

The Income Trust Announcement Leak: An Event Study Analysis

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Abstract

The alleged income trust announcement leak of 23 November 2005 provides a remarkable example of the sensitivity of event study analysis to the treatment of cross-sectional dependence in returns. Whereas a leak should chiefly have affected the returns on other securities, not income trusts, we find that a mechanical application of standard event study methodology yields the seemingly strong but spurious finding that income trust returns were affected. The treatment of cross-sectional dependence reverses this finding.

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If the test statistic in an event study is calculated ignoring cross-dependence in the data, even a fairly small amount of cross-correlation in data will lead to serious misspecification of the test. In particular, the test will reject the null of no effect far more often than the size of the test.

S.P. Kothari and J.B. Warner (2007) “Econometrics of Event Studies”

Event studies seek to assess the effect of an event on the price of some class of assets, such as the effect on share prices of a stock split, a rights issue, a merger or acquisition, an earnings announcement, or an issue of new debt or equity. These are examples of the typical case in which the event occurs at different calendar dates for the different assets. In studying the effect of stock splits on the valuation of firms, for example, the split will have occurred on different dates for the different firms in the sample. In the terminology of the literature, there is no “clustering in time” of the event in a common “event window.” The typical analysis therefore treats abnormal returns at the time of the event as statistically independent across the assets; test statistics for the hypothesis of an absence of excess abnormal returns are constructed using this independence assumption.

A less common situation is one in which the event occurs at a single date (or dates close in calendar time); that is, there is a common event window (or overlapping windows). Examples include the effect of macroeconomic events or a change in the regulatory or tax environment. In this case the independence assumption may be untenable, complicating the derivation of test statistics and their distributions in ways that depend on the nature of the event and the extent to which event windows overlap. As indicated in the opening quotation from Kothari and Warner, the small number of studies that have shed light on the empirical importance of the time-clustering phenomenon, such as Collins and Dent (1984), suggest that it is of practical, even crucial, significance.

This paper presents evidence supporting this view by considering a well-defined event that is particularly clean in the specification of the time-clustering phenomenon. We study the abnormal returns of Canadian income trusts on Wednesday 23 November 2005, the day of a now-infamous alleged leak of an announcement regarding their tax status. We begin, in Section 1, by describing the event, focusing on the features that have implications for the

design of the study and the relevant data. We then turn, in Section 2 and the companion appendix, to formulating the empirical methodology for studying it. Section 3 reports the results, and Section 4 concludes.

1 The Income Trust Affair

A corporation exists as a legal entity separate from those who own it, and is taxed accordingly. In contrast, a trust is a legal arrangement established under, in Canada, provincial law, in which assets are managed by trustees for beneficiaries. With its affairs suitably arranged, the trust is not itself subject to corporate taxation; the cash flows generated by the assets “flow through” to the beneficiaries and are taxed in their hands alone. Thus the tax status of a trust is akin to that of a sole proprietorship or partnership; all are sometimes called flowthrough entities.

When there are many beneficiaries their ownership of the trust is best effected through publicly issued trust units, tradeable in capital markets; in this case the beneficiaries are called unitholders. Such publicly constituted trusts are referred to generally in Canada as income trusts.¹

The tax status of income trusts has made them an appealing vehicle for investment in certain types of enterprises, typically involving mature assets that generate fairly steady revenues. Canadian tax law recognizes three general categories of income trusts: real estate investment trusts (REITs), royalty trusts, and business trusts. Prior to the late 1990s the first two were the most important: REITs hold diversified portfolios of revenue properties such as shopping centres and apartment and commercial buildings, while royalty trusts invest in oil and gas production or energy utilities such as pipelines and power generation.

By contrast, the third category, a business trust, holds the assets of a single operating company. Of little importance a decade ago, the tax advantages of the trust structure have led businesses as diverse as investment managers, pizza chains, and the Yellow Pages to constitute themselves as, or convert to, income trusts. A decade ago income trusts in total accounted for less than 1% of the capitalization of the Toronto stock exchange; today they account for around 9%, with business trusts representing a majority of that.

