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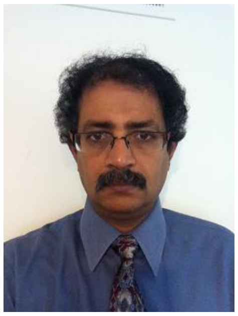

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Abstract

- Conditional event-study methods: standard event-study procedures are misspecified if
  - Events are voluntary and
  - Investors are rational
- However, this paper argues that standard procedures
  - Provides statistically valid inferences and
  - Are superior even under the rational expectations specifications (by conditional methods papers)
- Displays an equilibrium justification; Suggests a link between conditional versus standard models

Intro

- Event studies test
  - Existence of an information effect
  - Factors that explains changes in firm value on the event date
- Fama et al. (1969, IER)
  - Significance of a stock-price reaction on the event date
  - Linear regression to identify factors that explain the cross-section of announcement effects
- Conditional methods: Acharya (1998, JF; 1993, JF), Eckbo, Maksimovic and Williams (1990, RFS)
  - Traditional methods are misspecified in a rational expectations context
  - Unexpected portion of such information should determine the stock-price reaction to the event
  - Resulting nonlinear cross-sectional regressions: conventional methods should not be used

- This paper displays
  - Simple exposition of conditional methods (specifically, their economic content)
  - Traditional techniques are misspecified, but still valid under usual conditions
    - For example, under Acharya's setup, (1) FFJR method is still valid and (2) the conventional cross-sectional method yields parameter estimates proportional to the true model parameters
    - Equilibrium justification for the conventional event-study procedures
  - Choice between conventional vs. conditional: depends on the $\exists$ of NE firms in the data
    - If $\exists$ NE samples: conditional $\succ$ conventional
    - If $\nexists$ NE samples: conditional $\sim$ conventional

1. Conditional Methods

- Empirical procedure for carrying out event studies
  1. Estimate the unexpected information that the event reveals (for each firm)
  2. Compute the cross-correlation between information and abnormal return

$$\begin{aligned}\tau_i &= \text{the information arrives at firm i on an information arrival date}\\ &= \text{subsequently revealed to markets via the event on an event date}\end{aligned}$$

Information arrival date ——————— Event date

τ_i ——————— Revealed to markets

- Three possible assumptions
  1. (assumption) Markets know that τ_i has arrived at firm i before the event (Acharya, 1988)
  2. Markets don't know the arrival (Eckbo, Maksimovic and Williams, 1990)
  3. Market assess a probability p∈(0,1) that τ_i has arrived at firm i (Prabhala, 1997)

Under Assumption 1 (Acharya, 1988)

$$\begin{aligned}E_{-1}[\tau_i] &= \underline{\theta}'\underline{x}_i = \boldsymbol{\theta}^\top \mathbf{x}_i, && \text{where } x_i = \text{firm specific variables}\\ \psi_i &= \tau_i - E_{-1}[\tau_i], && \text{where } \psi_i = \text{firm i's private information}\end{aligned}$$

The firm's decision depends on its information τ_i (endogenous choice of firms)

$$\begin{aligned}E &\Leftrightarrow \tau_i \geq 0 \Leftrightarrow \psi_i + \theta^\top x_i \geq 0\\ NE &\Leftrightarrow \tau_i < 0 \Leftrightarrow \psi_i + \theta^\top x_i < 0\end{aligned}$$

- Firm i's choice between E and NE partially reveals its private information ψ_i
- If $\exists$ an information effect, abnormal returns should be related to unexpected information
  4. (assumption) Investors are risk-neutral towards the event risk
  5. Conditioning information is a linear signal of expected return, i.e. $E(r_i|\psi) = \pi\psi_i$

