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Weaknesses of the Indicator Variable Approach in Short-term Event Studies

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ABSTRACT

Savickas [2003, *Journal of Financial Research* 26 (2), 165-178] proposes a new method - an indicator variable approach for testing abnormal returns in short-term event studies and finds the superiority of this approach over seminal methods (i.e., the parametric standardized cross-sectional approach of Boehmer, Musumeci, and Poulsen, 1991; the nonparametric approach of Corrado, 1989) in terms of test power. Through large-scale simulations of several variations of the GARCH models, we find that when an indicator variable is included in the conditional mean portion of the model, the increased power observed is due to the fact that an overall event hypothesis is being tested. This overall event test has little ability to detect event effects on different days in the event window. Neither does the indicator variable in the conditional variance portion of the model have much effect on the test power. The indicator variable approach needs to be carefully applied and interpreted for future event studies.

JEL Classification: *G14, C15, C52*

Keywords: *Event Study; Indicator Variable; Test Power; Stock Returns; Test Statistic; GARCH; Simulation*

I. INTRODUCTION

Researchers in traditional event study methodologies often assume an insignificant event-induced volatility. Brown and Warner (1985) recognize that violations of such assumptions could lead to an inflated Type I error rate and less power in tests. Since then, researchers have proposed various ways to handle the event-induced volatility (i.e., Corrado 1989; Boehmer, Musumeci, and Poulsen 1991; Savickas 2003; Harrinton and Shrider 2007; Bremer and Zhang 2007).

Corrado (1989) proposes the seminal rank test for an individual-day event window that is more powerful than previous parametric methods. Boehmer, Musumeci, and Poulsen (BMP, 1991) propose the seminal parametric standardized cross-sectional test that allows non-constant variance across securities and for each security between the estimation and the event windows. However, they implicitly assume the event-induced volatility for a given security is constant over the event window.

Savickas (2003) proposes a new parametric indicator variable approach that allows an individual security's event-induced volatility to vary over the event window. He finds that the proposed test is more powerful than the individual event day tests of BMP (1991) and Corrado (1989).

In this paper, we present major weaknesses of the test proposed by Savickas (2003). The use of indicator variables in the conditional mean and conditional variance portions of a market model will be investigated separately as well as jointly. Robustness properties of the resulting tests will be investigated for event patterns where the event effect is not the same for each day in the event window.

The ability to detect whether there is an event effect on each day separately within the event window is fundamental to event study methodology. The effect of an event may not be immediate or it may be temporary (i.e., Brown, Harlow, and Tinic, 1993; Ross, 1989). Methods that work correctly only under the assumption that the event has the same (mean) effect on each day within the event window are not adequate.

The proposed approach by Savickas (2003) is found to have very weak robustness properties with respect to more challenging conditional mean and/or conditional variance structures. The tests by Savickas (2003) for each day within the event window are essentially the same test of an overall event effect on at least one day within the event window. This fact accounts for the observed increase in power but also results in poor robustness properties when different mean and variance structures are present over different event days.

The paper proceeds as follows. In the next section, we provide the test statistics. In section III, we discuss the simulation design. Section IV presents the simulation results. We conclude in section V.

II. TEST STATISTICS

In the following discussions, we assume that for each security, i, for which the event has occurred, the time series of returns is measured for Q days, where T of the values are measured before the event date (the estimation window) and Q-T of the values are measured thereafter (the event window)[1]. The market model to be considered is

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \gamma_i \cdot D \cdot I_m + \eta_{i,t}, \tag{1}$$

$$\eta_{i,t} = \sqrt{h_{i,t}} \cdot e_{i,t}, \tag{2}$$

$$h_{i,t} = a_i + \sum_{j=1}^{p} b_{i,j} \cdot h_{i,t-j} + \sum_{k=1}^{q} c_{i,k} \cdot \eta_{i,t-k}^2 + d_i \cdot D \cdot I_v, \tag{3}$$

$$D = \begin{cases} 0, & t < T+1 \\ 1, & t \geq T+1 \end{cases}. \tag{4}$$

Here I_m (0 or 1) and I_v (0 or 1) are dummy variables of whether the indicator variable D is in the mean and/or the variance portion of the model, respectively. All four combinations of I_m and I_v equaling 0 and 1 will be considered. The conditional variance portion of the market model will be investigated without a GARCH structure first and then with a GARCH (1,1) structure. The standardized cross-sectional method of BMP (1991) and Savickas (2003) method are special cases of this model. The test statistic is

$$t = \frac{\frac{1}{N}\sum_{i=1}^{N} S_{i,t}}{(\hat{\sigma}_S)_t / \sqrt{N}}, \tag{5}$$

where

$$(\hat{\sigma}_S)_t = \sqrt{\frac{1}{N-1}\sum_{i}^{N}\left(S_{i,t} - \frac{1}{N}\sum_{i=1}^{N} S_{i,t}\right)^2}, \tag{6}$$

$$S_{i,t} = \begin{cases} \dfrac{A_{i,t}}{\sqrt{\hat{h}_{i,t}}}, & I_m = 0 \\ \dfrac{\hat{\gamma}_i}{\sqrt{\hat{h}_{i,t}}}, & I_m = 1 \end{cases}. \tag{7}$$

