

Value-at-Risk: An Analysis of January and Non-January Returns

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In this study, we examine the relationship between a cross-section of realized equity returns and a value-at-risk (VaR) measure. Although we find that the measure of VaR is consistent across time, we find that the relationship between VaR and cross-sectional returns varies across time. Specifically, we find that the relationship between VaR and cross-sectional returns is much stronger in the month of January than in the remainder of the year. We make the conjecture that the seasonality in the relationship between VaR and returns is consistent with the tax-loss-selling hypothesis.

Introduction

For decades, documented evidence has exhibited abnormally high stock returns during the month of January, compared to the remainder of the year (e.g., Wachtel, 1942; Basu, 1983; Kiem, 1983). Further, Haug and Hirshchy (2006) report that the January effect continues to exist in small-cap stocks. Motivated by the continued presence of the January effect and the inability of financial theory to explain the differing risk-return relationship when comparing January and non-January months, we investigate the January effect relative to a downside risk measure, value-at-risk (VaR). Our main contribution is the examination of the seasonality in the relationship between VaR and the cross-section of security returns, particularly the month of January.

We find that VaR is related negatively to equity returns for both January and non-January months; however, the relationship between VaR and returns is much stronger in January than in the remainder of the year. We also find that the relationship between VaR and returns remains significant after traditional control variables are included in our primary regression model.

Background and Literature Review

As a risk measure commonly used by financial institutions, VaR can be defined as the expected loss of a financial asset, or portfolio of assets, over a given time period at a given confidence level. As presented by Jorion (2001), VaR was developed in response to financial debacles of the 1990s (such as Orange County, Barings Bank, and Metallgesellschaft, to name a few). VaR currently is used by financial institutions to measure their maximum downside exposure, ensuring that the institutions maintain a sufficient level of capital in the event that the expected maximum exposure is realized. Many regulatory agencies, including the Basel Committee on Banking Supervision and the U.S. Federal Reserve Bank, require the use of VaR to determine capital adequacy levels. Although many of the financial debacles of the 1990s involved derivative securities, VaR has the flexibility of being applied to a number of other financial situations. Institutional investors find VaR useful in developing hedging strategies, while individual investors, who are concerned about the maximum loss exposure on a specific stock (i.e., downside risk) find VaR useful because it is not subject to some of the estimation issues associated with measures such as beta (e.g., use of market proxy and normal return distribution).

Since Fama and French (1992) began reporting the insignificance of beta in explaining cross-sectional returns, researchers have investigated potential explanations for this finding and analyzed alternative estimations of beta. Howton and Peterson (1998) report that bull- and bear-market betas are related significantly to returns. Closer examination reveals that bear-market betas are not significant in January. They find that returns in January, in their sample period spanning from July 1977 to June 1994, are different than returns in non-January months when controlling for firm size, ratio of book-to-market value of equity, earnings yield, and negative earnings.

Tinic and West (1984) find that the relationship between systematic risk (beta) and return is inconsistent across months. Pettengill, Sundaram, and Mathur (1995) postulate that the relationship between realized returns and beta is conditional upon market excess returns. They argue that, because the return of the market is expected to be greater than the risk free rate of return, a positive relationship between beta and expected returns is always predicted. The authors argue, however, that when the market excess return is negative, the relationship between beta and returns is reversed. Consistent with their argument, they find that during periods of negative excess market returns, a negative relationship exists between realized returns and beta. The results of their study confirm that, after accounting for expectations, they find a significant and consistent relationship between beta and returns. Similarly, we find that the relationship between VaR and returns is consistently negative for January and non-January months alike.

Empirical investigations of the capital asset pricing model, such as Fama and MacBeth (1973), incorporate a portfolio-based methodology to reduce the measurement error problem associated with calculating beta. The formation of portfolios serves as an appropriate method to reduce the errors-in-variables problem; however, this approach does not address the issues outlined by Roll (1977). Specifically, Roll (1977) states that in addition to the problem of identifying and measuring the true market index, the calculation of beta requires that returns are distributed normally and that the relationship between the market index and the individual stock remains stable over time.