Hence if $\exists$ an information effect, then π should be significant in the following nonlinear specifications

$$\underbrace{E[\varepsilon_i|E]}_{\substack{\text{expected}\\ \text{abnormal}\\ \text{return}}} = \underbrace{\pi E[\psi_i|E]}_{\text{by Assumption 5}} = \pi E[\psi_i|\boldsymbol{\theta}^\top \mathbf{x}_i + \psi_i \geq 0] = \pi \underbrace{E[\psi_i|\psi_i \geq -\boldsymbol{\theta}^\top \mathbf{x}_i]}_{\text{truncated}}$$

$$\text{If } \psi_i \sim N(0, \sigma^2), \qquad \text{then } \underbrace{E[\varepsilon_i|E] = \pi\sigma \frac{\overbrace{n(\boldsymbol{\theta}^\top \mathbf{x}_i/\sigma)}^{\substack{\text{revealed}\\ \text{information}}}}{N(\boldsymbol{\theta}^\top \mathbf{x}_i/\sigma)} = \pi\sigma \overbrace{\lambda_E(\boldsymbol{\theta}^\top \mathbf{x}_i/\sigma)}^{\substack{\text{revealed}\\ \text{information}}}}_{\text{Acharya (1988)}}$$

- Two tests are possible though Acharya's model
  - ∃ <u>information effect</u>: Significant π indicates the ∃ of an information effect
  - Factors explaining <u>announcement effect</u>: Significant $\boldsymbol{\theta}$ implies that $\mathbf{x}_j$ can explain ε_i

Note that

$$E[\psi_i|\psi_i \geq -\boldsymbol{\theta}^\top\mathbf{x}_i] = E[Z|Z \geq -\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma] = \frac{n(-\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}{1 - N(-\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}\sigma = \frac{\overbrace{n(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}^{n(-c)=n(c)}}{\underbrace{N(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}_{1-N(-c)=N(c)}}$$

Under Assumption 2 (Eckbo, Maksimovic and Williams, 1990)

$$E[\varepsilon_i|E] = \pi E[\tau_i|E] = \pi E[\tau_i|\tau_i \geq 0] = \pi[\boldsymbol{\theta}^\top\mathbf{x}_i + \sigma\lambda_E(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)] = \underbrace{\pi\boldsymbol{\theta}^\top\mathbf{x}_i + \pi\sigma\lambda_E(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}_{\text{truncated regression}}$$

- In Acharya's model, the price incorporates the unconditional expectation $\boldsymbol{\theta}^\top\mathbf{x}_i$ prior to the event
- In EMV model, pre-event expectations were not formed; hence $\boldsymbol{\theta}^\top\mathbf{x}_i$ appears on the event date

Under Assumption 3 (Prabhala, 1997): nests both Acharya and EMW cases

$$E[\varepsilon_i|E] = \underbrace{\pi(1-p)\boldsymbol{\theta}^\top\mathbf{x}_i + \sigma\lambda_E(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)}_{\text{truncated regression}} = \begin{cases} \text{Acharya's model,} & \text{as } p \to 1 \\ \text{EMW model,} & \text{as } p \to 0 \end{cases}$$

This paper hereafter focuses on Acharya's model.

2. On Inferences Via Traditional Methods

- Even when event-study data are generated exactly under Acharya's environment
  - FFJR procedure is well-specified as a test for ∃ of information effect (i.e. H_0: $\pi=0$)
  - Traditional cross-sectional procedure yields $\boldsymbol{\beta}$s proportional to the true cross-sectional $\boldsymbol{\theta}$s
  - Misspecification problem may not be as serious as the previous paper suggests

Recall Acharya's specification

$$E[\varepsilon_i|E] = \pi\sigma\lambda_E(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma), \qquad \cdots (7)$$

The specification of conventional methods

$$E[\varepsilon_i|E] = \beta_0 + \boldsymbol{\beta}^\top\mathbf{x}_i, \qquad \cdots (12)$$

<u>Pivotal question</u>: Are $\boldsymbol{\beta}$ related in some way to the true parameters $\boldsymbol{\theta}$?