The abnormal returns in the event window are calculated as

$$A_{i,t} = R_{i,t} - \hat{R}_{i,t}, \; t = T+1, \ldots, Q. \tag{8}$$

When $I_m = 1$ and $I_v = 1$ (the Savickas model) or when $I_m = 1$ and $I_v = 0$, estimation of the parameters of the conditional mean and variance portions of the model is performed using data from both the estimation and the event windows. The indicator variable in the mean portion of the market model will capture the event effect and the indicator in the GARCH portion of the model will capture the changes in the mean structure on different days within the event window.

When $I_m = 0$ and $I_v = 0$, the model estimation is performed using data only in the estimation window from which abnormal returns and conditional variances within the event window are determined. When no GARCH is present, the model becomes that of BMP (1991).

The case $I_m = 0$ and $I_v = 1$ is an extension of the BMP (1991) method which includes an indicator variable and potentially a GARCH structure in the conditional variance portion of the market model.[2] The abnormal return is obtained separately for each day within the event window; consistent with the BMP (1991) method. However, the one-stage estimation method used for the $I_m = 1$ ($I_v = 0$ or 1) cases is no longer reasonable here: since the conditional mean portion of the market model will remove much if not all of the event information from the abnormal return estimates if estimation is performed using the data in both the estimation and the event windows. In order for the indicator variable in the conditional variance portion of the model to have an effect, the data in both the estimation and the event windows must be used. To accommodate these conflicting requirements, a two-stage estimation method is used. In the first stage, all parameters of the model are estimated using the data in the estimation window only. Based on this estimated model the abnormal returns are calculated for the event window as in the BMP (1991) method (except a GARCH model may be used to model the conditional variances). In the second stage, the parameters of the model are re-estimated using data in both the estimation and the event window from which the conditional variance estimates within the event window are obtained. The test statistic is calculated using[3]

$$S_{i,t} = \frac{A_{i,t}}{\sqrt{\hat{h}_{i,t}}}. \tag{9}$$

A. Overall Event Effect versus Individual Event Day Effect

In event studies, multiple days are often investigated since the event effect might be different on different days within the event window. In the discussion here and in the simulation below, there are 250 consecutive days of returns, the estimation window contains the first 245 days while the event window the last 5 days. Let μ_{246}, μ_{247}, …, μ_{250} be the true mean abnormal return for all securities affected by the event for the first, second, …, fifth day within the event window. The classical tests to study an event effect investigate the hypotheses:

$$H_0 : \mu_t = 0, t = 246, 247, \cdots, 250. \tag{10}$$

When the indicator variable is added to the conditional mean portion of the market model (1), that is $I_m = 1$ ($I_v = 0$ or 1), then the null hypotheses in (10) are turned into the common hypothesis[4]

$$H_0 : \mu = \sum_{t=246}^{250} \mu_t / 5 = 0 \tag{11}$$

for each day within the event window. The power of the test of (11) is greater than that of the tests of (10). The increased power, in this case, is a result of the fact that μ is estimated from five times as much data as an individual μ_t; the use of more data results in a smaller standard error.

In Savickas (2003), the estimate of γ_i in (1) represents the overall event window effect for a given security and is an estimate of μ in (11).[5] In his paper, the estimate of μ is then standardized by the conditional standard deviation estimated separately for each security and for each day within the event window. A t-test is then performed on these standardized estimates of μ. Standardizing the γ_i estimate with different conditional standard deviation estimates on each day within the event window does not change the fact that γ_i is an estimate of μ, thus hypothesis (11) is being tested on each day within the event window with the increased power associated with an overall event test. Savickas (2003) claims that the power increase come from standardization with the conditional standard deviation after including the indicator in the conditional mean portion of the model. The discussion above and the simulations in Section III and findings in Section IV demonstrate that the increased power is a result of performing a test of (11) instead of (10), not a result of the standardization process.

III. SIMULATION DESIGN

The Center for Research in Security Prices (CRSP) Daily Return File from 1962 to the end of 2003 is used to generate 300 portfolios (runs) of 50 randomly sampled securities. A time series of 250 consecutive days of returns is randomly chosen for each randomly selected security, and these returns are matched with the CRSP equally-weighted index.[6] The estimation window contains the first 245 days and the event window includes the last 5 days. No missing values are allowed in the 250 consecutive returns and no more than 40 zero returns are allowed.[7]

We investigate the following factors in the simulation:

1. *Whether to Include an Indicator Variable in the Conditional Mean Portion of the Market Model*: $I_m = 1$ (Y_m) or $I_m = 0$ (N_m).
2. *Whether to Include an Indicator Variable in the Conditional Variance Portion of the Market Model*: $I_v = 1$ (Y_v) or $I_v = 0$ (N_v).
3. *Whether to Include a GARCH Structure*: G = 0 (No GARCH) and G = 1 (GARCH (1,1)).
4. *The Event Effect on the Mean (volatility):* An event can affect both the mean and volatility structure of returns. The mean (volatility) effect structure will be an additive (multiple) increase in the return (see equation (12)). The mean magnitudes (MM) and volatility magnitudes (VM) of the event effect = 0, low = 1, medium = 3, and high = 5 (see Table 1). The induced mean structures (IMS) and induced volatility structures (IVS) investigated are: (1) the IMS (IVS) level 1, which presents a permanent effect; (2) the IMS (IVS) level 2, which shows effects only on certain days in the event window; and (3) the IMS (IVS) level 3, which has a decreasing effect with event magnitudes ranging from high to low (see Figure 1).

Table 1

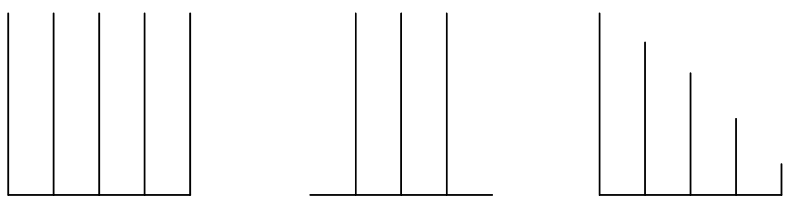
Magnitudes of simulated event and volatility effects

The M_{lower}, M_{upper}, V_{lower} and V_{upper} are the magnitude of the simulated mean effects and volatility effects.

Magnitude	M_{lower}	M_{upper}	V_{lower}	V_{upper}
1 (low)	0	1%	1	1.5
2	0.25%	1.25%	1.25	1.75
3 (medium)	0.5%	1.5%	1.5	2.00
4	0.75%	1.75%	1.75	2.25
5 (High)	1%	2%	2.00	2.50

Figure 1

Induced mean structures (IMS) and induced volatility structures (IVS)



1 2 3

The event can result in effects on the mean structure of returns and on the variance structure of the returns. The IMS (or the IVS) level 1 shows a permanent and constant effect in the event window. The IMS (or the IVS) level 2 has an identical effect on the second, third and fourth day of the five event days. The IMS (or the IVS) level 3 shows a decreasing effect with event magnitudes ranging from high to low. The IMS (or the IVS) level 1 and 2 vary by only the magnitude while the IMS (or the IVS) level 3 has a fixed set of magnitudes associated with each day within the event window.

Let U_m and U_v be the uniform random variables over the ranges M_{lower} to M_{upper} and V_{lower} and V_{upper}, respectively. The magnitudes of the simulated mean effects (M_{lower}, M_{upper}) and volatility effects (V_{lower}, V_{upper}) are summarized in Table 1. If there is an induced change in both volatility and mean, the transformation

$$R_{i,t}(\text{with event effect}) = U_m + U_v * R_{i,t,} \qquad (12)$$

is used. If there is no event-induced mean effect, $U_m = 0$, and if there is no event-induced volatility, $U_v = 1$.

IV. SIMULATION RESULTS

A. Type I Error and Power Comparisons for the Base Design

In the base design, with constant mean and volatility structure (the IMS and the IVS level 1 in Figure 1) on all event days, the event induces an additive shift in the mean abnormal return of a magnitude of 1, 3 or 5 and a multiple increase in the volatility of a magnitude of 0, 1, 3, or 5. For the base design, Table 2 shows all methods under consideration are well-specified. The Type I error properties of the Savickas method (Ym-Yv) and others are robust to different induced volatility structures.

Table 2
Average type I error rates and power over the five event days
under the base design for different mean and volatility magnitudes.

mm	vm	G	N_m-N_v	Y_m-Y_v	N_m-Y_v	Y_m-N_v
0	1	0	0.037	0.007	0.040	0.035
0	1	1	0.038	0.023	0.040	0.022
0	3	0	0.044	0.014	0.043	0.040
0	3	1	0.043	0.024	0.040	0.029
0	5	0	0.042	0.017	0.046	0.054
0	5	1	0.043	0.035	0.044	0.030
1	0	0	0.292	0.760	0.329	0.847
1	0	1	0.358	0.872	0.349	0.404
1	1	0	0.217	0.630	0.245	0.693
1	1	1	0.274	0.729	0.251	0.352
1	3	0	0.161	0.408	0.175	0.505
1	3	1	0.187	0.499	0.181	0.266
1	5	0	0.134	0.281	0.138	0.396
1	5	1	0.140	0.329	0.138	0.228
3	0	0	0.725	1.000	0.791	1.000
3	0	1	0.813	1.000	0.803	0.694
3	1	0	0.570	0.986	0.623	0.990
3	1	1	0.662	0.996	0.650	0.679
3	3	0	0.379	0.897	0.413	0.951
3	3	1	0.459	0.943	0.434	0.635
3	5	0	0.276	0.760	0.312	0.832
3	5	1	0.328	0.798	0.323	0.576
5	0	0	0.938	1.000	0.974	1.000
5	0	1	0.977	1.000	0.977	0.831
5	1	0	0.841	0.997	0.889	1.000
5	1	1	0.914	1.000	0.908	0.831
5	3	0	0.635	0.997	0.697	0.995
5	3	1	0.724	0.999	0.718	0.805
5	5	0	0.469	0.976	0.508	0.980
5	5	1	0.544	0.977	0.527	0.783

