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It's all about volatility of volatility: evidence from a two-factor stochastic volatility model *

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Abstract

The persistent nature of equity volatility is investigated by means of a multi-factor stochastic volatility model with time varying parameters. The parameters are estimated by means of a sequential matching procedure which adopts as auxiliary model a time-varying generalization of the HAR model for the realized volatility series. It emerges that during the recent financial crisis the relative weight of the daily component dominates over the monthly term. The estimates of the two factor stochastic volatility model suggest that the change in the dynamic structure of the realized volatility during the financial crisis is due to the increase in the volatility of the persistent volatility term. A set of Monte Carlo simulations highlights th correctness of the methodology adopted to extract the variability in the parameters.

Keywords: Time-Varying Parameters, On-line Kalman Filter, Simulation-based inference, Predictive Likelihood, Volatility Factors.

JEL Classification:G01, C00, C11, C58

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1 Introduction

The aim of this paper is to evaluate whether the observed changes in the dynamic behavior of the realized volatility (RV) series, in correspondence to the financial crises, are linked to changes in the structural parameters governing the stochastic volatility (SV) dynamics. In other words the observed changes in the dynamic pattern of RV series during the financial crises may be seen as the outcome of structural breaks in the parameters governing the dynamics of the continuous-time SV process. The volatility dynamics are assumed to be driven by a two factors SV model (TFSV), which as noted by Gallant et al. (1999) and Meddahi (2002, 2003), successfully accounts for the long range dependence of the volatility process. Given the difficulty of a direct estimation of breaks in the TFSV parameters, we adapt the indirect inference procedure suggested by Corsi and Reno (2012) to the case in which the SV parameters are allowed to be recursively updated. A sequential matching of the parameters is therefore adopted. The proposed method exploits a flexible specification for the auxiliary model, built on an ex-post measure of the integrated variance. The auxiliary model is a time varying extension of the well-known HAR model of Corsi (2009), and it represents a tool to evaluate to what extent the parameters governing the dynamic structure of the RV process vary over time. The time-varying HAR (TV-HAR) is interesting per se as it constitutes a tool to evaluate the evolution of the relative weight of each volatility component to the overall volatility persistence. Following Raftery et al. (2010) and Koop and Korobilis (2012), we use a fast *on-line* method to extract the TV-HAR parameters, allowing for a rapid update of the estimates as each new piece of information arrives. The advantage of the proposed estimation method is that it does not require to identify the number of change points and avoids the use of computationally intensive algorithms, such as MCMC. Interestingly, the model selection procedure, based on the predictive likelihood, excludes that breaks in the long-run mean during the financial crises are responsible for the increase in the observed persistence of the volatility series.

The empirical analysis is carried out on the volatility series of 15 assets traded on the NYSE, that are representative of the main sectors of the US economy. The estimates of the TFSV model clearly indicate the instability of the TFSV parameters. The main finding is that the parameters governing the speed of mean reversion and the volatility of volatility of the persistent factor display a significant dynamic behavior. Specifically, the speed of mean reversion drops during the financial crisis, while the volatility of volatility increases, especially for the assets belonging to the bank and financial sector. As a consequence, the change in persistence in the volatility series can be attributed to the increase of the relative weight of the persistent volatility component. The relative increase of the persistent volatility factor generates trajectories that deviate for longer periods from the unconditional mean, hence producing the impression of level shifts in the observed realized series. Moreover, the higher volatility of the persistent volatility factor increases the degree of dispersion of the volatility around its long-run value, and thus the volatility of RV (see Corsi et al., 2008). Interestingly, the growth of the volatility of the persistent factor is reflected in an increase of the relative weight of the daily volatility component in the auxiliary TV-HAR model. In particular, the daily term becomes the main factor during the financial crisis. On the other hand, the monthly component has a larger role during the low volatility period which characterizes the years 2004-2007.

The paper is organized as follows. First, Section 2 introduces the auxiliary TV-HAR model. Section 3 sets the notation of the TFSV model and proposes a dynamic matching method for the TFSV model using the TV-HAR as auxiliary model. Section 4 presents the results of the empirical analysis based on 15 stocks traded on NYSE. Section 5 provides Monte Carlo simulations to evaluate the robustness of the empirical results presented in Section 4 and the possible presence of leverage effects. Section 6 concludes.

2 Auxiliary model: the TV-HAR

Strong empirical evidence, dating back to the seminal papers of Engle (1982) and Bollerslev (1986), supports the idea that the volatility of financial returns is time varying, stationary and long-range dependent. This evidence is confirmed by the statistical analysis of the ex-post volatility measures, such as RV, which are precise estimates of latent integrated variance and are obtained from intradaily returns, see Andersen and Bollerslev (1998), Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002) among many others. In the last decade, particular effort has been spent in developing discrete time series models for ex-post volatility measures, which are able to capture the persistence of the *observed* volatility series.[1] Reduced form time series models for RV have been extensively studied during the last decade. For instance, Andersen et al. (2003), Giot and Laurent (2004), Lieberman and Phillips (2008) and Martens et al. (2009) report evidence of long memory and model RV as a fractionally integrated process. As noted by

[1]Recent papers by McAleer and Medeiros (2011) and Asai et al. (2012) present detailed surveys of alternative models for RV.

Ghysels et al. (2006) and Forsberg and Ghysels (2007) mixed data sampling approaches are also empirically successful in accounting for the observed strong serial dependence. In particular, Corsi (2009) approximates the long range dependence by means of a long lagged autoregressive process, called heterogeneous-autoregressive model (HAR). The main feature of the HAR model is its interpretation as a volatility cascade, where each volatility component is generated by the actions of different types of market participants with different investment horizons. HAR type parameterizations are also suggested by Corsi et al. (2008), Andersen et al. (2007) and Andersen et al. (2011).

In its simplest version, the HAR model of Corsi (2009) is defined as

$$X_t = \alpha + \phi^d X_{t-1} + \phi^w X_{t-1}^w + \phi^m X_{t-1}^m + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2), \tag{1}$$

where $X_t = \log(RV_t)$, $X_t^w = \frac{1}{5}\sum_{j=0}^{4} X_{t-j}$, $X_t^m = \frac{1}{22}\sum_{j=0}^{21} X_{t-j}$, and $\theta = \left[\phi^d, \phi^w, \phi^m\right]$. It is clear that the HAR model is a AR(22) with linear restrictions on the autoregressive parameters. In particular, there are three free parameters with an autoregressive equation with 22 lags. Corsi et al. (2008) and Corsi (2009) show that the HAR model is able to reproduce the long-range dependence typical of RV series. However, as noted by Maheu and McCurdy (2002) and McAleer and Medeiros (2008), the dynamic pattern of RV is subject to structural breaks and could potentially vary over time. This evidence is also confirmed by Liu and Maheu (2008), Choi et al. (2010) and Bordignon and Raggi (2012) who find that structural breaks in the mean are partly responsible for the persistence of RV.

