PREDICTION OF SYSTEMATIC RISK: A CASE FROM TURKEY

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Abstract

This study compares Bayesian and time-varying models to adjust for the regression tendency of betas present in standard asset pricing applications. Beta adjustment techniques are applied to the Istanbul Stock Exchange (ISE) data. Empirical findings show that Mean Square Error (MSE) is lowest among all models used in the study when log-linear or square-root linear Blume models are used and betas predicted according to Bayesian models, have lower MSE than unadjusted betas. Also, it is observed that inefficiency part of the MSE changes most when various adjustment techniques are used.

ملخص

تجري الدراسة مقارنة بين نموذجي بيزين Bayesian والزمن المتغير Time-varying لتعديل ميل انحدار معاملات بيتا Beta على البيانات الخاصة ببورصة اسطنبول للاوراق المالية. وتشير النتائج التطبيقية الى ان متوسط مربع الخطأ يكون اقل في كافة النماذج المستخدمة في الدراسة وذلك عندما تستخدم نماذج القياس الخطي او الجذر التربيعي الخطي لنماذج بلوم Blume كما ان متوسط مربع الخطأ لمعاملات بيتا التي تم احتساب تقديراتها المتوقعة وفق نماذج بيزين، يكون اقل بالقياس للمعاملات التي لم يتم تصحيحها. كما يلاحظ ان الجزء غير الفعال في متوسط مربع الخطأ يتغير اكثر عندما تستخدم اساليب التصحيح المختلفة.

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I. INTRODUCTION

ESTIMATION OF SYSTEMATIC RISK is one of the most critical topics in finance. As a relevant measure of risk in security analysis, the beta coefficient has been widely used in the recent past. The power of measuring the ex-ante security risk highly depends on the degree of predictability and the temporal stability of security betas over future time periods.

As the beta predictions, like all the other predictions in economics, the simplest method is to assume that the future will be like the past. Historical betas could then be used directly. But such methods rest on the assumption that the underlying processes must stable over time and the past record is an adequate reflector of their essential characteristics.

There are several objections arised against these methods. First of all, in order to catch the information hidden in the return for the security, a long period must be studied. But when the estimation-prediction period was kept long, the simple system by itself would be inadequate to explain the structural change.

As Sharpe (1970) stated[1]

> "...The investigator may be faced with the choice of learning enough about the wrong thing or too little about the right one."

Most economists who observed the inefficiency of the above prediction method that the future will be exactly like the past, tried several other adjustment procedures.

Blume and *Levy* (1971) found that security beta coefficients did not predict the betas in the subsequent periods. They also observed that as betas departed from the average, prediction accuracy got worsened, high betas were overpredicted whereas the low ones were underpredicted.

The studies of *Eubank* and *Zumwalt* (1979) showed that Mean Square Error as a consistent criteria to estimate prediction error decreased when portfolio size or estimation-prediction period was increased. *Bera* and *Kannan* (1986) found that as different beta adjustment procedures were utilized, the Mean Square Error could be reduced upto a point.

The Vasicek(1973) proposed a Bayesian estimation procedure to predict beta coefficients. Using the knowledge prior to sampling it became possible to improve the prediction significantly. *Bera* and *Kannan* (1986) used this technique and compared it with the other standart prediction methods and concluded that Bayesian methods performed better then most of the other techniques.

Beside the above techniques, this study uses also a very poverful estimation technique proposed by Stein(1961) and generalized by Efron & Morris (1972) which has not yet been applied in finance.

[1] Portfolio Theory and Capital Markets, p.179.

The objectives of this study are twofold. First we try different adjustment techniques, such as naive adjustment,time-varying adjustments or Bayesian adjustments, to find a model which fits best to predict the ex-ante security beta coefficients using the data from the Istanbul Stock Exchange (ISE).

Second, we investigate the sources of forecast error (MSE), the bias, inefficiency and random error, and furnish more detailed answers concerning the effects of various adjustment procedures on MSE.

II. LITERATURE SURVEY

Some previous research has adopted the standard single index model (SIM) to estimate systematic risk. The characteristic line used in the literature is as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}; \tag{1}$$

where R_{it} and R_{mt} are, respectively, the return to the security i, and the return to the market portfolio in period t, and ϵ_{it} is the random disturbance with mean zero and homoscedastic variance and is uncorrelated with market return, α_i and β_i are regression parameters. This model of *Markowitz* (1959) depends on the assumption that β_i (and also α_i) are time invariant. According to this assumption the differences between betas for a specific security in different periods are caused by sampling errors.