The increasing use of the trust structure by firms that would normally have incorporated, and the rumoured conversion to trusts of some flagship corporations such as Bell Canada Enterprises (BCE) and Telus, did not go unnoticed by the federal Department of Finance. Mintz (2006) has estimated the annual loss of federal and provincial tax revenues due to trust conversions at \$700 million; were BCE and Telus to convert, this would increase to \$1.1 billion.

¹For a more detailed review of income trusts that is possible here, see King (2003).

This trend prompted then-finance minister Ralph Goodale to attempt to level the playing field between trusts and corporations by announcing, on Wednesday 23 November 2005, an enhanced dividend tax credit that would have the effect of reducing taxes on dividends from large corporations; income trusts would be left alone.² Although, following standard practice, the announcement was made after the close of financial markets, the final hours of trading that day were marked by a noticeable increase in trading volume and the prices of affected stocks.

In the election that soon followed, the suspected leak of the announcement was popularly perceived as part of a larger culture of government corruption and malfeasance, a perception that was credited with contributing to the defeat of the governing Liberal party. Following a 15 month RCMP investigation, a Director General of Taxation within the Department has been charged with breach of public trust for insider trading on advance knowledge of the announcement. In the meantime, the successor Conservative government included the enhanced dividend tax credit in its May 2006 budget and, in October 2006, incurred the enmity of income trust investors by announcing a tax on trust disbursements comparable to that on dividends.

Implications for Abnormal Returns

Although intended to stem the tide of income trust conversions, the announcement of Wednesday 23 November 2005 did not affect their returns; it was a tax reduction on dividends and so affected only the after-tax returns on dividend-paying corporations. Therefore the prices of income trust units should have been affected only to the extent that they were discounted in anticipation of an adverse change to their own tax treatment. And, indeed, the descriptive evidence indicates that they were so discounted: as shown in Figure 1(b), prices of income trusts showed a dramatic improvement on the day following the announcement. However anyone acting on advance knowledge of the announcement would have been wisest to purchase the stocks of the high dividend-yielding firms that were the direct beneficiaries of the tax change, like BCE and Telus, rather than income trusts themselves. Illustrating with BCE, Figure 1(a) shows that this stock did experience unusually large returns on both Nov. 23 and 24. By contrast Figure 1(b) shows that, although the average return on income trusts was unusually large on Nov. 24 after the announcement became public, the return on Nov. 23 was well within a normal range. Thus, while the anecdotal evidence of a leak having affected stocks like BCE might be viewed as compelling, it is less so for income trusts themselves.

The income trust affair is clean in the specification of the time-clustering phenomenon

²The press release for Goodale's announcement is available at www.fin.gc.ca/news05/05-082e.html.

in the sense that, if a leak occurred, it occurred unambiguously on Nov. 23; any effect of a leak on returns occurred only on that day for all firms. Hence, in treating any statistical dependence across firms, there are no issues of aggregation of daily returns in a multi-day event window, asynchronous but overlapping event windows, uncertainty with respect to the event date, or other problems that often complicate the treatment of dependence in other settings.

Data

The Toronto stock exchange now lists over 200 income trusts. Our sample is limited to those that were in existence in the autumn of 2005 for a long enough period prior to Nov. 23 to estimate an expected return. The longer the sample period chosen for estimation, the smaller will be the available sample of trusts. We balance these considerations by using as our estimation window the period between Labour Day and the event; that is, our sample consists of the close-over-close daily returns from Sept. 7 through Nov. 22, an estimation window of $T = 54$ observations. Closing prices during this period are available from the Yahoo Canada Finance database for $N = 114$ Canadian income trusts, both unadjusted and adjusted for disbursements; we have computed daily returns as the log-differences of these prices.

In exploratory work, we have found that our substantive results are unaffected by longer estimation windows.

2 Methodology: The Benchmark Case of No Time Clustering

When the assumption of cross-sectional independence is tenable the relevant test statistics are well established. Even so, in the literature they appear in many variations that reflect the specifics of individual studies, such as uncertainty of event dates or, in Campbell, Lo, and MacKinlay (1997, Chap. 4), the treatment of multi-day event windows. It is therefore useful to begin by establishing notation for our relevant situation of a single-day event window; this will then serve as the benchmark against which our treatment of cross-sectional dependence in the appendix is compared.

