The Other January Effect: Nothing More than a Statistical Artifact*

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October 2007

Abstract

This paper investigates the predictive power of stock market returns in January for the subsequent eleven months' returns across 14 countries, thereby contributing to the literature on stock market seasonalities. In addition to the presentation of international empirical findings on the Other January Effect, we investigate the forecasting capability of stock market returns in each of the remaining eleven months. Only three out of 14 countries' stock markets exhibit the Other January Effect, and for those countries the stock market anomaly mostly disappears after 1980. As for the predictive power of individual months, we do not identify a consistent pattern across countries or over time. In light of this evidence, we conclude that the Other January Effect is not a real phenomenon but rather a result of data-snooping.

JEL Classification: G10, G11, G12, G14

Keywords: Stock market efficiency, Other January Effect, Stock market anomalies

*The authors would like to thank Judith Lischewski, Sarah Stölting and David Sondermann and especially Christiane Goodfellow for helpful comments on an earlier draft of this paper. Bohl is also grateful to the Alexander von Humbold foundation for financial support.

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Abstract

This paper investigates the predictive power of stock market returns in January for the subsequent eleven months' returns across 14 countries, thereby contributing to the literature on stock market seasonalities. In addition to the presentation of international empirical findings on the Other January Effect, we investigate the forecasting capability of stock market returns in each of the remaining eleven months. Only three out of 14 countries' stock markets exhibit the Other January Effect, and for those countries the stock market anomaly mostly disappears after 1980. As for the predictive power of individual months, we do not identify a consistent pattern across countries or over time. In light of this evidence, we conclude that the Other January Effect is not a real phenomenon but rather a result of data-snooping.

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"October. This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August, and February." (Mark Twain (1894))

1 Introduction

Since the late 1970s, a large body of research in finance has been questioning the efficient markets hypothesis. More recently, Cooper, McConnell, and Octchinnikov (2006) report significant predictive power of January stock market returns in the U.S. for returns in the remainder of the calendar year and thus confirm the market wisdom 'As goes January, so goes the year'. We investigate the presence of the Other January Effect in 14 countries, thereby broadening empirical evidence to stock markets with dissimilar institutional and regulatory characteristics. By reducing the data-snooping bias, we ascertain whether the Other January Effect is a real phenomenon, or just a statistical artifact. While the results for the U.S. are confirmed , we do not find empirical evidence supporting the Other January Effect for most of the other 13 countries in our sample.

The Other January Effect was first discovered for the U.S. by Yale Hirsch in 1972 (Hirsch and Hirsch (2007)) and termed January Barometer. Hirsch and Hirsch (2007) report a 91.1% accuracy ratio for this barometer for S&P 500 data since 1950, with extreme events such as wars being responsible for the exceptions from the rule. They identify major political events as the fundamental force driving the January Barometer. These are the conventions of the new Congresses, the President's State of the Union message, the presentation of the annual budget of the government, and the setting of national goals and priorities by the President. In the U.S., these political events occur in January, and Hirsch and Hirsch (2007) hypothesise that moving such incidents to other months could eliminate the January Barometer. However, as they address mainly practitioners, they do not conduct a rigorous econometric investigation of the phenomenon.

Bloch and Pupp (1983) test for the January Barometer with S&P 500 data from 1950 to 1982. Once controlled for long-term overall upward trends in the stock market, the January Barometer does not hold statistically significant forecasting power. Consistently, Fuller (1978) reports that a trading strategy based on the January Barometer is as profitable as a naive buy-and-hold strategy. By contrast, Hensel and Ziemba (1995a) propose a trading rule for the U.S. market that recommends buying after a positive January return, whereas no conclusive investment advice can be derived from a negative stock return in January. Hensel and Ziemba (1995b) investigate the January Barometer's forecasting power internationally. They confirm their earlier results for the U.S. and find predictive power of the January Barometer when January returns are positive for Australia, Canada, Japan, and the U.K. Hensel and Ziemba (1995b) attribute the January Barometer to economic activity such as Christmas sales. Using data from the New York Stock Exchange, Brown and Juo (2006) find that negative January returns are a reliable predictor for the rest of the year, while positive January returns' predictive power is much weaker.

Cooper, McConnell, and Octchinnikov (2006) provide the first profound econometric investigation of the Other January Effect. They examine value-weighted and equally-weighted CRSP market returns from 1940 to 2003 and stock market return time series for the NYSE index from 1825 to 2003. In their analysis, macroeconomic and business cycle variables, the Presidential cycle, and investor sentiment indices are accounted for as control variables. The stock market returns in January reliably predict the return for the rest of the year, while the stock market returns in the other eleven months cannot predict future returns.

Seemingly significant calendar effects in stock markets can be the result of extensive search for abnormal patterns in non-experimental and limited datasets (Sullivan, Timmermann, and White (2001)). Apparent deviations from unpredictable stock returns are deemed surprising and hence journals publish disproportionately more papers reporting regularities. In particular, the Other January Effect might be the result of snooping the U.S. stock market data for such an anomaly. Moreover, Lo and MacKinlay (1990) and Sullivan, Timmermann, and White (2001) argue that statistical inference based on the empirical properties of a particular sample or time series is prone to data-snooping biases and hence potentially misleading. To control for data-snooping Cooper, McConnell, and Octchinnikov (2006) propose a randomized-bootstrap procedure. Alternatively, Schwert (2003) suggests to use data from other countries.

Following this approach, we analyse 13 additional stock markets whose return-generating processes are largely independent of each other, thereby reducing any data-snooping bias. Moreover, we construct a large set of control variables to capture political and calendar anomalies as well as varying risk due to business cycle fluctuations. Specifically, we raise four research questions. First, is the Other January Effect an international phenomenon or a peculiarity of the U.S. stock market? Second, do other months in other countries have forecasting power similar to Januarys in the U.S.? Third, can a pattern across months or across countries be detected? Fourth, does the Other January Effect disappear internationally after it became well-known in the early 1970s?

The paper is organized as follows. We introduce the methodology in section 2 and the dataset in section 3. Section 4 presents the empirical results before section 5 summarises our findings and concludes.