It has been a topic of discussion in the literature what the market rate of return really is. Most of the investigators used the average of the values for the individual securities as the rate of return to the market portfolio:

$$R_{Mt} = \frac{1}{N}\sum_{i=1}^{N} R_{it} \tag{2}$$

where R_{it} = security rate of return in time period t, R_{Mt} = market rate of return in time period t and N = number of securities.

By assigning equal weights to all security returns in the calculation of the market rate of return, it is assumed that equal dollar amount is invested in every security.

As it should be obvious the expected return depends only on market rate of return:

$$E(R_i) = \alpha_i + \beta_i E(R_m) \tag{3}$$

As in the preceeding equilibrium approach, the risk consists of two parts :

$$\sigma_i^2 = \beta_i^2\sigma_m^2 + \sigma_{\epsilon_i}^2; \tag{4}$$

where the first term on the RHS denotes the systematic risk and the second one the unsystematic risk.

Blume (1971) empirically showed that security betas did change over time. By regressing betas on their lagged value, he found a regular pattern. Assuming betas were normally distributed, β_i is expected to fall this period if it was too high last period, and vice versa. This tendency of betas towards their mean value implies that taking historical betas as the only variables to explain or predict future betas is inadequate.

A somewhat similar procedure to *Blume*'s was used in the Security Risk Evaluation Service by *Merrill Lynch, Pierce, Fenner & Smith, Inc.* (1973) Assuming mean of cross-sectional betas is equal to one irrespective of the estimation period, they predicted future betas. *Vasicek* (1973) provided that if the information prior to sampling were utilized, the expected mean square loss could decrease. In his paper he summarizes the reason why he prefers Bayesian estimates to classical sampling-theory as follows:

> **"First Bayesian procedures provide estimates that minimize the loss due to misestimation, while sampling theory estimates minimize the error of sampling.**
>
> **...Secondly, Bayesian theory weights the expected losses by a prior distribution of the parameters, thus incorporating knowledge which is available to the sample information."**

The topic was raised later in the literature in the work of *Bera* and *Kannan* (1986). The authors predicted future betas by using various adjustment procedures. They found that time-varying models such as Blume's model best performed to predicted beta as a measure of systematic risk.

To understand which method was best among all in forecasting betas, most analysist used the Mean Square Error criteria. Moreover, decomposing mean square error into the components of *bias, inefficiency* and *random error* it was possible to test the real power of any prediction method. This method was firstly described by *Eubank* and *Zumwalt* (1979) in finance, and used by many investigators.

Bias indicates the part of MSE due to overestimation or underestimation of the mean from one period to the next. When the portfolio size is big enough, empirically it is observed that the means of predicted and estimated betas are almost the same and therefore bias in this case is negligible.

Inefficiency shows that the tendency of the prediction errors to be positive for low predicted values and negative for high predicted betas. Inefficiency does exist and positively related to the sample variance in predicted betas unless the slope coefficient obtained from the regression of actual betas on predicted betas is one. *Klemkosky* and *Martin* (1975) claimed that *Blume* and *Levy*'s observation that beta extrapolations have a tendency to regress toward the mean was the evidence of inefficiency in the forecasts.

Random error is the part of MSE that is unexplained by the prediction model. *Blume*'s findings supported *Eubank*'s and *Zumwalt*'s result that random error was almost independent of the model used and could only be reduced by increasing the portfolio size. *Eubank* and *Zumwalt* also showed that increasing the length of estimation-prediction period, one may get larger random error components possibly because some structural change have occured.

So the differences between MSE's were caused mainly by the effects of different models on reducing the bias and inefficiency components. *Bera* and *Kannan* (1986) empirically observed that Bayesian methods are always superior to unadjusted estimates (classical sampling estimates) for predicting future methods, since the former gives smaller MSE. They also showed that it is the *Blume*'s method which is the best among the all including the Bayesian methods, indicating the existence of a regular trend of betas over time unlike what was assumed by *Markowitz*.