We use the two most commonly employed models of expected returns: the constant expected return model and the market model. Since the former is merely a special case of the latter, we proceed by formulating the latter.

The market model describes expected returns as depending linearly on the market return. The market model for firm i , $i = 1, \dots, N$, is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}, \quad \text{var}(\varepsilon_{it}) = \sigma_i^2.$$

For day t , R_{it} denotes the return on security i and R_{mt} the return on the market; for the latter we use the S&P/TSX Composite Index. These $N = 114$ classical regressions are estimated over the pre-event sample $t = 1, \dots, T$. In matrix notation,

$$\mathbf{R}_i = \mathbf{X}\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \quad \text{var}(\boldsymbol{\varepsilon}_i) = \sigma_i^2 I_T, \quad (i = 1, \dots, N), \quad (1)$$

where \mathbf{R}_i is the $T \times 1$ vector of returns on security i and \mathbf{X} , $\boldsymbol{\beta}_i$, and $\boldsymbol{\varepsilon}_i$ are of dimensions $T \times 2$, 2×1 , and $T \times 1$. The $T \times 2$ matrix \mathbf{X} is defined as $\mathbf{X} \equiv [\mathbf{i}; \mathbf{R}_m]$, where \mathbf{i} denotes a column vector of ones and \mathbf{R}_m is the $T \times 1$ vector of market returns R_{mt} ; note that \mathbf{X} is common to all N regressions and so is not indexed by i . Note that the constant expected return model, which describes the returns R_{it} as varying around a constant mean rather than linearly with the market return, is simply the special case of this framework in which $\boldsymbol{\beta}_i = 0$ for all i and $\mathbf{X} \equiv \mathbf{i}$.

Given market efficiency the returns \mathbf{R}_i are taken to be independent over time with constant variance σ_i^2 ; hence the classical covariance structure $\text{var}(\boldsymbol{\varepsilon}_i) = \sigma_i^2 I_T$. Nevertheless, at a point in time, the $1 \times N$ vector of returns $\mathbf{R}_t \equiv [R_{1t}; \dots; R_{Nt}]$ is in general taken to be multivariate normal, so the associated $1 \times N$ cross-sectional disturbance vector $\boldsymbol{\varepsilon}_t \equiv [\varepsilon_{1t}; \dots; \varepsilon_{Nt}]$ is specified as

$$\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}), \quad (2)$$

where $\boldsymbol{\Sigma} = E(\boldsymbol{\varepsilon}_t' \boldsymbol{\varepsilon}_t) = [\sigma_{ij}]$ is an $N \times N$ covariance matrix. Note that, in relation to the variance σ_i^2 in the specification of the market model regression (1), the diagonal elements of $\boldsymbol{\Sigma}$ are defined as $\sigma_{ii} \equiv \sigma_i^2$.

Given their classical covariance structure, and for the moment ignoring the cross-sectional dependence given by (2), the market model regressions (1) are individually estimated by ordinary least squares (OLS): $\hat{\boldsymbol{\beta}}_i = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{R}_i$. The residual vectors are

$$\mathbf{e}_i = \mathbf{R}_i - \hat{\mathbf{R}}_i = \mathbf{R}_i - \mathbf{X}\hat{\boldsymbol{\beta}}_i = \mathbf{R}_i - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{R}_i = M\mathbf{R}_i,$$

which can, in general, be used to estimate the σ_{ij} with the sample variances and covariances

$$s_{ij} \equiv \mathbf{e}_i' \mathbf{e}_j / (T - 2), \quad (i, j = 1, \dots, N). \quad (3)$$

It will sometimes be convenient to denote the sample variances ($i = j$) by $s_i^2 \equiv s_{ii}$.

Consider now the event day τ , the market return $R_{m\tau}$ on that day, and let $\mathbf{X}_\tau \equiv [1; R_{m\tau}]$. For security i the market model predicts a normal return of $\hat{R}_{i\tau} = \mathbf{X}_\tau' \hat{\boldsymbol{\beta}}_i$ and a corresponding abnormal return of $e_{i\tau} = R_{i\tau} - \hat{R}_{i\tau}$, the variance of which is the standard expression for a single-period OLS forecast error variance:³

$$\text{var}(e_{i\tau}) = [1 + \mathbf{X}_\tau' (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}_\tau] \sigma_i^2, \quad (i = 1, \dots, N).$$

³This is the special case of expression (4.4.9) of Campbell, Lo, and MacKinlay (1997). Their more general expression is for the case of a multiperiod event window, and is the standard expression for a multiperiod OLS forecast error covariance matrix as presented in, for example, equation (4.11) of Theil (1971).