2 Methodology

To test the statistical significance of the Other January Effect, we follow the methodology proposed by Cooper, McConnell, and Octchinnikov (2006). We compare monthly stock market returns over eleven months following positive Januarys with monthly stock market returns in the eleven months following negative Januarys by estimating

$$r_t = \alpha + \beta JanD_t + \gamma X_t + \phi Z_{t-1} + u_t \ , \tag{1}$$

where r_t is the excess stock market return, α the constant, $JanD_t$ the January dummy, X_t and Z_{t-1} vectors of control variables, and u_t the error term.

The indicator variable $JanD_t$ takes the value of 1 for February to December following Januarys with positive excess stock returns and 0 otherwise. If the estimated coefficient of the dummy variable is statistically significantly different from 0 and positive, the spread between the 11-month holding-period returns following a positive January return is significantly higher than the 11-month return following a negative January return. This implies that January stock returns have predictive power for the returns in the following eleven months.

Januarys' predictive power might be associated with other variables and phenomena which potentially explain stock returns. Therefore, we take contemporaneous and lagged control variables in the vectors X_t and Z_{t-1} into account.[1] The contemporaneous vector X_t contains dummy variables capturing political and calendar effects.

Santa-Clara and Valkanov (2003) provide empirical evidence for the U.S. that stock returns are economically and statistically significantly higher under a Democrat government

[1] The impact of outliers is also considered. In particular we control for the large monthly declines of stock markets in October 1987 and in September 2001. Including an outlier dummy variable does not affect our empirical results qualitatively unchanged.

than under a Republican presidential administration. Hence, the first control variable contained in X_t is the political dummy variable $PolD_t$ which takes the value of 1 whenever a right-wing government is in office and 0 otherwise.[2] Bouman and Jacobsen (2002) provide international evidence in favour of substantially lower returns for May to October than for the rest of the calendar year. This phenomenon is commonly referred to as the Halloween Effect. Therefore, the Halloween indicator variable $HallD_t$ is included in the control vector X_t, which takes the value 1 for each month from November to April and 0 for the remaining months.

The lagged vector Z_{t-1} comprises ex ante observable variables related to the business cycle and international stock market dependencies. Five lagged macroeconomic control variables related to the business cycle are included in Z_{t-1}. The variables are a proxy for changes in equilibrium expected stock returns. These variables are:

1. lagged dividend yield DIV_{t-1};
2. lagged default spread DEF_{t-1}, which is defined as the difference between the return on a portfolio of corporate bonds and the return on long-term government bonds;
3. lagged term spread $TERM_{t-1}$, measured as the difference between a long-term government bond yield and the short-term interest rate;
4. lagged relative interest rate $RREL_{t-1}$, which is calculated as the deviation of the short-term interest rate from its one-year moving average;
5. expected inflation $E_{t-1}(INF_t)$ formed in $(t-1)$.

There is broad evidence that those control variables can forecast stock returns (Fama and French (1988, 1986), Campbell and Shiller (1988), Chen, Roll, and Ross (1986), Keim and Stambaugh (1986) and Jensen, Mercer, and Johnson (1996)). Finally, lagged U.S. stock market returns r_{t-1}^{US} are included to capture the linkages between the U.S. stock market and the markets in other countries. This variable is not included in the regression for the U.S.

Furthermore, we investigate the predictive power of stock returns in each of the remaining calendar months, i.e. February to December. For this, we compare the 11-month holding-period returns following any given month with a positive return to those 11-month

[2] Santa-Clara and Valkanov (2003) assume that the political variables are known at the beginning of the return period and are included with one lag. Our empirical results are robust to lagging the political dummy variable.

holding-period returns following the same month with a negative return. This requires the estimation of regression (1) in eleven different specifications substituting dummies for February to December for the January dummy variable $JanD_t$. Since January returns are included into those regressions we additionally control for the well-known January Effect. Therefore, we further include the dummy variable JD_t in the set of control variables. JD_t takes the value of 1 in Januarys, and 0 otherwise. The general model specification is therefore

$$r_t = \alpha + \beta MonthD_t + \gamma X_t^* + \phi Z_{t-1} + u_t \ , \tag{2}$$

with $Month = Feb, ..., Dec$ indicating the calendar months February to December and X_t^* denotes the control vector of dummy variables including JD_t. A statistically significant estimated coefficient of $MonthD_t$ implies predictive power of that calendar month.

The regression equations are estimated using ordinary least squares (OLS). The standard errors are corrected for heteroskedasticity and autocorrelation in the residuals using the method proposed by Newey and West (1987). The bandwidth for the Newey-West approach is set to 3 lags to account for quarterly autocorrelation.[3] We start estimating an unrestricted model which consists of the indicator variable and the full set of controls. Using the general-to-specific methodology we reduce the complexity of the general model by eliminating control variables with coefficients that are not statistically significant at the 10% level. This leads to a specific model with only statistically significant parameters for the control variables. In order to strengthen statistical inference, we use bootstrapped standard errors which are obtained from resampling the residuals of the regression with 10,000 replications.

[3]We consider a maximum lag length of 6 for the Newey-West approach. The empirical results are robust concerning the number of lags. In addition, using heteroskedasticity-consistent standard errors proposed by White (1980) does not change the empirical results either.

3 Data

Our dataset comprises monthly observations on stock price indices and macroeconomic variables for 14 countries: Austria, Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Sweden, the U. K., and the U.S. All stock market and macroeconomic time series are denominated in local currency units. For most countries, the time series cover the period from January 1970 to December 2006. Due to data availability, the sample starts in January 1971 for Austria and Australia and in January 1973 for Denmark and Norway. The political dummy variable until 2003 is taken from Bohl and Gottschalk (2006), with the time series being extended until 2006 based on their approach.

Stock returns for each country are calculated using value-weighted performance indices with gross dividends contained in Morgan Stanley Capital International (MSCI).Fama (1998) argues that value-weighted returns, rather than equal-weighted ones, are the appropriate data to test for an anomaly as they replicate the investment performance. We assume continuously compounding on stock markets, while on money and bond markets are based simple returns. The excess stock return in % per month is calculated as

$$r_t = \left(\ln(I_t/I_{t-1}) - \ln(1 + \frac{i_t^s}{12 \cdot 100}) \right) \cdot 100 \ , \qquad (3)$$

where I_t is the value of the performance index and i_t^s is the short-term interest rate in % per annum.