Note: mm and vm indicate mean and volatility magnitude, respectively. G = 0 or 1 indicates no GARCH or GARCH (1,1) is used. N_m-N_v indicates no indicator variable in either the mean or variance portion of the model, Y_m-Y_v (Savickas's method) indicates opposite; N_m-Y_v indicates no indicator variable in the mean portion but an indicator variable in the variance portion of the model, Y_m-N_v indicates the opposite. When G = 0, N_m-N_v indicates the BMP (1991) method.

Table 2 also shows the power of all four methods tested. The inclusion of the indicator variable in the conditional mean portion of the model (Y_m-Y_v or Y_m-N_v) results in an increase in the power as noted by Savickas. The inclusion of the indicator variable only in the conditional variance portion of the model (N_m-Y_v) also results in increases in power relative to the BMP approach (N_m-N_v when no GARCH is used). The overall nature of the tests when the indicator variable is included in the mean portion of the model and the fact that the base design matches the assumptions under which using an indicator variable in the mean portion of the market model are consistent with the observed power increase over the BMP approach claimed by Savickas.

B. Type I Error and Power Comparisons for the IMS Levels 2 and 3

For the IMS level 2, there is an effect on the conditional mean for days 247-249 but no effect on day 246 or 250. The Type I error rates and the power for the different methods under the IMS level 2 are summarized in Table 3 and graphically depicted for the case of mean magnitude size 3 (mm = 3), volatility magnitude size 3 (vm = 3) and no GARCH (G = 0) in Figure 2.

By design, the IMS level 2 has no event effect on day 1 or day 5 within the event window. The methods that include an indicator variable in the mean structure of the market model have Type I errors much larger than the 0.05 level (see the Y_m-Y_v or Y_m-N_v column in Table 3 when mm = 0). The model misspecification is apparent.

As discussed in Section II, a single estimate of the γ parameter is the estimated overall event effect for all days within the event window. When there is an event effect on any day within the event window, the true value for γ will be different from zero. Savickas claims explicitly that when an indicator variable is included in the mean portion of the market model, a separate test is performed for each day within the event window. The results here provide the first indication that essentially a same test is performed on each day in the event window when an indicator is included in the mean portion of the market model. If significance is found for one day, it is very likely to be found for all days. For the IMS level 2, there is no event effect on day 1 or day 5; yet the Type I error is equivalent to the power of the test for days when there is an effect (Ym-Yv or Ym-Nv). This is clearly seen in Figure II for the typical portion of the IMS level 2 graphed. Savickas test is an overall event effect test which accounts for the power increase, it is not an individual event effect test and the test power cannot be compared with that of the BMP (1991) method.

Figure 2 also shows that the other two methods (no indicator in the mean portion of the market model) are well-specified. The model having an indicator only in the variance portion of market model (Nm-Yv) slightly dominates the BMP approach (Nm-Nv and G = 0).

Table 3
Average type I error rates and power over the five event days under the IMS level 2 for different mean and volatility magnitudes.

mm	vm	G	N_m-N_v	Y_m-Y_v	N_m-Y_v	Y_m-N_v
0	0	0	0.040	0.737	0.040	0.795
0	0	1	0.037	0.811	0.034	0.803
0	1	0	0.042	0.639	0.040	0.721
0	1	1	0.040	0.733	0.036	0.718
0	3	0	0.044	0.510	0.042	0.586
0	3	1	0.041	0.567	0.035	0.554
0	5	0	0.049	0.398	0.044	0.452
0	5	1	0.043	0.429	0.036	0.391
3	0	0	0.737	0.870	0.787	0.936
3	0	1	0.809	0.950	0.809	0.219
3	1	0	0.569	0.719	0.630	0.851
3	1	1	0.661	0.861	0.646	0.215
3	3	0	0.385	0.565	0.428	0.614
3	3	1	0.461	0.607	0.451	0.216
3	5	0	0.279	0.401	0.300	0.460
3	5	1	0.326	0.426	0.316	0.210
5	0	0	0.931	0.993	0.974	0.995
5	0	1	0.978	1.000	0.974	0.424
5	1	0	0.852	0.962	0.895	0.985
5	1	1	0.917	0.986	0.907	0.421
5	3	0	0.657	0.839	0.696	0.906
5	3	1	0.716	0.884	0.707	0.401
5	5	0	0.468	0.692	0.524	0.718
5	5	1	0.577	0.715	0.536	0.366

Note: mm and vm indicate mean and volatility magnitude, respectively. G = 0 or 1 indicates no GARCH or GARCH (1,1) is used. N_m-N_v indicates no indicator variable in either the mean or variance portion of the model, Y_m-Y_v (Savickas's method) indicates opposite; N_m-Y_v indicates no indicator variable in the mean portion but an indicator variable in the variance portion of the model, Y_m-N_v indicates the opposite. When G = 0, N_m-N_v indicates the BMP (1991) method.