Across firms the average abnormal return is $\sum_{i=1}^N e_{i\tau}/N$. In an event study the null hypothesis is that the event did not affect the market value of the typical firm, so that the expected average abnormal return is zero. This is the restriction that

$$\mathbb{E}\left(\sum_{i=1}^N e_{i\tau}\right) = 0. \quad (4)$$

Under the assumption of cross-sectional independence, so that the off-diagonal components of Σ are zero and the matrix specializes to $\Sigma = \text{diag}[\sigma_i^2]$, the variance of this statistic is

$$\text{var}\left(\sum_{i=1}^N e_{i\tau}\right) = \sum_{i=1}^N \text{var}(e_{i\tau}) = [1 + \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_\tau] \sum_{i=1}^N \sigma_i^2,$$

which is estimated by

$$\hat{v}_1 \equiv [1 + \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_\tau] \sum_{i=1}^N s_i^2. \quad (5)$$

The hypothesis (4) is therefore tested with a t statistic of the form

$$t_1 = \frac{\sum_i e_{i\tau}}{\sqrt{\hat{v}_1}}. \quad (6)$$

Even if returns are not normal so that this statistic does not literally have a t distribution in finite samples, the usual central limit theorem ensures that for $N = 114$ firms the statistic will have a distribution virtually identical to the standard normal.

The appendix generalizes this test statistic to allow for cross-sectional dependence among the abnormal returns; we denote this generalized statistic t_2 . Although conceptually this generalization is straightforward, it involves some technicalities that are best relegated to the appendix.

3 Results

We have applied the statistics t_1 and t_2 to our data. Their p -values (marginal significance levels) are presented in Table 1, and show that inferences depend critically on the treatment of cross-sectional dependence in a way that is not sensitive to the model of expected returns or the use of disbursement-adjusted returns.

Recall that in an event study the null hypothesis is that the event had no effect; in our case, that abnormal returns on income trusts were, on average on Nov. 23, not unusually large. The descriptive evidence in Figure 1(b) suggests that the data are consistent with this null; income trusts had unusually large returns on Nov. 24 after the announcement became public, but not on the 23rd when the leak is alleged to have occurred. Yet, according to the p -values in the first column of Table 1, when cross-sectional dependence is not treated the data appear to reject this null very strongly, seemingly supporting the belief that a leak occurred and returns were affected accordingly. But these apparently strong rejections are

Table 1: p -values for the null of an absence of effect

Model of expected returns	Cross-sectional dependence	
	Untreated	Treated
Constant expected return model		
Returns unadjusted for disbursements	0.00000162	0.163
Returns adjusted for disbursements	0.00000151	0.160
Market model		
Returns unadjusted for disbursements	0.0000206	0.157
Returns adjusted for disbursements	0.0000130	0.152

the spurious outcome of failing to treat cross-dependence; as the second column of Table 1 reveals, treating it leads to values of t_2 that do not reject at conventional significance levels.

4 Conclusions

It may be useful to cast these implications in a slightly different light. Consider a statistical consultant who is hired by a regulatory agency or crown prosecutor to provide expert opinion on accusations of insider trading. The consultant is asked whether statistical analysis can shed light on the accusations. The consultant proposes that an event study be conducted on, in our case, income trust returns, not thinking carefully enough about the institutional context to realize that the effect of any insider trading should have been felt chiefly in the prices of other assets.

The consultant's practice involves the application of many statistical techniques to a wide range of applied problems, and only the occasional use of event study methodology. As a casual user of the technique, the consultant applies it in its standard form, as explicated in Section 2. The consultant's report presents the p -values given in the first column of Table 1, noting that this apparently strong evidence of insider trading is robust to alternative models of expected returns and an adjustment for disbursements. A regulatory board or court might well find this evidence persuasive; yet it is entirely the spurious outcome of failing to treat cross-sectional dependence.

