INTERNATIONAL JOURNAL OF BUSINESS, 8(3), 2003 ISSN:1083-4346

Measuring the Systematic Risk of IPO's Using Empirical Bayes Estimates in the Thinly Traded Istanbul Stock Exchange

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ABSTRACT

The systematic risk of IPO's in the thinly traded Istanbul Stock Exchange (ISE) are estimated using Empirical Bayes Estimators (EBE). The sectors that the firms belong to, provide the priors. Comparisons are made with OLS estimators across different estimation and forecasting periods. Two benchmark criteria are used; sum of squared residuals and sum of absolute residuals. The application requires some complicated manipulation of the theory where some inferiors of the ordinary Bayesian approach are avoided. Results show that using the EBE procedure, betas can be calculated with greater precision than OLS. This enables us to evaluate IPO's on similar intuition with other stocks, i.e. in a portfolio context rather than in isolation.

JEL: C2, C11, C52, G1, G12

Keywords: Empirical Bayes method; Beta estimation; Forecasting; Capital Asset Pricing Model; Initial public offering.

I. INTRODUCTION

The capital-asset-pricing model (CAPM) of Sharpe (1964) and Litner (1965) constitutes a cornerstone in finance literature. CAPM is still popular among academics as well as practitioners in estimating expected returns. It has a powerful intuition that centers on the assumption that investors hold mean-variance efficient portfolios as described by Markowitz (1959) and the underlying economics is clear-cut. Estimation of expected returns using CAPM is simple and straightforward.

Almost all textbooks in corporate finance recommend CAPM expected returns for estimating the cost of capital. Academics in empirical finance typically use CAPM to estimate benchmark expected returns. Despite the sound theoretical foundations and, simple estimation procedure, empirical problems remain. Considerable empirical evidence is reported that the market β alone is not sufficient to describe the expected returns on individual securities[1]. Several multi-factor alternatives have been offered the most prominent of which is the Arbitrage Pricing Theory of Roll and Ross (1984). Also, it is known that tests of CAPM are sensitive to the proxies used for market portfolio (Stambaugh, 1982) and the relationship between stock returns and systematic risk contains non-linearities (Tinic and West, 1986). Still, the market model is widely used as a benchmark for performance evaluation and for measurement of abnormal returns in event studies, due to its strong intuition and straightforward estimation.

One way to circumvent the trade-off between empirical problems in describing expected returns and the practical need for a straightforward measure of systematic risk is to use alternative estimation procedures. Depending upon the needs of the researchers, different estimation procedures have been proposed. Fama-MacBeth (1973) two-pass regressions and Fama-French (1992) three factor model are the most well known. Karolyi (1992) argues that adjustment techniques based on cross-sectional information are uninformative and introduces prior information in the form of size and sector based cross-sectional distributions. Berra and Kannan (1986), suggest a multiple root-linear model to adjust the betas, assuming that betas are changing over time with a regular pattern towards the mean value. Vazicek (1973) proposed a Bayesian adjustment technique where the weighted-average of historical and cross-sectional betas is used. Dimson (1979) considered the case of infrequent trading and proposed an aggregated coefficients method for estimating the betas. Siegel (1995) estimates betas from observed option prices to account for the implicit volatility of the stock. Wittkemper and Steiner (1996) use neural networks to predict the betas. This way, they account for the non-linear interdependencies between a number of variables besides the past returns. In that sense, they actually employ a multi-factor model.

The purpose of this paper is to introduce an alternative estimation procedure, Empirical Bayes (EB) Estimates, to tackle another problematic case, the initial public offerings, (IPOs). The available technology for measuring betas is based on regression analysis of historical data. In the case of an IPO, it is extremely difficult to estimate the betas due to the limited number of observations on the stock price. However, the practical need remains to estimate expected returns by using the same intuition applied to other stocks that the portfolio manager follows. There is little doubt that the portfolio manager wants to use the most widely accepted and simple-to-implement criterion to make inferences about the risky asset under consideration, the IPO.

CAPM is intuitive and simple to employ. The expected return on any security depends only on the sensitivity of its return to the market return, i.e. its market beta. The procedure is straightforward then. All you need to do is to choose an index to represent the market portfolio, and compute the betas against this index. Despite the overwhelming literature on the skepticism about several stock indices being proper representations of the market we shall not discuss the issue here. Rather we shall assume that, in practice, the stock index being readily available at the same frequency as the stock price data, will be used to represent the market.

In the case of IPO's the main problem is that historical data are extremely limited, a couple of days in fact. Therefore, this paper introduces the Empirical Bayes Estimates that will deal with the estimation problem. We use prices of other stocks in the same sector as priors, and calculate betas accordingly.

We show that the price forecasts improve considerably, when instead of Ordinary Least Squares (OLS), Empirical Bayes estimates are used with sector information as the prior. The basic difference between our Empirical Bayes method and the ordinary Bayesian method is that in the Empirical Bayes method we refer to the data set itself to assign the priors, which alleviates the problem of prior determination. Indeed, the EBE estimates use the OLS estimators but have some extra advantages over them. They also utilize the additional information provided by the data set itself. We refer to this issue in detail while we present the relevant formulas for OLS and EB estimators in the methodology section.

Stambaugh (1997) uses Bayesian predictive distributions of future returns successfully in constructing minimum variance portfolios for emerging markets. In that case, the need for the Bayesian approach arises due to the fact that the length of available histories differ across the assets traded on separate exchanges and he does not want to discard returns to truncate some markets. Other successful applications include Pastor and Stambaugh (1999) whereby cost of equity for individual firms is estimated in a Bayesian framework using several factor-based pricing models. They show that in the absence of mispricing uncertainty, uncertainty about betas become nearly as important as uncertainty about factor premiums.

Using sector information as the prior has a number of practical and theoretical advantages. The intuition behind CAPM and the simplicity of application remain. We employ a single-factor rather than a multi-factor alternative. The expected returns on securities are calculated considering their sensitivity to the market return. The stock index is still used as a representation of the market. However, adjustments are made giving as prior information the prices of the securities in the same industry as the IPO under investigation. Our results show that, using this Empirical Bayes procedure, betas can be calculated for the IPO's with great precision. This enables us to evaluate IPO's on similar intuition with other stocks, i.e. in a portfolio context, rather than in isolation.

The rest of the paper is organized as follows: Section 2 gives the empirical framework and section 3 the details of the data set. Measures used to compare OLS and EBE are presented in section 4. Empirical results are given in section 5, and section 6 concludes.

