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On the Information Uncertainty Risk and the January Effect*

I provide a risk-based rational explanation for the seasonal regularity of January in stock returns by suggesting a common risk factor related to the information uncertainty caused by earnings volatility. When the two-factor model with the market risk factor and this common risk factor is used, there is a remarkable improvement in explaining the January effect. With the adjustment of raw returns for risk through this two-factor model, the systematic pattern in the residual returns across firm size disappears. This risk factor also dominates the other risk factors in explaining the cross section of stock returns in January.

I. Introduction

Numerous empirical studies have documented seasonal regularities in stock returns. The most prominent regularity finds that returns on common stocks in January are significantly and consistently larger than those in any other calendar month. Rozeff and Kinney (1976) were among the first to point out this January effect. They report that one-third of the annual returns occurred in January alone in the U.S. stock market. The January effect is particularly strong for small firms. Keim (1983) reports that nearly 50% of the average magnitude of the size anomaly, noted by Banz (1981) and Reinganum (1983), is due to January abnormal returns. Roll (1983) confirms Keim's results. The January effect has been studied abroad as well. Using data from 17 industrialized countries, Gultekin and Gultekin (1983) find a much higher return in January than in non-January months for all 17 countries. This January seasonality is one of the strong empirical inconsistencies with market efficiency since if the markets are efficient, investors should eliminate the predictable abnormal returns in January by readjusting their portfolios.

While the size-related January effect itself is well documented, there is little consensus concerning the

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cause of such a seasonal pattern. Several explanations for this phenomenon are offered. Among those, the most extensively investigated explanation is the tax loss selling hypothesis. This hypothesis suggests that tax-motivated investors sell off previously declined shares in price toward the end of the calendar year in order to realize capital losses and take advantage of tax benefits, which create downward pressure on stock prices. After the turn of the year, prices bounce up as the selling pressure is relieved. Since the stock prices of small firms tend to be more volatile than those of large firms, small firms' stocks are more likely to have capital losses and therefore may be candidates for tax loss selling.[1] The empirical evidence on this explanation is mixed. Using U.S. data, Branch (1977), Dyl (1977), Reinganum (1983), Roll (1983), Schultz (1985), and Brauer and Chang (1990) at least partially support the tax loss selling hypothesis, whereas Jones, Pearce, and Wilson (1987) report results inconsistent with the tax loss selling hypothesis.[2] Using international data, Brown et al. (1983; Australian data),[3] Berges, McConnell, and Schlarbaum (1984; Canadian data),[4] and Kato and Schallheim (1985; Japanese data)[5] report evidence inconsistent with the tax loss selling hypothesis. On the other hand, Reinganum and Shapiro (1987), using British data, partially support this hypothesis.[6]

The second explanation for the January effect is the information hypothesis. Rozeff and Kinney (1976) and Keim (1983) suggest that for firms with a year end fiscal closing, the month of January marks a period of increased uncertainty due to the impending release of important fiscal year end accounting information, and this uncertainty depresses stock prices. When this uncertainty is resolved, stock prices rise. In fact, approximately 65% of the firms listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) have a December 31 fiscal year end. According to the information

1. Constantinides (1984) concludes from his theoretical model and simulations that the optimal strategy is not to delay capital losses until the end of the year, and tax trading does not explain the January effect if the market is efficient.

2. Jones et al. studied the period 1871–1917, before the introduction of income taxes, and reported that the January effect, which existed long before income taxes, is not significantly different from the January effect found after the introduction of income taxes.

3. Since Australia has a July–June tax year, a small-firm July premium is predicted. However, Brown et al. find that Australian returns show pronounced December–January and July–August seasonals.

4. Berges et al. report that January returns in Canada exceed returns for other months of the year before and after the introduction of a capital gains tax in 1973.

5. Kato and Schallheim find a significant January effect, even though there is no tax on capital gains for individual investors in Japan, nor is there a tax benefit for capital losses. There are taxes on capital gains for Japanese corporations. However, they can choose their fiscal year arbitrarily.

6. Prior to the introduction of capital gains taxes in 1965, seasonality in the returns of firms traded on the London Stock Exchange is not detected. However, after the imposition of a capital gains tax, the data exhibit apparent tax effects in both January and April. British individuals close their tax year on April 5, whereas partners and corporations select a December tax year end. After closer inspection of the differential returns of winners and losers in both months, Reinganum and Shapiro conclude that all of the January effect cannot be attributed to tax loss selling, whereas the April effect is consistent with the tax loss selling hypothesis.

hypothesis, firms having a non-December fiscal year end should earn high returns in the calendar month following their fiscal year end, but not in January. Reinganum and Gangopadhyay (1991) report that regardless of their fiscal year end, the average returns of small firms are high in January, which is inconsistent with the information hypothesis.

The third explanation is a microstructure explanation for a part of the January effect. Keim (1989) finds systematic tendencies for closing prices to be recorded at the bid in the last trade in December and at the ask in early January, which causes the return to appear spuriously high in the first few days of January, even if the bid-ask spread is not changed. The tendency for stocks to be at the bid price for the last trade in December is more pronounced for small and low-priced stocks. He argues, therefore, that the relatively large returns for small firms on the first several trading days of the year are partly attributable to the trading pattern bias.

To date, any proposed explanation does not account satisfactorily for the observed small firm's January phenomenon. The fact that this January phenomenon is robust over such a long period of time suggests that the January effect in fact may be a phenomenon consistent with equilibrium pricing. One of the reasons that previous attempts to explain the January effect have failed is that the misspecified models might have been used in calculating abnormal returns. In order to adjust raw returns for risk, most studies have used the single-factor capital asset pricing model or control portfolios (such as the market portfolio, size-sorted portfolios, or beta-sorted portfolios). Chan, Chen, and Hsieh (1985) use a multifactor model using macroeconomic variables to adjust raw returns for risk, but still find strong positive January abnormal returns.[7] Some studies do not adjust for risk and use raw returns.

The purpose of this paper, therefore, is to identify and develop a common risk factor that provides a rational explanation for the January effect. The risk factor to be suggested is related to earnings information uncertainty caused by *earnings volatility*. I differentiate this information uncertainty from the information uncertainty mentioned in the information hypothesis in that the latter is caused by the impending release of earnings announcement and the scarcity of information. When earnings information is volatile, investors face increased information uncertainty regarding a firm's future earnings and thus greater risk. In this case, when actual earnings are announced, there is a greater possibility that investors would face large unexpected earnings surprises (positive or negative). Therefore, investors in firms with greater variability in earnings forecast errors would require greater returns in the next period.

I use the standard deviation of the forecast errors (FESTD) as a proxy for earnings information uncertainty or earnings quality. The forecast errors are computed as the difference between the actual earnings and the forecasted

7. Chang and Pinegar (1986, 1989) find that there is a seasonal pattern in the growth rates of industrial production and argue that seasonal real growth in industrial production provides a partial explanation for the January returns among small stocks.

(fitted) earnings as in Foster, Olsen, and Shevlin (1984). The reason that the statistical earnings forecasts are used rather than financial analysts' earnings forecasts is that the standard deviation of financial analysts' earnings forecasts does not have a monotonic positive relation with returns (see Diether, Malloy and Scherbina 2002; Kim and Kim 2003). In particular, Diether et al. argue that their evidence is inconsistent with a view that dispersion in analysts' earnings forecasts proxies for risk. Therefore, the standard deviation of financial analysts' earnings forecasts is not appropriate to use as a proxy for information uncertainty, under the conventional wisdom that risk comes from uncertainty.

The common risk factor for information uncertainty is constructed in a way similar to that in Fama and French (1993). That is, the common risk factor, FESTD, is calculated as the return on firms with greater FESTD values minus the return on firms with smaller FESTD values. When the FESTD factor is combined with the market risk factor, there is a significant improvement in explaining the January effect. With the adjustment of raw returns for risk by using this two-factor model, the systematic pattern in the residual returns (and the abnormal returns) across firm size disappears. In particular, the residual return in January on the smallest-size portfolio is not significant at all. Furthermore, the arbitrage residual return in January, which is the difference in the average residual returns between the smallest- and largest-size portfolios, also is not significant. For robustness, I have also examined various models: combination of Fama and French's (1993) three factors, Carhart's (1997) momentum factor representing Jegadeesh and Titman's (1993) stock price momentum,[8] and FESTD. However, any combined factor model does not perform as well as the parsimonious two-factor model (the market risk factor and the FESTD factor).

In order to investigate whether FESTD is a priced risk factor, I have estimated the cross-sectional relationship between average returns and the factor loadings or betas on the risk factors using Fama-MacBeth's (1973) two-pass estimation methodology. I have found that the factor loadings or betas on FESTD have an economically and statistically significant explanatory power for average stock returns and dominate the factor loadings on the other risk factors in explaining the cross section of stock returns in January. The fact that the FESTD factor explains the January effect fairly well indicates that large returns in January might be a risk premium for taking information uncertainty risk concerning earnings and unexpected earnings surprises faced at the earnings announcement.

The paper is organized as follows: Section II describes the data, and Section III revisits the tax loss selling hypothesis and the information hypothesis and provides simple tests for the hypotheses. Section IV explains in detail how

8. The momentum factor is constructed as the equal-weight average of firms with the highest 30% 11-month returns lagged one month minus the equal-weight average of firms with the lowest 30% 11-month returns lagged one month.

to construct the common risk factor related to the information uncertainty concerning earnings. Section V presents the estimation results of the time-series factor models and the cross-sectional regression models and examines a relation between the information uncertainty risk factor and the quality rating of Standard and Poor's. Section VI provides concluding remarks.

II. Data and Size Portfolio Formation

The sample consists of firms that were listed on the NYSE and AMEX over the period 1972–2003. These firms should have return data of a full calendar year prior to the portfolio formation with firm size and of January of the first year after portfolios are formed. These firms also should have at least 16 consecutive quarterly earnings data over the period 1966–2003. Return observations are obtained from the Center for Research in Security Prices (CRSP) monthly return file, and quarterly accounting data are obtained from the COMPUSTAT Quarterly Industrial, Full Coverage, and Research files. The most recent 24 consecutive quarters' earnings per share (EPS) data (with a minimum of the most recent 16 consecutive quarters' data) are used to forecast the current quarter's EPS. Owing to the availability of the earnings data, the testing period in this paper is January 1972 through December 2003.

Each year all sample firms are ranked on the market value of their common equity at the end of the year. Then each of the firms is allocated into one of 10 size portfolios on the basis of NYSE break points. Portfolio 1 (10) contains the smallest (largest) firms. Thus each portfolio is updated annually. The value-weighted CRSP market returns, which contain all NYSE, AMEX, and NASDAQ returns, are used for the proxy of the market portfolio, and the one-month Treasury bill returns are taken from Ibbotson (2004) as the riskless returns.

III. Revisiting the January Effect and Simple Tests of the Information Hypothesis and the Tax Loss Selling Hypothesis

A. Average Returns on Size Portfolios

Table 1 shows the average raw returns on each of the 10 size portfolios across calendar months over the testing period from January 1972 through December 2003. As expected, average returns in January are higher than in other calendar months in any size portfolio. Most notably, the average return in January on the smallest-size portfolio is 11.428%. The difference in January average returns between the smallest and largest portfolios is 9.922%. This is potentially a large arbitrage return that investors may earn in January. February is also a month in which the difference in average returns between those two extreme size portfolios is significant: it is 2.207%.

