Predicting international equity returns: Evidence from time-varying parameter vector autoregressive models

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A b s t r a c t

In this paper, we forecast monthly stock returns of eight advanced economies using a time-varying parameter vector autoregressive model (TVP-VAR) with mixture innovations. Compared to standard TVP-VARs, our proposed model automatically detects whether time-variation in the parameters is needed through the introduction of a latent process. This framework is capable of dynamically detecting whether a given regression coefficient is constant or time-varying during distinct time periods. We moreover compare the performance of this model with a wide range of nested alternative time-varying and constant parameter VAR models. Our results indicate that our proposed framework outperforms its competitors in terms of point and density forecasts. A portfolio allocation exercise confirms the superiority of our proposed model. In addition, a copula-based analysis shows that it pays off to adopt a multivariate modeling framework during periods of stress, like the recent financial crisis.

Keywords:
International equity markets; Time-varying vector autoregression; Point and density forecasts; Portfolio allocation

1. Introduction

The existing literature on forecasting international stock returns (for developed and developing economies alike), based on a wide array of models and predictors is vast (see, for example, Rapach, Wohar, & Rangvid, 2005, Rapach & Zhou, 2013, Sousa, Vivian, & Wohar, 2016, Aye, Balcilar, & Gupta, 2017, Jordan, Vivian, & Wohar, 2017a, Jordan, Vivian, & Wohar, 2017b, among others). While practitioners in finance require real-time forecasts of stock returns for asset allocation, academics are particularly interested in stock return forecasts, since they have important implications for producing robust measures of market efficiency, which in turn helps to produce more realistic asset pricing models (Rapach & Zhou, 2013). However, stock return forecasting is highly challenging, since it inherently contains a sizable unpredictable component. The resulting predictive performance therefore usually strongly depends on the indices, sample periods, models and potential predictors adopted.

Recent literature has identified at least two common features of successful models as a means to outperforming standard benchmark specifications in terms of predictive accuracy. First, a large information set in terms of a vast number of predictors (i.e. macroeconomic, financial, technical indicators; see Bekiros, Gupta, & Majumdar, 2016, Gupta, Majumdar, & Wohar, 2017, or Gupta, Mwamba, & Wohar, 2017) appears to be required in order to successfully challenge standard random walk forecasts. Second, stock return predictions using a-theoretical techniques (which tend to exploit information on the recent behavior of stock prices based on statistical approaches, as well as machine learning and computational intelligence techniques) typically tend to perform better than theoretically motivated empirical models (see, for example, Chen, Leung, & Daouk, 2003; Enke & Thawornwong, 2005).

Against this backdrop, and particularly building on the latter point mentioned above, the objective of our paper is to forecast stock returns of eight developed markets (Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom, and the United States) based on time-varying parameter vector autoregressive (TVP-VAR) models. The choice of these eight equity markets is quite natural given their importance for the global economy, with these countries representing nearly two-third of global net wealth, and nearly half of world output. Note that the decision to look at only the past value of stock returns of the various economies in the model emanates from the evidence in favor of increased co-movement between asset prices, and stock markets in particular, due to financial integration across economies (Diebold & Yilmaz, 2009; Diebold & Yilmaz, 2012). While this regularity has received considerable attention in the academic literature on the dynamics of stock markets, for some reason, this has not been exploited to its fullest in the forecasting literature. An exception to this is the recent work by Huber, Krisztin, and Piribauer (2017), which advocates the use of large Bayesian vector autoregressive (BVAR) model specifications with common stochastic volatility as a means to forecasting monthly global equity indices. The time-varying specification of the covariance structure moreover accounts for sudden shifts in the level of volatility. In an out-of-sample exercise, the proposed model specification is moreover shown to markedly outperform the random walk for both point and density forecasts. In addition, it is well-established that stock market movements serve as a leading indicator for the wider economy (Stock & Watson, 2003; Gupta & Hartley, 2013; Plakandaras, Cunado, Gupta, & Wohar, 2017). Hence, we do not incorporate the information of any other predictors in our multivariate models, barring the lagged stock returns of the domestic and foreign economies.

Following Huber et al. (2017), but realizing the well-established fact that stock returns evolve in a nonlinear fashion (McMillan, 2005), we extend the constant parameter approach of Huber et al. (2017) to a time-varying framework. Specifically, we use a flexible variant of a TVP-VAR model. This framework, as recently proposed by Huber, Kastner, & Feldkircher, 2019, is an approximation to a mixture innovation model that allows one to dynamically detect whether a given regression coefficient is constant or time-varying by using ideas from the literature on latent threshold models. In particular, this threshold TVP-VAR (TTVP-VAR) approach introduces a set of latent thresholds that controls the degree of time-variation separately for each parameter at each point in time. The proposed framework nests a wide variety of competing models, like the standard time-varying parameter model, a change-point model with an unknown number of regimes, mixtures between different models, and also the simple constant parameter model. Finally, to assess systematically, in a data-driven fashion, which predictors should be included in the model, Huber et al., 2019 impose a set of Normal-Gamma priors on the initial state of the system.

While this is our primary proposed framework for forecasting equity returns of the eight advanced economies, we compare the performance of this model with a battery of nested alternative models. To the best of our knowledge, this is the first paper which produces both point and density forecasts of equity returns using medium-scale time-varying approaches, and in particular, a threshold time-varying vector autoregressive model. In a forecast exercise this applied paper adopts a set of recent multivariate modeling techniques to produce predictions of stock returns of developed equity markets. Another key contribution of this paper is to analyze which model features turn out to be crucial for obtaining reliable predictive densities over time. We therefore make use of a copula-based decomposition to quantitatively assess whether using cross-country information pays off for predictive purposes.

The remainder of the paper is organized as follows: Section 2 outlines the main econometric model used in our forecasting exercise, while Section 3 presents the data and results, with the latter including also a portfolio exercise. Finally, Section 4 concludes the paper.

2. Econometric framework

2.1. A time-varying parameter VAR for modeling international equity returns

Our goal is to develop a model that accounts for international linkages in financial markets. To this end, we postulate that the growth rate of a set of N equity price indices in $\{y_t\}_{t=1}^{T}$ follows a time-varying parameter VAR,

$$y_t = (I_M \otimes x_t')\beta_t + Q_t v_t, \quad v_t \sim \mathcal{N}(0, H_t), \tag{2.1}$$

with

- $x_t = (y_{t-1}, \ldots, y_{t-p}, 1)'$ denoting a $M = pN + 1$ vector of lagged endogenous variables as well as an intercept term,[1]
- β_t is a $K = NM$-dimensional vector of dynamic regression coefficients. Notice that β_t is, in principle, allowed to evolve over time according to some specific law of motion described in Section 2.2.
- v_t is a set of N white noise shocks that follow a multivariate Gaussian distribution and Q_t is a lower uni-triangular (i.e. lower triangular with unit diagonal) matrix of dimension $N \times N$. We store the $v = N(N-1)/2$ free elements of Q_t in a v-dimensional vector q_t.
- Finally, $H_t = \text{diag}(e^{h_{1t}}, \ldots, e^{h_{Nt}})$ is a diagonal matrix that stores the variance parameters.

The model in Eq. (2.1) is the observation equation of a multivariate state space model that has been proposed in Primiceri (2005) and Cogley and Sargent (2005). Notice that the elements in β_t, v_t and $h_t = (h_{1t}, \ldots, h_{Nt})$ feature a specific law of motion. Typically, researchers assume that the states evolve according to a random walk with an unrestricted state innovation variance covariance matrix. This, however, potentially leads to overfitting issues that might be detrimental for forecasting accuracy. To circumvent such issues, we follow Huber et al. (2019) and use a parsimonious law of motion for the latent states.

