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Asset Allocation in Transition Economies

Abstract

Designing an investment strategy in transition economies is a difficult task, because stock markets opened through time, time series are short, and there is little guidance how to obtain expected returns and covariance matrices necessary for mean-variance asset allocation. Moments of market returns can be expected to be time varying as structural changes occur in nascent market economies. We develop an ad-hoc optimal asset-allocation strategy with a flavor of Bayesian learning adapted to these various characteristics. Since an extreme event often heralds a new state of the economy, we re-initialize learning when unlikely returns materialize. By considering a Cornell benchmark, we show the usefulness of our strategy for certain types of re-initializations. Our model can also be used in situations when new industries emerge or when companies are subject to important restructuring.

Résumé

Définir une stratégie d'investissement dans les économies en transition est une tâche difficile, car l'ouverture des marchés d'actions a été progressive, les séries chronologiques sont courtes et il existe peu d'éléments permettant d'évaluer les rendements anticipés et la matrice de variance-covariance nécessaires à l'allocation d'actifs. Les moments des rendements du marché sont susceptibles de varier dans le temps, à l'occasion de changements structurels. Nous adoptons une stratégie d'allocation optimale d'actifs, fondée sur un processus d'apprentissage Bayésien, adapté à ces différentes caractéristiques. Puisque un événement extrême traduit souvent un nouvel état de l'économie, nous ré-initialisons l'apprentissage lorsque des rendements peu probables se réalisent. En considérant la stratégie de référence de Cornell, nous montrons la pertinence de notre stratégie pour certains types de ré-initialisation. Notre modèle peut aussi être mis en œuvre dans des situations telles que l'émergence de nouvelles industries ou d'importantes restructurations d'entreprises.

Keywords: Emerging markets, mean-variance allocation, sequential Bayesian learning, structural breaks.
Mots-clés: Marchés émergents, allocation moyenne-variance, apprentissage Bayésien séquentiel, ruptures structurelles.
JEL classification: F30, G11, C11, C32.

1 Introduction

This research is motivated by the puzzling result that, when we solved the mean-variance asset-allocation problem involving stock indices of several Eastern and Central European countries as well as the ones of the UK and Germany, using constant estimates of the means and the covariance matrix, no wealth should be allocated to transition economies. This result contrasts with anecdotal evidence and has led us to consider various techniques where the moments of market returns are rendered time varying.

A first approach consists in designing regression models, in which explanatory variables describe conditional moments of market returns. For countries with a long tradition of relatively stable markets, such moments may be obtained from linear models, GARCH models or switching regressions. Research that document some degree of predictability for expected return is by Keim and Stambaugh (1986), Campbell (1987), Fama and French (1988), Ferson and Harvey (1991). Solnik (1993) forecasts future risk premia and shows how a simple investment rule may improve portfolio performance. Schwert (1989) and Whitelaw (1994) also document a set of economic variables that help to predict variances and/or covariances of returns. For emerging markets, research on predictability of returns and risk is by Harvey (1995) and Bekaert and Harvey (1997). The implications of the predictability of emerging markets' returns on asset allocation is studied in Harvey (1994). In a preliminary research, the results of which are available from the authors, we obtain that, for Eastern European countries, market returns cannot be forecast using simple regressions such as in Solnik (1993).[1] A conditional model, therefore, requires a more sophisticated approach.

We build on the existing sequential Bayesian-learning literature to develop a model that is suited to transition economies. Contributions to this literature are by Jorion (1985, 1986), Frost and Savarino (1986), Dumas and Jacquillat (1990), or Harvey and Zhou (1990). Kandel, McCulloch, and Stambaugh (1995) and Kandel and Stambaugh (1996) imbed predictability within a Bayesian framework. Pástor and Stambaugh (2001) show

[1] Solnik assumed a stable relation between the risk premium and macroeconomic explanatory variables. If structural changes occur, as this is likely to be the case in transition economies, it is difficult to expect such a stable relation. Note also that Harvey (1995) obtained a large degree of predictability in emerging-market returns, mostly related to local information variables. He did not consider Eastern European markets, however, since most of them opened only after the completion of the study.

how, within a Bayesian framework, one may learn even if there are multiple structural changes. The estimation of their model requires, however, the availability of long time series. Comon (2000) shows how extreme realizations may affect portfolio allocation under learning.

The model that we propose incorporates information gradually by updating parameters according to sequential Bayesian learning. If a new stock-market index becomes available, its link with the other indices gets quantified. Also, when large events occur, we re-initialize the learning procedure. As such, this model takes into account some specificities of transition economies. Among these specificities, we have the fact that only very small samples are available, that new stock markets opened, that the economies were subject to structural changes, and that structural changes were likely to occur after a stock market reacted wildly. Our model could also get applied to other contexts where parameters evolve through time and new series become available. Examples include the emergence of new industries or companies, or situations where a company gets radically restructured.

The structure of the paper is as follows. In the next section, we present the countries involved in our asset-allocation model. Section 3 describes our model. We recall the way sequential Bayesian learning works and how we modify it to take into account the specificities of the transition economies. Section 4 describes the asset-allocation problem that we solve to update the portfolio weights. Our optimum portfolio assumes that the investor is concerned with return distributions over a single period. In that section, we also provide a discussion of the Cornell (1979) performance measure. This performance measure appears to be valuable in situations where no benchmark portfolio exists. In section 5, we present the results and show that our model may explain the puzzle. For certain parameters, the Bayesian learning significantly outperforms unconditional moments. This result is obtained if we neglect transaction costs. In section 6, we conclude.

2 Data

2.1 Country selection and notation

Given our interest in asset allocation, the frequency over which the data is sampled is important. Most of the studies involving developed markets use monthly data. These studies often assume that moments are constant throughout the sample. When moments are time-varying, certain studies involve weekly frequency, e.g. Kandel and Stambaugh (1987) or Kandel, McCulloch, and Stambaugh (1995). Moreover, Froot and Ramadorai (2001) show that US-based mutual funds tend to reallocate actively their capital in emerging markets, resulting in important cash flows at a weekly frequency. Since emerging markets are subject to frequent shocks, we believe that investors will stick to a weekly rather than to the monthly frequency used in most papers on asset allocation involving developed economies. Furthermore, even if the data used in asset allocation is updated at weekly frequency, this does not prevent investors to leave their portfolio unchanged over longer periods, as the parameters required for the mean-variance allocation remain constant.

For asset-allocation purpose, we express market returns in a common currency. Therefore, we need data for stock-market indices and exchange rates. Besides data for the UK and Germany, we use series for ten transition economies. These countries are Croatia, the Czech Republic, Estonia, Hungary, Lituania, Poland, Romania, Russia, Slovakia, and Slovenia. Essentially, the data covers the period from January 1991 to December 2000. Table 1 reports, for each country, the name of the stock index, a label that we will use throughout, and the date when each series becomes available. This table also provides some information on the availability of the exchange rates. In our data base, the Hungarian and Polish stock markets became first available. Stock indices in Croatia and Romania are available since 1997 only.

We define $R_{i,t} = \ln(P_{i,t+1}/P_{i,t})$, the weekly market return of country i, over the period from t to $t{+}1$, expressed in local currency. We also express returns in a common currency and since we focus on European stock markets, we consider the Sterling as reference currency. Thus, we denote by $s_{i,t} = \ln(S_{i,t+1}/S_{i,t})$ the return of the foreign currency, with $S_{i,t}$ the amount of Sterling that may be obtained for a unit of (local) currency of country i. The market return of country i, denominated in Sterling, is then defined as: $\tilde{R}_{i,t} = R_{i,t} + s_{i,t}$. Last, the corresponding excess return is defined as: $er_{i,t} = \tilde{R}_{i,t} - r_{UK,t}$, where $r_{UK,t}$ denotes the UK 7-day LIBOR interest rate over the period from t to $t+1$, expressed on a weekly basis.[2]

[2]The results reported in this paper correspond to returns expressed in Sterling. If we express returns in German mark, the main conclusions are not altered.

