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RESEARCH ARTICLE

THE MORE, THE MERRIER? HOW THE NUMBER OF PARTNERS IN A STANDARD-SETTING INITIATIVE AFFECTS SHAREHOLDER'S RISK AND RETURN[1]

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Appendix A

Examples of Events

Date	Ticker	FIRMCOUNT	Risk Adjusted Return (γ)	Change in Market Risk (β')	Change in Idiosyncratic Risk (σ^2 after – σ^2 before)
2/20/1996	FDC	2	-0.006087476	0.02552937	6.32225E-05
5/7/1996	ISLI	2	0.0243426	-1.892630856	-0.002437866
5/7/1996	SUNW	2	-0.007177306	-1.025868233	-0.000912965
5/20/1996	NSCP	6	0.017395648	0.827543911	-0.000930735
5/20/1996	ORCL	6	0.00570959	-1.492743834	-0.000170551
5/20/1996	SUNW	6	0.010269372	-0.741954827	-0.000735972
5/20/1996	AAPL	6	-0.011087047	0.453908597	0.000461451
5/20/1996	IBM	6	0.008333754	-0.783104337	-0.000173145
7/23/1996	MSFT	1	-0.01014626	0.109996717	3.65691E-06
7/26/1996	MSFT	1	-0.000402748	0.030131026	-2.24841E-06
9/3/1996	ISLI	1	0.002197317	-0.187824693	-0.000458735
6/7/2005	APA	9	-0.002690234	0.238221825	0.000109512
6/7/2005	SAP	9	0.007471843	0.133098243	-4.35429E-05
6/7/2005	ORCL	9	0.003635138	-0.678397138	-8.57553E-05
6/7/2005	IBM	9	-0.000961421	-0.32067959	-6.28663E-05
6/29/2005	COL	3	-0.00357972	-0.371034951	-4.96182E-05
6/29/2005	RTN	3	-0.000414139	-0.108476688	-6.52509E-06
7/22/2005	VSNT	1	0.055943344	0.618384879	-0.000278402
9/22/2005	KEYW	3	-0.023036531	0.11372799	-1.67123E-05
10/3/2005	PHG	5	0.001534706	-0.169006842	-9.90286E-06
10/3/2005	SNE	5	0.011567974	-0.353971047	-2.09123E-05
10/3/2005	MC	5	0.010582315	1.003300833	0.00022589

Note: For a complete list of events, please contact the authors.

Appendix B

Examples of Announcements

Example Announcement #1: Business Wire, June 11, 1997

DISTRIBUTION: Business Editors
HEADLINE: Firefly, Netscape and Microsoft cooperate to build upon previously proposed OPS standard for personalization with privacy
DATELINE: Washington
BODY:
June 11, 1997—Companies Agree to Cooperate on Further Development of OPS within the World Wide Web Consortium's Recently Launched P3 Privacy Initiative

Firefly Network Inc., Netscape Communications Corp. and Microsoft Corp. today announced that they are cooperating to build upon the previously proposed Open Profiling Standard (OPS), which provides a framework with built-in privacy safeguards for the trusted exchange of profile information between individuals and Web sites. This announcement marks a unique moment when technology and business differences have been put aside to coordinate support for a proposed standard that places particular emphasis on individuals' rights to privacy, while creating a context for personalized network experiences and the building of community online.

Firefly, Netscape, Microsoft and VeriSign will work together on the OPS proposal during the remainder of the standards review process of the World Wide Web Consortium (W3C). "We're delighted that Microsoft, Netscape and Firefly have chosen to work together with our staff and our other member organizations," said Jim Miller, leader of the technology and society domain of the World Wide Web Consortium. "The industry must address the legitimate privacy concerns of Internet users. The W3C P3 Project will ensure that all vendors can implement privacy protection in a consistent way that also respects international requirements." Further information about the OPS specification is located at the following site: http://www.firefly.net/OPS/index.html.

OPS Supported as Global Standard

OPS is a proposed global standard that creates a framework for the trusted exchange of information between consenting parties, which will facilitate the growth of personal privacy, as well as personalized electronic commerce and advertising.

Example Announcement #2: PR Newswire, October 2, 2000

DISTRIBUTION: TO AUTO, BUSINESS AND TECHNOLOGY EDITORS
HEADLINE: FlexRay Consortium Being Formed to Drive Initiative for Advanced Automotive Communication System
DATELINE: EINDHOVEN, Netherlands, Oct. 2
BODY:
Automotive manufacturers BMW and DaimlerChrysler, and semiconductor manufacturers Motorola and Philips Semiconductors, an affiliate of Royal Philips Electronics (NYSE: PHG), today announce their intention to form an industry consortium to drive forward the development and implementation of an advanced automotive communication system named FlexRay. Aimed to be a standard for innovative high-speed control applications in the car, such as x-by-wire, FlexRay technology will be available for everybody in the worldwide market.