- The true slope s_j of (7) is attenuated relative to θ_j.

$$s_j = \frac{\partial E[\varepsilon_i|E]}{\partial x_{ij}} = -\theta_j \times \underbrace{\pi}_{\in(-1,1)} \times \underbrace{\lambda_E\left(\frac{\boldsymbol{\theta}^\top\mathbf{x}_i}{\sigma}\right)\left[\lambda_E\left(\frac{\boldsymbol{\theta}^\top\mathbf{x}_i}{\sigma}\right) + \boldsymbol{\theta}^\top\mathbf{x}_i\right]}_{=\delta(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)\in(0,1)}$$

  - Each β_j has the opposite sign of θ_j if $\pi>1$
  - Underestimation is greater if $|\pi|$ is small (i.e. low announcement effect)
  - Underestimation is greater if $\delta(\boldsymbol{\theta}^\top\mathbf{x}_i/\sigma)$ is small (i.e. highly anticipated events)

Proposition 1 (1) E occurs iff $\theta_0+\boldsymbol{\theta}^{\top}x_i+\psi>0$

(2) Information ψ and abnormal return ε are bivariate Normal with correlation π and marginal distributions $N(0,1^2)$

(3) Regressor $\mathbf{x}_i$ is multivariate Normal, independent of ψ

$$\text{then } \beta_j = -\theta_j\pi\frac{(1-R^2)(1-t)}{t+(1-R^2)(1-t)} = -\theta_j\pi\mu$$

$$\text{where } t = \frac{Var[\tau|E]}{Var[\tau]}, \qquad \tau = \boldsymbol{\theta}^{\top}\mathbf{x}_i + \psi$$

$$R^2 = R^2 \text{ in the population regression of } \tau \text{ on } \mathbf{x}_i$$

$$\mu = \frac{(1-R^2)(1-t)}{t+(1-R^2)(1-t)}, \qquad \text{proportionality factor}$$

- The term μ represents the unexpected component of information τ revealed by event E
- Also represents the fraction of information τ that remains in event E
  - μ is small when the event reveals little information
  - μ is large for highly surprising events

Lemma 1 (1) $0<\mu<1$

(2) μ is small when event E is highly anticipated

  - Downward bias: $|\beta_j|\leq|\theta_j|$
  - Opposite sign: $\text{sign}(\beta_j)\neq\text{sign}(\theta_j)$
  - More attenuation when $|\pi|$ is small (i.e. low announcement impact)
  - More attenuation when E are highly anticipated (i.e. not surprising event)
- Overall, Proposition 1 implies that <u>the traditional cross-sectional procedure may be used for cross-sectional inferences in event studies</u>
- Specifically, <u>tests for $\boldsymbol{\beta}$ are equivalent to tests for $\boldsymbol{\theta}$ of the conditional model</u>

3. Issues in Choosing Event-Study Methodology

- Then what do we have to choose? Traditional model? Conditional model?
  - All assumptions are satisfied
    - <u>If data have both E and NE, then Conditional $\succ$ Traditional</u>
    - <u>If data only have E, then Traditional $\succ$ Conditional</u>
    - NE data include
      1) Set of firms that were anticipated to announce but chose not to announce the event
      2) The time when markets learn of the non-announcement
      3) Cross-sectional and announcement effect data on this date
    - Usually such information cannot be obtained: Lanen and Thompson (1988, JAE)
  - Some assumptions are not satisfied
    - Non-Normality of the private information ψ
    - Noise in announcement effect (difficult to isolate the portion attributable to announcement)
    - Cross-sectional correlation: Brown and Warner (1985, JFE)

- Computational issues
  - If we have both E and NE
    1) ML
    2) NLS
    3) <u>Two-step procedure</u> (Heckman, 1979): Estimate $\hat{\boldsymbol{\theta}}$, $\hat{\lambda}_C(\cdot)$ by Probit and $\hat{w}$ by OLS
       - ✓ Free from the noise in announcement-effect data
       - ✓ Simple and consistent, but inefficient (just slightly)
  - If we only have E
    1) Two-step procedure is unavailable
    2) Must be estimated via ML or NLS, but computationally expensive

