and October. The Small/Down portfolio outperforms the Big/Down portfolio in only four months but the cumulative size premium between Down portfolios (Small/Down – Big/Down) is still positive, 1.50%. The cumulative size premiums between Value portfolios and between Growth portfolios are also positive.

Figure 1.1 shows that certain style portfolios outperform the others in a specific month and that this is not limited to the turn-of-the-year period. For example, the Small/Down portfolio is the best performing style portfolio in January, the Small/Value is in August, the Big/Value is in April and July, and the Big/Up is in June and October. Interestingly, the Small/Up portfolio is the best performing style portfolio in the remaining six months. This varied performance among the style portfolios in different months motivates us to try our innovative style rotation strategies based on the seasonality which will be discussed in section 4.

1.3 Seasonality Test of Style Portfolio Returns

We now set a framework to test seasonality in style returns. To formally test the null hypothesis that the style returns in each calendar month are not different from the unconditional mean monthly return, we use the following time series regression model for the return (R_{it}) on the ith style portfolio in month t:

$$R_{it} = \alpha_i + \beta_{i1} M_{1t} + \beta_{i2} M_{2t} + \quad \dots \quad + \beta_{i12} M_{12t} + e_{it} \tag{1}$$

where α_i is the unconditional monthly mean return, M_{jt} is the calendar month dummy variable that is to equal one if the month t is the jth month of the year and zero otherwise, and e_{it} is the error term. We impose the restriction that the sum of the coefficients of the calendar month dummy variable is to be zero for each style portfolio i (i.e. $\sum_{j=1}^{12} \beta_{ij} = 0$).

Under this restriction, the OLS estimate of the regression intercept, $\hat{\alpha}_i$, now becomes the cross-month average return, whereas the estimated coefficient for each month dummy, $\hat{\beta}_{ij}$, indicates how the mean return for the month differs from the cross-month average return. Note that this paper is concerned with establishing overall seasonal patterns in each style portfolio, rather than narrowly focusing on the January effect.

Table 1.2 provides the seasonality test results. First, the intercept shows that the Small/Up is the best performing style fund and the Big/Down is the worst performing style fund in general. Also, the size premium, value premium, and the momentum premium are clearly present. The mean monthly Small/Growth (Small/Value, Small/Down, Small/Up) portfolio return is 0.12% (0.30%, 0.13%, 0.47%) higher than the mean monthly Big/Growth (Big/Value, Big/Down, Big/Up) portfolio return. The mean monthly Small/Value (Big/Value) portfolio return is 0.50% (0.33%) higher than the

Table 1.2: Seasonality Test of Style Portfolio Returns

This table reports the OLS regression results of the six size/book-to-market portfolios and the six size/prior-return portfolios. At the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The median NYSE market equity is the size breakpoint; the 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints; and the monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. We impose the restrictions that for each model with a different portfolio the sum of coefficients of the independent variables must be zero so that the intercept becomes the overall mean return over the entire sample period. The *t*-statistics are reported in the parenthesis. The analysis uses NYSE, AMEX, and NASDAQ-listed stocks for the period January 1927 through December 2006. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

	Small/Growth	Small/Neutral	Small/Value	Big/Growth	Big/Neutral	Big/Value	Small/Down	Small/Lateral	Small/Up	Big/Down	Big/Lateral	Big/Up
Intercept	1.033 ***	1.332 ***	1.537 ***	0.913 ***	1.01 ***	1.24 ***	0.81 ***	1.304 ***	1.73 ***	0.685 ***	0.893 ***	1.261 ***
	(4.09)	(5.82)	(5.77)	(5.24)	(5.39)	(5.30)	(2.75)	(5.51)	(7.30)	(2.80)	(4.90)	(7.01)
Jan	2.597 ***	2.831 ***	4.418 ***	0.134	0.853	2.212 ***	5.402 ***	3.329 ***	2.511 ***	1.816 **	0.657	0.067
	(3.10)	(3.73)	(5.00)	(0.23)	(1.37)	(2.85)	(5.53)	(4.24)	(3.19)	(2.24)	(1.09)	(0.11)
Feb	-0.154	0.08	0.223	-0.433	-0.334	-0.505	-0.155	0.042	0.158	-0.705	-0.395	-0.223
	(-0.18)	(0.11)	(0.25)	(-0.75)	(-0.54)	(-0.65)	(-0.16)	(0.05)	(0.20)	(-0.87)	(-0.65)	(-0.37)
Mar	-0.754	-0.52	-0.475	-0.247	-0.414	-0.723	-0.84	-0.73	-0.36	-0.626	-0.659	-0.003
	(-0.90)	(-0.69)	(-0.54)	(-0.43)	(-0.67)	(-0.93)	(-0.86)	(-0.93)	(-0.46)	(-0.77)	(-1.09)	(-0.01)
Apr	-0.364	0.14	0.05	0.138	0.371	0.517	-0.137	-0.255	-0.004	0.433	0.136	0.223
	(-0.43)	(0.18)	(0.06)	(0.24)	(0.60)	(0.67)	(-0.14)	(-0.32)	(-0.01)	(0.53)	(0.23)	(0.37)
May	0.023	-0.505	-0.385	-0.23	-0.648	-0.634	-0.208	-0.268	-0.385	-0.433	-0.389	-0.491
	(0.03)	(-0.67)	(-0.44)	(-0.40)	(-1.04)	(-0.82)	(-0.21)	(-0.34)	(-0.49)	(-0.53)	(-0.64)	(-0.82)
Jun	-0.159	-0.021	-0.446	0.222	0.079	0.101	-0.614	-0.155	-0.118	0.18	-0.017	0.356
	(-0.19)	(-0.03)	(-0.50)	(0.38)	(0.13)	(0.13)	(-0.63)	(-0.20)	(-0.15)	(0.22)	(-0.03)	(0.60)
Jul	-0.117	0.093	0.718	0.463	0.698	1.169	0.537	0.285	-0.221	0.993	0.841	0.205
	(-0.14)	(0.12)	(0.81)	(0.80)	(1.12)	(1.51)	(0.55)	(0.36)	(-0.28)	(1.22)	(1.39)	(0.34)
Aug	0.314	0.212	0.333	0.347	0.543	0.48	0.699	0.292	0.051	1.147	0.625	0.04
	(0.37)	(0.28)	(0.38)	(0.60)	(0.87)	(0.62)	(0.72)	(0.37)	(0.06)	(1.41)	(1.03)	(0.07)
Sep	-1.519 *	-1.648 **	-2.233 **	-1.744 ***	-1.816 ***	-2.179 ***	-2.252 **	-1.726 **	-1.707 **	-2.117 ***	-1.583 ***	-1.867 ***
	(-1.81)	(-2.17)	(-2.53)	(-3.02)	(-2.92)	(-2.81)	(-2.31)	(-2.20)	(-2.17)	(-2.61)	(-2.62)	(-3.13)
Oct	-1.518 *	-1.527 **	-2.165 **	-0.407	-0.482	-1.108	-1.797 *	-1.494 *	-1.655 **	-0.694	-0.441	-0.58
	(-1.81)	(-2.01)	(-2.45)	(-0.70)	(-0.78)	(-1.43)	(-1.84)	(-1.90)	(-2.10)	(-0.85)	(-0.73)	(-0.97)
Nov	0.932	0.501	0.145	0.94	0.383	0.169	0.325	0.452	0.511	0.442	0.703	0.887
	(1.11)	(0.66)	(0.16)	(1.63)	(0.62)	(0.22)	(0.33)	(0.58)	(0.65)	(0.54)	(1.16)	(1.49)
Dec	0.719	0.365	-0.181	0.817	0.767	0.499	-0.959	0.228	1.217	-0.435	0.52	1.385 **
	(0.86)	(0.48)	(-0.21)	(1.41)	(1.23)	(0.64)	(-0.98)	(0.29)	(1.55)	(-0.54)	(0.86)	(2.32)
N	960	960	960	960	960	960	960	960	960	960	960	960
adj-R^2	0.007	0.0117	0.0252	0.0042	0.0049	0.0109	0.0283	0.0153	0.0102	0.0062	0.0036	0.0073
F value	1.61 *	2.03 **	3.25 ***	1.37	1.43	1.96 **	3.53 ***	2.35 ***	1.9 **	1.55	1.31	1.65 *

mean monthly Small/Growth (Big/Growth) portfolio return. The mean monthly Small/Up (Big/Up) portfolio return is 0.92% (0.58%) higher than the mean monthly Small/Down (Big/Down) portfolio return.

As can be seen from the table, the January dummy variable is significantly positive for most of the twelve style portfolios at the 5-percent level or better except Big/Growth, Big/Neutral, Big/Lateral, and Big/Up portfolios. Specifically, the January dummy is significant for all Small portfolios (Small/Growth, Small/Neutral, Small/Value, Small/Down, Small/Lateral, and Small/Up) at the 1-percent level confirming that the January effect is driven by small firms. However, the January dummies for the Big/Value and Big/Down portfolio are also significantly positive suggesting that the January effect is also related with investor sentiment and tax-loss selling.

Notably, the September dummy is significantly negative for each of the twelve style portfolios at any conventional level. In particular, the September dummy is significant for all Big portfolios (Big/Growth, Big/Neutral, Big/Value, Big/Down, Big/Lateral, and Big/Up) at the 1-percent level. It is also noted that the October dummy has a negative coefficient for every style portfolio, but it is significant only for Small portfolios at the 10- or 5-percent level. In addition, the December dummy is found to be positively significant for one portfolio, Big/Up portfolio, at the 5-percent level. F-statistics indicate that the month dummy variables are collectively significant for eight out of the twelve style portfolios at the 10-percent level or better. It is noted that the adjusted R-square is rather small for all style portfolios.

Overall, the test results presented in Table 1.2 indicate that small-cap oriented portfolios are significantly subject to the January, September, and October effects, whereas large-cap oriented portfolios are mostly subject to the September effect. Clearly, the September effect is the most pervasive, affecting every category of style portfolios. Although practitioners are aware of this September effect, it has received little attention from academic researchers. This is in sharp contrast to the January effect that spawned a long strand of papers offering alternative documentations and explanations.

1.4 Seasonality Based Style Rotation Strategies

The seasonality of style portfolios presented in Table 1.1 and 1.2 motivates us to try new style rotation strategies based on historical returns. We form the following relative strength strategy to exploit the effect of lagged returns at distinct annual intervals. Unlike other style momentum strategies that use the contiguous past performance information to form portfolio weights, our portfolio weights depend on the relative performances of style portfolios during the same calendar month in previous years. For example, the trading strategy that is formed based on past January returns during year 1 through 5 ranks the twelve style portfolio returns according to their average returns during the previous five Januaries.

More specifically, consider buying or selling style portfolios at the beginning of each month t based on their performance in the same calendar month j over the previous k year(s). For example, at the beginning of January 2005, the portfolios are constructed based on the performance in five Januaries from year 2000 to 2004 considering k of 5. The performance of a style portfolio is determined relative to the average performance of the twelve style portfolios in this study. Finally, let $w_{ijt}(k)$ denote the fraction of the trading strategy portfolio devoted to a style portfolio i over a calendar month j, that is,

$$w_{ijt}(k) = (\mu_{ijt}(k) - \overline{\mu}_{jt}(k))/12 \quad (2)$$

where $\mu_{ijt}(k)$ is the average calendar month *j* return of the style portfolio *i* over the past *k* years and $\overline{\mu}_{jt}(k)$ is the mean of $\mu_{ijt}(k)$'s of the twelve style portfolios. The holding period is one month while we use four different portfolio formation periods *k* years, i.e., 1, 5, 10, and 20 to see whether relying on more years in ranking would generate additional returns.

Table 1.3 shows the average profit for trading strategies separately implemented for each calendar month during the period January 1947 through December 2006[5]. The last column reports the annual average cumulative return from the strategy. The corresponding Newey-West *p*-values are also reported in parentheses. We note several interesting features of the profitability of the trading strategy. First, the strategy yields profits across all calendar months other than September. When we use the previous 20 years historical returns with annual lags to form the portfolio, the strategy yields profits in every calendar month and the returns are significantly positive at the 5-percent level in 7 out of 12 calendar months. This strategy yields the largest profit in January (4.52%), followed by December (2.69%), November (2.47%), and March (1.74%) and these are all statistically and economically significant. Therefore, our strategy is quite successful not only in the turn-of-year period as the previous literature on seasonality would suggest, but also in nearly every calendar month.

[5] To compare the returns of strategies based on previous one year's performance to those based on previous 20 year's performance, we use the sample starting from the year 1947 instead of 1928.

Table 1.3: Seasonal Strategy Returns with the Style Portfolios

At the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. The median NYSE market equity is the size breakpoint and the 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The monthly size breakpoint is the median NYSE market equity and the monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. At the end of each month, firms are sorted independently along book-to-market ratio and prior (2-12) return to construct Value, Neutral, Growth, Up, Lateral, and Down portfolios. The 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints. The monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. We calculate twelve style portfolio percentage returns by month and rank them according to various categories based on past performance of the calendar month indicated. For example, the trading strategy that is formed based on past January returns during year 1 through 5 ranks the twelve style portfolio returns according to their average returns during the previous five Januaries. The strategy has the weight of $(\mu_{it} - \overline{\mu}_t)/12$, where μ_{it} is the average return during the five Januaries of the portfolio *i* and $\overline{\mu}_t$ is the mean of the average portfolio returns. The mean returns from the strategy are reported separately for every calendar month during the period January 1947 through December 2006. The last column reports the annual average cumulative return from the strategy. The corresponding Newey-West *p*-values are also reported in parenthesis.

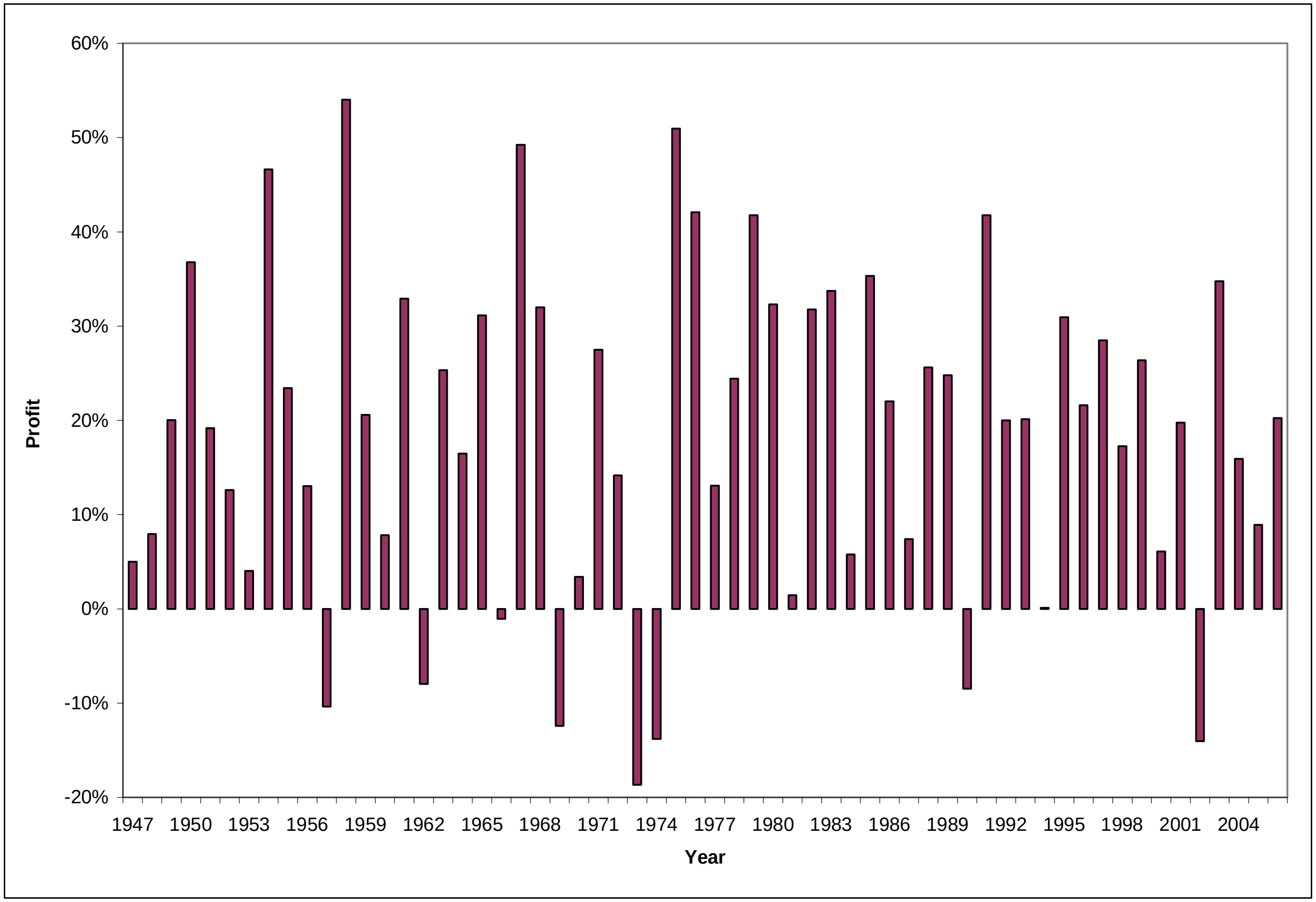
Strategy	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan - Dec
Year 1	3.88	0.66	1.47	1.30	0.88	0.68	0.64	0.82	-0.18	0.56	2.98	2.46	16.16
	(0.00)	*(0.21)*	*(0.01)*	*(0.02)*	*(0.13)*	*(0.21)*	*(0.29)*	*(0.26)*	*(0.76)*	*(0.46)*	*(0.00)*	*(0.00)*	*(0.00)*
Year 1 - 5	4.15	0.74	1.65	1.51	0.75	0.74	0.97	0.80	-0.05	0.72	2.63	2.58	17.19
	(0.00)	*(0.23)*	*(0.00)*	*(0.00)*	*(0.19)*	*(0.27)*	*(0.12)*	*(0.19)*	*(0.94)*	*(0.27)*	*(0.00)*	*(0.00)*	*(0.00)*
Year 1 - 10	4.43	0.93	1.48	1.48	0.81	0.66	1.13	0.84	-0.01	0.88	2.60	2.49	17.72
	(0.00)	*(0.12)*	*(0.00)*	*(0.00)*	*(0.20)*	*(0.27)*	*(0.07)*	*(0.11)*	*(0.98)*	*(0.07)*	*(0.00)*	*(0.00)*	*(0.00)*
Year 1 - 20	4.52	1.35	1.74	1.45	0.79	0.81	1.09	0.77	0.11	0.90	2.47	2.69	18.68
	(0.00)	*(0.01)*	*(0.00)*	*(0.00)*	*(0.20)*	*(0.16)*	*(0.11)*	*(0.10)*	*(0.72)*	*(0.04)*	*(0.00)*	*(0.00)*	*(0.00)*

Second, unlike previous studies about the performance of the return-based strategies[6], our strategy yields similar profits over short-, intermediate-, or long-term horizons. The cumulative profit of the strategy per year is 16.2 percent when we use only previous one year's calendar month return and is 18.7 percent when we use twenty years of historical returns with annual lags. The increase in the profit from using the longer historical returns to form the portfolio is marginal. In May and November, the strategy using previous one year's calendar month return yields the best performance. In April, the strategy using five years of historical returns with annual lags yields the best performance. In July and August, the strategy using ten years of historical returns yields the best performance.

Since our strategy requires rebalancing the portfolio every month, the transaction costs would have considerable impact on the return. Jegadeesh and Titman (1993) consider a 0.5% one way transaction cost, and find that the risk-adjusted return of the momentum trading rule is still reliably different from zero. However, Grundy and Martin (2001) find that the profits on their momentum strategies are driven to zero after applying the round trip transaction costs of 1.03%. Following the previous literature, we assume the 1.0% of round-trip transaction cost. Since the portfolio weight of the individual stock in each style portfolio is not available to us, we also assume conservatively 100% of turnover every month. When we apply these transaction costs and turnover rate to our strategy using twenty years of historical returns with annual lags, the cumulative profit remains 6.7 percent per year, which is significantly positive at 1-percent level. January

[6] See, for example, DeBondt and Thaler (1985, 1987), Jegadeesh (1991), and Jegadeesh and Titman (1993, 2001). They show evidence of short-term reversal, intermediate-term momentum, and long-term reversal.

Figure 1.2: Annual Seasonal Strategy Returns with the Style Portfolios



We calculate twelve style portfolio percentage returns by month and rank them based on the past 20 years of performance of the calendar month indicated. For example, the trading strategy that is formed based on past January returns ranks the twelve style portfolio returns according to their average returns during the previous 20 Januaries. The strategy has the weight of $(\mu_{it} - \overline{\mu}_t)/12$, where μ_{it} is the average return during the 20 Januaries of the portfolio i and $\overline{\mu}_t$ is the mean of the average portfolio returns. We plot the sum of the returns of the strategy each month across each year during the period January 1947 through December 2006.

(3.52%), November (1.47), and December (1.69%) returns are still significantly positive at 5-percent level after considering the transaction costs.

Figure 1.2 plots the cumulative profits of the strategy per year using twenty years of historical returns with annual lags. It clearly shows that the strategy yields positive returns in 52 out of 60 years over the sample period, 1947 through 2006.[7] The strategy yields profits exceeding 10 percent in 41 years. The best performing year was 1958 with the profit of 54 percent but the worst performing year was 1974 with the loss of 19 percent. Overall, our strategy yields persistent and significant profits.

The strategy using the weight in equation (2) enables us to decompose the expected profit into two distinct sources: time-series predictability in style portfolio returns and profits due to cross-sectional dispersion in mean returns of the portfolios[8]. Suppose $\pi_{jt}(k)$ is the profit of the strategy over the month t using the previous k year's return with annual lags in calendar month j with the weight $w_{ijt}(k)$ and R_{it} is the return on the style portfolio i over the month t, then the expectation of $\pi_{jt}(k)$ can be decomposed as follows:

$$E(\pi_{jt}(k)) = \sum_{i=1}^{12} E(w_{ijt} R_{it})$$

---

[7] Fama-French four factor return spreads would be good benchmarks over the same period. Unreported reports show that the market premium (long the market portfolio and short the risk-free asset) was negative in 17 years and the average return was 7.5%. The size premium (long the small stocks and short the big stocks) was negative in 30 years and the average return was 1.7%. The value premium (long the value stocks and short the growth stocks) was negative in 20 years and the average return was 5.0%. The momentum premium (long the prior winners and short the losers) was negative in 10 years and the average return was 10.0%.

[8] Lo and MacKinlay (1990) and Conrad and Kaul (1998) decomposed the momentum profits in a similar way.

$$= \frac{1}{12}\sum_{i=1}^{12} E(\mu_{ijt} R_{it}) - E(\overline{\mu}_{jt} \frac{1}{12}\sum_{i=1}^{12} R_{it})$$

$$= \frac{1}{12}\sum_{i=1}^{12} \{Cov(\mu_{ijt}, R_{it}) + \mu_{ij}^2\} - \frac{1}{12}\sum_{i=1}^{12} \{Cov(\overline{\mu}_{jt}, \frac{1}{12}\sum_{i=1}^{12} R_{it}) + \mu_{mj}^2\} \qquad (3)$$

assuming $E(\mu_{ijt}) = E(R_{it}) = \mu_{ij}$ and $E(\overline{\mu}_{jt}) = E(\frac{1}{12}\sum_{i=1}^{12} R_{it}) = \mu_{mj}$. Finally, the equation (3) becomes

$$E(\pi_{jt}(k)) = -Cov(\overline{\mu}_{jt}, \frac{1}{12}\sum_{i=1}^{12} R_{it}) + \frac{1}{12}\sum_{i=1}^{12} Cov(\mu_{ijt}, R_{it}) + (\frac{1}{12}\sum_{i=1}^{12} \mu_{ij}^2 - \mu_{mj}^2)$$

$$= P_j(k) + \sigma^2(\mu_j(k)) \qquad (4)$$

where $P_j(k)$ is the predictability index and $\sigma^2(\mu_j(k))$ is the dispersion index.

As we observed in Figure 1, the dispersion among style portfolio returns varies substantially across the calendar month. For example, in January the difference between the best performing style portfolio return and the worst performing style portfolio return is 5.2% but the difference in August is merely 0.6%. Therefore, by decomposing the strategy profit as discussed above, we can clearly show whether the source of the profit is the information contained in past returns of the style portfolios or the cross-sectional dispersion that would arise even if the style portfolio returns are unpredictable.

Table 1.4 shows the decomposition of the seasonal returns of the strategy reported in Table 1.3, the proportion of each part relative to the mean return for all calendar months, and the portfolio formation periods. The surprising result is that the main source of the profit is the predictability component for each calendar month and portfolio formation period. There are only four cases with the dispersion component explaining

Table 1.4: The Decomposition of the Seasonal Strategy Returns with the Style Portfolios

This table reports the decomposition of the seasonal returns of weighted relative strength strategies with the style portfolios reported in Table 4. The decomposition is given by the equation (4), $E(\pi_{jt}(k)) = P_j(k) + \sigma^2(\mu_j(k))$, where the predictability index is given by $P_j(k)) = -Cov(\overline{\mu}_{jt}, \frac{1}{12}\sum_{i=1}^{12} R_{it}) + \frac{1}{12}\sum_{i=1}^{12} Cov(\mu_{ijt}, R_{it})$ and the dispersion index is given by the cross-sectional variance of the monthly mean returns of the twelve style portfolio returns by month, $\sigma^2(\mu_j(k)) = (\frac{1}{12}\sum_{i=1}^{12} \mu_{ij}^2 - \mu_{mj}^2)$. The proportion of each part relative to the mean return is reported in parenthesis.

Strategy		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Year 1	Predictability	3.80	0.60	1.43	1.26	0.85	0.64	0.60	0.79	-0.22	0.51	2.93	2.41
	(% of Profit)	*(97.8%)*	*(90.8%)*	*(97.4%)*	*(96.8%)*	*(96.0%)*	*(94.0%)*	*(93.7%)*	*(96.5%)*	*(119.6%)*	*(90.5%)*	*(98.3%)*	*(98.2%)*
	Dispersion	0.09	0.06	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.05	0.05	0.04
	(% of Profit)	*(2.2%)*	*(9.2%)*	*(2.6%)*	*(3.2%)*	*(4.0%)*	*(6.0%)*	*(6.3%)*	*(3.5%)*	*(-19.6%)*	*(9.5%)*	*(1.7%)*	*(1.8%)*
Year 1 - 5	Predictability	4.11	0.73	1.65	1.50	0.74	0.73	0.96	0.79	-0.06	0.70	2.62	2.57
	(% of Profit)	*(99.1%)*	*(98.3%)*	*(99.6%)*	*(99.3%)*	*(99.1%)*	*(98.2%)*	*(99.0%)*	*(99.2%)*	*(117.7%)*	*(98.2%)*	*(99.5%)*	*(99.5%)*
	Dispersion	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(% of Profit)	*(0.9%)*	*(1.7%)*	*(0.4%)*	*(0.7%)*	*(0.9%)*	*(1.8%)*	*(1.0%)*	*(0.8%)*	*(-17.7%)*	*(1.8%)*	*(0.5%)*	*(0.5%)*
Year 1 - 10	Predictability	4.39	0.92	1.48	1.47	0.80	0.66	1.12	0.84	-0.02	0.87	2.60	2.49
	(% of Profit)	*(99.3%)*	*(99.4%)*	*(99.7%)*	*(99.6%)*	*(99.6%)*	*(99.0%)*	*(99.5%)*	*(99.6%)*	*(146.9%)*	*(99.1%)*	*(99.7%)*	*(99.7%)*
	Dispersion	0.03	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01
	(% of Profit)	*(0.7%)*	*(0.6%)*	*(0.3%)*	*(0.4%)*	*(0.4%)*	*(1.0%)*	*(0.5%)*	*(0.4%)*	*(-46.9%)*	*(0.9%)*	*(0.3%)*	*(0.3%)*
Year 1 - 20	Predictability	4.49	1.35	1.74	1.44	0.79	0.80	1.08	0.76	0.11	0.89	2.47	2.69
	(% of Profit)	*(99.2%)*	*(99.7%)*	*(99.9%)*	*(99.7%)*	*(99.7%)*	*(99.5%)*	*(99.6%)*	*(99.7%)*	*(97.5%)*	*(99.3%)*	*(99.8%)*	*(99.8%)*
	Dispersion	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01
	(% of Profit)	*(0.8%)*	*(0.3%)*	*(0.1%)*	*(0.3%)*	*(0.3%)*	*(0.5%)*	*(0.4%)*	*(0.3%)*	*(2.5%)*	*(0.7%)*	*(0.2%)*	*(0.2%)*

more than 5 percent of the profit and they are all the cases when we use one year's previous calendar month return. From this we argue that the historical performance of the style portfolio in each month has strong predictable power for the future style portfolio return and we can implement this for generating profits.

The seasonal strategies discussed above require rebalancing the portfolio every month. In this respect, the transaction costs would consume the profits. In order to mitigate the impact of the transaction costs, we examine an alternative return based strategy, which is seasonal winner – loser strategy. Instead of taking long or short position on every style portfolio, we take long (short) position on the best (worst) performing style portfolio over all months with the annual interval and measure the returns over the next month. For example, the 1 – 5 years winner (loser) style portfolio held (shorted) in January 2006 is the Small/Down (Big/Up) portfolio of which the average January return from 2001 to 2005 is 3.6% (-1.7%).

Table 1.5 shows the returns to seasonal winner – loser strategy with the twelve style portfolios. The last column reports the annual average cumulative return from the strategy. The corresponding Newey-West *p*-values are also reported in parenthesis. We note several interesting features of the profitability of the trading strategy. First, the strategy yields profits across most calendar months with the exceptions of March, May, or August depending on the formation period. When we use the previous 10 years historical returns with annual lags to form the portfolio, the strategy yields profits in each calendar month and the returns are significantly positive at 5-percent level in 7 out of 12 calendar months. The strategy yields the largest profit in January (4.37%) when we use

Table 1.5: Seasonal Winner – Loser Strategy Returns with Style Portfolios

At the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. The median NYSE market equity is the size breakpoint and the 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The monthly size breakpoint is the median NYSE market equity and the monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. At the end of each month, firms are sorted independently along book-to-market ratio and prior (2-12) return to construct Value, Neutral, Growth, Up, Lateral, and Down portfolios. The 30th and 70th NYSE book-to-market percentiles are the book-to-market breakpoints. The monthly prior (2-12) return breakpoints are 30th and 70th NYSE percentiles. We calculate twenty-one style portfolio percentage returns by month and rank them according to various categories based on past performance of the calendar month indicated. For example, the trading strategy that is formed based on past January returns during year 2 through 5 ranks the twenty one style portfolio returns according to their average returns during the previous four Januaries until two years back. The strategy is to buy the top portfolio and short the bottom portfolio for January. The average monthly returns of the top and bottom portfolios and their differences are reported separately for every calendar month during the period January 1947 through December 2006. The last column reports the annual average cumulative return from the strategy. The corresponding Newey-West *p*-values are also reported.

Strategy		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan - Dec
Year 1	Top	3.95	0.39	1.63	1.13	0.77	0.78	0.63	0.97	-0.09	0.52	3.01	2.50	16.20
	Bottom	2.01	0.71	1.22	0.43	1.02	-0.26	0.58	0.55	-0.99	0.00	1.32	1.12	7.71
	Difference	1.94	-0.32	0.42	0.70	-0.25	1.04	0.05	0.42	0.91	0.52	1.68	1.38	8.49
	(p-value)	*(0.01)*	*(0.65)*	*(0.37)*	*(0.12)*	*(0.60)*	*(0.06)*	*(0.91)*	*(0.32)*	*(0.02)*	*(0.35)*	*(0.02)*	*(0.01)*	*(0.00)*
Year 1 - 5	Top	4.44	0.99	1.84	2.25	0.79	0.96	0.58	0.74	0.16	1.00	2.90	3.08	19.73
	Bottom	2.28	0.44	0.86	0.56	1.05	-0.56	0.24	0.91	-0.70	-0.37	1.38	0.82	6.90
	Difference	2.16	0.55	0.98	1.69	-0.27	1.52	0.33	-0.17	0.86	1.37	1.52	2.26	12.82
	(p-value)	*(0.02)*	*(0.35)*	*(0.05)*	*(0.00)*	*(0.56)*	*(0.02)*	*(0.53)*	*(0.74)*	*(0.05)*	*(0.02)*	*(0.00)*	*(0.00)*	*(0.00)*
Year 1 - 10	Top	5.09	1.13	1.34	2.04	0.80	0.66	1.11	0.96	0.25	1.20	2.93	3.01	20.53
	Bottom	1.09	0.58	1.25	0.30	0.55	-0.84	0.01	0.78	-0.65	-0.74	1.63	0.97	4.93
	Difference	4.00	0.55	0.09	1.73	0.25	1.50	1.10	0.18	0.90	1.95	1.30	2.04	15.59
	(p-value)	*(0.00)*	*(0.29)*	*(0.73)*	*(0.00)*	*(0.32)*	*(0.00)*	*(0.02)*	*(0.64)*	*(0.13)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.00)*
Year 1 - 20	Top	5.35	1.59	1.94	1.92	0.85	1.14	1.61	0.91	0.70	1.27	2.57	3.41	23.24
	Bottom	0.98	0.05	1.15	0.23	1.10	-0.65	0.45	0.87	-0.66	-0.54	2.00	1.43	6.40
	Difference	4.37	1.54	0.79	1.69	-0.25	1.78	1.16	0.04	1.36	1.81	0.58	1.97	16.84
	(p-value)	*(0.00)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.30)*	*(0.00)*	*(0.00)*	*(0.88)*	*(0.04)*	*(0.00)*	*(0.36)*	*(0.00)*	*(0.00)*

the previous 20 years of returns with annual lags to form the portfolio. Further the profits in December (1.96%), October (1.81%), June (1.78%) and February (1.54%) are also statistically and economically significant. Thus, the strategy is also successful in nearly every calendar month. Although it is not appropriate to compare the profit of the seasonal winner – loser strategy with that of the seasonal strategy presented in Table 3 due to the different portfolio weight[9], the seasonal winner – loser strategy yields comparable profits with possibly reduced transaction costs.