2.2. A parsimonious law of motion for the coefficients

We complete the model description by outlining a law of motion for β_t, q_t and h_t. Following Huber et al. (2019), we assume that the elements of $\xi_t = (\beta_t', q_t')'$, $\xi_{jt} (j = 1, \ldots, v + K)$ follow a random walk process,

$$\xi_{jt} = \xi_{jt-1} + \sqrt{\theta}_{jt}\eta_{jt}, \quad \eta_{jt} \sim \mathcal{N}(0, 1), \tag{2.2}$$

where θ_{jt} is a time-varying process innovation variance that follows

$$\theta_{jt} = d_{jt}\sigma_{j0,t}^2 + (1 - d_{jt})\sigma_{j1,t}^2, \tag{2.3}$$

with $\sigma_{j0,t}^2 \gg \sigma_{j1,t}^2$ and

$$d_{jt} = \begin{cases} 1 & \text{with probability} \quad p_j \\ 0 & \text{with probability} \quad 1 - p_j. \end{cases} \tag{2.4}$$

Eq. (2.4) implies that d_{jt} follows a Bernoulli distribution, implying that the proposed model framework closely resembles a standard mixture innovation model (for a VAR application, see Koop, Leon-Gonzalez, & Strachan, 2009). One key advantage of the proposed specification is that if parameter movements appear to be rather small, we effectively zero them out while we allow for large swings. This strikes a balance between using a model with a few regimes as opposed to a model with many regimes ($T - 1$ in the case of an unrestricted TVP model). One shortcoming, however, is that in high dimensions, estimation of such a model is unfeasible.[2]

We thus follow Huber et al. (2019) and approximate the indicators d_{jt} during MCMC sampling by using

$$d_{jt}^{(l)} = \begin{cases} 1 & \text{if} \quad |\Delta\xi_{jt}^{(l)}| > c_j^{(l-1)}, \\ 0 & \text{if} \quad |\Delta\xi_{jt}^{(l)}| \leq c_j^{(l-1)}. \end{cases} \tag{2.5}$$

Hereby, we let l denote the lth draw obtained by using our MCMC algorithm (detailed below). Eqs. (2.3) and (2.5) imply that if the absolute change in the lth draw of ξ_{jt} is sufficiently large (i.e. exceeds a threshold c_j), the indicator d_j equals unity and a rather large process innovation variance $\sigma_{j0,t}^2$ is adopted. By contrast, if the change is too small (i.e. below c_j), the process innovation variance is close to zero ($\sigma_{j1,t}^2 \approx 0$) and thus the change in the parameters ξ_{jt} is small, i.e. $|\Delta\xi_{jt}| \approx 0$. Introducing the indicators d_j constitutes a flexible means of controlling for model

[1] In the empirical application, we include a single lag of y_t for computational reasons.

[2] In this paper, we follow Huber et al. (2019) and set $\sigma_{j1,t}^2 = 10^{-5} \times \hat{\sigma}_{jt}^2$, with $\hat{\sigma}_{jt}^2$ denoting the OLS variance from a time-invariant VAR model.

uncertainty by performing a stochastic model specification task. These indicators allow us to assess whether certain regions of the parameter space feature time-variation or may be regarded as being constant over time. This effectively alleviates overfitting issues, making the model more robust with respect to outlier fitting

For h_t, we follow Kastner and Frühwirth-Schnatter (2014) and assume that the log-volatilities follow an AR(1) process,

$$h_{jt} = \mu_j + \rho_j(h_{jt-1} - \mu_j) + \epsilon_{jt}, \quad \epsilon_{jt} \sim \mathcal{N}(0, \varsigma_j^2), \tag{2.6}$$

for $j = 1,\ldots,N$. Hereby, we let μ_j denote the unconditional mean of h_{jt},ρ_j the autoregressive parameter and ς_j^2 is the variance of the log-volatility process.

2.3. Prior specification

Our prior setup closely follows Hotz-Behofsits, Huber, and Zörner (2018). More specifically, we use weakly informative Gamma priors on $\sigma_{j1,t}^{-2} \sim \mathcal{G}(0.001, 0.001)$ and uniform priors on the thresholds,

$$c_j | \sigma_{j0,t} \sim \mathcal{U}(\pi_0 \sigma_{j0,t}, \pi_1 \sigma_{j0,t}). \tag{2.7}$$

We specify $\pi_0 = 0.1$ and $\pi_1 = 1.5$. This prior choice bounds the thresholds away from zero, implying that high frequency movements in ξ_{jt} are effectively shrunk towards zero.

On the initial state ξ_{j0} we use a Normal-Gamma (NG) shrinkage prior (see Griffin & Brown, 2010),

$$\xi_{j0} | \tau_j^2 \sim \mathcal{N}(0, \tau_j^2), \quad \tau_j^2 \sim \mathcal{G}(\delta, \delta\lambda/2), \lambda \sim \mathcal{G}(n_0, n_1). \tag{2.8}$$

The scaling parameters τ_j^2 follow a Gamma distribution that depends on δ and λ. The hyperparameter δ controls the excess kurtosis of the marginal prior obtained by integrating out the local scaling parameters τ_j^2. Small values imply a heavy tailed prior that allows for non-zero values of ξ_{j0} in the presence of a large global shrinkage parameter λ. The parameter λ pulls all elements in ξ_0 to zero. Given its importance, we use an additional Gamma prior and consequently infer λ from the data. In what follows we set $\delta = 0.1$ and $n_0 = n_1 = 0.01$, introducing significant amounts of shrinkage but at the same time allow for heavy tails and thus sufficient flexibility to capture signals.

Finally, we follow Kastner and Frühwirth-Schnatter (2014) and use a weakly informative Gaussian prior on μ_j, a Beta prior on $(\rho_j + 1)/2 \sim \mathcal{B}(25,5)$ and a non-conjugate Gamma prior on $\varsigma_j^2 \sim \mathcal{G}(1/2, 1/2)$. This choice translates into a Gaussian prior on $\pm\varsigma_j \sim \mathcal{N}(0, 1)$.

Estimation of the model is carried out using Markov chain Monte Carlo (MCMC) techniques. Our MCMC algorithm simulates the latent states on an equation-by-equation basis using forward-filtering backward-sampling (FFBS) techniques (Carter & Kohn, 1994; Frühwirth-Schnatter, 1994). The thresholds are simulated using a Griddy Gibbs step that is based on constructing an approximation to the cumulative distribution function of the conditional posterior of c_j and then perform inverse transform sampling. Here, it suffices to say that this is computationally straightforward since the conditional posterior is proportional to the density of a univariate Gaussian distribution times the uniform prior. The state innovation variances $\sigma_{j0,t}^2$ are simulated from an inverted Gamma distribution that takes a standard form. Last, the log-volatilities and the parameters of the state equation are obtained by using the algorithm outlined in Kastner and Frühwirth-Schnatter (2014) and implemented in the R package stochvol (Kastner, 2016).

The algorithm is repeated 20,000 times with the first 15,000 draws being discarded as burn-in. Convergence appears to be no issue with average inefficiency factors well below 30 in almost all cases. Repeated estimation based on randomly initializing certain coefficients also indicates that our algorithm performs well empirically. For further information and computation time, we refer the reader to Huber et al. (2017). It suffices to say that estimation of the model can be carried out using parallel computing techniques that allow estimation of the different equations of the VAR simultaneously. This speeds up computation considerably, with estimation of the model proposed in this section taking around 30 min on a Macbook Pro late 2016 with a 3.5 GHz Intel Core i5.

3. Forecasting international equity returns

3.1. Data overview and model specification

The data used in this paper are monthly stock price indices of eight industrialized economies namely, Canada (S&P TSX 300 Composite Index), France (CAC All-Tradable Index), Germany (CDAX Composite Index), Italy (Banca Commerciale Italiana Index), Japan (Nikkei 225 Index), Switzerland (All Share Stock Index), the United Kingdom (FTSE All Share Index), and the United States (S&P500 Index). The data on the total returns indices are quoted in US dollars and obtained from the Global Financial Data database.[3] The indices are then converted into log returns and multiplied by 100 to obtain percentage changes.

The dataset covers the period from May, 1986 (1986:M05) to February, 2017 (2017:M02). In Appendix A, Table 4 provides basic summary statistics. Note that there exists significant evidence that returns are non-Gaussian and quite heterogenous across countries. For instance, Italy displays the highest while Germany the lowest average returns. Moreover, volatility also strongly differs, with Germany exhibiting the highest and the US the lowest volatility. The non-normality of the data calls for an appropriate modeling device that allows for heteroscedasticity and potential changes in the conditional mean of the involved time series. Our proposed modeling framework is capable of capturing such features of the involved time series in a flexible manner.