This is not to suggest that, in the income trust affair, a leak did not occur; only that the relevant evidence lies in the returns on other assets, not income trusts themselves. A failure to realize this, joint with a failure to treat cross-dependence in the data, can easily give rise to seemingly compelling statistical evidence where none exists.

Appendix

Although other authors have sought to treat cross-sectional dependence in event studies, there does not appear to be any standard reference for the relevant statistical analysis. This appendix seeks to rectify this; it generalizes the benchmark analysis of Section 2 to the case of a non-diagonal covariance matrix Σ .

This generalization is best achieved by building on the notation established in Section 2 and assembling the N market model regressions (1) into a single multivariate regression (MR) model

$$\mathbf{R} = \mathbf{X}\mathbf{B} + \mathbf{E}.$$

Here $\mathbf{R} \equiv [\mathbf{R}_1; \dots; \mathbf{R}_N]$ denotes the $T \times N$ matrix of asset returns (with rows \mathbf{R}_t , columns \mathbf{R}_i); $\mathbf{B} \equiv [\beta_1; \dots; \beta_N]$ denotes the $2 \times N$ matrix of regression coefficients; and, as in Section 2, $\mathbf{X} \equiv [i; \mathbf{R}_m]$. The $T \times N$ disturbance matrix $\mathbf{E} \equiv [\varepsilon_1; \dots; \varepsilon_N]$ has columns ε_i having a covariance structure as in (1), and rows ε_t specified as (2).

The MR model is often presented in textbooks as the “special case” of a system of seemingly unrelated regressions having a common set of explanatory variables \mathbf{X} . It is well known that, despite the cross-sectional dependence described by Σ that might suggest the need for generalized least squares (GLS) estimation, in this context GLS reduces to equation-by-equation OLS as the efficient estimator. The $2 \times N$ matrix of estimated market model coefficients is therefore

$$\hat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{R} = \mathbf{B} + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}$$

Now consider the event date $t = \tau$. According to the model, the returns \mathbf{R}_τ are generated as $\mathbf{R}_\tau = \mathbf{X}_\tau\mathbf{B} + \varepsilon_\tau$. Normal returns are predicted to be

$$\hat{\mathbf{R}}_\tau = \mathbf{X}_\tau\hat{\mathbf{B}} = \mathbf{X}_\tau\mathbf{B} + \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E},$$

and event day abnormal returns are given by the $1 \times N$ residual vector $\mathbf{e} \equiv [e_i]$

$$\mathbf{e} = \mathbf{R}_\tau - \hat{\mathbf{R}}_\tau = \varepsilon_\tau - \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}$$

The aggregate abnormal return over the N firms is $\sum_i e_i = \mathbf{e}\mathbf{i}$, the variance of which must be derived in order to test the null hypothesis (4).

The variance of the aggregate abnormal return is

$$\begin{aligned}
\text{var}(\mathbf{e}\mathbf{i}) &= \mathbb{E}(\mathbf{e}\mathbf{i})^2 = \mathbb{E}((\mathbf{e}\mathbf{i})'\mathbf{e}\mathbf{i}) = \mathbb{E}(\mathbf{i}'\mathbf{e}'\mathbf{e}\mathbf{i}) \\
&= \mathbb{E}[\mathbf{i}'(\boldsymbol{\varepsilon}_\tau - \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E})'(\boldsymbol{\varepsilon}_\tau - \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E})\mathbf{i}] \\
&= \mathbb{E}(\mathbf{i}'\boldsymbol{\varepsilon}'_\tau\boldsymbol{\varepsilon}_\tau\mathbf{i}) + \mathbb{E}[\mathbf{i}'(\mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E})'(\mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E})\mathbf{i}] \quad (7a) \\
&= \mathbf{i}'\mathbb{E}(\boldsymbol{\varepsilon}'_\tau\boldsymbol{\varepsilon}_\tau)\mathbf{i} + \mathbb{E}[\mathbf{i}'\mathbf{E}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_T\mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}\mathbf{i}] \quad (7b) \\
&= \mathbf{i}'\boldsymbol{\Sigma}\mathbf{i} + (\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})\mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_T \quad (7c) \\
&= (\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})[1 + \mathbf{X}_\tau(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_T] \quad (7d)
\end{aligned}$$

We now proceed to justify the steps in this derivation.