Second, unlike the seasonal strategy presented in Table 3, the profit of the seasonal winner – loser strategy increases as we use longer term historical returns to select the winner and loser style portfolio. The cumulative profit of the strategy is 8.5 percent per year when we use only previous one year's calendar month return and is 16.8 percent when we use twenty years of historical returns with annual lags. In January (October), the strategy using the previous one year's calendar month return yields the profit of 1.9 percent (0.5 percent), but the strategy using twenty years of historical returns with annual lags yields the profit of 4.4 percent (1.8 percent). In only two out of twelve calendar months, August and November, the strategy using the one year interval outperforms the strategy using twenty year intervals.

1.5 A Seasonal Pattern in Style Portfolio Returns in the Major Stock Markets

This section examines a seasonal pattern in style portfolio returns in the major foreign stock markets and the performance of the seasonal strategy in them. The style

[9] The sum of the absolute portfolio weight of the seasonal winner – loser strategy is 200% but that of the seasonal strategy is 100%.

premium is not exclusively present in the U.S. It has also been noticed to be strong in the major foreign stock markets such as the U.K., Japan, and Germany.[10] For this reason, the empirical tests in this section use monthly returns from January 1982 through December 2006 in those three major foreign stock markets. We also examine a seasonal pattern in style portfolio returns and the performance of the seasonal strategy in the U.S. stock market for the same sample period of 1982 to 2006. We compare this with the major foreign markets. Thus this section performs robustness checks for our seasonal strategy.

First, we collect the monthly return data, the market values, and the market-to-book ratios for the all of the individual equities listed in the stock exchanges in the U.K., Japan, and Germany from DataStream. We then construct the six size/book-to-market sorted portfolios and six size/prior-return sorted portfolios following the same way[11] for the U.S. style portfolios. We compute the mean return by calendar month for each of the twelve style portfolios over the period from January 1982 to December 2006. The results are presented in Figure 3.

Style returns exhibit substantial seasonal variations across calendar months in each major stock market. Figure 1.3 presents that the strong size effect in January is prevalent across all major stock markets. The Small/Up portfolio is the best performing style portfolio in Germany and the U.K. and the Small/Down portfolio is the best performing one in Japan and the U.S. The worst performing style portfolio in January is

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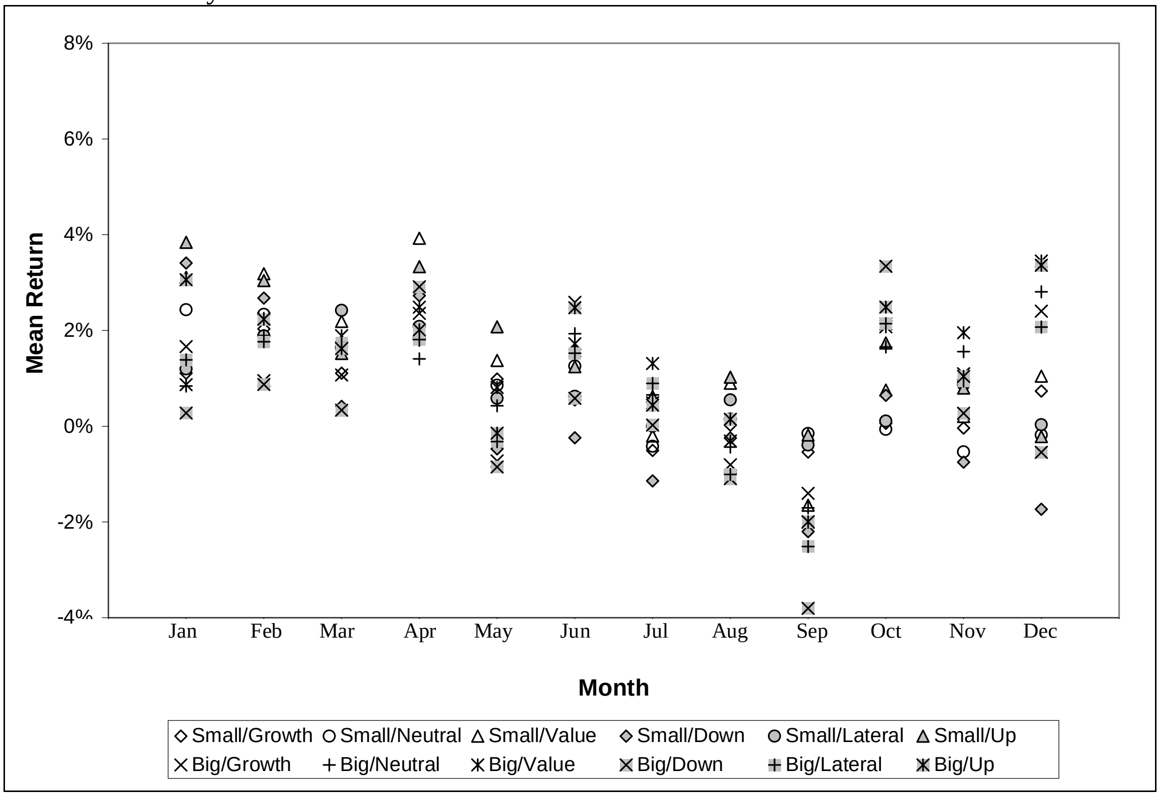
[10] See, for example, Capaul, Rowley, and Sharpe (1993), Arshanapalli, Coggin, and Doukas (1998), Fama and French (1998), and Levis and Liodakis (2001).

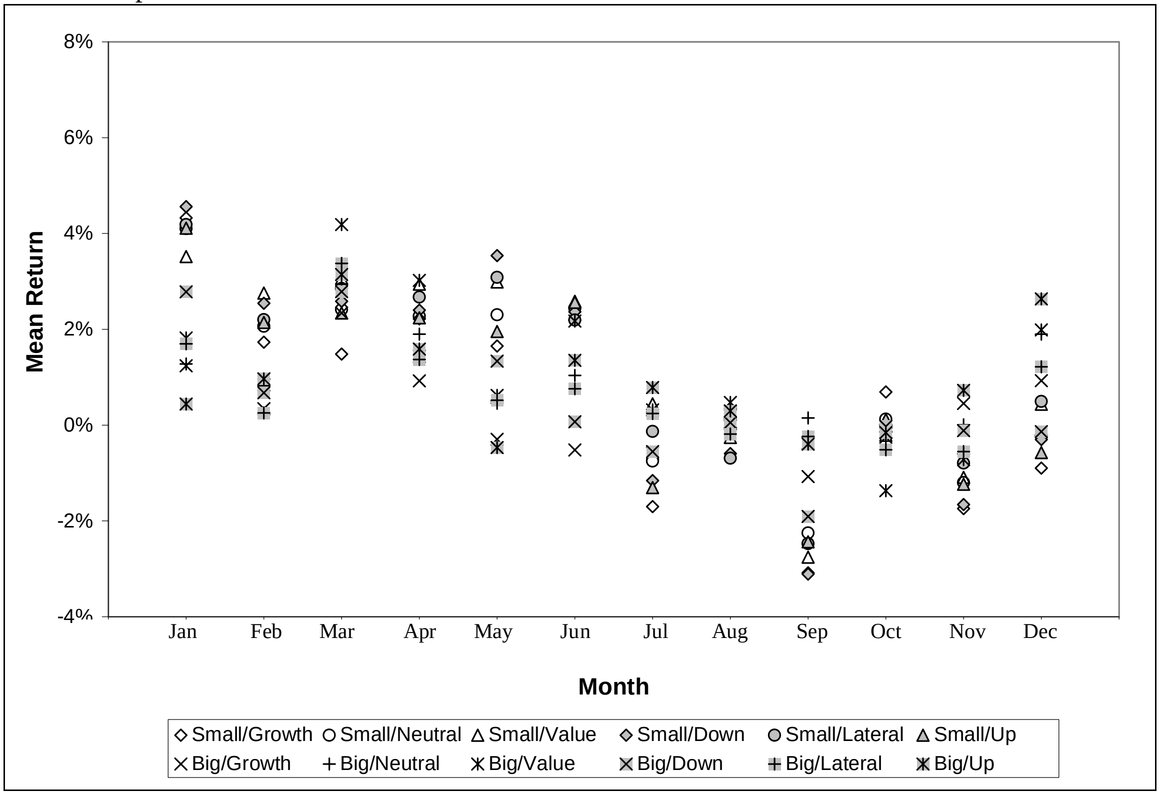
[11] For Japanese size/book-to-market portfolios, the size are ranked at the end of September and the book-to-market ratios are ranked at the end of March because the fiscal year of most Japanese firms ends in March.

Figure 1.3: Size/Book-to-Market and Size/Prior-Return Portfolio Returns by Month in the Major Stock Markets

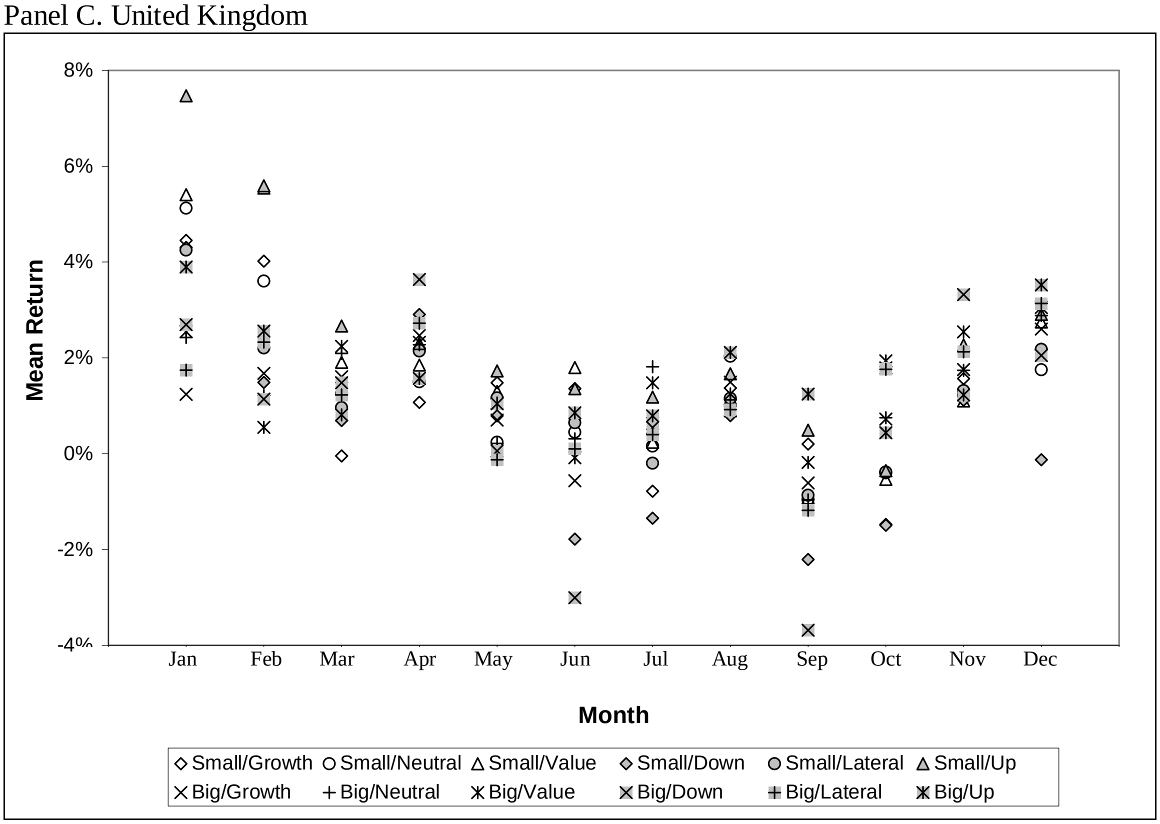
Panel A. Germany



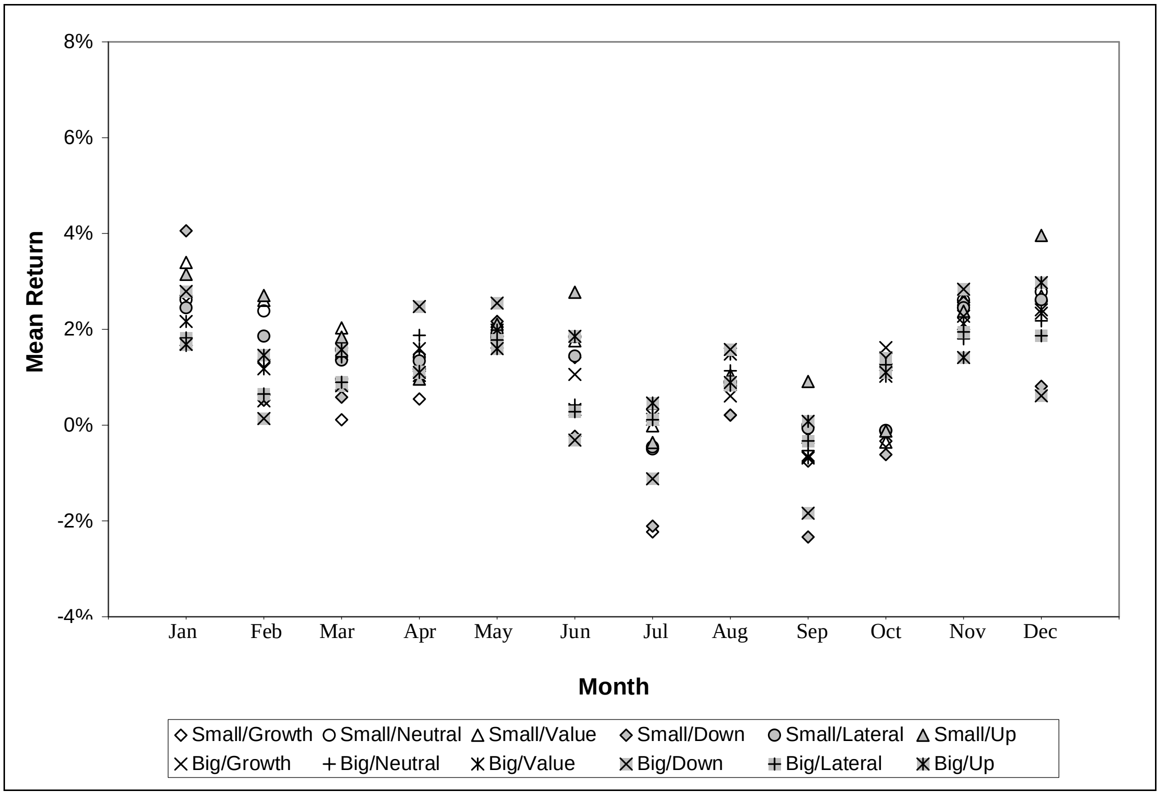
Panel B. Japan



Panel C. United Kingdom



Panel D. United States



We plot the monthly mean returns of the six size/book-to-market portfolios and the six size/prior-return portfolios in Germany, Japan, the U.K., and the U.S. by month. For Japan, at the end of each September, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. For other markets, at the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The size breakpoint is the median size of the stock market; the book-to-market breakpoints are the 30th and 70th book-to-market percentiles; and the monthly prior (2-12) return breakpoints are 30th and 70th percentiles. Portfolio percentage returns are calculated by month. The returns are calculated in the local currency for the period from January 1982 through December 2006.

also one of the Big portfolios: Big/Down, Big/Up, Big/Growth, and Big/Neutral in Germany, Japan, the U.K., and the U.S., respectively. However, the performance of these style portfolios is reversed in December; the Big portfolios outperform the Small portfolios. Although the Small (Big) portfolios outperform the Big (Small) portfolios at the beginning (at the end) of the year, the overall performance of these style portfolios are comparable[12]. This is consistent with Cochrane (1999, 2005) and Campbell (2000) who find that the size effect has disappeared in the 1980's.

An interesting finding is that the relative style portfolio performance caused by the tax-loss selling or the window dressing in December does not seem to be reversed in January in European countries. In Germany (U.K.), the size controlled Up portfolios outperform the Down portfolios up to 3.9 percent (3.0 percent) in December and the Up portfolios still outperform the Down portfolios up to 2.8 percent (3.2 percent) in January. However, in the U.S., the size controlled Up portfolios outperforms the Down portfolios up to 3.2 percent in December but the Down portfolios outperform the Up portfolios up to 1.1 percent in January.

Most style portfolios have been the best or the worst performing style portfolios in some month, in some country. For example, the Small/Value portfolio is the best performing style portfolio in February and April in Germany, in February and June in Japan, in June in the U.K., and in March in the U.S. Also it is the worst performing style portfolio in November in the U.K. The only exceptions are the Big/Lateral and the Small/Up portfolios; the Big/Lateral portfolio has never been the best performing style

[12] The Size premium (Small – Big) in Germany, Japan, the U.K., and the U.S. is -0.19%, 0.18%, 0.17%, and 0.02% per month, respectively.

and the Small/Up has never been the worst performing style in any sample countries over the sample period. Overall, style portfolios tend to have relatively high (or low) returns in a specific calendar month across all the major stock markets.

Table 1.6 reports the seasonality test of style portfolio returns in the major stock markets. We run the OLS regression model in equation (1) for the twelve style portfolio returns in Germany, Japan, the U.K., and the U.S. With the restriction that for each model with a different portfolio, the sum of coefficients of the independent variable should be zero; the intercept becomes the overall return over the entire sample period; and the beta coefficient indicates how the mean return for the month differs from the cross-month average return. First, the intercept shows that the Small/Up is the best performing style in countries other than Japan, in general. In Japan, the Small/Value is the best performing one. The Big/Down is the worst performing style in Germany and the Small/Down is the worst performing one in the U.K. and the U.S. In Japan, the Big/Growth is the worst performing style over the last twenty five years. Thus the momentum strategy, buying the winner and selling the loser, appears to work profitably in most major stock markets with the exception of Japan.

In Germany, the Big portfolios outperform the Small portfolios after controlling for the book-to-market ratio. On average, the Big/Growth, Big/Neutral, and Big/Value portfolios yield 0.37%, 2.9%, and 0.3% more than the Small/Growth, Small/Neutral, and Small/Value portfolios per month, respectively. This is quite the opposite result in other

Table 1.6: Seasonality Test of Style Portfolio Returns in the Major Stock Markets

This table reports the OLS regression results of the six size/book-to-market portfolios and the six size/prior-return portfolios in Germany, Japan, the U.K., and the U.S.. For Japan, at the end of each September, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. For other markets, at the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The size breakpoint is the median size of the stock market; the book-to-market breakpoints are the 30th and 70th book-to-market percentiles; and the monthly prior (2-12) return breakpoints are 30th and 70th percentiles. We impose the restrictions that for each model with different portfolios the sum of coefficients of the independent variables must be zero so that the intercept becomes the overall mean return over the entire sample period. *t*-statistics are reported in parenthesis. The returns are calculated in the local currency for the period from January 1982 through December 2006. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Panel A. Germany

	Small/Growth	Small/Neutral	Small/Value	Big/Growth	Big/Neutral	Big/Value	Small/Down	Small/Lateral	Small/Up	Big/Down	Big/Lateral	Big/Up
Intercept	0.61 **	0.762 ***	1.349 ***	0.984 ***	1.048 ***	1.376 ***	0.238	0.832 ***	1.572 ***	0.214	0.865 **	1.388 ***
	(2.07)	(2.98)	(4.39)	(2.69)	(3.14)	(3.70)	(0.63)	(3.29)	(4.91)	(0.45)	(2.45)	(3.77)
Jan	0.497	1.672 **	1.761 *	0.679	-0.207	-0.508	3.171 **	0.364	2.271 **	0.064	0.519	1.67
	(0.51)	(1.98)	(1.73)	(0.56)	(-0.19)	(-0.41)	(2.53)	(0.44)	(2.15)	(0.04)	(0.44)	(1.37)
Feb	1.421	1.575 *	1.838 *	-0.03	0.845	0.875	2.438 *	1.052	1.472	0.661	0.898	0.845
	(1.45)	(1.86)	(1.81)	(-0.03)	(0.77)	(0.71)	(1.95)	(1.26)	(1.39)	(0.42)	(0.77)	(0.69)
Mar	0.499	1.022	0.733	0.191	0.533	0.505	0.105	1.582 *	-0.032	0.225	0.862	0.248
	(0.50)	(1.19)	(0.71)	(0.15)	(0.47)	(0.40)	(0.08)	(1.86)	(-0.03)	(0.14)	(0.72)	(0.20)
Apr	1.189	1.073	2.579 **	1.374	0.357	1.11	2.492 **	1.253	1.762 *	2.698 *	0.947	0.626
	(1.22)	(1.27)	(2.54)	(1.14)	(0.32)	(0.90)	(1.99)	(1.50)	(1.66)	(1.71)	(0.81)	(0.51)
May	0.378	0.094	0.024	-1.708	-0.622	-0.568	-0.71	-0.247	0.503	-1.065	-1.185	-1.532
	(0.39)	(0.11)	(0.02)	(-1.41)	(-0.56)	(-0.46)	(-0.57)	(-0.30)	(0.48)	(-0.67)	(-1.01)	(-1.26)
Jun	-0.06	0.335	0.107	1.482	0.846	0.363	-0.649	-0.18	-0.334	0.499	0.621	0.993
	(-0.06)	(0.39)	(0.10)	(1.20)	(0.75)	(0.29)	(-0.51)	(-0.21)	(-0.31)	(0.31)	(0.52)	(0.80)
Jul	-1.115	-1.177	-1.551	-0.495	-0.394	-0.064	-1.378	-0.832	-0.951	-0.189	0.027	-0.947
	(-1.14)	(-1.39)	(-1.53)	(-0.41)	(-0.36)	(-0.05)	(-1.10)	(-0.99)	(-0.90)	(-0.12)	(0.02)	(-0.78)
Aug	-0.586	-0.613	-0.451	-1.788	-1.484	-1.683	-0.482	-0.283	-0.545	-1.306	-1.873	-1.244
	(-0.60)	(-0.72)	(-0.44)	(-1.48)	(-1.34)	(-1.37)	(-0.39)	(-0.34)	(-0.51)	(-0.83)	(-1.60)	(-1.02)
Sep	-1.148	-0.914	-2.999 ***	-2.388 **	-2.754 **	-3.384 ***	-2.436 *	-1.223	-1.754 *	-4.016 **	-3.379 ***	-3.384 ***
	(-1.18)	(-1.08)	(-2.95)	(-1.98)	(-2.49)	(-2.75)	(-1.95)	(-1.46)	(-1.66)	(-2.54)	(-2.89)	(-2.78)
Oct	-0.549	-0.826	-0.592	1.152	0.608	0.701	0.409	-0.722	0.167	3.129 **	1.277	1.098
	(-0.56)	(-0.98)	(-0.58)	(0.95)	(0.55)	(0.57)	(0.33)	(-0.86)	(0.16)	(1.98)	(1.09)	(0.90)
Nov	-0.65	-1.298	-1.144	0.113	0.511	0.577	-0.988	0.036	-0.773	0.06	0.08	-0.346
	(-0.66)	(-1.53)	(-1.13)	(0.09)	(0.46)	(0.47)	(-0.79)	(0.04)	(-0.73)	(0.04)	(0.07)	(-0.28)
Dec	0.125	-0.943	-0.305	1.418	1.76	2.077 *	-1.972	-0.799	-1.787 *	-0.759	1.205	1.974
	(0.13)	(-1.11)	(-0.30)	(1.17)	(1.59)	(1.69)	(-1.58)	(-0.96)	(-1.69)	(-0.48)	(1.03)	(1.62)
N	300	300	300	300	300	300	300	300	300	300	300	300
adj-R^2	-0.012	0.020	0.042	0.005	0.003	0.009	0.033	0.002	0.015	0.009	0.014	0.018
F value	0.67	1.56	2.18 **	1.14	1.09	1.23	1.93 **	1.04	1.41	1.25	1.37	1.49

Panel B. Japan

	Small/Growth	Small/Neutral	Small/Value	Big/Growth	Big/Neutral	Big/Value	Small/Down	Small/Lateral	Small/Up	Big/Down	Big/Lateral	Big/Up
Intercept	0.564	0.951 **	1.201 ***	0.314	0.902 ***	1.081 ***	0.926 **	1.133 ***	0.833 **	0.533	0.662 *	0.91 **
	(1.34)	(2.58)	(3.35)	(0.92)	(2.87)	(3.19)	(2.28)	(3.15)	(2.25)	(1.30)	(1.90)	(2.50)
Jan	3.761 ***	3.151 **	2.316 *	0.924	0.373	0.739	3.634 ***	3.052 **	3.279 ***	2.25 *	1.036	-0.469
	(2.70)	(2.58)	(1.95)	(0.81)	(0.36)	(0.66)	(2.69)	(2.56)	(2.67)	(1.65)	(0.90)	(-0.39)
Feb	1.165	1.114	1.554	0.03	-0.079	-0.24	1.615	1.07	1.311	0.144	-0.408	0.057
	(0.83)	(0.91)	(1.31)	(0.03)	(-0.08)	(-0.21)	(1.20)	(0.90)	(1.07)	(0.11)	(-0.35)	(0.05)
Mar	0.919	1.462	1.863	2.025 *	2.041 *	3.106 ***	1.659	1.721	1.506	2.252 *	2.712 **	2.235 *
	(0.66)	(1.20)	(1.57)	(1.78)	(1.95)	(2.76)	(1.23)	(1.44)	(1.23)	(1.66)	(2.35)	(1.85)
Apr	1.656	1.323	1.739	0.611	0.995	1.939 *	1.475	1.542	1.405	0.902	0.707	0.679
	(1.19)	(1.08)	(1.46)	(0.54)	(0.95)	(1.72)	(1.09)	(1.29)	(1.15)	(0.66)	(0.61)	(0.56)
May	1.085	1.352	1.789	-0.609	-0.447	-0.461	2.612 *	1.952	1.121	0.803	-0.141	-1.378
	(0.78)	(1.11)	(1.50)	(-0.54)	(-0.43)	(-0.41)	(1.94)	(1.64)	(0.91)	(0.59)	(-0.12)	(-1.14)
Jun	1.626	1.489	1.384	-0.835	0.135	1.09	1.438	1.059	1.732	-0.464	0.098	0.443
	(1.16)	(1.22)	(1.16)	(-0.73)	(0.13)	(0.97)	(1.07)	(0.89)	(1.41)	(-0.34)	(0.08)	(0.37)
Jul	-2.266	-1.701	-0.759	-0.901	-0.628	-0.763	-2.085	-1.262	-2.137 *	-1.086	-0.42	-0.124
	(-1.62)	(-1.39)	(-0.64)	(-0.79)	(-0.60)	(-0.68)	(-1.55)	(-1.06)	(-1.74)	(-0.80)	(-0.36)	(-0.10)
Aug	-0.66	-0.838	-1.458	-0.037	-0.582	-0.606	-1.52	-1.822	-0.765	-0.482	-0.85	-0.612
	(-0.47)	(-0.69)	(-1.23)	(-0.03)	(-0.56)	(-0.54)	(-1.13)	(-1.53)	(-0.62)	(-0.35)	(-0.74)	(-0.51)
Sep	-3.646 ***	-3.201 ***	-3.956 ***	-1.39	-0.752	-1.457	-4.034 ***	-3.608 ***	-3.267 ***	-2.438 *	-0.899	-1.305
	(-2.61)	(-2.62)	(-3.33)	(-1.22)	(-0.72)	(-1.30)	(-2.99)	(-3.02)	(-2.67)	(-1.79)	(-0.78)	(-1.08)
Oct	0.126	-0.825	-1.413	-0.57	-1.161	-2.451 **	-0.986	-1.14	-0.715	-0.56	-1.177	-1.066
	(0.09)	(-0.68)	(-1.19)	(-0.50)	(-1.11)	(-2.18)	(-0.73)	(-0.95)	(-0.58)	(-0.41)	(-1.02)	(-0.88)
Nov	-2.307 *	-2.152 *	-2.293 *	0.137	-0.895	-1.802	-2.584 *	-1.924	-2.066 *	-0.65	-1.214	-0.184
	(-1.65)	(-1.76)	(-1.93)	(0.12)	(-0.86)	(-1.60)	(-1.92)	(-1.61)	(-1.69)	(-0.48)	(-1.05)	(-0.15)
Dec	-1.46	-1.173	-0.766	0.615	0.999	0.906	-1.225	-0.64	-1.405	-0.67	0.557	1.725
	(-1.05)	(-0.96)	(-0.64)	(0.54)	(0.96)	(0.81)	(-0.91)	(-0.54)	(-1.15)	(-0.49)	(0.48)	(1.43)
N	300	300	300	300	300	300	300	300	300	300	300	300
adj-R^2	0.039	0.043	0.058	-0.014	-0.009	0.031	0.063	0.055	0.050	-0.003	-0.005	-0.007
F value	2.11 **	2.21 **	2.69 ***	0.64	0.76	1.88 **	2.83 ***	2.58 ***	2.41 ***	0.92	0.87	0.8

Panel C. United Kingdom

	Small/Growth	Small/Neutral	Small/Value	Big/Growth	Big/Neutral	Big/Value	Small/Down	Small/Lateral	Small/Up	Big/Down	Big/Lateral	Big/Up
Intercept	1.197 ***	1.422 ***	1.591 ***	1.088 ***	1.241 ***	1.492 ***	0.372	1.125 ***	2.31 ***	0.807	1.171 ***	1.605 ***
	(2.80)	(4.18)	(4.56)	(3.69)	(4.00)	(4.65)	(0.96)	(3.61)	(6.28)	(1.62)	(3.60)	(4.50)
Jan	3.254 **	3.461 ***	3.107 ***	0.07	0.693	0.671	3.763 ***	3.066 ***	4.75 ***	1.489	0.113	2.138 *
	(2.30)	(3.08)	(2.69)	(0.07)	(0.68)	(0.63)	(2.94)	(2.97)	(3.91)	(0.91)	(0.10)	(1.81)
Feb	2.823 **	2.541 **	3.543 ***	0.815	0.315	-0.847	1.092	1.215	3.219 ***	0.573	1.561	1.398
	(2.00)	(2.26)	(3.07)	(0.84)	(0.31)	(-0.80)	(0.85)	(1.18)	(2.65)	(0.35)	(1.45)	(1.19)
Mar	-1.243	-0.625	-0.674	0.11	0.672	0.458	0.054	-0.608	0.245	0.306	-0.392	-0.976
	(-0.88)	(-0.56)	(-0.58)	(0.11)	(0.65)	(0.43)	(0.04)	(-0.59)	(0.20)	(0.19)	(-0.36)	(-0.83)
Apr	-0.126	0.389	0.789	1.425	1.078	0.741	2.656 **	0.994	0.155	2.885 *	1.631	-0.079
	(-0.09)	(0.35)	(0.68)	(1.46)	(1.05)	(0.70)	(2.07)	(0.96)	(0.13)	(1.75)	(1.52)	(-0.07)
May	0.282	-0.423	-0.123	0.001	-0.507	-0.069	0.589	0.571	-0.259	-0.616	-0.876	-0.003
	(0.20)	(-0.38)	(-0.11)	(0.00)	(-0.49)	(-0.06)	(0.46)	(0.55)	(-0.21)	(-0.37)	(-0.81)	(0.00)
Jun	0.158	-0.602	0.647	-1.365	-0.981	-1.395	-1.804	-0.388	-1.06	-4.149 **	-0.843	-0.735
	(0.11)	(-0.54)	(0.56)	(-1.40)	(-0.96)	(-1.32)	(-1.41)	(-0.38)	(-0.87)	(-2.52)	(-0.78)	(-0.62)
Jul	-1.981	-1.184	-1.477	-0.56	0.988	0.385	-1.864	-1.479	-1.211	0.027	-0.856	-0.417
	(-1.37)	(-1.03)	(-1.26)	(-0.56)	(0.94)	(0.36)	(-1.43)	(-1.41)	(-0.98)	(0.02)	(-0.78)	(-0.35)
Aug	-0.851	-0.08	-0.879	-0.072	-0.873	-0.839	0.154	-0.312	-0.835	-0.568	-0.633	-0.292
	(-0.59)	(-0.07)	(-0.75)	(-0.07)	(-0.83)	(-0.78)	(0.12)	(-0.30)	(-0.67)	(-0.34)	(-0.58)	(-0.24)
Sep	-0.997	-2.633 **	-2.729 **	-1.725 *	-2.493 **	-1.774 *	-2.643 **	-2.243 **	-2.03 *	-4.827 ***	-2.528 **	-0.506
	(-0.71)	(-2.34)	(-2.37)	(-1.77)	(-2.43)	(-1.67)	(-2.06)	(-2.18)	(-1.67)	(-2.94)	(-2.35)	(-0.43)
Oct	-2.673 *	-1.46	-2.044 *	-0.419	-0.536	0.456	-1.885	-1.617	-2.638 **	1.102	0.664	-1.167
	(-1.89)	(-1.30)	(-1.77)	(-0.43)	(-0.52)	(0.43)	(-1.47)	(-1.57)	(-2.17)	(0.67)	(0.62)	(-0.99)
Nov	0.37	0.157	-0.745	0.297	0.159	0.778	0.719	0.004	-0.696	2.425	0.454	-1.001
	(0.26)	(0.14)	(-0.65)	(0.30)	(0.16)	(0.73)	(0.56)	(0.00)	(-0.57)	(1.48)	(0.42)	(-0.85)
Dec	0.983	0.459	0.584	1.423	1.487	1.434	-0.832	0.798	0.36	1.354	1.704	1.64
	(0.70)	(0.41)	(0.51)	(1.46)	(1.45)	(1.35)	(-0.65)	(0.77)	(0.30)	(0.82)	(1.58)	(1.39)
N	300	300	300	300	300	300	300	300	300	300	300	300
adj-R^2	0.016	0.038	0.055	-0.005	0.004	-0.008	0.042	0.032	0.065	0.034	0.011	-0.008
F value	1.41	1.99 **	2.45 ***	0.89	1.1	0.8	2.09 **	1.82 *	2.71 ***	1.88 **	1.28	0.81