3.2. Competing models and design of the forecasting exercise

Our empirical forecasting design is recursive. This implies that we specify an initial estimation period that ranges from May 1986 to February 2002 (i.e., 1986:M05 to 2002:M02), and compute the one-step-ahead predictive densities for 2002:M03. The initial estimation period is then subsequently expanded by a single month and this procedure is repeated until the final observation in the sample (2017:M02) is reached.

Forecasts are then evaluated using log predictive scores (LPS) motivated in, for instance, Geweke and Amisano (2010). The LPS of the one-step-ahead forecast is closely related to the marginal likelihood, a popular Bayesian model selection criterion. LPS are computed by summing over the evaluation of the realized values under the predictive density of a given model specification. Marginal LPS for a given element in y_t, y_{it}, are then computed by integrating out the remaining $M - 1$ elements of the joint predictive density. This is achieved by exploiting the fact that, within the MCMC algorithm, we obtain draws from the predictive distribution from a multivariate Gaussian density. The marginal LPS are then trivially obtained by selecting the relevant elements from the mean and variance-covariance of this predictive distribution (conditional on the draws of the remaining model parameters/states). More details can be found in Huber et al. (2017).

To assess the merits of our empirical model we include a wide range of alternative model specifications. In a addition to our proposed specification (TTVP) we consider the following benchmark specifications:

(i) TVP: This specification is a variant of the TVP-VAR with SV proposed in Primiceri (2005). The main differences stem from the fact that we use shrinkage priors on the initial state of the system and Gamma priors on the inverse of the state innovation variances. Note that this model is nested within our approach by setting $d_{jt} = 1 \forall j,t$.

(ii) TVP NG: Similar to TVP, this specification is also a variant of a

[3] http://www.globalfinancialdata.com/.

TVP-VAR with SV. However, in TVP NG we additionally employ shrinkage priors on all regions of the parameter space. This model thus introduces Normal-Gamma shrinkage priors on both the initial state as well as the state innovation variances.[4]

(iii) Minn-VAR: A constant parameter VAR using a non-conjugate Minnesota prior where the tuning parameters are integrated out in a Bayesian fashion.

(iv) NG-VAR: A constant parameter VAR using Normal-Gamma shrinkage priors (see Huber & Feldkircher, 2017).

(v) SSVS: A constant parameter VAR using stochastic search variable selection (SSVS) priors (see George, Sun, & Ni, 2008).

(vi) Flat-no-SV: A constant parameter VAR with uninformative prior structure without SV.

(vii) Flat-SV: A constant parameter VAR with uninformative prior structure including SV.

(viii) AR-SV: An AR(1) model with stochastic volatility.

(ix) EWMA: A standard exponentially weighted moving average (EWMA) specification with the forgetting factor set to 0.95.

It is, moreover, worth noting that both point and density predictions for all model alternatives under scrutiny are calculated relative to the predictive performance of a random walk with SV (RW-SV) specification.

3.3. *Forecasting results*

Table 1 presents a summary of the out-of-sample predictive performance for the models under consideration. The bottom panel of the table provides summary metrics for the model-specific forecasting performance in terms of point forecasts. Specifically, we focus on well-known root mean-squared forecasting errors (RMSE) as a means to compare the predictive accuracy among the models considered. For all the models, we compute point forecasts by considering the median of the posterior predictive distribution.

Summary metrics for the point predictions provided in the bottom panel of the table are moreover standardized with respect to random-walk forecasts. Values below unity thus indicate predictive outperformance vis-á-vis to the random-walk predictions in terms of point predictions, while values above one indicate a comparatively weaker performance of a given model.

The top panel of Table 1 provides summary metrics for the respective out-of-sample forecast performance in terms of marginal LPS. While standard RMSEs only focus on point forecasts, LPS provide a well known measure for comparing forecast performance by explicitly accounting for higher order moments of the predictive density. As such, log predictive scores aim to enrich the comparison of predictive performance by also taking into account a potential bias-variance trade off. Similar to the point forecasts, Table 1 also shows the respective measures for the density predictions relative to RW forecasts. Specifically, negative values indicate underperformance relative to the random-walk benchmark, and conversely, positive values for the respective density forecasts indicate outperformance.

Overall results for point predictions show that no-change forecasts arising from the random walk model are particularly poor as compared to other specifications. RMSEs of almost all indices considered appear to be well below unity. Moreover, LPS point towards a relatively poor predictive performance of the (stochastic volatility-augmented) RW specifications. The autoregressive model with stochastic volatility (AR-SV), however, appears to perform much better. The table shows that the proposed TTVP modeling framework sketched above appears to perform particularly well in terms of producing both accurate point as well as density predictions. For most equity markets considered, the proposed specification ranks among the best performing approaches.

As expected from prior studies on forecasting with large VARs (Carriero, Clark, & Marcellino, 2013; Huber & Feldkircher, 2017; Feldkircher et al., 2017), the estimation framework without shrinkage yields forecasts which are much more imprecise. This is the well-known curse of dimensionality that hint towards severe overfitting of the TVP VAR without shrinkage. This result appears to be quite general and holds for all equity indices considered.[5] This finding holds true for both RMSEs and LPSs. Accounting for potential structural breaks in the static and dynamic relations across equity indices thus appears particularly beneficial.

While a TVP model without proper shrinkage priors seems to perform relatively poor due to overfitting problems, the additional use of Bayesian shrinkage in terms of a Normal-Gamma prior (TVP NG) appears to markedly improve forecast performance. For all country-specific indices in the sample, TVP NG produces more precise out-of-sample forecasts as compared to TVP for RMSEs as well as log predictive scores. However, comparing results for TVP NG with those of TTVP shows that TTVP tends to slightly outperform the former. This outperformance is particularly pronounced when focusing on point predictions. For all indices considered, TTVP produces slightly lower overall RMSEs as compared to TVP NG.[6] This finding also translates to density forecasts. Only for the United Kingdom, TVP NG appears to slightly outperform TTVP in terms of LPS. The joint performance for density forecasts, however, also identifies TTVP as the best performing model.

Turning attention to the remaining constant-parameter VAR specifications (Minn-VAR, NG-VAR, SSVS, Flat-no-SSVS, and Flat-SV) shows that all of these appear to outperform the standard TVP specification both in terms of point as well as density predictions. With some country-specific exceptions, the vector autoregressive model using a Minnesota prior specification (Minn-VAR) produces the most precise forecasts among these specifications. The constant-parameter VAR specification with Normal-Gamma shrinkage priors (NG-VAR), as well as those using SSVS priors only slightly underperform relative to the Minnesota specification. A much more notable drop in forecast performance relative to the Minnesota specification can be seen in the predictive summary metrics for the VAR specification using non-informative prior setups (Flat-no-SV and Flat-SV). Among these, Table 1 shows that the setup using a SV specifications (Flat-SV) appears to slightly outperform the variant without SV (Flat-no-SV) both in terms of point and density prediction.

Comparing the Normal-Gamma shrinkage setting with time-variation in the parameters (TVP NG), with its constant-parameter counterpart (NG-VAR) reveals that the former slightly outperforms the latter in terms of joint LPS. However, inspection of the index-specific predictive performances in terms of log predictive scores reveals that the constant parameter setting slightly outperforms TVP NG in almost all cases. Looking at the metrics on point predictions corroborate these findings. NG-VAR produces lower RMSEs as compared to TVP NG for all indices under scrutiny.

Table 1, moreover, suggests that the autoregressive process with SV (AR-SV) produces rather precise country-specific predictions. However, joint predictive performance of AR-SV appears markedly weaker. The EWMA model, on the other hand, produces rather moderate out-of-sample predictions both in terms of country-specific as well as joint

[4] For a detailed description of the model and the prior setup, see Feldkircher, Huber, and Kastner (2017) and Hotz-Behofsits et al. (2018).

[5] Based on the Diebold and Mariano (1995) test as reported in Table 5 in Appendix A, the null hypothesis of equal forecast errors is overwhelmingly rejected at the highest level of significance between the TTVP and TVP models.

[6] In Table 5, we find that while the TTVP outperforms the RW and TVP models, its performance is equally as good as the TVP NG model. This statement is based on carrying out Diebold-Mariano tests to test accuracy differences between the TTVP and the TVP NG specification. Nevertheless, from a decision theoretic perspective, the optimal choice would still be the model that yields the highest LPS.

Table 1
Evaluation of point and density forecasts.