In light of the recent global financial crisis, and the different behavior of the RV series during periods of high and low trading activity, a time-varying coefficients model may lead to a better understanding of the volatility dynamics. For example, in the GARCH framework, time-varying parameter models are found to be empirically successful by Dahlhaus and Rao (2007a,b), Engle and Rangel (2008), Bauwens and Storti (2009) and Frijns et al. (2011), among others. Since the underlying data-generating process of a time varying coefficient model is unknown, a flexible and simple model structure is assumed. Primiceri (2005), Cogley and Sargent (2005) and Koop et al. (2009) among others, testify the empirical success of such models in characterizing macroeconomic series. In contrast to Liu and Maheu (2008) and McAleer and Medeiros (2008), the proposed discrete-time model allows for a potentially large number of changing points of the HAR parameters, if the parameters ϕ^d, ϕ^w and ϕ^m are assumed to follow pure random walk dynamics. In this setup, the parameters ϕ_t^d, ϕ_t^w and ϕ_t^m measure the proportion of the total variance that is captured by each volatility component at time t and are interpreted as time varying weights for each volatility component. The TV-HAR model is given by

$$\begin{aligned} X_t &= \alpha_t + \phi_t^d X_{t-1} + \phi_t^w X_{t-1}^w + \phi_t^m X_{t-1}^m + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{N}(0, \mathrm{H}_t), \\ \alpha_t &= \alpha_{t-1} + \eta_t^{\alpha}, \qquad \phi_t^d = \phi_{t-1}^d + \eta_t^{\phi^d}, \\ \phi_t^w &= \phi_{t-1}^w + \eta_t^{\phi^w}, \qquad \phi_t^m = \phi_{t-1}^m + \eta_t^{\phi^m}. \end{aligned} \tag{2}$$

where H_t is a scalar and $\eta_t \equiv [\eta_t^{\alpha}, \eta_t^{\phi^d}, \eta_t^{\phi^w}, \eta_t^{\phi^m}] \sim \mathrm{N}(\mathbf{0}, \mathrm{Q}_t)$ and Q_t is a 4×4 covariance matrix.

Alternatively, assuming that the unconditional mean of X_t is constant, it is possible to work on the centered log-volatility series,

$$y_t \;=\; \phi_t^d y_{t-1} + \phi_t^w y_{t-1}^w + \phi_t^m y_{t-1}^m + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2), \tag{3}$$

where $y_t = X_t - \bar{X}_t$ with $\bar{X}_t \xrightarrow{p} \mu \equiv \mathrm{E}(X_t)$, so that both sides of equation (3) have zero mean. Both models in equations (2) and (3) can be easily extended to include other covariates, such as price jumps, past negative returns, or other financial variables. Excluding the intercept from model (2) rules out the possible presence of level shifts in the mean of the process. In this case, changes in the persistence of the process can only be generated by changes in its autoregressive structure. This parameterization avoids the lack of identification of the unconditional mean when the roots of the autoregressive polynomial of the TV-HAR are such that the process is in the non-stationarity region. This issue will be further discussed in Section 4.

The models in equations (2) and (3) present a flexible structure, that depends not only on the autoregressive behavior of X_t and y_t, but also on the dynamics of the HAR parameters. At each point in time, a different set of parameters must be estimated. The adopted estimation algorithm for the TV-HAR model follows the methodology proposed by Raftery et al. (2010) and Koop and Korobilis (2012), and extracts the time-varying parameters by means of a modified Kalman filter routine based on the so called *forgetting* parameter, λ. We propose a selection method for the forgetting parameter, such that λ is calibrated in order to minimize the mean squared one-step-ahead forecasting error. Given λ, the Koop and Korobilis (2012) estimation method allows for a fast update of the estimates as each new piece of information becomes available, from which the name *on-line* method. The details on the *on-line* estimation method and the selection of the forgetting parameter are presented in Appendix A.

3 The two-factor stochastic volatility model

A deeper understanding of the volatility dynamics can be achieved from a structural point of view, exploiting the TV-HAR as an auxiliary model for the estimation of the parameters of a TFSV model. From this point of view, the TV-HAR is considered as a flexible reduced form model, that allows to summarize the dynamic features of the RV series and to provide informations regarding possible breaks in the parameters of the structural model. Finding a link between the HAR and the TFSV parameters is thus necessary to interpret the origin of the observed structural changes of the RV dynamics as generated by breaks in the parameters of the latent SV model.

In order to find a link between the TV-HAR and the continuous time SV model, we implement a sequential estimation of the SV parameters, based on the matching of the parameters of the time-varying auxiliary model. Similarly to the indirect inference method of Gourieroux et al. (1993), the sequential matching involves the simulation of the trajectories of RV from the structural model. We assume that the structural model for the spot volatility follows a TFSV:

$$\begin{aligned} \mathrm{d}p(t) &= \gamma(t)\mathrm{d}W_1^p(t) + \zeta(t)\mathrm{d}W_2^p(t), \\ \mathrm{d}\gamma^2(t) &= \kappa[\omega - \gamma^2(t)]\mathrm{d}t + \eta\gamma(t)\mathrm{d}W^\gamma(t), \\ \mathrm{d}\zeta^2(t) &= \delta[\omega - \zeta^2(t)]\mathrm{d}t + \nu\zeta(t)\mathrm{d}W^\zeta(t), \end{aligned} \tag{4}$$

where $\mathrm{d}p(t)$ is the log price, $W_1^p(t)$, $W_2^p(t)$, $W^\gamma(t)$ and $W^\zeta(t)$ are Brownian motions. The parameters κ and δ govern the speed of mean reversion, while η and ν determine the volatility of the volatility innovations. The parameter ω is the long-run mean of each volatility component and, as in Corsi and Reno (2012), it is assumed to be the same for both $\gamma^2(t)$ and $\zeta^2(t)$, in order to guarantee the identification. Corsi and Reno (2012) provide estimates of the parameters of the TFSV model based on the estimates of the HAR-RV model.[2]

We follow a similar approach as Corsi and Reno (2012), by exploiting the TV-HAR as auxiliary model for the estimation of the TFSV parameters. However, given that the estimates of the TV-HAR change at each point in time, then the matching of the parameters must be carried out sequentially, thus resulting in a sequence of values for the parameters of the TFSV model. In particular, at each point in time, the estimation algorithm returns the set of TFSVparameters that minimizes the distance between the estimates of the auxiliary model obtained on the

[2] In the RV context, the simulation-based inference methods have been already employed by Bollerslev and Zhou (2002), Andersen et al. (2002).

observed data and on the simulated series.

The estimation algorithm proceeds as follow. Denote by Ψ_t the parameter vector of the TFSV model at time t:

i. Estimate the auxiliary model on the observed data and denote the estimated parameter vector by $\hat{\Theta}_t$, for $t = 1, \ldots, T$.

ii. At time t, generate $S = 100$ trajectories of $\bar{M} = 78$ intradaily returns (Euler discretization) for $\bar{N} = 1500$ days from the TFSV with parameter vector Ψ_t. Each return trajectory is denoted by $r_{\bar{N},\bar{M}}$.

iii. For each simulated trajectory, compute the daily RV series, $RV_n^* = \sum_{i=1}^{\bar{M}} r_{n,i}^2$ for $n = 1, \ldots, \bar{N}$.

iv. Estimate the HAR model on each $\log RV_n^*$ series. The estimates are denoted by $\Theta_j^*(\Psi_t)$ with $j = 1, \ldots, S$.

v. The parameters of the TFSV model at time t are estimated by $\hat{\Psi}_t = \arg\min_{\Psi_t} \Xi_t$ with

$$\Xi_t = \left(\sum_{j=1}^{S} \left[\hat{\Theta}_t - \Theta_j^*(\Psi_t) \right] \right)' \bar{\mathrm{W}}_t \left(\sum_{j=1}^{S} \left[\hat{\Theta}_t - \Theta_j^*(\Psi_t) \right] \right) \tag{5}$$

where the $\bar{\mathrm{W}}_t$ is a suitable weight matrix. Following Corsi and Reno (2012), $\bar{\mathrm{W}}_t$ is chosen as the inverse of the covariance matrix of the auxiliary parameters in each period t, $\bar{\mathrm{W}}_t = \mathrm{Q}_t^{-1}$.[3]

vi. Finally, iterating ii) - v) for $t = 1, \ldots, T$, produces a sequence of estimates of Ψ_t.

The model in equation (4) can be extended by assuming that the log-price, $p(t)$, follows a jump-diffusion process. Since the main interest of the present paper is on the volatility dynamics, the daily volatility is measured by a non-parametric estimator robust to price jumps. Therefore, the empirical analysis is carried out on the bi-power variation (BPV), which is a precise ex-post measure of volatility robust to jump in prices, see Barndorff-Nielsen and Shephard (2006). In this way, the estimates of the TFSV are robust to the nuisance parameters governing the jump prices.[4]

[3]Note that, when the number of structural parameters is equal to the number of auxiliary parameters (exactly identified case), then the weighting matrix could be set equal to the identity matrix.