II. EMPIRICAL FRAMEWORK

The CAPM is a one factor model which basically states that the expected return *[E(R_{it})]* on any security i (i=1,2,…,N)[2] at time t (t=1,2,…,T) depends only on the sensitivity of its return *(R)* to the market return *(M)*, i.e. its market beta *(β_1)*:

$$R_t = \beta_0 + \beta_1 M_t + \varepsilon_t \tag{1}$$

where

$$\hat{\beta}_1 = \frac{Cov(R_t, M_t)}{Var(M_t)} \tag{2}$$

Market risk is measured by β_1, that represents the volatility of security returns relative to the market, and is calculated as the ratio of the covariance between the stock and the market, *[$Cov(R_t, M_t)$]*, to the variance, i.e. the total risk in the market, *[$Var(M_t)$]*.

When we use OLS to estimate equation (1) the error terms have the following dimension, and variance terms:

$$\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T) \tag{3}$$

Hence, using OLS, beta estimate will be based on:

$$\left\lfloor \varepsilon \mid \sigma^2 \right\rfloor = N(0 \;, \sigma^2) \tag{4}$$

where OLS estimates of beta coefficients are:

$$\left[\hat{\beta}^{OLS} \mid \beta, \sigma^2 \right] = N(\beta \;, \sigma^2 (X'X)^{-1}) \tag{5}$$

$$\hat{\beta}^{OLS} = (X'X)^{-1} X'R \tag{6}$$

Here *X=[**1** M]*, where ***1*** is a T × 1column vector of ones and $\beta = (\beta_0, \beta_1)'$ is a 2 × 1 vector of regression coefficients for equation 1. The OLS estimates the common variances of the disturbance terms as:

$$\hat{\sigma}^2 = \frac{\sum_{t=1}^{T} \hat{u}_t^2}{T - 2} \tag{7}$$

where u terms are the OLS residuals.

Note that the OLS approach to estimate Equations 1 through 4 assumes that parameter estimates for one stock tells us nothing about the likely true parameter values for any other stock. While this is a standard conservative assumption, it is quite restrictive for estimating betas in the case of IPO's. Indeed, there is some more information embedded in the data, which is ignored by OLS. The information we utilize in this paper is the likely coordinated action of the stocks within the same sector. The idea leading to the extra information employed by Empirical Bayes is that the stocks within the same sector are affected from the exogenous shocks to that sector together, therefore their behaviors are similar. This piece of information is used in our second approach, Empirical Bayes, which assumes that the true parameter values for the individual stocks are interrelated. In particular, the Empirical Bayes model is obtained by assuming that β has a normal prior distribution of the form:

$$[\beta|(\theta,\Lambda)] \sim N(\theta,\Lambda) \tag{8}$$

The standard Bayesian approach now tries to specify the hyperparameters $\boldsymbol{\theta}$ (for the mean of β) and Λ (for the variance-covariance matrix of β) and use Bayes' rule for estimation. This leads to the Bayesian estimator:

$$\hat{\beta}^{\text{Bayes}} = D^{-1}(\sigma^{-2}(X'X)\hat{\beta}^{\text{OLS}} + \Lambda^{-1}\theta) \tag{9}$$

where

$$D = \sigma^{-2}(X'X) + \Lambda^{-1} \tag{10}$$

This estimator is a weighted average of the OLS estimate and the assumed prior mean where the weights are the estimated variances of the OLS estimate and the assumed prior variance. Note that the expression in the parenthesis above is the OLS estimate of β pre-multiplied by the inverse of the OLS covariance estimate, $\sigma^2(X'X)^{-1}$. The ordinary Bayesian approach has some difficulties in suggesting priors. That is why we prefer the Empirical Bayes approach in which we refer to the data in order to set the priors. So we estimate θ and Λ directly from the interstock distribution of the OLS parameters. In particular an initial estimate for θ is;

$$\hat{\theta} = \left[\sum_{i=1}^{N} \sigma_i^{-2}(X_i'X_i)\right]^{-1}\left[\sum_{i=1}^{N} \sigma_i^{-2} X_i'R_i\right] \tag{11}$$

which is essentially a weighted average of the stock-specific OLS estimates where the weights are inversely related to the parameter's estimated variance.

Here we assume all off-diagonal entries of Λ are zero. This means we do not let any prior covariance across the coefficients, and this is called the D-Prior method of Empirical Bayes, D standing for the diagonal. With this assumption and our initial estimate of θ we form an initial estimate of Λ via:

$$\hat{\Lambda} = \begin{bmatrix} \hat{\lambda}_1^+ & 0 \\ 0 & \hat{\lambda}_2^+ \end{bmatrix}, \qquad \hat{\lambda}_j^+ > 0 \tag{12}$$

$$\hat{\lambda}_j = \frac{1}{N-1} \sum_{i=1}^{N} ((\beta_{ij} - \hat{\theta}_j)^2 - \hat{\sigma}_i^{-2} (X_i{}'X_i)_j)^+ \tag{13}$$

where i indexes stocks and j indexes regressors so that, for example, $(M_i{}'M_i)_j$ refers to the j^{th} diagonal element of $(M_i{}'M_i)$. In essence, each estimate for λ_j is an estimate of the interstock variance of parameter j, corrected for sampling error. We then reestimate β_i's and also reestimate each element of θ with:

$$\hat{\theta}_j = \sum_{i=1}^{N} (\sigma_i^{-2} (X_i{}'X_i)_j + \hat{\lambda}_j^{-1})^{-1} \left[\sum_{i=1}^{N} \sigma_i^{-2} (X_i{}'R_i)_j + \hat{\lambda}_j^{-1} \hat{\beta}_{ij} \right] \tag{14}$$

Note that the calculation of θ, Λ and β's in the above equations require the solutions for each other, that is why we solve them iteratively. A GAUSS program[3] is coded to find these values as soon as some convergence criteria hold. The program is around 200 lines including the comments. We required the values obtained for these parameters to be stable, iteration after iteration. With solutions to these parameters in hand, the estimated variance of the posterior distribution of the β_i's is computed as:

$$\mathrm{Var}(\hat{\beta}_i^{EB}) = (\hat{\Lambda}^{-1} + \left[\hat{\sigma}_i^2 (X_i{}'X_i)^{-1}\right]^{-1})^{-1} \tag{15}$$

Note that the estimated variance of the Empirical Bayes estimator is smaller than the variance of the OLS estimator by construction. The increased precision is a result of the increased information introduced into the model.

III. THE DATA SET

The data set consists of the daily closing prices of all stocks traded at Istanbul Stock Exchange (ISE) from January 1st 1988 through July 11th 2001.[4] We have started with an initial sample of 276 firms. For each IPO, we require that the sector have at least three firms with continuous price data, so that we can calculate the priors. The resulting sample consists of 248 such firms. ISE's sector groupings are followed and a total of 248 firms are grouped into 19 sectors with 6 to 28 firms in each sector[5]. The ISE-composite, which is a value-weighted index and is available on a continuous basis during trading, is used to represent the market. The returns on individual stocks and the index are calculated as log differences, to ensure continuously compounded returns.