For the IMS level 2, the induced identical event effect on the mean structure occurs on the second, the third and the fourth day during the event window, but no effect on the first or the fifth day. The Savickas method (Ym-Yv) and its variation (Ym-Nv), represented by the top two lines above, are misleading and have artificially high power even on day one and day five when no induced event effect is present. The BMP method (Nm-Nv, the bottom line) and the method (Nm-Yv) that has an indicator variable only in the variance portion of the model are consistent wuth the underlying IMS level 2 structure.

Figure 2

Type I error and power for different methods for the IMS level 2 for mm = 0 (time = 246 or 250) or mm = 3 (time = 247, 248 or 249), vm = 3 and G = 0.

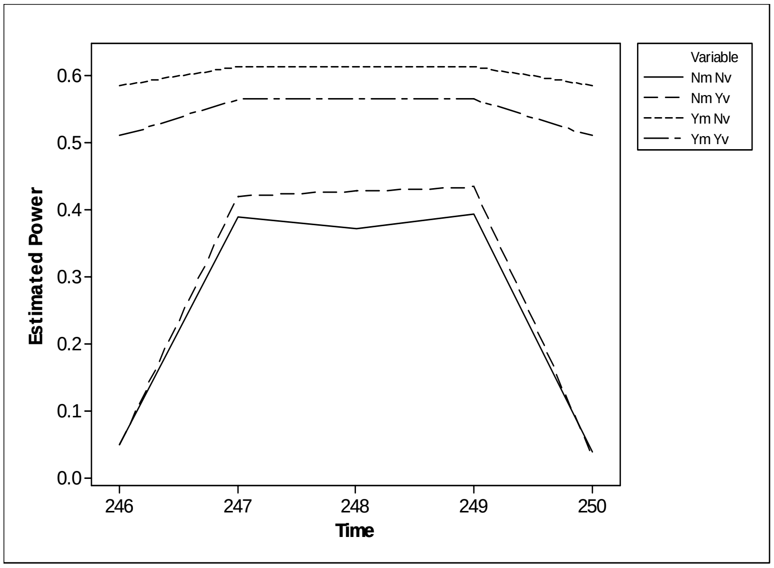
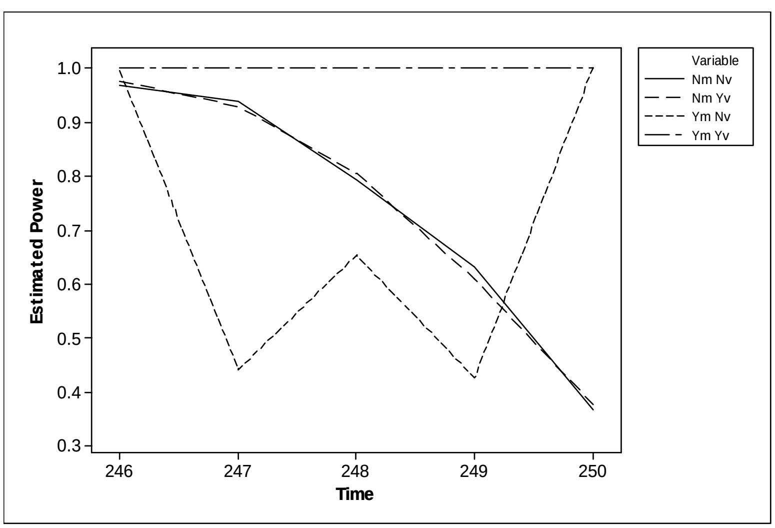


Figure 3

Power for different methods for the IMS level 3, vm = 3 and G = 1.



The power of the different methods for the IMS level 3 is summarized in Table 4 and graphically depicted for vm = 3 and G = 1 in Figure 3. The findings are consistent with those found for the IMS level 2. The methods that do not include an indicator in the conditional mean portion of the model (Nm-Nv and Nm-Yv) have power characteristics consistent with the underlying structure of the IMS level 3 where the mean event effect declines over the event window. If an indicator is included in the conditional mean portion of the model, the results are consistent with that of the overall test (11), not of individual tests of (10).