[4]For a detailed study of the impact of nuisance parameters on the indirect inference estimates see Guay and Scaillet (2003) and Dridi et al. (2007).

4 Empirical results

The empirical analysis is based on daily series of $\log BPV$ for 15 assets traded on the NYSE. The sample covers the period from January 2, 2004 to December 31, 2009 for a total of 1510 days. The stocks are selected in order to be representative of the main sectors of the US economy, see Table 1. Due to the inclusion of the sub-prime financial crisis in the sample, 8 out of the 15 stocks are selected from the banking and financial sectors. The selected stocks from this sector are: American Express, AXP, Bank of America, BAC, Citygroup, C, Goldman-Sachs, GS, JP-Morgan, JPM, Met-Life, MET, Morgan-Stanley, MS, Wells-Fargo, WFC. Other included companies are Boeing, BA, General Electrics, GE, International Business Machines, IBM, Mc Donalds, MCD, Procter & Gamble, PG, AT&T, T, Exxon, XOM.

Our primary dataset consists of tick-by-tick transaction prices, which are sampled once every 5 minutes, according to the *previous-tick* method. The daily BPV series is then computed using 5 minutes logarithmic returns. During the period 2004-2007 the log-volatilities are rather stable and low, whereas during the financial crisis period the level of volatility increases significantly.[5] Even though the log-volatility series is found to be stationary using standard unit-root tests, it is interesting to evaluate if the peculiar patterns of the series in the period 2008-2009 is reflected in a change in the TV-HAR parameters.

The *on-line* estimation method, described in Appendix A, requires a prior on the initial states. Following Koop and Korobilis (2012), we set $\theta_0 \sim \mathrm{N}(0, 100)$, so that the learning algorithm is rather unstable for the initial observations, which are not plotted. Figure 1 reports the estimated parameters of the TV-HAR model for the period 2006-2009 for three volatility series.[6] From all figures, an interesting stylized fact emerges: the daily volatility component becomes more relevant during the period 2008-2009, i.e. during the financial crisis. On the other hand, the weight of the weekly component does not present a clear trend, while the monthly component drops after August 2007 and becomes insignificant in the last period. The extent of the variation with respect to the OLS estimates (blue dashed line) is notable especially for ϕ_d and ϕ_m. In particular, the *on-line* estimates of ϕ_d lie below the 90% OLS confidence interval at the beginning of the sample, while they lie above at the end of the sample. The opposite behavior characterizes the *on-line* estimates of ϕ_m.

Table 2 reports some sample statistics pertaining to the TV-HAR parameters. It is interest-

[5] Due to space constraints, some graphs are reported in the Web Appendix. A plot of the daily $\log BPV$ for three assets is reported in Figure 1 in the Web Appendix.

[6] The results for AXP, GE and IBM are only reported. Graphs for all stocks are available upon request.

ing to note the extent of the variation of ϕ_d and ϕ_m, such that the contribution of each volatility component to the overall market activity decreases with the horizon of aggregation during the period 2008-2009. The period 2006-2007 is characterized by the weekly and monthly volatility components while, at the end of the sample, the daily volatility becomes the relevant term. The estimation of the TV-HAR parameters has also been performed on the log BPV series including the intercept as in model (2).

In order to evaluate if the assumption of constant unconditional mean is coherent with the data, the out-of-sample performances of models (2) and (3) are compared following the approach suggested in Eklund and Karlsson (2007). Hence, the log predictive likelihood, $\log(PL)$, is computed for each model as a measure of predictive accuracy. The use of predictive measures of fit offers protection against in-sample over-fitting. A solution to the in-sample over-fitting is indeed to consider explicitly the out-of-sample (predictive) performance of each model. First it is necessary to split the sample $Y_T = (y_1, \ldots, y_T)^{'}$ into two parts with s and t observations respectively, with $T = s + t$. The first part of the sample, $Y_s = (y_1, \ldots, y_s)^{'}$, is used in the model estimation and the second part, $Y_t = (y_{s+1}, \ldots, y_T)^{'}$, is used for evaluating the model performance. Given the information set $Y_s = (y_1, \ldots, y_s)^{'}$, the predictive likelihood, for model M_k is defined for the data $y_s, \ldots, y_t$ as

$$p(y_s, \ldots, y_t \mid Y_{s-1}, M_k) = \int p(y_s, \ldots, y_t \mid \theta_k, Y_{s-1}, M_k) p(\theta_k | Y_{s-1}, M_k) d\theta_k \tag{6}$$

where $p(y_s, \ldots, y_t \mid \theta_k, Y_{s-1}, M_k)$ is the conditional density given Y_{s-1}, see Geweke (2005). The predictive likelihood contains the out-of-sample prediction record of a model. Equation (6) is simply the product of the individual predictive likelihood:

$$\begin{aligned} p\left(y_s, \ldots, y_t \mid Y_{s-1}, M_n\right) &= \prod_{j=s}^{T} p\left(y_j \mid Y_{j-1}, M_n\right) \\ &= \prod_{j=s}^{T} \mathrm{N}\left(\mathrm{Z}_t^{(n)} \theta_{t|t-1}^{(n)}, \mathrm{H}_t^{(n)} + \mathrm{Z}_t^{(n)} \Sigma_{t|t-1}^{(n)} \mathrm{Z}_t^{(n)'}\right), \end{aligned} \tag{7}$$

where each element on the right hand side is automatically obtained by the *on-line* Kalman filter routine.

Table 3 reports a comparison in terms of out-of-sample forecasting ability between models (2) and (3). The out-of-sample period starts on August 1, 2007, as suggested in Covitz et al. (2012), such that the out-of-sample period includes the sub-prime financial crisis, where it is expected to observe shifts in the long-run mean of the volatility series. The RMSFE and the $\log(PL)$ indicate that the model based on the centered series outperforms in most cases the model with time varying intercept. This evidence confirms that the model in equation (2) is not superior in describing the data than the model based on the centered series. This result implies that the variability of the HAR parameters is not necessarily the spurious outcome of a neglected time-varying intercept. Indeed, the variations in the dynamic pattern of volatility can be better thought of as mainly due to changes in its autoregressive structure, and not as shifts in the long-run mean.

An explanation for this result emerges from Figures 2-4 in the Web-Appendix, the estimates of ϕ_t^d, ϕ_t^w and ϕ_t^m are almost identical to those obtained on the centered series, since the variation of $\mu_t = \alpha_t/(1 - \phi_t^d - \phi_t^w - \phi_t^m)$ is generally negligible when compared to the variation of the HAR parameters. The main difference is in the estimates of ϕ_t^m, as a consequence of the lack of identification of μ_t during the year 2007, see Figure 5 in the Web-Appendix. It emerges that, when the largest eigenvalue of the TV-HAR characteristic polynomial is above 1, the estimated unconditional mean, μ_t, is no longer identified.

The impulse response functions (IRF) calculated with two different sets of parameters, obtained at different points in time, are plotted in Figure 2. The main evidence is the large increase in persistence during the crisis. For example, the impact of an innovation on the one-step-ahead volatility is approximately 30% larger during the financial crisis than during previous periods. After one month, the gap between the two IRFs remains above 10%. This suggests that the increasing role of the daily volatility component during the financial crisis is reflected in an increase in the persistence of the volatility process.