In an effort to avoid the beta measurement problem, we study an alternative risk measure, VaR. VaR is a measure of the largest expected loss, given a specific time horizon and a degree of confidence. Similar to Bali and Cakici (2004), our calculation of VaR is not dependent on knowing the distribution of each firm's return. In our study, we follow Bali and Cakici's (2004) method of calculating VaR. Based on their findings, we define the lowest return in the prior 11 months as a proxy for the 10 percent VaR for each observation (actually, our VaR is closer to a 9 percent VaR with a 91 percent confidence level). Because we are examining the January effect, we use an 11-month estimation period to avoid confounding the current year's January return with the prior year's January return. Because VaR is not subject to the same assumptions as the calculation of beta, formation of portfolios is unnecessary in our study.¹

Bali and Cakici (2004) investigate VaR for time horizons of one month, with confidence levels of 99 percent, 95 percent, and 90 percent. Because most estimates of return VaRs are negative, they define VaR as negative 1 multiplied by the maximum loss, for the given time horizon and confidence level. They report that the coefficients on their cross-sectional regressions of individual stock returns on VaR are positive. Thus, as one would expect, the greater the potential for loss (higher values of the variable VaR times negative 1), the greater the expected return. Their results are pervasive across the three levels of confidence. Based on the consistency of their results with respect to differing confidence levels, we proceed using a 10 percent VaR in investigating the relationship between VaR and the January effect.

Empirical Questions

Based on the mixed results of prior research related to the January effect, weak evidence of tax-loss selling, the inability of traditional measures of beta to explain realized returns, and the development of VaR as an alternative risk measure, we address the following research questions:

¹The primary measure of VaR used in this study is a downside risk measure and not a measure of systematic risk. We also investigate a market-adjusted measure of VaR and find qualitatively similar results.

1. Is the level of risk as measured by VaR consistent across January and non-January months?
2. Is there a significant relationship between VaR and cross-sectional stock returns?
3. Is there seasonality in the relationship between VaR and cross-sectional stock returns?

Data and Methodology

Our initial sample consists of firms belonging to the Standard & Poor's Super Composite Index, S&P 1500, over the 1985-2003 sample period. The S&P 1500 comprises firms in the S&P 500, S&P 600, and S&P 400. We exclude firms from the financial services industry. After removing observations with missing data values, the final data set contains 217,597 observations over the 228 month sample period. All return and financial data are from Compustat. We reduce the impact of survivorship bias in our sample by including all observations with data. Specifically, we do not exclude an observation because the firm does not have data over the entire 1985-2003 sample period. This results in an unbalanced panel; however, we find similar results for our primary analysis even when we perform the analysis on a balanced panel of the 379 firms that have data for each of the 228 months included in our sample period. All firm-specific annual data is from the prior year's annual report in order to avoid a look-ahead bias.

Using the following model, we investigate the relationship between VaR and the stock returns of individual firms:

$$R_{it} = \gamma_0 + \gamma_1 \ln(1 + \text{VaR}_{it}) + \varepsilon_{it}$$

where:

VaR_{it} = Value-at-Risk for security i in month t (calculated as the lowest return value over the previous 11 months in decimal form).²

Empirical Results: Descriptive Statistics and Univariate Analysis

Table 1 presents descriptive statistics of the key variables used in our study. Panel A contains statistics for the whole sample (all months of the year), Panel B contains statistics for the January subsample, and Panel C contains statistics for the non-January subsample of the data. The left column of statistics in Table 1 displays the descriptive statistics for the entire sample (or subsample for Panel B and Panel C), and the five columns on the right display descriptive statistics for various VaR quintiles of the sample or subsample. For the entire sample, as shown in Panel A, the

²In our analysis we found a possible nonlinear relationship between VaR and stock returns. We correct for this problem by taking the log of $(1+\text{VaR})$. An alternative analysis using VaR produced similar results.

average monthly return is 1.85 percent with a standard deviation of 13.25 percent. The average VaR is -15.96 percent (i.e., $1 + \text{VaR}$ is 0.8404) with a standard deviation of 10.53 percent.

Table 1—Univariate Analysis of Variables Used in Analysis for the Total Sample and for VaR Quintiles over the 1985 to 2003 Sample Period