Table 4

Daily test power over the five event days with declining mean magnitudes (IMS 3), with or without a GARCH (1,1).

mm	vm	G	N_m-N_v	Y_m-Y_v	N_m-Y_v	Y_m-N_v
5	0	0	0.939	0.998	0.963	1.000
5	0	1	0.977	1.000	0.966	0.990
4	0	0	0.88	0.998	0.906	1.000
4	0	1	0.939	1.000	0.933	0.431
3	0	0	0.712	0.998	0.788	1.000
3	0	1	0.777	1.000	0.791	0.644
2	0	0	0.528	0.998	0.593	1.000
2	0	1	0.621	1.000	0.609	0.426
1	0	0	0.301	0.998	0.333	1.000
1	0	1	0.359	1.000	0.357	1.000
5	3	0	0.935	0.995	0.960	1.000
5	3	1	0.968	1.000	0.976	0.995
4	3	0	0.877	0.995	0.916	1.000
4	3	1	0.939	1.000	0.929	0.441
3	3	0	0.715	0.995	0.791	1.000
3	3	1	0.793	1.000	0.805	0.653
2	3	0	0.521	0.995	0.593	1.000
2	3	1	0.631	1.000	0.609	0.426
1	3	0	0.304	0.995	0.350	1.000
1	3	1	0.366	1.000	0.377	1.000
5	5	0	0.939	0.997	0.960	1.000
5	5	1	0.968	1.000	0.970	0.995
4	5	0	0.887	0.997	0.912	1.000
4	5	1	0.945	1.000	0.936	0.431
3	5	0	0.718	0.997	0.764	1.000
3	5	1	0.767	1.000	0.798	0.663
2	5	0	0.54	0.997	0.589	1.000
2	5	1	0.605	1.000	0.616	0.426
1	5	0	0.295	0.997	0.357	1.000
1	5	1	0.359	1.000	0.374	1.000

Note: mm and vm indicate mean and volatility magnitude, respectively. G = 0 or 1 indicates no GARCH or GARCH (1,1) is used. N_m-N_v indicates no indicator variable in either the mean or variance portion of the model, Y_m-Y_v (Savickas's method) indicates opposite; N_m-Y_v indicates no indicator variable in the mean portion but an indicator variable in the variance portion of the model, Y_m-N_v indicates the opposite. When G = 0, N_m-N_v indicates the BMP (1991) method.

For the IMS level 3, the induced event effect declines over the event window. The Savickas method (Ym-Yv), represented by the top line and its variation (Ym-Nv), represented the W-shaped line above, are not capturing the induced decreasing event effect. The test power of the other two methods (Nm-Nv or Nm-Yv) declines according to the mean structure pattern, represented by the two lines declining over time.

Under the IMS level 3, when the mean magnitude declines over the event window, the same test power should decrease correspondingly. However, the Savickas method (Ym-Yv) has power of 1 or very close to 1 on all days. Again the high power achieved by Savickas is due to an overall event effect, not an individual event effect, is tested. Figure 3 confirms the findings in Table 4. Only the models without an indicator in the mean portion of the market model match the underlying pattern of the IMS level 3.

C. Power Comparisons for the IVS Levels 2 and 3

Statistical theory indicates that holding the mean effect constant increased variability will decrease the power of the test. For the IVS level 2 there is an effect on the conditional variance for days 247-249 but no effect on day 246 or 250. The power under the IVS level 2 for the different methods is summarized in Table 5 and graphically depicted for mm = 3, vm = 3 and G = 1 in Figure 4. The methods that use an indicator variable in the conditional mean structure of the model (Ym-Yv or Ym-Nv) are not noticeably affected by the changing volatility. When an indicator variable is not included in the conditional mean portion of the model (Nm-Nv or Nm-Yv), the power does decrease when the volatility increases. Figure 4 confirms the findings in Table 5. Only the models (Nm-Nv and Nm-Yv) without an indicator in the mean portion of the market model have lower power that is consistent with the underlying pattern of IVS level 2.

For the IVS level 2, the induced identical event effect on the variance structure occurs on the second, the third and the fourth day during the event window, but no effect on the first or the fifth day. The Savickas method (Ym-Yv), represented by the top line and its variation (Ym-Nv), represented the W-shaped line above, are not capturing the volatility pattern well at all. The extended BMP method (Nm-Nv, the solid line) and the Nm-Yv method are consistent with the underlying IVS level 2 structure.

The power for the four methods for the IVS level 3 is summarized in Table 6 and graphically depicted for mm = 3 and G = 0 in Figure 5. Under the IVS level 3, given the mean magnitude, as the volatility declines over the 5-day event window, the test power should increase. This is indeed the pattern observed when no indicator variable is included in the conditional mean portion of the model (Nm-Nv or Nm-Yv). The power of the tests when an indicator is included in the conditional mean portion of the model (Ym-Yv or Ym-Nv) is not affected by the changing volatility of the IVS level 3 and is artificially high due to the nature of the overall event test.