Now, we turn our attention to the sequential estimates of the TFSV model, reported in Figures 3 - 5. Consistently with the assumption that the changes in persistence are only due to changes in the autoregressive structure of the HAR, the parameter ω, for both $\gamma^2(t)$ and $\zeta^2(t)$, is kept fixed and equal to half the sample average of BPV. This is consistent with Corsi and Reno (2012) and it ensures identification of the unconditional mean of the TFSV process. Figure 3 plots the estimated objective function value, Ξ_t, for the period January 2007 - December 2009. There is a notable difference between the dynamic behavior of Ξ_t for the stocks belonging to the financial sector and the others. On average Ξ_t is higher for the banking sector, and it increases sharply during the period of the financial crisis. This indicates that the TFSV model may be not flexible enough to capture the extent of variation in the volatility dynamics of the financial stocks during the crisis. On the other hand, the criterion function, Ξ_t, has lower values for the companies not belonging to the banking and finance sector. Moreover, it remains more stable throughout the whole sample, with the only exception of the GE, which experienced a serious financial distress during the period January 2008 - March 2009.

The structural parameters governing the speed of mean reversion display an interesting dynamic pattern. The parameter κ, the speed of mean reversion of the fast moving factor, ranges between 5 and 55 as shown in Figure 4 and increases sharply at the end of the sample. This means that the fast volatility factor, $\gamma^2(t)$, reverts much faster to the long run mean during the period 2008-2009. Hence, $\gamma^2(t)$ is less persistent and it has noisy dynamics during the financial crisis. The parameter δ, see Figure 4, which governs the speed of mean reversion of the persistent factor is characterized in all cases by large structural breaks. For the bank sector, there is a common evidence that the value of δ drops to approximately 0.001 in the second part of the sample, meaning that a shock to the persistent volatility factor, $\zeta^2(t)$, produces effects for many periods in the future. In particular, in all cases the estimates are very close to 0 after January 2008, meaning that $\zeta^2(t)$ is a close-to-unit-root process, introducing high persistence in the volatility series. On average, the estimated parameter is close to those found by Corsi and Reno (2012).

The extent of the time variation of the TFSV parameters emerges also clearly from Figure 5, which reports the estimates of the parameters governing the volatility of the volatility. The parameter ν, which represents the volatility of the persistent factor, has an upward trend, especially for stocks belonging to the banking and financial sector. Also η has a upward trend pattern, but it is less evident compared to that of ν. For most of the stocks, η assumes values in the range between 0.02 and 0.15. On the other hand, ν increases from 0.01 to 0.15 for the banking sector and from 0.005 to 0.05 for most of the other stocks. As a consequence, during the financial crisis, the relative weight of the persistent volatility component increases with respect to the noisy factor (also due to the reduction of the mean-reversion parameter δ). Hence, the resulting volatility process, $\sigma^2(t)$, becomes more persistent and more volatile at the same time. This is particularly evident for the banking sector. The increase of the volatility of the persistent factor during the financial crisis not only induces the observed growth of the volatility levels, but also increases the degree of uncertainty around its long-run level. Therefore, the persistent volatility component, which mainly affects the size of the return variance and the investor's consumption in the long-run, plays an important role in the pricing of options and becomes more and more relevant as the the crisis approaches. Hence, the variations in the parameter ν, which summarizes the uncertainty of the investors toward the long-run investments, are responsible not only for the observed changes in persistence but also for the increase of the volatility of volatility. Finally, the evidence presented in this section indicates that, in performing option pricing under stochastic volatility, an important source of randomness, that cannot be neglected, is given by the variability in the SV parameters. A careful investigation of the consequence of breaks in SV on option pricing is left to future research.

5 Robustness Checks

The results of the simulations presented in this section are intended to verify that the empirical results outlined in Section 4 are not spuriously induced by the adopted estimation method. In particular, the estimation procedure outlined in Appendix A does not allow to test whether the variation of the parameters is statistically significant. Therefore this set of Monte Carlo simulations evaluates the ability of the *on-line* method to correctly estimate the time variation in the parameters and to show the robustness of the selection method for the *forgetting* parameter, λ.

Firstly, we verify whether the *on-line* method does not induce spurious variation in the TV-HAR estimates. Therefore, the first set of Monte Carlo simulations is carried out according to the following setup. We simulate $S = 1000$ times series of $T = 1200$ observations from a HAR model with constant parameters, $\phi_d = 0.4$, $\phi_w = 0.4$ and $\phi_m = 0.15$. In order to control for possible heteroskedastic effects in the data, the variance of ε_t is assumed to follow a GARCH(1,1)

$$\sigma^2_{\varepsilon,t} = \omega + \alpha\epsilon^2_{t-1} + \beta\sigma^2_{\varepsilon,t-1}, \tag{8}$$

with $\omega = 0.01$, $\alpha = 0.05$ and $\beta = 0.90$. For each Monte Carlo replication, the TV-HAR is estimated with a different choice of λ, where the latter is defined on the grid of values $[0.95, 0.955, \ldots, 0.995, 1]$. As in the empirical application, the optimal λ is each Monte Carlo replication in correspondence of the lowest mean squared one-step-ahead prediction error. Interestingly, the optimal value of λ is found to be equal to 1 in 89% of cases. When $\lambda = 1$, the variability of the parameters is almost zero and the estimates are well centered on the true values. Panels a)-c) in Figure 6 show the estimated TV-HAR parameters when the DGP is the constant HAR. The estimated parameters are extremely smooth and display small variation around the constant parameters. This means that when the parameters are constant, the *on-line* estimation method does not induce spurious variability, but the extent of time-variation in the estimates is negligible.

Secondly, we verify whether the parameter estimates obtained with the *on-line* method follow the true variation of the TV-HAR parameters. Therefore, in the second Monte Carlo setup, we simulate $S = 1000$ times a series of $T = 1200$ observations from model (3) where, in each Monte Carlo replication, the TV-HAR parameters are those estimated on the log-BPV series of AXP, see Section 4. The only sources of randomness are therefore the TV-HAR innovations, ε_t, which, as before, are assumed to be Gaussian with conditional variance evolving as in equation (8). In 76.5% of the cases, the value of λ is chosen to be equal to 0.995, while in 18% of cases it is chosen to be equal to 0.99%. Panels d)-f) in Figure 6 report the data-generating parameters with the 90% confidence intervals obtained from the Monte Carlo estimates. The 90% confidence intervals contain the true values in all cases, suggesting that the methodology is able to capture the variation in the parameters. Due to the recursive nature of the estimation algorithm, the confidence intervals are particularly wide at the beginning of the sample, while they become narrower as the information set becomes larger. We can conclude that, the *on-line* approach yields reliable estimates of the TV-HAR parameters and the proposed method for the choice of λ provides a robust selection method for the updating mechanism of the new information.

Thirdly, we verify whether the observed variation in the TV-HAR cannot be generated by a structural model with constant parameters. In particular, our goal is to evaluate whether the variation in the TV-HAR estimates is not spuriously induced by the *on-line* estimation algorithm, while the parameters of the TFSV model are constant. We therefore simulate $S = 1000$ daily BPV series from model (4), holding the structural parameters constant. Consistently with the findings presented in Section 4, the structural parameters are: $\kappa = 5$, $\delta = 0.001$, $\eta = 0.05$ and $\nu = 0.01$. In particular, each RV series is generated with $\bar{M} = 78$ intradaily returns for $T = 1500$ days. Panels a)-c) in Figure 7 report the estimation results. The *on-line* estimates are generally close to the OLS estimates, which are based on the full sample, and they always lie inside the OLS 90% confidence bands. This confirms that the observed variation in the TV-HAR estimates is not induced by the adopted *on-line* estimation method, but it reflects the presence of changes in the structural parameters.