	TTVP	TVP	TVP NG	Minn-VAR	NG-VAR	SSVS	Flat-no-SV	Flat-SV	AR-SV	EWMA
Log predictive scores										
Joint	774.593	311.458	650.631	639.294	630.625	631.966	530.636	537.553	406.095	544.810
UK	27.991	−16.812	28.293	40.246	37.624	40.142	24.443	34.456	36.797	27.943
CA	47.283	−9.371	46.907	47.618	47.486	43.990	52.624	45.519	50.564	45.258
FR	62.280	12.192	58.153	60.542	58.912	59.206	65.384	56.203	65.620	54.051
JP	50.883	−1.012	47.285	48.972	50.877	47.789	42.735	45.703	54.153	47.628
DE	66.972	14.706	47.888	62.608	62.697	64.259	10.983	61.625	55.989	61.791
IT	57.147	10.255	38.962	30.521	41.295	38.934	43.633	37.110	46.380	45.930
US	37.727	−26.596	33.194	28.591	28.288	26.950	32.893	24.201	40.829	27.531
CH	46.966	−15.535	46.768	45.382	44.029	39.767	45.202	40.990	50.837	37.089
Root mean square errors										
UK	0.720	0.941	0.726	0.719	0.720	0.721	0.728	0.723	0.721	0.731
CA	0.727	1.013	0.733	0.722	0.722	0.726	0.726	0.725	0.727	0.723
FR	0.711	0.905	0.721	0.701	0.705	0.703	0.709	0.711	0.700	0.715
JP	0.728	1.040	0.743	0.720	0.723	0.723	0.728	0.726	0.723	0.722
DE	0.710	0.905	0.711	0.696	0.696	0.697	0.755	0.702	0.702	0.703
IT	0.730	0.917	0.735	0.715	0.732	0.742	0.738	0.735	0.732	0.717
US	0.745	1.023	0.752	0.739	0.740	0.740	0.755	0.752	0.748	0.747
CH	0.697	0.936	0.700	0.687	0.692	0.692	0.695	0.697	0.694	0.699

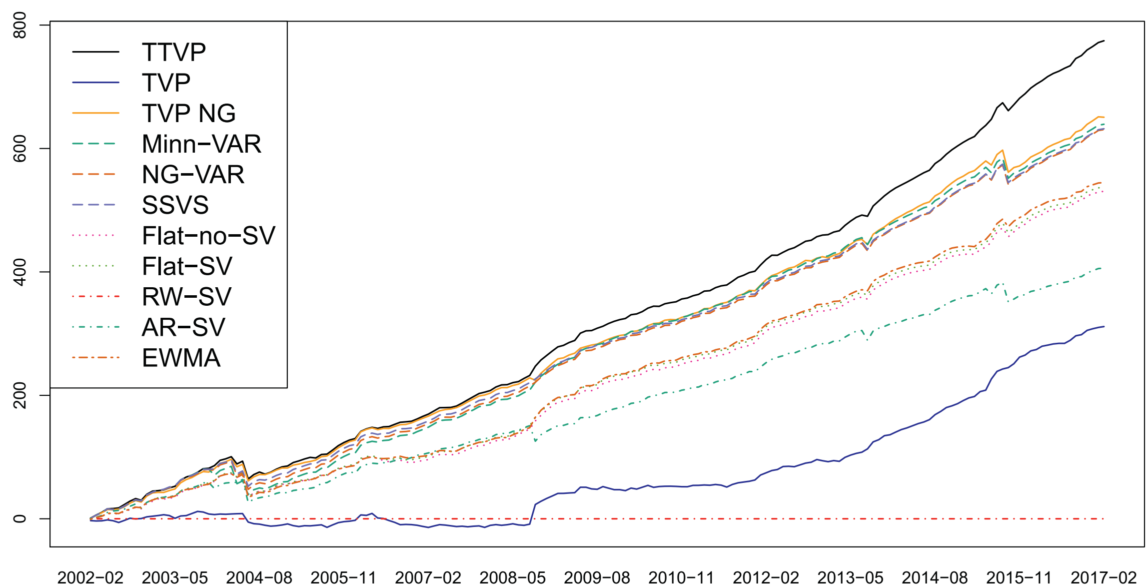


Fig. 1. Joint log predictive scores relative to the RW-SV model.

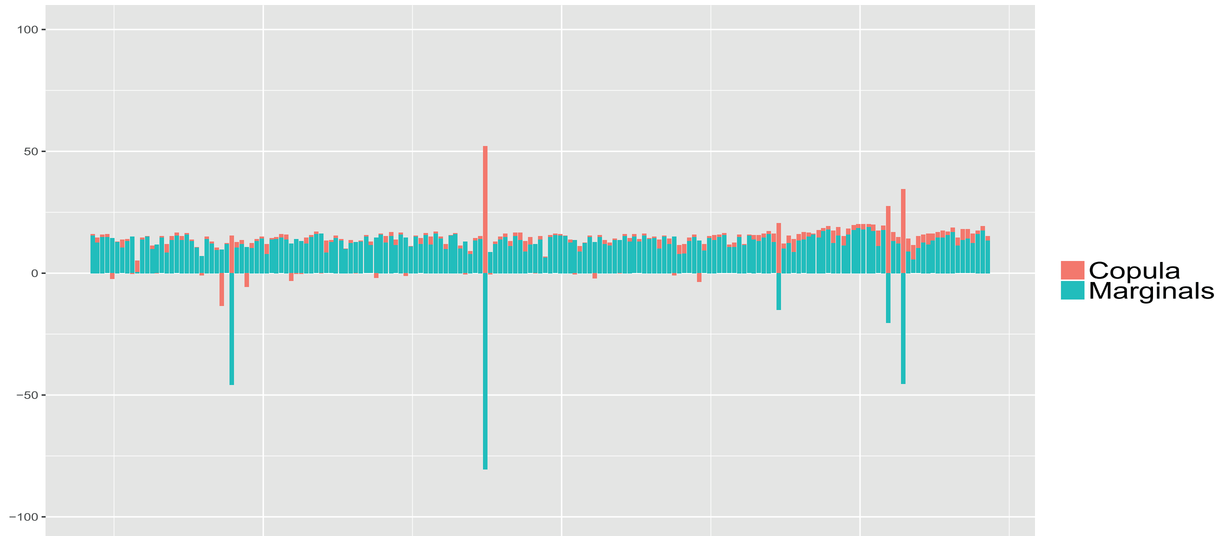
performance.

While Table 1 presents overall metrics for out-of-sample forecast performance, Fig. 1 depicts the evolution of the cumulative LPS for the specifications under scrutiny over time. The model-specific cumulative LPS are measured relative to the random-walk benchmark, which is given by the zero line. Country-specific performance profiles are provided in the Appendix. Fig. 1 corroborates the overall finding of Table 1, hinting towards a clear outperformance of the proposed model framework (TTVP) as compared to the alternative specifications. In the beginning of the sampling period, a time-varying parameter specification with a Normal-Gamma shrinkage prior (TVP NG) produces a similar predictive performance as compared to TTVP. However, around the year 2009, TTVP appears to supersede the alternative specifications in terms of forecast performance. During the economic and financial turmoils (2003/2004 and 2008/2009), the modeling framework without the threshold specification (TVP) performs particularly well in terms of density predictions. This is mainly due to the overall larger variance in the predictive densities of this model, resulting in a less severe penalization of large forecast errors as compared to competing specifications.[7]