Step (7a) holds because the cross-product term is zero, the event-day disturbance $\boldsymbol{\varepsilon}_\tau$ being independent of the estimation window disturbances $\boldsymbol{\varepsilon}_t$, $t = 1, \dots, T$ that comprise \mathbf{E} .

The step from line (7b) to (7c) is more involved, and requires the following lemma.

Lemma. *Any matrix expression that yields a scalar is invariant to any cyclic permutation of that expression that also yields a scalar.*

Proof. Consider a matrix expression such as $ABCD$ that yields a scalar, the implication being that A is a row vector and D a column vector. Cyclic permutations are expressions such as $DABC$, $CDAB$, or $BCDA$; all are square matrices defined with respect to matrix multiplication given that the original $ABCD$ is. Consider any one of these permutations that also happens to yield a scalar, say $CDAB$. It is a well known property of the trace operator that it is invariant to cyclic permutations, i.e. $\text{tr}(AB) = \text{tr}(BA)$; as well, it is trivially the case that the trace of a scalar is that scalar. By these properties we have that

$$(\text{scalar}) \quad ABCD = \text{tr}(ABCD) = \text{tr}(CDAB) = CDAB \quad (\text{scalar})$$

This proof generalizes trivially to arbitrary matrix expressions, not just those of the form $ABCD$. □

Consider applying this lemma to line (7b).⁴

⁴We simplify the manipulation of mathematical expectations by treating the market model as a classical regression in which \mathbf{X} is nonstochastic. In reality, of course, the market return is stochastic. Treating this explicitly requires working with conditional expectations. Although this would complicate the notation, the resulting variance expressions and statistics are unchanged.

$$\begin{aligned}
& \mathbb{E}[\mathbf{i}'\mathbf{E}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau}\mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}\mathbf{i}] \quad (\text{scalar expression}) \\
&= \mathbb{E}[\mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{E}\mathbf{i}\mathbf{i}'\mathbf{E}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau}] \quad (\text{also a scalar expression}) \\
&= \mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbb{E}(\mathbf{E}\mathbf{i}\mathbf{i}'\mathbf{E}')\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau} \\
&= \mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})I_T\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau} \\
&= (\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})\mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau} \\
&= (\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})\mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau}
\end{aligned} \tag{8}$$

Step (8) is justified as follows. Consider the $T \times T$ matrix $\mathbb{E}(\mathbf{E}\mathbf{i}\mathbf{i}'\mathbf{E}')$. Note that $\mathbf{E}\mathbf{i}$ is a $T \times 1$ column vector with typical component $\varepsilon_t\mathbf{i} = \sum_i \varepsilon_{it}$. Therefore, using the fact that off-diagonal components are zero because they are cross-products over time,

$$\begin{aligned}
\mathbb{E}(\mathbf{E}\mathbf{i}\mathbf{i}'\mathbf{E}') &= \mathbb{E}\left(\sum_i \varepsilon_{it}\right)^2 I_T \\
&= \mathbb{E}(\mathbf{i}'\boldsymbol{\varepsilon}'_t\boldsymbol{\varepsilon}_t\mathbf{i})I_T \\
&= \mathbf{i}'\mathbb{E}(\boldsymbol{\varepsilon}'_t\boldsymbol{\varepsilon}_t)\mathbf{i}I_T \\
&= \mathbf{i}'\boldsymbol{\Sigma}\mathbf{i}I_T
\end{aligned}$$

This completes the derivation of the general variance expression (7d) which, given the covariance matrix estimator $\hat{\boldsymbol{\Sigma}} \equiv [s_{ij}]$ with the s_{ij} as in (3), is estimated by

$$\hat{v}_2 \equiv (\mathbf{i}'\hat{\boldsymbol{\Sigma}}\mathbf{i})[1 + \mathbf{X}_{\tau}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_{\tau}].$$