In order to compare the performance of the OLS and Empirical Bayes methods, the time series data for each stock are split into two sets of different lengths; namely the estimation and the forecast periods. We pretend as follows: the time series data for stocks during the estimation period are assumed to be known by the investor. The time series data for the same stocks during the forecast period are assumed to be unknown to the estimator. The actual (realized) values of stock prices in the forecast period are then used to compare the performance of two beta estimation methods; the OLS and the Empirical Bayes.

Several estimation and forecast periods are employed assuming different investment strategies. Since the purpose of the paper is to calculate betas for IPO's we start with very short estimation and forecast periods. Then we extend them to longer intervals. We estimate betas for the first five days (a week) after an IPO has been introduced and forecast the expected price for next week, which is the next five trading days. Finally, we estimate the betas using a 120-day (six months) estimation period and 20 day (one month) forecast period, which is consistent with the estimation, and portfolio adjustment periods employed by market practitioners as well as many researchers. Table 1 below displays the ten estimation and forecast periods that we used in this study.

Table 1
Estimation and forecast periods of different investment strategies

We assume that the investor uses the following ten estimation and forecast periods for different investment strategies based on them. The investment strategies are labeled A through J. For example, investment strategy J has a 120-day estimation period and a 20 day forecast period.

Investment Strategy	A	B	C	D	E	F	G	H	I	J
Estimation Period (days)	5	10	15	20	20	40	60	80	100	120
Forecast Period (days)	5	5	5	5	20	20	20	20	20	20

We compare the performances of OLS and Empirical Bayes estimates for each investment strategy, i.e. each estimation and forecast period, as follows: First we compare the performance of OLS and Empirical Bayes methods for the ten forecast and estimation periods for the initial public offerings (IPO's). Then we repeat the exercise for seasoned issues, i.e. the firms that had already been trading at ISE in the particular sector that the IPO was introduced.

In each case, both for the IPO's and for the seasoned issues, we had set the initial dates of the regressions to the days where a new stock, IPO, is introduced to the sector. For example, for strategy (A) the estimation period starts the day the IPO is introduced (t=1) and the first five days of trading (t=1,2,3,4,5) are used to estimate the betas. Then performance is measured for the forecast period, which is another 5 days after the estimation period ends (t=10). Alternatively, for strategy (J), estimation period also starts the day the IPO was introduced (t=1) and uses the 120 consecutive observations (t=1,2,3…120) following the introduction of the IPO for estimating betas. The forecast period is twenty days immediately following the estimation period (t=20). The time series data for each stock in all 19 sectors and the index are arranged in such a way to let the date at which an IPO is introduced to initiate the regressions.

IV. COMPARISON OF OLS AND EMPIRICAL BAYES ESTIMATORS

The performance of the OLS and Empirical Bayes estimators are compared by considering two forecast error measures; (1) Sum of Squared Residuals (F_{SSR}), and (2) Sum of Absolute Residuals (F_{SAR}). Both of them measure the discrepancy between the predicted values of stock returns using CAPM (Equation 1) and the true ones. Both forecast errors are similar to each other in the sense that they measure the discrepancy between the forecasted and actual values of stock returns. However, F_{SSR} uses squared errors and penalizes the larger discrepancies more by taking their square and summing up. Similarly, the smaller discrepancies, the ones less than 1, are praised by becoming even smaller when squared. F_{SAR} on the other hand, is more tolerant towards large forecast errors, and less tolerant to smaller errors by using the absolute values. The formulae for F_{SSR} , and F_{SAR} are given below:

$$F_{SSR} = \sum_{t=1}^{T} (\hat{R}_{it} - R_{it})^2 \tag{16}$$

$$F_{SAR} = \sum_{t=1}^{T} | \hat{R}_{it} - R_{it} | \tag{17}$$

We compare the performances of OLS and Empirical Bayes estimators via F_S (or F_A) which is the ratio of the F_{SSR} (or the F_{SAR}) calculated from the Empirical Bayes and OLS estimators. F_S (or F_A) is calculated as follows:

$$F_S = (F_{SSR,EB} - F_{SSR,OLS}) \big/ (F_{SSR,OLS} + F_{SSR,EB}) \tag{18}$$

$$F_A = (F_{SAR,EB} - F_{SAR,OLS}) \big/ (F_{SAR,OLS} + F_{SAR,EB}) \tag{19}$$

where |.| stands for the absolute value, *i*, refers to firm *(i)* in each case ($i=1,\dots n_s$), n_s being the number of firms in the s^{th} sector), $F_{SSR,OLS}$ stands for the sum of squared residuals from OLS estimations, $F_{SSR,EB}$ stand for the sum of squared residuals from Empirical Bayes estimations, similarly $F_{SAR,OLS}$ stands for the sum of absolute residuals from OLS estimations, and $F_{SAR,EB}$ stands for the sum of absolute residuals from Empirical Bayes estimations.

F_S is zero ($F_S = 0$) if the squared forecast errors estimated from Empirical Bayes and OLS are equal ($F_{SSR,EB} = F_{SSR,OLS}$). In this case neither method is superior to other. F_S is less than zero ($F_S < 0$) if the forecast errors estimated by Empirical Bayes are less than the forecast errors estimated by OLS ($F_{SSR,EB} < F_{SSR,OLS}$). If, $F_S < 0$, we understand that the Empirical Bayes estimates of beta are superior to the OLS estimates. F_S is greater than zero ($F_S > 0$) if the forecast errors estimated by Empirical Bayes are greater than the forecast errors estimated by OLS ($F_{SSR,EB} > F_{SSR,OLS}$). If $F_S > 0$, we understand that the OLS estimates of beta are superior to the Empirical Bayes estimates. The investor is advised to prefer estimating betas by the Empirical Bayes method if $F_S < 0$.

Alternatively, F_A is zero ($F_A = 0$) if the absolute forecast errors estimated by Empirical Bayes and OLS and are equal ($F_{SAR,EB} = F_{SAR,OLS}$). In this case neither method is superior to other. F_A is less than zero ($F_A < 0$) if the forecast errors of Empirical

Bayes are less than the forecast errors of OLS ($F_{SAR,EB} < F_{SAR,OLS}$). If $F_A < 0$, we understand that the Empirical Bayes estimates of beta are superior to the OLS estimates. F_A takes a value greater than zero ($F_A > 0$) if the forecast errors of Empirical Bayes are greater than the forecast errors of OLS ($F_{SAR,EB} > F_{SAR,OLS}$). If $F_A > 0$, we understand that the OLS estimates of beta are superior to the Empirical Bayes estimates. The investor is advised to prefer estimating betas by the Empirical Bayes method if $F_A < 0$.