4. Experiment Design

1. Event

$$
\begin{aligned}
&\mathrm{E} \Leftrightarrow \theta_0 + \theta_1 x_{1i} + \theta_2 x_{2i} + \psi_i \geq 0 \\
&\mathrm{NE} \Leftrightarrow \theta_0 + \theta_1 x_{1i} + \theta_2 x_{2i} + \psi_i < 0 \\
&\theta_0 = 1, \qquad \theta_2 = -1, \qquad \theta_2 = .01 \\
&x_{2i} \sim \text{Uniform}(0,100), \qquad \text{fixed for all 400 simulations} \\
&x_{1i} \sim \text{Uniform}, \qquad \text{fixed as well}, \qquad \text{supports vary} \\
&\psi_i \sim N(0,1), \qquad \text{Laplace}, \qquad \text{Logistic}, \qquad \chi^2, \qquad \text{Student's t}
\end{aligned}
$$

The supports of x_{1i} depend on the average event probability$\in\{25\%,50\%\}$

2. Abnormal return

$$
\begin{aligned}
&\varepsilon_i = w\psi_i + v_i, \qquad \text{where } v_i \sim \text{iid}, \qquad E[v_i] = 0, \qquad \text{Var}[v_i] = 1 - w^2 \\
&w \in \{.30, .50, .75\}
\end{aligned}
$$

The distribution of v_i is identical to that of ψ_i; N(0,1), Laplace, Logistic, χ^2 and Student's t

3. Sample size: Each set of 400 simulations was repeated for two sample sizes$\in\{100,250\}$
4. Number of replications: 400 replications of each simulation

- Recipe
  - Choose the target event probability, sample size, w and the distribution of ψ_i
  - Generate x_{1i} and x_{2i} and use them for all 400 simulations
  - Generate ψ_i (and hence E or NE) and ε_i
  - Estimate $\boldsymbol{\theta}$, w and $\boldsymbol{\beta}$ and compute corresponding t-stat
- Mean, standard error and mean t-statistic are reported.

5. Simulation Results

Table 1
Performance of conditional model: base case

Model parameter	Truth	Sample size = 100 Mean	Std. error	Mean t-stat	Sample size = 250 Mean	Std. error	Mean t-stat
Average event probability = 25%							
w	0.30	0.31	0.13	2.30	0.30	0.09	4.27
w	0.50	0.50	0.13	3.81	0.50	0.08	6.01
w	0.75	0.74	0.11	6.38	0.75	0.08	10.13
θ_0	1.00	1.04	0.51	2.05	0.99	0.31	3.27
θ_1	−1.00	−1.04	0.52	−1.97	−0.98	0.32	−3.12
$100\theta_2$	1.00	1.02	0.52	1.99	0.96	0.31	3.08
Average event probability = 50%							
w	0.30	0.30	0.12	2.37	0.32	0.08	4.45
w	0.50	0.50	0.12	4.12	0.50	0.08	6.64
w	0.75	0.76	0.11	6.83	0.74	0.07	10.74
θ_0	1.00	0.99	0.75	1.36	0.97	0.46	2.08
θ_1	−1.00	−1.00	0.48	−2.15	−0.98	0.30	−3.36
$100\theta_2$	1.00	1.00	0.47	2.20	1.02	0.29	3.46

Base case

- **θ** is close to truth
- 'w's are close to truth
- Standard error estimates are close to the true standard error

Table 2
Normality-based estimator when information is laplace distributed

Model parameter	Truth	Sample size = 100 Mean	Std. error	Mean *t*-stat	Sample size = 250 Mean	Std. error	Mean *t*-stat
Average event probability = 25%							
w	0.30	0.28	0.14	2.13	0.28	0.09	3.32
w	0.50	0.47	0.14	3.40	0.47	0.07	5.55
w	0.75	0.70	0.12	6.06	0.70	0.08	8.86
θ_0	1.00	1.26	0.59	2.22	1.24	0.36	3.46
θ_1	−1.00	−1.25	0.53	−2.41	−1.23	0.31	−3.85
$100\theta_2$	1.00	1.25	0.53	2.43	1.21	0.31	3.85
Average event probability = 50%							
w	0.30	0.27	0.13	2.10	0.28	0.08	3.50
w	0.50	0.46	0.12	3.73	0.45	0.07	5.77
w	0.75	0.69	0.12	6.40	0.69	0.07	9.76
θ_0	1.00	1.41	0.80	1.80	1.36	0.46	2.90
θ_1	−1.00	−1.41	0.50	−2.80	−1.36	0.30	4.54
$100\theta_2$	1.00	1.40	0.49	2.82	1.35	0.31	4.44