By trying several Box-Cox transformation on betas, which aims to normalize the random disturbances in betas, *Bera* and *Kannan* succeded in reducing MSE further. They eventually concluded that had longer lagged betas has been included in Blume's equation of estimation, the smaller MSE's would have been obtained.

III. A REVIEW OF THE TURKISH CAPITAL MARKETS

In the beginning of the 1980s, Turkish governments started a liberalization program to transform the country to a free market economy. By this program, both in the international trade and in financial markets some new regulations and new policies were adopted.

To promote the development of Turkish Capital Markets, Central bank simplified reserve and liquidity requirement system and an interbank money market was founded. Exports were promoted and tariffs on imports were reduced. The control on prices and exchange rate was removed. The Turkish Lira was made convertible.

The Capital Market Law was enacted in 1981 and the main regulatory body that is responsible for the regulation and supervision of the primary and secondary markets, The Capital Markets Board, is established in 1982.[2]

All these liberalizations in early 80s, prepared the necessary grounds on which a security exchange was founded, so in 1986 the Istanbul Securities Exchage (ISE) restarted its operations. Investors of any country of origin were allowed to freely trade in stock market. Moreover capital controls were removed.

In October 1987, the ISE adopted a new trading system to provide a continuous auction and transparency of transactions executed on the board. By allowing daily newspapers to publicate transaction volume and price regularly, ISE created a mood of confidence among investors.

Recently, the Capital Board of Turkey brought new regulations related to short-selling, repo-transactions and the effective control of issuing new securities. One of the main motive forces underlying the rapid growth of ISE was no doubt the reforms which permits revaluation.

IV. THE DATA AND DESCRIPTIVE STATISTICS

The data used are adjusted daily, weekly and monthly share prices from the Istanbul Stock Exchange. Since the returns were not readily available, they were calculated using the adjusted prices by

$$R_{it} = log(P_{it}/P_{it-1}); \tag{5}$$

where R_{it} is the return of the i^{th} security at time t, P_{it} and P_{it-1} are price of the i^{th} security at time t and $t-1$, respectively.

Daily returns are available for 32 securities and cover the period of 04/01/88 - 27/12/90. Weekly returns are available for 37 securities starting from the first week of February 1986 until the second week of January 1990. Finally, for 41 securities in the ISE monthly returns are used for the period of January 1988 - August 1991.

[2] Akdoğan H. (1992) has an excellent review on the Turkish Capital Markets.

V. METHODOLOGY

The various adjustment procedures in this study can be described by the expression:

$$\hat{\beta}_{ti} = f^{-1}(\delta_{1i} + \delta_{2i} f(\beta_{t-1i})); \tag{6}$$

where β_{ti} is the predicted beta of security i for period t, and β_{t-1i} is the historical beta of security i in period $t-1$, f denotes a Box-Cox transformation, and in this study it takes the forms of identity, square-root and logarithmic functions.

Depending on the ways to calculate δ_{1i} and δ_{2i}, different adjustment techniques have arised in the finance literature. We suggest here a time-varying model dealing with the problems associated with the regression tendency of betas. We shall also compare ours to the previously-used adjustment techniques.

1. Naive Adjustment

   Unadjusted betas are obtained by substituting $\delta_{1i} = 0, \delta_{2i} = 1$ and when f is an identity function. The assumption behind the setting is that it is only the recent past that we can use as information to predict future. We can then write the predicted beta as:

$$\hat{\beta}_{ti} = \beta_{t-1i}; \tag{7}$$

2. Blume's Adjustment

   In Blume's adjustment procedure β_{ti} is predicted as follows:

$$\hat{\beta}_{ti} = \delta_1 + \delta_2 \beta_{t-1i}; \tag{8}$$

   where δ_1 and δ_2 are the OLS estimates of λ_1 and λ_2 in the below equation, and the same for each security.[3]

$$\beta_{t-1} = \lambda_1 + \lambda_2 \beta_{t-2} + u_{t-1}; \tag{9}$$

   where β_{t-1} and β_{t-2} are column matrices of cross-sectional betas in period $t-1$ and $t-2$ respectively, and u_{t-1} is the column matrix of cross-sectional disturbance terms. Since $\hat{\lambda}_1 = \bar{\beta}_{t-1} - \hat{\lambda}_2 \bar{\beta}_{t-2}$, the model can be written as follows:[4]

$$\hat{\beta}_{ti} = \bar{\beta}_{t-1} + \hat{\lambda}_2(\beta_{t-1i} - \bar{\beta}_{t-2}). \tag{10}$$

   The hypotheses of Blume that over time betas appear to take less extreme values and exhibit a tendency towards its mean value is clearly reflected in equation (10). Shifts of betas towards the mean are proportional to distance of beta from the past mean value and the proportionality constant is the same for all securities.