Table 5
Average type I error rates and power over the five event days under the IVS Level 2 for different mean and volatility magnitudes.

mm	vm	G	N_m-N_v	Y_m-Y_v	N_m-Y_v	Y_m-N_v
0	0	0	0.043	0.010	0.042	0.030
0	0	1	0.039	0.021	0.035	0.049
0	1	0	0.032	0.010	0.036	0.030
0	1	1	0.036	0.024	0.044	0.003
0	3	0	0.043	0.010	0.039	0.030
0	3	1	0.037	0.022	0.045	0.017
0	5	0	0.039	0.010	0.039	0.030
0	5	1	0.037	0.018	0.040	0.017
3	0	0	0.711	0.968	0.792	0.965
3	0	1	0.819	0.973	0.813	0.943
3	1	0	0.570	0.997	0.623	1.000
3	1	1	0.652	0.997	0.642	0.485
3	3	0	0.378	0.976	0.438	0.980
3	3	1	0.460	0.984	0.448	0.457
3	5	0	0.270	0.932	0.304	0.916
3	5	1	0.330	0.934	0.315	0.467
5	0	0	0.944	1.000	0.971	0.998
5	0	1	0.979	1.000	0.976	0.995
5	1	0	0.845	1.000	0.891	1.000
5	1	1	0.903	1.000	0.902	0.719
5	3	0	0.644	1.000	0.702	1.000
5	3	1	0.719	1.000	0.709	0.708
5	5	0	0.469	1.000	0.511	0.995
5	5	1	0.548	1.000	0.535	0.680

Note: mm and vm indicate mean and volatility magnitude, respectively. G = 0 or 1 indicates no GARCH or GARCH (1,1) is used. N_m-N_v indicates no indicator variable in either the mean or variance portion of the model, Y_m-Y_v (Savickas's method) indicates opposite; N_m-Y_v indicates no indicator variable in the mean portion but an indicator variable in the variance portion of the model, Y_m-N_v indicates the opposite. When G = 0, N_m-N_v indicates the BMP (1991) method.

Figure 4
Power for different methods for the IVS Level 2, mm = 3, vm = 0 (time = 246 and 250) or vm = 3 (time = 247, 248 and 249) and G = 1.

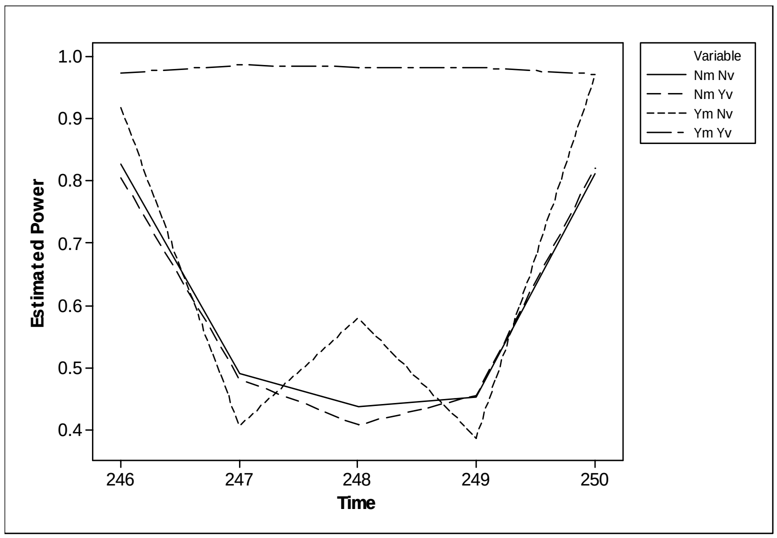


Figure 5
Power for different methods for the IVS level 3, mm = 3 and G = 0.

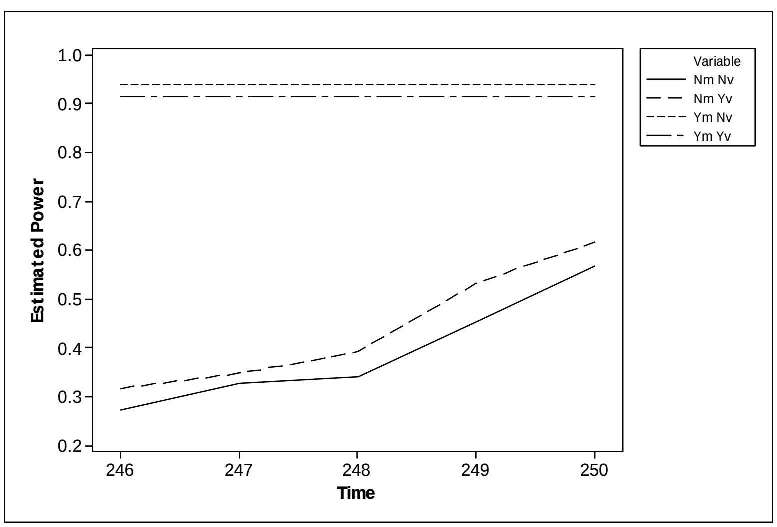


Table 6
Daily test power over the five event days with declining volatility magnitudes (IVS 3), with or without a GARCH (1,1).