V. EMPIRICAL RESULTS

We have run 21,170 regressions and calculated betas for a total of 210 IPO's. We have calculated the betas for each stock using first the OLS and then the EB. Using both methods we have calculated the betas under 10 different estimation-forecast period pairs. Using both methods and all ten estimation-forecast period pairs, we have calculated betas each time an IPO entered the sector. We calculate F_S and F_A for 10 different estimation-forecast horizons (A, B…J). Thereby, for each estimation-forecast horizon, we can compare the performance of Empirical Bayes and OLS estimators. Note here that the Empirical Bayes is superior to OLS if $F_S < 0$ and/or if $F_A < 0$.

In the case of IPO's, the major problem is that the time-series data are not available, and the number of observations to be used for estimating betas are severely limited. This way we can understand if Empirical Bayes is a convincing alternative to estimate betas with limited number of data points in the case of IPO's. The second problem in the case of IPO's is the number of firms in each sector that we use as the prior. In our data set, a sector is defined if it includes at least three firms. Therefore, the number of firms in each sector starts from 3 and gradually increases to 28 as new firms enter the sector. This gave us an opportunity to observe the successes of the Empirical Bayes estimators when the number of firms in each sector is changing as a result of which the priors we use are changing. Table 2 reports the mean values of F_S and Table 3 reports the mean values of F_A for IPO's.

Considering Tables 2, and 3, that report the mean F_S and F_A for the IPO's, one can easily observe that, overall, the Empirical Bayes technique does better then the OLS with improved results when the estimation period is shorter. In Table 2, we can see that regardless of the number of firms in the sector which we use to get the prior, for shorter estimation periods of 5 to 20 days (columns A through D) in 67 out of 76 cases $F_S < 0$, indicating that Empirical Bayes is better. A similar picture is apparent in Table 3. For shorter estimation periods of 5 to 20 days (columns A through D) in 66 out of 76 cases $F_A < 0$. This brings additional support that Empirical Bayes is a better method to estimate the betas for IPO's.

The same is true when the estimation period moves from 1 month (20 days) to 6 months (120 days) and the forecast period is fixed at one month (20 days), columns (E) through (J). In Table 2 we observe see that for the 20 days' forecast period, in 86 out of 114 cases $F_S < 0$. In Table 3, $F_A < 0$ in 87 out of 114 cases. Overall, we can say that Empirical Bayes estimators dominate OLS estimators, but the level of domination diminishes as the estimation period becomes longer and the number of observations used in regressions increases from 5 to 120. The main reason behind this is not the deterioration in the performance of EBE as the estimation period gets larger; it is the progress of OLS performance as the number of observations in the estimations increase.

Table 2

Mean F_S for IPO's under different investment strategies

This table reports the mean values of F_S under different investment strategies for firms in each sector. The investment strategies are given in the first row. The sector codes are given in the first column. F_S is described in equation (18) in the text as the ratio of the difference of the squared forecast errors estimated using Empirical Bayes and OLS to the sum of the two. F_S takes the value zero (F_S =0) if the squared forecast errors estimated from Empirical Bayes and OLS and are equal ($F_{SSR,\ EB} = F_{SSR,OLS}$). In this case neither method is superior to other. F_S takes a value less than zero ($F_S < 0$) if the forecast errors estimated from Empirical Bayes are less than the forecast errors estimated from OLS regressions ($F_{SSR,\ EB} < F_{SSR,OLS}$). If, $F_S < 0$, we understand that the Empirical Bayes estimators of beta were superior to the OLS estimators, and thus Empirical Bayes is a better method to estimate the betas. F_S takes a value greater than zero ($F_S > 0$) if the forecast errors estimated from Empirical Bayes are greater than the forecast errors estimated from OLS regressions ($F_{SSR,\ EB} > F_{SSR,OLS}$). If, $F_S > 0$, we understand that the OLS estimators of beta were superior to the Empirical Bayes estimators, and thus OLS is a better method to estimate the betas. The investor is advised to prefer estimating betas using the Empirical Bayes method if $F_S <$ 0.

Sector	A	B	C	D	E	F	G	H	I	J
1	-0.242	-0.091	-0.051	0.030	-0.046	-0.015	-0.012	0.000	-0.011	-0.021
2	-0.236	-0.039	0.154	-0.095	0.024	-0.061	-0.012	-0.051	0.034	0.116
3	-0.178	-0.125	-0.091	-0.049	-0.075	0.002	-0.008	-0.009	-0.042	-0.041
4	-0.065	-0.220	-0.134	-0.107	-0.093	-0.209	-0.259	-0.103	-0.066	-0.125
5	-0.244	0.025	-0.106	-0.141	-0.062	-0.052	-0.044	-0.009	-0.015	-0.023
6	0.023	-0.320	-0.179	0.174	0.017	-0.195	0.006	0.006	-0.036	-0.013
7	-0.194	-0.210	-0.099	-0.098	-0.108	-0.036	-0.020	-0.027	-0.015	-0.011
8	-0.113	-0.120	-0.132	-0.115	-0.058	-0.005	-0.068	-0.020	-0.050	-0.020
9	-0.181	-0.133	-0.056	-0.048	-0.046	0.063	0.041	-0.018	0.003	0.006
10	-0.094	-0.268	-0.096	-0.049	-0.053	-0.020	-0.083	-0.023	0.064	0.001
11	0.001	-0.114	-0.082	-0.013	-0.111	-0.011	-0.015	-0.055	0.013	-0.018
12	-0.240	-0.056	-0.067	-0.070	-0.053	-0.052	-0.016	-0.016	-0.016	-0.040
13	-0.228	-0.093	-0.056	-0.195	-0.076	0.002	-0.018	-0.019	-0.004	0.008
14	-0.263	-0.272	-0.129	-0.036	-0.004	0.010	0.013	-0.018	0.003	-0.009
15	-0.329	0.006	-0.217	-0.136	-0.035	0.005	-0.094	-0.030	0.004	-0.016
16	-0.339	-0.567	-0.154	-0.444	0.054	-0.049	-0.003	-0.013	0.007	0.018
17	-0.233	-0.210	-0.027	-0.079	-0.111	-0.062	-0.025	-0.020	-0.058	-0.015
18	-0.482	-0.065	0.041	-0.164	-0.051	-0.023	-0.009	-0.010	-0.213	-0.157
19	0.064	0.112	0.001	0.223	0.075	0.023	-0.003	-0.011	-0.035	0.008
mean	-0.188	-0.145	-0.078	-0.074	-0.043	-0.036	-0.033	-0.023	-0.023	-0.018