Finally, we evaluate whether an increase in the volatility of the persistent volatility factor in the TFSV induces the TV-HAR parameters to follow the trajectories obtained with the *on-line* estimation method. Therefore, in the final Monte Carlo simulations, we let the parameter ν in the TFSV model to be time-varying, with a dynamic behavior as in Figure 5. The other structural parameters are kept constant at the values $\kappa = 5$, $\delta = 0.001$, $\eta = 0.05$. Panels d)-f) in Figure 7 show strong variation in the estimated TV-HAR parameters, which is consistent with the findings presented in the empirical analysis. In particular, the weight of the daily volatility component sharply increases, while the weekly and monthly volatility terms become less and less relevant at the end of the sample. Compared to the OLS estimates, based on the full sample, the TV-HAR parameters have clear trends, similar to those obtained with the observed realized volatility series, and they generally lie outside the 90% confidence bands. These results confirm the reliability of the inference methods adopted and the robustness of the empirical analysis.

5.1 Leverage effect

An important stylized fact in the empirical financial literature is the negative and significant correlation between volatility and returns, the so called leverage effect. Model (4) can be easily extended to include leverage effect, i.e. $\rho_{p,\gamma} = \text{Corr}(W_1^p(t), W^\gamma) \neq 0$ and $\rho_{p,\zeta} = \text{Corr}(W_2^p(t), W^\zeta) \neq 0$. In this case $\rho_{p,\gamma}$ and $\rho_{p,\zeta}$ need to be estimated, such that the auxiliary model must include at least two additional parameters in order to be able to identify all the structural parameters. Similarly to Corsi and Reno (2012), past negative returns can be included as explanatory variables in TV-HAR model. Hence, the TV-HAR model (3) would be modified as

$$y_t = \phi_t^d y_{t-1} + \phi_t^w y_{t-1}^w + \phi_t^m y_{t-1}^m + \delta_t^d r_{t-1}^- + \delta_t^w r_{t-1}^{w,-} + \delta_t^m r_{t-1}^{m,-} + \varepsilon_t, \qquad \varepsilon_t \sim \text{N}(0, \sigma_\varepsilon^2), \tag{9}$$

where r_{t-1}^- is the past negative return and $r_t^{w,-} = \frac{1}{5}\sum_{j=0}^{4} r_{t-j}^-$ and $r_t^{w,-} = \frac{1}{22}\sum_{j=0}^{21} r_{t-j}^-$. This auxiliary model is named TV-HAR-L. It should be noted that in the TFSV, the parameters $\rho_{p,\gamma}$ and $\rho_{p,\zeta}$ cannot be interpreted automatically as the correlation between volatility and prices, since in presence of two factors, the interpretation of the leverage effect is not trivial as explained in Chernov et al. (2003).

The sequential estimation of the TFSV model has been repeated allowing for the possibility of leverage effect, using the TV-HAR-L model in equation (9) as auxiliary model. The estimates of $\rho_{p,\gamma}$ and $\rho_{p,\zeta}$ are in line with those reported by Corsi and Reno (2012). However, an interesting clue emerges when investigating the identification condition of the TFSV with leverage when the HAR-L is adopted as auxiliary model. The identification condition is verified by computing the determinant of the matrix of partial derivatives $\Delta = \frac{\partial \Theta(\Psi)}{\partial \Psi}\Big|_{\hat{\Psi}}$.[7] As shown in Figure 8, the value of the determinant of the matrix Δ based on the estimates of the TFSV model without leverage is always far from zero. This means that the parameters of the TFSV model, when the leverage is absent, are well identified since the matrix Δ is far to be singular. On the other hand, the determinant of the matrix Δ for the TFSV with leverage is always very close to zero, thus implying a not bijective binding function. In other words, a variation in the structural parameter is not reflected in variation of all the auxiliary parameters, so that the matrix of partial derivatives Δ is singular. As a consequence, the indirect inference estimates of the TFSV model with leverage are not consistent. A possible reason for this lack of identification is that in the TFSV model the correlation between the innovations in returns and volatility is contemporaneous, while in the auxiliary model the negative return enters with a lag. Given that the autocorrelation in the returns is almost absent, this induces the past negative returns to be weak instruments to capture the leverage effect in the TFSV model. Due to this lack of identification, the results of the recursive estimates of the TFSV model with leverage are not further discussed. Future research will study an alternative auxiliary model that is not affected by this problem of identification.

6 Conclusions

The persistent nature of equity volatility as a mixture of processes at different frequencies is investigated by means of a TFSV model. The parameters are estimated using a novel and fast algorithm based on the state-space representation of the TV-HAR. From the TV-HAR estimates it emerges an increasing role of the daily volatility component during the financial crisis, whereas the monthly term becomes insignificant. The main finding that arise from the estimates of the TFSV model is the crucial role played by the persistent volatility factor during the financial crisis. In particular, the speed of mean reversion drops and the volatility of volatility increases, thus inducing the observed realized process to diverge from the long run mean and to become extremely volatile. The evidence arising from the descriptive analysis of the present paper could provide a guidance for refined option pricing models, accounting for parameter instability in the SV process.

[7] The evaluation of Δ is carried out based on the estimates of the HAR model with leverage and with constant parameters.

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Appendix A: Estimation Method

The estimation methodology requires a state-space specification of the TV-HAR model in equation (3),

$$
\begin{aligned}
y_t &= \mathrm{Z}_t\theta_t + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{N}(0, \mathrm{H}_t), \\
\theta_t &= \theta_{t-1} + \eta_t \qquad \eta_t \sim \mathrm{N}(0, \mathrm{Q}_t),
\end{aligned}
\tag{10}
$$

where y_t is the observed variable, $\mathrm{Z}_t = [y^d_{t-1}, y^w_{t-1}, y^m_{t-1}]$ is a 1×3 vector containing the HAR lag structure, and $\theta_t = [\phi^d_t, \phi^w_t, \phi^m_t]'$ is a 3×1 vector of time varying parameters, which are assumed to follow random-walk dynamics. In this setup, the HAR parameters are considered as state variables, while the past values of y_t are the explanatory variables. The errors ε_t and η_t are assumed to be mutually independent at all leads and lags.

Once model (3) is casted in the state space form (10) , the parameter vector θ_t can be easily estimated with a standard Kalman filtering technique. The prediction step for given values of H_t and Q_t is:

$$
\begin{aligned}
\theta_{t|t-1} &= \theta_{t-1|t-1} \\
\Sigma_{t|t-1} &= \Sigma_{t-1|t-1} + \mathrm{Q}_t \\
\epsilon_{t|t-1} &= y_t - \mathrm{Z}_t\theta_{t|t-1}.
\end{aligned}
\tag{11}
$$

where $\Sigma_{t|t-1}$ is the covariance matrix of $\theta_{t|t-1}$. However, the estimation of Q_t requires computationally intensive algorithms, such as MCMC methods. Therefore Raftery et al. (2010) suggest to substitute the prediction equation of $\Sigma_{t|t-1}$ in equation (11) with

$$
\Sigma_{t|t-1} = \frac{1}{\lambda}\Sigma_{t-1|t-1}, \tag{12}
$$

so that $\mathrm{Q}_t = (\lambda^{-1} - 1)\Sigma_{t-1|t-1}$ where $0 < \lambda < 1$. This approach has been introduced in the state space literature by Fagin (1964) and Jazwinsky (1970), to reduce the computational burden of the traditional Kalman filter. Raftery et al. (2010) provide a detailed discussion of this approximation, especially regarding the tuning parameter λ. The parameter λ can be considered as a *forgetting factor*, since the specification in equation (12) implies that the weight associated to the observations j periods in the past is equal to λ^j. Following Raftery et al. (2010) and

Koop and Korobilis (2012), the parameter λ must be chosen large enough in order to guarantee a sufficient degree of smoothness. For quarterly data, Koop and Korobilis (2012) suggest that λ should be chosen between 0.95 and 0.99. In this paper, the choice of λ is such that it minimizes the mean squared one-step-ahead prediction error. With daily data, we find that the optimal λ is equal to 0.995. This value for λ is consistent with a fairly stable model where changes of the coefficients are gradual. For example, observations 22 days ago receive approximately 90% of the weight given to the last observation, whereas with $\lambda = 0.95$ they receive approximately 33%.