Variable ^a		Total Sample	VaR Quintiles				
			Low VaR	2	3	4	High VaR
Panel A: Descriptive Statistics for January through December							
N		217,597	43,572	43,491	43,490	43,484	43,560
R _{it}	μ	1.8474	2.6992	1.9490	1.6184	1.5014	1.4682
	σ	13.2487	18.9486	14.0237	11.8509	10.0148	8.9413
ln(1+VaR _{it})	μ	-0.1832	-0.4058	-0.2134	-0.1460	-0.1006	-0.0501
	σ	0.1440	0.1588	0.02531	0.0151	0.0122	0.0309
(1+VaR _{it})	μ	0.8404	0.6736	0.8081	0.8643	0.9044	0.9516
	σ	0.1053	0.0876	0.0204	0.0130	0.0111	0.0340
Panel B: Descriptive Statistics for January only							
N		18,041	3,663	3,601	3,520	3,563	3,694
January, R _{it}	μ	3.0048	5.6584	2.9629	2.4439	2.3222	1.6073
	σ	14.4878	21.0705	15.1820	12.4284	10.8307	9.5065
January, ln(1+VaR _{it})	μ	-0.1839	-0.4088	-0.2140	-0.1458	-0.1006	-0.0482
	σ	0.1465	0.1589	0.0255	0.0151	0.0122	0.0346
January, (1+VaR _{it})	μ	0.8401	0.6718	0.8076	0.8644	0.9044	0.9536
	σ	0.1075	0.0888	0.0205	0.0130	0.0110	0.0373
Panel C: Descriptive Statistics for Non-January months (February through December)							
N		199,556	39,909	39,890	39,970	39,921	39,866
R _{it}	μ	1.7428	2.4276	1.8575	1.5456	1.4281	1.4553
	σ	13.1259	18.7187	13.9110	11.7961	9.9356	8.8871
ln(1+VaR _{it})	μ	-0.1832	-0.4056	-0.2133	-0.1460	-0.1006	-0.0503
	σ	0.1438	0.1588	0.0253	0.0151	0.0122	0.0305
(1+VaR _{it})	μ	0.8404	0.6738	0.8081	0.8643	0.9044	0.9514
	σ	0.1051	0.0875	0.0204	0.0130	0.0111	0.0336

R_{it} is the monthly return adjusted for dividends for security i for month t

$\ln(1 + \text{VaR}_{it})$ is the natural logarithm of $1 +$ the lowest return of the prior 11 months for security i for month t

^a the top number is the mean and the bottom number is the standard deviation

Empirical Results: VaR Quintiles

Partitioning the sample into quintiles based on VaR reveals several interesting characteristics. Like Bali and Cakici (2004), our results indicate that the quintile with the lowest value of VaR (i.e., highest expected loss exposure) has the highest average return. Furthermore, the returns associated with the VaR quintiles decline nearly monotonically for all three subsamples.³

³The only exception is that when moving from the fourth to the fifth VaR quintile in the non-January subsample, the mean of returns increases slightly from 1.43 to 1.46 percent (Panel C of Table 1).

In Panel A of Table 1, we find that average return decreases monotonically from 2.70 percent for the lowest VaR (greatest loss exposure) quintile to 1.47 percent for the highest VaR (smallest loss exposure) quintile. Similarly, the standard deviation of returns for each quintile decreases monotonically from 18.95 percent for the lowest VaR quintile to 8.94 percent for the highest VaR quintile. Therefore, it appears as though quintiles with higher loss exposure (i.e., lower values of VaR) are characterized by higher returns and greater volatility. To test the significance of the differences in returns across months and various VaR quintiles, we compare the means of the lowest VaR quintile to the other four quintiles, as shown in Panel D of Table 1.⁴ The low VaR quintile has a significantly higher average return than the other VaR quintiles, i.e., 2.70 percent and 1.63 percent, respectively.

Empirical Results: January Effect and VaR

In Panel B of Table 1, we report that the average January return for the lowest VaR quintile is 5.66 percent, and the average for the highest VaR quintile's is 1.61 percent. An inspection of the relationship across the VaR quintiles reveals that, for the January subsample, both the average return and the average standard deviation of returns decrease monotonically as VaR increases. In addition, as shown in Panel C of Table 1, with the exception of the highest VaR quintile, a monotonically decreasing relationship across the VaR quintiles and the current month's return measure is found when examining the non-January subsample of firms.

In Panel D of Table 1 we employ a t-test to test for differences in means between various subsamples. As shown in Panel D, we document the presence of a January effect in our sample. Specifically, the average January return of 3.00 percent is significantly higher than the average non-January return of 1.74 percent. Panel D of Table 1 also shows that there appears to be no difference between the means of VaR when comparing January to the remainder of the year. That is, we do not find any evidence of seasonality in our measure of VaR. Thus, it appears that the presence of a January effect is not due to changing levels of downside risk, as measured by VaR. Therefore, it appears as though the January effect is not due to seasonality in downside risk, as measured by VaR.