The FlexRay consortium is coming together in response to changing industry needs. Future automotive applications demand high-speed bus systems that are both deterministic and fault-tolerant, capable of supporting distributed control systems. FlexRay technology is designed to meet these requirements, complementing major in-vehicle networking standards CAN, LIN, and MOST.

Appendix C

The BEGLS Estimator

The OLS estimator of equation (3) assumes that the covariance matrix of the error term is an identity matrix times a constant, $\sigma^2 I$, so that there is no covariance between observations. However, we believe that the covariance matrix does have covariance between observations, both within firms and within events. Thus, we believe the covariance matrix is $\sigma^2\Psi$, where Ψ has some nonzero elements off the diagonal. To understand the consequences of this, we rewrite equation (3) as $\boldsymbol{y} = X\boldsymbol{\beta} + \boldsymbol{e}$. Here, X is a matrix of all the independent variables and control variables, $\boldsymbol{y}$ is a vector of the dependent variable, $\boldsymbol{\beta}$ is a vector of the coefficients to be estimated and $\boldsymbol{e}$ is a vector of error terms with the covariance matrix $\sigma^2\Psi$. If this is true, then the generalized least squares estimator of the parameters, $\boldsymbol{\beta}_{GLS} = (X`\Psi^{-1}X)^{-1}X`\Psi^{-1}\boldsymbol{y}$, is more efficient than the OLS estimator, $\boldsymbol{\beta}_{OLS} = (X`X)^{-1}X`\boldsymbol{y}$ (Judge et al. 1988).

$\boldsymbol{\beta}_{GLS}$ and $\boldsymbol{\beta}_{OLS}$ are both unbiased so that the expected value of the estimate equals the true value of the parameter being estimated. But the variance of $\boldsymbol{\beta}_{GLS}$ is less than the variance of $\boldsymbol{\beta}_{OLS}$. This means that if many samples are taken and $\boldsymbol{\beta}$ is estimated many times, overall the GLS estimates will be closer than the OLS estimates. However, this requires that we use the true value of Ψ, which in practice we do not know, thus we must estimate it.

We postulate that there is covariance within standard setting events and that there is covariance within firms. To make this concrete, take a sample of size six, where the first standard (1) involves Sun Micro (s), Microsoft (m), and IBM (i). The second standard (2) involves Dell (d) and IBM (i), and the third standard (3) involves only IBM (i). Then the covariance matrix of the error term will look like this:

$$\sigma^2\Psi = \sigma^2\begin{bmatrix} 1 & \varphi_{m,s,1} & \varphi_{i,s,1} & 0 & 0 & 0 \\ \varphi_{m,s,1} & 1 & \varphi_{i,m,1} & 0 & 0 & 0 \\ \varphi_{i,s,1} & \varphi_{i,m.1} & 1 & 0 & \varphi_{i,i,2,1} & \varphi_{i,i,3,1} \\ 0 & 0 & 0 & 1 & \varphi_{i,d,1} & 0 \\ 0 & 0 & \varphi_{i,i,2,1} & \varphi_{i,f,2} & 1 & \varphi_{i,i,3,2} \\ 0 & 0 & \varphi_{i,i,3,1} & 0 & \varphi_{i,j,3,2} & 1 \end{bmatrix}$$

There are two different types of terms here. The first is those like $\varphi_{m,s,1}$, which is the covariance between Microsoft (m) and Sun (s) for the first standard (1). The second is those like $\varphi_{i,i,2,1}$, which is the covariance between IBM (i) in standard two (3) and IBM (i) in standard one (1). Note that the covariances are symmetrical across the diagonal. There is no a priori reason to believe that the covariances within an announcement are the same. It is easy to imagine, for example, that the fortunes of Sun and Microsoft might have negative covariance while the fortune of IBM and Microsoft have positive covariance for a particular standard, like a Java standard. Similarly, there is no particular reason to believe that the covariance between a particular firm in two different standards is the same as the covariance between that firm in some other pair of standards. For example, the covariance between IBM in two software standards might be different than the covariance between IBM in a hardware and a software standard.