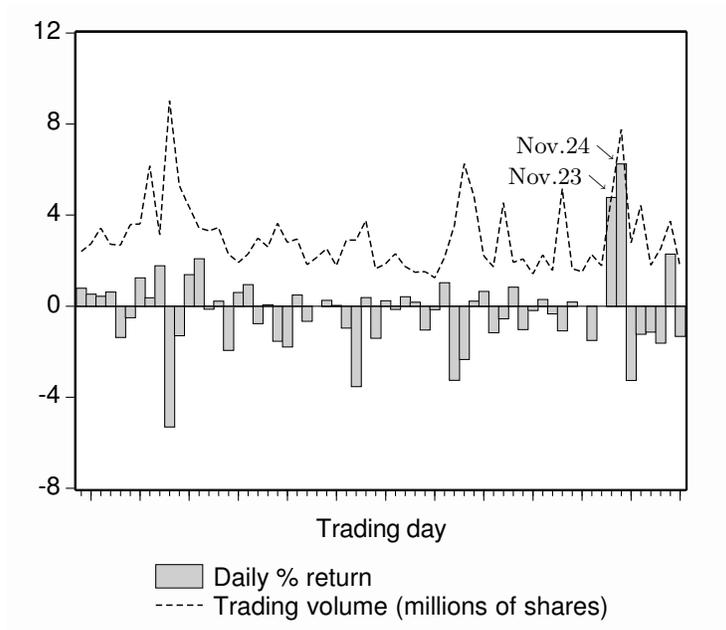
This specializes to the earlier estimator \hat{v}_1 given by (5) in the special case of $\boldsymbol{\Sigma}$ diagonal. The test statistic analogous to (6) is

$$t_2 = \frac{\sum_i e_{i\tau}}{\sqrt{\hat{v}_2}}.$$

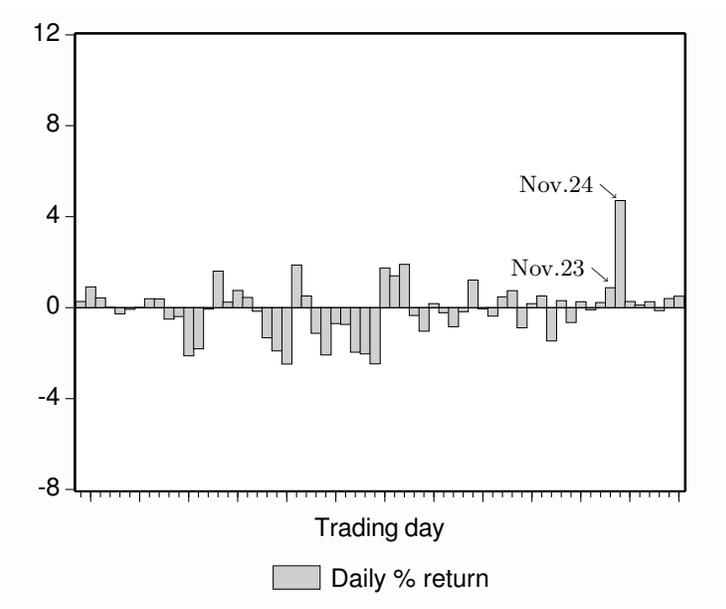
Abnormal returns clustered in time will tend to move in the same direction, if for no other reason than simply their correlation with the market. The off-diagonal components of $\hat{\boldsymbol{\Sigma}}$ will therefore tend to be positive, and so it will typically be the case that $\hat{v}_1 < \hat{v}_2$ and, in turn, $|t_1| > |t_2|$. That is, when cross-sectional dependence is present the failure to treat it will typically result in an artificially large absolute value of the t statistic; the null of an absence of effect of the event will tend to be rejected too frequently. Hence the quotation from Kothari and Warner (2007) that opens this paper.

In the special case of the constant expected return model $\mathbf{X} = \mathbf{i}$ and the variance (7d) reduces to

$$\text{var}(\mathbf{e}\mathbf{i}) = (\mathbf{i}'\boldsymbol{\Sigma}\mathbf{i})\left(1 + \frac{1}{T}\right).$$



(a) BCE Inc.



(b) Average return on 114 income trusts

Figure 1: Daily Returns (unadjusted for dividends/disbursements) 7 September–2 December 2005

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