Panel D. United States

	Small/Growth	Small/Neutral	Small/Value	Big/Growth	Big/Neutral	Big/Value	Small/Down	Small/Lateral	Small/Up	Big/Down	Big/Lateral	Big/Up
Intercept	0.824 **	1.443 ***	1.583 ***	1.104 ***	1.219 ***	1.267 ***	0.551	1.308 ***	1.768 ***	0.995 ***	1.019 ***	1.349 ***
	(2.10)	(5.24)	(6.00)	(4.03)	(5.03)	(5.35)	(1.45)	(5.08)	(5.17)	(3.15)	(4.29)	(5.00)
Jan	1.884	1.177	1.814 **	0.598	0.446	0.897	3.505 ***	1.142	1.381	1.796 *	0.799	0.338
	(1.45)	(1.29)	(2.07)	(0.66)	(0.55)	(1.14)	(2.78)	(1.34)	(1.22)	(1.71)	(1.01)	(0.38)
Feb	0.499	0.939	1.022	-0.596	0.152	-0.09	-0.032	0.548	0.937	-0.858	-0.37	0.107
	(0.38)	(1.03)	(1.17)	(-0.66)	(0.19)	(-0.11)	(-0.03)	(0.64)	(0.83)	(-0.82)	(-0.47)	(0.12)
Mar	-0.714	0.124	0.446	-0.248	0.204	0.22	0.03	0.047	0.067	-0.174	-0.124	0.229
	(-0.55)	(0.14)	(0.51)	(-0.27)	(0.25)	(0.28)	(0.02)	(0.05)	(0.06)	(-0.17)	(-0.16)	(0.26)
Apr	-0.278	-0.029	-0.28	-0.069	0.656	0.329	0.46	0.032	-0.805	1.482	0.104	-0.249
	(-0.21)	(-0.03)	(-0.32)	(-0.08)	(0.82)	(0.42)	(0.36)	(0.04)	(-0.71)	(1.41)	(0.13)	(-0.28)
May	0.9	0.386	0.581	0.625	0.542	0.716	1.611	0.604	0.337	1.553	0.76	0.249
	(0.69)	(0.42)	(0.66)	(0.69)	(0.67)	(0.91)	(1.28)	(0.71)	(0.30)	(1.48)	(0.97)	(0.28)
Jun	0.589	0.403	0.177	-0.046	-0.802	-0.94	-0.785	0.134	1.007	-1.306	-0.74	0.503
	(0.45)	(0.44)	(0.20)	(-0.05)	(-1.00)	(-1.20)	(-0.62)	(0.16)	(0.89)	(-1.24)	(-0.94)	(0.56)
Jul	-3.055 **	-1.942 **	-1.599 *	-0.985	-0.885	-1.069	-2.657 **	-1.762 **	-2.133 *	-2.114 **	-0.908	-0.889
	(-2.35)	(-2.12)	(-1.83)	(-1.08)	(-1.10)	(-1.36)	(-2.11)	(-2.06)	(-1.88)	(-2.01)	(-1.15)	(-0.99)
Aug	-0.614	-0.561	-0.54	-0.497	-0.084	0.217	-0.344	-0.404	-0.845	0.585	-0.19	-0.458
	(-0.47)	(-0.61)	(-0.62)	(-0.55)	(-0.10)	(0.28)	(-0.27)	(-0.47)	(-0.74)	(0.56)	(-0.24)	(-0.51)
Sep	-1.575	-1.444	-1.84 **	-1.765 *	-1.75 **	-1.952 **	-2.887 **	-1.372	-0.856	-2.832 ***	-1.347 *	-1.269
	(-1.21)	(-1.58)	(-2.10)	(-1.94)	(-2.18)	(-2.48)	(-2.29)	(-1.61)	(-0.75)	(-2.70)	(-1.71)	(-1.42)
Oct	-1.157	-1.563 *	-1.938 **	0.514	-0.023	-0.247	-1.165	-1.42 *	-1.892 *	0.407	0.241	-0.25
	(-0.89)	(-1.71)	(-2.21)	(0.57)	(-0.03)	(-0.31)	(-0.93)	(-1.66)	(-1.67)	(0.39)	(0.31)	(-0.28)
Nov	1.738	1.169	1.045	1.167	0.585	0.85	2.008	1.142	0.611	1.844 *	0.928	0.064
	(1.34)	(1.28)	(1.19)	(1.28)	(0.73)	(1.08)	(1.59)	(1.34)	(0.54)	(1.76)	(1.18)	(0.07)
Dec	1.783	1.341	1.11	1.303	0.959	1.07	0.257	1.31	2.191 *	-0.383	0.847	1.626 *
	(1.37)	(1.47)	(1.27)	(1.43)	(1.19)	(1.36)	(0.20)	(1.53)	(1.93)	(-0.36)	(1.08)	(1.82)
N	300	300	300	300	300	300	300	300	300	300	300	300
adj-R^2	0.009	0.016	0.031	-0.004	-0.005	0.009	0.033	0.014	0.009	0.037	-0.006	-0.014
F value	1.25	1.43	1.88 **	0.89	0.87	1.25	1.93 **	1.39	1.25	2.03 **	0.84	0.61

countries where the Small portfolios generally outperform the Big portfolios.[13] The January small firm effect is much stronger in Japan and the U.K. than in Germany and the U.S. In Japan and the U.K., the Small portfolios yield January returns at least three times greater than the average monthly return of the style portfolio. However, the Small/Growth portfolio return in Germany or the Small/Neutral portfolio return in the U.S. is not significantly different from the unconditional mean return of the portfolio. Notably, September is the worst month for most of the style portfolios in all countries examined. The September dummy is negative for each of the style portfolios in all countries and most of them are significant at the 10-percent level or better. October appears to be a poorly performing month for each style portfolio but the effect is rather marginal.

Figure 1.3 and Table 1.6 show the various seasonal patterns of each style portfolio returns in each country. Utilizing this we form the relative strength strategy discussed in the previous section. Consider buying or selling style portfolios with the weight $w_{ijt}(k)$ in equation (2) at the beginning of a month *j* based on their month *j* performance over the previous *k* year(s). The holding period is one month and we use two different portfolio formation periods *k* years, i.e., 1 and 5, due to the data availability.

Table 1.7 shows the average profit for trading strategies separately implemented for each calendar month during the period January 1987 through December 2006. The last column reports the annual average cumulative return from the strategy. The

[13] In the U.S., the Big/Growth portfolio outperforms the Small/Growth portfolio but the Small/Neutral and Small/Value portfolios outperform the Big/Neutral and Big/Value portfolios, respectively. As Table 2 shows, the Small/Growth portfolio outperforms the Big/Growth portfolio over the longer period.

Table 1.7: Seasonal Strategy Returns with the Style Portfolios in the Major Stock Markets

This table reports the profit of the seasonal strategy with the six size/book-to-market portfolios and the six size/prior-return portfolios in Germany, Japan, the U.K., and the U.S. For Japan, at the end of each September, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. For other markets, at the end of each June, firms are sorted independently along size and book-to-market ratio to construct Small, Big, Value, Neutral, and Growth portfolios. At the end of each month, firms are sorted independently along size and prior (2-12) return to construct Small, Big, Up, Lateral, and Down portfolios. The size breakpoint is the median size of the stock market; the book-to-market breakpoints are the 30th and 70th book-to-market percentiles; and the monthly prior (2-12) return breakpoints are 30th and 70th percentiles. We calculate twelve style portfolio percentage returns by month and rank them according to various categories based on past performance of the calendar month indicated. For example, the trading strategy that is formed based on past January returns during year 1 through 5 ranks the twelve style portfolio returns according to their average returns during the previous five Januaries. This strategy has the weight of $(\mu_{it} - \overline{\mu}_t)/12$, where μ_{it} is the average return during the five Januaries of the portfolio i and $\overline{\mu}_t$ is the mean of the average portfolio returns. The mean returns from the strategy are reported separately for every calendar month during the period January 1987 through December 2006. The last column reports the annual average cumulative return from the strategy. The corresponding Newey-West *p*-values are also reported in parenthesis.

Country	Strategy	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan - Dec
Germany	Year 1	2.78	2.77	0.49	2.34	1.80	1.12	1.22	-1.36	-1.96	1.46	1.02	0.86	12.56
		(0.03)	*(0.04)*	*(0.56)*	*(0.08)*	*(0.10)*	*(0.32)*	*(0.29)*	*(0.22)*	*(0.14)*	*(0.39)*	*(0.38)*	*(0.35)*	*(0.03)*
	Year 1 - 5	1.91	2.90	0.58	1.64	1.79	1.37	0.61	-1.36	-2.41	0.91	0.75	2.38	11.07
		(0.06)	*(0.01)*	*(0.51)*	*(0.00)*	*(0.05)*	*(0.18)*	*(0.58)*	*(0.23)*	*(0.16)*	*(0.65)*	*(0.48)*	*(0.01)*	*(0.02)*
Japan	Year 1	3.16	1.64	2.96	1.52	2.99	1.51	-1.09	-0.60	-1.45	-0.24	-1.43	0.14	9.11
		(0.06)	*(0.27)*	*(0.09)*	*(0.26)*	*(0.05)*	*(0.30)*	*(0.38)*	*(0.70)*	*(0.33)*	*(0.86)*	*(0.34)*	*(0.90)*	*(0.16)*
	Year 1 - 5	3.75	1.37	2.31	2.16	3.56	1.66	-0.21	-1.20	-1.40	-0.91	-0.69	1.00	11.39
		(0.02)	*(0.20)*	*(0.13)*	*(0.01)*	*(0.07)*	*(0.36)*	*(0.83)*	*(0.42)*	*(0.16)*	*(0.51)*	*(0.69)*	*(0.39)*	*(0.05)*
U.K.	Year 1	3.51	3.78	0.74	2.30	1.27	1.21	1.71	-0.35	-1.69	-0.19	1.25	2.91	16.45
		(0.01)	*(0.01)*	*(0.46)*	*(0.07)*	*(0.21)*	*(0.40)*	*(0.20)*	*(0.76)*	*(0.27)*	*(0.91)*	*(0.41)*	*(0.00)*	*(0.00)*
	Year 1 - 5	4.11	4.49	0.86	1.83	1.11	0.55	1.59	0.03	-0.63	0.26	0.87	2.83	17.90
		(0.00)	*(0.00)*	*(0.29)*	*(0.01)*	*(0.16)*	*(0.63)*	*(0.14)*	*(0.98)*	*(0.70)*	*(0.90)*	*(0.56)*	*(0.00)*	*(0.00)*
U.S.	Year 1	3.19	1.00	1.44	0.92	1.76	1.52	-0.15	-0.09	-0.01	0.43	2.85	3.21	16.08
		(0.01)	*(0.37)*	*(0.15)*	*(0.31)*	*(0.11)*	*(0.15)*	*(0.90)*	*(0.95)*	*(0.99)*	*(0.75)*	*(0.08)*	*(0.00)*	*(0.00)*
	Year 1 - 5	2.25	1.01	1.66	1.16	1.98	1.69	0.46	-0.04	-0.02	0.47	2.20	3.37	16.18
		(0.03)	*(0.50)*	*(0.02)*	*(0.08)*	*(0.01)*	*(0.13)*	*(0.67)*	*(0.97)*	*(0.99)*	*(0.77)*	*(0.04)*	*(0.00)*	*(0.00)*

corresponding Newey-West *p*-values are also reported in parenthesis. Although our seasonal strategy performs better in the U.K. and the U.S. than Germany and Japan, the annual cumulative returns are all positive and economically and statistically significant. Our strategy that uses five years to form the portfolio yields the profit of 11.1 % in Germany, 11.4 % in Japan, 17.9 % in the U.K., and 16.2 % in the U.S. per year.

The strategy yields notably high profits in the turn-of-the-year months in each country. However, they are not the only months producing profit. In Germany and the U.K., the best performing month is February with the profit of 2.9 % and 4.5 %, respectively. The seasonal strategy yields a loss, albeit insignificant, in September in each country. Not only do all style portfolios perform poorly in September, but also their relative performance is difficult to predict.

Overall this section has examined a seasonal pattern in style portfolio returns in the major foreign stock markets and the performance of the seasonal strategy within them. The results show that such strong patterns exist in the style returns in the U.S. as well as the major foreign stock markets. The strategy utilizing this seasonal pattern yields considerable profits in each of the major stock markets.

1.6 Concluding Remarks

This paper examines seasonal patterns in style returns and develops a style rotation strategy to exploit such patterns. Style returns exhibit substantial variations across calendar months. Some of the variations could be explained by the previously examined hypotheses such as tax-loss selling, window dressing or turn-of-the-year effect. We find that the seasonal pattern of the style returns is not limited to January or

December. Small stocks perform poorly in October and the Big/Value portfolios beat the market in April and July.

Our seasonal strategy yields significant profits of 18.7 percent per year. In January, the strategy yields much higher profits of 4.5 percent. Also, the decomposition of the profit shows that the main source of the profit is the predictability component, implying that the seasonal patterns among returns have significant power to forecast future relative style performance. Finally, we find substantial seasonal patterns in style returns not only in the U.S. but also in other major stock markets and the seasonal style rotation strategy yields comparable profits in each country. Collectively, the relative performance of style portfolios depends on the calendar month and this is prevalent in the major stock markets.

CHAPTER 2

THE SEPTEMBER PUZZLE

2.1 Introduction

Over the last two hundred years, the stock market in the United States has generally yielded lower returns in September than any other month. The mean return in September from 1802 to 2007 is -0.24 percent. Given that stocks are risky assets, it is a puzzle that investors tolerate the negative return. It is also puzzling that the September effect has received little attention from academic researchers. The media, however, repeatedly covered the historical reality about the September effect. Some illustrative quotes are: "For investors, September is the cruelest month" (*CNBC,* 09/01/2007), "September is historically the worst month for stocks" (*Business Week,* 08/29/2005), "A September selloff? Yes, if history is a guide" (*The New York Times*, 09/20/1998).

Academic researchers extensively examined the seasonal patterns in stock returns such as the January effect, the turn-of-the-month effect, and the weekend effect [14]. However, to our knowledge, the abnormal patterns of stock returns in September, have not been examined with the sole exception of Haug and Hirshey (2007). They document the abnormally negative September returns in the US stock market and test the consistency of the anomalous negative return in September using out-of-sample replication. They argue that the negative return is linked to the increased investor risk

[14] See, for example, Rozeff and Kinney (1976), Keim (1983), Reinganum (1983), Roll (1983), Lakonishok and Smidt (1986), Ariel (1987), Ritter and Chopra (1989), Agrawal and Tandon (1994), French (1980), and Lakonishok and Maberly (1990)

aversion due to September's large loss in daylight. Instead of focusing on the US stock market, we examine the seasonal patterns of stock returns in September across 18 developed countries. Further, we search for a macroeconomic explanation for this September effect as well.

In this paper we examine four main issues. First, we examine whether stock returns in September are significantly lower than the unconditional monthly mean returns over our sample periods in 18 developed countries. Next, as the January effect is known to be driven by the small cap stocks, we examine whether the September effect is limited to some specific style portfolios. Third, we find the linkage of the expected future economic growth to the stock market return and we also examine the alternative explanations for the September effect. Lastly, we propose the investment strategy based on the September effect and test the performance of the strategy.

Our empirical findings are as follows: First, in 16 countries the September return is negative on average and in 15 countries it is significantly lower than the unconditional monthly mean return over the whole sample period, which varies from 38 years to 208 years upon data availability. In the U.K. and U.S. stock markets, we find the significant September effect over the more than 200 years period. This September effect has not weakened in the recent period. Over the period 1970 to 2007, we find that in all 18 countries, the September return is negative and in 15 countries it is significantly lower than the overall mean return.

Second, to test whether the September effect is driven by some specific styles, we examine size, book-to-market, and momentum decile portfolio returns, and 17 industry portfolio returns in the US market over the period 1927 to 2007. The results show that the

September effect is the most pervasive anomalous phenomenon that is independent of size, book-to-market ratio, past performance, or industry. Larger firms seem to be subjective to the September effect more strongly than smaller firms, but the test results show that in 9 out of 10 size sorted portfolios the September return is significantly lower than the unconditional mean return.

Third, we test the linkage between the expected future economic growth and the stock market return seasonality. The variables of interest are the expected growth in industrial production (EIPG), the surprise in industrial production growth (SIPG), and the surprise in the predicted industrial production growth for the next month (SPIPG). We predict the industrial production growth using the ARIMA (12,1,0) model. We find a significant explanatory power of SPIPG for the stock return at any conventional level. That is, if investors believe the future economic growth would be smaller (greater) than their original expectations, then they would sell (buy) more stocks. Combined with the generally negative economic growth in the last quarter, we argue that this forward looking nature of stock price causes the September effect.

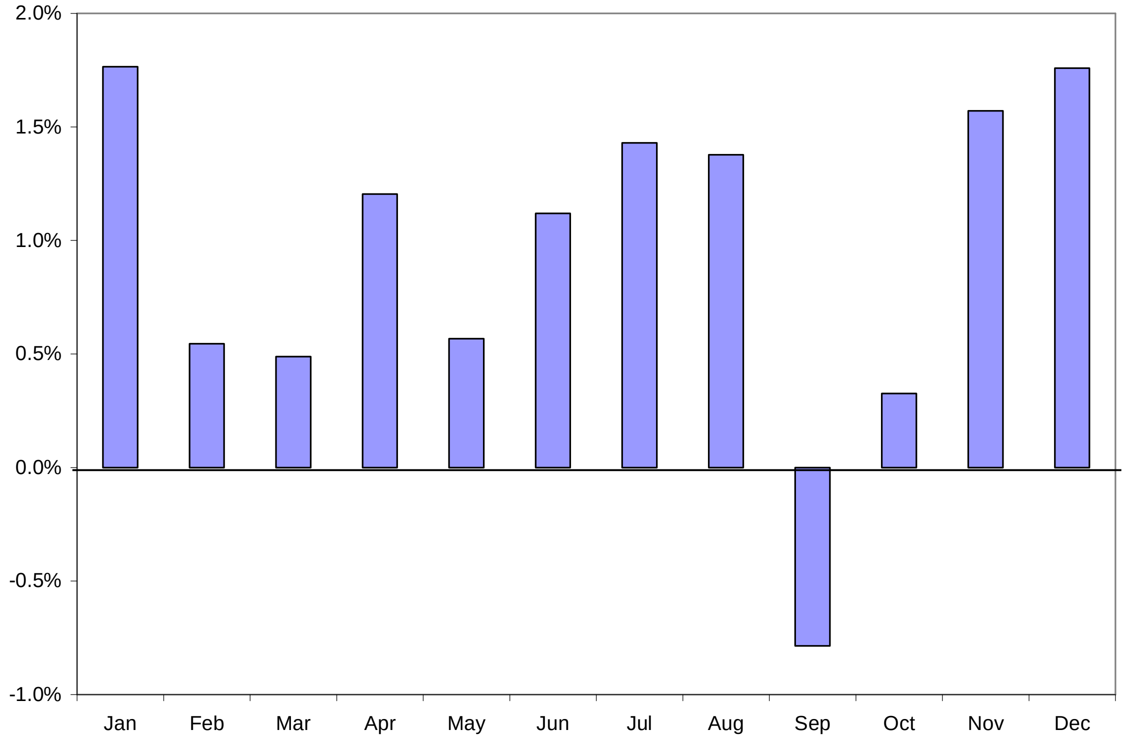
Kamstra, Kramer, and Levi (2003) argue that the depressed investors in the fall would become more risk averse resulting in the poor performance of the stock market. They measure investor depression using the seasonal affective disorder (SAD) variable. After controlling for the SAD effect, our economic growth variable remains significantly positively correlated with the stock returns. Notably, the interaction term between SAD and SPIPG is significantly negative, suggesting that the stock prices reflect the future economic growth more in the fall when the most investors become more risk averse. We also test whether alternative explanations suggested by the media would explain the

September effect such as the mutual funds fiscal/tax year-end, the back-to-school mentality, or a fear of stock market crash in October. We do not find any evidence that any of them causes the September effect.

Finally, we propose an investment strategy based on the September effect. To avoid the poor performance of stock markets in September, we suggest that investors exit the stock markets at the end of August and reenter at the end of September. That is, we assume that investors place 100 percent of their portfolio into a risk-free asset during the month of September and into the stock market portfolio for the rest of the year. This strategy yields a higher mean return than the buy-and-hold strategy in all countries except Australia and Japan and a lower standard deviation than the buy-and-hold strategy in all countries except Singapore. Thus, our strategy yields substantially higher returns with lower volatility. If an investor put $1 into the US stock market according to the buy-and-hold strategy at the beginning of 1927, she would have $2,363 at the end of 2007. However, she would triple the wealth up to $6,784 at the end of 2007 if she followed our strategy.

The rest of this paper proceeds as follows. In Section 2 we present the September puzzle and discuss the data and methodology that we use to establish the September effect. Section 3 reports the seasonality test results of various style portfolio returns in the US stock market. Section 4 explains the macroeconomic factors affecting the September effect. Section 5 examines alternative explanations of the September effect. Section 6 presents the implications of the September effect for the investor wealth. Finally, Section 7 concludes.

Figure 2.1: Mean US Stock Market Return by Month



We plot the monthly mean returns of the CRSP value-weighted indices by month for the period January 1927 through December 2007.

2.2 The September Puzzle

According to the efficient market hypothesis (EMH), the stock return should not be predictable and thus, the behavior of the stock returns inconsistent with the EMH is considered an “anomaly”. A simple example of the anomaly is the seasonality such as the January effect or the weekend effect. Our paper is most closely related to the literature examining the seasonal patterns in stock returns. We find an evidence of a new kind of seasonality, the September effect, which is distinct from previously studied seasonal patterns of returns. Figure 2.1 plots the monthly CRSP value-weighted mean returns by calendar month from 1927 to 2007. Notably, September is the only month with a negative mean return. This negative return in September is a puzzle given that stocks are risky assets which investors require the risk premium to hold. Here we test the significance of the September effect across the 18 developed stock markets over the sample periods, which vary from 38 years to 208 years depending upon data availability.

2.2.1 Data

We collect monthly stock market return data across 18 developed markets from two sources – Global Financial Data (GFD) total return indices and the Morgan Stanley Capital International's (MSCI) developed markets country indices. These countries are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. In both series, the dividends are reinvested and the returns are measured in local currency.

The first series, GFD total return series, covers substantially longer time periods up to over 200 years for some countries than the sample periods examined by the previous literature[15]. GFD total return index is constructed by combining multiple stock market index series from various sources. For Japan, for example, the National Bank Index is used from December 1920 through December 1932, and the Oriental Economist Index is used from 1933 through September 1948. The Fisher index is used from September 1948 through April 1949. The Nikkei 225 is used from May 1949 through present day. Although the GFD total return index for the U.S. is available from January 1800, it is constructed with the base of December 1982 = 115.31. Relative to this base value, the index becomes 0.0001 (the smallest unit) in every month from the period January 1800 to November 1808. This would be a problem to measure the monthly return correctly; so we use 1802 – 1926 data from Schwert (1990) and Center for Research on Stock Prices (CRSP) value-weighted portfolio returns from 1927 to 2007.[16]

The second series, MSCI developed markets country indices, provides information over the common period 1970 – 2007 for the 18 developed countries in our sample. These countries account for 76 percent of the world stock market capitalization as of December 2007[17]. In constructing these indices, MSCI consistently applies its index construction and maintenance methodology. This consistent approach and the common sample period make it possible to compare the seasonal patterns in the stock market

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[15] See: Bouman and Jacobsen (2002) and Kamstra, Kramer, and Levi (2003).

[16] The only country facing this similar problem is the United Kingdom. The return series for the UK begins with September 1694 but it is constructed with the base of December 1992 = 1,000. To exclude the round error, we use only the UK data from January 1800 where the total return index was 0.0044.

[17] Source: World Federation of Exchanges. (http://www.world-exchanges.org)

Table 2.1: Summary Statistics and Mean Returns by Month over the Whole Sample Period

This table reports the mean returns of the stock market returns in eighteen countries by month. We use US data from Schwert (1990) for 1802 – 1926 and from the CRSP value-weighted market return series for 1927 – 2007. We collect the monthly stock market returns for the other countries from Global Financial Data (GFD) from the start date to December 2007. Start date is the first month for which stock market total return index data are available in GFD. # obs is the number of observations with the valid monthly return data. # missing is the number of missing observations in the period between the start and end of the return series. Monthly mean returns in local currencies are reported as a percentage.

Country	Start Date	# obs	# missing	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Australia	1882:09	1,503	0	2.09	0.36	0.89	1.60	0.78	0.97	1.62	0.67	0.44	1.25	0.31	1.64
Austria	1969:12	456	0	1.16	3.01	1.23	1.62	0.39	0.52	0.81	-0.30	-1.16	-0.11	0.44	3.08
Belgium	1950:12	684	0	2.62	1.80	0.61	1.95	0.66	0.50	1.14	0.55	-0.95	-0.27	0.88	1.67
Canada	1933:12	888	0	2.48	0.77	0.70	0.69	0.70	0.26	1.24	0.67	-0.42	0.27	1.57	2.19
Denmark	1969:12	456	0	3.81	0.09	0.14	1.82	1.68	1.81	1.37	0.21	-0.80	1.80	-0.20	2.74
France	1895:01	1,343	12	3.04	1.39	1.73	1.65	-0.19	-0.47	0.83	2.00	-0.03	0.57	0.67	1.30
Germany	1869:12	1,603	53	2.76	1.10	0.59	0.90	-0.14	0.20	0.26	0.85	0.10	-0.81	0.35	1.98
Hong Kong	1969:12	456	0	4.36	4.21	-1.41	2.18	3.12	1.59	2.49	-0.42	-0.64	3.89	-0.37	4.50
Italy	1924:12	995	1	3.40	1.81	0.69	1.96	1.43	-0.39	0.88	2.71	-0.89	0.31	0.94	1.86
Japan	1920:12	1,034	10	3.54	1.69	1.76	1.08	0.49	0.63	0.18	1.05	0.64	-0.04	0.94	2.36
Netherlands	1950:12	684	0	2.80	0.82	2.38	2.14	0.37	0.56	1.04	0.24	-1.44	0.82	1.06	1.94
Norway	1969:12	456	0	4.45	0.18	0.82	4.04	1.44	0.94	2.53	0.44	-1.73	0.54	-0.04	1.74
Singapore	1969:12	456	0	4.66	1.38	-0.06	1.30	1.66	1.08	-0.33	-0.80	-0.52	1.59	0.24	3.66
Spain	1940:03	813	0	3.03	2.31	1.14	1.58	0.12	0.39	1.03	1.77	-0.31	0.65	1.19	1.36
Sweden	1918:12	1,068	0	2.89	1.26	0.71	1.57	1.07	0.41	2.73	-0.44	-1.15	0.28	0.78	1.57
Switzerland	1966:01	503	0	2.23	0.22	1.06	0.96	0.35	0.94	0.33	0.17	-1.28	1.25	1.11	2.19
UK	1800:01	2,490	5	1.75	0.59	0.06	1.49	-0.06	-0.03	0.73	0.84	-0.19	0.99	0.51	0.67
USA	1802:01	2,468	4	1.10	0.54	0.77	0.81	0.59	0.72	0.79	1.30	-0.24	0.43	0.81	1.23

returns in each country without the noise that could be caused by the different index construction method or by specific sample period.

In Table 2.1, we report the mean of the monthly stock market returns using the GFD total return index. The starting date of the index varies across countries based on data availability, but all indices end in December 2007. The longest sample period is for the United Kingdom starting in January 1800 and the shortest is for Austria, Denmark, Hong Kong, Norway, and Singapore starting in December 1969. Stock markets were closed occasionally resulting in missing observations in the sample. For example, due to World War I, the U.S. stock market was closed from August to November in 1914 and the German stock market[18] was closed in August 1914 and reopened in December 1917. No French data are available for September 1939 and from June 1940 until February 1941 because the stock market was closed due to World War II. In addition, no data are available for April 1974 and for March 1979 due to strikes that closed the Paris bourse.

Table 2.1 shows that the stock markets perform poorly in September across international stock markets over a substantially long period. In 15 of the 18 countries, the stock markets yield negative mean returns in September. In 6 of those 15 countries September is the only month with a negative mean return and in 12 countries September is the worst performing month. The table presents the strong turn-of-the-year effect. In 15 countries, January is the best performing month. For Austria and Hong Kong, the best performing month is December but their sample period is short relative to other countries. Notably, the best performing month for the United States is August. This, however,

[18] We also exclude the hyperinflation period, January to December in 1923, for German stock market return data.

would be explained by the rebound in August 1932 after the stock market hit the lowest point since the 19^{th} century. On July 8, 1932 the Dow Jones Industrial Average closed at 41.22, the historical lowest point, but the market recovered in July (26 percent) and August (36 percent) of the year.

In Table 2.2, we report the mean returns of the value-weighted MSCI developed markets country indices in 18 countries over the common sample period of January 1970 to December 2007. We also report the mean returns of the MSCI world market index to examine the worldwide seasonal patterns in stock market returns.

Table 2.2 shows that the world market index yields negative return only in September (-0.79%) and yields the largest returns in January (1.98%) and December (1.99%). That is, both the September effect and the turn-of-the-year effect hold in the global stock market. It appears that the September effect has been becoming stronger. In all countries, the mean return in September is negative. Compared to the mean September return over the longer period reported in Table 2.1, the mean September return decreased in 14 countries. In Spain, the mean monthly return in September was -1.7 percent over 1970 – 2007 while it was -0.3 percent over 1940 – 2007.

January is the best performing month in 12 countries and December is the best in 5 countries. That is, the turn-of-the-year effect is also widespread. The only exception is Japan with the best performing month of March, but January and December returns in Japan are also high relative to other months. The strongly positive return in March would be explained by the fact that the end of the fiscal year is March for most Japanese firms. In the United States, the August return becomes lower than the one reported in Table 2.1. Certainly, it is not the best performing month of the US stock market in the recent years.

Table 2.2: Mean Returns by Month over the Common Sample Period: 1970 - 2007

This table reports the mean returns of the value-weighted MSCI stock market indices in eighteen countries and the world market by month. We collect the monthly stock market returns from Datastream from January 1970 to December 2007. Monthly mean returns in local currencies are reported as a percentage.

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Australia	2.31	0.03	1.29	2.17	1.12	0.46	1.06	1.00	-0.23	0.50	0.27	2.85
Austria	1.17	3.02	1.23	1.62	0.31	0.52	0.82	-0.29	-1.15	-0.10	0.45	3.09
Belgium	2.76	1.96	1.10	2.64	-0.66	0.79	1.46	-0.19	-0.93	0.70	0.95	2.61
Canada	2.33	1.16	0.88	0.05	1.18	0.51	1.30	1.00	-1.09	0.11	1.79	2.84
Denmark	3.72	0.13	0.36	1.62	1.58	1.64	1.44	0.27	-0.90	1.90	-0.15	2.78
France	2.95	1.96	2.19	2.78	0.27	-0.89	0.91	0.45	-1.43	1.01	1.26	1.64
Germany	1.91	1.34	1.40	1.54	-0.74	1.17	1.04	-0.49	-1.77	1.48	1.38	2.20
Hong Kong	4.43	4.16	-1.31	2.03	2.51	1.37	2.60	-0.42	-0.51	3.68	-0.24	4.64
Italy	4.84	2.40	1.98	1.75	-0.51	-0.78	0.30	1.13	-1.60	0.22	1.27	1.48
Japan	1.80	0.82	2.25	1.26	0.28	0.75	0.00	-0.34	-0.48	-0.35	0.93	2.09
Netherlands	2.55	0.98	2.50	2.44	0.29	0.91	1.23	0.10	-2.25	0.68	1.06	2.31
Norway	4.45	0.18	0.82	4.04	1.44	0.94	2.53	0.44	-1.73	0.54	-0.04	1.74
Singapore	4.66	1.38	-0.05	1.30	1.66	1.07	0.14	-1.46	-0.84	1.68	0.70	3.65
Spain	3.34	2.91	1.29	1.96	1.33	0.48	0.13	0.46	-1.71	1.34	2.07	0.69
Sweden	4.01	3.22	1.50	2.17	0.52	0.71	2.60	-1.70	-1.74	1.35	2.90	1.84
Switzerland	2.23	0.22	1.23	0.96	0.16	1.16	0.72	-0.24	-1.45	1.41	1.41	2.18
UK	3.21	1.79	1.15	2.98	-0.19	-0.21	0.70	1.21	-0.75	0.77	0.84	2.38
USA	1.86	0.40	1.04	1.22	0.81	0.87	0.33	0.45	-0.58	1.32	1.79	1.83
World	1.98	0.75	1.16	1.47	0.35	0.34	0.42	0.32	-0.79	0.96	1.36	1.99

2.2.2 The September effect

In the previous section, we show the pervasive poor performance of stock markets in September across 18 developed countries. To test the statistical significance of this September effect we use the OLS regression. We incorporate twelve calendar month dummy variables in the following regression:

$$R_{it} = \alpha_i + \beta_{i1} M_{1t} + \beta_{i2} M_{2t} + \quad ... \quad + \beta_{i12} M_{12t} + e_{it} \tag{1}$$

where R_{it} is the stock market return in country *i* over the month *t*, α_i is a constant, M_{jt} is the calendar month dummy that equals to one if the month *t* is the *j*th month of the year and zero otherwise, and e_{it} is the error term. We impose the restriction that the sum of the coefficients of the calendar month dummy is to be zero for each country *i* (i.e., $\sum_{j=1}^{12} \beta_{ij} = 0$). This restriction enables the model in equation (1) to avoid the perfect multicollinearity between the monthly dummy variables.