Following Campbell (1999), dividend yields DY_t are extracted from price indices P_t and performance indices I_t as

$$DY_t = (I_t/I_{t-1})(P_{t-1}/P_t) \ . \qquad (4)$$

Both I_t and P_t time series are included in the MSCI database. Thus, dividend yields are a moving average of the dividends in the previous 11 months and the current month divided by the price index at the end of the current month. Due to a change in the methodology applied by MSCI, dividend yields cannot be extracted in this simple way after 2000. Therefore, from January 2001 to December 2006, we use dividend yields from Thomson Financial Data which are consistent with the former MSCI approach. Finally, we convert the simple compounded dividend yields DY_t into continuously compounded dividend yields $DIV_t = \ln(1 + DY_t) \cdot 100$.

We use data on corporate bond yields from Global Financial Data (GFD) and national sources to measure the returns on corporate bonds. As several corporate bond yields compiled by GFD are reported at daily frequency, the monthly returns CYM_t are calculated from the corresponding set of simple compounded daily returns $[CYD_1, CYD_2, ..., CYD_n]$ by

$$CYM_t = \sqrt[n]{\prod_{i=1}^{n}(CYD_i)} - 1 \ . \tag{5}$$

This results in simple compounded monthly returns on corporate bonds which are consistent with those series reported by GFD at monthly frequency.

The main source of data on short-term interest rates, long-term government bond yields and inflation rates is the International Monetary Fund's International Financial Statistics (IFS). The time series in the IFS database are generally based on national sources. Therefore, the interest rate time series available for each country and their sample periods vary slightly across countries. As the short-term interest rate, we use the Treasury bill rate or, alternatively, the money market rate. For France and Italy the time series available in the IFS are substantially shorter than for the remaining countries. We therefore substitute short-term interest rate measures from the respective national central banks for those two IFS time series. As long-term government bond rate, we choose the 10-year government bond yield. The expected inflation rate $E_t(INF_{t+1})$ is approximated by the change in consumer prices observed in $(t + 1)$.

4 Empirical Results

Table 1 summarises the estimation results of equation (1) for the general model and the specific model with a reduced number of control variables. In the parsimonious specification for the U.S., monthly excess stock market returns are, on average, higher by 1.05% following positive Januarys than after Januarys scoring negative returns. This result is statistically significant at the 5% level and consistent with Cooper, McConnell, and Octchinnikov (2006). While the Other January Effect is significant and remarkably large for the U.S., it vanishes as the sample is extended internationally. In particular, the countries with stock markets that are not subject to the Other January Effect are Austria, Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Sweden, and the U.K. By contrast, Norwegian excess stock returns are, on average, significantly higher by 2.12% after positive Januarys compared with negative ones. Similarly, the Dutch stock market exhibits the Other January Effect at the 10% level of significance.

Insert Table 1 about here

Table 1 further reports the estimated coefficients of the control variables with their p-values. The point estimates when statistically significant have the theoretically expected signs in most cases. Only stock markets in Austria, France, Germany, Italy, and the U.S. are influenced by political effects, with Germany and Austria showing a significant right-wing premium. The Halloween Effect is statistically significant for most of the countries. Exceptions are Australia, Denmark, and Norway. This confirms the results of Bouman and Jacobsen (2002). Among those control variables capturing the impact of business cycle fluctuations on excess stock returns, dividend yield and inflation are the most influential ones. This is plausible as economic theory predicts positive stock returns as dividend cash flows increase under otherwise equal conditions. Moreover, the national excess returns are, overall, positively correlated with the U.S. stock market. Across most countries and model specifications, the empirical results are largely robust to statistical inference with standard p-values or bootstrapped ones. As in, for example, Fama and French (1988), the adjusted coefficient of determination $\bar{R}^2$ for regressions of monthly returns varies between 1% and 10%.

In summary, the Other January Effect is an American peculiarity and cannot be detected for most of the remaining 13 stock markets in our dataset. In fact, large and highly developed stock markets other than the U.S., such as the U.K. or Japan, do not exhibit the Other January Effect. These results give rise to the hypothesis that the Other January Effect is not a widely observed phenomenon.

Next, we investigate the predictive power of each of the remaining months. Table 2 reports the estimated parameters and their p-values for the February to December dummies, while the estimated coefficients and p-values for the model including the control variables are available on request. It turns out that some other calender months in a few countries have statistically significant predictive power for the following eleven months. The month with significant forecasting power in the most countries is May. Monthly stock returns following positive returns in May are, on average, significantly higher than monthly returns after negative Mays in Austria, Belgium, Germany, Italy, Sweden, U.K., and the U.S. Estimated coefficients on the various indicator variables are usually positive when they appear to be statistically significant different from zero. On average, excess stock returns are between 1% and 2.5% higher after positive returns of the indicator month. Those magnitudes are comparable to the results we report for the Other January Effect. In Germany and the Netherlands monthly stock market returns following positive Marchs are significantly lower compared to monthly stock returns after negative Marchs. Another exception is the negative coefficient of the July dummy for Germany.

Insert Table 2 about here

In essence, internationally, almost every calendar month has some forecasting power for some specific countries comparable to the Other January Effect in the U.S. with May being an exception. Nevertheless, a consistent pattern across all months or all countries cannot be identified.

The empirical evidence reported by Cooper, McConnell, and Octchinnikov (2006) on the Other January Effect is sensitive to the selection of the sample period. While the anomaly is significant for the full sample (1973-2003), it disappears in disjoint 10-year subperiods from 1980 onwards. Schwert (2003) and Black (1993) argue that anomalies disappear as soon as they have been documented. In light of this, the subsiding of the Other January Effect could be attributed to its discovery in 1972. Table 3 presents the predictive power of each month by country over time by reporting p-values of the estimated coefficient for the respective month dummy. For brevity we only report the results for the general model. Detailed estimation results are available on request. Panel A summarises the statistical significance of each month's forecasting capability from 1980 to 2006, whereas Panel B focuses on the more recent years from 1990 to 2006.