Empirical Results: Primary Analysis

Panel A of Table 2 reports our investigation of the relationship between our proxy for a 10 percent VaR variable and the monthly returns in our sample. Consis-

⁴Although not reported, we find other measures of risk and return produce similar results. For example, the excess return over the market also decreases monotonically across VaR quintiles. Likewise, a standardized measure of excess return, defined as the excess return over the market standardized by $(1+VaR)$, also is consistent with positive risk return tradeoff. We also find that the low VaR quintile's average beta is statistically different from the other quintiles, which is consistent with the positive risk return trade-off.

tent with the results of Bali and Cakici (2004), the negative coefficient for the $(1+VaR)$ variable confirms our univariate findings, suggesting that as the potential for loss (low values of VaR) increases, so does the potential for greater stock returns.^{5,6}

Table 1 (cont.)—Univariate Analysis of Variables Used in Analysis for the Total Sample and for VaR Quintiles over the 1985 to 2003 Sample Period

		January minus Non-January			Low VaR minus Non-Low VaR		
	^a	February					
Variable	μ σ	January Only	through December	Difference (t-statistic)	Low VaR	Non-Low VaR	Difference (t-statistic)
Panel D: T-test of Mean Differences for Total Sample							
N		18,041	199,556		43,572	174,025	
R_{it}	μ	3.0048	1.7428	1.2620***	μ 2.6992	1.6342	1.0650***
	σ	14.4878	13.1259	(11.289)	σ 18.9486	11.3733	(11.236)
$\ln(1+VaR_{it})$	μ	-0.1839	-0.1832	-0.007	μ -0.4058	-0.1275	-0.2784***
	σ	0.1465	0.1438	(-0.645)	σ 0.1588	0.0640	(358.725)
$(1+VaR_{it})$	μ	0.8401	0.8404	-0.0003	μ 0.6736	0.8821	-0.2085***
	σ	0.1075	0.1051	(-0.332)	σ 0.0876	0.0570	(-472.650)

R_{it} is the monthly return adjusted for dividends for security i for month t

$\ln(1+VaR_{it})$ is the natural logarithm of $1 +$ the lowest return of the prior 11 months for security i for month t

^a the top number is the mean and the bottom number is the standard deviation

* Significant at the 10 percent level

** Significant at the 5 percent level

*** Significant at the 1 percent level

In Panels B and C of Table 2, we test the possibility of seasonality in the risk return relationship by separating January returns from non-January returns. By dividing the sample into January and non-January months, we are able to utilize a Chow test to test for differences in model structure between the two subsamples. Although not reported, this test statistic leads us to conclude that there is a difference in model structure when comparing January to non-January months; therefore, the relationship between VaR and stock returns is not consistent across the different months of the year.

⁵We test the functional form of the relationship by including both a squared and a natural log transformation of our measure of VaR. The combination of better fit and model simplicity leads us to choose the natural log of $(1+VaR)$ as our independent variable. By taking the natural log of $(1+VaR)$, we are able to limit the influence of extreme values of VaR.

⁶Tests of model specification find that our regression models violate the assumption of homoskedasticity. We correct for this problem by computing a heteroskedastic-consistent covariance matrix, which allows us to test the significance of each coefficient by using a chi-square test. Our large sample size allows us to convert the chi-square to an approximate Z-score, which we report in the tables.

Table 2—Cross-sectional Regressions of Monthly Individual Stock Returns on VaR Measure from 1985 to 2003 for All Months, January, and Non-January for the Model:
 $R_{it} = \gamma_0 + \gamma_1 \ln(1 + \text{VaR}_{it}) + \varepsilon_{it}$ (approximate z in parentheses)

Constant	Coefficient for $\ln(1+\text{VaR}_{it})$
Panel A: 217,597 Monthly Returns for January through December	
1.165*** (25.360)	-3.727*** (-12.071)
Panel B: 18,041 Monthly Returns for January	
1.127*** (6.543)	-10.212*** (-8.660)
Panel C: 199,556 Monthly Returns for February to December	
1.172*** (24.650)	-3.114*** (-9.787)

R_{it} is the monthly return adjusted for dividends for security i for month t
 $\ln(1+\text{VaR}_{it})$ is the natural logarithm of 1 + the lowest return of the prior 11 months for security i for month t

* Significant at the 10 percent level

** Significant at the 5 percent level

*** Significant at the 1 percent level

Like Tinic and West (1984), who find seasonality between risk (measured by beta) and return, we find that, when using VaR as a measure of risk, there appears to be seasonality present in the relationship between downside risk (measured by VaR) and return. Specifically, the slope coefficient of our VaR measure, i.e., $\ln(1+\text{VaR})$, for January returns is more than three times the slope coefficient for non-January returns t (-10.212 compared to -3.114), indicating a more potent relationship between VaR and January returns. Therefore, although the *measure* of VaR is not subject to any form of seasonality, the *relationship* between VaR and stock returns does exhibit a pronounced seasonality.