Note that under this restriction, the OLS estimate of the regression intercept, $\hat{\alpha}_i$, becomes the unconditional monthly mean return over the whole sample period, whereas the estimated coefficient for each month dummy, $\hat{\beta}_{ij}$, indicates how the mean return for the calendar month differs from the unconditional mean return. Instead of testing whether the stock market return in an arbitrary month (e.g., January) is different from returns in other months, we test whether the stock market return in calendar month *j* is significantly different from the unconditional mean return.

Table 2.3 provides the seasonality test results with the GFD total return indices

Table 2.3: Seasonality Test over the Whole Sample Period

This table reports the OLS regression results of the stock market returns in eighteen countries over the whole sample period. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. The analysis uses US data from Schwert (1990) for 1802 – 1926 and from the CRSP value-weighted market return series for 1927 – 2007. For the other seventeen counties, the monthly stock market returns from Global Financial Data (GFD) from the start date to December 2007 are used. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Country	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N (Adj R^2)
Australia	1.051 ***	1.039 ***	-0.692 **	-0.166	0.553 *	-0.272	-0.080	0.570 *	-0.384	-0.615 *	0.202	-0.743 **	0.587 *	1,503
	(11.04)	(3.29)	(-2.19)	(-0.52)	(1.75)	(-0.86)	(-0.25)	(1.80)	(-1.22)	(-1.94)	(0.64)	(-2.36)	(1.86)	(0.015)
Austria	0.891 ***	0.270	2.121 ***	0.335	0.726	-0.503	-0.371	-0.077	-1.191	-2.048 **	-0.999	-0.454	2.189 ***	456
	(3.62)	(0.33)	(2.60)	(0.41)	(0.89)	(-0.62)	(-0.45)	(-0.09)	(-1.46)	(-2.51)	(-1.22)	(-0.56)	(2.68)	(0.027)
Belgium	0.931 ***	1.688 ***	0.872 *	-0.321	1.024 **	-0.272	-0.431	0.212	-0.386	-1.876 ***	-1.198 **	-0.050	0.738	684
	(5.99)	(3.27)	(1.69)	(-0.62)	(1.99)	(-0.53)	(-0.84)	(0.41)	(-0.75)	(-3.64)	(-2.32)	(-0.10)	(1.43)	(0.037)
Canada	0.928 ***	1.552 ***	-0.154	-0.225	-0.237	-0.227	-0.670	0.317	-0.259	-1.350 ***	-0.658	0.646	1.265 ***	888
	(6.57)	(3.31)	(-0.33)	(-0.48)	(-0.51)	(-0.49)	(-1.43)	(0.68)	(-0.55)	(-2.88)	(-1.41)	(1.38)	(2.70)	(0.022)
Denmark	1.205 ***	2.604 ***	-1.116	-1.064	0.611	0.472	0.609	0.161	-0.993	-2.007 ***	0.596	-1.404 *	1.532 **	456
	(5.46)	(3.56)	(-1.53)	(-1.46)	(0.83)	(0.65)	(0.83)	(0.22)	(-1.36)	(-2.75)	(0.81)	(-1.92)	(2.10)	(0.048)
France	1.040 ***	1.997 ***	0.347	0.690	0.608	-1.230 **	-1.514 ***	-0.206	0.963 *	-1.073 **	-0.470	-0.368	0.256	1,343
	(6.78)	(3.91)	(0.68)	(1.36)	(1.20)	(-2.43)	(-2.98)	(-0.40)	(1.89)	(-2.10)	(-0.92)	(-0.72)	(0.50)	(0.021)
Germany	0.678 ***	2.081 ***	0.423	-0.088	0.220	-0.821	-0.481	-0.418	0.173	-0.575	-1.488 ***	-0.327	1.300 **	1,603
	(4.20)	(3.90)	(0.79)	(-0.16)	(0.41)	(-1.54)	(-0.90)	(-0.78)	(0.32)	(-1.07)	(-2.78)	(-0.61)	(2.43)	(0.013)
Hong Kong	1.960 ***	2.403	2.253	-3.373 **	0.222	1.157	-0.365	0.534	-2.379	-2.596 *	1.929	-2.326	2.541 *	456
	(4.28)	(1.58)	(1.48)	(-2.22)	(0.15)	(0.76)	(-0.24)	(0.35)	(-1.57)	(-1.71)	(1.27)	(-1.53)	(1.67)	(0.021)
Italy	1.228 ***	2.176 ***	0.582	-0.534	0.737	0.199	-1.614 **	-0.349	1.481 *	-2.114 ***	-0.913	-0.286	0.635	995
	(5.04)	(2.69)	(0.72)	(-0.66)	(0.91)	(0.25)	(-2.00)	(-0.43)	(1.83)	(-2.62)	(-1.13)	(-0.35)	(0.79)	(0.012)
Japan	1.193 ***	2.349 ***	0.497	0.567	-0.117	-0.703	-0.559	-1.014	-0.145	-0.555	-1.236 *	-0.252	1.167 *	1,034
	(6.22)	(3.69)	(0.78)	(0.89)	(-0.18)	(-1.11)	(-0.88)	(-1.60)	(-0.23)	(-0.87)	(-1.94)	(-0.39)	(1.83)	(0.014)
Netherlands	1.060 ***	1.741 ***	-0.241	1.316 **	1.078 *	-0.693	-0.503	-0.021	-0.824	-2.499 ***	-0.238	0.003	0.880	684
	(5.88)	(2.91)	(-0.40)	(2.20)	(1.80)	(-1.16)	(-0.84)	(-0.04)	(-1.38)	(-4.18)	(-0.40)	(0.01)	(1.47)	(0.037)
Norway	1.279 ***	3.166 ***	-1.097	-0.460	2.764 **	0.164	-0.342	1.248	-0.838	-3.013 ***	-0.740	-1.317	0.464	456
	(3.89)	(2.90)	(-1.01)	(-0.42)	(2.53)	(0.15)	(-0.31)	(1.14)	(-0.77)	(-2.76)	(-0.68)	(-1.21)	(0.43)	(0.031)
Singapore	1.155 ***	3.501 ***	0.223	-1.215	0.142	0.506	-0.079	-1.482	-1.954	-1.677	0.438	-0.912	2.508 **	456
	(3.13)	(2.86)	(0.18)	(-0.99)	(0.12)	(0.41)	(-0.06)	(-1.21)	(-1.60)	(-1.37)	(0.36)	(-0.75)	(2.05)	(0.016)
Spain	1.189 ***	1.841 ***	1.118 *	-0.048	0.392	-1.066 *	-0.795	-0.157	0.578	-1.495 **	-0.542	0.003	0.172	813
	(6.76)	(3.14)	(1.91)	(-0.08)	(0.67)	(-1.83)	(-1.36)	(-0.27)	(0.99)	(-2.57)	(-0.93)	(0.00)	(0.30)	(0.018)
Sweden	0.974 ***	1.919 ***	0.288	-0.260	0.594	0.100	-0.561	1.759 ***	-1.413 ***	-2.127 ***	-0.698	-0.199	0.600	1,068
	(6.36)	(3.78)	(0.57)	(-0.51)	(1.17)	(0.20)	(-1.11)	(3.46)	(-2.78)	(-4.19)	(-1.38)	(-0.39)	(1.18)	(0.038)
Switzerland	0.794 ***	1.439 **	-0.575	0.267	0.170	-0.449	0.146	-0.469	-0.621	-2.076 ***	0.452	0.319	1.397 **	503
	(3.84)	(2.08)	(-0.84)	(0.39)	(0.25)	(-0.65)	(0.21)	(-0.68)	(-0.91)	(-3.03)	(0.66)	(0.47)	(2.04)	(0.016)
UK	0.612 ***	1.138 ***	-0.024	-0.556 **	0.878 ***	-0.671 ***	-0.646 ***	0.118	0.225	-0.802 ***	0.381 *	-0.100	0.058	2,490
	(8.93)	(5.00)	(-0.10)	(-2.45)	(3.87)	(-2.96)	(-2.85)	(0.52)	(0.99)	(-3.52)	(1.68)	(-0.44)	(0.26)	(0.024)
USA	0.738 ***	0.358	-0.195	0.033	0.077	-0.149	-0.014	0.048	0.557 *	-0.971 ***	-0.305	0.067	0.492	2,472
	(8.13)	(1.19)	(-0.65)	(0.11)	(0.26)	(-0.50)	(-0.05)	(0.16)	(1.85)	(-3.23)	(-1.01)	(0.22)	(1.64)	(0.003)

over the whole sample period.[19] In all 18 countries the September return is lower than the unconditional mean return and in 15 countries the difference is significant at the 10 percent level. The effect is extremely strong for 10 countries in which the difference remains significant at the 1 percent level. In Norway, the September return is 3.0 percent lower than the cross-month average return of 1.3 percent.

Although the value-weighted return indices are examined, in 15 countries the January return is significantly higher than the unconditional mean return at the 5 percent level or better. This is not consistent with the general belief that the January effect is mainly driven by the small firm returns. It is noteworthy that the January return in the United States is higher than the unconditional mean return but not significant. The other two countries with no January effect are Austria and Hong Kong. However, they have significantly higher December returns, but the December return in the United States is still not significantly different from the mean return.

It appears that the United States is the only country showing no evidence of the turn-of-the-year effect over the whole sample period. In fact, there are only two months when the US stock market performs statistically significantly different from the mean return: August and September. Given the rebound in August 1932 from the Great Depression in the early 1930s which shifted the August mean return higher than the unconditional mean return, the September effect is the unique calendar month anomaly in the US stock market.

[19] We reran the regression analysis excluding the whole calendar year with missing observations and we obtained qualitatively similar results.

Table 2.4: Seasonality Test over the Common Sample Period

This table reports the OLS regression results of the value-weighted returns on the MSCI stock market indices of the eighteen developed countries and the world market from January 1970 to December 2007. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Country	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N (Adj R^2)
Australia	1.069 ***	1.238	-1.041	0.224	1.101	0.049	-0.607	-0.009	-0.073	-1.297	-0.571	-0.798	1.783 **	456
	(4.02)	(1.40)	(-1.18)	(0.25)	(1.25)	(0.06)	(-0.69)	(-0.01)	(-0.08)	(-1.47)	(-0.65)	(-0.90)	(2.02)	(0.002)
Austria	0.891 ***	0.279	2.131 ***	0.340	0.728	-0.582	-0.367	-0.069	-1.182	-2.040 **	-0.990	-0.445	2.198 ***	456
	(3.62)	(0.34)	(2.61)	(0.42)	(0.89)	(-0.71)	(-0.45)	(-0.08)	(-1.45)	(-2.50)	(-1.21)	(-0.55)	(2.69)	(0.028)
Belgium	1.099 ***	1.658 **	0.860	-0.002	1.543 **	-1.759 **	-0.306	0.361	-1.289 *	-2.030 ***	-0.399	-0.151	1.513 **	456
	(4.96)	(2.25)	(1.17)	(-0.00)	(2.10)	(-2.39)	(-0.42)	(0.49)	(-1.75)	(-2.76)	(-0.54)	(-0.20)	(2.06)	(0.039)
Canada	1.004 ***	1.327 *	0.152	-0.124	-0.954	0.174	-0.498	0.292	-0.005	-2.093 ***	-0.891	0.785	1.834 **	456
	(4.48)	(1.79)	(0.20)	(-0.17)	(-1.28)	(0.23)	(-0.67)	(0.39)	(-0.01)	(-2.82)	(-1.20)	(1.06)	(2.47)	(0.020)
Denmark	1.199 ***	2.520 ***	-1.066	-0.841	0.426	0.379	0.444	0.246	-0.934	-2.102 ***	0.703	-1.351 *	1.577 **	456
	(5.22)	(3.31)	(-1.40)	(-1.10)	(0.56)	(0.50)	(0.58)	(0.32)	(-1.22)	(-2.76)	(0.92)	(-1.77)	(2.07)	(0.040)
France	1.092 ***	1.854 **	0.868	1.099	1.689 *	-0.822	-1.983 **	-0.179	-0.642	-2.519 ***	-0.078	0.169	0.544	456
	(4.05)	(2.07)	(0.97)	(1.23)	(1.89)	(-0.92)	(-2.22)	(-0.20)	(-0.72)	(-2.82)	(-0.09)	(0.19)	(0.61)	(0.026)
Germany	0.871 ***	1.034	0.472	0.533	0.664	-1.609 *	0.299	0.166	-1.361	-2.641 ***	0.607	0.508	1.328	456
	(3.37)	(1.21)	(0.55)	(0.62)	(0.77)	(-1.88)	(0.35)	(0.19)	(-1.59)	(-3.08)	(0.71)	(0.59)	(1.55)	(0.019)
Hong Kong	1.912 ***	2.520	2.252	-3.227 **	0.119	0.600	-0.540	0.686	-2.328	-2.426	1.765	-2.148	2.726 *	456
	(4.10)	(1.63)	(1.46)	(-2.09)	(0.08)	(0.39)	(-0.35)	(0.44)	(-1.51)	(-1.57)	(1.14)	(-1.39)	(1.76)	(0.017)
Italy	1.039 ***	3.796 ***	1.356	0.938	0.711	-1.545	-1.820 *	-0.736	0.088	-2.640 **	-0.815	0.231	0.437	456
	(3.32)	(3.66)	(1.31)	(0.90)	(0.69)	(-1.49)	(-1.75)	(-0.71)	(0.08)	(-2.55)	(-0.79)	(0.22)	(0.42)	(0.034)
Japan	0.753 ***	1.051	0.072	1.500 *	0.510	-0.474	0.001	-0.753	-1.088	-1.232	-1.102	0.178	1.339 *	456
	(3.08)	(1.30)	(0.09)	(1.85)	(0.63)	(-0.59)	(0.00)	(-0.93)	(-1.34)	(-1.52)	(-1.36)	(0.22)	(1.65)	(0.007)
Netherlands	1.066 ***	1.488 *	-0.091	1.429 *	1.375 *	-0.772	-0.153	0.164	-0.971	-3.320 ***	-0.391	-0.004	1.244	456
	(4.59)	(1.93)	(-0.12)	(1.86)	(1.79)	(-1.00)	(-0.20)	(0.21)	(-1.26)	(-4.31)	(-0.51)	(-0.01)	(1.62)	(0.043)
Norway	1.279 ***	3.166 ***	-1.097	-0.460	2.764 **	0.164	-0.342	1.248	-0.838	-3.013 ***	-0.740	-1.317	0.464	456
	(3.89)	(2.90)	(-1.01)	(-0.42)	(2.53)	(0.15)	(-0.31)	(1.14)	(-0.77)	(-2.76)	(-0.68)	(-1.21)	(0.43)	(0.031)
Singapore	1.156 ***	3.501 ***	0.229	-1.210	0.141	0.501	-0.088	-1.016	-2.615 **	-2.000	0.527	-0.461	2.490 **	456
	(3.14)	(2.87)	(0.19)	(-0.99)	(0.12)	(0.41)	(-0.07)	(-0.83)	(-2.14)	(-1.64)	(0.43)	(-0.38)	(2.04)	(0.020)
Spain	1.191 ***	2.153 **	1.718 *	0.097	0.773	0.143	-0.711	-1.064	-0.735	-2.899 ***	0.151	0.879	-0.505	456
	(4.36)	(2.37)	(1.89)	(0.11)	(0.85)	(0.16)	(-0.78)	(-1.17)	(-0.81)	(-3.20)	(0.17)	(0.97)	(-0.56)	(0.024)
Sweden	1.449 ***	2.565 **	1.776 *	0.047	0.722	-0.930	-0.738	1.156	-3.150 ***	-3.186 ***	-0.098	1.447	0.390	456
	(4.84)	(2.58)	(1.79)	(0.05)	(0.73)	(-0.94)	(-0.74)	(1.16)	(-3.17)	(-3.21)	(-0.10)	(1.46)	(0.39)	(0.046)
Switzerland	0.833 ***	1.395 *	-0.612	0.394	0.131	-0.669	0.327	-0.111	-1.075	-2.279 ***	0.575	0.578	1.347 *	456
	(3.74)	(1.89)	(-0.83)	(0.53)	(0.18)	(-0.91)	(0.44)	(-0.15)	(-1.45)	(-3.08)	(0.78)	(0.78)	(1.82)	(0.019)
UK	1.157 ***	2.052 **	0.635	-0.009	1.825 **	-1.351	-1.369	-0.458	0.058	-1.909 **	-0.384	-0.313	1.222	456
	(4.29)	(2.29)	(0.71)	(-0.01)	(2.04)	(-1.51)	(-1.53)	(-0.51)	(0.06)	(-2.13)	(-0.43)	(-0.35)	(1.37)	(0.019)
USA	0.946 ***	0.918	-0.547	0.099	0.278	-0.139	-0.076	-0.615	-0.496	-1.531 **	0.379	0.847	0.883	456
	(4.65)	(1.36)	(-0.81)	(0.15)	(0.41)	(-0.21)	(-0.11)	(-0.91)	(-0.74)	(-2.27)	(0.56)	(1.26)	(1.31)	(0.002)
World	0.858 ***	1.124 *	-0.111	0.300	0.607	-0.508	-0.516	-0.441	-0.536	-1.650 ***	0.097	0.499	1.134 *	456
	(4.75)	(1.88)	(-0.19)	(0.50)	(1.01)	(-0.85)	(-0.86)	(-0.74)	(-0.89)	(-2.76)	(0.16)	(0.83)	(1.89)	(0.015)

Table 2.4 provides the seasonality test results with the MSCI developed markets country indices over the common sample period of 1970 to 2007. Consistent with the seasonality test results over the whole sample period, the September return is lower than the unconditional mean return in all 18 countries and in most countries the difference is significant at the 5 percent level. Australia, Hong Kong, Japan, and Singapore are the countries without significant September effects. Australia and Singapore are located either in the southern hemisphere or close to the equator. Thus, the September effect would be related with the fluctuations in daylight as Kamstra *et al*. (2003) argue. Additionally, the fiscal year end of most companies in Australia and Japan is different from December 31. For Hong Kong, the fiscal year end of the government is March 31. Therefore, the September effect would be related with the yearly business cycle as wll. We discuss this in detail in the section 4.

The January effect seems to have weakened in the recent period[20]. In only 9 countries, the January return is significantly higher than the unconditional mean return at the 5 percent level, while there are 15 countries with the significant January effect at the same level over the whole sample period. Except Singapore, the countries without the September effect do not have the January effect either. All of them, however, show somewhat higher returns in December. For the United States, September is the only calendar month with a stock return that is significantly different from the overall mean return. This confirms that the outperformance in August reported in Table 2.3 is caused

[20] Schwert (2002) shows that the small-firm turn-of-the-year effect became weaker in the years after it was first documented in the academic literature. Our finding of the weakened January effect in the recent period, 1970 – 2007, would be explained by the activities of investors who try to take advantage of the anomalous behavior of stock returns as the January effect was documented by Rozeff and Kinney (1976).

by the outlier in 1932.The turn-of-the-year effects in the United States are not observed in the recent period. The last row reports the seasonality test results with the MSCI world market index. It corroborates that the September effect is the strongest calendar month anomaly worldwide. It also shows the existence of the global turn-of-the-year effect, but the significance is marginal.

2.3 The September effect in the United States

In the previous section, we show that the September effect is the most pervasive one affecting every country in our sample and that it is getting stronger in the recent period. Since we use the value-weighted return indices, the September effect could be driven by large-cap stocks, as opposed to the January effect that is known to be driven by small-cap stocks. To test whether the September effect is limited to some specific style portfolios, we rerun the regression model described in equation (1) with size, book-to-market, and momentum decile portfolio returns, and 17 industry portfolio returns in the US market over the period 1927 to 2007.[21]

In Table 2.5, we report the OLS regression results for equation (1) of the returns on the 10 US size portfolios. At the end of each June, firms are sorted based on the June market equity value to construct the portfolios using NYSE breakpoints. Decile1 is the smallest portfolio and Decile10 is the largest portfolio. We impose the restriction that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return.

[21] We thank Kenneth French for making the data available. The data on the style portfolios are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2.5: Seasonality Test: US 10 Size Portfolios

This table reports the OLS regression results of the returns on the 10 US size portfolios from January 1927 to December 2007. At the end of each June, firms are sorted based on the June market equity to construct the portfolios using NYSE breakpoints. Decile1 is the Small portfolio and Decile10 is the Big portfolio. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N ($Adj\ R^2$)
Decile1 (Small)	1.513 ***	6.912 ***	0.480	-1.071	-0.236	-0.139	-0.605	0.482	-0.200	-1.544	-2.390 **	-0.448	-1.240	972
	(4.65)	(6.40)	(0.45)	(-0.99)	(-0.22)	(-0.13)	(-0.56)	(0.45)	(-0.19)	(-1.43)	(-2.21)	(-0.42)	(-1.15)	(0.036)
Decile2	1.312 ***	4.597 ***	0.388	-0.872	-0.199	0.003	-0.250	0.213	0.163	-2.021 **	-1.846 *	0.316	-0.493	972
	(4.60)	(4.86)	(0.41)	(-0.92)	(-0.21)	(0.00)	(-0.26)	(0.23)	(0.17)	(-2.14)	(-1.95)	(0.33)	(-0.52)	(0.020)
Decile3	1.293 ***	3.609 ***	0.045	-0.685	-0.067	-0.259	-0.323	0.243	0.334	-1.956 **	-1.587 *	0.515	0.130	972
	(4.96)	(4.17)	(0.05)	(-0.79)	(-0.08)	(-0.30)	(-0.37)	(0.28)	(0.39)	(-2.26)	(-1.83)	(0.60)	(0.15)	(0.014)
Decile4	1.240 ***	2.781 ***	-0.071	-0.526	-0.005	-0.139	-0.216	0.130	0.270	-1.688 **	-1.608 **	0.411	0.661	972
	(5.13)	(3.47)	(-0.09)	(-0.66)	(-0.01)	(-0.17)	(-0.27)	(0.16)	(0.34)	(-2.11)	(-2.01)	(0.51)	(0.82)	(0.010)
Decile5	1.204 ***	2.335 ***	-0.023	-0.519	0.130	-0.430	-0.118	0.102	0.637	-1.769 **	-1.558 **	0.696	0.516	972
	(5.21)	(3.05)	(-0.03)	(-0.68)	(0.17)	(-0.56)	(-0.15)	(0.13)	(0.83)	(-2.31)	(-2.03)	(0.91)	(0.67)	(0.009)
Decile6	1.178 ***	1.921 ***	-0.142	-0.473	0.178	-0.510	-0.163	0.245	0.474	-1.878 **	-1.318 *	0.709	0.956	972
	(5.32)	(2.62)	(-0.19)	(-0.64)	(0.24)	(-0.69)	(-0.22)	(0.33)	(0.65)	(-2.56)	(-1.79)	(0.97)	(1.30)	(0.008)
Decile7	1.154 ***	1.367 **	0.041	-0.438	0.105	-0.455	-0.119	0.265	0.488	-1.786 **	-1.100	0.663	0.970	972
	(5.52)	(1.97)	(0.06)	(-0.63)	(0.15)	(-0.66)	(-0.17)	(0.38)	(0.70)	(-2.57)	(-1.59)	(0.96)	(1.40)	(0.005)
Decile8	1.084 ***	1.065	-0.095	-0.315	-0.083	-0.474	-0.037	0.346	0.670	-1.992 ***	-0.825	0.929	0.811	972
	(5.48)	(1.62)	(-0.14)	(-0.48)	(-0.13)	(-0.72)	(-0.06)	(0.53)	(1.02)	(-3.04)	(-1.26)	(1.42)	(1.24)	(0.007)
Decile9	1.038 ***	1.030 *	-0.100	-0.375	-0.025	-0.408	-0.011	0.349	0.480	-1.731 ***	-0.628	0.578	0.841	972
	(5.51)	(1.65)	(-0.16)	(-0.60)	(-0.04)	(-0.65)	(-0.02)	(0.56)	(0.77)	(-2.77)	(-1.00)	(0.93)	(1.35)	(0.004)
Decile10 (Big)	0.897 ***	0.321	-0.557	-0.325	0.425	-0.346	0.216	0.588	0.346	-1.739 ***	-0.231	0.601	0.701	972
	(5.48)	(0.59)	(-1.03)	(-0.60)	(0.78)	(-0.64)	(0.40)	(1.08)	(0.64)	(-3.20)	(-0.43)	(1.11)	(1.29)	(0.006)

The September return is lower than the unconditional monthly mean return in every size portfolio and the difference is statistically significant at the 5 percent level or better in all portfolios except the smallest one. In general, the magnitude of the *t*-statistics increases as the size increases. Thus, the September effect is stronger among large portfolios but not confined to them. The October return is lower than the unconditional monthly mean return in every deciles but the difference is statistically significant at the 10 or 5 percent level only in deciles 1 through 5. This is consistent with Lo and MacKinlay (1990) who show that the returns of large stocks lead those of smaller stocks. That is, returns of smaller stocks in October are correlated with returns of larger stocks in September, but not vice-versa.

The January return is higher than the unconditional mean return in every size deciles. The magnitude of the *t*-statistics increases as the size decreases and this is consistent with the previous findings that the January effect is driven by small stocks. Across all size deciles, each calendar month return is not significantly different from their unconditional mean return other than in January, September, and October. If the negative performance of smaller firms in October is the lagged reaction to the negative performance of bigger firms in September as we discussed above, January and September seem to be the only seasonal challenge to the efficient market hypothesis across all size portfolios. Furthermore, the September effect is more pervasive than the January effect when it comes to the statistical significance.

In Table 2.6, we report the OLS regression results for equation (1) of the returns on the 10 US book-to-market portfolios over 1927 – 2007. At the end of each June, firms are sorted based on the June book-to-market ratio (BE/ME) to construct the portfolios

Table 2.6: Seasonality Test: US 10 Book-to-Market Portfolios

This table reports the OLS regression results of the returns on the 10 US book-to-market portfolios from January 1927 to December 2007. At the end of each June, firms are sorted based on the June BE/ME to construct the portfolios using NYSE breakpoints. The BE used in June of year *t* is the book equity for the last fiscal year end in *t-1*. ME is price times shares outstanding at the end of December of *t-1*. Decile1 is the Growth portfolio and Decile10 is the Value portfolio. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N ($Adj\ R^2$)
Decile1 (Growth)	0.872 ***	-0.025	-0.581	-0.133	0.253	-0.076	0.261	0.269	0.421	-1.761 ***	-0.405	0.999	0.778	972
	(4.74)	(-0.04)	(-0.95)	(-0.22)	(0.41)	(-0.12)	(0.43)	(0.44)	(0.69)	(-2.88)	(-0.66)	(1.64)	(1.27)	(0.003)
Decile2	0.973 ***	0.412	-0.384	-0.452	0.110	-0.354	0.070	0.690	0.452	-1.532 ***	-0.476	0.714	0.750	972
	(5.51)	(0.70)	(-0.66)	(-0.77)	(0.19)	(-0.60)	(0.12)	(1.18)	(0.77)	(-2.61)	(-0.81)	(1.22)	(1.28)	(0.002)
Decile3	0.960 ***	0.637	-0.334	-0.236	0.062	-0.225	-0.034	0.324	0.104	-1.528 ***	-0.503	0.767	0.965 *	972
	(5.60)	(1.12)	(-0.59)	(-0.42)	(0.11)	(-0.40)	(-0.06)	(0.57)	(0.18)	(-2.69)	(-0.89)	(1.35)	(1.70)	(0.003)
Decile4	0.968 ***	0.660	-0.123	-0.459	0.421	-0.444	0.165	0.496	0.539	-1.920 ***	-0.567	0.424	0.807	972
	(4.99)	(1.03)	(-0.19)	(-0.71)	(0.65)	(-0.69)	(0.26)	(0.77)	(0.84)	(-2.98)	(-0.88)	(0.66)	(1.25)	(0.003)
Decile5	1.038 ***	0.830	-0.374	-0.272	0.448	-0.656	0.167	0.535	0.400	-1.568 ***	-0.693	0.452	0.730	972
	(5.75)	(1.39)	(-0.62)	(-0.45)	(0.75)	(-1.09)	(0.28)	(0.89)	(0.67)	(-2.62)	(-1.16)	(0.76)	(1.22)	(0.004)
Decile6	1.080 ***	1.403 **	-0.155	-0.354	0.143	-0.831	-0.012	0.636	0.552	-1.796 ***	-0.565	0.247	0.732	972
	(5.47)	(2.14)	(-0.24)	(-0.54)	(0.22)	(-1.27)	(-0.02)	(0.97)	(0.84)	(-2.74)	(-0.86)	(0.38)	(1.12)	(0.006)
Decile7	1.103 ***	1.832 **	-0.769	-0.465	0.493	-0.682	0.202	0.808	0.650	-1.896 ***	-0.814	0.173	0.466	972
	(5.15)	(2.58)	(-1.08)	(-0.65)	(0.69)	(-0.96)	(0.28)	(1.14)	(0.92)	(-2.67)	(-1.15)	(0.24)	(0.66)	(0.008)
Decile8	1.255 ***	2.039 ***	-0.373	-0.612	0.509	-0.515	0.000	1.019	0.559	-2.141 ***	-0.970	0.248	0.238	972
	(5.64)	(2.76)	(-0.51)	(-0.83)	(0.69)	(-0.70)	(0.00)	(1.38)	(0.76)	(-2.90)	(-1.32)	(0.34)	(0.32)	(0.010)
Decile9	1.312 ***	2.757 ***	-0.429	-0.665	0.369	-0.559	0.004	0.942	0.592	-2.203 ***	-1.251	0.041	0.402	972
	(5.40)	(3.42)	(-0.53)	(-0.83)	(0.46)	(-0.69)	(0.00)	(1.17)	(0.73)	(-2.73)	(-1.55)	(0.05)	(0.50)	(0.013)
Decile10 (Value)	1.397 ***	4.065 ***	0.059	-0.730	0.204	-0.311	-0.489	1.247	0.171	-2.187 **	-2.275 **	-0.312	0.558	972
	(4.69)	(4.12)	(0.06)	(-0.74)	(0.21)	(-0.32)	(-0.50)	(1.26)	(0.17)	(-2.22)	(-2.31)	(-0.32)	(0.57)	(0.017)

using NYSE breakpoints, where BE is the book equity for the last fiscal year end in *t*-1 and ME is the price times shares outstanding at the end of December of *t*-1. Decile1 is the lowest book-to-market (Growth) portfolio and Decile10 is the highest book-to-market (Value) portfolio.

The September return is lower than the unconditional monthly mean return in every book-to-market portfolio and the difference is statistically significant at the 1 percent level in all portfolios but Decile10. The magnitudes of the *t*-statistics for each portfolio are similar to each other. Thus, the September effect is pervasive and does not depend on the book-to-market ratio. The October return is lower than the overall mean return in all deciles, but the difference is only statistically significant at the 5 percent level in the highest book-to-market portfolio.

The January return is higher than the mean return in most book-to-market deciles but the difference is statistically significant only for the value portfolios (Decile6 through 10). The *t*-statistics increase as the book-to-market ratio increases suggesting that the January effect is driven by the value stocks as well. Other than January and September, each calendar month return is not significantly different from their unconditional mean return in every book-to-market decile. As we have seen in size sorted portfolios, the strongly negative September returns are the most anomalous and they are not explained by the book-to-market ratios.

In Table 2.7, we report the OLS regression results for equation (1) of the returns on the 10 US momentum portfolios over 1927 – 2007. The portfolios are constructed monthly using NYSE prior (2-12) return decile breakpoints. Decile1 is the worst-performing portfolio and Decile10 is the best-performing portfolio. The intercept

Table 2.7: Seasonality Test: US 10 Momentum Portfolios

This table reports the OLS regression results of the returns on the 10 US momentum portfolios from January 1927 to December 2007. The portfolios are constructed monthly using NYSE prior (2-12) return decile breakpoints. Decile1 is the Down portfolio and Decile10 is the Up portfolio. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N ($Adj\ R^2$)
Decile1 (Down)	0.317	3.804 ***	-0.524	-0.704	0.100	-0.233	-0.089	0.844	1.329	-2.331 **	-1.370	0.447	-1.271	972
	(1.04)	(3.76)	(-0.52)	(-0.70)	(0.10)	(-0.23)	(-0.09)	(0.83)	(1.31)	(-2.30)	(-1.36)	(0.44)	(-1.26)	(0.013)
Decile2	0.712 ***	2.282 ***	-0.537	-0.781	0.646	-0.285	-0.102	1.171	1.109	-2.084 **	-0.863	0.164	-0.720	972
	(2.75)	(2.66)	(-0.63)	(-0.91)	(0.75)	(-0.33)	(-0.12)	(1.36)	(1.29)	(-2.43)	(-1.01)	(0.19)	(-0.84)	(0.008)
Decile3	0.717 ***	1.775 **	-0.591	-0.577	0.396	-0.507	0.334	0.643	0.985	-1.808 **	-0.644	0.274	-0.280	972
	(3.21)	(2.39)	(-0.80)	(-0.78)	(0.53)	(-0.68)	(0.45)	(0.87)	(1.33)	(-2.44)	(-0.87)	(0.37)	(-0.38)	(0.005)
Decile4	0.863 ***	1.252 *	-0.413	-0.780	0.362	-0.073	-0.008	0.873	0.386	-1.602 **	-0.558	0.484	0.077	972
	(4.18)	(1.83)	(-0.60)	(-1.14)	(0.53)	(-0.11)	(-0.01)	(1.27)	(0.56)	(-2.34)	(-0.82)	(0.71)	(0.11)	(0.002)
Decile5	0.866 ***	0.955	-0.273	-0.753	0.266	-0.424	-0.017	0.733	0.821	-1.590 **	-0.673	0.432	0.523	972
	(4.52)	(1.50)	(-0.43)	(-1.18)	(0.42)	(-0.67)	(-0.03)	(1.15)	(1.29)	(-2.50)	(-1.06)	(0.68)	(0.82)	(0.004)
Decile6	0.938 ***	0.677	-0.422	-0.449	0.227	-0.412	-0.211	0.748	0.689	-1.223 **	-0.733	0.501	0.609	972
	(5.01)	(1.09)	(-0.68)	(-0.72)	(0.36)	(-0.66)	(-0.34)	(1.20)	(1.11)	(-1.97)	(-1.18)	(0.81)	(0.98)	(0.000)
Decile7	1.031 ***	0.542	-0.376	-0.609	-0.128	-0.454	0.208	0.788	0.306	-1.810 ***	-0.321	1.070 *	0.784	972
	(5.76)	(0.91)	(-0.63)	(-1.03)	(-0.22)	(-0.76)	(0.35)	(1.33)	(0.52)	(-3.05)	(-0.54)	(1.80)	(1.32)	(0.007)
Decile8	1.170 ***	0.361	-0.324	-0.285	0.334	-0.349	0.167	0.448	-0.010	-1.897 ***	-0.494	0.910	1.140 **	972
	(6.77)	(0.63)	(-0.57)	(-0.50)	(0.58)	(-0.61)	(0.29)	(0.78)	(-0.02)	(-3.31)	(-0.86)	(1.59)	(1.99)	(0.008)
Decile9	1.259 ***	0.280	-0.316	0.035	0.112	-0.459	0.376	0.143	0.161	-1.684 ***	-0.602	0.760	1.193 **	972
	(6.91)	(0.46)	(-0.52)	(0.06)	(0.19)	(-0.76)	(0.62)	(0.24)	(0.27)	(-2.78)	(-1.00)	(1.26)	(1.97)	(0.004)
Decile10 (Up)	1.590 ***	0.224	-0.132	0.398	0.426	-0.576	-0.010	-0.520	-0.109	-1.621 **	-0.584	0.642	1.862 ***	972
	(7.62)	(0.32)	(-0.19)	(0.57)	(0.61)	(-0.83)	(-0.01)	(-0.75)	(-0.16)	(-2.34)	(-0.84)	(0.93)	(2.69)	(0.004)

represents the unconditional mean return and the coefficient represents the difference between the return in the calendar month and the unconditional monthly mean return.