In order to examine the relation between average returns and firm size in each calendar month, the average returns on the 10 size portfolios are cross-

TABLE 1 **Average Monthly Returns (in Percent) on 10 Size Portfolios at Each Calendar Month from January 1972 through December 2003**

Size Portfolio	Calendar Months 1	2	3	4	5	6	7	8	9	10	11	12	All Months	Non-January
1	11.428	2.750	1.998	1.275	1.987	1.211	.716	−.140	−.500	−2.037	.990	.152	.764	1.653
2	6.236	1.677	1.656	1.041	1.477	1.050	.457	−.033	−.682	−1.393	1.365	1.074	.699	1.160
3	5.155	1.363	1.814	1.715	1.385	.888	.458	.445	−.866	−1.240	1.966	1.424	.850	1.209
4	4.229	1.566	1.801	1.944	1.619	1.366	.246	.452	−.700	−.874	1.845	2.049	1.029	1.295
5	3.607	1.231	1.626	1.711	1.757	1.355	.057	.744	−.720	−1.024	1.795	2.275	.983	1.201
6	3.245	1.288	1.891	1.847	1.685	1.054	.156	.695	−.715	−.969	1.996	2.415	1.031	1.216
7	2.611	1.210	1.655	1.619	1.702	1.000	.316	.984	−.700	.028	1.940	2.260	1.092	1.219
8	2.175	1.001	1.792	1.548	1.708	.749	.323	.672	−1.030	.102	2.177	2.292	1.030	1.126
9	2.060	.869	1.434	1.485	1.614	.723	.136	.684	−.989	.763	2.239	2.075	1.003	1.091
10	1.506	.543	1.342	1.469	1.701	.639	.299	.778	−1.159	1.643	1.843	1.721	.984	1.027
Average	4.743	1.428	1.606	1.405	1.538	.964	.326	.397	−.673	−.789	1.573	1.470	.840	1.166
P1–P10	9.922	2.207	.656	−.194	.286	.572	.417	−.919	.659	−3.679	−.852	−1.569	−.220	.625
Slope	−1.333	−.283	−.083	.026	−.004	−.094	−.058	.146	−.091	.572	.137	.231	.045	−.069
	(−4.87)	(−6.07)	(−3.50)	(.53)	(−.14)	(−2.76)	(−2.01)	(3.44)	(−4.88)	(12.46)	(2.73)	(2.21)	(2.51)	(−3.48)

NOTE.—Firms that were listed on the NYSE and AMEX and had at least 16 quarterly earnings data on COMPUSTAT quarterly files are ranked on the market value of their common equity at the end of the year. Then each of the firms is allocated into one of 10 size portfolios based on NYSE break points. Portfolio 1 (10) contains the smallest (largest) firms. P1–P10 is the difference between the average residual returns of portfolio 1 and portfolio 10. Slope is the slope coefficient estimate (*t*-statistic in parentheses) in the cross-sectional regression of the average returns of 10 size portfolios on the natural logarithm of the average market value of the portfolios in each calendar month.

sectionally regressed on the natural logarithm of their average market values in December (when portfolios are formed). The slope coefficient estimates are reported in the last row of table 1. I find that the relation between average returns and firm size is significantly negative in January, February, March, July, and September, and this negative relation is most pronounced in January. However, in August, October, November, and December, the relation is significantly positive. This positive relation is most pronounced in October. Note that the smallest firms earn mostly negative returns in these months. On average, I find roughly a positive relation in non-January months, which somewhat contradicts Keim's (1983) findings (a negative relation in any calendar month). One reason is that the sample periods are different. Keim uses the sample period 1963–79. Using the same sample used in table 1 for Keim's sample period, I find a significantly negative relation in non-January months as Keim reported. However, for the period 1980–2003, I find a significantly positive relation in non-January months.

B. A Test of the Tax Loss Selling Hypothesis

As the tax loss selling proxy variable, Reinganum (1983) and Reinganum and Shapiro (1987) selected the ratio of stock price on December 31 of the previous year to the highest month end price of the previous year. This variable is bounded between zero and one. The measure of one would indicate that the stock is selling at its highest price on December 31 of the previous year, whereas the measure close to zero would indicate that the stock is selling at a relatively low price. According to the tax loss selling hypothesis, stocks with a low value of this proxy variable are more likely to have experienced losses and therefore be plausible candidates for tax loss selling, and should experience high returns after the close of the tax year (i.e., in January). Constantinides (1984), Brauer and Chang (1990), and Brickley, Manaster, and Schallheim (1991) argue that stocks with a large return variability also are more likely to have experienced losses and be plausible tax loss selling candidates.

In order to construct the tax loss selling proxy portfolios, therefore, I use three proxy variables; one is Reinganum's, and the other two are the standard deviation of the previous year's monthly returns and the average monthly returns in the previous year (year $t - 1$). At the end of each year $t - 1$, firms are allocated into one of five quintile portfolios according to their magnitude of the tax loss selling proxy variable and are maintained in the same portfolio for January in year t. Table 2 presents the average returns in January and non-January months on the five tax loss selling proxy portfolios sorted by Reinganum's proxy variable (in panel A), the standard deviation of the previous year's returns (in panel B), and the previous year's average returns (in panel C). In each panel, portfolio 1 (portfolio 5) contains firms having the smallest (the largest) magnitude of the proxy variable. As expected, portfolios with a lower Reinganum proxy value earn lower returns in the preceding year (year

TABLE 2 **January and Non-January Returns on the Tax Loss Selling Proxy Portfolios**

Tax Loss Selling Portfolio	Return after Forming Portfolios			Previous Year's Return			Firm Size		Price
	January	Non-January	All Months	January	Non-January	All Months	($M)	BM	($)
	A. By the Ratio of the Price in December to the Highest Month End Price of the Previous Year								
1	11.516	.422	1.347	8.113	−2.665	−1.767	441	1.479	9.32
2	6.189	.913	1.353	5.650	−.131	.351	1,200	1.856	19.31
3	4.607	1.108	1.400	4.801	.933	1.255	1,960	1.238	16.84
4	3.434	1.252	1.434	4.119	1.921	2.104	2,540	1.110	35.53
5	2.483	1.376	1.468	5.218	3.695	3.822	2,736	.922	30.09
	B. By the Standard Deviation of the Previous Year's Monthly Returns								
1	2.953	1.177	1.325	1.884	.806	.896	3,005	1.742	25.59
2	3.674	1.170	1.379	2.733	.812	.972	2,981	1.413	42.68
3	4.718	1.101	1.402	3.849	.764	1.021	1,776	1.220	18.69
4	6.229	1.020	1.454	6.036	.772	1.211	947	1.087	15.37
5	10.019	.728	1.502	13.494	1.478	2.479	390	.955	10.64
	C. By the Average Return of the Previous Year								
1	8.616	.559	1.230	.545	−3.180	−2.870	857	1.658	11.34
2	5.361	.926	1.296	2.532	−.408	−.164	1,812	1.414	26.00
3	4.637	1.117	1.410	4.364	.880	1.170	2,128	1.202	22.60
4	4.053	1.254	1.487	7.047	2.138	2.547	2,466	1.132	25.92
5	4.765	1.319	1.606	13.613	5.118	5.826	1,867	.921	27.35

NOTE.—Each year t firms are allocated into one of five quintile portfolios according to their tax loss selling proxy variable; the ratio of stock price in December of the previous year (year $t-1$) to the highest month end price of the previous year, the standard deviation of the previous year's monthly returns, or the average monthly returns of the previous year. In each panel, portfolio 1 (5) contains firms having the smallest (largest) magnitude of the proxy variable.

$t-1$) and larger returns in January in the current year (year t). However, this reversal in returns occurs in January only. In non-January months in year t, portfolios with a lower (larger) Reinganum proxy value earn lower (larger) returns. The continuation in returns is observed overall in year t, which is similar to the momentum phenomenon in stock prices (Jegadeesh and Titman 1993). I also find a similar pattern in the portfolios sorted by the previous year's average returns.

On the other hand, the average returns on the portfolios sorted by the standard deviation of the previous year's returns (in panel B) show a different pattern. Contrary to the prediction by Constantinides (1984), Brauer and Chang (1990), and Brickley et al. (1991), stocks in the portfolio with larger return variability earn larger returns in year $t-1$, which might be a compensation for taking high risk. These stocks are not likely to be candidates for tax loss selling. However, these stocks have also earned greater returns in January in the following year (in year t). The results in panel B show support for the momentum phenomenon in stock prices rather than support for the tax loss selling hypothesis. It would be hard to argue, therefore, that the standard deviation of the previous year's returns is a good proxy for the tax loss selling hypothesis.

In order to more specifically examine whether the tax loss selling proxies explain the January effect, I compute the tax loss selling effect–adjusted returns as raw returns on each stock minus returns on the portfolio sorted by the tax loss selling proxy variable in which the stock is contained. Then I construct portfolios according to firm size as in table 1 and fiscal year end month within each size portfolio. Table 3 presents the average tax loss selling effect–adjusted returns in *January* only on fiscal year end months in each of 10 size portfolios. The tax loss selling effect–adjusted returns in January still show patterns across firm size observed with raw returns similar to those in table 1, no matter which tax loss selling proxy variable considered is used. For example, when Reinganum's proxy variable is used, the overall average tax loss selling effect–adjusted returns in January on the smallest and largest portfolios are 3.78% and −2.21%, respectively. Only the difference between January returns on the smallest portfolio and on the largest portfolio is slightly reduced (9.922% in the raw returns vs. 5.99%). This typical pattern in January is also observed in any fiscal year end month group. That is, no matter which fiscal year end month firms have, their tax loss selling effect–adjusted returns are higher in January than in any other calendar months. Thus table 3 confirms that the tax loss selling hypothesis is apparently not a sufficient explanation for the January phenomenon in stock returns.