mm	vm	G	N_m-N_v	Y_m-Y_v	N_m-Y_v	Y_m-N_v
1	5	0	0.13	0.43	0.14	0.50
1	5	1	0.14	0.46	0.13	0.36
1	4	0	0.14	0.43	0.13	0.50
1	4	1	0.14	0.46	0.15	0.14
1	3	0	0.17	0.43	0.17	0.50
1	3	1	0.18	0.45	0.17	0.17
1	2	0	0.17	0.43	0.22	0.50
1	2	1	0.24	0.45	0.23	0.12
1	1	0	0.22	0.43	0.25	0.50
1	1	1	0.26	0.45	0.25	0.44
3	5	0	0.27	0.91	0.32	0.94
3	5	1	0.34	0.93	0.33	0.83
3	4	0	0.33	0.91	0.35	0.94
3	4	1	0.38	0.92	0.38	0.41
3	3	0	0.34	0.91	0.39	0.94
3	3	1	0.45	0.93	0.42	0.60
3	2	0	0.45	0.91	0.53	0.94
3	2	1	0.55	0.93	0.53	0.41
3	1	0	0.57	0.91	0.62	0.94
3	1	1	0.63	0.93	0.62	0.96
5	5	0	0.47	1.00	0.54	1.00
5	5	1	0.56	1.00	0.53	0.95
5	4	0	0.59	1.00	0.63	1.00
5	4	1	0.68	1.00	0.66	0.60
5	3	0	0.61	1.00	0.67	1.00
5	3	1	0.68	1.00	0.68	0.79
5	2	0	0.75	1.00	0.81	1.00
5	2	1	0.82	1.00	0.80	0.65
5	1	0	0.84	1.00	0.90	1.00
5	1	1	0.91	1.00	0.91	1.00

Note: mm and vm indicate mean and volatility magnitude, respectively. G = 0 or 1 indicates no GARCH or GARCH (1,1) is used. N_m-N_v indicates no indicator variable in either the mean or variance portion of the model, Y_m-Y_v (Savickas's method) indicates opposite; N_m-Y_v indicates no indicator variable in the mean portion but an indicator variable in the variance portion of the model, Y_m-N_v indicates the opposite. When G = 0, N_m-N_v indicates the BMP (1991) method.

For the IVS level 3, as the induced event volatility decreases over the event window, the test power increases as correctly reflected by the BMP method (solid line) and the method that has an indicator variable only in the variance portion of the model (Nm-Yv). The Savickas method (Ym-Yv) and its variation (Ym-Nv), represented by the top two lines, have artificially high power due to the overall event effect test that is not affected by the underlying induced event volatility structure.

V. SUMMARY AND CONCLUSIONS

Based on the standardized cross-sectional method of BMP (1991), Savickas (2003) proposes an indicator variable approach to test abnormal returns in event studies and observes superiority in test power over the BMP method. We investigate the Savickas approach under more challenging induced event effects on the conditional mean and conditional variance structures within the event window, and compare the power of these test variations. Inclusion of indicator variables in the conditional mean and conditional variance portion of the model is investigated independently resulting in four variations.

We find that the inclusion of an indicator variable in the conditional mean structure of the market model results in little ability to distinguish days for which there is an event effect from those days for which there is no event effect. The tests on all days in the event window are essentially equivalent and represent a test of an overall event effect, not tests of event effects on each day within the event window. The test of the overall event effect is the main reason for the increased power noted by Savickas.

The GARCH(1,1) structure handles gradual stationary changes in conditional variances over time well but does not capture abrupt changes. To capture abrupt changes better, an indicator variable only in the conditional variance portion of the model need to be used. The indicator variable also ensures the model to be well-specified. The proposed method by Bremer and Zhang (2007) scales abnormal returns with conditional variance, which is estimated with GARCH(1,1) and an indicator of the event in a two-stage estimation. This method improves the Boehmer, Musumeci, and Poulsen (1991) approach on model specification and test power, even under challenging event-induced mean and volatility structures, and is the best model we recommend for short-horizon event studies.

ENDNOTES

1. We recognize that some studies allow a time interval between the estimation and event windows. Whether the interval exists or not, however, has no effect on our tests below.
2. This model is the same as the proposed method in Bremer and Zhang (2007) except that here we scale the abnormal returns with standard deviation to be consistent with Savickas (2003). Bremer and Zhang (2007) use variance to scale abnormal returns and find their proposed method to have the best statistical properties among a wide variety of variations of the standardized cross-sectional method of BMP (1991).
3. See Bremer and Zhang (2007), Chandra and Balachandran (1990), Collins and Dent (1984) and Sanders and Robins (1991) for motivation of using the conditional variance in the test statistic. Scaling abnormal returns with conditional variance leads to better statistical properties and is strongly recommended by Bremer and Zhang (2007).
4. See Seber (1977) on linear models for discussions of the effect of including indicator variables in regression models.
5. See the reference in footnote 4.

6. The CRSP value-weighted index was also tested. Almost identical results were obtained; these results are not reported in the paper.
7. Similar simulation restrictions, when applicable, can be found in Brown and Warner (1985), Corrado (1989), Boehmer, Musumeci, and Poulsen (1991), Savickas (2003), Harrington and Shrider (2007) and Bremer and Zhang (2007).

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