2.2 Descriptive statistics

As a first look at the data, we compute univariate summary statistics for weekly percentage stock returns, expressed in Sterling. Table 2 reports univariate moments and the test statistics for normality, serial correlation, and heteroskedasticity. We find that mean returns range between -1% a week in Romania and 0.37% in Estonia. This compares with the 0.203% for UK and 0.275% for Germany. The large standard error of means in emerging markets suggests that there are potential gains that can be made by considering time variation in the expected returns. Volatility of market indices in transition economies is high when compared to the ones in the UK and Germany. For instance, the volatility of the Lituanian and Czech indices, which are the least volatile, is nearly twice as high as for the UK or Germany. This great variability may be due to the fact that these markets are rather thin. Assets in thin markets have higher bid/ask spreads that lead in turn to higher stock-price variability. The higher variability of market indices in emerging markets may, therefore, reflect that a liquidity premium is likely to exist.[3] Six out of the ten Eastern European market returns are found to be left skewed. This result indicates that crashes are more likely to occur than booms. But, when standard errors are computed with the GMM procedure proposed by Richardson and Smith (1993), most of these skewness coefficients are found to be non-significantly different from zero. Contrary to what is usually found for mature markets, we obtain a positive skewness in the Czech Republic, Lituania, Slovakia, and Slovenia. On these stock markets, the largest increase in return exceeds the largest decrease. These positive jumps may be explained by political events that led to huge inflows of foreign capital. For all stock markets, we also obtain a significant positive excess kurtosis. Thus, market-return distributions have fatter tails than the normal distribution. Finally, we test for normality, using the Wald statistic (Richardson and Smith, 1993). Under the null hypothesis, skewness and excess kurtosis are jointly equal to zero. As reported in Table 2, most market returns in transition economies are not normally distributed, whereas normality of returns in the two developed markets cannot be rejected over the given sample and frequency.

We obtain a significant serial correlation in squared returns, as indicated by the Engle test statistics. In most countries, we also find a strong serial correlation in returns, when measured by the usual Ljung-Box Q test statistic. When this statistic is corrected to

[3] We are grateful to a referee for reminding this.

account for heteroskedasticity, however, we do not obtain such a strong serial correlation, except for Hungary and Lituania.

Table 3 reports the correlation matrix between market returns expressed in Sterling.[4] For each pair of stock markets, correlation was computed over the largest sample available. The magnitude of the correlations is rather large. First, we find a very strong link between the UK and the German stock indices, with a correlation as high as 0.6. Second, more developed stock markets in transition economies (the Czech Republic, Hungary, Poland, Russia, with the exception of Slovakia) are rather strongly interrelated, and they are also more connected with the UK and Germany. Last, less developed markets are generally characterized by lower correlations, with the exception of Croatia. Over the period 1997-2000, the Croatian return has been strongly linked to the Czech, Hungarian, and Polish returns (with a correlation larger than 0.4). Since correlations between mature and emerging markets are, broadly speaking, rather low when compared with correlations across mature markets alone, portfolio diversification involving emerging markets is likely to be very helpful to reduce portfolio risk.

3 Bayesian learning

3.1 The model

In this section, we outline a technique that renders the moments of returns time varying under the specificities described in the introduction. The first specificity, the shortness of time series, implies that an investor must have some prior of the values on moments of the data. As time goes by and new observations become available, the investor will update these priors. This type of learning may be captured within a Bayesian framework.[5] We will now recall how sequential Bayesian updating works, specify the notations and then extend this framework to other features that are specific to transition economies.

We assume that the vector of excess returns, $y_t = (er_{1,t}, er_{2,t}, \cdots, er_{N,t})'$, is distributed

[4] The correlations in local currency are available upon request.

[5] Traditional Bayesian updating can be implemented within the Kalman filter framework, see Rockinger and Urga (2000) for an illustration involving transition economies.

normally:[6]

$$y_t \sim \mathcal{N}(\mu_t, \Sigma_t), \qquad t = 1, \cdots, T, \tag{1}$$

where μ_t and Σ_t denote the mean vector and the covariance matrix, respectively. If μ_t and Σ_t were known, then they could be used in a mean-variance portfolio allocation. In practice, investors have to learn the actual values of these parameters.[7] Bayesian updating assumes that μ and Σ follow a certain distribution. Each new observation yields an update of the distribution. Sequential Bayesian updating is well documented in the literature, e.g. Zellner and Chetty (1965), Zellner (1971), Box and Tiao (1992), or more recently Gelman, Carlin, Stern, and Rubin (2000, chap. 3). We assume that the covariance matrix Σ_t follows an inverted-Wishard with parameters Λ_t and ν_t. Here, Λ_t represents the matrix of cumulated centered second moments up to t and ν_t is a measure of the strength of belief placed in Λ_t. Conditional on Σ_t, the mean is distributed according to a normal with mean μ_t and variance-covariance matrix Σ_t/κ_t. Here, κ_t measures the strength of belief in μ_t. Traditional Bayesian updating assumes that, starting from some priors μ_{t-1}, Λ_{t-1}, κ_{t-1}, and ν_{t-1}, posterior estimates are given by

$$\begin{aligned}
\kappa_t &= \kappa_{t-1} + 1, \qquad \nu_t = \nu_{t-1} + 1, \\
\lambda_t &= \kappa_{t-1}/\kappa_t, \\
\mu_t &= \lambda_t \mu_{t-1} + (1 - \lambda_t)\, y_t, \\
\Lambda_t &= \Lambda_{t-1} + \lambda_t (y_t - \mu_{t-1})(y_t - \mu_{t-1})', \\
\Sigma_t &= \Lambda_t/\nu_t.
\end{aligned}$$

Note that, in empirical applications, κ_t and ν_t are equal to the number of observations used for computing moments. This iterative sequence needs to get evaluated, starting with some μ_0, Λ_0, κ_0, and ν_0.

This traditional updating has been used in the finance literature by Brown (1979) or Frost and Savarino (1986). Some authors provided estimates for prior parameters derived from the data (see Morris, 1983). Using this empirical Bayesian approach, Jorion (1985)

[6] We will later show that the assumption of normality at a given time is not incompatible with returns being non-normal over the sample period.

[7] We assume in this study that the mean-variance analysis still holds. In other words, we assume that investors do not change their objective function to explicitly take into account the randomness of the parameters μ and Σ.

describes how to obtain an endogenous value for κ_0 and μ_0. Frost and Savarino (1986) provide ML estimation techniques for estimating κ_0 and ν_0. We will later provide an ad-hoc rule to get priors, in cases where learning gets re-initialized.

We now turn to the other specificities of emerging markets: appearance of new economies and structural changes. Often, a large movement of a stock-market index reflects a change in the structure of the economy. Anecdotal evidence of this observation can be easily provided for transition economies. For instance, when Yeltsin replaced Gorbachov, worldwide turbulences could be felt in financial markets. Clearly, this was accompanied by a new policy pursued by Yeltsin. Inspired by models where a change in structure occurs as a threshold is exceeded, such as in Tong (1993), we will re-initialize the learning process whenever a return is of a magnitude that is very unlikely to occur with a normal distribution. We specify a high quantile, and when the return at time t exceeds this threshold, we start a new learning process. Such a re-initialization allows to take care of the possibility that completely new situations arise.[8] It is these re-initializations that distinguish our Bayesian learning model from the traditional ones.

Another important feature of our learning process is that we re-initialize the learning process only for the country where the abnormal event took place, rather than for all countries. This means that we are able to keep all useful information (see Stambaugh, 1999). Analogously, when a new economy emerges, we start learning its parameters. Given the shortness of the time series, tools such as GARCH models or switching regressions cannot be estimated. As an alternative, we suggest a rule-of-thumb learning procedure.

More formally, consider the return of country i at time t. This return should be distributed marginally as a normal distribution with mean $\mu_{i,t}$ and variance $\Sigma_{i,t}$, the ith element on the diagonal of the covariance matrix Σ_t. Assume that an extreme event occurs at time $t-1$ on market i, for instance that $|er_{i,t-1}|$ exceeds the 99% threshold of the normal distribution with mean $\mu_{i,t-1}$ and variance $\Sigma_{i,t-1}$.[9] In that case, we re-initialize

[8] In many models where learning occurs, it is assumed beforehand that only a given number of states may occur. This is the case with Hamilton's (1994) switching regression. Models where the space of states may increase is given by Chib (1998). See also Kim and Nelson (1999) for a review of a large selection of models allowing several states. There, a large number of data points is, however, required in the estimation.

[9] This means that $|er_{i,t-1}| > \mu_{i,t-1} + 2.326\sqrt{\Sigma_{i,t-1}}$.

the model as will be discussed below.