[3]Note that the Box-Cox transformation function is identity function also in this adjustment.

[4]The bar operator $^{-}$ denotes the arithmetic mean.

3. MLPFS Adjustment

The adjustment procedure used by MLPFS assumes that cross-sectional mean of betas are constant and is equal to one regardless of the period. Thus MLPFS betas are obtained via the prediction equation below:

$$\hat{\beta}_{ti} = 1 + \hat{\lambda}_2(\beta_{t-1i} - 1). \tag{11}$$

If as a Box-Cox transformation logarithm and square-root functions are chosen in the general model (6), the following log-linear and square-root linear Blume type model are obtained.

4. Log-Linear Blume Adjustment

We can write the log-linear model as follows:

$$\hat{\beta}_{ti} = exp\,(\delta_1 + \delta_2 log(\beta_{t-1i}))\,; \tag{12}$$

where δ_1 and δ_2 are OLS estimates of λ_1 and λ_2 in the equation below:

$$log(\beta_{t-1}) = \lambda_1 + \lambda_2 log(\beta_{t-2}) + u_{t-1}. \tag{13}$$

β_{t-1}, β_{t-2} are cross-sectional betas in periods $t-1$ and $t-2$ respectively, and u_{t-1} is zero mean disturbance term. Substituting $\hat{\lambda}_1 = \overline{log(\beta_{t-1})} - \hat{\lambda}_2\overline{log(\beta_{t-2})}$, where $\overline{log(\beta_{t-j})}$ denotes the cross-sectional mean in period $t-j$, for any j, we finally obtain the following:

$$\hat{\beta}_{ti} = exp\left(\overline{log(\beta_{t-1})} + \hat{\lambda}_2\left(log(\beta_{t-1i}) - \overline{log(\beta_{t-2})}\right)\right) \tag{14}$$

5. Square-Root Linear Blume Adjustment

A similar analysis to above is utilized to obtain the following prediction equation when the Box-Cox transformation is taken as the square-root function:

$$\hat{\beta}_{ti} = \left(\overline{\sqrt{\beta_{t-1}}} + \hat{\lambda}_2(\sqrt{\beta_{t-1i}} - \overline{\sqrt{\beta_{t-2}}})\right)^2 \tag{15}$$

where $\hat{\lambda}_2$ is the OLS estimate of λ_2 in the below equation:

$$\sqrt{\beta_{t-1}} = \lambda_1 + \lambda_2\sqrt{\beta_{t-2}} + u_{t-1}. \tag{16}$$

As it should be clear from (10),(14) and (15), the difference between these log-linear and square-root linear models and that of the Blume is the assumption brought on the normality of the betas. In these log-linear and square-root linear Blume type models not the original betas but their logs and square-roots are thought to be normally distributed.

We should now introduce the Bayesian adjustment techniques in an attempt to shrink beta values towards the cross-sectional mean using the accuracy of betas obtained from a prior information.

6. Vasicek Adjustment

Vasicek's Bayesian technique (1973) adopts the following prediction model:

$$\hat{\beta}_{ti} = \delta_{1i} + \delta_{2i}\beta_{t-1i}; \tag{17}$$

where $\delta_{1i} = \bar{\beta}_{t-1}w_{t-1i}$ and $\delta_{2i} = 1 - w_{t-1i}$ for some security specific parameter (so called weight) w_{t-1i} and for the mean of cross-sectional betas in period $t-1$. Vasicek calculated this weight "w_{t-1i}" in terms of sampling and prior information about betas as such:

$$w_{t-1i} = v_{t-1i}/(\bar{v}_{t-1} + v_{t-1i}); \tag{18}$$

v_{t-1i} is the estimated variance of the i^{th} security beta in period $t-1$ and $\bar{v}_{t-1}$ is the cross-sectional variance of betas in period $t-1$. Clearly, w_{t-1i} is always between zero and one, and that is why this Bayesian adjustment technique is called shrinkage estimation. Writing predicted beta as

$$\hat{\beta}_{ti} = w_{t-1i}\bar{\beta}_{t-1} + (1 - w_{t-1i})\beta_{t-1i}; \tag{19}$$

one can think of the forecast betas as the convex linear combination of the historical betas and the prior information, the cross-sectional betas in this case.