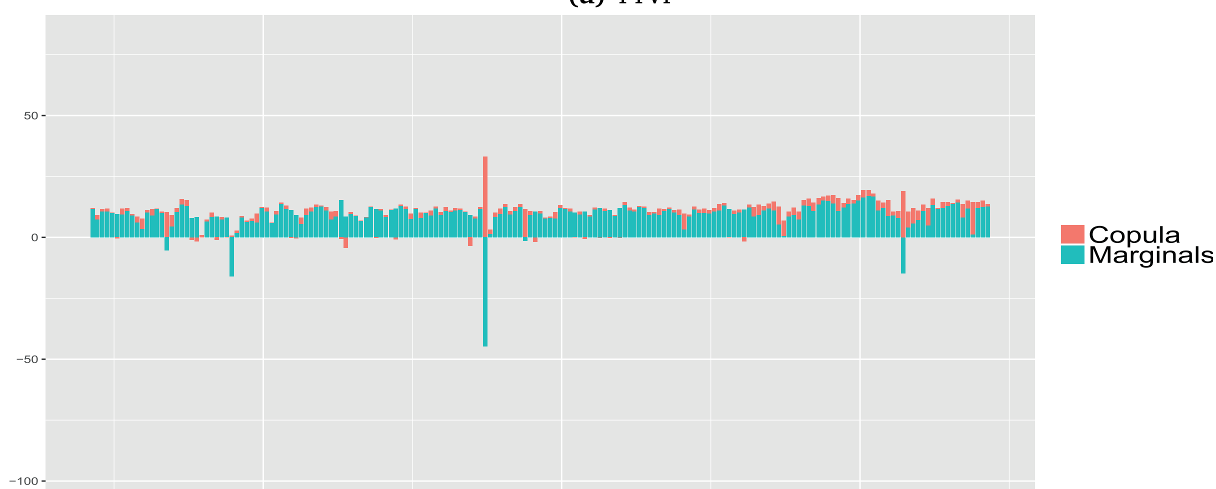
3.4. Dissecting the log predictive likelihood

The previous section highlighted sustained predictive gains for most multivariate models considered. One additional question that typically arises centers on whether the gains stem from a positive feedback on the univariate marginal predictive densities or arise from joint modeling all elements in y_t simultaneously. To this end, we follow Dovern, Feldkircher, and Huber (2016) and decompose the joint log predictive likelihood of model j as follows,

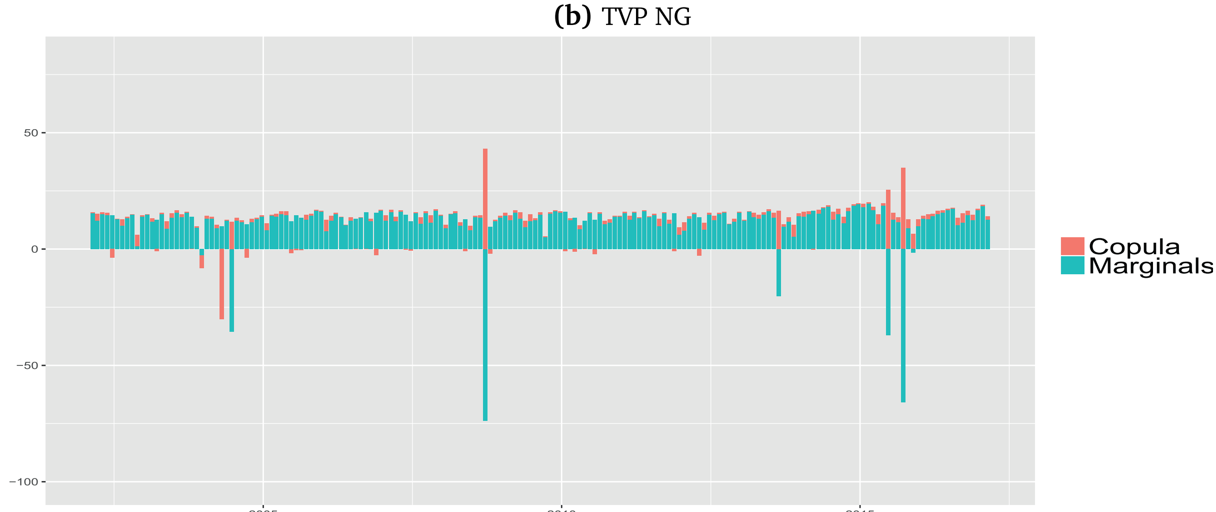
[7] In this discussion, we exclusively focus on point and density predictions. Another option would be to consider directional forecasts or evaluate competing techniques by considering hit rates. Here, we focus on traditional evaluation criteria first and then, in Section 3.5, we undertake a portfolio exercise that provides further insights beyond considering point and density forecasts.



(a) TTVP



(b) TVP NG



(c) Minn-VAR

Fig. 2. Contribution of the copula term to the joint predictive likelihood.

$$\log p(y_{t+1}|y_{1:t}, \mathcal{M}_j) = \sum_{j=1}^{N} \log p(y_{jt+1}|y_{1:t}, \mathcal{M}_j) + \log c\{P^{-1}(y_{1t+1}), \ldots, P^{-1}(y_{Nt+1})\}. \tag{3.1}$$

Herewith, we let $p(y_{t+1}|y_{1:t}, \mathscr{M}_j)$ denote the predictive likelihood of model j, $\mathscr{M}_j$, evaluated at the outcome y^o_{t+1}, $p(y_{jt+1}|y_{1:t}, \mathscr{M}_j)$ are the N univariate marginal predictive likelihoods, $P(y_{jt+1})$ is the corresponding cdf and $c(\bullet)$ denotes the probability density function of a Gaussian copula. Eq. (3.1) indicates that the joint LPS can be decomposed in terms of a sequence of univariate marginal log scores and a copula term that establishes the covariance structure of the predictive density.

Fig. 2 provides a graphical representation of Eq. (3.1) for the three top performing models over time. A few findings are worth mentioning. First, notice that across the (multivariate) models, we observe a pronounced degree of time variation in the contribution of the copula term to the overall predictive likelihood. Especially during periods that are characterized by economic stress such as the recent financial crisis, it seems to pay off to adopt a multivariate model and to exploit information from the cross section in an effective manner. This effect is especially pronounced during the recent financial crisis, where the marginal LPS have been grossly negative and the copula term contributed positively to the joint predictive performance of the model. Second, we also observe some periods with a negative contribution, especially during the first part of the sample. This hints towards periods where most multivariate models fail to adequately recover the predictive covariance structure. Third, and finally, the strong overall predictive performance of the TTVP specification is complemented by a particularly accurate modeling of the predictive covariance structure.

3.5. *A portfolio exercise*

Next, we assess whether using our multivariate models also leads to better economic performance, as measured by (annualized) Sharpe ratios. More specifically, we assume that the models considered are used to guide the behavior of an investor who aims to invest in all N markets considered. To this end, we consider different trading strategies.

The first strategy, labeled 'Equal weights', implies that we weight all N markets equally. This equal weights strategy translates into an N-dimensional model-specific weight vector $w_{it} = (1/N, \ldots, 1/N)'$. Our second strategy consists of weighting the different markets according to their historical variances while the third strategy is based on splitting the predicted returns across markets into tertiles and investing in the (historically) best performing markets (defined as the markets belonging to the top tertile) while shorting markets that belong to the bottom tertile.

The next strategy is based on the well-known global minimum-variance portfolio (GMV) strategy that aims to minimize the portfolio variance. Let $p_{it|t-1}$ denote the mean of the one-step-ahead predictive density of model i and $P_{it|t-1}$ the corresponding predictive variance (all quantities condition on information up to time $t-1$. The optimization problem is

$$\underset{w_{it}}{\text{minimize}} \quad w_{it} P_{it|t-1} w'_{it}$$
$$\text{subject to} \quad \sum_{j=1}^{N} w_{it} = 1. \tag{3.2}$$

The final strategy, labeled the target global minimum variance portfolio (TGMV) augments Eq. (3.2) by an additional constraint. This constraint states that the weights are chosen such that the portfolio variance is minimized subject to a pre-specified target return τ^*. In what follows, we choose three target returns $\tau^* \in \{\frac{10\%}{12}, \frac{15\%}{12}, \frac{20\%}{12}\}$.

Table 2 shows annualized Sharpe ratios across models and strategies. In general, using economic evaluation criteria corroborate the findings based on LPS described above. For most strategies, we find that the majority of models yield positive Sharpe ratios, indicating a positive porfolio return (for a full list of portfolio returns, see the top panel of Table 6). Across all models and strategies considered, the TVP NG specification yields the highest Sharpe ratio for the GMV strategy. Within strategies, we also find model performance to be quite heterogeneous, with some models showing a strong performance (see, for instance, the Flat-no-SV specification) on average while some models appear to be inferior (for instance, the Flat-SV specification for the tertile strategy).

Table 2
Annualized Sharpe ratios across different portfolio allocation strategies.