Since we discard all the past observations for a country i that gets re-initialized, the weights required for computing the mean vector, λ_t, and for the covariance matrix, ν_t, will differ from one market to the other. Therefore, it becomes necessary to perform a precise accounting of elements. Concerning the mean vector μ_t, we now use the $(N,1)$ vector κ_t, with element $\kappa_{i,t}$ corresponding to the number of observations used for country i. κ_t is updated as before, $\kappa_{i,t} = \kappa_{i,t-1} + 1$, and the $(N,1)$ vector of weights for the mean is defined as $\lambda_{i,t} = \kappa_{i,t-1}/\kappa_{i,t}$, $i = 1, \cdots, N$. For the matrix of cumulated centered second moments Λ_t, since the number of observations for two countries is likely to be different, we use now a matrix of weights, δ_t, of dimension (N,N), defined as: $\delta_{ij,t} = \sqrt{\lambda_{i,t} \cdot \lambda_{j,t}}$. Finally, the covariance matrix is computed as follows. Diagonal terms of Σ_t (say $\Sigma_{i,t}$) are simply obtained by dividing $\Lambda_{i,t}$ by the number of observations used for country i, i.e. $\Sigma_{i,t} = \Lambda_{i,t}/\nu_{i,t}$, with $\nu_{i,t} = \nu_{i,t-1} + 1$. Off-diagonal terms of Σ_t (say $\Sigma_{ij,t}$) are obtained by dividing $\Lambda_{ij,t}$ by $\nu_{ij,t} = \sqrt{\nu_{i,t} \cdot \nu_{j,t}}$.

Therefore, the updating rules become

$$\begin{aligned} \mu_t &= \lambda_t \odot \mu_{t-1} + (I_{n,1} - \lambda_t) \odot y_t, \\ \Lambda_t &= \Lambda_{t-1} + \delta_t \odot \left(y_t - \mu_{t-1}\right)\left(y_t - \mu_{t-1}\right)', \\ \Sigma_{ij,t} &= \frac{\Lambda_{ij,t}}{\nu_{ij,t}}, \qquad i,j = 1, \cdots, N, \end{aligned}$$

where $\odot$ denotes the element-by-element product of matrices and $I_{n,m}$ is the $(n \times m)$ matrix (possibly degenerated to a row or column vector) of ones.[10]

In the way our model is conceived, returns on a given day are normal with a given mean and variance. Because mean and variance vary through time, our model can be viewed as a model of a mixture of normals. There is an abundant literature, going back to Clark (1973), that shows that if returns are generated as a mixture of normals, the unconditional distribution will be non-normal. More recent contributions are by Harris (1987) and Richardson and Smith (1994).

[10] For instance, if $A = \{a_{i,j}\}$ and $B = \{b_{i,j}\}$, then $A \odot B = \{a_{i,j} b_{i,j}\}$ with A and B two conformable matrices. Note also that we write $\Sigma_{i,t}$ instead of $\Sigma_{ii,t}$.

3.2 Initializing priors

When a new market i opens at time $t-1$, or when an extreme event occurs on market i at time $t-1$, moments associated with this market are (re-)initialized at time t: $\kappa_{i,t} = \kappa_i^0$, $\nu_{i,t} = \nu_i^0$, $\mu_{i,t} = \mu_{i,t}^0$, and $\Lambda_{ij,t} = \Lambda_{ij,t}^0$, $j = 1, \cdots, N$. Several methods to re-initialize priors are possible. We suggest that investors wait for some time to see how the market evolves, for instance for 3 weeks.[11] Given the way we construct our prior, we set $\kappa_i^0 = \nu_i^0 = 3$.

Concerning re-initialization of moments $\mu_{i,t}^0$ and $\Lambda_{ij,t}^0$, we may think to use, in the usual way, the sample mean and the sample matrix of cumulated second moments over the last three observations. However, given that the last observation is an extreme event, it is likely to affect strongly the moments of returns, see also Dumas and Jacquillat (1990). We would like to emphasize that in our model investors do not predict a crash. As a crash occurs, they suffer it fully. Because of the crash, moments change in such a way that, when we run our optimal portfolio choice model, the market is most likely to be excluded. Our Bayesian approach allows to weight down the crash in the computation of the moments. Therefore, we introduce three additional parameters $\alpha = (\alpha_M, \alpha_V, \alpha_C)$ that down-weight the sample estimates of moments. For instance, we initialize the mean return as $\mu_{i,t}^0 = \alpha_M \overline{y}_{i,t-1}$, where $\overline{y}_{i,t-1} = \frac{1}{3}\sum_{\tau=1}^{3} y_{i,t-\tau}$ is the sample mean over the last three observations (including the crash). We assume $\alpha_M \in [0,1]$. Choosing $\alpha_M = 1$ means that we believe that the sample mean over the last three observations is a rather accurate estimate of the excess-return mean that will prevail in the future. In contrast, choosing $\alpha_M = 0$ indicates that we believe that nothing can be inferred from past data to forecast future returns. In other words, we assume that future returns will not be affected by the current crash, so that we simply assume zero future returns. We discuss in the next section how the re-initialization parameters α affect the asset allocation.

We turn now to the covariance matrix. First, we initialize variances as $\Sigma_{i,t}^0 = \alpha_V s_{i,t-1}^2$, where $s_{i,t-1}^2$ denotes the sample variance over the last three observations and $\alpha_V \in [0,1]$. Second, covariances are set up such that $\Sigma_{ij,t}^0 = \alpha_C \rho_{ij,t-1}\sqrt{\Sigma_{i,t}^0 \cdot \Sigma_{j,t}}$, where $\rho_{ij,t-1}$ denotes the correlation estimate just before the extreme event. The choice of α_C is

[11] This is the lower bound to obtain a sensible covariance matrix. Although this assumption may appear drastic, Borensztein and Gelas (2000) report massive flows of institutional investors around crises. Notice that our reported results remain quantitatively the same if the time period is extended to several more weeks.

quite challenging.[12] On one hand, since an extreme event occurred on market i, we are reluctant to set a large parameter α_C, to avoid "contaminating" other stock markets. On the other hand, some empirical evidence obtained with various techniques indicates that correlation tends to increase in period of turbulence, so that stock markets are more related during crashes and booms (Ramchand and Susmel, 1998, Longin and Solnik, 2001). Possible values for α_C are $\left[-1/\rho_{ij,t-1}, 1/\rho_{ij,t-1}\right]$, but we typically tried values in the range $[0,1]$. Finally, $\Lambda^0_{ij,t}$ is set equal to $\nu^0_{ij,t}\Sigma^0_{ij,t}$, with $\nu^0_{ij,t} = \sqrt{\nu^0_{i,t} \cdot \nu_{j,t}}$.

Note that, in few cases, a second crash occurs during the re-initialization period of the previous one. In such a situation, we forget the first crash and re-initialize parameters for the second one using realized excess returns, as describe above.

Note also that, during the re-initialization period, it is assumed that the investors who use our approach do not invest in country i. This does not mean that no one should invest during this period. We are aware that this assumption is strong. In particular, it implies that our investors may by their actions amplify negative movements. We leave the implications of our model from a general equilibrium point of view to some other research.

3.3 Assessment of Bayesian learning

The re-initialization parameters are calibrated rather than estimated. Consequently, we performed several experiments to assess our Bayesian-learning procedure. Table 4 reports some statistics on Bayesian learning. To begin, we indicate first and second unconditional moments of excess returns.[13] We then report averages of first and second conditional moments of excess returns associated with various sets of re-initialization parameters $\alpha = (\alpha_M, \alpha_V, \alpha_C)$. We also present the number of re-initializations for each stock market.

A first result is that the number of re-initializations increases when we decrease the

[12] Elton and Gruber (1973) emphasize that, whereas the expected return and the variance of an asset are relatively easy to compute, the correlation between assets tends to be difficult to quantify. They provide various techniques to measure correlations, however, their model differs fundamentally from ours. We estimate the correlations directly, whereas they obtain them indirectly via the betas in a single factor model. Because in our model there is no factor, we cannot adopt their approach.

[13] The difference of the statistics displayed here and Table 2 is that, now, we use excess returns rather than returns.

parameter α_V. A low value of α_V is associated with a low value of the variance in case of a re-initialization. This implies that, everything else being equal, a further re-initialization is more likely to occur since the standardized return is more likely to exceed the re-initialization threshold. For instance, when we chose $\alpha = (1, 1, 1)$, the number of re-initializations is 21 in Hungary, 10 in Romania, and 8 in Russia. When we choose $\alpha = (1, 0.5, 1)$, this number is as high as 32, 17, and 21, respectively. In parallel, the average conditional standard deviation also decreases with the parameter α_V. In most emerging markets, the conditional standard deviation is lower than the unconditional standard deviation whatever the re-initialization parameter.