Table 3

Mean F_A for IPO's under different investment strategies

This table reports the mean values of F_A under the different investment strategies for firms in each sector. The investment strategies are given in the first row. The sector codes are given in the first column. F_A is described in equation (19) in the text as the ratio of the difference of absolute forecast errors estimated using Empirical Bayes and OLS to the sum of the two. F_A takes the value zero (F_A =0) if the squared forecast errors estimated from Empirical Bayes and OLS and are equal ($F_{SAR,\ EB} = F_{SAR,OLS}$). In this case neither method is superior to other. F_A takes a value less than zero ($F_A < 0$) if the forecast errors estimated from Empirical Bayes are less than the forecast errors estimated from OLS regressions ($F_{SAR,\ EB} < F_{SAR,OLS}$). If, $F_A < 0$, we understand that the Empirical Bayes estimators of beta were superior to the OLS estimators, and thus Empirical Bayes is a better method to estimate the betas. F_A takes a value greater than zero ($F_A > 0$) if the forecast errors estimated from Empirical Bayes are greater than the forecast errors estimated from OLS regressions ($F_{SAR,\ EB} > F_{SAR,OLS}$). If, $F_A > 0$, we understand that the OLS estimators of beta were superior to the Empirical Bayes estimators, and thus OLS is a better method to estimate the betas. The investor is advised to prefer estimating betas using the Empirical Bayes method if $F_A < 0$.

Sector	A	B	C	D	E	F	G	H	I	J
1	-0.111	-0.034	0.002	0.049	-0.030	-0.004	-0.005	-0.006	-0.007	-0.009
2	-0.059	0.028	0.085	-0.023	0.012	-0.036	-0.019	-0.042	0.026	0.066
3	-0.100	-0.073	-0.056	-0.032	-0.045	0.004	-0.002	-0.005	-0.025	-0.030
4	-0.032	-0.090	-0.060	-0.045	-0.039	-0.127	-0.161	-0.061	-0.052	-0.100
5	-0.141	0.039	-0.059	-0.070	-0.033	-0.024	-0.025	-0.003	-0.006	-0.015
6	0.056	-0.172	-0.075	0.086	-0.009	-0.112	0.006	0.001	-0.021	-0.009
7	-0.117	-0.112	-0.089	-0.062	-0.063	-0.017	-0.018	-0.010	-0.013	-0.008
8	-0.051	-0.077	-0.077	-0.057	-0.030	-0.010	-0.041	-0.020	-0.024	-0.011
9	-0.112	-0.063	-0.036	-0.009	-0.026	0.038	0.025	-0.013	0.006	0.005
10	-0.054	-0.123	-0.018	-0.008	-0.016	-0.026	-0.037	-0.011	0.044	0.012
11	-0.010	-0.064	-0.060	-0.013	-0.093	-0.001	-0.009	-0.034	0.015	-0.007
12	-0.124	-0.032	-0.028	-0.026	-0.024	-0.028	-0.008	-0.008	-0.008	-0.025
13	-0.124	-0.068	-0.005	-0.125	-0.039	0.016	-0.006	-0.002	-0.003	0.000
14	-0.140	-0.129	-0.077	-0.040	-0.015	0.007	0.003	-0.019	0.009	-0.003
15	-0.170	-0.015	-0.107	-0.055	0.001	0.006	-0.046	-0.019	0.000	-0.005
16	-0.224	-0.326	-0.136	-0.291	-0.034	-0.019	0.004	0.006	0.006	0.013
17	-0.127	-0.098	-0.017	-0.048	-0.084	-0.037	-0.012	-0.011	-0.034	-0.008
18	-0.303	-0.034	0.033	-0.079	-0.012	-0.021	-0.004	-0.001	-0.147	-0.095
19	0.021	0.065	-0.020	0.108	0.021	-0.020	-0.004	-0.020	-0.023	0.035
mean	-0.101	-0.073	-0.042	-0.039	-0.029	-0.022	-0.019	-0.015	-0.013	-0.010

Table 4

Mean F_S for non-IPO's under different investment strategies

This table reports the mean values of F_S under different investment strategies for non-IPO's in each sector. The investment strategies are given in the first row. The sector codes are given in the first column. F_S is described in equation (18) in the text as the ratio of the difference of the squared forecast errors estimated using Empirical Bayes and OLS to the sum of the two. F_S takes the value zero ($F_S = 0$) if the squared forecast errors estimated from Empirical Bayes and OLS and are equal ($F_{SSR, EB} = F_{SSR,OLS}$). In this case neither method is superior to other. F_S takes a value less than zero ($F_S < 0$) if the forecast errors estimated from Empirical Bayes are less than the forecast errors estimated from OLS regressions ($F_{SSR, EB} < F_{SSR,OLS}$). If, $F_S < 0$, we understand that the Empirical Bayes estimators of beta were superior to the OLS estimators, and thus Empirical Bayes is a better method to estimate the betas. F_S takes a value greater than zero ($F_S > 0$) if the forecast errors estimated from Empirical Bayes are greater than the forecast errors estimated from OLS regressions ($F_{SSR, EB} > F_{SSR,OLS}$). If, $F_S > 0$, we understand that the OLS estimators of beta were superior to the Empirical Bayes estimators, and thus OLS is a better method to estimate the betas. The investor is advised to prefer estimating betas using the Empirical Bayes method if $F_S < 0$.

Sector	A	B	C	D	E	F	G	H	I	J
1	-0.171	-0.047	-0.024	-0.009	-0.016	-0.012	-0.005	-0.004	-0.006	-0.009
2	-0.241	-0.043	0.273	-0.066	-0.052	-0.003	0.047	0.069	0.122	0.312
3	-0.155	-0.090	-0.062	-0.041	-0.037	-0.022	-0.009	-0.006	-0.009	-0.004
4	-0.010	-0.230	0.013	-0.049	-0.068	-0.030	0.005	0.000	-0.005	-0.008
5	-0.102	-0.056	-0.002	-0.026	-0.014	-0.018	-0.019	-0.015	0.000	-0.004
6	-0.196	0.025	0.068	-0.030	-0.144	-0.052	0.144	0.010	-0.016	-0.033
7	-0.105	-0.092	-0.029	-0.048	-0.034	-0.017	-0.009	-0.007	-0.004	-0.006
8	-0.119	-0.046	-0.022	-0.025	-0.021	0.018	-0.020	-0.016	-0.012	-0.009
9	-0.117	-0.042	-0.005	0.039	0.005	0.029	0.035	-0.002	-0.010	-0.008
10	-0.080	-0.202	-0.003	-0.038	-0.029	-0.028	-0.011	-0.013	0.048	0.011
11	0.001	0.038	0.156	0.059	0.055	0.012	-0.006	-0.045	-0.007	-0.019
12	-0.128	-0.068	-0.068	-0.038	-0.031	-0.035	-0.026	-0.003	-0.010	-0.005
13	-0.095	-0.061	-0.025	-0.027	-0.029	0.000	-0.007	-0.013	-0.017	-0.001
14	-0.113	-0.045	-0.054	-0.038	-0.038	-0.018	-0.013	0.001	0.000	-0.005
15	-0.038	0.103	-0.170	-0.006	-0.008	0.007	0.006	-0.023	0.002	-0.004
16	-0.029	-0.088	-0.047	0.072	0.004	0.088	-0.003	-0.023	0.008	-0.002
17	-0.131	-0.047	-0.021	-0.019	-0.025	-0.008	-0.017	-0.006	-0.009	-0.009
18	-0.150	-0.036	-0.005	-0.016	0.008	-0.029	-0.009	-0.003	0.070	-0.007
19	0.356	0.038	-0.001	0.238	0.111	0.020	-0.015	-0.012	-0.015	0.019
Mean	-0.085	-0.052	-0.001	-0.004	-0.019	-0.005	0.004	-0.006	0.007	0.011