Insert Table 3 about here

The results of Cooper, McConnell, and Octchinnikov (2006) are confirmed for our data set. There are very few countries in which a particular month has persistently predictive power over time. When examining the forecasting capability of each month from 1970 to 2006, May stands out as the month that can predict stock returns most accurately. In the more recent subperiods, however, February and June yield more reliable return forecasts than any other month. While Australia appears to have the most efficient market across the entire sample period (Table 2), Japan takes this over when analysed from 1980 to 2006 and from 1990 to 2006 (Table 3). Whereas September has lost predictive power over time, November has gained it for a number of countries including the U.S.

5 Summary and Conclusion

The aim of this paper is to investigate the presence of the Other January Effect in 14 countries. This effect stems from the market wisdom 'As January goes, as goes the year' and refers to the observation that U.S. stock market returns in January can serve as a reliable predictor for the market return in the subsequent eleven months. We provide international empirical evidence on the Other January Effect, as existing literature on this anomaly focuses on the U.S. stock market. By including stock markets other than the U.S. one in our sample, data-snooping biases are reduced. Moreover, we investigate the predictive power of the remaining eleven months February to December and provide findings for subsample.

For the U.S., we find evidence in favour of the Other January Effect, which is consistent with the findings in Cooper, McConnell, and Octchinnikov (2006). Among the 13 other countries in our sample, only the Netherlands and Norway exhibit this stock market anomaly. Hence, there is no empirical evidence in favour of an international Other January Effect. Highly developed stock markets such as the U.K. or Japan are not affected by this phenomenon. Regarding the forecasting power of the remaining months, we find that January is not unique in its capability to predict stock market returns. In fact, almost every month shows statistically significant forecasting power across the 14 countries under investigation without a consistent pattern. As reported in Cooper, McConnell, and Octchinnikov (2006), the Other January Effect in the U.S. disappears after 1980. Regarding the forecasting capability of the remaining months, no pattern can be identified over time.

In essence, only three out of 14 countries exhibit the Other January Effect, with May, and more recently June, showing more reliable predictive power than January in our sample. Therefore, systematically predicting stock returns based on previous return observations appears to be impossible. Instead, the existence of statistically significant forecasting power of particular month is determined by the selection of stock markets or sample periods. The Other January Effect is a result of snooping U.S. stock market data. Thus, we conclude that this anomaly is nothing more than a statistical artifact.

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Table 1: The Other January Effect

Country	Model	Regression coefficients (p-values)										$\bar{R}^2$
		$Constant$	$JanD_t$	$PolD_t$	$HallD_t$	DIV_{t-1}	DEF_{t-1}	$TERM_{t-1}$	$RREL_{t-1}$	$E_{t-1}(INF_t)$	r^{US}_{t-1}	
Austria	General	−1.91	0.45	1.05	1.81	0.57	−0.18	0.14	0.26	−0.23	0.24	0.067
		(0.155)	(0.515)	(0.142)	(0.000)***	(0.188)	(0.808)	(0.473)	(0.316)	(0.094)	(0.001)***	
		[0.082]*	[0.466]	[0.154]	[0.001]***	[0.204]	[0.849]	[0.562]	[0.368]	[0.149]	[0.000]***	
	Specific	−1.03	0.16	1.19	1.81	–	–	–	–	–	0.24	0.071
		(0.013)**	(0.777)	(0.051)*	(0.000)***						(0.001)***	
		[0.021]**	[0.762]	[0.076]*	[0.001]***						[0.000]***	
Australia	General	−2.35	0.03	0.47	0.68	0.72	0.24	0.15	−0.16	−0.19	0.16	0.016
		(0.297)	(0.958)	(0.473)	(0.241)	(0.184)	(0.665)	(0.637)	(0.615)	(0.163)	(0.007)***	
		[0.112]	[0.967]	[0.457]	[0.246]	[0.027]**	[0.639]	[0.585]	[0.496]	[0.136]	[0.015]**	
	Specific	1.77	−0.25	–	–	–	–	–	–	–	0.16	0.010
		(0.655)	(0.636)								(0.008)***	
		[0.707]	[0.672]								[0.016]**	
Belgium	General	−1.18	0.86	−0.75	1.62	0.40	−0.18	0.08	−0.19	−0.31	0.15	0.063
		(0.214)	(0.183)	(0.267)	(0.000)***	(0.026)**	(0.620)	(0.672)	(0.535)	(0.001)***	(0.009)***	
		[0.183]	[0.121]	[0.260]	[0.000]***	[0.026]**	[0.531]	[0.748]	[0.561]	[0.003]***	[0.005]***	
	Specific	−0.07	0.66	–	1.57	–	–	–	–	−0.21	0.15	0.062
		(0.907)	(0.277)		(0.000)***					(0.003)***	(0.005)***	
		[0.881]	[0.197]		[0.000]***					[0.005]***	[0.004]***	
Canada	General	−0.89	−0.37	−0.30	0.85	0.784	−0.44	0.12	−0.10	−0.26	0.12	0.020
		(0.554)	(0.409)	(0.664)	(0.068)*	(0.121)	(0.572)	(0.637)	(0.664)	(0.056)*	(0.024)**	
		[0.494]	[0.448]	[0.643]	[0.075]*	[0.065]*	[0.564]	[0.595]	[0.637]	[0.058]*	[0.027]**	
	Specific	−0.17	−0.24	–	0.85	–	–	–	–	–	0.12	0.014
		(0.694)	(0.624)		(0.082)*						(0.030)**	
		[0.690]	[0.619]		[0.080]*						[0.031]**	
Denmark	General	−0.44	0.67	−0.26	0.22	0.52	−0.21	−0.01	−0.23	−0.23	0.02	0.022
		(0.686)	(0.306)	(0.685)	(0.675)	(0.004)***	(0.489)	(0.913)	(0.078)*	(0.007)***	(0.754)	
		[0.642]	[0.238]	[0.643]	[0.658]	[0.008]***	[0.472]	[0.922]	[0.089]*	[0.013]**	0.748	
	Specific	−0.78	0.76	–	–	0.49	–	–	−0.24	−0.22	–	0.033
		(0.325)	(0.238)			(0.005)***			(0.009)***	(0.003)***		
		[0.234]	[0.177]			[0.009]***			[0.022]**	[0.012]**		
France	General	−1.56	−0.04	−1.95	1.98	1.17	1.05	0.31	−0.18	−0.59	0.13	0.074
		(0.132)	(0.954)	(0.001)***	(0.000)***	(0.000)***	(0.147)	(0.222)	(0.396)	(0.000)***	(0.073)*	
		[0.106]	[0.948]	[0.002]***	[0.000]***	[0.001]***	[0.154]	[0.194]	[0.425]	[0.001]***	[0.045]**	
	Specific	−1.32	−0.04	−1.93	1.99	1.09	–	–	−0.39	−0.47	0.13	0.072
		(0.181)	(0.957)	(0.001)***	(0.000)***	(0.001)***			(0.062)*	(0.000)***	(0.068)*	
		[0.257]	[0.949]	[0.003]***	[0.000]***	[0.001]***			[0.080]*	[0.001]***	[0.045]**	
Germany	General	−3.27	0.95	1.34	1.41	1.08	−0.22	0.06	−0.36	−0.48	0.15	0.055
		(0.051)*	(0.121)	(0.100)*	(0.008)***	(0.033)**	(0.809)	(0.732)	(0.054)*	(0.011)**	(0.061)*	
		[0.046]**	[0.136]	[0.075]*	[0.012]**	[0.040]**	[0.799]	[0.799]	[0.148]	[0.053]*	[0.012]**	
	Specific	−3.42	1.01	1.40	1.40	1.12	–	–	−0.39	−0.49	0.16	0.059
		(0.030)**	(0.097)*	(0.074)*	(0.008)***	(0.027)**			(0.009)***	(0.013)**	(0.060)*	
		[0.010]***	[0.104]	[0.039]**	[0.012]**	[0.030]**			[0.042]**	[0.029]**	[0.012]**	
Italy	General	−2.64	0.56	−2.11	2.00	0.99	−1.05	−1.05	0.35	−0.03	0.17	0.052
		(0.040)**	(0.410)	(0.011)**	(0.002)***	(0.025)**	(0.180)	(0.113)	(0.233)	(0.661)	(0.033)**	
		[0.057]*	0.452	[0.030]**	[0.002]***	[0.032]**	[0.251]	[0.157]	[0.270]	[0.651]	[0.020]*	