Bad case (Non-normality)

- **θ** is quite different from its true value
  - Normality-based estimator is inconsistent when ψ is non-Normal
  - But the sign and order are similar to the previous case
  - The associated t-statistics are also of a similar magnitude
  - There seems to be little impact on one's inferences
- 'w's are close to truth but are slightly attenuated
  - Non-Normality ⇒ "measurement error" into $\lambda_k(\cdot)$ ⇒ errors-in-variables bias
  - The amount of attenuation is small
- Non-Normality does lead to inconsistent parameter estimates but does not appear to impact one's inferences about the significance of model parameters

Noise in announcement effects (just qualitative descriptions): The two-step procedure does stand up to moderate amounts of noise at levels typical of event studies that use windows of a few days to measure announcement effects

Cross-sectional correlation in information (just qualitative descriptions): Non-Normality and cross-sectional correlation in private information in private information appear to matter less than imprecisely measured announcement effects

Table 3
Performance of conventional cross-sectional procedure

Panel A: Normally distributed information and 25% average event probability

True parameter	Estimated parameter	Sample size = 100 Mean	Std. error	Mean t-stat	Sample size = 250 Mean	Std. error	Mean t-stat
Correlation $(w) = 0.30$							
$\theta_0 = 1.00$	β_0	0.05	0.74	0.07	0.02	0.47	0.04
$\theta_1 = -1.00$	β_1	0.21	0.33	0.62	0.22	0.20	1.05
$100\theta_2 = 1.00$	$100\beta_2$	−0.22	0.33	−0.64	−0.23	0.20	−1.11
Correlation $(w) = 0.50$							
$\theta_0 = 1.00$	β_0	0.02	0.71	0.02	0.05	0.48	0.10
$\theta_1 = -1.00$	β_1	0.39	0.32	1.26	0.39	0.22	1.86
$100\theta_2 = 1.00$	$100\beta_2$	−0.38	0.29	−1.29	−0.38	0.19	−1.95
Correlation $(w) = 0.75$							
$\theta_0 = 1.00$	β_0	0.02	0.58	0.03	0.02	0.42	0.02
$\theta_1 = -1.00$	β_1	0.57	0.25	2.21	0.57	0.18	3.25
$100\theta_2 = 1.00$	$100\beta_2$	−0.57	0.26	−2.18	−0.56	0.18	−3.31

Panel B: Normally distributed information and 50% average event probability

True parameter	Estimated parameter	Sample size = 100 Mean	Std. error	Mean t-stat	Sample size = 250 Mean	Std. error	Mean t-stat
Correlation $(w) = 0.30$							
$\theta_0 = 1.00$	β_0	0.08	0.58	0.14	0.05	0.35	0.16
$\theta_1 = -1.00$	β_1	0.17	0.38	0.47	0.19	0.20	0.89
$100\theta_2 = 1.00$	$100\beta_2$	−0.19	0.32	−0.60	−0.18	0.23	−0.89
Correlation $(w) = 0.50$							
$\theta_0 = 1.00$	β_0	0.12	0.55	0.22	0.08	0.32	0.26
$\theta_1 = -1.00$	β_1	0.30	0.35	0.90	0.32	0.20	1.50
$100\theta_2 = 1.00$	$100\beta_2$	−0.30	0.33	−0.92	−0.31	0.22	−1.48
Correlation $(w) = 0.75$							
$\theta_0 = 1.00$	β_0	0.15	0.50	0.30	0.15	0.27	0.66
$\theta_1 = -1.00$	β_1	0.47	0.29	1.57	0.47	0.16	2.70
$100\theta_2 = 1.00$	$100\beta_2$	−0.47	0.28	−1.68	−0.48	0.17	−2.89

Conventional cross-sectional procedure (Table 3 Panel A and Panel B)