7. Efron&Morris Adjustment

Contrary to Vasicek, Efron&Morris (1975) used the Fisher information in historical betas to deduce the variance of prior betas. Adopting this technique to the Vasicek's prediction model we obtain an alternative adjustment procedure in this study.

Using the Fisher information hidden in sampling estimates of betas, the Vasicek weights can be rewritten as:

$$w_{t-1i} = v_{t-1i}/(\hat{A}_{t-1} + v_{t-1i}); \tag{20}$$

where $\hat{A}_{t-1}$ is the solution to the following equations:

$$A_{t-1} = \sum_{i=1}^{k} \left(\frac{\left((\beta_{t-1i} - \bar{\beta}_{t-1})^2 - v_{t-1i}\right) I_i(A_{t-1})}{\sum_{j=1}^{k} I_j(A_{t-1})} \right) \tag{21}$$

$$I_j(A_{t-1}) = \frac{1}{(2(A_{t-1} + v_{t-1j}))^2}; \tag{22}$$

Now we can write the prediction equation using the equations (19) and (20).

$$\hat{\beta}_{t-1i} = \beta_{t-1i} + \frac{v_{t-1i}}{\hat{A}_{t-1} + v_{t-1i}}(\bar{\beta}_{t-1} - \beta_{t-1i}) \tag{23}$$

After having described the 7 adjustment techniques in the study, we are now ready to define our criteria, MSE (Mean Square Error) criteria to be used in the evaluation process of predictions.

Mean Square Error is simply given by:

$$MSE_t = \frac{1}{k}\sum_{i=1}^{k}(\beta_{E,ti} - \beta_{P,ti})^2; \tag{24}$$

where $\beta_{E,ti}$ and $\beta_{P,ti}$ are, respectively, estimated and predicted betas in period t, and k is the number of securities in the market portfolio in period t. As shown by *Eubank* and *Zumwalt*, it is possible to write Mean Square Error in terms of its components as:

$$MSE_t = \underbrace{(\bar{\beta}_{E,t} - \bar{\beta}_{P,t})^2}_{bias} + \underbrace{(1-\hat{b})^2\sigma^2_{BP,t}}_{inefficiency} + \underbrace{(1-r^2)\sigma^2_{BE,t}}_{random\ error} \tag{25}$$

$\sigma_{BE,t}$ and $\sigma_{BP,t}$ are the standard deviations of estimated and predicted cross-sectional betas, respectively, and $\hat{b}$ (slope) and r^2 (coefficient of determination) are obtained from the linear regression of $\beta_{E,t}$ on $\beta_{P,t}$ as below:

$$\beta_{E,t} = a + b\beta_{P,t} + u; \tag{26}$$

VI. Results

The Mean Square Error and its components, *bias, inefficiency and random error*, were calculated for 7 different prediction methods for monthly, weekly and daily returns and are presented in the following tables.

In Table 1, the mean square errors of the prediction for monthly returns are given.

TABLE 1
MSE's of the Predicted Betas
(Monthly Returns)

	MSE	Bias	Inefficiency	Random Error
Unadjusted*	**0.202**	0.000	0.083	0.118
Vasicek	**0.183**	0.000	0.065	0.118
Efron&Morris	**0.181**	0.000	0.062	0.118

Estimation Period : 01/88-10/89
Prediction Period : 11/89-08/91

As it may be seen, betas predicted using the Vasicek adjustment and Efron Morris adjustment performed slightly over the unadjusted betas. It is striking that all the reduction in the error was due to the decrease in the inefficiency part. The bias and random error part are seen not to be affected anyway.

In Table 2, the Mean Square Errors for the betas for weekly returns are shown. As shown, again the Bayesian methods performed better than sampling estimates and with respect to the case for monthly returns, the size of the error is shown as about three times smaller.