Such a result does not hold for the parameter α_M associated with the return re-initialization. The position of the unconditional mean with respect to the conditional mean is strongly related to the skewness of the distribution. Positive skewness indicates that booms are more likely to occur than crashes, so that re-initializing learning is likely to decrease the conditional mean. We observe such a phenomenon in Lithuania, Slovakia, and Slovenia. In emerging markets, reducing the parameter α_M from 1 to 0 generally leads to a conditional mean that is much closer to the unconditional mean. This translates the fact that extreme returns are not persistent.

When we consider the consequences of a change of α_C, controlling the weight put on correlation, we notice that it does not affect conditional mean nor standard deviation. This suggests that down-weighting correlations does not affect the series of mean and standard deviation of excess returns of a given country. In contrast, it will have an impact on the series of covariances and consequently also on portfolio allocation.

4 Asset allocation under Bayesian learning

4.1 The asset-allocation problem

Now, we use our Bayesian-learning procedure to construct a dynamic asset allocation. First, investors forecast the expected excess return (μ_t) and the covariance matrix (Σ_t), for the period between t and $t+1$, using the procedure described in the preceding section. Second, they solve the following mean-variance asset-allocation problem:

$$\max_{\{w_t\}} \qquad w_t \mu_t - \frac{\theta}{2} w_t' \Sigma_t w_t, \tag{2}$$

$$w_{j,t} \geq 0, \qquad j = 1, \cdots, N_t, \tag{3}$$

$$\sum_{j=1}^{N_t} w_{j,t} \leq 1, \tag{4}$$

where w_t denotes the column vector of portfolio weights in risky assets, chosen at date t for the period $(t, t+1)$. The weight affected to the riskless asset is therefore $1 - \sum_{j=1}^{N_t} w_{j,t}$. The parameter θ denotes the coefficient of risk aversion. This is exactly the optimization problem solved by Solnik (1993) to derive his intertemporal allocation (with $\theta = 2$).[14] Whenever we take a sum involving a varying number of elements, we assume that the ordering of the series is such that j runs over the existing series. We assume that there are no transaction costs. Given that short-selling is not allowed in many countries, we also do not allow it here. For this reason, all weights are constrained to be non-negative, as in (3). Inequality (4) also imposes that margin purchases are not allowed. Running the mean-variance program using the time-varying expected excess returns and covariance matrix yields a time series of portfolio weights associated with the Bayesian-learning procedure.[15] We deduce the excess return for the period $(t, t+1)$ of the portfolio chosen at time t as:

$$R_t^p = \sum_{j=1}^{N_t} w_{j,t} er_{j,t} = w_t' er_t. \tag{5}$$

4.2 The performance test

As stressed by Solnik (1993), theoretical international asset pricing models do not provide a benchmark portfolio that could be used to gauge alternative investment strategies. The reason for this is that hedging against currency risk requires holding a combination of the domestic risk-free asset and the world market portfolio plus a position in foreign risk-free assets. Therefore, the measurement of the performance of our model cannot be based on a predetermined benchmark. For this reason, we follow Dumas and Jacquillat (1990), who apply the approach proposed by Mayers and Rice (1979) and Cornell (1979). Grinblatt and Titman (1990) find that this approach has good properties.

To give a formal intuition of this approach, we consider the excess return of a given stock-market index j between time t and $t+1$, $er_{j,t}$. Under the assumption of rational

[14] As emphasized by Elton and Gruber (1997), the optimization over single-period return distributions yields sub-optimal allocations. This type of allocation yields, however, easily computable solutions.

[15] We solve this quadratic optimization problem using the GAUSS QP module.

expectations, it is always possible to write

$$er_{j,t} = m_{j,t} + e_{j,t},$$

where $m_{j,t}$ is the expected excess return, given by some asset pricing model. In the following, $m_{j,t}$ will be chosen as the unconditional excess return. The $e_{j,t}$ is a random error. Rational expectations imply that the conditional expectation of the error is zero, $E_t[e_{j,t}] = 0$. E_t represents the conditional expectation using all information up to time t. An informed strategy will be able to make a prediction concerning the error. Assume for instance that $e_{j,t} > 0$ and that a given model is able to predict this. This means that the returns will be higher than they should, conditional on their risk level. Clearly, at time t, this asset should be purchased or the position increased. This implies that the weight, $w_{j,t}$, allocated to asset j at time t, will be positively correlated with $e_{j,t}$. Formally, we expect $Cov(e_{j,t}, w_{j,t}) > 0$. A simple reasoning shows that if news concerning an index are bad, the same sign should still hold for the covariance. Thus, whatever the news, we expect for an informed strategy a positive covariance. In our empirical section, the "informed" investor will be assumed to use the Bayesian-learning procedure to forecast expected excess returns and covariance matrix at each date t. On the other hand, the uninformed strategy, based on unconditional moments, will have a zero covariance. "Uninformed" investors will select the market portfolio, assuming that informed investors have zero weight in the market.[16]

We now wish to test whether the Bayesian-learning procedure is valuable. If this procedure is worthy, an uninformed investor should observe that, when computed with unconditional mean returns, the expected excess return of the portfolio selected by the informed investor is larger than the excess return of the market portfolio (selected by the uninformed investor). In contrast, under the null hypothesis that the Bayesian learning is worthless, the conditional distribution of excess returns reduces to the unconditional one. Therefore, an informed investor should obtain the same portfolio excess return as an uninformed investor. Thus, the performance test designed by Cornell (1979) and Solnik (1993) consists in comparing the portfolio return obtained by the informed investor (using the Bayesian-learning procedure) with the expected return of the portfolio measured by an uninformed investor (using unconditional moments).

[16] As pointed out by Mayers and Rice (1979) and Cornell (1979), the zero-weight assumption is necessary for the CAPM to hold.

At this stage, we have to indicate how the uninformed investor computes the unconditional moments. On one hand, Copeland and Mayers (1982) suggest to compute the mean excess return of market j using the whole sample period (including the period posterior to date t). This sample mean is denoted: $m_{j,t}^{\mathrm{CM}} \equiv \frac{1}{T}\sum_{s=1}^{T} er_{j,s} = \overline{er}_j$. On the other hand, Cornell (1979) estimates the mean excess return using data over the sample period preceding time t. He uses, therefore, $m_{j,t}^{\mathrm{CO}} \equiv \frac{1}{t-1}\sum_{s=1}^{t-1} er_{j,s}$. The unconditional covariance matrix is computed in a similar fashion. We, thus, define V_t^{CM} and V_t^{CO} the unconditional covariance matrix obtained using data over the whole sample period and data over the sample period preceding time t, respectively. Solnik (1993), using highly-developed economies, argues that biases due to the use of the whole sample are likely to be small and estimates an unconditional mean with the largest data sample. Since, to our knowledge, there is no consensus which sample period should be used, we will present results for both situations.

Therefore, the expected excess return of the Bayesian asset allocation selected at time t, computed by an uninformed investor using the unconditional mean, is $\sum_{j=1}^{N_t} w_{j,t} m_{j,t}^k$, with k =CM, CO. We also define the portfolio uninformed unexpected excess return as

$$u_t^k = w_t' \left(er_t - m_t^k \right), \qquad \text{with } k = \text{CM, CO.} \tag{6}$$

Cornell noticed that

$$E[u_t^k] = \sum_j Cov\left(w_{j,t}, er_{j,t} - m_{j,t}^k\right) = \sum_j Cov\left(w_{j,t}, e_{j,t}^k\right).$$

In analogy with what has been stated earlier, if the Bayesian-learning model is valuable, an informed investor will have a positive covariance between asset-jth optimal weight and unexpected excess return, $e_{j,t}^k$. As a consequence, on average, the portfolio unexpected excess return, u_t^k, will be positive. Under the null hypothesis that the Bayesian-learning procedure is worthless, the realized excess return of the optimal portfolio, R_t^p, is not significantly different from its uninformed expectation, so that the portfolio unexpected excess return should be equal to zero on average.

To construct a test of this hypothesis, we define the uninformed variance of the portfolio excess return. It is computed using optimal weights w_t and the unconditional covariance matrix V_t^k:

$$(\sigma_t^k)^2 = w_t' V_t^k w_t, \qquad \text{with } k = \text{CM, CO.}$$

Then, we compute the time series of standardized unexpected excess returns and build a t-statistic. These are

$$\tau^k = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \frac{u_t^k}{\sigma_t^k}, \qquad \text{with } k = \text{CM, CO.} \tag{7}$$

For the case where the Bayesian-learning model is worthless, the null hypothesis is $\tau^{\text{CM}} = 0$ and $\tau^{\text{CO}} = 0$. By invoking the central limit theorem, both statistics are distributed, under the null, as a normal, $\mathcal{N}(0, 1)$. As a consequence, it is easy to perform a formal statistical test.