- Recall the findings of Lemma 1
  - Downward bias: $|\beta_j| \leq |\theta_j|$
    - Everywhere
  - Opposite sign: $\text{sign}(\beta_j) \neq \text{sign}(\theta_j)$
    - Everywhere
  - More attenuation when $|\pi|$ ($|w|$ in this case) is small (i.e. low announcement impact)
    - For 100 sample size and 25% average event probability
    - $\hat{\beta}_1 = .21 \text{ for } w = .30$
    - $\hat{\beta}_1 = .39 \text{ for } w = .50$
    - $\hat{\beta}_1 = .57 \text{ for } w = .75$
  - More attenuation when E are highly anticipated (i.e. not surprising event)
    - For 100 sample size and w=30%
    - $\hat{\beta}_1 = .21 \text{ for } 25\% \text{ average event probability}$
    - $\hat{\beta}_1 = .17 \text{ for } 50\% \text{ average event probability}$
- Simulation results are consistent with its implied comparative statics
- The usual OLS standard errors seem to be appropriate for carrying out significance tests for cross-sectional parameters **β**
  - For 25% average event probability, 100 sample size, w=30%
    - Standard error estimate=.21/.62=.3387
    - True standard error=.33
- The t-statistics for the linear regression coefficients are generally smaller
  - Even though the linear model produces smaller standard errors, it is less powerful than the conditional model in picking up cross-sectional effects
- Measurement error in announcement effects: **β** is affected (low t-stat), but **θ** is remain unchanged
- Attenuation: low |w| and high event probability cause this underestimation
- The statistical significance of the linear regression coefficients **β** serves as a <u>lower bound</u> on significance of the **θ**
  - <u>Conservative</u> means of conducting cross-sectional inferences
  - <u>If one rejects the hypothesis $\beta_j=0$ at significance level α, one also rejects the hypothesis $\theta_j=0$</u>

Table 4
Performance of conditional model with truncated sample 50% average event probability

Parameter	Truth	Sample size = 100 Mean	Std. error	Mean t-stat	Sample size = 250 Mean	Std. error	Mean t-stat
$w = 0.30$							
$w_1 = \frac{w}{\sqrt{1-w^2}}$	0.31	0.93	1.19	1.39	0.67	0.79	1.91
θ_0	1.00	2.43	11.98	2.41	0.91	3.32	0.37
θ_1	−1.00	−2.24	6.09	−0.73	−1.19	2.39	−0.79
$100\theta_2$	1.00	2.46	4.96	0.69	1.90	2.99	0.99
$w = 0.50$							
$w_1 = \frac{w}{\sqrt{1-w^2}}$	0.58	1.12	1.39	1.69	0.89	0.81	2.37
θ_0	1.00	1.52	3.60	0.66	1.17	1.84	1.02
θ_1	−1.00	−1.56	2.15	−0.96	−1.37	1.34	−1.51
$100\theta_2$	1.00	1.00	2.00	0.99	1.17	1.08	1.40
$w = 0.75$							
$w_1 = \frac{w}{\sqrt{1-w^2}}$	1.13	1.45	1.07	1.91	1.17	0.54	2.77
θ_0	1.00	0.91	1.29	1.03	0.90	0.85	1.52
θ_1	−1.00	−1.20	0.82	−1.54	−1.16	0.63	−2.28
$100\theta_2$	1.00	1.53	1.00	1.45	1.17	0.54	2.21

Conditional model without nonevent information

- Absent NE data, how does the (conditional) model perform?
  - The conditional model may be estimated by NLS or ML
- The t-statistics reported in Table 4 are much smaller than those in Table 1
  - Severe negative impact on the conditional model's performance
- Why are NE data so crucial?
  - By combining both data, one increases the sample size
  - Use of NE data expands the type of information being used in estimation
- Results also indicate that the properties of the ML estimator are unsatisfactory
  - Parameter estimates are upward-biased
  - Standard errors are slightly understated
  - The t-statistics are no better than those produced by OLS
- <u>Absent NE data, there is little evidence that the specification of the conditional model analyzed here has any practical value, relative to the much simpler OLS procedure</u>