Table 1 (continued): The Other January Effect

Country	Model	Regression coefficients (p-values)										$\bar{R}^2$
		$Constant$	$JanD_t$	$PolD_t$	$HallD_t$	DIV_{t-1}	DEF_{t-1}	$TERM_{t-1}$	$RREL_{t-1}$	$E_{t-1}(INF_t)$	r^{US}_{t-1}	
	Specific	−2.53	0.34	−2.42	1.96	0.95	–	–	–	–	0.15	0.055
		(0.045)**	(0.612)	(0.001)***	(0.003)***	(0.030)**					(0.046)**	
		[0.059]**	[0.612]	[0.001]***	[0.002]***	[0.032]**					[0.033]**	
Japan	General	−1.44	0.41	0.08	1.38	0.90	−0.23	−0.05	−0.27	−0.21	0.17	0.057
		(0.341)	(0.509)	(0.954)	(0.007)***	(0.019)**	(0.577)	(0.855)	(0.260)	(0.023)**	(0.002)***	
		[0.304]	[0.470]	[0.952]	[0.007]***	[0.018]**	[0.590]	[0.871]	[0.272]	[0.039]**	[0.003]***	
	Specific	−1.48	0.44	–	1.37	0.95	–	–	–	−0.22	0.18	0.063
		(0.045)**	(0.476)		(0.007)***	(0.011)**				(0.001)***	(0.002)***	
		[0.014]**	[0.411]		[0.007]***	[0.004]***				[0.001]***	[0.002]***	
The Netherlands	General	−1.73	1.08	−0.38	1.77	0.45	−0.41	0.23	−0.20	−0.44	0.13	0.083
		(0.111)	(0.064)*	(0.612)	(0.000)***	(0.023)**	(0.493)	(0.172)	(0.118)	(0.004)***	(0.062)*	
		[0.075]*	[0.053]*	[0.604]	[0.000]***	[0.039]**	[0.530]	[0.227]	[0.249]	[0.004]***	[0.014]**	
	Specific	−1.89	0.95	–	1.76	0.38	–	0.41	–	−0.44	0.14	0.085
		(0.030)**	(0.094)*		(0.000)***	(0.043)**		(0.000)***		(0.000)***	(0.056)*	
		[0.019]**	[0.086]*		[0.000]***	[0.045]**		[0.002]***		[0.000]***	[0.012]**	
Norway	General	−4.64	2.13	−0.23	0.77	1.57	1.39	−0.04	0.03	−0.54	0.10	0.050
		(0.005)***	(0.017)**	(0.822)	(0.273)	(0.003)***	(0.042)**	(0.865)	(0.906)	(0.001)***	(0.404)	
		[0.001]***	[0.012]**	[0.783]	[0.298]	[0.000]***	[0.042]**	[0.889]	[0.923]	[0.000]***	[0.240]	
	Specific	−4.40	2.12	–	–	1.56	1.49	–	–	−0.53	–	0.055
		(0.009)***	(0.014)**			(0.001)***	(0.023)**			(0.000)***		
		[0.001]***	[0.011]**			[0.000]***	[0.024]**			[0.000]***		
Sweden	General	−0.75	−0.27	−0.21	1.83	0.48	0.04	−0.13	−0.36	−0.16	0.18	0.032
		(0.547)	(0.756)	(0.814)	(0.005)***	(0.283)	(0.915)	(0.601)	(0.117)	(0.238)	(0.049)**	
		[0.449]	[0.706]	[0.812]	[0.004]***	[0.127]	[0.909]	[0.576]	[0.118]	[0.121]	[0.011]**	
	Specific	−0.26	−0.44	–	1.84	–	–	–	–	–	0.20	0.034
		(0.759)	(0.588)		(0.005)***						(0.034)**	
		[0.689]	[0.525]		[0.004]***						[0.006]***	
U.K.	General	−1.98	0.85	−0.02	1.58	0.53	−0.37	0.00	−0.13	−0.13	0.06	0.020
		(0.127)	(0.148)	(0.970)	(0.002)***	(0.198)	(0.481)	(0.994)	(0.472)	(0.104)	(0.408)	
		[0.076]*	[0.134]	[0.968]	[0.003]***	[0.091]*	[0.432]	[0.995]	[0.515]	[0.077]*	[0.296]	
	Specific	−1.10	0.82	–	1.62	–	–	–	–	–	–	0.023
		(0.047)**	(0.161)		(0.002)***							
		[0.024]**	[0.133]		[0.002]***							
U.S.	General	−1.04	0.85	−0.82	0.74	0.76	0.31	−0.18	−0.26	−0.37	–	0.042
		(0.445)	(0.061)*	(0.062)*	(0.052)*	(0.006)***	(0.543)	(0.519)	(0.347)	(0.010)**		
		[0.450]	[0.061]*	[0.095]*	[0.077]*	[0.002]***	[0.545]	[0.440]	[0.316]	[0.004]***		
	Specific	−1.31	1.05	–	0.80	0.66	–	–	–	−0.32	–	0.040
		(0.072)*	(0.018)**		(0.034)**	(0.006)***				(0.005)***		
		[0.054]*	[0.018]**		[0.058]*	[0.003]***				[0.002]***		