C. A Test of the Information Hypothesis

The information hypothesis states that owing to the impending release of accounting information around fiscal year end months, uncertainty depresses stock prices, and with uncertainty resolved, stock prices recover. According

TABLE 3 Average Monthly Returns (in Percent) in January on the Size Portfolios after Adjusting for Returns on the Tax Loss Selling Proxy Portfolios

Size Portfolio	Overall	Fiscal Year End Month Portfolio 1	2	3	4	5	6	7	8	9	10	11	12
	A. By the Ratio of the Price in December to the Previous Year's Highest Month End Price												
1	3.78	3.47	1.94	4.05	3.39	5.58	5.43	1.96	1.09	4.99	1.64	3.62	3.61
2	.08	−.11	−1.09	1.42	−3.59	1.18	−.51	−.21	.01	1.33	.95	−.11	.12
3	−.54	−1.56	−.92	−.10	−2.96	−3.81	−2.12	−1.91	−.15	.47	.41	−.26	−.40
4	−1.14	−2.68	.72	−2.24	−.15	−1.58	−1.79	−.81	−.74	−1.24	−1.55	−.55	−.89
5	−1.50	−3.45	−2.93	−1.91	−2.13	−3.08	−.56	−2.58	−2.30	−2.87	−1.08	.18	−1.29
6	−1.52	−2.62	2.29	−1.52	−4.07	−4.24	−1.30	−2.12	−1.99	−1.37	−2.64	−.36	−1.41
7	−1.87	−2.67	−1.47	−2.69	−4.44	3.45	−2.12	−.22	−1.76	−.52	−1.51	−2.85	−1.87
8	−2.17	−2.51	.14	−2.72	−5.55	−4.16	−1.68	−4.29	−3.79	−.69	−2.29	−2.74	−2.11
9	−1.94	−1.50	−2.38	−2.07	−.73	−1.01	−1.20	−3.59	−1.18	−.36	−2.77	1.03	−2.04
10	−2.21	−1.71	−.93	−.89	−3.59	−3.17	−2.39	−4.98	−.76	−.65	−.56	−.68	−2.29
Average	−.90	−1.53	−.41	−.79	−2.34	−.97	−.82	−1.86	−.51	−.09	−.90	−.21	−.86
	B. By the Standard Deviation of the Previous Year's Monthly Returns												
1	4.38	4.07	2.52	4.65	3.99	6.38	6.03	2.56	1.69	5.59	2.24	4.22	4.21
2	.20	.02	−.97	1.54	−3.59	1.30	−.38	−.12	−.12	1.45	1.07	.01	.24
3	−.56	−1.58	−.94	−.03	−2.96	−3.83	−2.14	−1.91	−.17	.45	.39	−.28	−.42
4	−1.30	−2.83	.56	−2.39	−.32	−1.74	−1.94	−.95	−.90	−1.39	−.71	−.71	−1.05

5	−1.74	−3.70	−3.18	−2.15	−2.39	−3.33	−.81	−2.83	−2.53	−3.12	−1.33	−.08	−1.54
6	−1.73	−2.82	2.06	−1.72	−4.30	−4.51	−1.51	−2.32	−2.20	−1.58	−2.84	−.59	−1.62
7	−2.18	−2.98	−1.65	−3.00	−4.78	3.14	−2.43	−.35	−2.09	−.83	−1.84	−3.21	−2.18
8	−2.48	−2.82	−.16	−3.05	−5.92	−4.55	−1.99	−4.64	−4.08	−1.00	−2.63	−3.26	−2.42
9	−2.20	−1.76	−2.63	−2.52	−1.11	−1.16	−1.46	−3.65	−1.32	−.62	−3.07	.28	−2.30
10	−2.32	−1.82	−1.03	−1.08	−3.84	−3.44	−2.50	−5.07	−.72	−.76	−.67	−.86	−2.40
Average	−.99	−1.62	−.47	−.90	−2.46	−1.07	−.91	−1.92	−1.21	−.18	−.99	−.33	−.95
	C. By the Average Return of the Previous Year												
1	5.01	4.70	3.18	5.29	4.63	7.02	6.67	3.20	2.33	6.22	2.88	4.86	4.85
2	−.41	.23	−.75	1.75	−3.29	1.52	−.17	.10	.35	1.66	1.28	.22	.45
3	−.49	−.50	−.87	.04	−2.92	−3.78	−2.07	−1.86	−.10	.52	.46	−.21	−.35
4	−1.38	−2.92	.45	−2.48	−.41	−1.83	−2.03	−1.06	−.98	−1.48	−1.80	−.81	−1.14
5	−1.82	−3.77	−3.25	−2.22	−2.46	−3.41	−.88	−2.87	−2.59	−3.19	−1.40	−.16	−1.61
6	−2.04	−3.13	1.75	−2.03	−4.61	−4.76	−1.81	−2.63	−2.51	−1.88	−3.17	−.89	−1.93
7	−2.55	−3.35	−2.05	−3.38	−5.16	2.74	−2.80	−.70	−2.46	−1.20	−2.23	−3.60	−2.55
8	−2.82	−3.16	−.48	−3.36	−6.18	−4.74	−2.34	−4.98	−4.50	−1.35	−2.97	−3.62	−2.77
9	−2.78	−2.34	−3.22	−2.89	−1.66	−1.82	−2.04	−4.35	−2.03	−1.20	−3.66	.07	−2.87
10	−3.08	−2.58	−1.72	−1.73	−4.46	−4.12	−3.26	−5.84	−1.40	−1.52	−1.43	−1.58	−3.12
Average	−1.15	−1.78	−.59	−1.01	−2.56	−1.20	−1.07	−2.07	−1.36	−.34	−1.15	−.42	−1.12

NOTE.—According to the market value of their common equity at the end of each year, firms are allocated into one of 10 size portfolios based on NYSE break points. Firms within a size portfolio are then reallocated into one of 12 fiscal year end portfolios according to their fiscal year end month. The tax loss selling effect–adjusted returns are calculated as the January return on the size-sorted portfolios minus the January return on the tax loss selling proxy portfolio in which stocks are contained. The construction of the tax loss selling proxy portfolios is explained in table 1.

to this hypothesis, returns in the fiscal year end month should be low, but returns in the next month after the fiscal year end month should be high. Also, returns in January should be higher than in other months for firms having a December fiscal quarter end month, but not for firms having a non-December fiscal quarter end month.

To test this hypothesis, I divide firms into one of 12 groups within each size portfolio according to their fiscal year end month. Among the sample firms, 65.8% have a December fiscal year end month. Table 4 reports the average returns in each fiscal year end month (in panel A) and the average returns in the next month after the fiscal year end month (in panel B) on fiscal year end month groups within each size portfolio. I find that among the 12 fiscal year end month cases, only four cases (February, April, October, and December) have lower returns in the fiscal year end month than in the next month after the fiscal year end month. This pattern is commonly observed across firm size. Moreover, no matter which fiscal year end month firms have, their average returns in January are higher than in any other calendar months. These results are inconsistent with the information hypothesis. Moreover, in order for this hypothesis to explain high January returns on small firms, small firms should tend to have a December fiscal year end month. However, only 51.1% of the firms in the smallest portfolio have a December fiscal year end month. Instead, large firms are more likely to have a December fiscal year end month (82.0% of firms in the largest-size portfolio).[9]

IV. Construction of a New Risk Factor: Earnings Information Uncertainty Risk

A. Computation of the Proxy for Uncertainty of Earnings Forecasts

In this section, I present the method of forecasting earnings and examine the relationship between firm size and the standard deviation of earnings forecast errors, which is a surrogate of information uncertainty. The forecast error (FE) in quarter q of firm i is defined as

$$FE_{i,q} = Q_{i,q} - E(Q_{i,q}|I_{q-1}), \tag{1}$$

where $Q_{i,q}$ is actual earnings (EPS) of firm i in quarter q, and $E(Q_{i,q}|I_{q-1})$ is the forecasted quarterly earnings of firm i in quarter q using information available up to quarter $q-1$, I_{q-1}. In order to obtain $E(Q_{i,q}|I_{q-1})$, I first estimate the following AR(1) process by using the 24 most recent consecutive quarters' EPS observations (with a minimum of the 16 most recent consecutive quarters' data):

$$Q_{i,q} - Q_{i,q-4} = \phi_{i0} + \phi_{i1}(Q_{i,q-1} - Q_{i,q-5}) + \varepsilon_{i,q}. \tag{2}$$

9. The percentages of firms having a December fiscal year end month in the 10 decile size portfolios (from smallest to largest) are 51.1, 57.0, 58.9, 61.9, 64.0, 66.2, 71.1, 76.0, 80.1, and 82.0, respectively.

Then, the earnings forecast is calculated as

$$E(Q_{i,q}|I_{q-1}) = Q_{i,q-4} + \hat{\phi}_{i1}(Q_{i,q-1} - Q_{i,q-5}) + \hat{\phi}_{i0}. \tag{3}$$

The standard deviation of the forecast errors (FESTD) is computed as the standard deviation of the fitting errors over the 24 sample quarters (i.e., $FE_{i,q}$, $q = 1, \dots, 24$). I use FESTD as a surrogate of earnings information uncertainty. The sample period of forecasting earnings in this paper is the fourth fiscal quarter of 1971 through the fourth fiscal quarter of 2003 ($q = 0, 1, \dots, 132$).[10] FESTD values are scaled by the stock price at the last month of the forecasting quarter.[11]

B. *Characteristics of the Portfolios Formed by FESTD*

At the last day of a portfolio formation month (December, March, June, and September), firms are assigned into one of the 10 decile FESTD portfolios according to their fiscal quarter $q - 1$'s FESTD values. Here, the fiscal quarter $q - 1$ is the most recent quarter of firms prior to the portfolio formation month. Note that the portfolio formation days actually equal the last day of December, March, June, and September in each year. Firms are maintained in the portfolio for the fiscal quarter $q + 1$. The fiscal quarter $q - 1$'s values are used to sort firms to avoid the hindsight bias. Portfolio returns are then computed with equal weights. Portfolio 1 (portfolio 10) contains firms having the smallest (largest) FESTD values.

Table 5 presents some characteristics of the FESTD portfolios. The average monthly returns are almost monotonically increasing with the magnitude of the FESTD from 1.275% to 1.913%. The greater return on the firms with larger FESTD is a compensation for taking earnings information uncertainty risk before earnings are released. This positive association between FESTD and average returns is most significant in the first month of the fiscal quarter $q + 1$ (month $+1$). That is, the average return on the smallest FESTD portfolio is 1.05%, whereas that on the largest FESTD portfolio is 3.07%. However, this strong positive association observed in month $+1$ almost disappears in the second and third months of the quarter, and the relation is flat (not reported). One of the reasons might be that earnings information uncertainty is almost lifted in the second and third months. In the month before the portfolio formation (month 0), which is the last month of the fiscal quarter q, the relation between the average return and the magnitude of the FESTD is strongly negative. That is, investors have already severely punished firms having greater earnings information uncertainty (greater FESTD) in month 0 but have rewarded firms having less information uncertainty. This negative relation is

10. The first earnings forecast is made for the fourth fiscal quarter of 1971 by using 23 quarters' data (with a minimum of 16 consecutive quarters' data) from the first fiscal quarter of 1966 to the third fiscal quarter of 1971. After the fourth quarter of 1971, the most recent 24 quarters' data are used to forecast earnings.

11. I also scaled the FESTD and EPS by dividing the value by the average of the absolute EPS values used for estimating the AR(1) process of eq. (2). The results are similar.