6. Conclusions

- Acharya's (1988) model is empirically valuable when
  - One has a set of NE firms in addition to data on E firms
  - If such data are available, the conditional model is valuable means of inference
  - In this case, Heckman's (1979, EMA) method is useful for estimating the conditional model
    - Free from usual data problems (event-date uncertainty, clustering of event dates)
    - Inferences are not severely affected by incorrect distributional assumptions
    - Also valid for other conditional models (Eckbo, Maksimovic and Williams, 1990)
- In reality, NE data are not available
  - Conditional model becomes computationally burdensome and less powerful
  - Results concerning traditional methods assume the greatest force
    - $\boldsymbol{\beta}$ in the traditional model is proportional to $\boldsymbol{\theta}$ in the conditional model
    - OLS standard errors appear to be appropriate
    - Traditional OLS method may be used for carrying out cross-sectional inferences (though the coefficients are potentially inconsistently estimated)
- In a nutshell
  - Conditional model$\succ$OLS when both E and NE data are available
  - OLS$\succ$Conditional model when one has E data only
- If you have both E and NE data: Use the conditional model
- If you only have E data: Use OLS and the results are conservative lower bounds

Replicated results of Table 1

		Size=100		Size=250	
Parameter	Truth	Mean	Standard Err.	Mean	Standard Err.
		Probability=25%			
ω	.25	.25	.15	.25	.10
ω	.50	.51	.14	.50	.09
ω	.75	.75	.11	.75	.07
θ_0	1.00	1.03	1.33	1.04	.76
θ_1	−1.00	−1.04	.59	−1.03	.33
$100\theta_2$	1.00	1.06	.49	1.03	.32
		Probability=50%			
ω	.25	.25	.13	.26	.08
ω	.50	.50	.12	.50	.07
ω	.75	.74	.10	.75	.07
θ_0	1.00	1.01	.78	1.02	.47
θ_1	−1.00	−1.01	.47	−1.01	.29
$100\theta_2$	1.00	1.02	.47	.99	.28

- Standard errors for θ_0s are bigger than those from Table 1

Replicated results of Table 2 Panel A

Probability=25%		Size=100		Size=250	
True	Estimated	Mean	Standard Err.	Mean	Standard Err.
		Correlation ω=.25			
θ_0=1.00	β_0	.03	.79	.03	.54
θ_1=−1.00	β_1	.18	.35	.18	.24
$100\theta_2$=1.00	$100\beta_2$	.20	.34	−.20	.23
		Correlation ω=.50			
θ_0=1.00	β_0	−.01	.75	.00	.47
θ_1=−1.00	β_1	.38	.33	.38	.21
$100\theta_2$=1.00	$100\beta_2$	−.34	.31	−.36	.20
		Correlation ω=.75			
θ_0=1.00	β_0	−.01	.64	−.01	.42
θ_1=−1.00	β_1	.58	.29	.58	.19
$100\theta_2$=1.00	$100\beta_2$	.57	.27	−.56	.18

Replicated results of Table 2 Panel B

Probability=50%		Size=100		Size=250	
True	Estimated	Mean	Standard Err.	Mean	Standard Err.
		Correlation ω=.25			
θ_0=1.00	β_0	.06	.52	.05	.34
θ_1=−1.00	β_1	.15	.33	.16	.22
$100\theta_2$=1.00	$100\beta_2$	−.15	.35	−.16	.22
		Correlation ω=.50			
θ_0=1.00	β_0	.07	.47	.08	.32
θ_1=−1.00	β_1	.32	.31	.32	.20
$100\theta_2$=1.00	$100\beta_2$	−.28	.32	−.31	.20
		Correlation ω=.75			
θ_0=1.00	β_0	.14	.45	.14	.29
θ_1=−1.00	β_1	.47	.30	.46	.18
$100\theta_2$=1.00	$100\beta_2$	−.46	.30	−.45	.18

- For each simulation, the author generates 100 or 250 samples containing only ‘E’ observations
- If one draws 100 or 250 samples and uses just ‘E’ data, then the standard errors will be different from those reported by the author