Notes: For most countries the sample covers the 1970:1 to 2006:12 period. For Austria and Australia the sample period starts in 1971:1 and in 1973:1 for Denmark and Norway. The estimated model is $r_t = \alpha + \beta JanD_t + \gamma X_t + \phi Z_{t-1} + u_t$, where r_t is the excess stock return and $JanD_t$ denotes a dummy variable which takes the value of 1 for February to December following Januarys with positive excess stock returns and 0 otherwise. X_t and Z_{t-1} are vectors of control variables as explained in the text. The last column contains the $\bar{R}^2$ of individual OLS regressions. The values in parentheses are p-values using Newey-West t-statistics with three lags. The values in brackets are p-values using bootstrap t-statistics. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 2: Predictive Power of February to December

Country	Model	Regression coefficients (p-values)										
		$FebD_t$	$MarD_t$	$AprD_t$	$MayD_t$	$JunD_t$	$JulD_t$	$AugD_t$	$SepD_t$	$OctD_t$	$NovD_t$	$DecD_t$
Austria	General	0.89	0.60	0.21	1.42	1.22	0.72	0.32	2.01	1.66	0.06	0.26
		(0.060)*	(0.340)	(0.743)	(0.028)**	(0.085)*	(0.243)	(0.656)	(0.032)**	(0.009)***	(0.925)	(0.787)
	Specific	0.74	0.50	0.24	1.24	0.91	0.70	0.39	1.93	1.34	0.03	0.28
		(0.151)	(0.377)	(0.671)	(0.044)**	(0.157)	(0.157)	(0.518)	(0.017)**	(0.018)**	(0.953)	(0.749)
Australia	General	0.61	0.51	0.31	0.08	0.07	−0.47	0.65	0.78	0.13	−0.16	0.74
		(0.329)	(0.391)	(0.579)	(0.894)	(0.923)	(0.412)	(0.209)	(0.159)	(0.785)	(0.771)	(0.271)
	Specific	0.47	0.33	0.09	−0.14	0.39	−0.63	0.47	0.65	−0.13	−0.09	0.71
		(0.450)	(0.565)	(0.876)	(0.800)	(0.547)	(0.218)	(0.390)	(0.210)	(0.798)	(0.872)	(0.341)
Belgium	General	1.25	−0.26	−0.47	1.61	0.49	0.57	0.66	0.25	−0.10	0.80	−0.26
		(0.016)**	(0.651)	(0.364)	(0.011)**	(0.446)	(0.250)	(0.244)	(0.582)	(0.858)	(0.154)	(0.663)
	Specific	1.27	−0.09	−0.27	1.16	0.03	0.65	0.77	0.21	−0.17	0.76	−0.57
		(0.009)*	(0.868)	(0.607)	(0.011)**	(0.959)	(0.194)	(0.111)	(0.666)	(0.741)	(0.167)	(0.298)
Canada	General	0.45	−0.12	0.94	−0.08	0.53	0.05	0.57	0.83	0.54	1.01	1.55
		(0.365)	(0.802)	(0.060)*	(0.896)	(0.297)	(0.915)	(0.235)	(0.192)	(0.332)	(0.058)*	(0.026)**
	Specific	0.45	−0.18	0.80	−0.15	0.42	0.05	0.69	0.68	0.48	0.96	1.47
		(0.364)	(0.724)	(0.108)	(0.794)	(0.403)	(0.917)	(0.141)	(0.288)	(0.328)	(0.070)*	(0.025)**
Denmark	General	0.66	−0.59	1.34	−0.05	1.40	0.44	1.13	2.80	0.91	0.39	0.49
		(0.237)	(0.316)	(0.029)**	(0.926)	(0.016)**	(0.463)	(0.043)**	(0.000)***	(0.144)	(0.519)	(0.512)
	Specific	0.49	−0.67	1.34	−0.06	1.32	0.35	1.11	2.53	0.83	0.50	0.42
		(0.392)	(0.252)	(0.029)**	(0.913)	(0.020)**	(0.516)	(0.030)**	(0.000)***	(0.150)	(0.385)	(0.510)
France	General	−0.06	0.80	1.07	0.67	1.56	−0.15	−0.19	0.64	−0.84	0.73	0.50
		(0.922)	(0.227)	(0.169)	(0.276)	(0.034)**	(0.790)	(0.750)	(0.312)	(0.194)	(0.268)	(0.462)
	Specific	0.01	0.89	1.13	0.76	1.67	−0.11	−0.08	0.65	−0.83	0.64	0.41
		(0.985)	(0.186)	(0.099)*	(0.207)	(0.009)***	(0.849)	(0.903)	(0.311)	(0.198)	(0.300)	(0.545)
Germany	General	0.82	−1.63	0.70	1.03	1.30	−0.95	−0.25	0.99	−0.08	0.94	1.50
		(0.113)	(0.007)***	(0.224)	(0.084)*	(0.032)**	(0.118)	(0.617)	(0.131)	(0.874)	(0.085)*	(0.122)
	Specific	0.63	−1.64	0.69	0.97	1.25	−0.99	−0.08	1.32	−0.18	1.02	1.47
		(0.254)	(0.006)***	(0.216)	(0.078)*	(0.033)**	(0.084)*	(0.879)	(0.013)**	(0.736)	(0.076)*	(0.058)*
Italy	General	1.64	0.07	1.92	1.57	2.53	0.88	1.16	2.16	−0.68	−0.69	0.55
		(0.005)***	(0.926)	(0.012)**	(0.022)**	(0.000)***	(0.233)	(0.117)	(0.003)***	(0.324)	(0.404)	(0.515)
	Specific	1.48	−0.27	1.79	1.50	2.55	0.90	0.72	2.18	−0.84	−0.33	0.36
		(0.015)**	(0.742)	(0.009)***	(0.024)**	(0.000)***	(0.212)	(0.284)	(0.003)***	(0.201)	(0.637)	(0.638)
Japan	General	0.46	0.25	−0.31	0.71	0.70	0.21	1.11	0.81	−0.47	0.47	−0.14
		(0.424)	(0.641)	(0.621)	(0.201)	(0.187)	(0.712)	(0.021)**	(0.132)	(0.333)	(0.356)	(0.808)
	Specific	0.51	0.27	−0.31	0.60	0.57	0.23	0.92	0.73	−0.37	0.32	−0.30
		(0.335)	(0.599)	(0.600)	(0.275)	(0.283)	(0.684)	(0.067)*	(0.165)	(0.457)	(0.546)	(0.601)
The Netherlands	General	1.39	−0.75	1.23	0.53	0.30	−0.63	−0.11	0.80	−0.28	−0.47	0.99
		(0.009)***	(0.122)	(0.119)	(0.386)	(0.548)	(0.307)	(0.827)	(0.123)	(0.560)	(0.326)	(0.180)
	Specific	1.41	−0.83	1.12	0.60	0.56	−0.74	−0.27	1.18	−0.25	−0.56	1.26
		(0.006)***	(0.086)*	(0.160)	(0.306)	(0.246)	(0.180)	(0.575)	(0.020)**	(0.602)	(0.208)	(0.047)*
Norway	General	2.08	1.28	1.46	0.36	0.79	−0.58	1.28	−0.39	0.15	0.39	0.79
		(0.031)**	(0.172)	(0.108)	(0.647)	(0.278)	(0.484)	(0.117)	(0.692)	(0.850)	(0.626)	(0.396)
	Specific	2.03	1.03	1.53	0.38	0.60	−0.47	1.16	−0.42	0.05	0.30	0.70
		(0.041)**	(0.214)	(0.053)*	(0.643)	(0.425)	(0.558)	(0.147)	(0.639)	(0.952)	(0.715)	(0.464)