It is interesting to note that the simplification used by Raftery et al. (2010) implies that Q_t does not need to be estimated. However, a method to estimate H_t, which is the variance of the irregular component, is still required. Raftery et al. (2010) recommend a simple plug-in method where an estimate of H_t is given by

$$\mathrm{H}_{t|t-1} = \frac{1}{t}\sum_{j=1}^{t}\left[(y_j + \mathrm{Z}_j\theta_{j-1|j-1})^2 - \mathrm{Z}_j\Sigma_{j|j-1}\mathrm{Z}_j^{'}\right]. \tag{13}$$

Since RV is shown to be heteroskedastic, see Corsi et al. (2008), so that the error variance is likely to change over time, we adopt an alternative method to compute the variance H_t. Following Koop and Korobilis (2012), H_t follows an exponentially weighted moving average,

$$\mathrm{H}_{t|t-1} = \kappa\mathrm{H}_{t-1|t-1} + (1-\kappa)(y_t - \mathrm{Z}_t\theta_{t|t-1})^2, \tag{14}$$

with $\kappa = 0.94$, so that the variance of the error term is allowed to vary over time and the estimates of the TV-HAR parameters are robust to heteroskedastic effects, especially during the financial crisis.

Finally, equations (15) and (16), conditional on $\mathrm{H}_{t|t-1}$, are all analytical expressions and thus no simulation-based methods are required. In particular, given $\mathrm{H}_{t|t-1}$ and $\Sigma_{t|t-1}$, the updating recursions for the parameters of the model are given by:

$$\theta_{t|t} = \theta_{t|t-1} + \Sigma_{t|t-1}\mathrm{Z}_t(\mathrm{H}_{t|t-1} + \mathrm{Z}_t\Sigma_{t|t-1}\mathrm{Z}_t^{'})^{-1}(y_t - \mathrm{Z}_t\theta_{t|t-1}) \tag{15}$$

and

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1}\mathrm{Z}_t(\mathrm{H}_{t|t-1} + \mathrm{Z}_t\Sigma_{t|t-1}\mathrm{Z}_t^{'})^{-1}\mathrm{Z}_t\Sigma_{t|t-1}. \tag{16}$$

Clearly different estimation approaches, based on Bayesian and maximum likelihood methods, can be applied. In principle, maximum likelihood estimation with the Kalman filter routine could be an alternative, see Durbin and Koopman (2001) for an introduction. However, the *on-line* method avoids the empirical drawbacks of standard likelihood methods such as multiple maxima, instability and lack of identification of the state vector parameters. Alternatively, in the Bayesian framework, an interesting approach has been proposed by Groen et al. (2012), who suggest to draw posteriors using an extension of the mixture sampling of Gerlach et al. (2000). This approach, although reliable, is computationally intensive and requires a proper choice of the priors. On the other hand the *on-line* estimation method allows for a fast updating of the parameters and does not require to select optimal priors for the initial states. The sequential method is also particularly appealing for real-time financial decisions, where the trader needs to update the parameters as new observations arrive. Indeed, the updating of the parameters only requires to run equations (12), (14), (15) and (16) once a new observation is available. This explains why this class of methods is often called *on-line*.

Appendix B: Figures and Tables

Sector	Ticker	Company
BANKING AND FINANCE	**AXP**	American Express
	BAC	Bank of America
	C	Citygroup
	GS	Goldman & Sachs
	JPM	JP Morgan
	MET	Met Life
	MS	Morgan Stanley
	WFC	Wells Fargo
OIL, GAS AND BASIC MATERIALS	**XOM**	Exxon
FOOD, BEVERAGE AND LEISURE	**MCD**	Mc Donalds
HEALTH CARE AND CHEMICAL	**PG**	Procter & Gamble
INDUSTRIAL GOODS	**BA**	Boeing
RETAIL AND TELECOMMUNICATIONS	**T**	AT&T
SERVICES	**GE**	General Electric
TECHNOLOGY	**IBM**	International Business Machines