	Inv. var	Tertile	GMV	TGMV $\tau^* = \frac{10\%}{12}$	TGMV $\tau^* = \frac{15\%}{12}$	TGMV $\tau^* = \frac{20\%}{12}$
TTVP	0.780	0.072	0.782	0.856	0.808	0.538
TVP	0.797	0.105	0.813	0.724	0.726	0.715
TVP NG	0.788	0.150	0.843	0.866	0.857	0.585
Minn-VAR	0.779	−0.295	0.801	0.805	0.820	0.476
NG-VAR	0.783	−0.078	0.829	0.836	0.828	0.569
SSVS	0.787	−0.105	0.828	0.863	0.872	0.628
Flat-no-SV	0.783	0.787	0.787	0.787	0.787	0.787
Flat-SV	0.779	−0.205	0.800	0.846	0.826	0.549
RW-SV	0.781	−0.099	0.771	0.695	0.687	0.649
AR-SV	0.775	0.150	0.760	0.751	0.800	0.648
EWMA	0.774	−0.134	0.568	0.038	0.009	−0.019
Equal weights	0.780					

Notes: GMV stands for global minimum-variance portfolio. Target global minimum variance portfolios (TGMV) additionally involve a minimization of the portfolio variance subject to a pre-specified target return τ^*.

Table 3
"Optimal" weights across portfolio allocation strategies.

	UK	CA	FR	JP	DE	IT	US	CH
GMV	0.17	−0.02	0.04	0.18	0.08	0.10	0.32	0.14
$\tau^* = \frac{10\%}{12}$	0.19	−0.04	0.04	0.20	0.07	0.05	0.36	0.12
$\tau^* = \frac{10\%}{12}$	0.17	−0.06	0.11	0.17	0.04	0.02	0.39	0.16
$\tau^* = \frac{10\%}{12}$	0.10	−0.15	0.33	0.10	−0.04	−0.09	0.47	0.28

Notes: GMV stands for global minimum-variance portfolio. Target global minimum variance portfolios (TGMV) additionally involve a minimization of the portfolio variance subject to a pre-specified target return τ^*.

Notice that, consistent with the findings based on LPS, the univariate and EWMA models seem to display an inferior performance across the space of different portfolio allocation schemes. When we look at the results for different target returns, we find comparable insights, except that for $\tau^* = \frac{20\%}{12}$, we observe that the Flat-no-SV yields the highest Sharpe ratio and outperforms all remaining models by quite large margins. Considering our proposed TTVP model shows that it tends to perform well for most strategies adopted (except for the tertile strategy), always appearing to be among the top performing models.

To provide further insights on portfolio returns, variances, and metrics such as value at risk (VaR), Table 6 provides additional details. It is interesting to notice that for the TGMV strategies, the annualized portfolio variance tends to increase with the target return. Moreover, and in general, models that perform well in terms of Sharpe ratios also tend to display a more favorable VaR metric.

Finally, one interesting aspect of this analysis is how different strategies and models lead to a diversified portfolio from a country-wise perspective. To shed some light on this question, Table 3 shows optimal portfolio weights for the two strategies that are based on optimizing some target function (i.e. GMV and TGMV). We observe that across different strategies, an optimal strategy consists in holding a considerable share of wealth in the US and UK stock markets while maintaining small short positions in Canada. Among European markets, the results indicate that money is also invested in France and Germany. Interestingly, using portfolio optimization techniques suggests that only small amounts of capital are moved into Italy.

4. Concluding remarks

The empirical regularity of increased co-movement between stock markets due to financial integration across economies has not been exploited to its fullest in the forecasting literature. Against this backdrop, this paper forecasts stock returns of eight developed markets namely, Canada, France, Germany, Italy, Japan, Switzerland, the United Kingdom, and the United States using time-varying parameter vector autoregressive models.

To alleviate concerns of overparameterization, this paper applies a recent approach to estimate time-varying parameter models. This Bayesian framework is an approximation to a high dimensional mixture innovation model that allows for flexible testing whether time variation in the VAR coefficients is necessary. This model, labeled threshold time-varying parameter vector autoregression (TTVP-VAR), nests a wide array of competing models such as structural break models, standard TVP models as well as the linear case.

In the empirical forecasting application, we use this approach to forecast equity returns for eight advanced economies and compare its performance to a wide range of nested alternative time-varying and constant parameter vector autoregressive models. Our results indicate that the TTVP-VAR outperforms its competitors for both point and density forecasts. We moreover observe sustained predictive gains for most multivariate models considered. Given this, and the fact that the joint log predictive scores can be decomposed in terms of a sequence of univariate marginal log scores and a copula term, we confirm that it pays off to adopt a multivariate modeling approach to exploit cross-sectional information in an effective manner. This observation, in turn, validates our decision to utilize a multivariate framework under the premise of increased co-movement between stock markets due to financial integration.

As a potential avenue of further research, one could extend our analysis to other financial markets like bonds and currencies, as well as to commodity markets. Given spillovers across asset classes, it would make sense to incorporate the various asset classes together using the model proposed in this paper, and then conduct a forecasting exercise. Note that, given that the focus of the paper is primarily to exploit the existing evidence of pronounced linkages across international equity markets for forecasting purposes, we only consider lagged values of equity returns of a particular country and that of other countries in our vector autoregressions. To assess whether other factors impact equity price returns within a dynamic framework, it would be interesting to extend our analysis by including popular predictors (such as momentum, reversals, valuation ratios, dividend yield, capitalization, beta, idiosyncratic volatility, trend, seasonality, etc.) used in the stock market literature into our framework.

Appendix A

Table 4
Summary statistics.

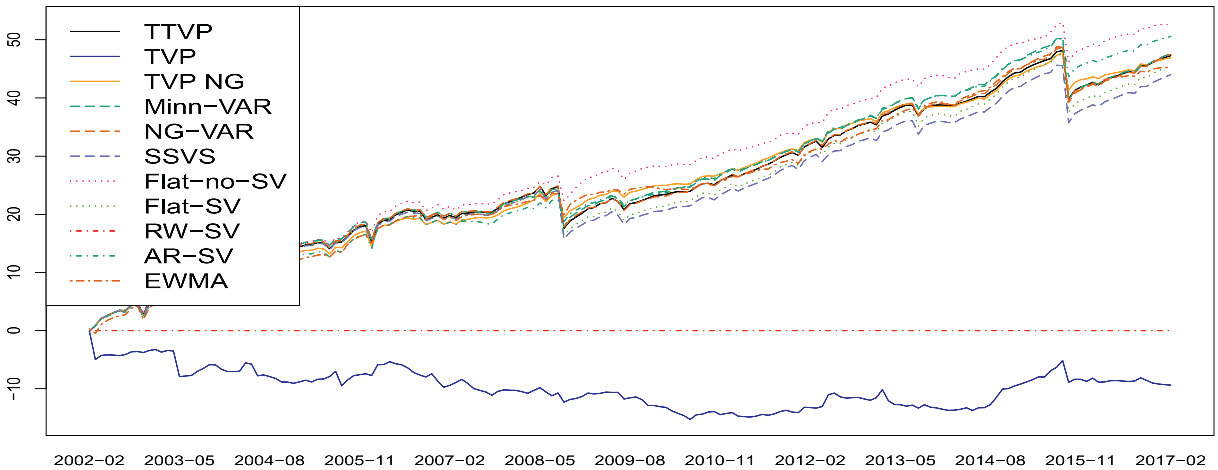
	Country							
Statistic	UK	CA	FR	JP	DE	IT	US	CH
Mean	0.840	0.671	1.174	0.793	0.557	0.931	0.708	0.825
Median	1.125	1.020	1.418	0.652	1.017	0.639	1.114	1.038
Std. Dev.	5.136	4.742	5.857	6.666	10.085	8.113	4.416	4.832
Skewness	0.407	−0.912	−0.215	1.496	−8.560	0.829	−1.677	−0.262
Kurtosis	18.808	6.681	4.812	14.967	123.384	8.326	11.079	9.841
Jarque-Bera	3862.577	260.142	53.496	2345.874	227,942.9	479.626	1179.740	725.753
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations				370				

Table 5
Diebold-Mariano test of equal point forecast accuracy between TTVP and selected alternatives.