Table 2 (continued): Predictive Power of February to December

Country	Model	Regression coefficients (p-values)										
		$FebD_t$	$MarD_t$	$AprD_t$	$MayD_t$	$JunD_t$	$JulD_t$	$AugD_t$	$SepD_t$	$OctD_t$	$NovD_t$	$DecD_t$
Sweden	General	0.32	−1.05	0.38	1.77	−0.71	−0.04	−0.73	1.13	1.40	0.78	0.21
		(0.649)	(0.135)	(0.610)	(0.026)**	(0.350)	(0.963)	(0.306)	(0.151)	(0.030)**	(0.272)	(0.746)
	Specific	0.20	−0.87	0.09	1.74	−0.40	−0.22	−0.77	1.39	1.26	0.93	−0.14
		(0.765)	(0.218)	(0.899)	(0.011)**	(0.550)	(0.790)	(0.249)	(0.056)*	(0.037)**	(0.137)	(0.834)
U.K.	General	0.54	−0.28	−0.38	1.04	0.20	0.33	−0.33	−0.79	−0.70	−0.33	2.43
		(0.449)	(0.605)	(0.557)	(0.061)*	(0.709)	(0.555)	(0.621)	(0.178)	(0.225)	(0.634)	(0.014)**
	Specific	0.51	−0.28	−0.33	1.08	0.03	0.24	−0.36	−0.78	−0.61	−0.21	1.97
		(0.354)	(0.649)	(0.608)	(0.033)**	(0.953)	(0.634)	(0.590)	(0.171)	(0.283)	(0.761)	(0.035)**
U.S.	General	0.69	−0.54	0.58	0.82	0.08	0.40	−0.12	−0.02	0.84	−0.05	−0.47
		(0.147)	(0.237)	(0.191)	(0.066)*	(0.850)	(0.394)	(0.788)	(0.969)	(0.077)	(0.921)	(0.433)
	Specific	0.77	−0.52	0.79	0.77	0.07	0.43	−0.19	0.07	0.63	0.00	−0.41
		(0.099)*	(0.233)	(0.076)*	(0.082)*	(0.866)	(0.341)	(0.650)	(0.865)	(0.140)	(1.000)	(0.504)

Notes: For most countries the sample covers the 1970:2 to 2006:11 period. For Austria and Australia the sample period starts in 1971:2 and in 1973:2 for Denmark and Norway. The estimated model is $r_t = \alpha + \beta MonthD_t + \gamma X_t^* + \phi Z_{t-1} + u_t$, where r_t is the excess stock return and $MonthD_t$ with $Month = Feb, ..., Dec$ denotes a dummy variable which takes the value of 1 for eleven month following the indicator month with a positive excess stock returns and 0 otherwise. X_t^* and Z_{t-1} are vectors of control variables as explained in the text. The values in parentheses are p-values using Newey-West t-statistics with three lags. $^{*}, ^{**}, ^{***}$ denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 3: Predictive Power of January to December in Subperiods