Finally, it is useful to consider how the portfolio excess return would have evolved through time. For this reason, we define the cumulative excess return, CER, for each measure of unconditional moments. It is defined as

$$\text{CER}_t^k = \sum_{s=1}^{t} \sum_{j=1}^{N_s} w_{j,s} m_{j,s}^k, \qquad \text{with } k = \text{CM, CO,} \tag{8}$$

for $t = 1, \cdots, T-1$. We also define the CER obtained for our Bayesian-learning model, using realized excess returns:

$$\text{CER}_t^{\text{B}} = \sum_{s=1}^{t} \sum_{j=1}^{N_s} w_{j,s} er_{j,s}. \tag{9}$$

As a consequence, plots of these series, as a function of t, and the comparison between CER_t^{B} on one hand and CER_t^k, k =CM, CO, on the other hand, are useful to detect periods where performance gains were particularly strong.

5 Results

In this section, we discuss the results obtained with our Bayesian-learning model. In order to implement this model, it is necessary to select a risk-aversion parameter. The choice of this parameter is rather arbitrary. A large range of parameters has been used in the empirical literature. Aït-Sahalia and Lo (2000) report several representative values of the risk-aversion parameter. Best and Grauer (1991) obtain estimates of θ ranging from 2.9 to 3.7. Solnik (1993) uses $\theta = 2$. Kandel and Stambaugh (1996) use values ranging from one to five, while Aït-Sahalia and Brandt (2001) use values between two and 20. We adopt, in the following, $\theta = 5$ as the reference level. Risk aversion parameters of 2 and 10 would characterize strongly aggressive and conservative investors, respectively.

5.1 Unconditional portfolio allocation

As a first case, for various levels of risk aversion, we consider the allocations, w, obtained by using the unconditional mean and covariance matrix estimated from the entire sample. In Table 5, we present various results for this unconditional framework. Since we need to compute unconditional moments, we restrict our allocation to countries for which a stock-market index is available over a long period of time. Therefore, we consider the Czech Republic, Hungary, Poland, Russia, Slovakia, and Slovenia, in addition to the UK and Germany. We thus compute moments over the period from September 1994 to December 2000.[17]

Panel A displays the portfolio weights obtained using the optimization program (2). Investors are allowed to invest in the riskless asset. For very conservative investors, i.e. with large θ, we find, as expected, that they invest very small amounts in equity (less than 20%). As risk aversion decreases, the fraction of wealth invested in the risky assets increases. Interestingly, even for rather low risk aversions, investors put at most 90% of their wealth in the UK and German indices. This comes from the fact that, during the period considered, stock markets offered a rather low excess return. We observe that no money would have been put in the set of transition economies. This suggests that, given the relatively low level of expected returns, transition economies do not offer sufficient diversification opportunities, as to offset the rather high level of volatility. These results are puzzling in the light that international investors actually invest in these economies. We recall that it is this finding that motivated initially our research.

So far, we considered the consequence on portfolio weights. Another issue is how much a given strategy would yield in terms of cumulative excess returns (CER). To answer this question, we present in Panel B of Table 5, for various levels of risk aversion, the CER, once for the optimal mean-variance allocation, and once for an equally-weighted investment strategy.

As the level of risk aversion decreases, the mean-variance strategy yields a higher level of returns. On the other hand, the risk of the strategy increases. As a consequence,

[17] Including the ten transition economies under study would restrict the sample used for computing unconditional moments to the period from September 1997 to December 2000. Note that when we perform this exercice for the ten transition economies, we obtain essentially the same results as those reported in the paper: Investors would not invest in emerging markets.

observation of the full sample CER only is misleading. A risk-adjusted measure is given by the Sharpe ratio. When we contemplate this statistic, we obtain a significant increase when we shift from equal weights to optimal weights, but only a marginal increase for higher levels of risk aversion.[18] We find that the investor who had invested according to mean-variance analysis would have realized a significant benefit over the equal-weight investor.

The results described so far are static. We now turn to investigate the contribution of the Bayesian-learning rule.

5.2 Conditional portfolio allocation

In Table 6, we follow Cornell, as well as Copeland and Mayers, and present the cumulative excess returns that are required in the performance measurement. In this table, we use all available transition economies, even if some of them only start in 1997.[19] We present the full sample cumulative excess return, CER_T^{CM}, CER_T^{CO} and the Bayesian one CER_T^{B}. Then, we present, in the last two columns, the τ^{CM} and τ^{CO} statistics, given by equation (7). The first statistics compares the ability of Bayesian forecasts to obtain a larger portfolio expected return than naive forecasts based on unconditional moments computed over a full sample (static measure). The second statistic compares the performance of the Bayesian forecasts to the one of naive forecasts based on unconditional moments computed over the sample period preceding the current period (dynamic measure). The two statistics are presented for various levels of risk aversion and various levels of initialization.

Given that the results are qualitatively the same as risk aversions change, we first focus in our discussion on the one for $\theta = 5$. For this value, we find that, whatever the level of initialization, the static measure provides a very small CER. In contrast, the CER is much larger for the dynamic measure. We explain this result by the fact that in transition economies many events occurred that changed significantly the level of the mean returns. Using the Bayesian learning, we also obtain very high CER for most initialization parameters. We find that our Bayesian learning obtains significantly better

[18]When investors can invest in the risk-free asset, the Sharpe ratio remains constant since the optimal risky portfolio is invariant.

[19]If we had excluded these countries, the results would not have been significantly affected.

expected excess returns than the static measure for low levels of variance re-initialization. It is marginally better than the dynamic measure. Note that the CER of the Bayesian learning is systematically larger than the CER of the dynamic measure, while the t-statistics τ^{CO} is sometimes negative.[20] This is because the t-statistics is defined as the sum of standardized unexpected excess return. It appears that the variance of the unexpected excess return is generally larger when the unexpected excess return is large. Therefore, when the Bayesian learning outperforms the dynamic measure, it is often down-weighted by an excessive risk-taking.

We turn now to discuss the changes in performance as the initialization parameters change. When the re-initialization parameter α_V for the variance decreases, moving from 1 to 0.1, we notice an improvement in the t-statistics. As variance becomes smaller, it means that our model will consider more aggressively even moderate returns as trigger values for a re-initialization. This result indicates that careful listening to the market is necessary after a turbulent event occurred, and that, in transition economies, over the sample considered, it may be necessary to reallocate the portfolio frequently. It also suggests that realizations corresponding to an extreme event should not be used in the computation of variances.

As we shift α_M from 1 to 0.5, meaning that we down-weight the three-week average, the t-statistics drop. This shows that investors should, when they rebalance their portfolios, use past information or, in other words, that persistence in the moments of excess returns is useful to improve forecasts and thus to obtain a higher portfolio return.

Last, we turn to the initialization of covariances by comparing the situation $\alpha_C = 1$ with $\alpha_C = 0.5$. This means that we down-weight correlation across the markets after a crash. We find that this does not affect the value of the t-statistics. Therefore, the impact of correlation changes, for the countries considered, will not be of major importance. This may be explained by the fact that, in emerging markets, changes in correlation are dominated by changes in return and variance from an asset allocation viewpoint.

In Figure 1, we display the evolution of cumulative excess returns obtained using the static and the dynamic measures as benchmarks and using Bayesian forecasts. The initialization parameter is $\alpha = (1, 0.1, 1)$ and we consider the ten transition economies.

[20] For instance, in Table 6, for $\theta = 2$ and $\alpha = (1, 1, 1)$, the CER is equal to 2.506 for the Cornell measure and 2.526 for the Bayesian learning. However, the t-statistics, τ^{CO}, is estimated to be equal to -0.757.

The lowest curve represents the cumulative excess returns for an uninformed investor who uses all the sample information to compute averages. This corresponds to the measure chosen by Copeland and Mayers (1982) and Solnik (1993). The curve in the middle corresponds to the knowledge assumed by Cornell (1979). Last, the highest curve corresponds to the actual excess returns realized by using Bayesian forecasts. The difference between the highest and the two other curves, when conveniently standardized, yields the statistics presented in Table 6.