The seasonality in the relationship between VaR and returns is consistent with the tax-loss-selling hypothesis. Investors who seek to minimize their tax liabilities by selling poorly performing stocks at the end of the year depress the prices of these poorly performing stocks. Then, at the turn of the year, investors reestablish their positions, leading to a price appreciation in the previously poor performing stocks. Stocks with low VaR values are most likely prime candidates for tax-loss-selling, as such stocks have experienced larger negative monthly returns throughout the year. Thus, investors who wish to realize tax losses sell low VaR stocks, most likely at the end of the year. Then, as discussed above, investors reestablish their positions in low VaR stocks at the turn of the year, leading to upward price pressure which then leads to a January effect. Although our results indicate that investors face the same level of

downside risk throughout the year, due to the structure of U.S. tax laws, investors seem to be better compensated for downside risk in the month of January.⁷

Empirical Results: Robustness Tests

The models reported in Table 2 do not control for firm size. We test for the robustness of the primary model results by forming size quartiles. Although not reported, the negative coefficient for VaR remains significant across all size quartiles, indicating that our primary model results are robust to differences in size.⁸

Since the seminal work by Fama and French (1992), most investigations of stock returns have included the firm-specific variables for market value of equity, ratio of book-to-market value of equity, earnings yield, and a dichotomous variable accounting for firms with negative earnings. In addition to our VaR measure, we include these four variables in our analysis. The coefficients for these models confirm the negative relationship between our VaR measure and January returns.⁹ Therefore, our primary results are robust, even after control variables are included in the analysis.

Conclusions

We extend the work of Bali and Cakici (2004), whose calculation of the VaR measure is not dependent on a return distribution or market proxy. We find that the negative relationship between VaR and returns remains significant even after controlling for firm size, ratio of book-to-market value, and earnings. Although we find that our VaR *measure* is consistent across time, we report that the *relationship* between VaR and equity returns is not consistent across time. Specifically, we document seasonality in the relationship between VaR and monthly returns, with the relationship between returns and VaR becoming more potent in the month of January.

⁷Haug and Hirschey (2006) find that small cap firms with negative returns in the prior year have high January returns, while small cap firms with positive returns do not have superior January returns. Griffin, Ji, and Martin (2005) find that a strategy of shorting losers and buying winners produces negative returns in January for U.S. markets. Our finding of a stronger relationship between VaR in the month of January is consistent with the findings of Griffin, Ji, and Martin (2005).

⁸The impact of firm size has been well documented in the literature. As such, we examine the impact of size on our findings by forming size quartiles. We form size quartiles each year by using the December market value of equity. In addition, we include firm size as an additional variable in our primary model as part of our robustness analysis. We also find similar results for our primary analysis when we perform the analysis on the 379 firms that have data for each of the 228 months.

⁹We also control for variables from the Fama and French (1992) study. First, in all models, we find that firm size is negatively related to cross-sectional returns. Second, we find a positive relationship between the ratio of book value-to-market value of equity and returns. Third, like Jaffe, Keim and Westerfield (1989), we find a positive relationship between earnings' yield and returns.

Although the level of downside risk appears to be constant through time, investors seem to be better compensated for risk in the month of January, as shown by the differing coefficient estimates of VaR when comparing January to non-January months. We make the conjecture that the seasonality in the relationship between VaR and returns is consistent with the tax-loss-selling hypothesis. Specifically, investors sell losers (firms with lower values of VaR) to capture tax losses. Then, at the turn of the year, investors buy back former losers, leading to upward price pressures (i.e., a January effect). Consistent with this hypothesis, we find that for former losers (firms with lower values of VaR), the relationship between VaR and returns is stronger (more negative) in the month of January than it is in the remainder of the year.

Our robustness tests employ multivariate models that include the control variables found to be significant by Fama and French (1992) and others. We find that the negative relationship between VaR and returns is robust across all models. Substituting risk adjusted return measures for the dependent variable produces similar results.

Our paper contributes to the literature by confirming and extending the analysis of the relationship between VaR and stock returns, found in Bali and Cakici (2004), by testing for seasonality in both VaR and the relationship between VaR and returns. Most importantly, we find that our firm-specific measure, VaR, is related significantly to future returns, with this relationship becoming much stronger in the month of January.

The implications of our finding is that VaR is a possible proxy for tax loss selling that is priced because of potential tax benefits. Based upon the results of our study, we concur with Bali and Cakici (2004) that future research on alternative optimal selection models warrants including VaR measures. The conclusions from behavioral finance literature and the lack of empirical evidence supporting the mean-variance approach also point in this direction.

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