TABLE 2
MSE's of the Predicted Betas
(Weekly Returns)

	MSE	Bias	Inefficiency	Random Error
Unadjusted	**0.072**	0.000	0.051	0.021
Vasicek	**0.051**	0.000	0.029	0.021
Efron&Morris	**0.046**	0.000	0.025	0.021

Estimation Period : 07/02/86-22/01/88
Prediction Period : 29/01/88-12/01/90

Finally, in Tables 3 to 5 the MSE's of the betas predicted by using daily returns are given for three consequative prediction periods.

TABLE 3
3. MSE's of the Predicted Betas
(Daily Returns)

	MSE	Bias	Inefficiency	Random Error
Unadjusted	**0.100**	0.000	0.036	0.065
Vasicek	**0.095**	0.001	0.030	0.064
Efron&Morris	**0.095**	0.001	0.030	0.064

Estimation Period : 04/01/88-30/09/88
Prediction Period : 03/10/88-26/06/89

TABLE 4
MSE's of the Predicted Betas
(Daily Returns)

	MSE	Bias	Inefficiency	Random Error
Unadjusted	**0.075**	0.000	0.061	0.013
Vasicek	**0.064**	0.000	0.051	0.013
Efron&Morris	**0.063**	0.000	0.050	0.013
Blume	**0.023**	0.000	0.009	0.013
MLPFS	**0.023**	0.000	0.009	0.013
SQRT	**0.026**	0.000	0.012	0.013
LOG	**0.015**	0.000	0.001	0.014

Estimation Period : 03/10/88-26/06/89
Prediction Period : 27/06/89-22/03/90

TABLE 5 MSE's of the Predicted Betas (Daily Returns)				
	MSE	Bias	Inefficiency	Random Error
Unadjusted	**0.048**	0.000	0.016	0.032
Vasicek	**0.043**	0.000	0.011	0.032
Efron&Morris	**0.043**	0.000	0.010	0.032
Blume	**0.032**	0.000	0.000	0.032
MLPFS	**0.032**	0.000	0.000	0.032
SQRT	**0.032**	0.000	0.000	0.032
LOG	**0.034**	0.000	0.002	0.032
Estimation Period : 27/06/89-22/03/90 Prediction Period : 23/03/90-27/12/90				

Results showed that Bayesian methods are slightly superior to naive adjustment case. With daily returns the size of the data permitted us to try time-varying adjustment procedures. The evidence showed that time varying procedures such as Blume,MLPFS,and logarithmic or square-root transformed Blume models performed better than Bayesian procedures. The inefficiency part was almost completely removed when Blume-type models were used. The reason why the mean square error of predictions was relatively higher with the monthly data and weekly data than with the daily data is simply the number of observations much lower for the former case.

VII. CONCLUSIONS

Predictions with all kind of data (monthly, weekly and daily) showed that predictions based upon the Bayesian Methods gave smaller mean square errors compared to unadjusted betas. The improvement in the errors are mainly due to the decreases in the inefficiency parts of the MSE's. Results showed that the adjustment technique proposed by Efron and Morris is not significantly superior to that of Vasicek.

Prediction results obtained with daily data indicate that although Bayesian methods decreased the inefficiency part of the MSE quite a lot, in general they did not reduce the MSE much, since the random error part constituted a much larger part of the MSE than inefficiency.

There seems very sharp decrease in MSE when time-varying beta adjustment techniques, such as Blume, MLPFS, Log-linear or Square-root-linear models are used. These findings indicate that in Istanbul Stock Exchange the betas are not constant but show significant changes over time. The results also showed that betas shifted towards the historical cross-sectional mean, and did not take extreme values through time exactly like what Blume previously observed with the NYSE data.

Since the means of cross-sectional betas in any period was equal to almost one, the Blume and MLPFS betas and hence relevant mean square errors are very close to each other as theoretically expected.

As a conclusion, if the multivariate models which involve more than two lags of beta are used (which is proposed by Blume but could not have been done in this study since the ISE data, which is quite short,was not appropriate for that purpose) more satisfactory results can be obtained. Also as time goes on, if we come to a point where ISE data technically allows us to use the mean and variance of past betas itself instead of those of cross-sectional betas as a prior information, it will be possible to decide which model really best fits the ISE data.

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