Country	*p*-values											
	$JanD_t$	$FebD_t$	$MarD_t$	$AprD_t$	$MayD_t$	$JunD_t$	$JulD_t$	$AugD_t$	$SepD_t$	$OctD_t$	$NovD_t$	$DecD_t$
Panel A. Sample Period: 1980:1 − 2006:12												
Austria	(0.383)	(0.067)*	(0.188)	(0.996)	(0.101)	(0.033)**	(0.295)	(0.429)	(0.032)**	(0.011)**	(0.468)	(0.490)
Australia	(0.513)	(0.078)*	(0.665)	(0.552)	(0.648)	(0.275)	(0.124)	(0.176)	(0.376)	(0.910)	(0.174)	(0.583)
Belgium	(0.064)*	(0.010)***	(0.802)	(0.328)	(0.016)**	(0.410)	(0.267)	(0.387)	(0.052)	(0.961)	(0.285)	(0.233)
Canada	(0.673)	(0.046)**	(0.417)	(0.169)	(0.179)	(0.226)	(0.762)	(0.917)	(0.224)	(0.002)***	(0.032)**	(0.214)
Denmark	(0.181)	(0.157)	(0.508)	(0.010)***	(0.883)	(0.023)**	(0.259)	(0.651)	(0.001)***	(0.599)	(0.289)	(0.920)
France	(0.672)	(0.948)	(0.943)	(0.392)	(0.389)	(0.055)*	(0.808)	(0.466)	(0.301)	(0.667)	(0.274)	(0.469)
Germany	(0.062)*	(0.054)*	(0.038)**	(0.672)	(0.046)**	(0.066)*	(0.152)	(0.884)	(0.042)**	(0.818)	(0.518)	(0.400)
Italy	(0.211)	(0.007)***	(0.429)	(0.167)	(0.325)	(0.000)***	(0.002)***	(0.944)	(0.002)***	(0.653)	(0.705)	(0.097)*
Japan	(0.600)	(0.679)	(0.237)	(0.474)	(0.720)	(0.100)*	(0.465)	(0.055)	(0.135)	(0.777)	(0.267)	(0.548)
The Netherlands	(0.072)*	(0.005)***	(0.409)	(0.152)	(0.558)	(0.105)	(0.312)	(0.947)	(0.048)**	(0.589)	(0.614)	(0.262)
Norway	(0.138)	(0.325)	(0.904)	(0.429)	(0.605)	(0.086)*	(0.337)	(0.163)	(0.911)	(0.755)	(0.885)	(0.197)
Sweden	(0.620)	(0.528)	(0.536)	(0.761)	(0.020)**	(0.403)	(0.473)	(0.387)	(0.183)	(0.125)	(0.138)	(0.939)
U.K.	(0.585)	(0.191)	(0.187)	(0.766)	(0.264)	(0.830)	(0.818)	(0.521)	(0.986)	(0.684)	(0.909)	(0.203)
U.S.	(0.455)	(0.674)	(0.033)**	(0.200)	(0.044)**	(0.516)	(0.540)	(0.711)	(0.247)	(0.060)*	(0.900)	(0.784)
Panel B. Sample Period: 1990:1 − 2006:12												
Austria	(0.330)	(0.545)	(0.414)	(0.005)***	(0.057)*	(0.004)***	(0.290)	(0.522)	(0.229)	(0.258)	(0.807)	(0.932)
Australia	(0.061)*	(0.002)***	(0.163)	(0.681)	(0.633)	(0.653)	(0.615)	(0.653)	(0.576)	(0.148)	(0.113)	(0.845)
Belgium	(0.010)***	(0.046)**	(0.442)	(0.763)	(0.033)**	(0.002)***	(0.737)	(0.867)	(0.021)**	(0.215)	(0.002)***	(0.736)
Canada	(0.601)	(0.080)*	(0.862)	(0.024)**	(0.763)	(0.057)*	(0.545)	(0.171)	(0.004)***	(0.010)***	(0.012)**	(0.643)
Denmark	(0.908)	(0.414)	(0.556)	(0.026)**	(0.692)	(0.001)***	(0.809)	(0.141)	(0.001)***	(0.465)	(0.087)*	(0.240)
France	(0.690)	(0.998)	(0.765)	(0.577)	(0.495)	(0.076)*	(0.768)	(0.543)	(0.078)*	(0.208)	(0.032)	(0.186)
Germany	(0.077)*	(0.006)***	(0.038)**	(0.916)	(0.116)	(0.011)**	(0.594)	(0.907)	(0.114)	(0.192)	(0.031)**	(0.538)
Italy	(0.726)	(0.321)	(0.943)	(0.162)	(0.746)	(0.115)	(0.073)*	(0.509)	(0.325)	(0.304)	(0.930)	(0.225)
Japan	(0.959)	(0.290)	(0.666)	(0.388)	(0.357)	(0.390)	(0.093)*	(0.077)*	(0.600)	(0.363)	(0.180)	(0.306)
The Netherlands	(0.422)	(0.005)***	(0.454)	(0.508)	(0.132)	(0.021)**	(0.998)	(0.731)	(0.372)	(0.217)	(0.381)	(0.606)
Norway	(0.040)**	(0.794)	(0.265)	(0.856)	(0.270)	(0.024)**	(0.285)	(0.041)**	(0.119)	(0.880)	(0.303)	(0.962)
Sweden	(0.971)	(0.839)	(0.530)	(0.224)	(0.008)***	(0.180)	(0.608)	(0.609)	(0.414)	(0.563)	(0.094)*	(0.166)
U.K.	(0.787)	(0.009)***	(0.233)	(0.998)	(0.043)**	(0.736)	(0.483)	(0.624)	(0.422)	(0.540)	(0.360)	(0.060)*
U.S.	(0.277)	(0.057)*	(0.221)	(0.007)***	(0.178)	(0.090)*	(0.508)	(0.828)	(0.192)	(0.024)**	(0.040)**	(0.108)

Notes: For the first column the estimated model is $r_t = \alpha + \beta JanD_t + \gamma X_t + \phi Z_{t-1} + u_t$, where $JanD_t$ denotes a dummy variable which takes the value of 1 for February to December following Januarys with positive excess stock returns and 0 otherwise. For the other columns the estimated model is $r_t = \alpha + \beta MonthD_t + \gamma X_t^* + \phi Z_{t-1} + u_t$, where $MonthD_t$ with $Month = Feb, ..., Dec$ denotes a dummy variable which takes the value of 1 for eleven month following the indicator month with a positive excess stock returns and 0 otherwise. In both models r_t is the excess stock return. X_t, X_t^* and Z_{t-1} are vectors of control variables as explained in the text. The values in parentheses are *p*-values using Newey-West *t*-statistics with three lags. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.