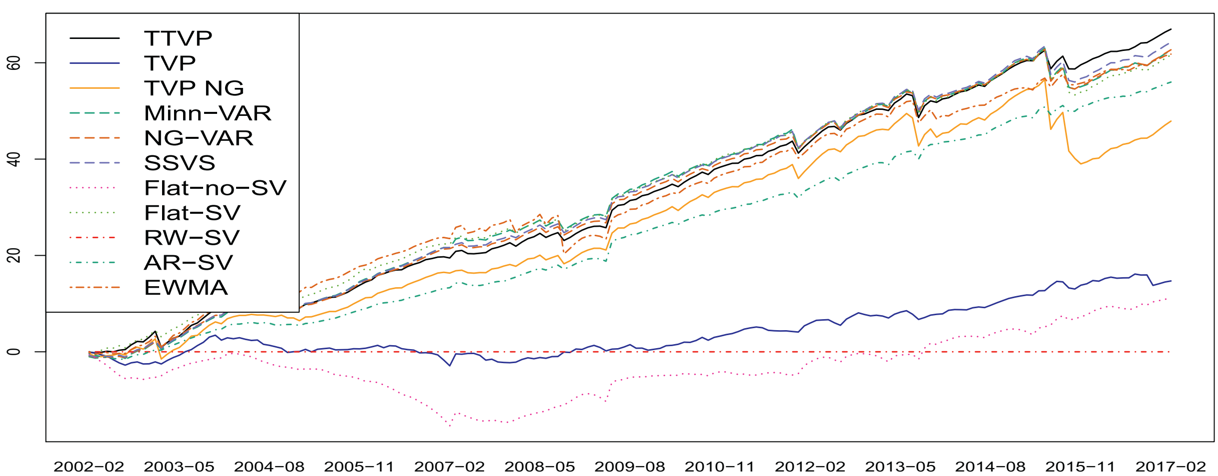
	UK	CA	FR	JP	DE	IT	US	CH
TVP	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
TVP NG	0.3212	0.1549	0.1194	0.2899	0.8929	0.3441	0.2942	0.5485
RW-SV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000

Table 6
Portfolio allocation exercise.

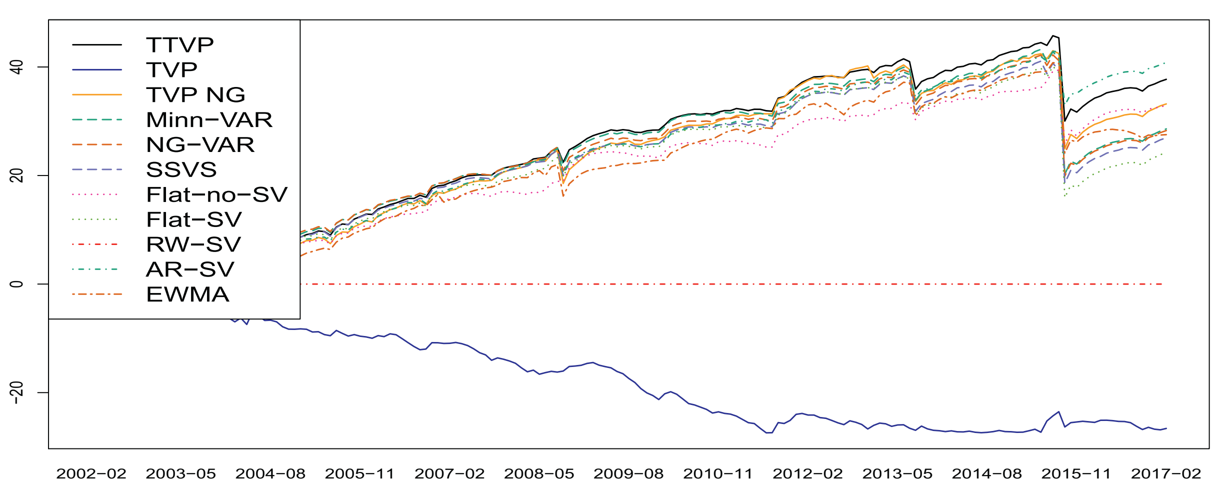
		$1/N$	Inv. var.	Tertile	GMV	$\tau^* = \frac{10\%}{12}$	$\tau^* = \frac{15\%}{12}$	$\tau^* = \frac{20\%}{12}$
Mean annualized returns	TTVP	0.104	0.102	0.003	0.099	0.113	0.117	0.128
	TVP	0.104	0.105	0.004	0.112	0.103	0.104	0.105
	TVP NG	0.104	0.103	0.006	0.108	0.112	0.110	0.106
	Minn-VAR	0.104	0.102	−0.012	0.106	0.109	0.117	0.138
	NG-VAR	0.104	0.102	−0.003	0.107	0.109	0.117	0.140
	SSVS	0.104	0.102	−0.004	0.106	0.113	0.119	0.135
	Flat-no-SV	0.104	0.104	0.104	0.104	0.104	0.104	0.104
	Flat-SV	0.104	0.102	−0.008	0.105	0.113	0.112	0.109
	RW-SV	0.104	0.100	−0.004	0.097	0.087	0.086	0.085
	AR-SV	0.104	0.09	0.006	0.096	0.096	0.101	0.116
	EWMA	0.104	0.100	−0.006	0.068	0.024	0.009	−0.037
Annualized portfolio s.d.	TTVP	0.133	0.130	0.044	0.127	0.132	0.145	0.238
	TVP	0.133	0.132	0.042	0.138	0.143	0.143	0.147
	TVP NG	0.133	0.131	0.043	0.128	0.129	0.129	0.181
	Minn-VAR	0.133	0.131	0.041	0.133	0.136	0.142	0.291
	NG-VAR	0.133	0.130	0.041	0.129	0.130	0.141	0.246
	SSVS	0.133	0.130	0.043	0.128	0.131	0.136	0.215
	Flat-no-SV	0.133	0.133	0.133	0.133	0.133	0.133	0.133
	Flat-SV	0.133	0.131	0.040	0.132	0.134	0.136	0.199
	RW-SV	0.133	0.128	0.044	0.126	0.125	0.126	0.131
	AR-SV	0.133	0.122	0.043	0.126	0.128	0.126	0.180
	EWMA	0.133	0.129	0.043	0.119	0.634	0.952	1.913
Sharpe ratios	TTVP	0.787	0.780	0.072	0.782	0.856	0.808	0.538
	TVP	0.787	0.797	0.105	0.813	0.724	0.726	0.715
	TVP NG	0.787	0.788	0.150	0.843	0.866	0.857	0.585
	Minn-VAR	0.787	0.779	−0.295	0.801	0.805	0.820	0.476
	NG-VAR	0.787	0.783	−0.078	0.829	0.836	0.828	0.569
	SSVS	0.787	0.787	−0.105	0.828	0.863	0.872	0.628
	Flat-no-SV	0.787	0.787	0.787	0.787	0.787	0.787	0.787
	Flat-SV	0.787	0.779	−0.205	0.800	0.846	0.826	0.549
	RW-SV	0.787	0.781	−0.099	0.771	0.695	0.687	0.649
	AR-SV	0.787	0.775	0.150	0.760	0.751	0.800	0.648
	EWMA	0.787	0.774	−0.134	0.568	0.038	0.009	−0.019
Value at risk	TTVP	−0.054	−0.053	−0.020	−0.052	−0.053	−0.059	−0.102
	TVP	−0.054	−0.054	−0.020	−0.056	−0.059	−0.059	−0.061
	TVP NG	−0.054	−0.053	−0.020	−0.052	−0.052	−0.052	−0.077
	Minn − VAR	−0.054	−0.053	−0.020	−0.054	−0.055	−0.058	−0.126
	NG VAR	−0.054	−0.053	−0.020	−0.052	−0.053	−0.057	−0.105
	SSVS	−0.054	−0.053	−0.021	−0.052	−0.053	−0.055	−0.091
	Flat-no-SV	−0.054	−0.054	−0.054	−0.054	−0.054	−0.054	−0.054
	Flat-SV	−0.054	−0.053	−0.020	−0.054	−0.054	−0.055	−0.085
	RW-SV	−0.054	−0.052	−0.021	−0.052	−0.052	−0.052	−0.055
	AR-SV	−0.054	−0.057	−0.020	−0.052	−0.053	−0.051	−0.075
	EWMA	−0.054	−0.053	−0.021	−0.051	−0.298	−0.450	−0.909



(a) Canada



(b) Germany



(c) United States

Fig. 3. Marginal log-predictive scores for Canada, Germany and the United States.