TABLE 4 Basic Statistics and Average Monthly Returns (in Percent) on Each Portfolio According to Fiscal Year End Month

	Fiscal Year End Month Portfolio											
	1	2	3	4	5	6	7	8	9	10	11	12
	A. Basic Statistics											
Frequency	.038	.017	.039	.020	.017	.068	.022	.018	.059	.026	.019	.658
Firm size ($M)	2,158	438	485	708	846	1,045	432	699	814	842	766	2,130
January return	5.50	6.67	6.83	6.65	6.51	7.24	6.00	5.80	7.07	6.51	7.41	4.72
non-January return	.94	.85	.72	.86	.90	.70	.83	1.09	.77	.74	.66	.88
	B. Returns in the Fiscal Year End Month											
Size portfolio:												
Smallest	11.12	3.60	2.01	1.67	1.47	.64	1.47	.42	−.24	−2.40	1.68	.26
2	6.05	2.94	1.46	1.60	.47	.70	.92	−.61	−1.19	−2.76	3.89	1.27
3	4.44	2.22	.82	2.34	1.74	1.25	1.42	−.34	−1.76	−3.53	2.75	1.34
4	2.69	.48	1.53	1.44	.80	1.47	1.54	−.50	−.73	−.63	1.71	1.83
5	1.65	2.37	1.45	4.24	2.28	.68	.09	−.06	−.29	−1.79	1.85	2.15
6	2.15	2.79	2.27	−.02	1.48	.95	−1.62	−.41	−.10	−.70	1.22	2.46
7	1.82	.88	.77	−2.17	2.74	1.02	−.11	−1.36	.02	−.34	1.16	2.15

8	1.83	.97	1.10	−.29	3.90	−.26	−.64	−.90	−1.06	.33	1.89	2.32
9	2.50	−2.11	.21	2.78	1.42	1.23	.15	−1.57	−.88	.18	1.45	2.10
Largest	2.01	−1.88	−2.04	−.83	3.69	−.16	−.64	5.07	−2.97	.32	3.12	1.76
Average	3.62	1.45	1.02	1.09	1.96	.78	.25	−.32	−.92	−1.17	2.10	1.76
	C. Returns in the Next Month After the Fiscal Year End Month											
Size portfolio:												
Smallest	3.41	2.01	.53	2.75	.02	.27	−.11	−2.01	−2.55	.89	−.68	11.27
2	2.86	.43	−.64	−.74	2.85	−.02	.21	−.35	−.56	.94	2.81	6.27
3	2.10	1.79	.89	2.10	3.20	.86	2.36	−.92	−.43	2.10	.95	5.30
4	2.37	2.75	1.89	2.36	1.56	.28	1.50	−1.01	−1.53	.57	1.77	4.48
5	1.11	.74	.51	1.52	2.80	−.80	1.42	−2.08	−.68	2.65	2.71	3.81
6	.83	2.40	.80	.01	−.07	−1.13	1.01	−1.93	−.67	2.80	1.43	3.36
7	2.44	2.73	.20	.08	3.45	.22	.34	.07	−.15	1.42	2.73	2.62
8	1.90	1.07	−.95	.71	1.57	1.06	1.86	−.12	−.24	3.22	2.16	2.23
9	.79	.18	.65	.37	1.70	.80	.38	.24	1.68	1.60	.92	1.96
Largest	1.94	3.23	1.93	3.54	1.01	.58	−.43	−3.32	1.54	4.42	2.87	1.43
Average	1.97	1.69	.58	1.39	1.82	.21	.86	−1.08	−.36	2.06	1.74	4.27

Note.—According to the market value of their common equity at the end of each year, firms are allocated into one of 10 size portfolios based on NYSE break points. Firms within a size portfolio are then reallocated into one of 12 fiscal year end portfolios according to their fiscal year end month. The formation of the size portfolios is explained in table 1. Portfolio 1 (10) is the smallest (largest) portfolio.

TABLE 5 Some Characteristics of the Standard Deviation of EPS Forecast (FESTD) Portfolios

FESTD Portfolio	Average Return	Return on Month 0	Return on Month +1	Firm Size ($M)	BM	Sales Growth Rate Standard Deviation	EPS Growth Rate Standard Deviation
1	1.275	2.57	1.05	4142	1.084	.202	.183
2	1.195	1.96	1.20	3356	1.201	.243	.265
3	1.251	1.61	1.31	2849	1.189	.273	.331
4	1.353	1.43	1.40	2542	1.116	.278	.375
5	1.300	1.26	1.47	2185	1.112	.285	.434
6	1.389	.98	1.52	1621	1.146	.302	.493
7	1.362	.90	1.67	1310	1.212	.323	.575
8	1.362	.46	1.85	863	1.195	.344	.790
9	1.540	.02	2.16	528	1.174	.370	1.103
10	1.913	−1.22	3.07	205	1.023	.433	1.543

NOTE.—At the first day of a portfolio formation month, firms are assigned into one of the 10 decile FESTD portfolios according to their fiscal quarter q's FESTD values. The portfolio cutoff points are determined on the basis of the FESTD values in the fiscal quarter $q-1$. Portfolio 1 (10) contains firms having the smallest (largest) FESTD values. Portfolio formation months are January, April, July, and October in each year. Month 0 indicates the month before the portfolio formation, and month +1 indicates the first month after the portfolio formation. Sales growth rates for quarter q are calculated as log(sales per share at quarter q) minus log(sales per share at quarter $q-4$), and EPS growth rates for quarter q are calculated as EPS at quarter q minus EPS at quarter $q-4$. FESTD, EPS, and sales per share are scaled by the price of the last month of the quarter.

drastically reversed in the next month (month +1) in fiscal quarter $q+1$. Table 5 also shows that, as expected, smaller firms have a greater information uncertainty proxy value. However, there is a very weak positive relation between book-to-market and FESTD values.

In order to examine whether FESTD is related to other possible proxies for earnings information uncertainty, I compute the variability of the sales growth rate and earnings growth rate of the firms in each of the FESTD portfolios. Sales growth rates for quarter q are calculated as log(sales per share at quarter q) minus log(sales per share at quarter $q-4$), and earnings growth rates for quarter q are calculated as EPS at quarter q minus EPS at quarter $q-4$. Table 6 shows that firms with greater FESTD have greater variability in growth rates in sales and earnings. These results indicate that FESTD might be a good proxy for earnings information uncertainty.[12]

C. *Constructing a Risk Factor Related to Earnings Information Uncertainty*

I use a method similar to that used by Fama and French (1993) to develop a common risk factor related to earnings information uncertainty that provides an explanation for the January seasonality in stock returns. Specifically, the

12. It is also observed that firms with greater FESTD have smaller (even negative) growth rates in sales and earnings than firms with smaller FESTD. Moreover, they have larger fluctuation in EPS as well. I also found that firms with greater FESTD have posteriori greater earnings surprise, i.e., greater divergence of the actual EPS from the anticipated EPS. This indicates that investors in firms with greater FESTD experience greater risk caused by unexpected earnings surprise (not reported).

TABLE 6 Average Returns (in Percent), Standard Deviations (in Percent), and Correlation Coefficient Matrix of the Risk Factors: January 1972 to December 2003

	Average Return			Standard Deviation		
Risk Factor	Whole Month	January	non-January	Whole Month	January	non-January
MKTRFT	.486	1.474	.396	4.437	5.201	4.358
SMB	.188	1.980	.025	3.342	3.673	3.267
HML	.472	1.689	.090	3.168	3.830	3.084
MMNT	.918	−1.465	1.134	4.328	6.329	4.042
FESTD	.491	8.843	−.268	3.931	5.951	3.057
MKT	.998	1.967	.910	4.861	7.388	3.745
RFT	.512	.493	.514	.238	.207	.241

Correlation Coefficient

	MKTRET	SMB	HMT	MMNT	FESTD	MKT	RFT
MKTRFT	1.000						
SMB	.135	1.000					
HML	−.348	−.295	1.000				
MMNT	−.107	.009	−.121	1.000			
FESTD	.149	.600	.101	−.575	1.000		
MKT	.999	.132	−.347	−.107	.141	1.000	
RFT	−.090	−.067	.037	.003	−.152	−.036	1.000

NOTE.—MKTRFT is the market risk premium ($R_{mt} - R_{ft}$); it is the difference between the returns on the value-weighted CRSP market index (MKT) minus one-month Treasury bill's returns (RFT). SMB and HML are Fama and French's (1993) risk factors related with firm size and book-to-market. FESTD is the risk factor related with earnings information uncertainty, and MMNT is the risk factor related with stock price momentum. Specifically, FESTD is the difference between the equal-weighted average return on the largest three FESTD portfolios (portfolios 10, 9, and 8) minus the equal-weighted average return on the smallest three FESTD portfolios (portfolios 1, 2, and 3).

risk factor, FESTD, is the difference between the equal-weighted average return on the two largest-FESTD portfolios (portfolios 10 and 9) minus the equally weighted average return on the two smallest-FESTD portfolios (portfolios 1 and 2). That is, the FESTD risk factor is the return on the top 20% firms in terms of the magnitude of FESTD minus the return on the bottom 20% firms.

In addition to the FESTD factor, I consider the widely accepted four risk factors to explain stock returns on the size portfolios: the market risk factor, MKTRFT ($R_{mt} - R_{ft}$, the value-weighted CRSP market returns minus one-month Treasury bill's return); Fama and French's (1993) SMB (small minus big) and HML (high minus low) factors related to firm size and book-to-market, respectively; and Carhart's (1997) one-year momentum factor, MMNT, which is related to Jegadeesh and Titman's (1993) stock price momentum.

Table 6 summarizes the average monthly return (or risk premium) and standard deviation of these five risk factors and the correlation coefficients among the factors over the period January 1972 to December 2003. The average risk premia on $R_{mt} - R_{ft}$, SMB, HML, MMNT, and FESTD are 0.486%, 0.188%, 0.472%, 0.918%, and 0.491% per month, respectively. Their standard deviations are 4.437%, 3.342%, 3.168%, 4.328%, and 3.931% per month, respectively. Table 6 also presents the average risk premium of each of the factors in January and non-January months. The average risk premia on the above factors in January (non-January) are 1.474% (0.0.396%), 1.980% (0.025%), 1.689% (0.090%), −1.465% (1.134%), and 8.843% (−0.268%), respectively. The remarkable finding is that the risk premium on FESTD in January is particularly high. The correlation coefficient between the two risk factors FESTD and SMB is relatively large: 0.600. The reason is that small firms tend to have greater earnings uncertainty than large firms.

V. Main Results

A. Estimating the Time-Series Risk Factor Models

A well-specified factor model should explain the intertemporal and cross-sectional behavior of stock returns. In this section I examine which set of the risk factors considered is relevant in explaining the January seasonality in stock returns. If all five factors are relevant, a five-factor time-series model can be suggested as follows:

$$R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\mathrm{SMB}_t + \beta_{3p}\mathrm{HML}_t + \beta_{4p}\mathrm{MMNT}_t + \beta_{5p}\mathrm{FESTD}_t + \varepsilon_{pt}, \quad (4)$$

where R_{pt} is the rate of return on the size portfolio p at time t, β_p's are factor loadings of the portfolio p to the corresponding risk factor, and ε_{pt} is the residual returns on the size portfolio p at time t. If equation (4) is a well-specified model, the intercept α_p should not be different from zero in any portfolio, and the residual or firm-specific returns ε_{pt} should not show any systematic pattern in the cross section.