Table 5
Mean F_A for non-IPO's under different investment strategies

This table reports the mean values of F_A under the different investment strategies for non-IPO's in each sector. The investment strategies are given in the first row. The sector codes are given in the first column. F_A is described in equation (19) in the text as the ratio of the difference of absolute forecast errors estimated using Empirical Bayes and OLS to the sum of the two. F_A takes the value zero (F_A =0) if the squared forecast errors estimated from Empirical Bayes and OLS and are equal ($F_{SAR, EB} = F_{SAR,OLS}$). In this case neither method is superior to other. F_A takes a value less than zero ($F_A < 0$) if the forecast errors estimated from Empirical Bayes are less than the forecast errors estimated from OLS regressions ($F_{SAR, EB} < F_{SAR,OLS}$). If, $F_A < 0$, we understand that the Empirical Bayes estimators of beta were superior to the OLS estimators, and thus Empirical Bayes is a better method to estimate the betas. F_A takes a value greater than zero ($F_A > 0$) if the forecast errors estimated from Empirical Bayes are greater than the forecast errors estimated from OLS regressions ($F_{SAR, EB} > F_{SAR,OLS}$). If, $F_A > 0$, we understand that the OLS estimators of beta were superior to the Empirical Bayes estimators, and thus OLS is a better method to estimate the betas. The investor is advised to prefer estimating betas using the Empirical Bayes method if $F_A < 0$.

Sector	A	B	C	D	E	F	G	H	I	J
1	-0.092	-0.027	-0.012	-0.010	-0.007	-0.003	0.001	0.002	-0.002	-0.004
2	-0.160	-0.003	0.162	-0.043	-0.020	0.002	0.009	0.037	0.062	0.196
3	-0.090	-0.045	-0.036	-0.024	-0.023	-0.014	-0.006	-0.002	-0.003	-0.003
4	-0.023	-0.145	0.004	-0.032	-0.007	-0.021	0.005	0.015	-0.003	-0.006
5	-0.057	-0.034	0.001	-0.011	-0.003	-0.009	-0.007	-0.004	0.000	-0.002
6	-0.125	0.005	0.001	-0.032	-0.102	-0.042	0.070	0.002	-0.014	-0.019
7	-0.064	-0.051	-0.016	-0.027	-0.021	-0.011	-0.004	-0.004	-0.002	-0.002
8	-0.072	-0.022	-0.009	-0.011	-0.006	0.009	-0.012	-0.009	-0.007	-0.007
9	-0.069	-0.022	-0.017	0.020	0.003	0.021	0.026	-0.001	-0.004	-0.002
10	-0.045	-0.103	-0.002	-0.022	-0.022	-0.017	-0.010	-0.006	0.035	0.002
11	0.029	0.065	0.116	0.073	0.070	0.008	0.000	-0.020	0.001	-0.011
12	-0.068	-0.038	-0.039	-0.011	-0.014	-0.017	-0.016	-0.004	-0.006	0.000
13	-0.053	-0.028	-0.019	-0.017	-0.022	-0.005	-0.005	-0.011	-0.011	-0.002
14	-0.066	-0.029	-0.026	-0.022	-0.022	-0.009	-0.007	0.000	0.003	-0.003
15	-0.015	0.065	-0.095	-0.008	-0.005	0.000	0.002	-0.011	0.001	-0.007
16	-0.017	-0.045	-0.033	0.050	0.009	0.049	-0.002	-0.015	0.004	-0.002
17	-0.078	-0.024	-0.009	-0.008	-0.013	-0.004	-0.009	-0.006	-0.007	-0.007
18	-0.084	-0.023	-0.004	0.011	0.011	-0.019	0.000	0.001	0.036	-0.002
19	0.217	0.022	-0.004	0.157	0.067	0.010	-0.013	-0.005	-0.006	0.009
Mean	-0.049	-0.025	-0.002	0.002	-0.007	-0.004	0.001	-0.002	0.004	0.007

Tables 4 and 5 report the mean F_S and F_A values for seasoned equities. The overall picture is similar to the case of IPO's. Empirical Bayes estimators dominate OLS estimators in general, and for short estimation periods in particular. Table 4 reports that for shorter estimation periods of 5 to 20 days (columns A through D) in 64 out of 76 cases $F_S < 0$, indicating that Empirical Bayes is better. Table 5 presents that for the same shorter estimation periods (columns A through D) in 62 out of 76 cases $F_A < 0$. Also, the values of F_S and F_A in columns (A) through (D) of Tables 4 and 5 respectively tend to become smaller, as the estimation period moves from one week (A) to four weeks (D).

The estimation period moves from 1 month (20 days) to 6 months (120 days) and the forecast period is fixed at one month (20 days) in columns (E) through (J) of Tables 4 and 5. In Table 4 we can see that for the estimation period, using 120 days' data, $F_S < 0$ in 82 out of 114 cases. In Table 5, for the estimation period using at most 120 days' data $F_A < 0$ in 78 out of 114 cases.

We are also interested in the success of Empirical Bayes estimators, as the number of firms in a specific sector is increasing when the IPO is launched. The number of firms in each sector is important because we use the beta coefficients of those firms as the priors of Empirical Bayes estimators. In our data set the minimum number of firms in a sector is 3 and the maximum is 28. This gives us an opportunity to observe the successes of the Empirical Bayes estimators when the number of firms in each sector is changing, thus the prior that we used was alternating accordingly. Table 6 is prepared to display F_S for IPO's as defined in (19).

Overall, we observe that $F_S < 0$, indicating that EB dominates OLS. Roughly speaking, F_S gets larger when an IPO is introduced to a sector with larger number of firms, indicating that EB is slightly superior to OLS when sector size is larger. However, the effect of sector size is not reported as the estimation period also changes. But, as we have observed in tables 2 and 4, F_S also becomes larger at shorter estimation periods.