During the first 100 observations, from 1991 to the beginning of 1993, our informed strategy is comparable with the uninformed ones. Transition economies, namely Hungary and Poland, represented an interesting investment opportunity. Our Bayesian learning would have recognized this performance.

In Figure 2, we display the weights of an investment in the UK and Germany versus the weight of the global investment in all available transition economies. We notice that one should have invested aggressively in the transition economies during certain periods. Returning to Figure 1, we notice that before mid-1993, only small gains were realized. Figure 2 shows that during this early period wild fluctuations in expected returns occurred, leading to large switching of the investments. In other words, returns were hardly predictable, meaning that no information could be gleaned from past returns.

From 1994 on, the dynamic measure remains rather stable, suggesting that the underlying parameters became more stable. Our Bayesian learning had two periods of higher returns, the first one was due to a higher investment in Hungary in 1994. The second period, 1996-97 involved Hungary, Poland, Russia, and Slovakia. The gain of our strategy is, therefore, not only due to a single country but to a portfolio. We notice that the Bayesian-learning rule yielded returns, which are increasing steadily with respect to the naive strategies. This suggests that our results are not driven by outliers, but reflect changes in investment opportunities in transition economies.

6 Conclusion

In this research, we address the issue of what an investor could rationally do to implement a dynamic asset allocation in transition economies. These economies are characterized by several specificities. First, new stock markets opened through time. Second, the expected returns and covariance matrices of these markets are not well established. Third, structural breaks are likely to occur.

To overcome these difficulties, we consider a Bayesian-learning model. Our model is novel insofar as we force a re-initialization of the learning process as returns exceed a certain threshold. In other words, we follow the intuition that, in transition economies, extreme changes in market returns are accompanied by a change in expected returns and covariance matrix.

We find that an asset allocation based on Bayesian forecasts outperforms an equal-weight strategy. In addition, when compared with a static measure of unconditional moments, Bayesian forecasts obtain significantly better portfolio expected returns. When compared with a dynamic measure of unconditional moments, for certain initializations, Bayesian forecasts remain better even though only marginally. In this light, we believe that Bayesian techniques may be of value in a asset-allocation strategy involving transition economies.

Certain reservations can be formulated with respect to our model. Our results are obtained by assuming a single-period optimization rather than a multiperiod optimization. We also neglect transactions costs.

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Captions

Table 1: This table summarizes the names, the label, and the date when each stock index and exchange rate becomes available for the investigated economies.

Table 2: This table reports summary statistics for stock-market returns, sampled at weekly frequency, expressed in Sterling. The first row indicates the date when a series start. All series end with June 29 2001. *nobs* is the number of observations in each series. Standard errors (std. err.) are computed using the GMM procedure suggested by Richardson and Smith (1993). The Wald statistic tests the null hypothesis that skewness and excess kurtosis are jointly equal to 0. Under the null, the statistic is distributed as a χ^2 with 2 degrees of freedom. $\rho(j)$ represents the j-th order autocorrelation. Engle(K) represents the Engle-test statistic for heteroskedasticity obtained by regressing squared returns on K lags. Under the null hypothesis of homoskedasticity, this statistic is distributed as a χ^2 with K degrees of freedom. $Q\,(K)$ represents the Box-Ljung statistics without correction for heteroskedasticity. The statistic with correction for heteroskedasticity is denoted $QW\,(K)$. Under the null hypothesis of no serial correlation, the statistic is distributed as a χ^2 with K degrees of freedom. At the 95% level, the critical value for a χ^2_4 is 9.94.

Table 3: This table reports cross-correlations between stock-market returns. Correlations are computed using for each pair of stock markets the largest available sample. Returns are all expressed in Sterling.

Table 4: This table reports statistics on Bayesian learning. We first display unconditional first and second moments of **excess** returns for various countries. Using our Bayesian-learning procedure we obtain series of conditional returns (μ_t) and covariance matrices (Σ_t). We present averages of these conditional means and associated standard deviations for various sets of re-initialization parameters $\alpha = (\alpha_M, \alpha_V, \alpha_C)$. The parameters α_M, α_V, and α_C weight, after a re-initialization, the 3-week mean, standard deviation and covariance used in the learning process. We also display how often in a given country learning is re-initialized.

Table 5: This table reports the optimal weights and statistics on the optimal portfolio for various levels of risk aversion θ, when we use unconditional moments. Unconditional

moments are computed over the period from September 1994 to December 2000 for the UK, Germany and the six transition economies for which data are available. In Panel A, we report optimal weights obtained by solving the optimization program (2) – (4), so that investment in the riskless asset is allowed, but not short sales. In Panel B, we compare cumulative excess returns (CER) and Sharpe ratios for the optimal asset allocation reported in Panel A (denoted 'Optimal weights') and for an equally-weighted risky portfolio (denoted 'Equal weights').

Table 6: This table presents the cumulative excess return at time T that may have been achieved for several risk aversions θ and re-initialization parameters α. Using the portfolio weights obtained with the Bayesian-learning model, we compute the CER for an uninformed investor who consider a static measure of unconditional moments (Copeland and Mayers, 1982) as well as a dynamic measure of unconditional moments (Cornell, 1979). We also compute the CER for an informed investor who consider conditional moments computed with the Bayesian-learning model:

$$\mathrm{CER}_T^{\mathrm{CM}} = \sum_{s=1}^{T}\sum_{j=1}^{N_s} w_{j,s} m_{j,s}^{\mathrm{CM}}, \qquad \mathrm{CER}_T^{\mathrm{CO}} = \sum_{s=1}^{T}\sum_{j=1}^{N_s} w_{j,s} m_{j,s}^{\mathrm{CO}},$$

$$\mathrm{CER}_T^{\mathrm{B}} = \sum_{s=1}^{T}\sum_{j=1}^{N_s} w_{j,s} er_{j,s}.$$

We also present the t-statistics for a test of the null hypothesis that the Bayesian-learning model is worthless as compared with unconditional moments computed with Copeland and Mayers (1982) as well as the Cornell (1979) approaches

$$\tau^{\mathrm{CM}} = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \frac{u_t^{\mathrm{CM}}}{\sigma_t^{\mathrm{CM}}},$$

$$\tau^{\mathrm{CO}} = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \frac{u_t^{\mathrm{CO}}}{\sigma_t^{\mathrm{CO}}}.$$

The * indicates that the statistic is significant at the 5% level.

Figure 1: This figure displays various cumulative excess returns over time. We have

$$\mathrm{CER}_t^{\mathrm{CM}} = \sum_{s=1}^{t}\sum_{j=1}^{N_s} w_{j,s} \hat{\mu}_{j,s}^{\mathrm{CM}}, \qquad \mathrm{CER}_t^{\mathrm{CO}} = \sum_{s=1}^{t}\sum_{j=1}^{N_s} w_{j,s} \hat{\mu}_{j,s}^{\mathrm{CO}},$$

$$\mathrm{CER}_t^{\mathrm{B}} = \sum_{s=1}^{t}\sum_{j=1}^{N_s} w_{j,s} er_{j,s}, \qquad \text{for } t = 1, \cdots, T.$$

The distance between CER_t^{B} and CER_t^{CO}, respectively between CER_t^{B} and CER_t^{CM}, is suggestive of the gain in performance of our Bayesian-learning model.

Figure 2: This figure presents the aggregated weights invested either in the UK and Germany or in the set of transition economies. Weights are obtained by solving the mean-variance asset-allocation problem (2) – (4) for each date t using the time-varying expected excess return and covariance matrix obtained with the Bayesian-learning model. Then, we take the sum of the weights at each point of time by distinguishing the weights corresponding to the UK and Germany from the transition economies.