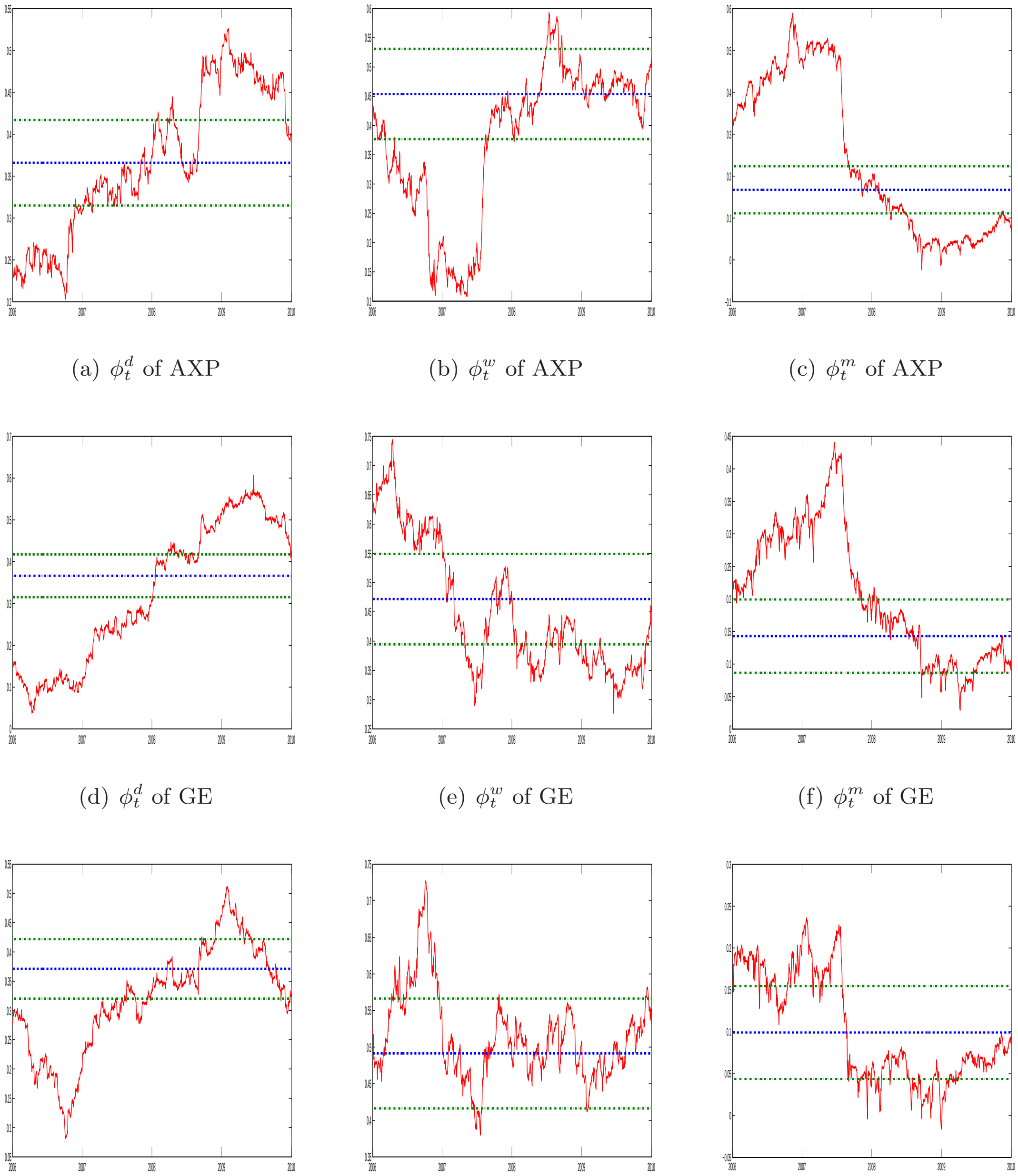
Table 1: Sector, Companies and Ticker

	ϕ_d					ϕ_w					ϕ_m				
	Min	Date	Max	Date	Range	Min	Date	Max	Date	Range	Min	Date	Max	Date	Range
AXP	0.2032	2006-10-06	0.5257	2009-02-06	0.3225	0.1086	2007-05-14	0.5927	2008-07-15	0.4841	-0.0233	2008-09-19	0.5877	2006-11-10	0.6110
BA	0.1803	2006-10-24	0.5349	2009-02-04	0.3546	0.2353	2009-10-16	0.5649	2006-02-21	0.3297	0.0201	2008-07-22	0.3670	2007-03-19	0.3469
BAC	0.2784	2006-04-12	0.6157	2008-09-16	0.3373	0.1002	2007-07-17	0.5047	2006-04-12	0.4045	-0.0062	2008-09-18	0.4213	2007-08-14	0.4275
C	0.2372	2006-08-08	0.6167	2009-05-13	0.3795	0.2150	2007-07-13	0.5233	2008-08-28	0.3083	-0.0099	2008-08-21	0.4054	2006-08-11	0.4153
GE	0.0390	2006-04-13	0.6064	2009-06-18	0.5674	0.2768	2009-06-18	0.7438	2006-04-18	0.4669	0.0298	2009-06-18	0.7438	2006-04-18	0.4669
GS	0.2681	2006-04-07	0.6321	2009-01-29	0.3640	0.2171	2007-03-21	0.5208	2007-12-10	0.3037	-0.0042	2008-09-18	0.3993	2006-05-11	0.4034
IBM	0.0819	2006-10-05	0.5109	2009-01-29	0.4290	0.3802	2007-07-23	0.7263	2006-10-05	0.3461	-0.0158	2008-12-31	0.2358	2007-01-26	0.2516
JPM	0.2409	2006-04-12	0.6948	2009-01-27	0.4539	0.1949	2007-06-26	0.5517	2008-07-15	0.3568	-0.0356	2008-09-19	0.3749	2007-06-21	0.4105
MCD	0.1139	2006-10-03	0.4275	2009-02-12	0.3136	0.2284	2006-05-10	0.5595	2008-12-30	0.3312	0.0104	2008-12-30	0.5100	2007-01-26	0.4996
MET	0.1804	2006-02-24	0.5533	2009-02-20	0.3729	0.2476	2007-03-20	0.6042	2007-12-10	0.3565	-0.0125	2008-09-19	0.4783	2007-06-04	0.4908
MS	0.2275	2006-12-26	0.6344	2009-01-27	0.4070	0.2544	2007-07-13	0.5187	2007-11-09	0.2643	-0.0091	2008-09-18	0.3781	2007-02-22	0.3872
PG	0.1071	2006-03-24	0.4004	2009-02-09	0.2933	0.2533	2007-03-20	0.6889	2006-03-24	0.4356	-0.0027	2008-07-28	0.3116	2007-07-16	0.3143
T	0.0261	2006-04-13	0.4263	2008-12-02	0.4002	0.3437	2007-03-15	0.7239	2006-02-21	0.3802	0.0133	2008-12-16	0.3321	2007-01-23	0.3188
WFC	0.0971	2006-04-17	0.5727	2009-01-26	0.4756	0.1045	2007-04-30	0.5725	2008-09-18	0.4680	-0.0108	2008-09-18	0.5363	2007-02-22	0.5471
XOM	0.2299	2006-10-11	0.5840	2009-01-15	0.3541	0.3220	2009-11-13	0.6519	2006-10-11	0.3299	-0.0460	2007-12-10	0.1068	2007-07-11	0.1528

Table 2: Summary statistics of the TV-HAR parameters. Table reports the minimum and the maximum of the observed values of the TV-HAR parameters with the corresponding dates. The column reports the range of variation of the parameters, calculated as $MAX - MIN$.

	RMSE^r	RMSE^u	$\log(PL)^r$	$\log(PL)^u$
AXP	**0.4763**	0.4786	**-421.9994**	-424.9833
BA	**0.5073**	0.5070	-468.7136	**-466.9602**
BAC	**0.5469**	0.5506	**-513.9557**	-516.8078
C	**0.6154**	0.6176	**-578.2686**	-580.6340
GE	**0.5578**	0.5613	**-525.0722**	-526.7052
GS	**0.4835**	0.4850	**-399.1553**	-399.1658
IBM	**0.4672**	0.4705	**-394.3845**	-394.5168
JPM	**0.4545**	0.4583	**-390.1873**	-394.0390
MCD	**0.5139**	0.5146	-452.3584	**-451.1535**
MET	**0.4948**	0.4961	**-450.8025**	-451.1418
MS	**0.5131**	0.5150	**-426.0185**	-427.4654
PG	**0.4987**	0.5006	-424.8467	**-422.7409**
T	**0.5157**	0.5161	-458.1966	**-456.0033**
WFC	**0.4888**	0.4912	**-430.6668**	-433.5275
XOM	**0.4394**	0.4407	-345.3549	**-344.0124**

Table 3: Out-of-sample forecast comparison. Table reports the RMSE and the log predictive likelihood ($\log(PL)$) for the model with (u) and without (r) the intercept. The out of sample period starts from August 1, 2007 to December 31, 2009.