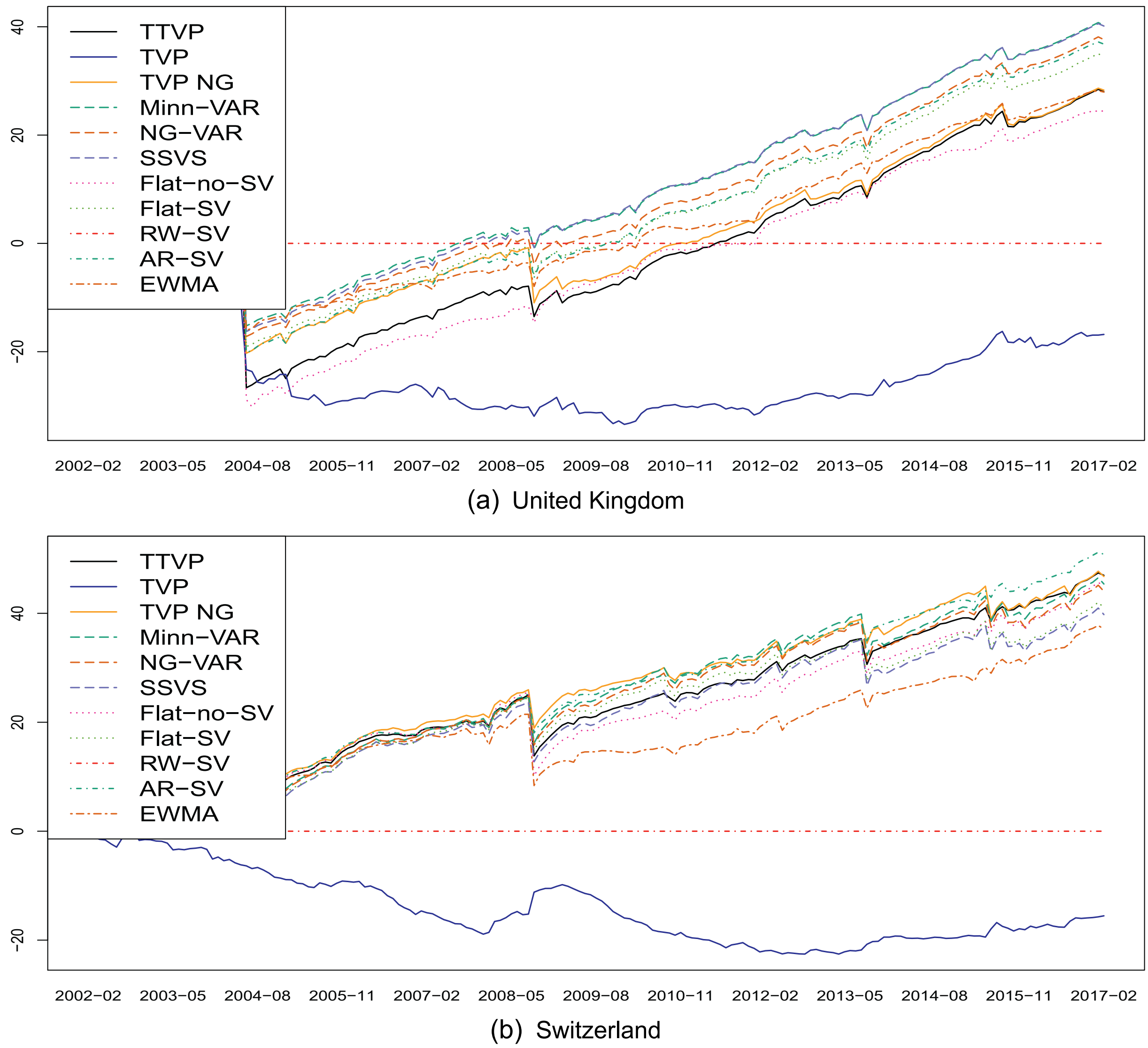
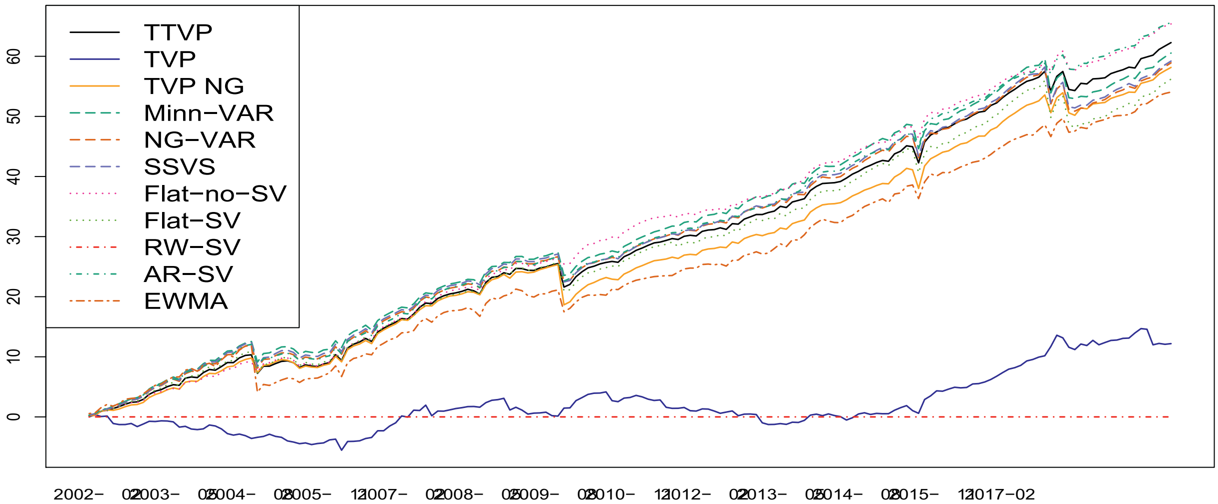
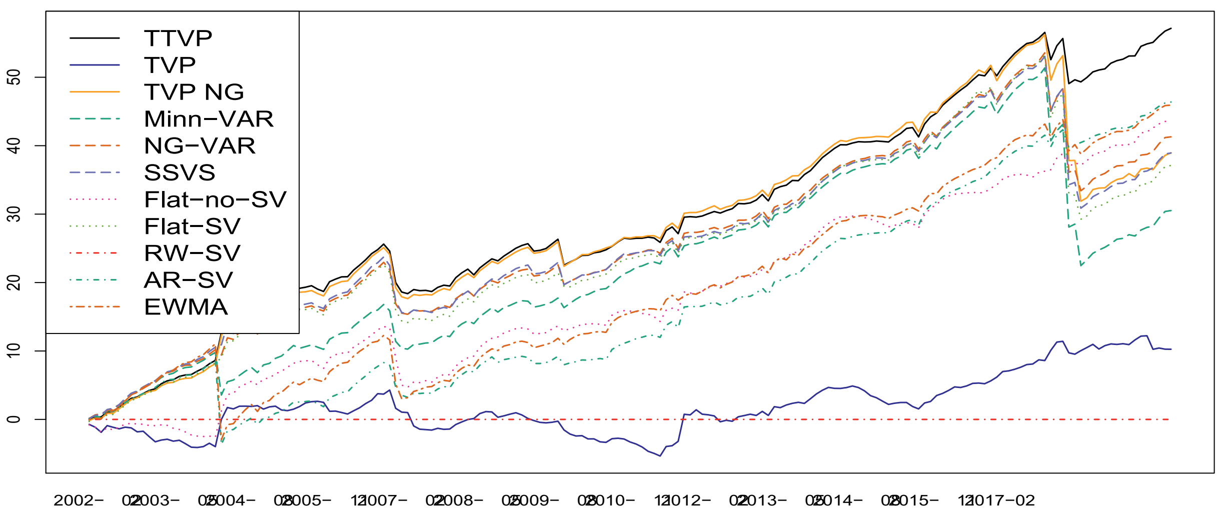


Fig. 4. Marginal log-predictive scores for the United Kingdom and Switzerland.



(a) France



(b) Italy

Fig. 5. Marginal log-predictive scores for France and Italy.

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