The September return is lower than the unconditional monthly mean return in every momentum portfolio and the difference is statistically significant at the 5 percent level in all portfolios. The magnitudes of the *t*-statistics for each portfolio are similar to each other. Thus, the September effect is pervasive and does not depend on the momentum effect. Table 2.7 shows the abnormally positive return in January for poorly-performed portfolios (Decile1 through 3) and in December for better-performed portfolios (Decile8 through 10). This can be explained by the window dressing around the turn-of-the-year period. Overall, September is the only month in which the returns deviated from their unconditional mean irrespective of the past performance.

Finally, we report the OLS regression results for equation (1) of the returns on the 17 US industry portfolios over 1927 – 2007 in Table 2.8. At the end of each June, the industry portfolios are constructed based on each stock's four-digit SIC code following Fama and French (1988). Table 2.8 shows that industries present various seasonal patterns in their monthly return. The oil industry performs well in April but poorly in September. The machinery industry performs well in January and November but poorly in September. However, the September return is lower than the unconditional monthly mean return in every industry and the difference is statistically significant at the 5 percent level in 14 industries. Thus, the September effect is pervasive and is not limited to some specific industries.

Overall, the September effect is the most pervasive anomalous phenomenon that is largely independent of size, book-to-market ratio, past performance, or industry. Now

Table 2.8: Seasonality Test: US 17 Industry Portfolios

This table reports the OLS regression results of the returns on the 17 US industry portfolios from January 1927 to December 2007. At the end of each June, the portfolios are constructed based on each stock's four-digit SIC code following Fama and Fench (1996). We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N ($Adj R^2$)
Food	1.016 ***	0.446	-0.451	-0.086	-0.060	0.313	0.125	0.178	-0.133	-1.577 ***	0.213	0.577	0.455	972
	(6.48)	(0.86)	(-0.87)	(-0.17)	(-0.12)	(0.60)	(0.24)	(0.34)	(-0.26)	(-3.03)	(0.41)	(1.11)	(0.87)	(0.001)
Mining and Minerals	1.021 ***	2.133 ***	0.481	0.050	-1.412 **	-0.339	-1.036	0.388	0.467	-0.962	-1.812 ***	1.144 *	0.898	972
	(4.89)	(3.08)	(0.69)	(0.07)	(-2.04)	(-0.49)	(-1.50)	(0.56)	(0.68)	(-1.39)	(-2.62)	(1.65)	(1.30)	(0.017)
Oil and Petroleum	1.132 ***	-0.439	-0.936	0.705	1.360 **	-0.407	-0.265	0.640	0.265	-1.595 **	-0.076	0.059	0.689	972
	(5.80)	(-0.68)	(-1.45)	(1.09)	(2.10)	(-0.63)	(-0.41)	(0.99)	(0.41)	(-2.46)	(-0.12)	(0.09)	(1.06)	(0.005)
Clothings	0.883 ***	2.496 ***	0.189	0.105	0.216	-0.359	-0.411	-0.154	-0.376	-1.193 *	-1.131 *	0.215	0.403	972
	(4.53)	(3.86)	(0.29)	(0.16)	(0.33)	(-0.56)	(-0.64)	(-0.24)	(-0.58)	(-1.85)	(-1.75)	(0.33)	(0.62)	(0.011)
Consumer Durables	0.943 ***	1.804 **	0.264	-0.431	0.197	-0.337	-0.502	0.058	1.410 *	-2.504 ***	-0.891	1.231	-0.299	972
	(3.82)	(2.20)	(0.32)	(-0.53)	(0.24)	(-0.41)	(-0.61)	(0.07)	(1.72)	(-3.06)	(-1.09)	(1.50)	(-0.37)	(0.009)
Chemicals	1.055 ***	-0.133	-0.036	-0.120	0.744	-0.138	-0.204	0.353	0.746	-2.140 ***	-1.400 **	0.708	1.620 **	972
	(5.29)	(-0.20)	(-0.05)	(-0.18)	(1.12)	(-0.21)	(-0.31)	(0.53)	(1.13)	(-3.23)	(-2.11)	(1.07)	(2.45)	(0.012)
Drugs, Soap, Tobacco	1.032 ***	0.387	-0.755	-0.434	0.644	-0.162	0.061	0.454	0.152	-1.816 ***	0.387	0.793	0.288	972
	(6.48)	(0.73)	(-1.43)	(-0.82)	(1.22)	(-0.31)	(0.12)	(0.86)	(0.29)	(-3.44)	(0.73)	(1.50)	(0.55)	(0.008)
Construction	0.973 ***	1.143	0.212	-0.131	-0.250	-0.388	-0.268	0.468	0.272	-2.260 ***	-1.141	1.187	1.155	972
	(4.44)	(1.57)	(0.29)	(-0.18)	(-0.34)	(-0.53)	(-0.37)	(0.64)	(0.37)	(-3.11)	(-1.57)	(1.63)	(1.59)	(0.008)
Steel	1.021 ***	1.937 **	-0.076	-0.496	0.160	-1.214	-0.234	1.488 *	0.757	-2.428 ***	-1.745 **	0.474	1.376	972
	(3.83)	(2.19)	(-0.09)	(-0.56)	(0.18)	(-1.37)	(-0.26)	(1.68)	(0.86)	(-2.75)	(-1.97)	(0.54)	(1.56)	(0.012)
Fabricated Products	0.961 ***	0.977	0.706	0.022	0.433	-0.451	0.092	0.125	0.455	-2.279 ***	-1.002	0.361	0.561	972
	(4.98)	(1.53)	(1.10)	(0.03)	(0.68)	(-0.70)	(0.14)	(0.20)	(0.71)	(-3.56)	(-1.56)	(0.56)	(0.88)	(0.009)
Machinery	1.119 ***	1.405 *	-0.521	-0.729	0.550	-0.545	-0.046	0.230	0.673	-2.662 ***	-0.963	1.512 **	1.097	972
	(4.92)	(1.86)	(-0.69)	(-0.97)	(0.73)	(-0.72)	(-0.06)	(0.30)	(0.89)	(-3.53)	(-1.28)	(2.00)	(1.45)	(0.014)
Automobiles	1.119 ***	1.355 *	-0.330	-0.097	1.134	-0.690	-0.083	1.593 *	0.667	-1.447 *	-1.856 **	-0.738	0.491	972
	(4.51)	(1.65)	(-0.40)	(-0.12)	(1.38)	(-0.84)	(-0.10)	(1.94)	(0.81)	(-1.76)	(-2.26)	(-0.90)	(0.60)	(0.007)
Transportation	0.963 ***	2.032 ***	-0.158	-0.961	0.098	-0.448	-0.451	1.157	-0.183	-1.961 ***	-0.816	0.784	0.905	972
	(4.23)	(2.69)	(-0.21)	(-1.27)	(0.13)	(-0.59)	(-0.60)	(1.53)	(-0.24)	(-2.60)	(-1.08)	(1.04)	(1.20)	(0.010)
Utilities	0.912 ***	1.205 **	-0.793	-0.789	-0.172	-0.112	0.476	0.545	0.546	-1.503 **	0.137	-0.248	0.709	972
	(5.00)	(1.99)	(-1.31)	(-1.30)	(-0.29)	(-0.19)	(0.79)	(0.90)	(0.90)	(-2.49)	(0.23)	(-0.41)	(1.17)	(0.005)
Retail Stores	1.002 ***	0.551	0.273	0.548	0.141	-0.103	0.297	0.023	0.590	-1.742 ***	-0.672	0.996	-0.902	972
	(5.23)	(0.87)	(0.43)	(0.86)	(0.22)	(-0.16)	(0.47)	(0.04)	(0.93)	(-2.75)	(-1.06)	(1.57)	(-1.42)	(0.004)
Financials	1.078 ***	1.155	-0.124	-0.354	-0.207	-0.631	0.259	0.694	0.626	-2.117 ***	-0.640	0.685	0.655	972
	(4.92)	(1.59)	(-0.17)	(-0.49)	(-0.29)	(-0.87)	(0.36)	(0.95)	(0.86)	(-2.91)	(-0.88)	(0.94)	(0.90)	(0.004)
Other	0.891 ***	0.924 *	-0.024	-0.439	0.024	-0.240	-0.044	-0.224	0.339	-1.330 **	-0.611	0.797	0.827	972
	(5.45)	(1.70)	(-0.04)	(-0.81)	(0.04)	(-0.44)	(-0.08)	(-0.41)	(0.62)	(-2.45)	(-1.13)	(1.47)	(1.52)	(0.004)

we turn to the potential source of this September effect in the next section.

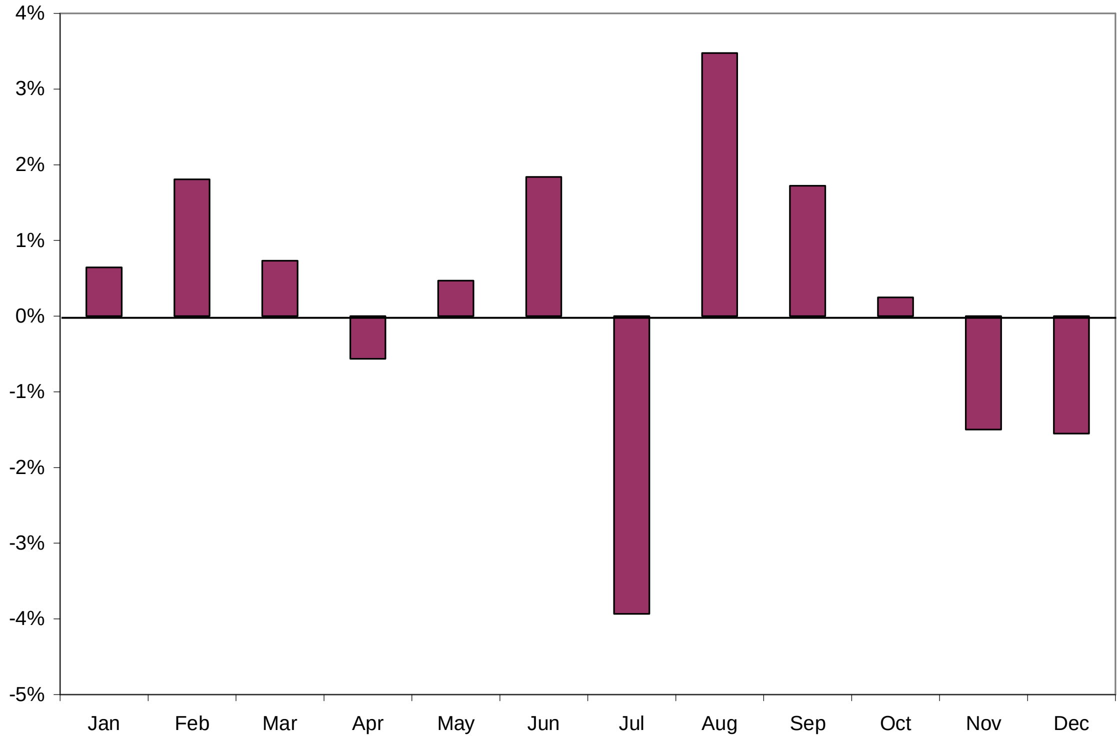
2.4. The influence of the predicted economic growth on the stock market return

Stock prices tend to react to the economic news. The pervasiveness of the September effect that we have shown suggests that it is likely to be caused by a macroeconomic factor rather than a sector specific one. For instance, industrial production is one of the macroeconomic variables that is demonstrated to be significant in explaining expected stock returns by the previous literature (see, for example, Reinganum (1984), Chan, Chen, and Hsieh (1985), Chang and Pinegar (1986), Chen, Roll, and Ross (1986), and Chang and Pinegar (1989)). The September effect could also be explained by investor behavior. As Kamstra *et al.* (2003) argue that the seasonal affective disorder (SAD) among investors would lower stock market returns during the fall, seasonal patterns in depression cause seasonal variation in risk aversion and hence stock returns. In this section, we examine the interrelationship between the stock market seasonality and the seasonal variations in industrial production and investor risk aversion.

2.4.1 The Variables

Chang and Pinegar (1989) show that the seasonal peaks in the industrial production growth occur in February and August and that these peaks follow the stock market peaks by one month. To test the relationship between the stock market seasonality and the seasonal patterns in industrial production, we obtain the index of seasonally unadjusted industrial production from the Board of Governors of the Federal Reserve System. The monthly growth is measured as the log difference of the industrial

Figure 2.2: Industrial Production Growth by Month



We plot the monthly mean industrial production growth by month for the period January 1927 through December 2007. We obtained the index of industrial production from the Board of Governors of the Federal Reserve System. The monthly growth is measured as the log difference of the industrial production index between time *t* and *t-1*.

production index between time t and t-1.

In Figure 2.2, we plot the monthly mean industrial production growth by month for the period of January 1927 to December 2007. Consistent with Chang and Pinegar (1989), the industrial production growth is the highest in August and the lowest in July. Notably, the industrial production growth in the fourth quarter is lower than the rest of the year. This is consistent with Graham, Harvey, and Rajgopal (2005) who survey the corporate executives and find that managers would sacrifice long-term value to smooth earnings. Especially, the financial executives admit that they would decrease discretionary spending and delay starting a new project to meet the desired earnings target. The lower growth of industrial production in the fourth quarter would be the result of the corporate strategy to smooth the earnings target. Thus, the poor performance of the stock market in September may be caused by the forward looking nature of stock prices combined with the negative growth in the industrial production in the last quarter of the year.

Chen *et al.* (1986), and Chang and Pinegar (1989) examine the relation between the industrial production growth at time t+1 and the stock market return at time t because industrial production is a flow and the industrial production growth measures the change in industrial production lagged by at least a partial month. Instead of using the industrial production growth at time t+1, we decompose the contemporaneous industrial growth (IPG_t) into two parts as follows:

$$\begin{aligned} IPG_t &= \log IP_t - \log IP_{t-1} \\ &= \{\log IP_t - E_{t-1}(\log IP_t)\} + \{E_{t-1}(\log IP_t) - \log IP_{t-1}\} \\ &= SIPG_t + EIPG_t \qquad (2) \end{aligned}$$

where $E_{t-1}(\log IP_t)$ is the next month's predicted industrial production at time *t*-1.

The first part of the equation (2), $SIPG_t$, is the surprise in the industrial production growth and the second part, $EIPG_t$, is the expected industrial production growth. We forecast the next month's industrial production ($E_{t-1}(\log IP_t)$) using ARIMA(12,1,0) model to incorporate the seasonal pattern and a unit root in industrial production.[22] We assume that at the end of each month investors can predict the next month's industrial production. If the realized industrial production is greater than the prediction then the stock price would increase. Thus, the relation between the surprise in the industrial production growth and the stock market return would be positive. The expected industrial production growth would incorporate the forward looking nature of stock prices. As investors anticipate the increase in industrial production next month, they would buy stocks increasing the price at time *t*-1. Thus, the relation between the expected industrial production growth and the stock market return would be negative.

If investors are forward looking, at time *t*-1, they would predict the industrial production growth not only for time *t* but also time *t*+1 and at time t, with the new information, they would change their predicted industrial production for time *t*+1. To capture this effect, we also consider the variable, $SPIPG_t$, defined as follows:

$$SPIPG_t = \{E_t(\log IP_{t+1}) - \log IP_t\} - \{E_{t-1}(\log IP_{t+1}) - E_{t-1}(\log IP_t)\} \qquad (3)$$

This variable represents the surprise in the predicted industrial production growth for the next month. If investors believe the industrial production growth for the next month

[22] The unreported analysis shows that the industrial production growth series has a unit root. The results are available upon request from the authors.

would be greater than their previous prediction then they would buy stocks at time *t*. Thus, the relation between the surprise in the predicted production growth for the next month and the stock market return would be positive.

Kamstra *et al.* (2003) argue that most people start suffering from SAD in the fall. If so, September and October should be the times when we see the largest impact if people start readjusting their portfolios when they first become risk averse. Kamstra *et al.* find the negative return effect in the fall season and the positive return effect for the SAD measure. Their SAD measure is the interaction term between a fall-winter dummy and the normalized number of hours of night so their finding supports Hirshleifer and Shumway (2003) who find that sunshine is significantly correlated with stock returns. We control for the investor risk aversion induced by the SAD effect in our model[23]. We also examine the interaction terms between the industrial production growth variables and the SAD measure to test whether investors are influenced by the economic information more strongly when they become more risk averse.

A number of researchers (see, for example, Fama and French (1993), Vassalou and Xing (2004), and Carhart (1997)) argue that Fama-French size factor (SMB), book-to-market factor (HML) and momentum factor (UMD) are factor-mimicking portfolios whose returns are related to systematic risk that is not captured solely by the stock market return. We add these three factors (SMB, HML, and UMD) to control for the unknown economic factors.

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[23] We thank Mark Kamstra for making the data available. SAD measures are obtained from his website: http://www.markkamstra.com/.

2.4.2 Empirical evidence

In Table 2.9, we report the results of our model for the CRSP monthly value-weighted market returns (R_t) from January 1927 to December 2007. The full model is:

$$R_t = \alpha_t + \beta_1 EIPG_t + \beta_2 SIPG_t + \beta_3 SPIPG_t + \beta_4 SAD_t + \beta_5 D_t^{Fall}$$
$$+ \beta_6 SIPG_t * SAD_t + \beta_7 SPIPG_t * SAD_t + \beta_8 SMB_t + \beta_9 HML_t + \beta_{10} UMD_t + \varepsilon_t \qquad (4)$$

where $EIPG_t$ is the expected growth in industrial production, $SIPG_t$ is the surprise in industrial production growth, $SPIPG_t$ is the surprise in the predicted industrial production growth for the next month, SAD_t is the SAD measure, D_t^{Fall} is the dummy variable for trading months in the autumn (e.g., September, October, and November), SMB_t and HML_t are the Fama-French size and book-to-market factors, UMD_t is the momentum factor, and ε_t is the error term.[24] All of the variables are as previously defined.

In the first column, the coefficient of the expected growth in industrial production is negative, albeit insignificant, and that of the surprise in the industrial production growth is significantly positive at the 5 percent level. However, when we add the surprise in the predicted industrial production growth for the next month, the surprise in the industrial production growth becomes insignificant and the coefficient of the surprise in the predicted industrial production growth for the next month is significantly positive at the 1 percent level. These results are consistent with the forward looking nature of stock prices. Stock prices reflect the contemporaneous economic growth as well as the upcoming economic growth as the economic environment varies. This variable remains

[24] We collect the Fama-French size and book-to-market factors and the momentum factors from Kenneth Frrench's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2.9: The Influence of the Predicted Economic Growth on the Stock Market Returns

This table reports the OLS regression results of the following model for the CRSP monthly value-weighted market returns from January 1927 to December 2007.

$$R_t = \alpha_t + \beta_1 EIPG_t + \beta_2 SIPG_t + \beta_3 SPIPG_t + \beta_4 SAD_t + \beta_5 D_t^{Fall} + \beta_6 SIPG_t * SAD_t + \beta_7 SPIPG_t * SAD_t + \beta_8 SMB_t + \beta_9 HML_t + \beta_{10} UMD_t + \varepsilon_t$$

The monthly market returns (R_t) are regressed on a constant, the expected growth in industrial production ($EIPG_t$), the surprise in industrial production growth ($SIPG_t$), the surprise in the predicted industrial production growth for the next month ($SPIPG_t$), the SAD measure (SAD_t), the dummy variable for trading months in autumn (D_t^{Fall}), the interaction between $SIPG_t$ and SAD_t, the interaction between $SPIPG_t$ and SAD_t, the Fama-French size and book-to-market factors (SMB_t and HML_t), and the momentum factor (UMD_t). *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.009 ***	0.009 ***	0.010 ***	0.007 ***	0.007 ***	0.009 ***
	(5.44)	(5.29)	(6.37)	(3.11)	(3.01)	(4.09)
Expected growth in industrial production	-0.091	-0.087	-0.157 **	-0.066	-0.047	-0.127 *
	(-1.25)	(-1.22)	(-2.39)	(-0.92)	(-0.65)	(-1.90)
Surprise in the industrial production growth	0.267 ***	0.060	-0.023	0.089	0.070	-0.040
	(3.63)	(0.65)	(-0.27)	(0.95)	(0.60)	(-0.38)
Surprise in the predicted industrial production growth for the next month		0.634 ***	0.375 **	0.602 ***	0.841 ***	0.570 ***
		(3.67)	(2.37)	(3.49)	(3.78)	(2.80)
SAD				0.004 **	0.004 **	0.002 *
				(2.50)	(2.52)	(1.67)
Fall Dummy				-0.008 *	-0.007 *	-0.004
				(-1.89)	(-1.84)	(-0.99)
Surprise in the industrial production growth * SAD					0.002	0.026
					(0.02)	(0.36)
Surprise in the predicted industrial production growth for the next month * SAD					-0.289 *	-0.242 *
					(-1.88)	(-1.73)
SMB			0.434 ***			0.420 ***
			(9.09)			(8.75)
HML			0.119 **			0.110 **
			(2.50)			(2.30)
UMD			-0.290 ***			-0.292 ***
			(-7.84)			(-7.89)
N	972	972	972	972	972	972
Adjusted R^2	0.017	0.030	0.202	0.036	0.039	0.204

significantly positive even after adding Fama-French size and book-to-market ratio factors and the momentum factor.

In the fourth column, we add the SAD measure and the fall season dummy variable to control for the effect of seasonal risk aversion on equity returns. The coefficient of the SAD measure is significantly positive and that of the fall season dummy is negative. This is consistent with Kamstra *et al.* (2003). That is, the stock market performs poorly in the fall season as SAD-influenced investors, who become risk averse, rebalance their portfolios in favor of relatively safe assets. However, it performs better in the following season as a result of a subsequent relief of depression-induced risk aversion as days begin to lengthen. In this model, the coefficient of the surprise in the predicted industrial production growth for the next month is still significantly positive at the 1 percent level. Thus, both the future economic growth and the investor depression factor are reflected in the stock price.

In the next column, we add the interaction terms between the SAD measure and the surprise in the industrial production growth and the surprise in the predicted industrial production growth. The second interaction term is significantly negative at the 10 percent level while the surprise in the predicted industrial production growth, the SAD measure, and the fall season dummy remain significant. That is, the stock prices reflect the future economic growth more in the fall season when the most investors become more risk averse. As the SAD measure increases, they would recover from the depression, become less risk averse and put less weight on the future economic growth for valuing their assets. This interaction term remains significant even after controlling for Fama-French size, book-to-market factor and the momentum factor as reported in the last column of Table 2.9.

Overall, the results from our model show the return seasonality to be correlated with the investor behavior represented by the SAD measure as well as the future economic growth. Further we find that investors put more weight on the future economic growth as they become more risk averse in the fall season. From this we argue that the September effect is caused by this investor behavior accompanied by the negative growth of industrial production in the last quarter.

2.4.3 Abnormal return in September and expected future economic growth

We test whether the September effect is related with the economic growth in the last quarter of the year. Most empirical tests of stock return anomalies examine the abnormal return against a benchmark such as the market return. For the September effect, however, it is about the anomalous behavior of the market return itself and most subportfolios constructed based on various characteristics follow the same seasonal pattern. Therefore, we use the mean monthly return over the previous eleven months as the benchmark to measure the abnormal return in September. We run the following OLS regression of this abnormal return in September (AR_t) on the economics growth variables described above:

$$AR_t = \alpha_t + \beta_1 EIPG_t + \beta_2 SIPG_t + \beta_3 SPIPG_t + \varepsilon_t \tag{5}$$

Table 2.10: The Influence of the Predicted Economic Growth on the Abnormal September Return

This table reports the OLS regression results of the following model for the abnormal September market return against the mean return for the prior 11 months.

$$AR_t = \alpha_t + \beta_1 EIPG_t + \beta_2 SIPG_t + \beta_3 SPIPG_t + \beta_4 D_t^{1986} + \varepsilon_t$$

The abnormal September returns (AR_t) are regressed on a constant, the expected growth in industrial production ($EIPG_t$), the surprise in industrial production growth ($SIPG_t$), the surprise in the predicted industrial production growth for the next month ($SPIPG_t$), and the dummy variable for the post-Tax Reform Act 1986 (D_t^{1986}). The model is estimated on monthly data spanning 1928 through 2007. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Variable	Model 1	Model 2	Model 3
Intercept	-0.024 ***	-0.019 **	-0.023 **
	(-2.89)	(-2.24)	(-2.02)
Expected growth in industrial production	0.219	0.095	0.204
	(0.70)	(0.30)	(0.54)
Surprise in the industrial production growth	0.580 **	0.018	0.051
	(2.01)	(0.04)	(0.12)
Surprise in the predicted industrial production growth for the next month		1.270 *	1.257 *
		(1.74)	(1.72)
Post-Tax Reform Act 1986 dummy			0.009
			(0.56)
N	80	80	80
Adjusted R^2	0.025	0.051	0.042

In Table 2.10 we report the OLS regression results[25]. The model is estimated on monthly data spanning from 1928 through 2007. The results are similar to what is reported in Table 2.9. In the first column, the coefficient of the expected growth in industrial production is insignificant but that of the surprise in the industrial production growth is significantly positive at the 5 percent level. However, when we add the surprise in the predicted industrial production growth for the next month in the next column, the surprise in the industrial production growth becomes insignificant and the coefficient of the surprise for the next month is significantly positive at the 10 percent level. Thus, the abnormal return in September can be explained by the forward looking nature of stock prices.

2.5 Alternative explanations of the September effect

Although the September effect has not received much attention from academic researchers, it has been covered repeatedly by the media. In this section, we examine the alternative explanations suggested by the media in some detail.

2.5.1 Mutual fund fiscal and tax year-end

[25] We ran the regression controlling for the Fama-French size (SMB), book-to-market (HML) factors and the momentum factor (UMD). The sign of each variable is the same. All variables became insignificant but the size factor (SMB). Given the small sample size of 80 observations, this would be caused by the multicollinearity among the variables. We decided not to report the results with SMB, HML, and UMD. The results are, however, available upon request from the authors.

One explanation presented by the media for the September effect is that many mutual funds close out their fiscal years at the end of September[26]. For window-dressing reasons, mutual funds want to sell the losers until they report holdings to shareholders. Further, the Tax Reform Act of 1986 (TRA) mandated an October 31 tax year-end for all funds to retain their pass-through tax status. The tax-loss selling by mutual funds prior to their tax year-end would intensify the abnormally negative return in September.

Gibson, Safieddine, and Titman (2000) find that in 1986 about 30 percent of equity funds had December fiscal year-ends and the other 70 percent of equity funds had fiscal year-ends that were distributed fairly evenly across each of the other eleven months. After TRA, many funds shifted their fiscal year-end to October 31 but only about 21 percent of funds had October fiscal year-ends in 1996. Since the mutual fund fiscal year-ends are not concentrated in September and October, they should not have any impact on the September effect.

To examine the October tax year-end mandated by TRA, we added to the regression model (5) the year 1986 indicator variable that takes on a value of one if the year is 1986 or later, and zero otherwise. The last column of Table 2.10 shows that the introduction of TRA does not have any impact on the abnormal negative return in September. In addition, window-dressing and tax-loss selling hypotheses suggest an asymmetric behavior across different portfolios based on their past return. Loser portfolios would underperform and winner portfolios would outperform prior to the fiscal and tax year-end. However, the results reported in Table 2.7 show that the September

[26] See, for example, "Uh oh. Here comes September" CNNMoney.com August 31 2006.

effect is pervasive regardless of prior performance. All portfolios from Decile1 through 10 suffer from the September effect. Hence, we reject the mutual fund fiscal and tax year-end as a possible explanation for the September effect.

2.5.2 Back-to-school mentality

Hong and Yu (2007) find that trading activity is lower during the summer, the typical vacation period, than during the rest of the year. Once fall begins, investors return to work and exit positions that they had been planning on selling. Especially, when they spent more during the vacation, they would feel financially constrained after the vacation. This back-to-school mentality[27] would be linked with the September effect. If this back-to-school mentality causes the September effect, then we would expect to see the abnormally negative performance of the Australian stock market in March, rather than in September, as the country is located in the Southern Hemisphere. However, as we reported in Table 2.1 and 2, the mean return of the Australian stock market in March is substantially higher than that in September. The mean return is 0.89 percent in March and 0.44 percent in September over 1882 – 2007. The difference has become wider recently. The mean return is 1.29 percent in March and -0.23 in September.

To examine whether the lower liquidity in the summer is related to the September effect, we run the OLS regression model (1) with 10 volume and 10 turnover[28] portfolios

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[27] Although investors do not go back to school literally, they think of the start of the fall season as a fresh start for their business. (*CNN*, 08/31/2006)

[28] The monthly turnover is calculated as the ratio of the monthly volume to the number of shares outstanding.