Table 1: Name and date of availability of stock indices and exchange rates

		Stock index		Currency	
Developed economies					
The UK	UK	FTSE-100	01/01/91	Sterling	01/01/91
Germany	GE	DAX	01/01/91	Mark	11/01/91
Transition economies					
Croatia	CR	Crobex	02/01/97	Kuna	03/06/94
Czech Republic	CZ	PX 50	06/04/94	Koruna	01/01/91
Estonia	ES	Aripaev index	07/04/95	Kroon	12/10/92
Hungary	HU	BUX	02/01/91	Forint	01/01/91
Lituania	LI	Litin A	29/12/95	Lita	04/10/93
Poland	PO	Warsaw General Index	16/04/91	Zloty	01/01/91
Romania	RO	BET	19/09/97	Leu	01/01/91
Russia	RU	RUR	01/09/94	Rouble	11/01/93
Slovakia	SL	SAX16	14/09/93	Koruna	11/01/93
Slovenia	SV	SBI	03/01/94	Tolar	12/10/92

Table 2: Summary statistics for market returns expressed in Sterling

	UK	GE	CR	CZ	ES	HU	LI	PO	RO	RU	SL	SV
beginning date	91/01/01	91/01/01	97/01/07	93/09/14	95/04/11	91/01/08	96/01/02	91/04/16	97/09/23	94/09/06	93/09/14	93/01/03
nobs	522	522	208	381	299	521	261	507	171	330	381	365
mean	0,203	0,275	-0,074	0,064	0,378	0,174	0,051	0,315	-1,009	0,032	-0,113	0,008
std. err.	*0,082*	*0,102*	*0,393*	*0,318*	*0,443*	*0,233*	*0,334*	*0,344*	*0,540*	*0,621*	*0,385*	*0,209*
standard deviation	2,091	2,803	5,427	4,462	5,985	4,525	4,197	6,693	6,721	8,759	4,796	4,002
std. err.	*0,111*	*0,170*	*0,626*	*0,421*	*0,762*	*0,421*	*0,584*	*0,493*	*0,571*	*0,739*	*0,940*	*0,288*
skewness	-0,210	-0,397	-0,205	0,593	-1,670	-0,152	1,653	-0,333	-0,239	-0,386	2,716	0,459
std. err.	*0,256*	*0,218*	*0,365*	*0,391*	*0,741*	*0,575*	*0,828*	*0,227*	*0,332*	*0,274*	*1,255*	*0,304*
excess kurtosis	1,753	1,645	3,228	3,016	10,302	6,279	11,933	2,925	1,797	2,436	22,929	2,725
std. err.	*0,694*	*0,887*	*1,435*	*1,232*	*4,027*	*1,556*	*3,200*	*0,579*	*0,704*	*0,704*	*5,545*	*0,771*
Wald stat.	6,468	3,565	12,124	6,520	6,548	16,464	14,216	25,684	6,523	12,148	19,121	12,520
p-value	*0,039*	*0,168*	*0,002*	*0,038*	*0,038*	*0,000*	*0,001*	*0,000*	*0,038*	*0,002*	*0,000*	*0,002*
ρ(1)	-0,107	-0,103	0,005	0,142	0,109	-0,003	0,329	0,081	0,028	0,115	0,424	0,018
ρ(2)	0,034	-0,029	0,055	0,176	0,168	0,140	0,119	0,040	-0,022	0,158	0,265	0,106
Engle(4)	13,055	27,730	28,116	58,805	30,645	30,825	20,483	46,050	3,268	15,188	51,045	4,689
p-value	*0,011*	*0,000*	*0,000*	*0,000*	*0,000*	*0,000*	*0,000*	*0,000*	*0,514*	*0,004*	*0,000*	*0,030*
Q(4)	10,344	9,512	1,484	24,621	15,305	25,470	32,377	8,218	2,533	15,696	101,648	5,469
p-value	*0,035*	*0,049*	*0,829*	*0,000*	*0,004*	*0,000*	*0,000*	*0,084*	*0,639*	*0,003*	0,000	0,243
QW(4)	9,036	5,715	1,298	5,786	7,504	10,946	10,344	4,125	2,459	6,305	6,420	4,304
p-value	*0,060*	*0,221*	*0,862*	*0,216*	*0,112*	*0,027*	*0,035*	*0,389*	*0,652*	*0,177*	0,170	*0,367*

Table 3: Cross-correlations between market returns expressed in Sterling

	UK	GE	CR	CZ	ES	HU	LI	PO	RO	RU	SL	SV
UK	1,000											
GE	0.625	1,000										
CR	0.351	0.398	1,000									
CZ	0.246	0.271	0.478	1,000								
ES	0.221	0.262	0.247	0.256	1,000							
HU	0.407	0.406	0.513	0.408	0.276	1,000						
LI	0.061	0.072	0.239	0.177	0.216	0.205	1,000					
PO	0.248	0.281	0.544	0.353	0.276	0.327	0.229	1,000				
RO	0.073	0.146	0.146	0.203	0.121	0.255	0.174	0.265	1,000			
RU	0.394	0.375	0.316	0.262	0.343	0.393	0.159	0.280	0.203	1,000		
SL	0.068	0.061	0.218	0.201	0.146	0.231	0.135	0.163	-0.135	0.113	1,000	
SV	0.185	0.239	0.418	0.117	0.148	0.216	0.133	0.113	0.181	0.133	0.163	1,000

Table 4: Statistics on Bayesian learning

$\alpha=(\alpha_M, \alpha_V, \alpha_C)$	UK	GE	CR	CZ	ES	HU	LI	PO	RO	RU	SL	SV
	Unconditional moments of excess returns											
mean	0.074	0.146	-0.190	-0.048	0.262	0.045	-0.063	0.189	-1.124	-0.083	-0.226	-0.105
standard deviation	2.092	2.806	5.441	4.468	5.997	4.531	4.206	6.701	6.744	8.775	4.804	4.007
α=(1,1,1)												
	Average conditional moments											
mean	0.165	0.031	-0.203	-0.234	-0.304	0.237	0.282	-0.299	-0.390	-0.505	0.553	0.027
standard deviation	2.405	3.377	4.378	4.384	5.819	5.665	4.043	8.326	4.453	8.613	6.320	4.040
	Re-initializations											
number	15	13	7	12	10	21	8	13	10	8	5	12
as a % of sample	0.029	0.025	0.034	0.032	0.034	0.041	0.031	0.026	0.060	0.024	0.013	0.033
α=(0.5,1,1)												
	Average conditional moments											
mean	0.206	0.135	-0.059	-0.254	-0.067	0.332	0.029	-0.033	-0.255	-0.475	0.198	-0.095
standard deviation	2.346	3.238	4.376	4.305	5.616	5.502	3.860	8.010	4.408	8.528	6.013	3.860
	Re-initializations											
number	15	11	6	12	10	19	7	12	10	7	4	12
as a % of sample	0.029	0.021	0.029	0.032	0.034	0.037	0.027	0.024	0.060	0.021	0.011	0.033
α=(1,0.5,1)												
	Average conditional moments											
mean	0.206	-0.006	-0.164	-0.214	-0.019	0.219	0.207	-0.408	-0.421	-0.530	0.554	-0.151
standard deviation	2.180	2.868	3.586	3.729	4.470	4.773	3.651	7.251	3.667	7.561	6.096	3.335
	Re-initializations											
number	21	28	9	19	23	32	11	21	17	21	7	21
as a % of sample	0.040	0.054	0.044	0.050	0.078	0.062	0.043	0.042	0.101	0.064	0.019	0.058
α=(1,1,0.5)												
	Average conditional moments											
mean	0.165	0.031	-0.203	-0.234	-0.304	0.237	0.282	-0.299	-0.390	-0.505	0.553	0.027
standard deviation	2.405	3.377	4.378	4.384	5.819	5.665	4.043	8.326	4.453	8.613	6.320	4.040
	Re-initializations											
number	15	13	7	12	10	21	8	13	10	8	5	12
as a % of sample	0.029	0.025	0.034	0.032	0.034	0.041	0.031	0.026	0.060	0.024	0.013	0.033

Table 5: Optimal weights computed using unconditional moments (sample: 1994:09-2000:12)

Risk aversion	UK	GE	CZ	HU	PO	RU	SL	SV
Panel A: Optimal weights								
θ=2	0,342	0,541	0,000	0,000	0,000	0,000	0,000	0,000
θ=5	0,137	0,216	0,000	0,000	0,000	0,000	0,000	0,000
θ=10	0,068	0,108	0,000	0,000	0,000	0,000	0,000	0,000

Panel B: CER and Sharpe ratio

	Equal weights			Optimal weights	
	CER	Sharpe ratio		CER	Sharpe ratio
			θ=2	0,329	0,811
	-0,385	-0,751	θ=5	0,132	0,811
			θ=10	0,066	0,811

Table 6: Cumulative excess returns (all transition economies)