Table 7 reports the frequencies with which either EB or OLS estimators perform better under alternative investment strategies. We prepared panels 1 and 3 of table 7 for absolute comparisons. For example, in the case of IPO's, take panel 1, for strategy A, where both the estimation and forecast periods are five days. EB performed better than OLS in 75% of the cases. Similarly for strategy J where the estimation and forecast periods are 120 and 20 days respectively, EP performed better than OLS in 63% of the cases. We prepared panels 2 and 4 of Table 7 by ignoring differences between the performances of the two methods up to five percent. For example, take panel 2 of Table 7. In the case of IPO's, and for strategy A, sum of absolute residuals (F_{SAR}) for EB estimates was at least 5% better than the sum of absolute residuals for OLS estimates in 81% of the cases. Similarly, this percentage is 76 for strategy J.

Overall, we observe from table 7 that EB performs much better than OLS in most of the cases. In general, we observe that EB performs better than OLS for both the IPO's and seasoned equities for shorter estimation and forecast horizons. Also the frequency of cases that EB performs better increases as we introduce the 5% benchmark. Sum of absolute residuals from EB estimates are at least 5% better than that of OLS estimates more frequently. For example, take strategy G. For IPO's EB performs better than OLS in 61% of the cases. The frequency increases to 75% when we consider only the cases where EB performs at least 5% better than OLS. Similarly, in the case of seasoned equities, EB performs better than OLS in 61% of the cases. However, this frequency increases to 73% when we consider only the cases where EB performs at least 5% better than OLS.

Table 6

Mean F_S for IPO's as sector size changes

This table reports the mean values of F_S under different investment strategies for firms in sectors with different number of firms when the IPO enters. The number of firms in the sector when the IPO enters is given in the first column. Estimation and forecasting periods are specified in the first row. F_S is described in equation (18) in the text as the ratio of the difference of the squared forecast errors estimated using Empirical Bayes and OLS to the sum of the two. F_S takes the value zero ($F_S =0$) if the squared forecast errors estimated from Empirical Bayes and OLS and are equal ($F_{SSR, EB} = F_{SSR,OLS}$). In this case neither method is superior to other. F_S takes a value less than zero ($F_S < 0$) if the forecast errors estimated from Empirical Bayes are less than the forecast errors estimated from OLS regressions ($F_{SSR, EB} < F_{SSR,OLS}$). If, $F_S < 0$, we understand that the Empirical Bayes estimators of beta were superior to the OLS estimators, and thus Empirical Bayes is a better method to estimate the betas. F_S takes a value greater than zero ($F_S > 0$) if the forecast errors estimated from Empirical Bayes are greater than the forecast errors estimated from OLS regressions ($F_{SSR, EB} > F_{SSR,OLS}$). If, $F_S > 0$, we understand that the OLS estimators of beta were superior to the Empirical Bayes estimators, and thus OLS is a better method to estimate the betas. The investor is advised to prefer estimating the betas using the Empirical Bayes method if $F_S < 0$.

Number of firms	A	B	C	D	E	F	G	H	I	J	Mean
3	-0.134	-0.039	-0.033	-0.010	-0.011	-0.015	-0.037	-0.012	-0.029	-0.013	-0.033
4	-0.070	-0.047	0.024	-0.005	-0.048	-0.021	-0.008	-0.036	0.018	0.009	-0.018
5	-0.031	-0.128	-0.038	-0.069	-0.048	-0.049	-0.019	-0.014	-0.025	-0.009	-0.043
6	-0.117	-0.052	-0.018	-0.032	-0.019	-0.033	-0.033	-0.003	-0.002	0.004	-0.031
7	-0.083	-0.062	-0.099	-0.063	-0.035	0.044	0.012	0.013	0.001	-0.043	-0.032
8	-0.189	-0.040	-0.032	-0.023	-0.026	0.024	-0.005	-0.013	0.002	-0.002	-0.030
9	-0.310	-0.059	-0.011	0.030	0.016	-0.011	0.005	0.000	-0.006	0.002	-0.034
10	-0.114	-0.028	0.002	-0.010	-0.028	-0.042	0.001	-0.009	-0.011	-0.014	-0.025
11	-0.017	-0.041	-0.009	0.024	-0.061	-0.024	-0.017	-0.013	-0.064	-0.064	-0.029
12	-0.123	-0.072	-0.083	-0.035	-0.018	-0.004	0.007	-0.011	-0.006	-0.010	-0.036
13	-0.109	-0.071	0.007	-0.050	-0.021	-0.002	-0.018	-0.005	0.008	-0.005	-0.027
14	-0.019	-0.095	-0.089	-0.104	-0.098	-0.003	-0.030	-0.010	-0.028	-0.006	-0.048
15	-0.052	-0.088	-0.015	0.000	-0.023	-0.022	0.000	-0.016	-0.002	0.004	-0.021
16	-0.085	-0.035	0.003	0.069	-0.021	0.031	-0.003	-0.006	-0.015	-0.009	-0.007
17	-0.256	-0.022	-0.042	-0.070	-0.055	-0.007	-0.017	-0.020	-0.002	0.003	-0.049
18	-0.061	0.077	-0.092	-0.046	-0.032	-0.007	-0.018	0.003	-0.012	-0.006	-0.019
19	-0.229	-0.255	-0.026	-0.096	-0.105	-0.082	-0.007	-0.065	-0.037	-0.007	-0.091
20	-0.121	-0.091	-0.074	-0.059	-0.030	-0.011	-0.003	-0.011	-0.006	-0.007	-0.041
21	-0.100	-0.245	-0.212	-0.132	0.044	-0.010	0.001	-0.038	0.004	-0.008	-0.069
23	-0.396	-0.205	-0.267	-0.146	-0.118	-0.067	-0.068	-0.005	0.002	-0.005	-0.127
24	-0.213	-0.058	-0.026	-0.056	-0.108	-0.020	-0.017	-0.011	0.009	-0.009	-0.051
28	-0.204	-0.234	0.054	0.027	-0.226	-0.007	-0.127	-0.017	0.012	-0.022	-0.074
Mean	-0.138	-0.086	-0.049	-0.039	-0.049	-0.015	-0.018	-0.014	-0.009	-0.010	

Table 7
Comparison of EB and OLS estimators using frequencies of better performance

In this table we report the frequencies with which EB estimation outperforms the OLS estimation. The investment strategies are given in the first row from A through J. We grouped the results into three. The first group reports the cases whereby Empirical Bayes estimators and the OLS estimators had smaller F_{SAR} (sum of absolute residuals), respectively. The second group reports the cases for IPO's whereby Empirical Bayes estimators and the OLS estimators had F_{SAR} values smaller by at least 5%, respectively. The third group reports the number of cases whereby for seasoned equities, Empirical Bayes estimators and the OLS estimators had smaller F_{SAR} (sum of absolute residuals), respectively. The fourth group reports the number of cases for seasoned equities whereby Empirical Bayes estimators and the OLS estimators had F_{SAR} values smaller by at least 5%, respectively. For each group, the first rows shows the number of cases where $F_{SAR, EB} < F_{SAR, OLS}$, the second row shows the number of cases where $F_{SAR, EB} > F_{SAR, OLS}$, and the third row shows the percentage of cases where $F_{SAR, EB} < F_{SAR, OLS}$.