Table 2.11: Seasonality Test: US 10 Volume Portfolios

This table reports the OLS regression results of the returns on the 10 US volume portfolios from January 1927 to December 2007. The portfolios are constructed monthly using NYSE prior 3 month volume decile breakpoints. Decile1 is the lowest volume portfolio and Decile10 is the highest volume portfolio. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N (Adj R^2)
Decile1	0.011 ***	0.017 ***	-0.001	0.003	-0.001	-0.004	-0.002	0.006	-0.003	-0.011 **	-0.003	0.000	0.000	972
	(7.38)	(3.47)	(-0.20)	(0.52)	(-0.29)	(-0.87)	(-0.35)	(1.14)	(-0.57)	(-2.24)	(-0.61)	(-0.05)	(0.04)	(0.008)
Decile2	0.011 ***	0.020 ***	-0.001	-0.003	-0.001	-0.005	0.000	0.009	0.002	-0.014 **	-0.011 **	0.003	0.001	972
	(7.01)	(3.81)	(-0.22)	(-0.57)	(-0.15)	(-0.94)	(-0.03)	(1.59)	(0.30)	(-2.56)	(-2.12)	(0.65)	(0.23)	(0.017)
Decile3	0.011 ***	0.023 ***	-0.002	0.001	-0.001	-0.004	-0.001	0.003	-0.001	-0.013 **	-0.012 **	0.006	0.002	972
	(6.73)	(4.52)	(-0.39)	(0.18)	(-0.24)	(-0.73)	(-0.18)	(0.59)	(-0.28)	(-2.48)	(-2.39)	(1.07)	(0.33)	(0.021)
Decile4	0.011 ***	0.019 ***	-0.001	-0.002	-0.003	-0.001	0.002	0.003	0.003	-0.014 **	-0.012 **	0.002	0.004	972
	(6.54)	(3.31)	(-0.11)	(-0.32)	(-0.46)	(-0.19)	(0.34)	(0.54)	(0.44)	(-2.44)	(-2.10)	(0.37)	(0.62)	(0.010)
Decile5	0.011 ***	0.018 ***	0.000	-0.003	0.002	-0.004	0.000	0.003	0.000	-0.015 ***	-0.012 **	0.006	0.005	972
	(6.05)	(3.15)	(-0.06)	(-0.45)	(0.34)	(-0.68)	(-0.04)	(0.53)	(-0.04)	(-2.64)	(-2.07)	(1.11)	(0.86)	(0.011)
Decile6	0.010 ***	0.014 **	-0.003	-0.001	0.001	-0.004	0.002	0.001	0.003	-0.015 ***	-0.012 **	0.006	0.009	972
	(5.72)	(2.43)	(-0.56)	(-0.22)	(0.14)	(-0.68)	(0.31)	(0.21)	(0.44)	(-2.63)	(-2.13)	(1.07)	(1.62)	(0.010)
Decile7	0.010 ***	0.013 **	-0.003	-0.004	0.001	0.001	0.002	0.002	0.003	-0.016 ***	-0.014 **	0.008	0.009	972
	(5.48)	(2.06)	(-0.50)	(-0.59)	(0.09)	(0.10)	(0.39)	(0.27)	(0.48)	(-2.68)	(-2.34)	(1.34)	(1.39)	(0.009)
Decile8	0.011 ***	0.009	0.000	-0.005	0.001	-0.003	0.005	0.002	0.003	-0.017 ***	-0.010 *	0.007	0.009	972
	(5.72)	(1.40)	(-0.06)	(-0.74)	(0.16)	(-0.43)	(0.80)	(0.28)	(0.44)	(-2.80)	(-1.71)	(1.17)	(1.47)	(0.006)
Decile9	0.010 ***	0.005	-0.003	-0.003	0.003	-0.004	0.002	0.003	0.003	-0.018 ***	-0.007	0.007	0.012 **	972
	(5.62)	(0.85)	(-0.48)	(-0.44)	(0.57)	(-0.68)	(0.35)	(0.51)	(0.45)	(-3.01)	(-1.22)	(1.14)	(1.98)	(0.006)
Decile10	0.009 ***	0.005	-0.003	-0.004	0.003	-0.006	0.001	0.007	0.006	-0.018 ***	-0.004	0.005	0.008	972
	(4.97)	(0.89)	(-0.56)	(-0.69)	(0.46)	(-0.94)	(0.18)	(1.07)	(0.94)	(-2.92)	(-0.60)	(0.83)	(1.33)	(0.004)

Table 2.12: Seasonality Test: US 10 Turnover Portfolios

This table reports the OLS regression results of the returns on the 10 US turnover portfolios from January 1927 to December 2007. The portfolios are constructed monthly using NYSE prior 3 month turnover decile breakpoints. Decile1 is the lowest turnover portfolio and Decile10 is the highest turnover portfolio. We impose the restrictions that the sum of coefficients of the independent variables must be zero so that the intercept becomes the unconditional mean return. *t*-statistics are reported in parenthesis. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Portfolio	Int	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	N ($Adj\ R^2$)
Decile1	0.010 ***	0.003	-0.003	0.001	0.002	-0.002	0.001	0.005	0.000	-0.011 **	-0.006	0.005	0.005	972
	(6.97)	(0.62)	(-0.57)	(0.25)	(0.40)	(-0.44)	(0.27)	(0.98)	(0.06)	(-2.37)	(-1.29)	(1.00)	(1.09)	(0.000)
Decile2	0.009 ***	0.007	-0.008	0.001	0.003	0.002	0.003	0.002	0.001	-0.014 ***	-0.008	0.004	0.006	972
	(5.88)	(1.30)	(-1.47)	(0.19)	(0.66)	(0.42)	(0.60)	(0.35)	(0.23)	(-2.75)	(-1.54)	(0.84)	(1.16)	(0.005)
Decile3	0.010 ***	0.008	-0.004	-0.005	0.004	-0.003	0.000	0.004	0.004	-0.015 ***	-0.005	0.007	0.004	972
	(5.62)	(1.49)	(-0.71)	(-0.81)	(0.78)	(-0.54)	(-0.00)	(0.65)	(0.71)	(-2.70)	(-0.82)	(1.17)	(0.78)	(0.003)
Decile4	0.010 ***	0.004	-0.004	-0.002	0.002	-0.005	0.002	0.005	0.005	-0.015 **	-0.004	0.004	0.009	972
	(5.57)	(0.75)	(-0.73)	(-0.39)	(0.30)	(-0.79)	(0.27)	(0.78)	(0.91)	(-2.55)	(-0.77)	(0.65)	(1.56)	(0.001)
Decile5	0.010 ***	0.010 *	-0.003	-0.004	0.002	-0.003	0.002	0.004	0.002	-0.018 ***	-0.003	0.006	0.006	972
	(5.58)	(1.65)	(-0.50)	(-0.62)	(0.28)	(-0.53)	(0.32)	(0.69)	(0.34)	(-3.10)	(-0.50)	(0.98)	(0.98)	(0.004)
Decile6	0.011 ***	0.010	-0.005	-0.001	0.004	-0.004	-0.001	0.006	0.003	-0.017 ***	-0.008	0.005	0.008	972
	(5.59)	(1.61)	(-0.73)	(-0.17)	(0.68)	(-0.70)	(-0.21)	(0.87)	(0.51)	(-2.61)	(-1.31)	(0.78)	(1.26)	(0.004)
Decile7	0.010 ***	0.015 **	-0.001	-0.005	0.004	-0.008	-0.001	0.004	0.006	-0.024 ***	-0.007	0.009	0.009	972
	(4.91)	(2.05)	(-0.10)	(-0.75)	(0.58)	(-1.11)	(-0.15)	(0.58)	(0.89)	(-3.38)	(-1.06)	(1.21)	(1.24)	(0.010)
Decile8	0.010 ***	0.016 **	-0.001	-0.005	0.000	-0.007	0.001	0.008	0.003	-0.022 ***	-0.010	0.008	0.010	972
	(4.57)	(2.23)	(-0.19)	(-0.71)	(-0.00)	(-1.01)	(0.07)	(1.03)	(0.46)	(-3.01)	(-1.42)	(1.12)	(1.41)	(0.010)
Decile9	0.010 ***	0.016 **	0.002	-0.009	-0.003	-0.008	-0.001	0.003	0.009	-0.017 **	-0.012	0.010	0.013	972
	(4.00)	(2.03)	(0.19)	(-1.18)	(-0.41)	(-1.03)	(-0.18)	(0.39)	(1.07)	(-2.14)	(-1.52)	(1.19)	(1.60)	(0.007)
Decile10	0.009 ***	0.015 *	-0.002	-0.009	-0.004	-0.009	-0.004	-0.001	0.010	-0.017 *	-0.008	0.014	0.014	972
	(3.28)	(1.65)	(-0.17)	(-0.96)	(-0.44)	(-0.99)	(-0.45)	(-0.12)	(1.05)	(-1.81)	(-0.88)	(1.58)	(1.54)	(0.003)

in the US stock markets over the period of 1927 to 2007. The portfolios are constructed monthly using NYSE prior 3-month volume (turnover) decile breakpoints. We report the results in Table 2.11 and 2.12. These tables present the pervasive September effect regardless of the prior 3 months' volume and turnover. All 10 volume and 10 turnover portfolios yield significantly negative returns in September relative to their unconditional mean returns. That is, the lower trading activity during the summer vacation period is not related with the September effect.

2.5.3 Fear of crash

Post Traumatic Stress Disorder (PTSD) is an overwhelming response to an extreme event such as an earthquake, a war, a fire, or a stock market crash. According to the commonly accepted stock-market damage meter on Wall Street, a decline of 20 percent or more in a single day or a few days is considered a crash.[29] Historically, there have been two crashes in the US stock market and both crashes happened to occur in October – October 29, 1929 and October 19, 1987. Thus, investors who are suffering from PTSD due to the stock market crashes in October would become more risk averse in September. As they leave the stock market in September, before October comes, the increased selling pressure would cause the negative performance of the stock market.

De Long and Shleifer (1991) find that the closed-end funds traded at premium relative to their net asset values before the stock market crash in 1929. In the third quarter of 1929, the median seasoned funds sold at a premium of 47 percent. However, starting

[29] See, The Wall Street Journal (January 24, 2008).

December 1929 through the early 1930's a substantial majority of seasoned funds sold at discounts. From this they argue that the closed-end funds premia reflect the investor sentiment. Many authors (see, for example, Lee, Shleifer, and Thaler (1991) and Neal and Wheatley (1998)) also have confirmed that the average discount on closed-end equity funds reflects the investor sentiment.

To test whether the investor sentiments are affected by PTSD, we examine the closed-end fund discount around the October 1987 stock market crash. We collect the monthly closed-end fund discount index from Baker and Wurgler (2007)[30]. In Figure 2.3, we plot the value-weighted average discount on closed-end mutual funds in September for the period 1966 – 2005. We also plot the difference between September closed-end fund discount and the monthly mean discount for the prior 11 months.

In 37 out of 40 Septembers, the closed-end funds were traded in discount. The discount in September is 9.9 percent on average and this is only 0.3 percent higher than the monthly mean discount for the prior 11 months[31]. In 1986 the discount in September was 3.6 percent and 12.1 percent in 1988. However, in September 1992, the closed-end funds were traded at 1.3 percent of premium. Even if the increased discount around the stock market crash in 1987 was caused by the fear that the market would crash again in October, investors appear to overcome the fear by 1992.Prior to the crash (e.g., 1966 – 1986), the mean discount in September is 12 percent while it is 7 percent after the crash

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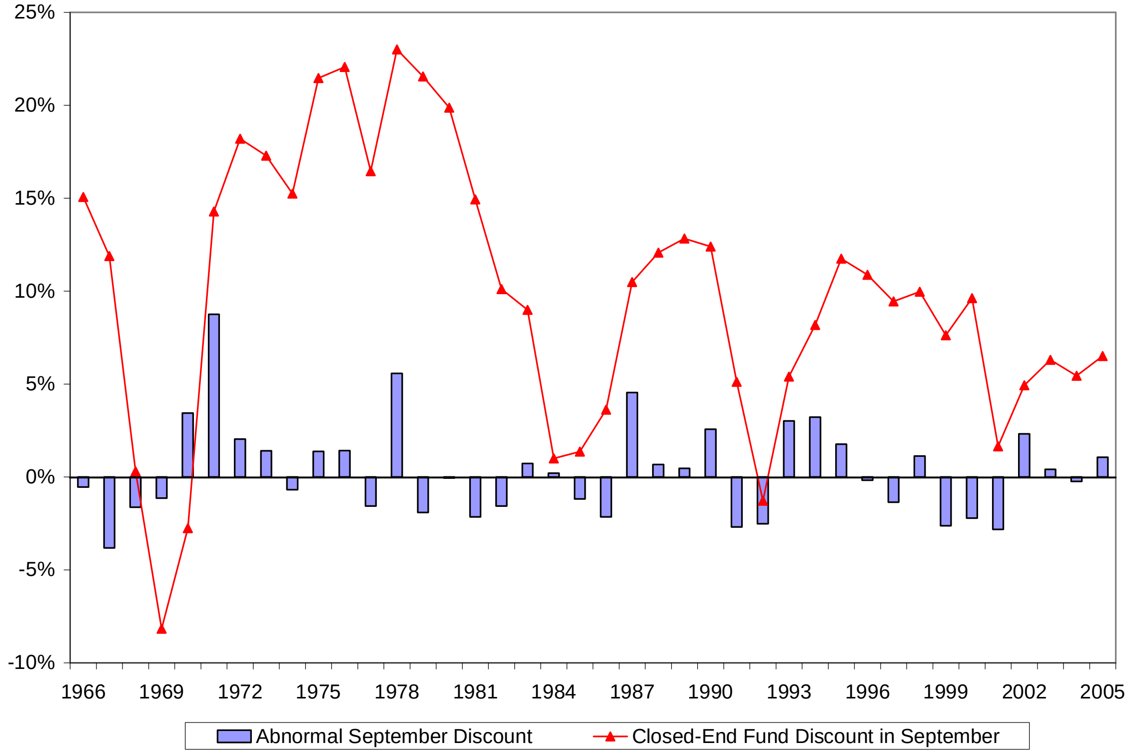
[30] We thank Jeffrey Wurgler for making the data available on his website: http://pages.stern.nyu.edu/ ~jwurgler.

[31] The unreported *t*-test results show that the closed-end fund discount in September is not significantly different from the mean discount for the prior 11 months.

Figure 2.3: Closed-End Fund Discount in September



We plot the value-weighted average discount on closed-end mutual funds in September for the period 1966 through 2005. The closed-end fund discount is the difference between the net asset value of a fund's actual security holdings and the fund's market price. We obtained the data from Baker and Wurgler (2007). We also plot the difference between September closed-end fund discount and the mean discount for the prior 11 months as the bar chart.

(e.g., 1990 – 2005). Investor sentiment in September doesn't seem to be different from the other months. Also, after the crash, investors are more optimistic than before the crash. From these findings, we cautiously reject that PTSD after the stock market crash in October causes the September effect.

2.6 Implications of the September effect on the investor wealth

The results in Tables 2.3 and 2.4 suggest potential gains from adopting an investment strategy based on the September effect. To avoid the poor performance of stock markets in September, we suggest that investors exit the stock markets at the end of August and reenter at the end of September. That is, we assume that investors place 100 percent of their portfolio into a risk-free asset in September and into the stock market portfolio for the rest of the year. We compare this September-*exit* strategy with the well-known benchmark strategy: the buy-and-hold strategy.

In Table 2.13 we report the mean and standard deviation of annual returns and the Sharpe ratios of two investment strategies in eighteen countries. The mean return results show that the September-*exit* strategy outperforms the buy-and-hold strategy in all countries except Australia and Japan. The standard deviation of the September-*exit* strategy is lower than that of the buy-and-hold strategy in all countries except Singapore. The Sharpe ratio of the September-*exit* strategy is higher than that of the buy-and-hold strategy in all countries. Overall, compared to the buy-and-hold strategy, the September-*exit* strategy yields substantially higher returns with lower volatility.

In Figure 2.4 we plot the end-of-period wealth of an initial investment of $1 in the U.S. stock market over the period 1927 through 2007 according to two investment

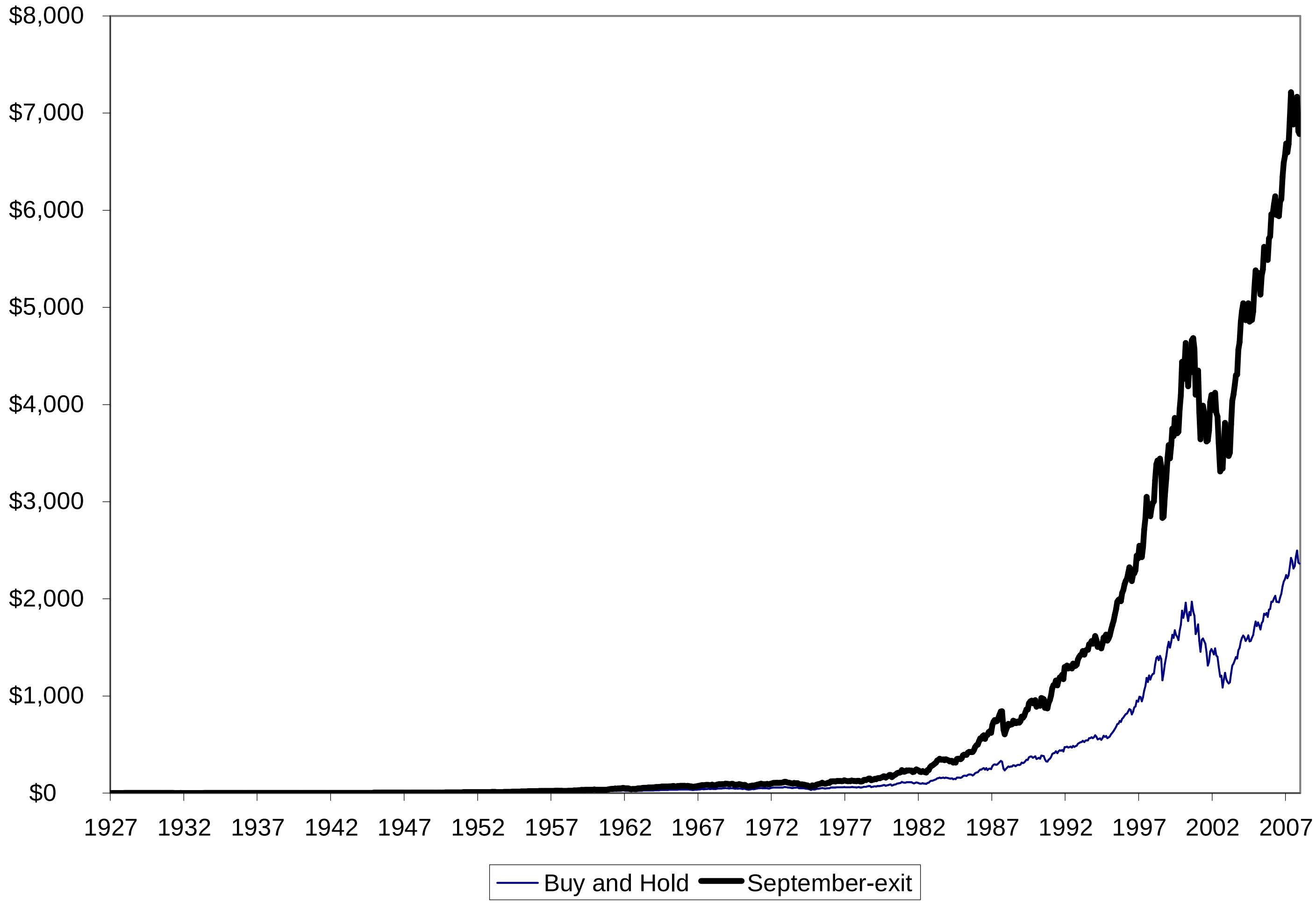
Table 2.13: The Relative Performance of the September-*exit* Strategy

This table reports the mean and standard deviation of annual returns and the Sharpe ratio of two investment strategies in eighteen countries: the buy-and-hold strategy and the September-*exit* strategy. The buy-and-hold strategy refers to the strategy in which investors hold the stock market portfolio through the whole sample period. The September-*exit* strategy refers to the strategy in which investors hold the risk-free asset in September and the market portfolio in other calendar months. Monthly mean returns and standard deviations are reported as a percentage. We use US data from Schwert (1990) for 1802 – 1926 and from the CRSP value-weighted market return series for 1927 – 2007. We collect the monthly stock market returns for the other countries from Global Financial Data (GFD) from the start date to December 2007. Start date is the first month for which stock market total return index data are available in GFD.

Country		Buy & Hold Strategy	September-*exit* Strategy
Australia	mean	13.57	13.33
	standard deviation	*16.27*	*14.80*
	(Sharpe Ratio)	(0.83)	(0.90)
Austria	mean	12.09	13.84
	standard deviation	*28.19*	*26.39*
	(Sharpe Ratio)	(0.43)	(0.52)
Belgium	mean	12.15	13.51
	standard deviation	*18.53*	*16.39*
	(Sharpe Ratio)	(0.66)	(0.82)
Canada	mean	11.65	12.47
	standard deviation	*15.79*	*14.34*
	(Sharpe Ratio)	(0.74)	(0.87)
Denmark	mean	17.59	18.80
	standard deviation	*31.39*	*27.97*
	(Sharpe Ratio)	(0.56)	(0.67)
France	mean	12.82	13.16
	standard deviation	*23.50*	*22.18*
	(Sharpe Ratio)	(0.55)	(0.59)
Germany	mean	9.71	9.96
	standard deviation	*29.87*	*28.55*
	(Sharpe Ratio)	(0.32)	(0.35)
Hong Kong	mean	27.64	28.07
	standard deviation	*46.50*	*42.70*
	(Sharpe Ratio)	(0.59)	(0.66)
Italy	mean	16.86	18.58
	standard deviation	*32.89*	*32.71*
	(Sharpe Ratio)	(0.51)	(0.57)

Country		Buy & Hold Strategy	September-*exit* Strategy
Japan	mean	16.45	16.09
	standard deviation	*30.24*	*27.82*
	(Sharpe Ratio)	(0.54)	(0.58)
Netherlands	mean	13.98	15.83
	standard deviation	*21.79*	*20.10*
	(Sharpe Ratio)	(0.64)	(0.79)
Norway	mean	18.90	20.74
	standard deviation	*41.72*	*36.77*
	(Sharpe Ratio)	(0.45)	(0.56)
Singapore	mean	17.59	18.92
	standard deviation	*45.96*	*47.41*
	(Sharpe Ratio)	(0.38)	(0.40)
Spain	mean	16.04	16.84
	standard deviation	*24.56*	*22.25*
	(Sharpe Ratio)	(0.65)	(0.76)
Sweden	mean	13.14	14.75
	standard deviation	*23.77*	*22.66*
	(Sharpe Ratio)	(0.55)	(0.65)
Switzerland	mean	11.63	13.21
	standard deviation	*22.52*	*21.43*
	(Sharpe Ratio)	(0.52)	(0.62)
UK	mean	7.94	8.50
	standard deviation	*16.84*	*16.15*
	(Sharpe Ratio)	(0.47)	(0.53)
USA	mean	9.33	10.82
	standard deviation	*17.51*	*17.44*
	(Sharpe Ratio)	(0.53)	(0.62)

Figure 2.4: End-of-Period Wealth



We plot the end-of-period wealth of an initial investment of $1 in three investment strategies over the period 1927 through 2007 in the United States. The solid line represents the buy-and-hold strategy and the bold line represents the September-*exit* strategy.

strategies. The solid line represents the buy-and-hold strategy and the bold line represents the September-*exit* strategy. Evidently, following the September-*exit* strategy would have yielded substantially higher wealth than the other strategy at the end of the period. If an investor put $1 in the September-*exit* strategy at the beginning of 1927, she would have $6,784 at the end of 2007. Instead, if she put $1 in the buy-and-hold strategy, she would have only $2,363.

2.7 Concluding Remarks

As the media have warned, September is the worst performing month of the stock market. Over the last two hundred years the U.S. stock market return in September was -0.24 percent, and it is the only month with the negative mean return. The United States is not the only market that is affected by the September effect though. We find that in 16 out of 18 developed countries in our sample the September return is negative, and in 15 countries it is significantly lower than the unconditional mean return. Unlike the January effect, this September effect has not weakened in the recent period. In all 18 countries, the mean return in September is negative and in 15 countries it is significantly lower than the unconditional mean return over the last 38 years. Furthermore, from examining the various style portfolios in the U.S. market, we find that the September effect is the most pervasive anomalous phenomenon that is independent of the size, the book-to-market ratio, past performance, or industry.

We find that the forward looking nature of stock prices together with the lower economic growth in the last quarter of the year causes the September effect. Especially in the fall season when most investors become more risk averse, the stock prices reflect the future economic growth more than the rest of the year. From this we argue that the September effect is caused by the seasonally affected investor reaction to their rational expectations. We tested whether alternative explanations suggested by the media would explain the September effect but failed to find any evidence supporting those explanations.

Finally, we propose an investment strategy based on the September effect. Our strategy yields higher mean return and lower standard deviation than the buy-and-hold strategy. The Sharpe ratio of our strategy is greater than that of the buy-and-hold strategy. The results suggest that adopting a simple strategy of exiting the stock market in September would provide considerable benefit to investors.

CHAPTER 3

SEASONALITY IN MUTUAL FUND FLOWS

3.1 Introduction

Investor demand for mutual funds has increased substantially over the years. At the end of year 2007, the U.S. mutual fund industry had $12 trillion in assets under management, and the net cash inflow to the mutual funds had increased from $112 billion in 1991 to $883 billion in 2007. Consequently, extensive academic research has examined the various aspects of the mutual fund industry. In particular, many studies examine the cash flows entering and exiting the mutual funds to gain a deeper understanding of the behavior of mutual fund investors (see Ippolito (1992), Gruber (1996), Sirri and Turano (1998), Zheng (1999), Frazzini and Lamont (2008), and Johnson and Poterba (2008)).

A voluminous literature has shown that there is a strong seasonal component to investors' trading behavior.[32] However, much less attention has been devoted to the seasonal regularity in the behavior of mutual fund investors. Mutual fund investors' behavior could be somewhat different from the individual investors' behavior in the stock market as they have different holding periods and face different fee structure, transaction costs, and tax treatment on distributions. This paper analyzes the seasonality in the

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[32] See, for instance, Chakravarty (2001), Ng and Wang (2004), Carhart, Kaniel, Musto, and Reed (2002), Hirshleifer and Shumway (2003), Bouman and Jacobsen (2002), and Hong and Yu (2007).

mutual fund investors' trading behavior by studying the seasonality in the cash flows of mutual funds.

Recently, Johnson and Poterba (2008) examine the impact of taxes on the timing of mutual fund purchases. They find that some investors time their purchases of mutual fund shares to avoid the tax acceleration associated with distributions. Considering that most equity mutual funds pay dividends in December, the investors' behavior to time their purchases would cause the net cash flows to equity funds to be high in January and low in December. Indeed, the *Investment Company Fact Book* reports that the net cash flow to equity mutual funds was $28.3 billion in January 2007, but only $1.3 billion in December 2007.

Abel, Eberly, and Panageas (2007) show that even a small observation cost can induce investors to review and adjust their holdings infrequently over time.[33] Jagannathan and Wang (2007) find that the consumption-based asset pricing model (CCAPM) performs better if the consumption growth is measured based on the fourth quarter rather than other quarters. Therefore, they suggest that all investors are likely to make their consumption and investment decisions simultaneously during the fourth quarter. Given that December is the end of the fiscal year of most firms and the tax year of individual investors, investors are induced to review their holdings and make asset allocation decisions around the turn-of-the-year. For mutual fund investors, the turn-of-the-quarter period would also be the time to review their holdings and make asset allocation decisions, because mutual funds must report their past performance up to the latest

[33] In their calculation, even a small observation of one basis point of wealth implies the eight months of decision interval.

calendar quarter end which is required by the advertising guidelines proposed by the National Association of Securities Dealers (NASD).

In this paper, we establish the presence of seasonality in the U.S. domestic equity mutual fund flows using the combined database from the CRSP and N-SAR filings. We find that the equity funds receive the highest net cash flows in January and the lowest in December. The large net flows in January are attributed to the increased purchases, and the small net flows in December are due to the increased redemptions. Thus, the turn-of-the-year is the time that the most mutual fund investors make their investment decisions. When we examine the seasonal patterns in the net flows inferred from the formula that the standard practice in the literature have used, we find that the inferred net flows are understated in December relative to the reported net flows. This inconsistency between the inferred net flows and the reported net flows could be caused by the way the inferring formula treats the distribution and reinvestment. Unlike the turn-of-the-year period, we do not find any abnormal increase or decrease in fund flows around the turn-of-the-quarter.

We try to identify the possible sources of seasonality in mutual fund cash flows. We examine the linkage between the seasonal pattern and the various factors, such as the seasonal component in the personal income and consumption, the tax treatment of distributions from mutual funds, style objectives of funds, and the past performance of the funds. We find that the seasonal component of their asset allocation decisions is not associated with the seasonal variations in personal income and consumption growth. The tax treatment of the distribution from mutual funds does not drive this seasonal pattern. Unlike the seasonal patterns in fund returns, which are extensively studied in the literature, the seasonal patterns in fund flows are indifferent to style objective.[34] Past performance, however, has an effect on the seasonality in the cash flows of equity funds. The January effect in the inflow to mutual funds is stronger for the funds with the higher past performance. We also find that investors are not sensitive to the past performance when they buy style funds but they sell the funds with the poor past performance in the turn-of-the-year period.

The rest of this paper is organized as follows. Section 2 describes the sample and provides preliminary analysis. Section 3 reports the empirical results of the seasonality test of the cash flows to the U.S. domestic mutual funds. Section 4 offers the possible explanations for the seasonality. Finally, Section 5 concludes.

3.2 Cash flows to mutual funds

3.2.1 Data

This study examines the seasonal patterns in net flows, inflow, and outflow to U.S. domestic equity mutual funds over the fourteen-year period beginning in January 1994 through December 2007. Our sample is based on the mutual fund database compiled by Center for Research in Security Prices Survivor Bias Free Mutual Fund Data base (hereafter referred to as CRSP database) and mutual funds' N-SAR filings with the U.S. Securities and Exchange Commission (SEC).

The CRSP database provides the fund share class level information on monthly total net assets (TNA), monthly returns, asset classes (equity vs. bond fund), style

[34] See, for example, Branch (1977), Dyl (1977), Keim (1983), Reinganum (1983), Roll (1983) and Ritter (1988).

objectives, and names for all open-end mutual funds. We include 15,283 U.S. domestic equity fund classes from January 1994 to December 2007 in this study.[35] To avoid the possible upward bias in the reported returns of the smallest funds, we eliminate funds with less than $15 million in assets under management following previous literature. (See, Elton, Gruber, and Blake (2001) and Chen, Hong, Huang, and Kubik (2004)). In doing so, we have 9,278 equity fund classes reported in the CRSP database.

All mutual funds are required to file N-SARs with the SEC every six months based on their fiscal year. N-SAR filings contain information on the dollar amount of new sales, reinvestment of dividends and distributions, other sales, and redemptions for each month covered by the filing. N-SAR filings also identify the total net assets of mutual funds at the end of the period that is covered by the filing. Due to data availability, we collect all N-SARs pertaining to calendar years 1994 through 2007 from the SEC's Edgar website.[36] We then match a fund's N-SAR filing with the CRSP database based on the fund and family names.

N-SARs report the monthly dollar flows in and out of mutual funds at the fund level, but the CRSP mutual fund database treats the fund share classes as different entities. Therefore, we manually identify the share classes of a fund according to fund names and calculate total net asset values and monthly fund returns at the fund level to match them to the N-SAR filings. As a result, we obtain matched mutual fund level data containing 3,346 domestic equity funds over the period from January 1994 to December 2007.

Table 3.1: Descriptive Statistics for U.S. Domestic Equity Funds

[35] We exclude the international funds, natural resources funds, and index funds.
[36] http://www.sec.gov/edgar.shtml

This table reports descriptive statistics of monthly total net asset value, monthly return, capital distribution, income distribution, and the number of fund classes to U.S. domestic equity mutual funds. We exclude funds with less than $15 million in assets under management. Out of 9,278 fund classes from CRSP Survivor-Bias-Free US Mutual Fund Database over the sample period from January 1994 to December 2007, the matched sample consists of 6,322 fund classes between CRSP database and N-SAR filings with the SEC.

		Matched	Unmatched	All
Monthly Total Net Asset Value ($ million)	mean	728.3	576.6	649.8
	(median)	(107.4)	(106.5)	(106.9)
Monthly Return (%)	mean	0.65	0.71	0.68
	(median)	(0.94)	(0.95)	(0.95)
Capital Distribution (%)	mean	0.38	0.42	0.40
	(median)	(0.00)	(0.00)	(0.00)
Income Distribution (%)	mean	0.06	0.08	0.08
	(median)	(0.00)	(0.00)	(0.00)
Number of Fund Classes	mean	1,919	2,058	3,976

Table 3.1 reports descriptive statistics of matched and unmatched equity mutual fund classes reported in the CRSP database. Out of 9,278 fund classes, the matched sample consists of 6,322 fund classes between CRSP database and N-SAR filings with the SEC. On average, the matched funds manage greater assets than the unmatched funds but they generate lower returns and make lower distributions. The median of each statistic, however, shows the matched and unmatched funds have similar characteristics.

3.2.2 Net flows, inflows, and outflows

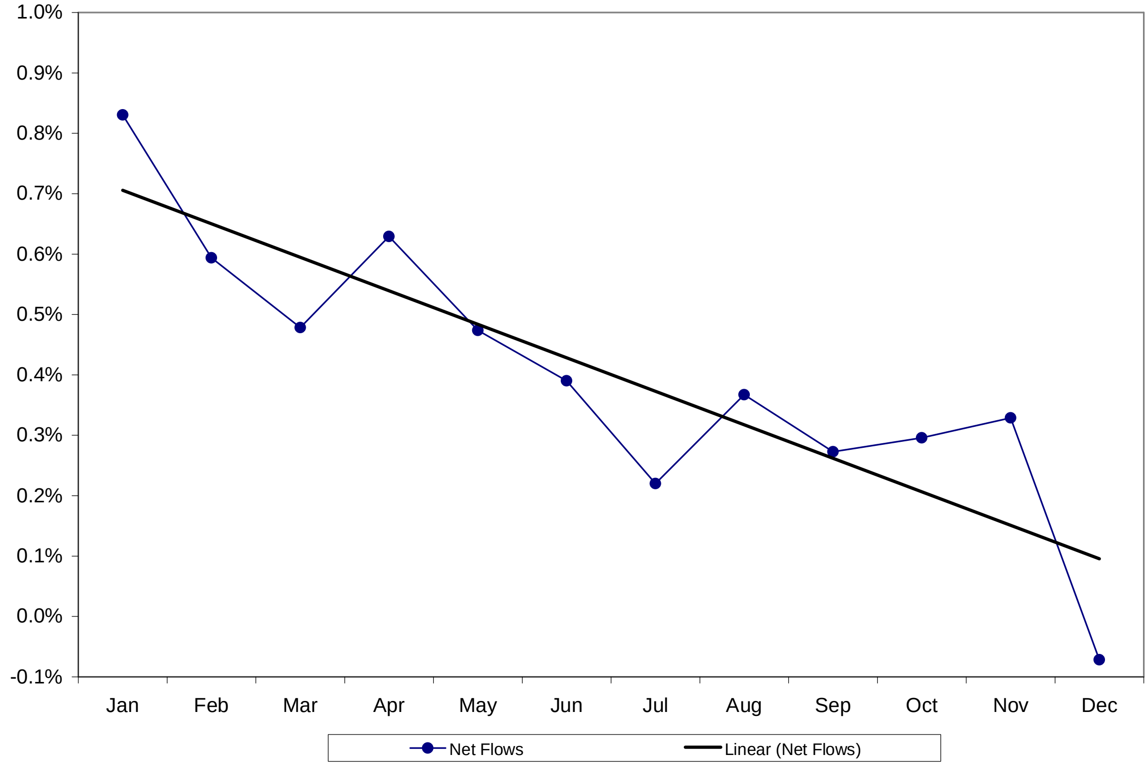
We calculate monthly net cash flows to mutual funds using the data from CRSP. Since the CRSP database does not directly report the flows, we infer net flows from fund returns and total net assets reported by CRSP. At the end of each month, we compute the net flows for fund *i*, $Net\ Flows_{i,t}^{CRSP}$, as the dollar value of difference between new issues and redemptions divided by the size of the fund at the beginning of the month using

$$Net\ Flows_{i,t}^{CRSP} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t}) - MGN_{i,t}}{TNA_{i,t-1}} \quad (1)$$

where $TNA_{i,t}$ is fund *i*'s total net assets at time *t*, and $r_{i,t}$ is the raw return of fund *i* in period *t*, and $MGN_{i,t}$ is the increase in total net assets due to mergers during the period *t*. Following the standard practice in the literature, we assume that inflows and outflows occur at the end of the month.[37]

[37] See, Zheng (1999), Sapp and Tiwari (2004), Frazzini and Lamont (2008).