Table 7 presents the estimation results of the intercept and the factor loadings of the time-series risk factor models with various sets of the risk factors or explanatory variables. Except for the two-factor model containing the market risk factor and the FESTD factor (in panel E), all considered models have at least one intercept estimate ($\hat{\alpha}_p$) significantly different from zero, especially the intercept estimate of the smallest portfolio. When the market risk factor is alone in the model (in panel A), the intercept estimate of the smallest portfolio is statistically significant in individual t-tests, but the other portfolios' intercepts are insignificant. Gibbons, Ross, and Shanken's (1989) simultaneous F-test for the null that $\alpha_1 = \alpha_2 = \cdots = \alpha_{10} = 0$ rejects the null, with a p-value of 0.0064. Fama and French's well-accepted three-factor model (in panel B) has three intercept estimates significantly different from zero. Moreover, the Gibbons et al. F-test also rejects the null hypothesis, with a p-value of 0.0051.

When either the MMNT factor or the FESTD factor is added into Fama and French's three-factor model (in panels C and D), some intercept estimates are still statistically significant. One noteworthy observation from the estimation of the four-factor model ($R_{mt} - R_{ft}$, SMB, HML, and FESTD) is that

TABLE 7 The Estimates of Time-Series Risk Factor Models for Each of the Size Portfolios: January 1972 to December 2003

Size Portfolio	Intercept ($\alpha_p \times 100$)	MKTRFT (β_{p1})	SMB (β_{p2})	HML (β_{p3})	MMNT (β_{p4})	FESTD (β_{p5})	Adjusted R^2
	A. $R_{pt} - R_{ft} = \alpha_p + \beta_{p1}(R_{mt} - R_{ft}) + \varepsilon_{pt}$; GRS = 2.505 ($p$ value = .0064)						
1	.637 (2.30)	1.037 (16.71)					.42
2	.147 (.76)	1.031 (23.74)					.59
3	.166 (.95)	1.092 (27.79)					.67
4	.258 (1.65)	1.081 (30.90)					.71
5	.168 (1.19)	1.072 (33.76)					.75
6	.187 (1.48)	1.064 (37.74)					.79
7	.186 (1.79)	1.070 (45.84)					.85
8	.086 (.97)	1.085 (54.13)					.88
9	.072 (.98)	1.042 (63.21)					.91
10	.028 (.64)	1.002 (101.61)					.96
	B. $R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(Rmt - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \varepsilon_{pt}$; GRS = 2.573 ($p$-value = .0051)						
1	.117 (.68)	1.040 (26.08	1.339 (25.76)	.566 (9.76)			.79
2	−.233 (−2.61)	1.022 (49.04)	1.052 (38.75)	.396 (13.09)			.92
3	−.222 (−2.45)	1.110 (52.28)	.907 (32.80)	.445 (14.43)			.92
4	−.045 (−.63)	1.072 (63.91)	.847 (38.77)	.314 (12.91)			.94
5	−.135 (−1.95)	1.079 (66.65)	.752 (66.62)	.337 (14.32)			.94
6	−.098 (−1.50)	1.080 (70.56)	.648 (32.48)	.330 (14.85)			.95
7	−.044 (−.62)	1.094 (66.16)	.456 (21.16)	.282 (11.75)			.93
8	−.115 (−1.72)	1.114 (71.31)	.343 (16.83)	.260 (11.47)			.94
9	−.080 (−1.26)	1.075 (72.34)	.195 (10.06)	.211 (9.80)			.94
10	.041 (1.04)	1.016 (110.10)	−.123 (−10.26)	.007 (.51)			.97
	C. $R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{4p}\text{MMNT}_t + \varepsilon_{pt}$; GRS = 4.255 ($p$-value = .0001)						
1	.590 (3.92)	.984 (25.89)	1.240 (27.54)	.476 (9.54)	−.388 (−12.02)		.81
2	−.052 (−.61)	1.001 (49.11)	1.015 (39.74)	.362 (12.80)	−.148 (−8.10)		.92
3	−.025 (−.29)	1.086 (54.59)	.866 (33.75)	.407 (14.33)	−.162 (−8.81)		.93
4	.052 (.72)	1.061 (64.88)	.827 (38.45)	.296 (12.42)	−.080 (−5.18)		.95
5	−.049 (−.70)	1.069 (68.15)	.734 (35.13)	.320 (13.84)	−.071 (−4.71)		.95

TABLE 7 ***(Continued)***

Size Portfolio	Intercept ($\alpha_p \times 100$)	MKTRFT (β_{p1})	SMB (β_{p2})	HML (β_{p3})	MMNT (β_{p4})	FESTD (β_{p5})	Adjusted R^2
6	−.041 (−.61)	1.073 (71.81)	.636 (31.75)	.319 (14.38)	−.047 (−3.29)		.95
7	.013 (.18)	1.087 (67.44)	.444 (20.48)	.271 (11.29)	−.046 (−2.98)		.94
8	−.071 (−1.03)	1.109 (72.47)	.333 (16.21)	.252 (11.05)	−.036 (−2.46)		.94
9	−.022 (−.33)	1.068 (75.04)	.183 (9.45)	.200 (9.32)	−.048 (−3.44)		.95
10	.073 (1.81)	1.012 (113.11)	−.130 (−10.75)	.001 (.06)	−.026 (−3.04)		.98
	D. $R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{5p}\text{FESTD}_t + \varepsilon_{pt}$; GRS = 3.013 ($p$-value = .0011)						
1	.162 (1.81)	.884 (41.15)	.563 (15.39)	.127 (3.80)		.781 (31.73)	.94
2	−.218 (−2.91)	.970 (53.86)	.794 (25.87)	.250 (8.94)		.260 (12.60)	.94
3	−.212 (−2.51)	1.073 (52.97)	.726 (21.03)	.342 (10.88)		.182 (7.84)	.93
4	−.043 (−.60)	1.062 (62.04)	.799 (27.37)	.287 (10.79)		.049 (2.50)	.94
5	−.135 (−1.94)	1.076 (64.64)	.737 (25.96)	.328 (12.70)		.015 (.78)	.94
6	−.101 (−1.54)	1.087 (69.45)	.685 (25.68)	.351 (14.44)		−.038 (−2.10)	.95
7	−.047 (−.67)	1.105 (65.78)	.514 (17.94)	.315 (12.07)		−.059 (−3.04)	.93
8	−.120 (−1.84)	1.131 (72.20)	.424 (15.87)	.306 (12.58)		−.082 (−4.54)	.94
9	−.084 (−1.35)	1.089 (72.77)	.264 (10.37)	.251 (10.80)		−.070 (−4.09)	.94
10	.039 (1.01)	1.022 (108.59)	−.095 (−5.62)	.023 (1.57)		−.029 (−2.66)	.97
	E. $R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{5p}\text{FESTD}_t + \varepsilon_{pt}$; GRS = 2.122 ($p$-value = .0360)						
1	.215 (1.91)	.870 (34.21)				1.024 (44.09)	.90
2	−.104 (−.85)	.932 (33.67)				.609 (24.11)	.84
3	−.045 (−.37)	1.008 (36.73)				.513 (20.46)	.84
4	.092 (.76)	1.015 (37.30)				.404 (16.25)	.83
5	.024 (.21)	1.016 (39.78)				.348 (14.95)	.84
6	.072 (.68)	1.019 (42.57)				.277 (12.68)	.85
7	.111 (1.18)	1.040 (48.85)				.183 (9.40)	.87
8	.036 (.43)	1.065 (55.76)				.122 (7.01)	.90
9	.046 (.64)	1.032 (63.25)				.063 (4.24)	.92
10	.055 (1.34)	1.012 (108.94)				−.065 (−7.66)	.97
	F. $R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \varepsilon_{pt}$; GRS = 2.465 ($p$-value = .0073)						

1	.471 (2.53)	.914 (21.69)	1.203 (21.51)				.74
2	.015 (.14)	.934 (39.36)	.958 (30.40)				.88
3	.056 (.51)	1.010 (40.50)	.800 (24.17)				.87
4	.151 (1.80)	1.002 (52.72)	.772 (30.60)				.92
5	.075 (.90)	1.004 (52.90)	.671 (26.63)				.91
6	.108 (1.35)	1.006 (55.36)	.569 (23.57)				.91
7	.133 (1.65)	1.031 (56.53)	.388 (16.04)				.91
8	.048 (.63)	1.056 (61.68)	.280 (12.33)				.92
9	.052 (.75)	1.028 (65.42)	.144 (6.91)				.92
10	.045 (1.18)	1.014 (116.35)	−.125 (−10.79)				.97
	G. $R_{pt} - R_{ft} = \alpha_p + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{5p}\text{FESTD}_t + \varepsilon_{pt}$; GRS = 4.111 ($p$-value = .0000)						
1	.761 (3.69)		.371 (4.38)	−.399 (−5.66)		1.015 (18.14)	.69
2	.440 (2.02)		.583 (6.52)	−.328 (−4.31)		.517 (8.75)	.50
3	.516 (2.14)		.493 (4.97)	−.297 (−3.53)		.466 (7.12)	.39
4	.678 (2.89)		.568 (5.88)	−.346 (−4.22)		.330 (5.17)	.36
5	.595 (2.51)		.503 (5.16)	−.313 (−3.78)		.299 (4.65)	.31
6	.637 (2.68)		.449 (4.58)	−.296 (−3.57)		.250 (3.86)	.26
7	.703 (2.89)		.274 (2.74)	−.343 (−4.05)		.234 (3.54)	.18
8	.647 (2.62)		.178 (1.75)	−.367 (−4.26)		.217 (3.24)	.14
9	.654 (2.75)		.028 (.29)	−.398 (−4.79)		.218 (3.37)	.11
10	.732 (3.35)		−.317 (−3.52)	−.585 (−7.67)		.241 (4.06)	.13

NOTE.—The risk factors considered are MKTRFT (the value-weighted CRSP market returns in excess of the one-month Treasury bill's return, $R_{mt} - R_{ft}$), Fama and French's (1993) SMB and HML (which are related with firm size and book-to-market, respectively), Carhart's (1997) MMNT (which is related with stock return momentum), and FESTD (the standard deviation of earnings forecast errors, which is related with earnings information uncertainty). R_{pt} is the rate of return on the size portfolio p at time t, β_p's are factor loadings to the corresponding risk factor, and ε_{pt} is the residual returns on the size portfolio p at time t. Numbers in parentheses indicate t-statistics. GRS is the F-statistic of Gibbons et al. (1989) for testing the hypothesis that the intercepts of all 10 size portfolios are all zero.

with the addition of the FESTD factor, the explanatory power of SMB and HML is weakened, especially in the small-size portfolios, whereas that of the market risk factor is little affected. The factor loading estimates on the FESTD factor are significantly positive in the small-size portfolios, whereas they are significantly negative in the large-size portfolios.

Remarkable results are obtained from the estimation of the two-factor model with the market risk factor and the FESTD factor (in panel E). I report that the intercept estimates are all insignificant in individual *t*-tests at the 5% significance level and in the Gibbons et al. *F*-test at the 1% significance level (with a *p*-value of 0.0360). In contrast to the other factor models, the residual returns from this two-factor model do not show any systematic pattern across firm size (to be discussed in the next section). Since the FESTD factor has a high correlation with SMB, in panel F I substitute SMB for FESTD factor in the above two-factor model. This allows me to compare the estimation results from both two-factor models. The results are quite different. Panel F shows that the intercept estimate of the two-factor model ($R_{mt} - R_{ft}$ and SMB) for the smallest-size portfolio is 0.471% per month, and it is economically and statistically significant (with *t*-statistics of 2.53), although the other intercept estimates are insignificant. The difference between the intercept estimates of the smallest and largest portfolios also is quite significant: 0.426% per month. The Gibbons et al. *F*-test for this two-factor model rejects the null with a *p*-value of 0.0073 as well.