	Investment strategies									
	A	B	C	D	E	F	G	H	I	J
IPO's										
EB was better	179	167	140	141	161	135	128	134	135	138
OLS was better	61	67	81	76	57	81	83	74	81	81
%EB was better	75%	71%	63%	65%	74%	63%	61%	64%	63%	63%
IPO's										
EB was at least 5% better	155	130	108	122	105	57	57	48	35	31
OLS was at least 5% better	36	50	54	42	32	25	19	16	15	10
%EB was at least 5% better	81%	72%	67%	74%	77%	70%	75%	75%	70%	76%
Seasoned Equities										
EB was better	1429	1249	1185	1163	1211	1197	1143	1119	1100	1070
OLS was better	521	695	709	718	678	688	731	747	788	809
%EB was better	73%	64%	63%	62%	64%	64%	61%	60%	58%	57%
Seasoned equities										
EB was at least 5% better	1045	894	694	685	590	383	291	188	183	156
OLS was at least 5% better	278	370	356	390	224	144	108	102	84	74
%EB was at least 5% better	79%	71%	66%	64%	72%	73%	73%	65%	69%	68%

VI. CONCLUDING REMARKS

This paper introduces EB as an alternative estimation procedure to estimate betas in the case of IPO's. In this instance, it is extremely difficult to estimate betas using traditional analysis of historical data mainly due to the limited number of observations on the stock prices. However, the practical need remains as portfolio managers want to use the same intuition applied to other stocks. Despite empirical considerations, CAPM is still a straightforward simple-to-implement model to value risky assets while at the same time being strong in theoretical foundations.

We use Empirical Bayes method to circumvent the estimation problem in IPO's by using the price of other stocks in the same sector as priors. Using sector information as prior enables us to employ a single factor rather than a multi-factor alternative. This way we do not deviate from the intuition behind CAPM, that IPO's similar to seasoned equities, should be evaluated in a portfolio context, rather than in isolation. At the same time we keep the application as simple as possible. We still use the index as a representation of the market and calculate risk as the sensitivity of stock to changes in the market. We introduce Empirical Bayes as a method of adjustment whereby prices of stocks in the sector that an initial public offering is made are used as prior information.

We have run more than twenty thousand regressions to calculate betas using alternative estimation periods. Empirical Bayes estimates are compared to the traditional ordinary least squares on three grounds. We used ten different estimation/forecast period pairs to calculate. We calculated two different forecast error measures, one magnifying large errors and the next being neutral to the size of the error. Finally, we compared the performance of EBE and OLS in estimating betas for IPO's as well as seasoned equities.

Empirical Bayes estimators dominate OLS estimators. However, the level of domination diminishes as the estimation period becomes longer and the number of observations used in the regression increases. The main reason behind this is the progress of OLS performance as the number of observations in the estimations increase. Empirical Bayes estimators do not deteriorate. For shorter estimation and forecast horizons Empirical Bayes estimators perform better than the OLS not only for the IPO's but also for the seasoned equity offerings.

The number of firms in each sector was important in this study because we use the beta coefficients of those firms as the priors of Empirical Bayes estimators. This gives us an opportunity to observe the successes of the Empirical Bayes estimators when the number of firms in each sector is changing, thus the prior that we used was alternating accordingly. When an IPO is introduced to a sector with larger number of firms, Empirical Bayes estimators are slightly superior to OLS estimates and this is more pronounced for shorter estimation periods.

Results reveal that overall, Empirical Bayes estimates perform better than OLS estimates. Besides, Empirical Bayes is more successful for shorter estimation periods, for IPO's rather than seasoned equities and for IPO's introduced into larger sectors rather than smaller ones. All of these attributes make EB an excellent technique to estimate betas for IPO's. This gives portfolio managers an exceptional opportunity to treat IPO's with the same intuition that they treat other stocks.

Empirical Bayes estimates is an outstanding method to avoid the trade off between the practical need to for a straightforward measure of systematic risk and empirical problems encountered in the case of IPO's. It gives market professionals the opportunity to use the same measure of market risk for calculating expected returns for both the IPO's and seasoned issues. The intuition behind the CAPM can thus be applied to all the securities that are used in a portfolio context.

The EB method used in this study can be executed within the Hierarchical Bayes framework that requires more complicated calculations and computer program coding. The Hierarchical Bayes procedure is different from the empirical one in estimating the hyperparameters. This method employs the Bayesian procedure to estimate the hyperparameters instead of the ML, OLS, or MOM. We retain the Hierarchical Bayes method, which is beyond the scope of this paper, for future research.

NOTES

1. See Fama (1991) for a review of related literature and Fama and French (1996) for further evidence that beta alone cannot explain expected returns
2. We drop subscript i which denotes the specific stock for the sake of simplicity in the following equations. N denotes the number of firms.
3. The algorithm of the GAUSS program used in this study is given in Appendix 1. The program itself is available from the authors upon request.
4. For a review of literature on ISE, refer to Müradoglu (2000).
5. The list of sectors and the number of firms in each sector are given in Appendix 2.

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Appendix 1
Gauss program algorithm

1. Arrange the data belonging to the determined period, sector, and firms.
2. Input the data set that includes the individual and market returns to the program.
3. Obtain the OLS estimates for the regression coefficients.
4. Obtain the D-Prior estimates for Empirical Bayes.

4.1. Start with any initial values of $\Lambda$and θ.

4.2. Do while $\Lambda$and θ do not converge to their ultimate values:

4.2.1. Calculate the estimate of θ given the value of Λ.

4.2.2. Calculate the estimate of Λ given the value of θ.

4.3. Endo—Get the converged values of $\Lambda$and θ.

5. Calculate the sum of squared and absolute residuals.

Appendix 2
Sector classifications

The Table below reports the sector classification used in this study. We categorized the firms into the following sectors conformable to the ISE classification. The first column of the table is the sector code, the second column gives the number of firms in that sector, and the third column gives the definition of the sector as it appears at ISE bulletins.

Sector code	**Number of firms in the sector (n_s)**	**Sector**
1	20	Banking
2	6	IT
3	33	Textiles
4	7	Electricity
5	11	Financial leasing and factoring
6	7	Real estates investment funds
7	25	Food, drinks and tobacco
8	19	Holding companies
9	15	Paper and publishers
10	9	Chemicals
11	6	Hotels and restaurants
12	33	Machinery
13	19	Investment funds
14	16	Metals
15	7	Retail
16	8	Insurance
17	22	Construction materials
18	7	Wholesale
19	6	Transportation