Figure 3.1: Net Flows to Mutual Funds by Month



This figure plots the mean of the value weighted average net flows to U.S. domestic equity mutual funds by month. *Net Flows*^{CRSP} is measured for 9,274 domestic equity mutual funds from the CRSP Survivor-Bias-Free US Mutual Fund Database over the sample period from January 1994 to December 2007. At the end of each month, *Net Flows*^{CRSP} is defined as $(TNA_{i,t} - TNA_{i,t-1} * (1+r_{i,t}) - MGN_{i,t}) / TNA_{i,t-1}$, where $TNA_{i,t}$ is fund *i*'s total net assets at time *t*, and $r_{i,t}$ is the raw return of fund *i* in period t, and $MGN_{i,t}$ is the increase in total net assets due to mergers during the period *t*. We exclude observations when the total net asset value is less than 15 million dollars or the net flows are less than -90% or greater than 100%. The linear trend is also presented.

In Figure 3.1, we plot the mean of the value weighted average net flows to equity funds by month.[38] Net flows to equity funds are the highest in January and these flows generally decrease until December, when the net flows are negative 0.8 percent. Although net flows rebound in April and August, the downward trend in the net flows to equity funds appears to be very strong. The negative net flows in December are especially quite surprising given the sharp growth of the mutual fund markets. Net flows in months other than January and December seem to be random, but in general net flows in the first half of the year are larger than the net flows in the second half of the year.

Net cash flows, by definition, can be affected by inflows and outflows, respectively. By using the combined database from the CRSP and N-SAR filings, we are able to identify monthly cash inflows and outflows to mutual funds separately. *Inflow* is defined as

$$Inflow_{i,t} = \frac{Sales_{i,t}}{TNA_{i,t-1}} \tag{2}$$

where $Sales_{i,t}$ is the amount of new money invested into a fund over a month. *Outflow* is defined as

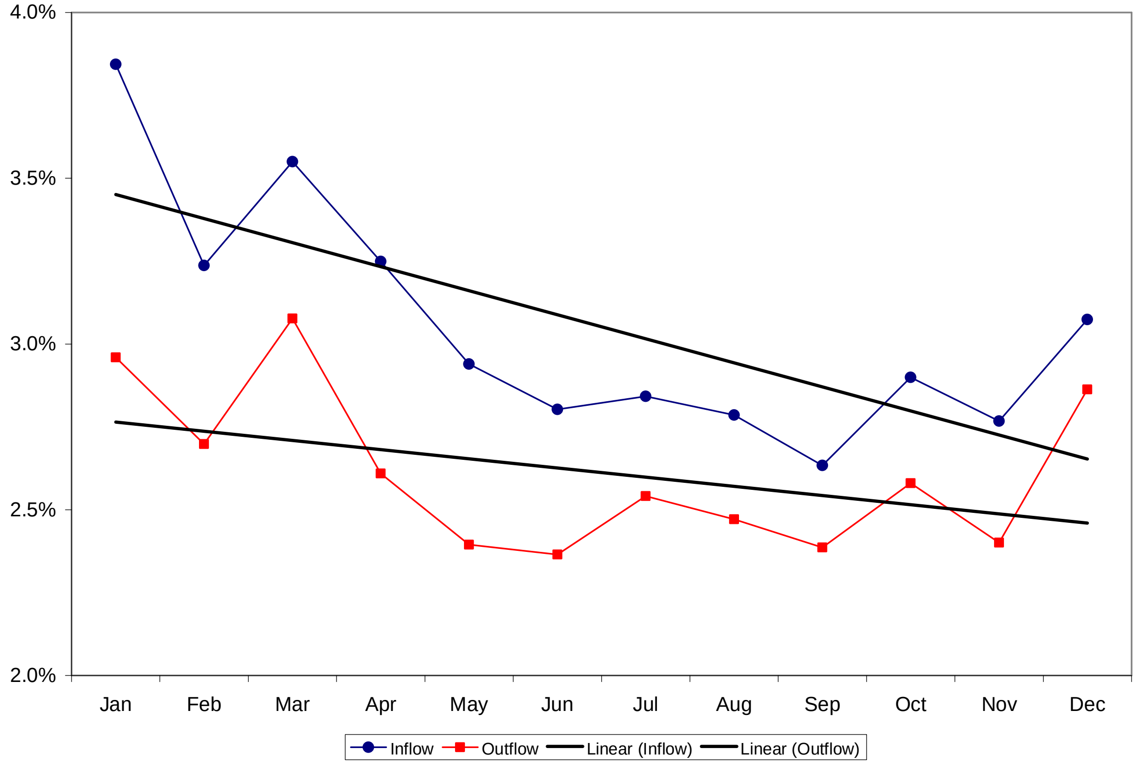
$$Outflow_{i,t} = \frac{Redemptions_{i,t}}{TNA_{i,t-1}} \tag{3}$$

where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over a month. We also define the net flows for a matched fund, *Net Flow*s, as

$$Net\ Flows_{i,t} = Inflow_{i,t} - Outflow_{i,t} \tag{4}$$

[38] In this study we report the results using the value weighted average flows to equity funds. We also reran all the analyses with the equally weighted average flows and the results are qualitatively the same.

Figure 3.2: Inflow and Outflow to Equity Funds by Month



This Figure 3.plots the mean of the value weighted average inflow and outflow to U.S. domestic equity mutual funds by month. *Inflow* and *Outflow* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}$/ $TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}$/ $TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. Linear trends are also presented.

We eliminate from the sample those observations that appear to have data entry errors. Specifically, we exclude observations with *Net Flows*, *Inflow*, or *Outflow* that is less than -90 percent or greater than 100 percent, leaving us with a final sample of 186,229 equity fund–month observations.[39]

We plot the mean of the value weighted average inflow and outflow to equity funds by month in Figure 3.2. Similar to the trend in net flows reported in Figure 3.1, there is a downward trend in both inflow and outflow to equity funds but the slope of the trend in outflow is much weaker than that of the trend in inflow. The seasonal patterns in the net flows to funds could be affected more by the seasonal patterns in inflow than that in outflow. However, we note that inflow and outflow tend to move together. For instance, January is the month, when both inflow and outflow to equity funds are at the highest. Later on, both inflow and outflow rebound in March, but they are low in September. It is interesting that December is neither the month with the lowest inflow nor the month with the highest outflow. Thus, to understand the seasonal patterns in net flows, it is necessary to study the patterns in both inflow and outflow to equity funds.

3.3 Seasonal patterns in cash flows to mutual funds

The most intriguing findings on the seasonal patterns in cash flows to equity funds are the highest net flows in January and the lowest net flows in December. In addition, the net flows rebound in April, August, and October as we observe in Figure 3.1. In this section, we first contrast the reported net flows and the inferred net flows that have

[39] We used various cutoffs of flows, but the results are qualitatively the same.

been used in previous studies, and we statistically examine whether the turn-of-the-year effect and the turn-of-the-quarter effect exist in cash flows to equity mutual funds.

3.3.1 The effect of distribution on the negative net flows in December

In December, the mean of the value weighted average net flows to equity funds reported in the CRSP database was -0.8 percent during our sample period. However, as presented in Figure 3.2, the inflow to equity funds is greater than the outflow in December for the matched sample funds. This inconsistency can be caused by the distribution and reinvestment amount. When we use the formula to infer the net flows in equation (1), we subtract the multiplied amount of the total net asset value in the previous month and one plus return from the total net asset value at the end of the month. Since the total net asset value at the end of the month contains only the reinvestment amount and the monthly return is adjusted for the entire distribution, the difference between the entire distribution and the reinvestment amount would reduce the inferred net flows to mutual funds in December.

For instance, suppose a fund with 100 shares and the net asset value of $10 per share decided to make a distribution of $1 per share. Assuming that there were no sales or redemptions over the month and the monthly raw return is zero, the distribution adjusted return would still be zero. If investors decided to reinvest only $50 out of their entire distribution of $100, the total net asset value at the end of the month would be $9,950, while the total net asset value at the beginning of the month multiplied by one plus the monthly return would be $10,000. As a result, the inferred net flows would be negative $50, while the reported net flows are zero because there were no sales or redemptions.

From this simple example, we suggest that the inferred net flows using the equation (1) would be understated in a month with distributions.

Another cause of this inconsistency can be a possible matching error when we combine the CRSP database and the N-SAR filings. In order to examine whether there is a systematic error in our matched sample, we first calculate the mean of the value weighted average inflow, outflow, and net flows to equity mutual funds in our matched sample by month. We also calculate the mean of the value weighted net flows to equity funds reported in the CRSP database by month. The results are reported in Table 3.2.

Net flows to equity funds in our matched sample are simply measured using the reported amount in the N-SAR forms, but the net flows to equity funds reported in the CRSP database are inferred via the equation (1). If we made a mistake when we combine the CRSP database and the N-SAR filings, we would observe considerable inconsistencies between the two net flows series across calendar months. The numbers reported in Table 3.2, however, show that the calculated mean net flows are close to each other in each calendar month except December. Therefore, we suggest that the standard method employed in the previous literature to infer the net flows to mutual funds using the CRSP database tend to underestimate the net flows to equity funds in December.

To examine whether the relatively low inferred net flows in December is related to the distribution schedule, we report the mean of the value weighted capital distribution ratio, $\textit{Capital Distribution}^{CRSP}$, and income distribution ratio, $\textit{Income Distribution}^{CRSP}$, by month in Table 3.2. We calculate $\textit{Capital Distribution}^{CRSP}$ ($\textit{Income Distribution}^{CRSP}$) as the amount of capital gain (income dividend) distribution per share divided by the reinvestment price. The results reported in Table 3.2 show that income distributions are

Table 3.2: Mean Mutual Fund Flows and Distributions by Month

This table reports the mean of the value weighted average inflow, outflow, and net flows to U.S. domestic equity mutual funds by month. *Inflow*, *Outflow*, *Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flows* are the difference between *Inflow* and *Outflow*. We also report the value weighted average net flows, capital distribution, and income distribution to 9,274 equity mutual funds from CRSP database by month. *Net Flows^{CRSP}* are defined as $(TNA_{i,t} – TNA_{i,t-1}*(1+r_{i,t}) – MGN_{i,t})/ TNA_{i,t-1}$, where $TNA_{i,t}$ is fund *i*'s total net assets at time *t*, and $r_{i,t}$ is the raw return of fund *i* in period t, and $MGN_{i,t}$ is the increase in total net assets due to mergers during the period *t*. *Capital Distribution^{CRSP}* is the amount of capital gain distribution per share divided by the reinvestment price. *Income Distribution^{CRSP}* is the amount of income dividend distribution per share divided by the reinvestment price. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. All numbers are reported in percentage.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg.
Inflow	3.84	3.24	3.55	3.25	2.94	2.80	2.84	2.79	2.63	2.90	2.77	3.07	3.05
Outflow	2.96	2.70	3.08	2.61	2.39	2.36	2.54	2.47	2.39	2.58	2.40	2.86	2.61
Net Flows	0.88	0.54	0.47	0.64	0.55	0.44	0.30	0.31	0.25	0.32	0.37	0.21	0.44
Net Flows^{CSRP}	0.83	0.59	0.48	0.63	0.47	0.39	0.22	0.37	0.27	0.30	0.33	-0.07	0.40
Capital Distribution^{CRSP}	0.02	0.02	0.07	0.02	0.15	0.08	0.04	0.05	0.19	0.11	0.35	3.79	0.41
Income Distribution^{CRSP}	0.01	0.02	0.16	0.02	0.03	0.21	0.03	0.02	0.17	0.04	0.02	0.59	0.11

made mostly at the end of each quarter and the most of capital distributions are made in December.

If investors reinvest most of their received distributions to the mutual fund, we would observe that the inferred net flows are close to the difference between reported sales and redemptions. On the other hand, if investors do not reinvest the distributions to the fund at all, then the difference between the inferred net flows and the measured net flows would be considerable. We find a number of examples that are consistent with this relation between the reinvestment and the understated inferred net flows in a month with distributions. For example, Fidelity Balanced Fund reported sales of $643,454,000, redemption of $497,030,000, and the reinvested distribution of $402,336,000 in December 2007 to the SEC. According to the CRSP database, they reported the monthly return of 0.15%, the capital distribution ratio of 0.15%, and the income distribution ratio of 0.61% in the same month. The total net assets of the fund increased from $27,053 million to $27,227 million over the period. The inferred net flows using the equation (1) are 0.50%, which is close to their reported net flows of 0.54%. Over the same period, Thornburg Core Growth Fund reported the net flows of 4.44% with zero reinvested distribution. The inferred net flows for the fund are 3.95% which is 0.49% lower than the reported net flows.

In summary, the inferred net flows according equation (1) would understate the net flows for a month with reinvested distributions. These understated net flows might affect the results reported in previous studies.

3.3.2 Seasonality tests in cash flows to mutual funds

Although the negative December net flows to equity mutual funds reported in the CRSP database could be affected by distributions and reinvestments, the reported net flows are still low in December relative to the net flows in other months of the year. In addition, January is the month with the highest net flows and the net flows in April and October are higher than those in the prior months. That is, investors would rebalance asset allocation more actively at the turn of the year and the turn of the quarter than the rest of the year. In this section, we statistically test whether these turn-of-the-year and the turn-of-the-quarter effects exist in cash flows to equity mutual funds.

We use the value weighted monthly average cash flows to mutual funds to estimate the following OLS regression:

$$Flow_t = \alpha + \beta_1 BOY_t + \beta_2 EOY_t + \beta_3 BOQ_t + \beta_4 EOQ_t + \varepsilon_t \tag{5}$$

In this regression, $Flow_t$ refers to the value weighted monthly average *Inflow*, *Outflow*, and *Net Flow*s to the U.S. domestic equity funds in our matched sample as defined in equations (2)-(4). BOY_t is an indicator variable for the beginning of the year which is one if the month at time t is January and zero otherwise. EOY_t is an indicator variable for the end of the year which is one if the month at time t is December and zero otherwise. BOQ_t is an indicator variable for the beginning of the quarter, which equals to one if the month at time t is April, July, or October and zero otherwise. EOQ_t is an indicator variable for the end of the quarter which equals to one if the month at time t is March, June, or September and zero otherwise. We also run this regression using the inferred net flows to equity funds reported in the CRSP database as defined in equation (1). The expected flows to mutual funds in February, May, August, and November is measured by α, while β_2 through β_4 represent the difference between the expected flows in these months and

Table 3.3: Seasonality in Mutual Fund Flows

This table presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds. *Inflow*, *Outflow*, *Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flows* are the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. In the last column, we report the OLS regression result on the value weighted average net flows to equity funds using 9,274 equity mutual funds from CRSP database. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. Flows are reported in percentage. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Inflow	Outflow	Net Flows	Net Flows^{CRSP}
Intercept	2.932 ***	2.491 ***	0.441 ***	0.441 ***
	(26.38)	(25.64)	(6.67)	(6.93)
Beginning of the Year	0.911 ***	0.469 **	0.443 ***	0.390 ***
	(3.67)	(2.16)	(2.99)	(2.74)
End of the Year	0.141	0.372 *	-0.230	-0.513 ***
	(0.57)	(1.71)	(-1.56)	(-3.61)
Beginning of the Quarter	0.064	0.086	-0.021	-0.059
	(0.38)	(0.58)	(-0.21)	(-0.61)
End of the Quarter	0.063	0.118	-0.055	-0.060
	(0.37)	(0.80)	(-0.54)	(-0.62)
N	168	168	168	168
Adj R^2	0.058	0.015	0.061	0.115

the expected flows at the turn-of-the-year and the turn-of-the-quarter.

In Table 3.3, we present the estimation results of equation (5) on the value weighted average inflow, outflow, and net flows to equity funds in our matched sample and on the value weighted average net flows to equity funds reported in the CRSP database. The coefficients of the beginning of the year variables are significantly positive in all models when we use different cash flow measures as the dependent variable. It is noted that both inflow and outflow are significantly higher in January than the other month of the year. In January the net flows to equity funds are higher than those in the other months of the year. The high net flows are driven by the increased inflow. In fact, the outflow is higher, not lower, in January. One of the possible reasons for the high outflow in January can be due to the investors who move from one fund to another. That is mutual fund investors rebalance their portfolios in January more actively than they do during the rest of the year.

In December, the inflow to the equity funds is not statistically significantly different from the other months, but the outflow increases significantly at ten percent level. This results in slightly lower net flows in December, but they are not significantly different from the rest of the year. In other words, current investors tend to sell their shares more in December, but the effect is not big enough to notably reduce the net flows. However, the inferred net flows to equity funds, reported in the last column of Table 3.3, show the significantly negative net flows in December. The coefficients in the model with the reported net flows and the inferred net flows are pretty similar to each other, except at the end of the year. Across all the flow variables, the coefficients of the beginning of the quarter and the end of the quarter are not significantly different from the other months of the year. Thus, the unique seasonal pattern in the cash flows to equity mutual funds is limited to the turn-of-the-year effect, and in general, there is no turn-of-the-quarter effect.

3.4 What causes the seasonal patterns in mutual fund flows?

In this section, we discuss the possible explanations for the observed seasonal patterns in the cash flows of mutual funds. Specifically, we examine whether the seasonal patterns exist after we control for various factors such as the growth of personal income and consumption, the tax effect on the fund distributions, style objectives, and past performance of funds. Since the seasonal patterns in the inferred net flows are similar to the reported net flows in our sample, we focus on the reported inflow, outflow, and net flows in this section.

3.4.1 Personal income and consumption

Miron and Beaulieu (1996) show that events such as Christmas or other holidays shift the marginal utility of consumption. In line with this finding, investors would rather spend money to buy gifts or to travel than purchase mutual funds in December. On the other hand, due to the end-of-year bonuses and dividend income from their holdings, investors would be able to buy mutual funds around the turn-of-the-year. These seasonal changes in the personal income and consumption can be related to the strong seasonal regularities in fund flows: the high net flows in January and the low net flows in December.

Table 3.4: The Effect of Consumption Growth and Income Growth on the Seasonality in Mutual Fund Flows

This table presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds. *Inflow*, *Outflow*, *Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. *Consumption Growth$_t$* and *Income Growth$_t$* are measured by the log difference between the personal consumption expenditure at time t and t-1 and the log difference between the disposable personal income at time t and t-1, respectively. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Inflow	Outflow	Net flows
Intercept	2.803 ***	2.383 ***	0.420 ***
	(20.83)	(20.21)	(5.19)
Beginning of the Year	0.947 ***	0.501 **	0.446 ***
	(3.81)	(2.30)	(2.98)
End of the Year	0.106	0.339	-0.233
	(0.43)	(1.56)	(-1.56)
Beginning of the Quarter	0.046	0.074	-0.028
	(0.27)	(0.50)	(-0.27)
End of the Quarter	0.086	0.136	-0.050
	(0.51)	(0.92)	(-0.49)
Consumption Growth $_t$	27.984 *	21.214	6.770
	(1.86)	(1.61)	(0.75)
Income Growth $_t$	-0.045	2.157	-2.202
	(-0.01)	(0.28)	(-0.42)
N	168	168	168
Adj R^2	0.066	0.020	0.053

We use the monthly personal consumption expenditures and disposable personal income data from National Income and Product Accounts (NIPA) to proxy for mutual fund investors' personal income and consumption. In the regression model in equation (5), we also include the personal consumption expenditure growth and disposable personal income growth, which are measured by the log difference between the personal consumption expenditure at time t and t-1 and the log difference between the disposable personal income at time t and t-1, respectively.

In Table 3.4, we present the estimation results of the value weighted average inflow, outflow, and net flows to equity mutual funds. The consumption growth is positively, albeit marginally significantly, related to the inflow to equity funds. Other than this, neither the consumption growth nor the income growth is strongly associated with the cash flows to equity funds. The seasonal patterns in the cash flows to equity funds remain the same as reported in Table 3.3, except that the high outflows in December is no longer significant. The coefficients of the beginning of the year variables for inflow, outflow, and net flows to equity funds are significantly positive at five percent level. The strong trading activity of mutual fund investors in January may not be related to the seasonal variation in personal income and consumption around the turn-of-the-year. However, the disappearance of the significance in the high outflow in December suggests that investors tend to sell their shares to increase their consumption around the holiday season.

3.4.2 Tax treatment of the distributions

Investors of a mutual fund are entitled to their share of the fund's net income and capital gains. In order to avoid being taxed as a corporation, the fund must pass through its net income and capital gains to investors as distributions, which generate tax liability for taxable investors. Johnson and Poterba (2008) find that some taxable shareholders time their purchases of mutual fund shares to avoid tax increases associated with distributions. Most equity funds distribute their capital gains and dividend incomes in December. If the mutual fund investors have an incentive to time their purchases, these seasonal patterns of distributions from funds may be related to the high net flows in January and the low net flows in December.

To further investigate this conjecture, we examine the effect of tax treatments of capital gain distribution and income dividend distribution on the seasonality in mutual fund flows separately. First, at the beginning of each year, we rank equity funds based on the proportion of capital gain distribution per share to the reinvestment price in December of the previous year. All capital gain distribution paying equity funds are classified into five quintiles. We calculate the value weighted monthly mean inflow, outflow, and net flows for each quintile and also for the non-payer funds. We run the OLS regression in equation (5) for each quintile and non-payer funds. If investors tend to time their purchases to avoid the capital gain distributions, we would expect a stronger inflow in January to funds making higher capital gain distributions.

The regression results presented in Table 3.5 indicate that the observed relation between the inflow to funds and their capital gain distribution is not consistent with the hypothesis that the investors time their purchases to avoid the capital gain distributions. January inflow to the funds paying the largest capital gain distributions, quintile 5, is not significantly different from the inflows in the other months of the year. On the contrary,

Table 3.5: The Effect of Tax Treatment of Capital Gain Distribution on the Seasonality in Mutual Fund Flows

At the beginning of each year, equity funds are ranked based on the proportion of capital gain distribution per share to the reinvestment price in December of the previous year. All capital gain distribution paying equity funds are classified into five quintiles. We calculate the value weighted monthly mean inflow, outflow, and net flows in each quintile and Non-payer funds. This Table 3.presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds in each quintile and the Non-payer funds. *Inflow, Outflow, Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Inflow

	Non payer	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5
Intercept	3.382 ***	3.031 ***	3.107 ***	2.714 ***	2.799 ***	2.841 ***
	(22.17)	(21.79)	(13.01)	(23.47)	(19.66)	(17.21)
Beginning of the Year	0.722 **	1.256 ***	1.150 **	1.227 ***	1.079 ***	0.376
	(2.12)	(4.04)	(2.15)	(4.74)	(3.39)	(1.02)
End of the Year	0.186	-0.193	-0.018	-0.075	0.669 **	0.266
	(0.55)	(-0.62)	(-0.03)	(-0.29)	(2.10)	(0.72)
Beginning of the Quarter	0.060	0.048	0.012	0.048	0.190	0.164
	(0.26)	(0.23)	(0.03)	(0.27)	(0.88)	(0.65)
End of the Quarter	-0.002	0.155	-0.009	0.160	0.170	-0.053
	(-0.01)	(0.73)	(-0.03)	(0.90)	(0.78)	(-0.21)
N	168	168	168	168	168	168
Adj R^2	0.006	0.082	0.008	0.111	0.057	-0.012

Panel B. Outflow

	Non payer	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5
Intercept	2.843 ***	2.195 ***	2.514 ***	2.114 ***	2.403 ***	2.728 ***
	(25.64)	(20.67)	(9.56)	(24.68)	(26.10)	(18.64)
Beginning of the Year	0.479 *	0.397 *	0.632	0.422 **	0.642 ***	0.443
	(1.93)	(1.67)	(1.07)	(2.20)	(3.12)	(1.35)
End of the Year	0.268	0.265	0.334	0.313	0.435 **	0.622 *
	(1.08)	(1.11)	(0.57)	(1.63)	(2.11)	(1.90)
Beginning of the Quarter	0.099	0.049	-0.045	0.072	0.140	0.331
	(0.59)	(0.30)	(-0.11)	(0.55)	(0.99)	(1.48)
End of the Quarter	0.068	0.123	0.053	0.168	0.209	0.154
	(0.40)	(0.76)	(0.13)	(1.28)	(1.49)	(0.69)
N	168	168	168	168	168	168
Adj R^2	0.002	-0.002	-0.015	0.017	0.047	0.008

Panel C. Net Flows

	(Low)					(High)
	Non payer	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Intercept	0.539 ***	0.836 ***	0.592 ***	0.600 ***	0.396 ***	0.114
	(5.99)	(7.32)	(5.79)	(6.52)	(3.45)	(1.02)
Beginning of the Year	0.243	0.859 ***	0.518 **	0.805 ***	0.438 *	-0.067
	(1.21)	(3.36)	(2.27)	(3.91)	(1.71)	(-0.27)
End of the Year	-0.082	-0.458 *	-0.352	-0.388 *	0.234	-0.356
	(-0.41)	(-1.79)	(-1.54)	(-1.88)	(0.91)	(-1.44)
Beginning of the Quarter	-0.039	0.000	0.058	-0.024	0.051	-0.167
	(-0.28)	(-0.00)	(0.37)	(-0.17)	(0.29)	(-0.99)
End of the Quarter	-0.070	0.032	-0.062	-0.008	-0.039	-0.207
	(-0.51)	(0.18)	(-0.40)	(-0.06)	(-0.22)	(-1.22)
N	168	168	168	168	168	168
Adj R^2	-0.009	0.076	0.034	0.104	0.001	-0.006

January inflows to equity funds paying lower capital gain distributions, quintile 1 through 4, and even to the non-payer funds are significantly higher than the other months of the year at the five percent level.

The lack of January increase in the inflow to funds paying higher capital gain distributions indicate that taxable investors may be discouraged to buy the fund's shares as suggested by Khorana and Servaes (1999). This is consistent with the finding that the outflows to funds in quintile 4 and 5 are significantly higher in December than the outflows in the other months of the year. Due to the combined effect of inflow and outflow around the turn-of-the-year, the net flows to fund in quintile 1 through 4 in January are higher than the rest of the year but the net flows to funds paying the highest capital gain distributions are not significantly different in January from the other months. These results suggest that the potential investors do not time their purchases, but rather avoid the funds paying capital gains in general, as they consider the tax burden due to the accumulated capital gains in the fund.

Next, we examine the effect of tax treatment of income dividend distributions on the seasonality in mutual fund flows. Investors can react differently to capital gain distributions and income dividend distributions because they can find alternative funds with similar strategies and lower accumulated capital gains. At the beginning of each year, we rank equity funds based on the proportion of income dividend distribution per share to the reinvestment price in December of the previous year. All income dividend distribution paying equity funds are classified into five quintiles. We calculate the value weighted monthly mean inflow, outflow, and net flows for each quintile and the non-paying funds. We run the OLS regression in equation (5) for each quintile and the non-payer funds. Similar to the expected relation between the fund flows and the capital gain distributions, if investors tend to time their purchases to avoid the income dividend distributions, we would expect a stronger inflow in January to the funds making higher distributions.

The regression results presented in Table 3.6 indicate that January inflows to funds across all quintiles and the non-paying funds are higher than the rest of the year. In addition, the magnitude of the coefficient of the beginning of the year variable in quintile 5 is much smaller than that of the coefficient for quintile 1. This coefficient is smaller than the coefficient on the beginning of the year variable for the non-payer funds. This result suggests that the increased inflow in January may not be driven by the delayed purchases of taxable investors to avoid the tax associated with the income dividend distributions. Equity funds experience increased outflows in December regardless of the size of their income dividend distribution. The coefficients of the beginning of the year variable for outflows of funds in all quintiles, except quintile 3, are statistically significant at the five percent level. Outflows to funds in the quintiles 2 and 4 are significantly higher in December but the outflows to funds in other groups are not significantly different from the other months. The regression results on the net flows show relatively high net flows to funds in quintiles 2 and 3 in January and low net flows to funds in quintiles 2 and 4 in December. Thus, the results reported in Table 3.6 reveal that there is relatively high trading activity around the-turn-of-the-year, but there is no strong association between this increased fund flows and the income dividend distributions made by the funds.

Table 3.6: The Effect of Tax Treatment of Income Dividend Distribution on the Seasonality in Mutual Fund Flows

At the beginning of each year, equity funds are ranked based on the proportion of income dividend distribution per share to the reinvestment price in December of the previous year. All income dividend distribution paying equity funds are classified into five quintiles. We calculate the value weighted monthly mean inflow, outflow, and net flows in each quintile and Non-payer funds. This Table 3.presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds in each quintile and the Non-payer funds. *Inflow, Outflow, Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/\ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/\ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Inflow

	Non payer	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5
Intercept	3.810 ***	3.098 ***	2.845 ***	2.543 ***	2.307 ***	2.464 ***
	(20.43)	(16.31)	(27.38)	(13.65)	(30.10)	(28.94)
Beginning of the Year	1.157 ***	1.598 ***	0.857 ***	1.223 ***	0.628 ***	0.911 ***
	(2.77)	(3.76)	(3.69)	(2.93)	(3.66)	(4.79)
End of the Year	0.184	0.125	0.057	0.260	-0.056	0.076
	(0.44)	(0.29)	(0.25)	(0.62)	(-0.33)	(0.40)
Beginning of the Quarter	0.104	0.171	0.059	0.057	-0.020	0.064
	(0.37)	(0.59)	(0.37)	(0.20)	(-0.17)	(0.49)
End of the Quarter	0.068	0.112	-0.030	0.121	0.004	0.178
	(0.24)	(0.39)	(-0.19)	(0.43)	(0.04)	(1.37)
N	168	168	168	168	168	168
Adj R^2	0.024	0.061	0.064	0.030	0.067	0.108

Panel B. Outflow

	Non payer	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5
Intercept	3.234 ***	2.558 ***	2.143 ***	2.310 ***	1.928 ***	2.168 ***
	(32.03)	(19.01)	(21.80)	(10.12)	(27.49)	(19.20)
Beginning of the Year	0.708 ***	0.727 **	0.477 **	0.569	0.385 **	0.589 **
	(3.14)	(2.42)	(2.17)	(1.12)	(2.45)	(2.33)
End of the Year	0.310	0.204	0.462 **	0.471	0.313 **	0.241
	(1.37)	(0.68)	(2.10)	(0.92)	(1.99)	(0.95)
Beginning of the Quarter	0.103	0.219	0.179	0.034	0.024	0.047
	(0.66)	(1.07)	(1.19)	(0.10)	(0.23)	(0.27)
End of the Quarter	0.122	0.193	0.133	0.199	0.133	0.073
	(0.79)	(0.94)	(0.88)	(0.57)	(1.24)	(0.42)
N	168	168	168	168	168	168
Adj R^2	0.038	0.012	0.022	-0.012	0.032	0.012

Panel C. Net Flows

	Non payer	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5
Intercept	0.575 ***	0.540 ***	0.701 ***	0.233 **	0.379 ***	0.296 ***
	(4.26)	(5.08)	(6.50)	(2.28)	(4.50)	(2.92)
Beginning of the Year	0.448	0.871 ***	0.380	0.654 ***	0.243	0.322
	(1.49)	(3.67)	(1.58)	(2.86)	(1.29)	(1.42)
End of the Year	-0.126	-0.078	-0.405 *	-0.212	-0.369 *	-0.165
	(-0.42)	(-0.33)	(-1.68)	(-0.93)	(-1.96)	(-0.73)
Beginning of the Quarter	0.002	-0.048	-0.120	0.023	-0.044	0.016
	(0.01)	(-0.30)	(-0.73)	(0.15)	(-0.34)	(0.11)
End of the Quarter	-0.054	-0.081	-0.162	-0.077	-0.128	0.105
	(-0.26)	(-0.50)	(-0.98)	(-0.50)	(-1.00)	(0.68)
N	168	168	168	168	168	168
Adj R^2	-0.006	0.073	0.023	0.044	0.021	-0.003

3.4.3 Style objectives of funds

The strongest seasonal pattern in the mutual fund flows pertains to the high inflow and outflow in January. As the literature on the January effect in stock returns suggests the better performance of small stocks or stocks with high book-to-market ratio, this high fund flows can be confined to funds with certain types of style objectives. To see if this is the case, we examine the turn-of-the-year effect in flows to equity funds with various style objectives.

We classify funds into six styles following the Lipper-Classification: Small-Cap, Mid-Cap, Large-Cap, Growth, Core, and Value. We use the value weighted monthly average cash flows to mutual funds in each style group to estimate the OLS regression in equation (5). We also test whether the seasonal patterns in flows to Small-Cap funds and Large-Cap funds (Value funds and Growth fund) are different.