Panel G of table 7 shows the results of a three-factor model with SMB, HML, and FESTD, without the market risk factor. The intercept estimates are substantially greater in magnitude than those of the four-factor model with the market risk factor included (in panel D); all are positively highly significant. Furthermore, the R^2 in each portfolio is substantially lower. These results show how important the market risk factor is in explaining the intertemporal behavior of average stock returns, although the explanatory power of the market risk (or beta) is weak in the cross section of stock returns (see Fama and French 1992). The exclusion of the market risk factor affects significantly the factor loading estimates on HML. Their sign is drastically changed from significantly positive (including $R_{mt} - R_{ft}$ in panel D) to significantly negative (excluding $R_{mt} - R_{ft}$ in panel G). When a four-factor model with SMB, HML, MMNT, and FESTD, without the market risk factor, is estimated, similar results also are obtained (not reported).

B. Residual Returns across Firm Size

Table 8 presents the average residual returns in January and in non-January months on the size portfolios generated from each of the selected factor models. When the single market risk factor model is estimated, the average residual returns in January across firm size are very similar to the cross section of raw returns observed in table 1. The average residual returns in January have a monotonic negative relation with firm size. The difference between the average residual returns on the smallest- and largest-size portfolios, 1–10, is highly significant. It is 9.26% per month, with a *t*-statistic of 5.69. Note that this difference is an arbitrage return by buying long the smallest portfolio and selling short the largest portfolio. This difference is comparable to the difference in the average raw returns in table 1, which is 9.922% per month, with a *t*-statistic of 5.37. These results indicate that the market risk factor really does not explain the systematic pattern in the cross section of stock returns in January. Fama and French's (1993) three-factor model also generates positively significant average residual returns in January on the smallest-size portfolio: 5.68% per month with a *t*-statistic of 7.16. The difference in the average residual returns in January, portfolios 1–10, is also quite positively significant: 5.97% per month with a *t*-statistic of 7.37. When the MMNT factor is added into Fama and French's three-factor model, I observe a negligible improvement in the magnitude of the residual returns. Even in non-January months, average residual returns on the smallest-size portfolio and portfolios 1–10 from each of the above three models are statistically significant.

When the four-factor model (Fama and French's three factors plus FESTD) is estimated, I find an improvement with respect to statistical significance of the average residual returns over the previous three models. The average residual returns on the size portfolios in non-January months are all insignificant, and those in January are much less significant. However, the average January residual return on the smallest portfolio is still significant (1.23% per month, with a *t*-statistic of 2.91), and portfolios 1–10 in January are also still significant (1.36%, with a *t*-statistic of 3.15). When I estimate the two-factor model with the market risk and FESTD factors, quite remarkably improved results are obtained. That is, the systematic pattern in the January residual returns across firm size almost disappears. Specifically, the average residual return in January on the smallest portfolio is 0.39% per month, with a *t*-statistic of 0.82. Moreover, the difference in the average January residual returns between the smallest and the largest portfolios, 1–10, is not significant at all: 0.35% per month, with a *t*-statistic of 0.69. Accordingly, this parsimonious model explains much better the January seasonality in stock returns than any other factor models considered.

Table 8 also shows that another two-factor model (the market risk factor and SMB) generates an increasing monotonic pattern in the average residual returns across firm size similar to that generated from the single market risk factor model. These results apparently indicate that the FESTD factor has unique explanatory power for the seasonal pattern in stock returns different from SMB, although the correlation between these two factors is relatively high.

In sum, I argue that the parsimonious two-factor model with the market risk factor and the FESTD factor explains the seasonal phenomenon in stock returns better than the other factor models considered. The intercept estimates for this two-factor model are all insignificant, and the average residual return

TABLE 8 Average Residual Returns (in Percent) on the Size Portfolios from the Estimated Models

Size Portfolio	January	Non-January	January	Non-January	January	Non-January
	f(MKTRFT)		*f*(MKTRFT, SMB, HML)		*f*(MKTRFT, SMB, HML, MMNT)	
1	8.77 (5.78)	−.80 (−3.58)	5.68 (7.16)	−.52 (−3.82)	3.80 (6.19)	−.35 (−2.70)
2	4.08 (4.18)	−.37 (−2.08)	1.72 (5.13)	−.16 (−1.85)	1.00 (3.72)	−.09 (−1.11)
3	2.89 (2.99)	−.26 (−1.62)	.70 (1.40)	−.06 (−.76)	−.08 (−.20)	.01 (.09)
4	1.89 (2.58)	−.17 (−1.13)	−.01 (−.03)	.00 (.01)	−.39 (−1.71)	.04 (.51)
5	1.37 (1.97)	−.12 (−.90)	−.40 (−1.39)	.04 (.53)	−.74 (−2.87)	.07 (1.02)
6	1.00 (1.74)	−.09 (−.73)	−.58 (−2.28)	.05 (.82)	−.81 (−3.32)	.07 (1.17)
7	.36 (.78)	−.03 (−.31)	−.83 (−3.45)	.08 (1.08)	−1.05 (−4.66)	.10 (1.39)
8	−.00 (−.01)	.00 (.00)	−.96 (−4.20)	.09 (1.34)	−1.14 (−5.03)	.10 (1.61)
9	−.04 (−.13)	.04 (.05)	−.68 (−3.26)	.06 (.98)	−.91 (−4.53)	.08 (1.35)
10	−.49 (−3.30)	.05 (.99)	−.29 (−2.91)	.03 (.66)	−.42 (−3.65)	.04 (.98)
P1–P10	9.26 (5.69)	−.84 (−3.45)	5.97 (7.37)	−.54 (−3.68)	4.22 (6.86)	−.39 (−2.63)
Slope	−1.26 (−4.77)	.11 (4.77)	−.76 (−2.94)	.07 (2.94)	−.55 (−2.70)	.05 (2.70)
	f(MKTRFT, SMB, HML, FESTD)		*f*(MKTRFT, FESTD)		*f*(MKTRFT, SMB)	
1	1.23 (2.91)	−.11 (−1.34)	.39 (.82)	−.04 (−.31)	6.74 (7.74)	−.61 (−4.16)
2	.24 (.87)	−.02 (−.28)	−.91 (−2.11)	.08 (.66)	2.46 (5.73)	−.22 (−2.27)
3	−.33 (−.74)	.03 (.38)	−1.31 (−2.47)	.12 (.99)	1.53 (2.73)	−.14 (−1.33)
4	−.29 (−1.16)	.03 (.36)	−1.42 (−3.94)	.13 (1.05)	.58 (1.83)	−.05 (−.61)
5	−.48 (−1.72)	.04 (.64)	−1.48 (−3.97)	.14 (1.18)	.23 (.66)	−.02 (−.25)
6	−.37 (−1.43)	.03 (.51)	−1.27 (−3.33)	.12 (1.08)	.04 (.12)	−.00 (−.04)
7	−.50 (−1.97)	.05 (.65)	−1.14 (−3.59)	.10 (1.09)	−.30 (−1.11)	.03 (.33)
8	−.50 (−2.23)	.05 (.70)	−1.00 (−3.01)	.09 (1.08)	−.48 (−1.62)	.04 (.56)
9	−.28 (−1.29)	.03 (.41)	−.56 (−2.07)	.05 (.69)	−.29 (−1.12)	.03 (.36)
10	−.13 (−1.30)	.01 (.29)	.04 (.38)	−.00 (−.09)	−.28 (−2.83)	.03 (.63)
P1–P10	1.36 (3.15)	−.12 (−1.25)	.35 (.69)	−.04 (−.23)	7.02 (7.79)	−.64 (−4.06)
Slope	−.16 (−1.96)	.01 (1.96)	.03 (.27)	−.00 (−.27)	−.91 (−3.47)	.08 (3.47)

	f(SMB, HML, FESTD)	
1	1.14 (1.17)	−.10 (−.52)
2	.13 (.13)	−.01 (−.06)
3	−.45 (−.41)	.04 (.17)
4	−.40 (−.40)	.04 (.15)
5	−.60 (−.57)	.05 (.23)
6	−.48 (−.45)	.04 (.18)
7	−.61 (−.60)	.06 (.23)
8	−.62 (−.57)	.06 (.23)
9	−.40 (−.39)	.04 (.15)
10	−.24 (−.26)	.02 (.10)
P1–P10	1.38 (3.24)	−.14 (−1.20)
Slope	−.16 (−1.96)	.02 (1.96)

NOTE.—The risk factors considered are MKTRFT (the value-weighted CRSP market returns in excess of the one-month Treasury bill's return, $R_{mt} - R_{ft}$, Fama and French's (1993) SMB and HML (which are related with firm size and book-to-market, respectively), Carhart's (1997) MMNT (which is related with stock return momentum), and FESTD (the standard deviation of earnings forecast errors, which is related with earnings information uncertainty). The estimated models are defined as follows:

$$f(\text{MKTRFT}):\ R_{pt} - R_{ft} = \alpha_p + \beta_{p1}(R_{mt} - R_{ft}) + \varepsilon_{pt},$$

$$f(\text{MKTRFT, SMB, HML}):\ R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \varepsilon_{pt},$$

$$f(\text{MKTRFT, SMB, HML, MMNT}):\ R_{pt} - R_{ft} + \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{4p}\text{MMNT}_t + \varepsilon_{pt},$$

$$f(\text{MKTRFT, SMB, HML, FESTD}):\ R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{5p}\text{FESTD}_t + \varepsilon_{pt},$$

$$f(\text{MKTRFT, FESTD}):\ R_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{5p}\text{FESTD}_t + \varepsilon_{pt},$$

$$f(\text{MKTRFT, SMB}):\ R_{pt} - R_{ft} + \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \varepsilon_{pt}.$$

Numbers in parentheses indicate *t*-statistics of the average residual returns. P1–P10 is the difference between the average residual returns of portfolio 1 and portfolio 10. Slope is the slope estimate of regressing the average residual returns on the natural logarithm of the average firm size.

on the smallest portfolio in January generated from this model is not significant. Moreover, the difference in the average residual returns in January between the smallest and largest portfolios (which is an arbitrage return) is also not significant. In fact, the sum of the intercept estimates and the average residual returns is the abnormal returns. Among the risk factor models considered, only this two-factor model provides no systematic pattern in the abnormal returns across firm size and no significance of the abnormal returns in January on the smallest portfolio. Specifically, the abnormal returns on the smallest and largest portfolios are 0.61% (*t*-statistic of 1.78) and 0.10% (*t*-statistic of 0.76), respectively. Thus the arbitrage return is 0.51% with a *t*-statistic of 1.23.