In general, Ψ is unknown and must be estimated. Using an estimated value of Ψ leads to the *estimated* generalized least squares (EGLS) estimator. For our specification, we have more elements of Ψ than we have data points. In the example above, we have seven φ's and only six events from which to estimate them. This rules out maximum likelihood methods. However, we do have another option. Because the OLS estimates are unbiased, they provide an unbiased estimate of the error vector, $\boldsymbol{e}$. Thus, $\boldsymbol{ee}$` provides an unbiased estimated $\sigma^2\Psi$. More to the point, $e_r e_c$ provides an unbiased estimate of $\varphi_{r,c}$, where r and c denote the row and column respectively. Thus, in the example above an unbiased estimate of $\varphi_{m,s,1}$ is $e_2 e_1$ because $\varphi_{m,s,1}$ is the element in the second row, and first column.

Therefore, to construct the estimate of $\sigma^2\Psi$, we first use OLS to estimate equation (3), then construct a matrix which has the value $e_r e_c$ in every place where the row and column have the same standard setting event or the same firm (and along the diagonal). Thus, the estimate, **V**, from our example would be

$$\hat{\sigma}^2\hat{\Psi} = \mathrm{V} = \begin{bmatrix} e_1e_1 & e_1e_2 & e_1e_3 & 0 & 0 & 0 \\ e_2e_1 & e_2e_2 & e_2e_3 & 0 & e_3e_5 & e_3e_6 \\ e_3e_1 & e_3e_2 & e_3e_3 & 0 & e_3e_5 & e_3e_6 \\ 0 & 0 & 0 & e_4e_4 & e_4e_5 & e_4e_6 \\ 0 & 0 & e_5e_3 & e_5e_4 & e_5e_5 & 0 \\ 0 & 0 & e_6e_3 & e_6e_4 & 0 & e_6e_6 \end{bmatrix}$$

There are a few points to notice. Obviously, $e_re_c = e_ce_r$. The σ^2 has been removed because the GLS estimator is invariant to multiplication by a constant and e_re_c is actually an estimate of the (r,c) element of $\sigma^2\Psi$ not of Ψ. Finally, rather than assuming a constant variance, we allow for the possibility of heteroskedasticity. In fact, the diagonal is the well known White's heterskedastictic consistent covariance matrix (White 1980).

The consequence of using an estimate of $\sigma^2\Psi$ rather than the true $\sigma^2\Psi$ is that the finite sample properties are unknown. That is to say, that as the number of firms in each standard setting event increases to infinity and the number of times a firm appears increases to infinity, the EGLS estimates converge to the GLS estimates. On the other hand, in this sample we have some very small standard setting events (i.e. few firms or one firm) and many firms appear only a few (or one) times. There is nothing to be done, but we want to make clear that the finite sample properties of this estimator are unknown.

Now we run into the tricky part. To follow the rules of probability, $\sigma^2\Psi$ must be positive definite. If it is not then it implies that more than 100% of the variance in one observation is explained. However, there is nothing to guarantee that an estimate of $\sigma^2\Psi$ will be positive definite (Swamy 1970). In fact, it is fairly common for estimates of a covariance matrix to be nonpositive definite. More to the point, in our sample we find that our estimate of $\sigma^2\Psi$ is not positive definite.

To overcome this, we use a procedure called *bending* (Hayes and Hill 1981). Bending uses an iterative procedure to insure that the covariance matrix is positive definite. The steps are as follows (Jorjani et al. 2003):

1. Obtain the estimated covariance matrix **V**.
2. Create a matrix of eigenvectors **U** and a diagonal matrix of eigenvalues **D**. Note that $\mathbf{V}_n = \mathbf{U}_n\mathbf{D}_n\mathbf{U}_n'$. The subscript *n* represents the iteration number.
3. Replace all the negative eigenvalues in $\mathbf{D}_n$ with a positive number ε to form $\mathbf{\Delta}_n$.
4. Calculate a new estimate of the covariance matrix $\mathbf{V}_{n+1} = \mathbf{U}_n\mathbf{\Delta}_n\mathbf{U}_n`$.
5. Repeat until $\mathbf{V}_{n+1}$ is positive definite.

This results in an estimate of the covariance matrix that is positive definite. We then use this estimate to perform generalized least squares. Thus, we term the estimator the BEGLS, which means *bended estimated generalized least squares* estimator. This estimator addresses three problems that might face the OLS estimate. First, if the model suffers from correlation within standard setting events and within firms, this procedure addresses the problem. By "suffer" we mean that there is meaningfully large correlation. If the correlation is small then the deviation from the OLS model will be small. Second, it can be estimated with the data available to us. Specifically, we do not know the true correlations, so we need to estimate them from the data we have. Third, it is calculable in the sense that positive definiteness is required to apply the GLS procedure.

References

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