We report the estimation results of equation (5) on inflow, outflow, and net flows to mutual funds in each style group in Table 3.7. The results show that January is the month with the highest cash inflow to equity mutual funds across all style objectives. The coefficients of the beginning of the year variable are significant across all style objectives at the five percent level. It is also noted that the incremental inflow to the Small-Cap funds (Value funds) in January is lower than the inflow to the Large-Cap funds (Growth funds), although the difference is not significant. In fact, the style objectives with the smallest coefficients on the beginning of the year variable are Small-Cap and Value. Even though the returns of stocks that these style funds are holding are expected to be high in January, investors do not buy more of these funds relative to the other style funds. Other than January, cash inflows to each style funds are not significantly different across

Table 3.7. The Effect of Style Objective on the Seasonality in Mutual Fund Flows

This table presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds across various style objectives. Funds are classified into various styles following Lipper-Classification. *Inflow*, *Outflow*, *Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}$/ $TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}$/ $TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. In the last column, we report the OLS regression result on the value weighted average net flows to equity funds using 9,274 equity mutual funds from CRSP database. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. Flows are reported in percentage. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Inflow

	Small-Cap	Mid-Cap	Large-Cap	Growth	Core	Value	Small - Large	Value - Growth
Intercept	4.624 ***	3.964 ***	2.597 ***	2.966 ***	2.922 ***	2.378 ***	2.027 ***	-0.587 ***
	(26.34)	(20.60)	(20.89)	(14.05)	(30.61)	(32.20)	(9.42)	(-2.63)
Beginning of the Year	0.826 **	1.023 **	0.840 ***	0.944 **	0.903 ***	0.555 ***	-0.015	-0.389
	(2.10)	(2.38)	(3.02)	(2.00)	(4.23)	(3.36)	(-0.03)	(-0.78)
End of the Year	0.367	0.155	0.165	0.265	0.214	-0.049	0.202	-0.314
	(0.94)	(0.36)	(0.59)	(0.56)	(1.00)	(-0.30)	(0.42)	(-0.63)
Beginning of the Quarter	0.044	0.044	0.099	0.078	0.107	0.071	-0.055	-0.007
	(0.16)	(0.15)	(0.52)	(0.24)	(0.74)	(0.63)	(-0.17)	(-0.02)
End of the Quarter	0.184	-0.071	0.036	0.048	0.061	-0.028	0.148	-0.076
	(0.69)	(-0.24)	(0.19)	(0.15)	(0.42)	(-0.25)	(0.45)	(-0.22)
N	168	168	168	168	168	168		
Adj R^2	0.007	0.016	0.033	0.002	0.082	0.054		

Panel B. Outflow

	Small-Cap	Mid-Cap	Large-Cap	Growth	Core	Value	Small - Large	Value - Growth
Intercept	4.056 ***	3.155 ***	2.262 ***	2.916 ***	2.337 ***	1.877 ***	1.794 ***	-1.039 ***
	(29.40)	(22.60)	(18.88)	(18.57)	(33.15)	(21.68)	(9.82)	(-5.80)
Beginning of the Year	0.437	0.555 *	0.468 *	0.621 *	0.370 **	0.306	-0.031	-0.315
	(1.42)	(1.78)	(1.75)	(1.77)	(2.35)	(1.58)	(-0.08)	(-0.79)
End of the Year	0.210	0.481	0.391	0.522	0.303 *	0.341 *	-0.181	-0.181
	(0.68)	(1.54)	(1.46)	(1.49)	(1.92)	(1.76)	(-0.44)	(-0.45)
Beginning of the Quarter	-0.009	0.142	0.076	0.049	0.101	0.071	-0.086	0.023
	(-0.04)	(0.67)	(0.42)	(0.20)	(0.93)	(0.54)	(-0.31)	(0.08)
End of the Quarter	0.127	0.078	0.092	0.117	0.099	0.050	0.036	-0.068
	(0.60)	(0.37)	(0.50)	(0.49)	(0.92)	(0.38)	(0.13)	(-0.25)
N	168	168	168	168	168	168		
Adj R^2	-0.008	0.005	0.003	0.005	0.022	0.005		

Panel C. Net Flows

	Small-Cap	Mid-Cap	Large-Cap	Growth	Core	Value	Small - Large	Value - Growth
Intercept	0.568 ***	0.809 ***	0.336 ***	0.050	0.585 ***	0.501 ***	0.232	0.452 ***
	(4.04)	(5.43)	(4.57)	(0.42)	(8.78)	(4.26)	(1.46)	(2.71)
Beginning of the Year	0.389	0.468	0.373 **	0.323	0.533 ***	0.249	0.016	-0.074
	(1.24)	(1.40)	(2.27)	(1.22)	(3.58)	(0.95)	(0.05)	(-0.20)
End of the Year	0.157	-0.326	-0.227	-0.257	-0.089	-0.390	0.384	-0.133
	(0.50)	(-0.98)	(-1.38)	(-0.97)	(-0.60)	(-1.48)	(1.08)	(-0.36)
Beginning of the Quarter	0.053	-0.098	0.022	0.029	0.007	0.000	0.031	-0.030
	(0.25)	(-0.43)	(0.20)	(0.16)	(0.07)	(-0.00)	(0.13)	(-0.12)
End of the Quarter	0.057	-0.149	-0.055	-0.070	-0.037	-0.078	0.112	-0.008
	(0.26)	(-0.65)	(-0.49)	(-0.39)	(-0.37)	(-0.43)	(0.46)	(-0.03)
N	168	168	168	168	168	168		
Adj R^2	-0.014	0.002	0.031	-0.004	0.068	-0.0001		

all calendar months.

As for the outflows, most style funds, except Small-Cap and Value funds, experience the increased outflow in January relative to the other months of the year, but the significance is marginal. It is intriguing that investors in these two style funds do not sell their shares more in January compared to the other style funds. Since the January effect of stock market returns is usually driven by small-cap and high book-to-market-ratio stocks and it is known to be strong in the first week of the month, the current investors of Small-Cap and Value funds would have had enough time to sell their shares in January after taking advantage of the January effect. Core funds and Value funds also experience increased outflows in December, but the significance is also marginal. There is no statistically significant difference between the outflows to the Small-Cap funds (Value funds) and the Large-Cap funds (Growth funds). Overall, season affects mutual fund investors' decision to sell their shares in some style funds, but the effect appears to be marginal.

Although the net flows to each style fund in January are higher than the other months of the year, only the Large-Cap funds and the Core funds have statistically significantly increased net flows in January. We do not observe any other significant seasonal patterns in net flows to funds in each style. Thus, the seasonal effect on net flows to equity funds is not consistent with the relative performance among style funds.

3.4.4 Past performance of funds

Cash flows to mutual funds are related to fund performance, as documented by an extensive literature. For example, Spitz (1970) finds a positive correlation between mutual fund performance and cash inflows. Ippolito (1992) and Sirri and Turano (1998) find that the performance-flow relationship is actually non-linear. That is, mutual fund investors go after returns, but they are not sensitive to poor performance. However, Barber, Odean, and Zheng (2000) show that the mutual fund investors buy the funds with strong past performance and the investors sell the funds with strong past performance as well. In this section, we test whether the increased inflow and outflow in January are driven by the funds with strong past performance.

First, we calculate the Carhart (1997) four-factor adjusted returns for each equity mutual fund in each month based on the returns over the prior 36 months. Specifically, we use the following regression models to estimate the factor loadings and alphas:

$$R_{it} - RF_t = \alpha_i + \beta_{iRMRF} RMRF_t + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iMOM} MOM_t + \varepsilon_{it} \quad (6)$$

where R_{it} is the rate of return of equity fund i, RF the one month T-bill rate, $RMRF$ the excess market return, SMB the return on the mimicking portfolio for the size factor in stock returns, HML the return on the mimicking portfolio for the book-to-market factor in stock returns, MOM the return on the mimicking portfolio for the momentum factor in stock returns, α the excess return of the corresponding factor model, and βs are the factor loadings of the corresponding factors.[40]

At the beginning of each month, all funds are divided into five quintiles based on their abnormal returns. Funds with the lowest abnormal returns are included in quintile 1,

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[40] We thank Kenneth French for making the data available. The Fama-French three factors and the momentum factor were downloaded from from his website: http://mba.tuck.dartmouth.edu/pages/faculty /ken.french/data_library.html. For further detailed calculation of factor returns, see Fama and French (1993) and Carhart (1997).

and the funds with the highest abnormal returns in quintile 5. We use the value weighted monthly average cash flows to mutual funds in each quintile to estimate the OLS regression in equation (5). We also test whether the seasonal patterns in flows to the funds with the highest past performance are different from the patterns in flows to the funds with the worst or medium past performance.

We report the estimation results of equation (5) on inflow, outflow, and net flows to mutual funds in each past performance quintile in Table 3.8. As the results suggest, investors buy more of the funds with the strongest past performance than the other funds. On average, the monthly inflow to funds in quintile 5 is 3.97 percent of their total net assets, which is much higher than the inflow to the funds in quintile 3 (2.52 percent) and quintile 1 (2.56 percent). On the other hand, investors sell the funds with the strong past performance, but they sell the funds with the poorest past performance more. The monthly outflow to funds in quintile 5 is 0.39 percent higher than quintile 3 but 0.94 percent less than quintile 1. This relation between the past performance and inflow and outflow to mutual funds results in the highest net flows to funds with the best past performance and the lowest net flows to funds with the worst past performance as reported in Panel C. Thus, mutual fund investors go after returns, and they do not tolerate poor performance.

The results reported in Panel A show that January is the month with the highest cash inflow to equity mutual funds in all quintiles. It is noted that the magnitude of the coefficients of the beginning of the year variable is the lowest for quintile 3. That is investors buy the funds with extreme past performance in January more than the funds with medium past performance. Other than this increased inflow to funds in January,

Table 3.8: The Effect of Past Performance on the Seasonality in Mutual Fund Flows

At the beginning of each month, funds are classified into five quintiles based on the four factor alphas over the last 36 months. We calculate the value weighted monthly mean inflow, outflow, and net flows in each quintile. This Table 3.presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds in each quintile. *Inflow, Outflow, Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. In the last column, we report the OLS regression result on the value weighted average net flows to equity funds using 9,274 equity mutual funds from CRSP database. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. Flows are reported in percentage. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Inflow

	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5	Q5 - Q1	Q5 - Q3
Intercept	2.564 ***	2.363 ***	2.523 ***	2.691 ***	3.971 ***	1.407 ***	1.448 ***
	(20.09)	(20.24)	(31.15)	(20.83)	(20.45)	(6.05)	(6.88)
Beginning of the Year	0.703 **	0.790 ***	0.518 ***	0.842 ***	1.377 ***	0.674	0.858 *
	(2.46)	(3.03)	(2.86)	(2.92)	(3.17)	(1.30)	(1.82)
End of the Year	-0.111	0.294	0.142	0.098	0.069	0.180	-0.072
	(-0.39)	(1.13)	(0.78)	(0.34)	(0.16)	(0.35)	(-0.15)
Beginning of the Quarter	0.030	0.138	0.061	0.022	0.002	-0.027	-0.059
	(0.15)	(0.77)	(0.49)	(0.11)	(0.01)	(-0.08)	(-0.18)
End of the Quarter	-0.128	0.078	0.054	0.100	0.026	0.155	-0.028
	(-0.66)	(0.44)	(0.44)	(0.51)	(0.09)	(0.44)	(-0.09)
N	168	168	168	168	168		
Adj R^2	0.026	0.034	0.027	0.030	0.042		

Panel B. Outflow

	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5	Q5 - Q1	Q5 - Q3
Intercept	3.566 ***	2.660 ***	2.234 ***	2.212 ***	2.624 ***	-0.942 ***	0.390 **
	(25.45)	(29.02)	(23.16)	(13.89)	(21.60)	(-5.08)	(2.51)
Beginning of the Year	0.458	0.489 **	0.279	0.496	0.481 *	0.023	0.202
	(1.46)	(2.39)	(1.29)	(1.39)	(1.77)	(0.06)	(0.58)
End of the Year	0.175	0.550 ***	0.214	0.411	0.301	0.127	0.087
	(0.56)	(2.68)	(0.99)	(1.15)	(1.11)	(0.31)	(0.25)
Beginning of the Quarter	0.079	0.074	0.077	0.004	0.159	0.080	0.082
	(0.37)	(0.53)	(0.52)	(0.01)	(0.86)	(0.28)	(0.35)
End of the Quarter	-0.010	0.057	0.184	0.096	0.125	0.135	-0.060
	(-0.05)	(0.40)	(1.25)	(0.40)	(0.67)	(0.48)	(-0.25)
N	168	168	168	168	168		
Adj R^2	-0.009	0.045	-0.007	-0.005	-0.001		

Panel C. Net flows

	(Low) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(High) Quintile 5	Q5 - Q1	Q5 - Q3
Intercept	-1.002 ***	-0.297 ***	0.289 ***	0.479 ***	1.348 ***	2.349 ***	1.058 ***
	(-10.23)	(-3.03)	(4.02)	(5.95)	(10.33)	(14.40)	(7.11)
Beginning of the Year	0.245	0.301	0.239	0.347 *	0.896 ***	0.651 *	0.656 **
	(1.12)	(1.37)	(1.49)	(1.93)	(3.07)	(1.78)	(1.97)
End of the Year	-0.286	-0.256	-0.072	-0.312 *	-0.232	0.054	-0.160
	(-1.30)	(-1.17)	(-0.45)	(-1.74)	(-0.80)	(0.15)	(-0.48)
Beginning of the Quarter	-0.049	0.064	-0.016	0.019	-0.157	-0.108	-0.141
	(-0.33)	(0.43)	(-0.15)	(0.15)	(-0.79)	(-0.43)	(-0.62)
End of the Quarter	-0.119	0.022	-0.130	0.004	-0.098	0.020	0.032
	(-0.79)	(0.15)	(-1.18)	(0.03)	(-0.49)	(0.08)	(0.14)
N	168	168	168	168	168		
Adj R^2	0.002	0.001	0.007	0.026	0.057		

there are no noticeable seasonal patterns in inflows to equity funds.

The outflows of equity funds, reported in Panel B, are rather sTable 3.across the year in each past performance quintile other than quintile 2. In quantile 2, the funds have higher outflow in January and December than the other month of the year. Results on the net flows reported in Panel C show that only the funds in the top quintile receive significantly higher net flows in January and this increased net flows are mainly due to the increased inflow in January. Overall, from the relation between fund flows and the past performance, we suggest that when investors buy mutual funds they prefer funds with better past performance, and this preference becomes more severe in January.

3.4.5 Relative performance among style funds

Our results so far have shown that January is the month with the highest trading activity among both the current and potential investors. Both inflow and outflow to mutual funds are high in January relative to other months of the year. This increased trading activity is stronger among the best performing funds, but it is not related to the fund style objectives. Since mutual funds tend to systematically follow their style objectives and the performance of funds employing such styles would be affected by the seasonal variation of performance of their holdings, investors should take the fund style objectives into account when they allocate their assets. In this section, we test whether the relative performance of the funds with different style objectives is related to the seasonal patterns in the fund flows.

At the beginning of each month, we calculate the four factor alphas over the last 36 months for each U.S. domestic equity fund using the equation (6). Funds are classified into six styles following the Lipper-Classification. The cross-sectional value weighted alphas are calculated for each style group. We rank the style groups based on this value weighted alpha each month. We use the value weighted monthly mean inflow, outflow, and net flows in each rank to estimate the OLS regression in equation (5). We also test whether the seasonal patterns in flows to the best performing style funds are different from the patterns in flows to the worst performing style funds.

We report the estimation results in Table 3.9. The magnitudes of the intercepts are similar across all ranks in Panel A and B. That is, the relative performance among the styles is not related to the fund flows in general. In January, most style funds receive more inflow than the rest of the year, except for the second and fifth ranked style funds. From this result, we suggest that investors are more likely to rebalance their portfolios in January, but they are not affected by the relative performance among different style funds. During the rest of the year, the inflow to equity funds is not associated with the relative performance among different styles.

We note that investors sell their shares in January and December more than the rest of the year, if they hold style funds with the worst performance. In Panel B, the coefficients of the beginning of the year and the end of the year variables in the worst performing style funds are statistically positively significant at the five percent level. The magnitude of those coefficients in the best performing style funds is comparable, but the statistical significance is rather marginal. The increased outflows in this period to the style funds with the past poor performance are big enough to consume the increased inflows so that we observe the significant increase of net flows in January only in the style funds with the medium past performance. Overall, from the relation between the

Table 3.9: The Effect of Relative Performance among Style Funds on the Seasonality in Mutual Fund Flows

At the beginning of each month, we calculate the four factor alphas over the last 36 months for each U.S. domestic equity fund. Funds are classified into six styles following Lipper-Classification. The cross-sectional value weighted alphas are calculated for each style group. We rank the style groups based on this value weighted alpha each month. We calculate the value weighted monthly mean inflow, outflow, and net flows in each rank. This Table 3.presents the OLS regression results on the value weighted average inflow, outflow and net flows to U.S. domestic equity mutual funds in each rank. *Inflow*, *Outflow*, *Net flows* are measured for 3,192 equity funds from a combination between the CRSP Survivor-Bias-Free US Mutual Fund Database and N-SAR filings with the SEC over the period from January 1994 to December 2007. *Inflow* is defined as $Sales_{i,t}/ TNA_{i,t-1}$, where $Sales_{i,t}$ is the amount of new money invested into a fund over the month. *Outflow* is defined as $Redemptions_{i,t}/ TNA_{i,t-1}$, where $Redemptions_{i,t}$ is the amount of money withdrawn from a fund over the month. *Net Flow* is the difference between *Inflow* and *Outflow*. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is January, zero otherwise. *End of the Year* is the dummy variable which is one if the calendar month at time *t* is December, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is April, July, or October, zero otherwise. *Beginning of the Year* is the dummy variable which is one if the calendar month at time *t* is March, Jun, or September, zero otherwise. In the last column, we report the OLS regression result on the value weighted average net flows to equity funds using 9,274 equity mutual funds from CRSP database. We exclude observations when the total net asset value is less than 15 million dollars or the flows are less than -90% or greater than 100%. Flows are reported in percentage. t-statistics are in parentheses. The asterisks, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Inflow

	(Worst) Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	(Best) Rank 6	R6 - R1
Intercept	3.081 ***	3.042 ***	2.935 ***	3.190 ***	3.675 ***	3.528 ***	0.447
	(17.23)	(19.21)	(19.40)	(18.20)	(17.25)	(15.75)	(1.56)
Beginning of the Year	1.181 ***	0.374	0.887 ***	0.906 **	0.697	1.044 **	-0.137
	(2.95)	(1.06)	(2.62)	(2.31)	(1.46)	(2.08)	(-0.21)
End of the Year	0.422	-0.027	0.398	-0.190	0.018	0.496	0.073
	(1.06)	(-0.08)	(1.18)	(-0.48)	(0.04)	(0.99)	(0.11)
Beginning of the Quarter	-0.036	0.008	0.136	0.220	0.040	0.075	0.111
	(-0.13)	(0.03)	(0.59)	(0.82)	(0.12)	(0.22)	(0.25)
End of the Quarter	-0.049	0.020	0.152	0.110	0.094	-0.096	-0.047
	(-0.18)	(0.08)	(0.66)	(0.41)	(0.29)	(-0.28)	(-0.11)
N	168	168	168	168	168	168	
Adj R^2	0.041	-0.017	0.021	0.015	-0.010	0.012	

Panel B. Outflow

	(Worst) Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	(Best) Rank 6	R6 - R1
Intercept	2.906 ***	2.772 ***	2.555 ***	2.680 ***	2.943 ***	2.746 ***	-0.159
	(18.67)	(18.20)	(21.57)	(17.88)	(18.66)	(14.80)	(-0.66)
Beginning of the Year	0.886 **	0.024	0.389	0.306	0.521	0.631	-0.255
	(2.55)	(0.07)	(1.47)	(0.91)	(1.48)	(1.52)	(-0.47)
End of the Year	0.717 **	0.124	0.381	0.128	0.137	0.761 *	0.044
	(2.06)	(0.37)	(1.44)	(0.38)	(0.39)	(1.83)	(0.08)
Beginning of the Quarter	0.040	0.016	0.130	0.031	0.114	0.098	0.058
	(0.17)	(0.07)	(0.72)	(0.14)	(0.47)	(0.35)	(0.16)
End of the Quarter	0.046	0.171	0.113	0.089	0.153	-0.009	-0.055
	(0.19)	(0.73)	(0.62)	(0.39)	(0.63)	(-0.03)	(-0.15)
N	168	168	168	168	168	168	
Adj R^2	0.038	-0.020	-0.003	-0.019	-0.011	0.010	

Panel C. Net Flows

	(Worst) Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	(Best) Rank 6	R6 - R1
Intercept	0.176	0.270 **	0.380 ***	0.510 ***	0.732 ***	0.782 ***	0.606 ***
	(1.53)	(2.24)	(3.68)	(4.82)	(5.77)	(6.58)	(3.67)
Beginning of the Year	0.295	0.351	0.498 **	0.600 **	0.176	0.414	0.118
	(1.15)	(1.30)	(2.16)	(2.54)	(0.62)	(1.56)	(0.32)
End of the Year	-0.294	-0.152	0.017	-0.318	-0.120	-0.265	0.029
	(-1.15)	(-0.56)	(0.07)	(-1.34)	(-0.42)	(-1.00)	(0.08)
Beginning of the Quarter	-0.076	-0.008	0.006	0.188	-0.073	-0.023	0.053
	(-0.44)	(-0.04)	(0.04)	(1.17)	(-0.38)	(-0.13)	(0.21)
End of the Quarter	-0.095	-0.151	0.039	0.021	-0.059	-0.087	0.008
	(-0.54)	(-0.82)	(0.25)	(0.13)	(-0.31)	(-0.48)	(0.03)
N	168	168	168	168	168	168	
Adj R^2	-0.002	-0.003	0.007	0.041	-0.019	0.004	

fund flows and the relative past performance among style funds, we suggest that investors are not sensitive to the past performance when they buy style funds, but they sell the funds with the poorly performed styles at the turn-of-the-year.

3.5 Concluding Remarks

In this paper, we study the seasonality in the cash flows of the U.S. domestic mutual funds and document a number of intriguing findings. We report that January is the month when the equity funds experience the largest net cash flows and December is the month with the smallest net cash flows. The large net flows in January are attributed to the increased purchases, and the small net flows in December are due to the increased redemptions. The inferred net flows are lower than the reported net flows in December, probably due to the way the distribution and reinvestment are treated in the inferred net flow formula.

This paper contributes to our understanding of mutual fund investors' trading behavior. We find that the investors make asset allocation decisions more actively around the turn-of-the-year. The seasonal component of their asset allocation decisions is not associated with the seasonal variations in personal income and consumption growth. The tax treatment of the distribution from mutual funds does not drive this seasonal pattern either. In addition, the seasonal patterns in the cash flows are indifferent across the style objectives of mutual funds. Past performance, however, has an effect on the seasonality in the cash flows of equity funds. The January effect in the inflow to mutual funds is stronger for the funds with the higher past performance. We also find that investors are not sensitive to the past performance when they buy style funds, but they sell the fund with the poorly performed styles at the turn-of-the-year.

REFERENCES

Abel, Andrew, Eberly, Janice and Panageas, Stavros, 2007, Optimal Inattention to the Stock Market, American Economic Review, vol. 97, 244-249

Agrawal, Anup and Kishore Tandon, 1994, Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries Journal of International Money and Finance, vol. 13, 83-106.

Ariel, Robert, 1987, A Monthly Effect in Stock Returns Journal of Financial Economics, vol. 18, 161-174.

Arshanapalli, Bala, T. Daniel Coggin, John Doukas, 1998, Multifactor Asset Pricing Analysis of International Value Investment Strategies, Journal of Portfolio Management, vol. 24, 10 – 23.

Asness, C., Friedman Krail, R. J., and Liew J. M., 2000, Style Timing: Value versus Growth, Journal of Portfolio Management, Spring 2000, 50-60.

Baker, Malcolm and Jeffrey Wurgler, 2007. Investor Sentiment in the Stock Market Journal of Economic Perspectives, vol. 21, 129-151.

Banz, R. ,1981, The Relationship Between Return and Market Value of Common Stock, Journal of FinancialEconomics, vol. 9, 3-18.

Barber, B.M. and J.D. Lyon, 1997, Firm Size, Book-to-Market Ratio, and Security Returns: A Holdout Sample of Financial Firms, The Journal of Finance vol. 52, 875 – 883.

Barber, Brad M., Terrance Odean, and Lu Zheng, 2000, The Behavior of Mutual Fund Investors, Unpublished working paper.

Barberis, Nicholas and Andrei Shleifer, 2003, Style Investing, Journal of Financial Economics, vol. 68, 161 – 199.

Bouman, Sven and Ben Jacobsen, 2002, The Halloween Indicator, Sell in May and Go Away: Another Puzzle, American Economic Review, vol. 92, 1618-1635.

Branch, Ben, 1977, A Tax Loss Trading Rule, Journal of Business, vol. 50, 198-207.

Campbell, John Y., 2000, Asset Pricing at the Millennium, Journal of Finance, vol. 55, 1515 – 1567.

Capual, Carlo, Ian Rowley, and William F. Sharpe, 1993, International value and growth stock returns, Financial Analysts Journal, vol. 49, 27 – 36.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, Journal of Finance, vol. 52, 57-82.

Carhart, Mark M., Ron Kaniel , David K. Musto & Adam V. Reed, 2002, Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds, Journal of Finance, vol. 57, 661-693.

Chakravarty, Sugato, 2001, Stealth-trading: Which Traders' Trades Move Stock Prices? Journal of Financial Economics, vol. 61, 289-307.

Chan, K. C., Nai-fu Chen, and David A. Hsieh, 1985, An Exploratory Investigation of the Firm Size Effect Journal of Financial Economics, vol. 14, 451-471.

Chan, Louis K C, Jason Karceski and Josef Lakonishok, 2000, New paradigm or same old hype in equity investing?, Financial Analysts Journal, vol. 56, 23 – 36.

Chang, Eric C and J. Michael Pinegar, 1986, Return Seasonality and Tax-loss Selling in the Market for Long-term Government and Corporate bonds Journal of Financial Economics, vol. 17, 391-415.

Chang, Eric C. and J. Michael Pinegar, 1989, Seasonal Fluctuations in Industrial Production and Stock Market Seasonals, Journal of Financial and Quantitative Analysis, vol. 24, 59-74.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik, 2004, Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, American Economic Review, vol. 94, 1276-1302.

Chen, Nai-Fu, Richard Roll and Stephen A. Ross, 1986, Economic Forces and the Stock Market, Journal of Business, vol. 59, 383-403.

Cochrane, John H., 1999, New Facts in Finance, Economic Perspective, vol. 23-3, Ferderal Reserve Bank of Chicago, 36 – 58.

Cochrane, John H., 2005, Asset Pricing – Revised Edition, Princeton University Press, Princeton, NJ.

Conrad, Jennifer and Gautam Kaul, 1998, An Anatomy of Trading Strategies, Review of Financial Studies, vol. 11, 489 – 519.

Daniel, K., and S. Titman, 1997, Evidence on the Characteristics of Cross-Sectional Variation in Stock Returns, Journal of Finance, vol. 52, 1-33.

De Long, J. Bradford and Andrei Shleifer, 1991. The Stock Market Bubble of 1929: Evidence from Closed-end Mutual Funds, Journal of Economic History, vol. 51, 675-700.

DeBondt, Werner F.M. and Richard Thaler, 1985, Does the stock market overreact? Journal of Finance, vol. 40, 793–808.

DeBondt, Werner .F.M. and Richard Thaler, 1987, Further Evidence on Investor Overreaction and Stock Market Seasonality, Journal of Finance, vol. 42, 557–581.

Dyl, Edward A., 1977, Capital Gains Taxation and the Year-end Stock Market Behavior, Journal of Finance, vol. 32, 165-175.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2001, A First Look at the Accuracy of the CRSP Mutual Fund Database and a Comparison of the CRSP and Morningstar Mutual Fund Databases, Journal of Finance, vol. 56, 2415-2430.

Fama, Eugene F. and Kenneth R. French, 1988. Permanent and Temporary Components of Stock Prices Journal of Political Economy, vol. 96, 246-273.

Fama, Eugene F. and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, Journal of Finance, vol. 47, 427 – 466.

Fama, Eugene F. and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics, vol. 33, 3-56.

Frazzini, Andrea and Owen A. Lamont, 2008, Dumb Money: Mutual Fund Flows and the Cross-section of Stock Returns, Journal of Financial Economics, vol. 88, 299-322.

French, Kenneth R., 1980, Stock Returns and the Weekend Effect Journal of Financial Economics, vol. 8, 55-69.

Gibson, Scott, Assem Safieddine, and Sheridan Titman, 2000, Tax-Motivated Trading and Price Pressure: An Analysis of Mutual Fund Holdings Journal of Financial and Quantitative Analysis, vol. 35, 369-386.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The Economic Implications of Corporate Financial Reporting Journal of Accounting and Economics, vol. 40, 3-73.

Gruber, Martin J., 1996, Another Puzzle: The Growth in Actively Managed Mutual Funds, Journal of Finance, vol. 51, 783-810.

Grundy, Bruce D. and J. Spencer Martin, 2001, Understanding the nature of risks and thesources of rewards to momentum investing, Review of Financial Studies, vol. 14, 29-78.

Haug, Mark and Mark Hirschey, 2007, The September swoon, Unpublished paper, University of Kansas.

Heston, Steven L. and Ronnie Sadka, 2008, Seasonality in the Cross-Section of Stock Returns, Journal of Financial Economics, vol. 87, 418 – 445.

Hirshleifer, David and Tyler Shumway, 2003, Good Day Sunshine: Stock Returns and the Weather, Journal of Finance, vol. 58, 1009-1032.

Hong, Harrison G. and Yu, Jialin, 2007, Gone Fishin': Seasonality in Trading Activity and Asset Prices, Unpublished paper, Princeton University.

Ippolito, Roger A., 1992, Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry, Journal of Law and Economics, vol. 35, 45-70.

Jagannathan, Ravi and Yong Wang, 2007, Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns, Journal of Finance, vol. 62, 1623-1661.

Jegadeesh, N. and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, Journal of Finance, vol. 48, 65-91.

Jegadeesh, N. and S. Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, Journal of Finance, vol. 56, 699-720.

Jegadeesh, Narasimhan, 1990, Seasonality in Stock Price Mean Reversion: Evidence from the U.S. and the U.K., Journal of Finance, vol. 46, 1427 – 1444.

Johnson, Woodrow T. and James M. Poterba, 2008, Taxes and Mutual Fund Inflows around Distribution Dates, Unpublished working paper.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2003, Winter Blues: A SAD Stock Market Cycle American Economic Review, vol. 93, 324-343.

Keim, Donald B., 1983, Size-related Anomalies and Stock Return Seasonality: Further Empirical Evidence Journal of Financial Economics, vol. 12, 13-32.

Khorana, Ajay and Henri Servaes, 1999, The Determinants of Mutual Fund Starts, Review of Financial Studies, vol. 12, 1043-1074.

La Porta, Rafel, 1996, Expectations and the Cross-Section of Stock Returns, Journal of Finance, vol. 51, 1715 – 1742.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishny, 1991, Window dressing by pension fund managers, American Economic Review, vol. 81, 227-231.

Lakonishok, Josef and Edwin Maberly, 1990, The Weekend Effect: Trading Patterns of Individual and Institutional Investors Journal of Finance, vol. 45, 231-243.

Lakonishok, Josef and Seymour Smidt, 1988, Are Seasonal Anomalies Real? A Ninety-Year Perspective Review of Financial Studies, vol. 1, 403-425.

Lee, Charles M. C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle Journal of Finance, vol. 46, 75-109.

Levis, M. and Liodakis, M., 1999, The profitability of Style Rotation Strategies in the United Kingdom, Journal of Portfolio Management, Fall 1999, pp. 73-86.

Levis, Mario and Manolis Liodakis, 2001, Contrarian strategies and investor expectations: The U.K. evidence, Financial Analysts Journal, vol. 57, 43 – 56.

Lewellen, J., 1999, The time-series relations among expected return, risk, and book-to-market, Journal of Financial Economics, vol. 54, 5 – 43.

Lo, Andrew W. and A. Craig MacKinlay, 1990, When Are Contrarian Profits Due to Stock Market Overreaction?, Review of Financial Studies, vol. 3, 175 – 205.

Lucas, André, Ronald van Dijk, and Teun Kloek, 2002, Stock Selection, Style Rotation, and Risk, Journal of Empirical Finance, vol. 9, 1 – 34.

Miron, Jeffrey, and Joseph Beaulieu, 1996, What Have Macroeconomists Learned about Business Cycles from the Study of Seasonal Cycles?, Review of Economics and Statistics, vol. 78, 54–66.

Neal, Robert and Simon M. Wheatley, 1998, Adverse Selection and Bid–Ask Spreads: Evidence from Closed-end Funds Journal of Financial Markets, vol. 1, 121-149.

Ng, Lilian and Qinghai Wang, 2004, Institutional Trading and the Turn-of-the-year Effect, Journal of Financial Economics, vol. 74, 343-366.

Peng, Lin and Wei Xiong, 2006, Investor Attention, Overconfidence, and Category Learning, Journal of Financial Economics, vol. 80, 563 – 602.

Reinganum, Marc R. 1983, The Anomalous Stock Market Behavior of Small Firms in January: Empirical Tests for Tax-Loss Selling Effects Journal of Financial Economics, vol. 12, 89-104.

Reinganum, Marc, 1984, Discussion: What the Anomalies Mean Journal of Finance, vol. 39, 837-840.

Ritter, Jay R. and Navin Chopra, 1989, Portfolio Rebalancing and the Turn-of-the-Year Effect Journal of Finance, vol. 44, 149-166.

Ritter, Jay R., 1988, The Buying and Selling Behavior of Individual Investors at the Turn of the Year, Journal of Finance, vol. 43, 701-717.

Roll, Richard, 1983, Vas Ist Das? The Turn-of-the-year Effect and the Return Premia of Small Firms, Journal of Portfolio Management, vol. 9, 18-28.

Rozeff, Michael S. and Willian R. Kinney, Jr., 1976. Capital Market Seasonality: The Case of Stock Returns Journal of Financial Economics, vol. 3, 379-402.

Sapp, Travis and Ashish Tiwari, 2004, Does Stock Return Momentum Explain the Smart Money Effect?, Journal of Finance, vol. 59, 2605-2622.

Schwert, G. William, 1990, Indexes of U.S. Stock Prices from 1802 to 1987, Journal of Business, vol. 63, 399-426.

Schwert, G. William, 2002. Anomalies and Market Efficiency, Handbook of the Economics of Finance, 937-972.

Sirri, Erik R. and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, Journal of Finance, vol. 53, 1589-1622.

Spitz, A. Edward, 1970, Mutual Fund Performance and Cash Inflows, Applied Economics, vol. 2, 141-145.

Vassalou, Maria and Yuhang Xing, 2004, Default Risk in Equity Returns Journal of Finance, vol. 59, 831-868.

Wang, Kevin Q., 2005, Multifactor Evaluation of Style Rotation, Journal of Financial and Quantitative Analysis, vol. 40, 349 – 372.

Zheng, Lu, 1999, Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability, Journal of Finance, vol. 54, 901-933.

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