C. Is FESTD a Priced Risk Factor?

In order to further investigate whether FESTD is a priced risk factor, I estimate the cross-sectional relationship between average returns and the factor loadings or betas on the risk factors using Fama-MacBeth's (1973) two-pass estimation methodology. As in Fama and French (1992), I allocate the full-period postranking β of a size β portfolio to each individual stock that is contained in the portfolio. Ten decile size portfolios are formed according to the market value of common equity in June of each year, and within each size portfolio, 10 decile β portfolios are formed according to preranking β's of individual stocks. The preranking β is estimated using five years of returns observations (at least 24 observations) before July of each year. The allocated full-period postranking β's are used in the cross-sectional regressions (CSR) for individual stocks. Note that since a stock can move across portfolios with year-to-year changes in the stock's size and β, the stock's β can change over time in the CSR estimation.

Table 9 reports the time-series averages (or risk premia estimates) of the slope coefficients from the month-by-month Fama-MacBeth ordinary least squares (OLS) CSR of stock returns on β's. When the single beta of each factor is separately used in the CSR over the whole months, no slope estimate is statistically significant at the conventional significance level. Only β on FESTD is marginally significant: the average slope is 0.496, with a *t*-statistic of 1.85. However, when the multiple betas are used, the slope estimate on the FESTD beta is the only one that is economically and statistically significant; those on the other betas are insignificant or inconsistent in terms of economic intuition. For example, in the two-factor model with MKT and FESTD that has explained well the January seasonality over time, the slope estimate on the FESTD beta is significant: 0.518% with a *t*-statistic of 2.31. In the four-factor (MKT, SMB, HML, and FESTD) and five-factor (MKT, SMB, HML, MMNT, and FESTD) models, the slope estimates on the FESTD beta are statistically significant: 1.369% with a *t*-statistic of 3.03 and 2.233% with a *t*-statistic of 3.32, respectively. However, those on the other factor loadings are insignificant or inconsistent with economic intuition. More noticeable results for the FESTD beta are obtained with January only. When the single beta of each factor is separately used, the January slope estimates of all models are highly statistically significant. However, when the multiple betas are used together, the FESTD beta is the only one that maintains its significance; the other betas lose their significance. These results indicate that the risk factor FESTD is robust and is significantly priced, and its factor loading dominates the other risk factor in explaining the cross section of returns in January.

D. Can FESTD Also Be a Proxy for "Speculation"?

At it heart, FESTD is a measure of earnings volatility. It is natural, therefore, to consider that FESTD could be some type of proxy for earnings quality or speculation. In order to test whether FESTD can be a proxy for low earnings quality or "speculation," I use Standard and Poor's stock quality rating data. Standard & Poor's gives stocks a quality rating based on the growth and stability of earnings and dividends history. Low-quality or speculative stocks tend to have more volatile earnings. According to the quality rating (A+: highest, A: high, A−: above average, B+: average, B: below average, B−: lower, C: lowest, D: in reorganization), I construct eight equally weighted portfolios by rebalancing the portfolios whenever the rating change occurs. Table 10 presents some basic characteristics (in panel A) and the factor loadings on each of the five factors (in panel B) over the period from January 1985 through December 2003. The degree of the quality rating tends to have clear monotonic relations with some characteristics of firms. Lower-quality stocks have smaller firm size and have greater volatility in stock returns. Lower-quality stocks also have greater standard deviations of (scaled) EPS, the growth rate of EPS, and the growth rate of sales. The degree of the quality rating has a monotonic relation with stock returns in January, but not in non-January months.

In order to examine the sensitivity of the risk factors to the returns on the quality rating portfolios, I estimate the factor loadings by regressing the returns on the portfolio on each of the risk factors (univariate) and on all risk factors together (multivariate), respectively. In the univariate regression, the factor loadings on MKTRFT, SMB, and FESTD are positive and increase as the quality rating becomes lower, whereas those on MMNT decrease. HML has mostly negative factor loadings, but not in a monotonic pattern. In the multivariate regression, however, only FESTD maintains the similar pattern (i.e., the lower the quality rating, the greater the factor loadings); the other factors have almost a random pattern. This implies that only FESTD is conditionally and unconditionally sensitive to the degree of the quality rating and that when I condition on FESTD, the other factors are not. I would argue, therefore, that FESTD can be a proxy for low quality or speculation.

The fact that FESTD explains well the January seasonality in stock returns and can be a proxy for speculation might explain why non-December fiscal

TABLE 9 Time Series Average (in Percent) of the Estimated Coefficients from the Cross-Sectional Regression of Individual Stocks' Returns on Betas: January 1972–December 2003

Intercept	MKT	SMB	HML	MMNT	FESTD
A. With Whole Months					
1.481 (7.28)	−.123 (−.38)				
1.080 (5.12)		.326 (1.48)			
1.426 (6.53)			.227 (.79)		
1.056 (4.85)				−.803 (−1.70)	
1.050 (4.67)					.496 (1.85)
1.477 (7.65)	−.518 (−1.68)				.518 (2.31)
1.052 (5.19)	.264 (.73)	−.731 (−2.23)	.523 (1.74)		1.369 (3.03)
1.005 (5.09)	.335 (.92)	−.983 (−2.72)	.350 (1.14)	1.154 (1.90)	2.233 (3.32)
B. With January Only					
2.601 (2.87)	3.080 (2.24)				
−.077 (−.08)		7.002 (6.11)			
5.124 (4.53)			2.157 (4.74)		
−.159 (−.16)				−16.070 (−6.51)	
.146 (.14)					9.247 (6.61)

2.666 (2.96)	−3.079 (−2.71)				8.192 (7.28)
3.524 (4.01)	−3.445 (−2.09)	−4.645 (−2.73)	−1.925 (−1.11)		14.967 (6.51)
3.539 (3.95)	−3.477 (−2.04)	−4.598 (−2.19)	−1.913 (−1.07)	−.206 (−.06)	14.815 (3.59)
C. With Non-January Months					
1.379 (6.70)	−.414 (−1.29)				
1.185 (5.56)		−.281 (−1.52)			
1.090 (5.27)			.052 (1.13)		
1.166 (5.35)				.585 (1.50)	
1.133 (4.99)					−.300 (−1.37)
1.369 (7.07)	−.285 (−.90)				−.180 (−.99)
.798 (4.07)	.601 (1.67)	−.376 (−1.19)	.745 (2.60)		.133 (.35)
.775 (3.96)	.682 (1.89)	−.655 (−1.91)	.556 (1.90)	1.278 (2.24)	1.089 (1.82)

NOTE.—Fama and MacBeth's (1973) two-pass methodology is used. In the first-pass time-series model, I estimate the coefficients of the factors or β's in each of 100 size- beta portfolios that are rebalanced on December of each year. As Fama and French (1992) did, I then allocate the full-period postranking β of a size-β portfolio to each individual stock that is contained in the portfolio. In the second pass, I estimate the cross-sectional regression models using the assigned β s to individual stocks by the OLS method. Numbers in parentheses indicate t-statistics.

TABLE 10 Basic Characteristics and the Factor Loadings on the Risk Factors of Standard & Poor's Earnings and Dividend Quality Rating Portfolios: January 1985–December 2003

	Earnings and Dividend Quality Rating Portfolios							
	A+	A	A−	B+	B	B−	C	D
	A. Basic Characteristics							
Average return (%):								
All months	1.37	1.26	1.41	1.25	1.32	1.40	1.72	−5.55
January	1.68	1.45	1.81	2.38	3.97	6.03	10.89	13.11
Non-January	1.35	1.25	1.36	1.15	1.09	.98	.90	−7.52
Standard deviation (%)	4.26	3.85	3.83	4.22	4.86	5.54	7.90	15.02
Firm size ($M)	14,450	5,354	4,153	2,301	1,497	584	224	154
Book-to-market	.503	.785	.779	.824	.956	1.124	.824	−1.034
Standard deviation:								
EPS	.231	.292	.361	.455	.714	.556	.579	4.915
EPS growth	.354	.440	.549	.698	1.125	1.762	1.997	2.082
Sales growth	.237	.231	.227	.260	.367	.645	1.026	.674
% of fiscal year end month:								
December	72.7	74.0	73.0	61.4	60.4	57.5	57.0	57.8
Non-December	27.3	26.0	27.0	38.6	39.6	42.5	43.0	42.2
	B. Factor Loadings (or β)							
Univariate regression:								
MKTRFT	.747	.728	.754	.891	1.050	1.168	1.452	1.789
SMB	−.078	.073	.151	.367	.625	.891	1.413	1.425
HML	−.204	−.176	−.169	−.328	−.536	−.723	−1.143	−.684
MMNT	−.103	−.106	−.112	−.206	−.293	−.411	−.743	−1.808
FESTD	−.022	.056	.103	.267	.463	.713	1.317	2.354
Multivariate regression:								
MKTRFT	1.055	.974	.979	1.016	1.052	.998	.878	.738
SMB	−.291	−.090	−.005	.107	.198	.264	.240	−.201
HML	.026	.122	.173	.091	−.045	−.194	−.600	−.269
MMNT	−.033	−.029	−.019	−.052	−.037	−.021	−.004	−.617
FESTD	−.450	−.406	−.385	−.312	−.170	.081	.741	1.660

NOTE.—Ratings based earnings and dividend quality: A+: highest; A: high; A−: above average; B+: average; B: below average; B−: lower; C: lowest; D: In reorganization.

year end stocks also do well in January. However, the reason that January may be a month that potentially tends to differentially reward low-quality or speculative stocks is still an unanswered question. One possible answer is that although non-December fiscal year end stocks do not have pressure from the impending release of important accounting information before the turn of the year, those stocks, especially speculative stocks, could also be vulnerable to earnings perspective and information environments provided by December fiscal year end companies. Therefore, stock prices of non-December fiscal year end companies are depressed as well, and when the earnings information uncertainty is resolved, their stock prices rise. Note that small firms tend to have more non-December fiscal year end months than large firms (see n. 9) and that low–quality rating firms also tend to have more non-December fiscal year end months than high–quality rating firms (see table 10).

E. Further Test of the Tax Loss Selling Hypothesis

In the previous section, we have found that the tax loss selling hypothesis fails to explain the January phenomenon in stock returns. It could be argued that this failure might result from no explicit adjustment of raw returns for risk. It would be interesting, therefore, to examine whether the tax loss selling hypothesis can explain the January effect after one adjusts for risk by using the widely accepted factor model such as the single market risk factor and Fama and French's (1993) three-factor models. Each year I adjust the raw returns in January for the tax loss selling effect. These adjusted returns in January are calculated as the January raw return on the size portfolio minus the cross-sectionally demeaned January return on the portfolios sorted by the tax loss selling proxy variable in which stocks are included. Since the cross-sectionally demeaned return is used, the cross-sectional sum of the January returns across firm size is not changed, but the cross-sectional variations in the January returns across firm size are changed to the extent that the tax loss selling effect is adjusted. Then I estimate the time-series factor models by regressing the tax loss selling effect–adjusted returns in each size portfolio on the risk factors as in table 8. If the seasonality in stock returns is related to the tax loss selling effect and the tax loss selling proxy variables are appropriate, then the average residual returns should not exhibit the seasonal pattern.