$\alpha=(\alpha_M, \alpha_V, \alpha_C)$	Copeland & Mayers	Cornell		Bayesian	
	CER_T^{CM}	CER_T^{COR}	τ^{CM}	CER_T^{B}	τ^{COR}
θ=2					
α=(1,1,1)	-0.152	2.506	1.593	2.526	-0.757
α=(0.5,1,1)	0.015	2.294	0.886	2.209	-1.116
α=(1,0.1,1)	0.057	2.588	3.514*	4.721	1.105
α=(1,1,0.5)	-0.158	2.533	1.580	2.364	-0.755
θ=5					
α=(1,1,1)	-0.044	2.419	1.782	2.898	-0.880
α=(0.5,1,1)	0.088	2.203	0.497	2.191	-1.680
α=(1,0.1,1)	0.037	2.559	3.619*	4.808	1.190
α=(1,1,0.5)	-0.048	2.444	1.771	2.834	-0.918
θ=10					
α=(1,1,1)	0.013	2.112	1.626	3.004	-1.086
α=(0.5,1,1)	0.126	1.916	0.502	2.146	-1.726
α=(1,0.1,1)	0.012	2.487	3.748*	5.047	1.322
α=(1,1,0.5)	0.014	2.175	1.662	2.971	-1.077

Figure 1: Cumulative Excess Returns using Various strategies

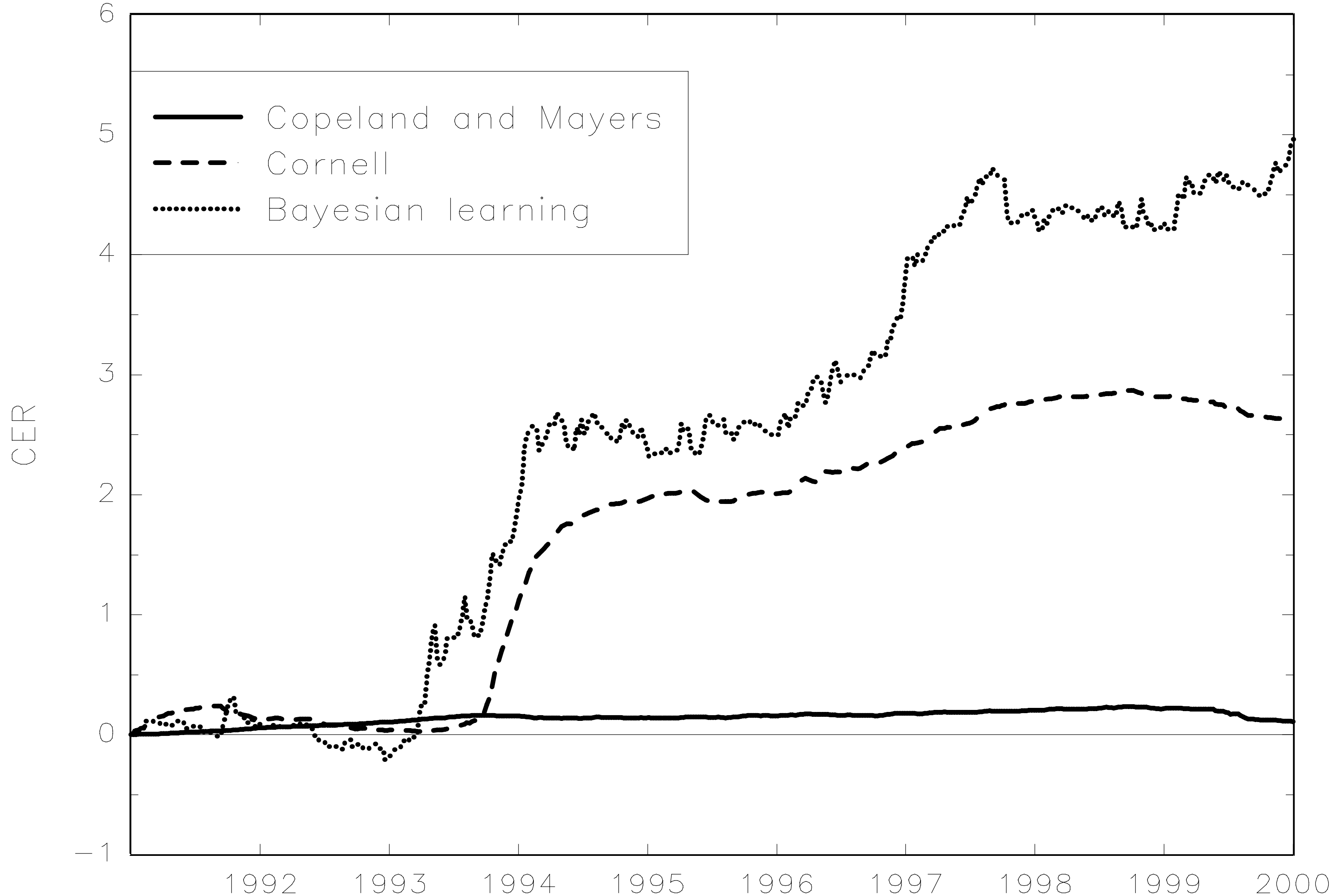
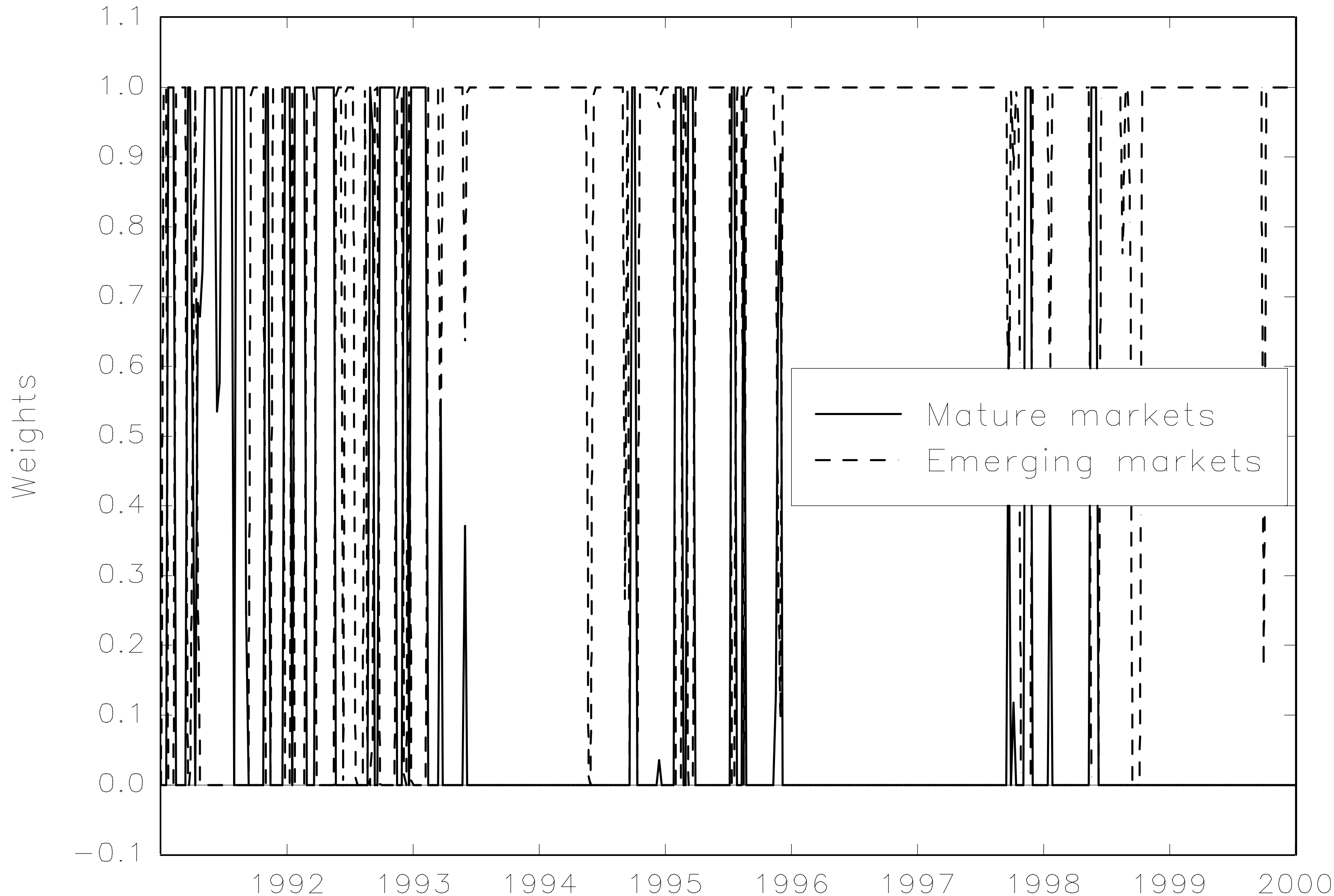


Figure 2: Weight of various areas



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