Table 11 presents the average residual returns in January on each size portfolio generated from the estimated time-series factor models using the tax loss selling effect–adjusted returns. I estimate all the factor models considered in table 7 except for the models including FESTD. No matter which previously known risk factor model and tax loss selling proxy variable are used, without the inclusion of the FESTD factor, I still find a systematic cross-sectional variation in the average residual returns across firm size that is similar to that obtained using the unadjusted raw returns. For example, when Fama and French's three-factor model is used with adjustment for the tax loss selling effect using Reinganum's tax loss selling proxy variable, the average residual return in January on the smallest portfolio is 3.69% per month, with a *t*-statistic of 9.03, and the difference in the average residual returns between the smallest and the largest portfolios, 1–10, is 2.91% per month, with a *t*-statistic of 7.15. Without adjustment for the tax loss selling effect, they were 5.68% (*t*-statistic of 7.16) and 5.97% (*t*-statistic of 7.37), respectively (see table 8).

TABLE 11 Average Residual Returns in January after Adjusting for the Returns of the Tax Loss Selling Proxy Portfolios

	Tax Loss Selling Proxy								
Size Portfolio	Ratio	Standard Deviation	PRET	Ratio	Standard Deviation	PRET	Ratio	Standard Deviation	PRET
	f^a(MKTRFT)			f^a(MKTRFT, SMB, HML)			f^a(MKTRFT, SMB)		
1	6.48 (6.10)	7.10 (5.60)	7.83 (5.81)	3.69 (9.03)	4.23 (6.34)	4.83 (7.65)	4.61 (9.37)	5.17 (7.67)	5.86 (7.87)
2	3.15 (3.85)	3.34 (3.82)	3.68 (3.96)	.91 (3.90)	1.09 (3.30)	1.34 (4.94)	1.59 (4.84)	1.77 (4.60)	2.08 (5.11)
3	2.37 (2.76)	2.44 (2.57)	2.65 (2.88)	.26 (.63)	.31 (.58)	.49 (1.09)	1.01 (2.26)	1.10 (1.94)	1.31 (2.55)
4	1.67 (2.42)	1.61 (2.26)	1.67 (2.45)	−.20 (−.86)	−.25 (−.90)	−.20 (−.96)	.38 (1.28)	.32 (.97)	.38 (1.35)
5	1.39 (2.04)	1.25 (1.84)	1.33 (1.97)	−.37 (−1.31)	−.51 (−1.74)	−.42 (−1.49)	.26 (.76)	.12 (.34)	.20 (.59)
6	1.33 (2.11)	1.22 (2.02)	1.09 (1.84)	−.29 (−.94)	−.39 (−1.43)	−.49 (−1.70)	.34 (1.01)	.25 (.76)	.12 (.38)
7	.94 (1.65)	.74 (1.47)	.55 (1.09)	−.32 (−.97)	−.49 (−1.91)	−.66 (−2.31)	.24 (.67)	.06 (.21)	−.13 (−.41)
8	.71 (1.44)	.51 (1.11)	.35 (.79)	−.32 (−1.06)	−.52 (−2.11)	−.64 (−2.51)	.19 (.55)	.01 (.03)	−.15 (−.51)
9	.98 (2.02)	.83 (2.03)	.45 (1.14)	.21 (.59)	.07 (.28)	−.24 (−.80)	.67 (1.68)	.53 (1.63)	.17 (.54)
10	.78 (3.16)	.77 (3.29)	.23 (1.37)	.78 (2.95)	.80 (3.21)	.34 (1.87)	.90 (3.28)	.90 (3.57)	.39 (2.20)
P1–P10	5.70 (6.00)	6.33 (5.13)	7.60 (5.60)	2.91 (7.15)	3.43 (5.45)	4.49 (7.43)	3.71 (8.40)	4.27 (6.46)	5.47 (7.54)
	f^a(MKTRFT, MMNT)			f^a(MKTRFT, SMB, HML, MMNT)			f^a(MKTRFT, SMB, MMNT)		
1	4.10 (4.26)	4.30 (4.38)	5.07 (4.31)	2.38 (5.30)	2.57 (6.09)	3.25 (5.55)	2.97 (5.20)	3.14 (6.08)	3.89 (5.31)
2	1.85 (2.48)	1.88 (2.53)	2.21 (2.68)	.42 (1.74)	.45 (1.71)	.73 (3.02)	.88 (2.49)	.90 (2.65)	1.23 (3.05)
3	.94 (1.29)	.88 (1.14)	1.13 (1.46)	−.40 (−1.16)	−.56 (−1.09)	−.24 (−.66)	.14 (.33)	.07 (.16)	.31 (.70)
4	.68 (1.10)	.57 (.93)	.69 (1.12)	−.53 (−2.44)	−.62 (−2.54)	−.52 (−2.71)	−.13 (−.44)	−.23 (−.77)	−.12 (−.42)
5	.43 (.71)	.31 (.52)	.37 (.66)	−.71 (−2.76)	−.82 (−3.05)	−.76 (−3.00)	−.27 (−.89)	−.39 (−1.12)	−.33 (−1.07)
6	.45 (.80)	.41 (.75)	.27 (.50)	−.60 (−2.16)	−.64 (−2.49)	−.76 (−2.85)	−.16 (−.50)	−.20 (−.62)	−.34 (−1.12)
7	.11 (.23)	.04 (.09)	−.17 (−.39)	−.70 (−2.47)	−.76 (−3.15)	−.95 (−3.75)	−.31 (−.99)	−.38 (−1.27)	−.58 (−2.08)

8	−.02 (−.05)	−.05 (−.12)	−.29 (−.75)	−.69 (−2.60)	−.73 (−2.94)	−.93 (−4.02)	−.34 (−1.07)	−.36 (−1.05)	−.59 (−2.08)
9	−.21 (−.51)	.23 (.59)	−.17 (−.50)	−.27 (−.93)	−.25 (−1.01)	−.60 (−2.31)	.04 (.10)	.06 (−.19)	−.33 (−1.12)
10	−.30 (−1.50)	.47 (1.88)	−.06 (−.36)	.33 (1.65)	.52 (1.96)	.04 (.24)	.39 (1.86)	.57 (2.13)	.06 (.37)
P1–P10	3.80 (4.14)	3.83 (4.08)	5.13 (4.23)	2.05 (4.14)	2.05 (4.80)	3.21 (5.46)	2.57 (4.55)	2.57 (5.26)	3.83 (5.23)

NOTE.—The tax loss selling proxy variables are defined as follows: Ratio is the ratio of the December end price to the highest price of the previous year's month end prices, standard deviation pertains to the previous year's monthly returns, and PRET is the average monthly returns of the previous year. The risk factors considered are MKTRFT (the value-weighted CRSP market returns in excess of the one-month Treasury bill's return, $R_{mt} - R_{ft}$, Fama and French's (1993) SMB and HML (which are related with firm size and book-to-market, respectively), Carhart's (1997) MMNT (which is related with stock return momentum), and FESTD (the standard deviation of earnings forecast errors, which is related with earnings information uncertainty). The estimated models are defined as follows:

$$f^a(\text{MKTRFT}):\ R^a_{pt} - R_{ft} = \alpha_p + \beta_{p1}(R_{mt} - R_{ft}) + \varepsilon_{pt},$$

$$f^a(\text{MKTRFT, SMB, HML}):\ R^a_{pt} - R_{ft} + \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \varepsilon_{pt},$$

$$f^a(\text{MKTRFT, SMB}):\ R^a_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{4p}\text{SMB}_t + \varepsilon_{pt},$$

$$f^a(\text{MKTRFT, MMNT}):\ R^a_{pt} - R_{ft} = \alpha_p + \beta_{p1}(R_{mt} - R_{ft}) + \beta_{4p}\text{MMNT}_t + \varepsilon_{pt},$$

$$f^a(\text{MKTRFT, SMB, HML, MMNT}):\ R^a_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{3p}\text{HML}_t + \beta_{4p}\text{MMNT}_t + \varepsilon_{pt},$$

$$f^a(\text{MKTRFT, SMB, MMNT}):\ R^a_{pt} - R_{ft} = \alpha_p + \beta_{1p}(R_{mt} - R_{ft}) + \beta_{2p}\text{SMB}_t + \beta_{4p}\text{MMNT}_t + \varepsilon_{pt}.$$

R^a_{pt} is the tax loss selling effect–adjusted returns, which are calculated as the return on the size-sorted portfolios minus the demeaned return on the tax loss selling proxy portfolio in which stocks are contained. Only January returns are adjusted. Numbers in parentheses indicate *t*-statistics of average residual returns. P1–P10 is the difference between the average residual returns of portfolio 1 and portfolio 10.

VI. Concluding Remarks

In order to provide a risk-based rational explanation for the seasonal regularity of January in stock returns, I construct a common risk factor related to information uncertainty caused by *earnings volatility* (FESTD factor) and suggest a two-factor model containing the market risk factor and this common factor. FESTD is measured by the standard deviation of the earnings forecasting errors, which I use as a proxy for the earnings information uncertainty. FESTD is at its heart a measure of earnings volatility. It is natural, therefore, to consider that FESTD could be some type of proxy for earnings quality or speculation. By using Standard and Poor's stock quality rating data, I have found that among the considered risk factors, only FESTD is sensitive to the degree of the quality rating.

When this two-factor model is used, there is a significant improvement in explaining the January effect. Specifically, with the adjustment of raw returns for risk by using this two-factor model, the systematic pattern in the residual returns (and the abnormal returns) across firm size disappears. In particular, the residual return in January on the smallest-size portfolio is not significant. Furthermore, the arbitrage residual return in January, which is the difference in the average residual returns between the smallest- and the largest-size portfolios, also is not significant.

In order to investigate whether FESTD is a priced risk factor, I have estimated the cross-sectional relationship between average returns and the factor loadings or betas on the risk factors using Fama-MacBeth's (1973) two-pass estimation methodology. I have found that the factor loadings or betas on FESTD have an economically and statistically significant explanatory power for average stock returns and dominate the factor loadings on the other risk factors in explaining the cross section of stock returns in January. The fact that the FESTD factor explains the January effect fairly well indicates that large returns in January might be a risk premium for taking information uncertainty risk concerning earnings and unexpected earnings surprises faced at the earnings announcement.

Several simple tests for the tax loss selling hypothesis are also performed. After I adjust raw returns for the tax loss selling effect, the systematic pattern in stock returns across firm size and the average return in January are all still economically and statistically significant. Even when raw returns are first adjusted for the tax loss selling effect and then adjusted again for risk by using the well-known factor models (such as the single-factor market model and Fama and French's [1993] three-factor model), I still find a prominent negative association between the residual returns and firm size and the significant residual return in January on the smallest-size portfolio. Without the inclusion of the FESTD risk factor, the previously known risk factor models and the tax loss selling hypotheses have failed to explain the January effect.

The findings that FESTD, a proxy for earnings volatility risk, earnings quality, or speculation, explains well January returns indicate that January may be a month that potentially tends to differentially reward "low-quality" or "speculative" stocks. It could be argued, on the basis of the findings of this paper, that the previously found strong January seasonality in stock returns might result from the use of misspecified models in adjusting for risk.

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