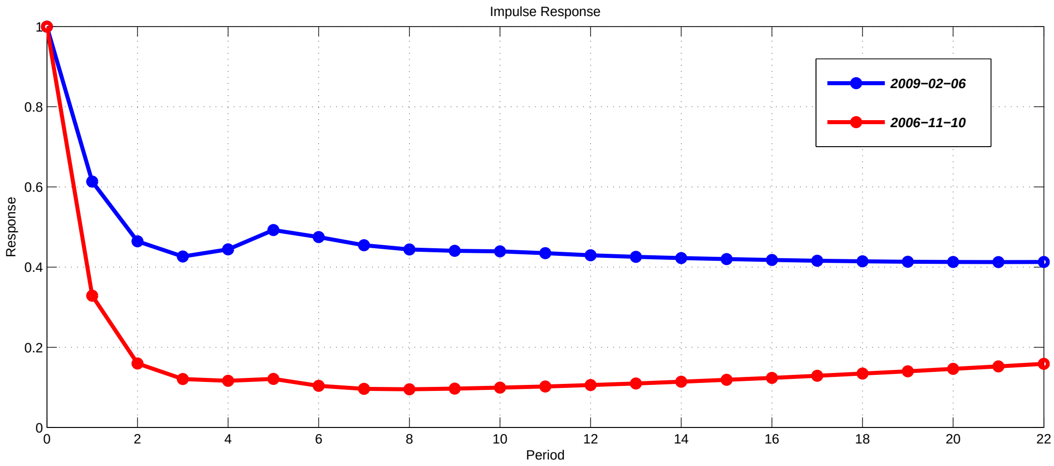


(a) ϕ_t^d of AXP (b) ϕ_t^w of AXP (c) ϕ_t^m of AXP

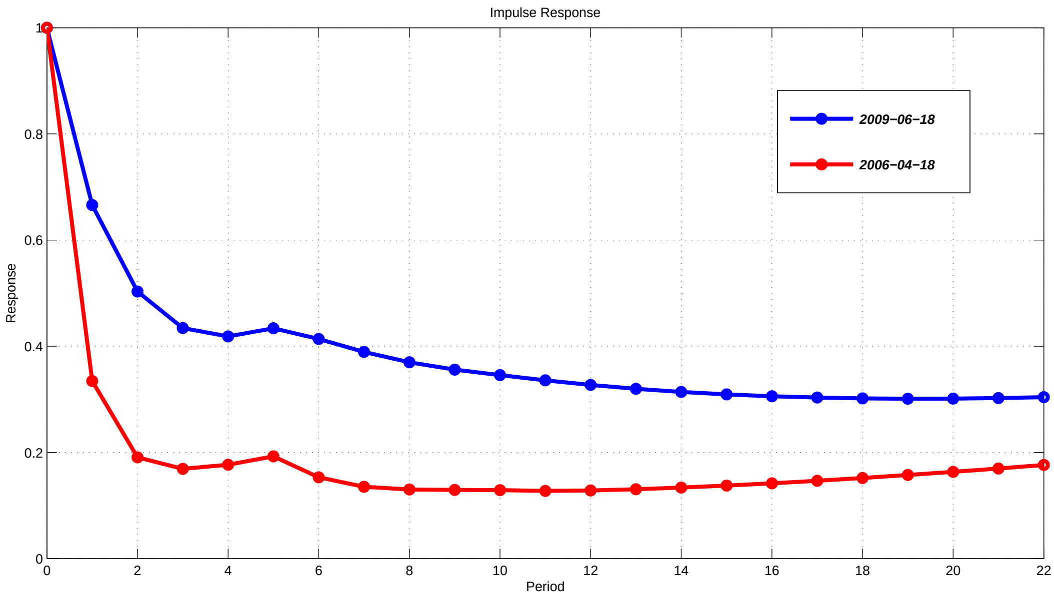
(d) ϕ_t^d of GE (e) ϕ_t^w of GE (f) ϕ_t^m of GE

(g) ϕ_t^d of IBM (h) ϕ_t^w of IBM (i) ϕ_t^m of IBM

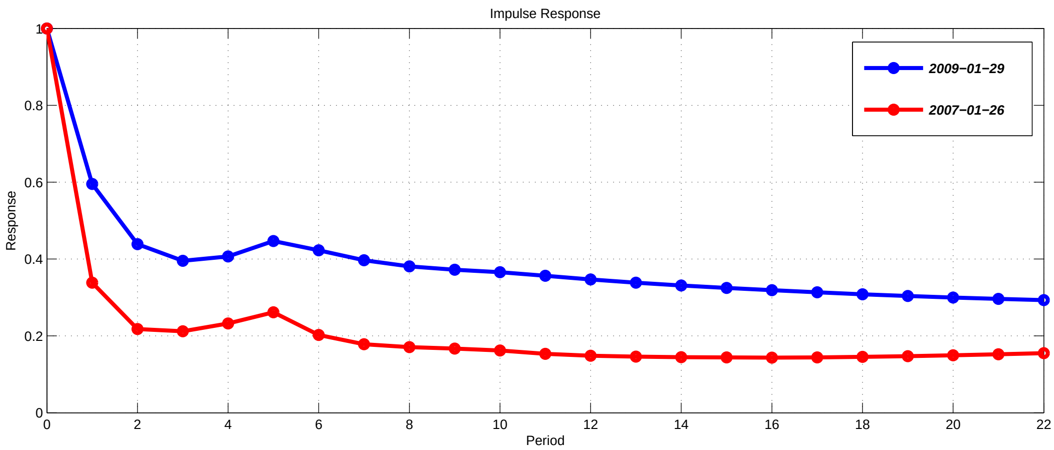
Figure 1: On-line estimates of the TV-HAR parameters, ϕ_t^d, ϕ_t^w and ϕ_t^w, of AXP, GE and IBM. The solid red line is the *on-line* estimate, while the blue dotted line is the OLS estimate based on the full sample. The dashed green lines correspond to the 90% confidence band.



(a) AXP

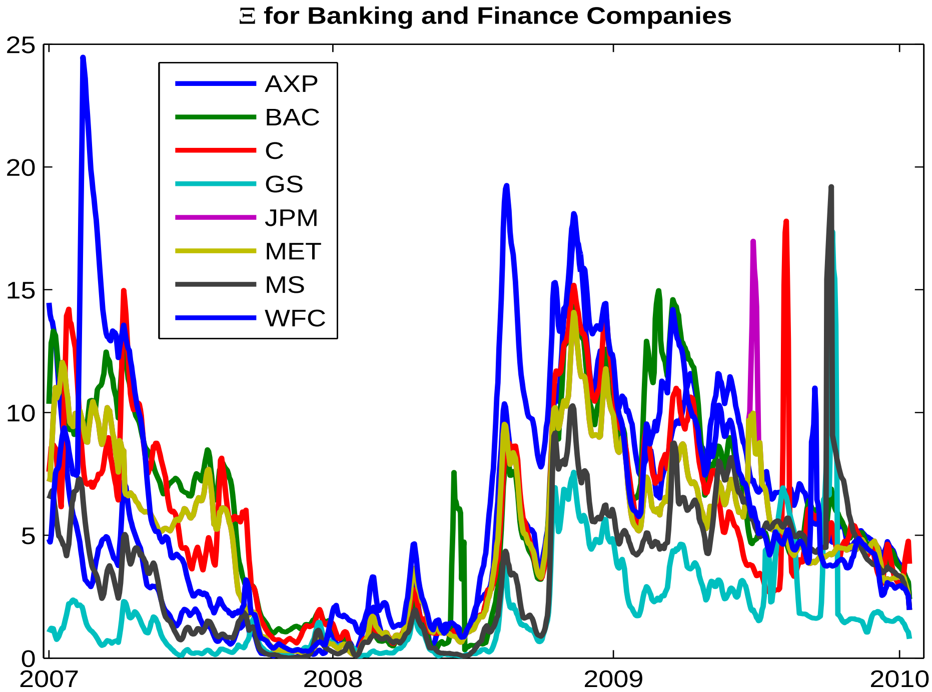


(b) GE

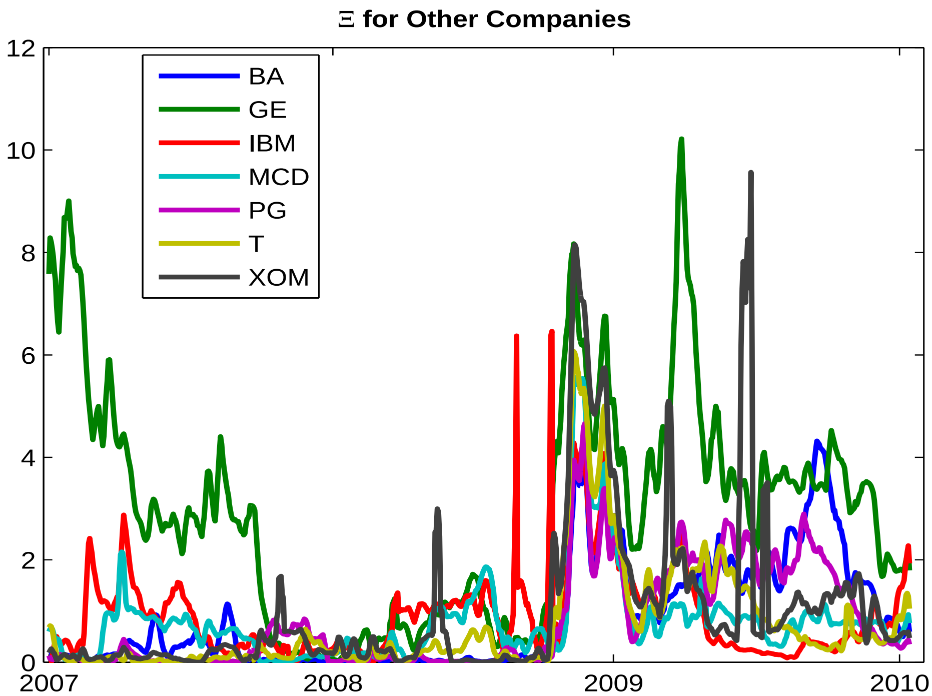


(c) IBM

Figure 2: Impulse response functions based on two different sets of parameters. The dates, t_1 and t_2, are chosen such that the difference $|\phi^d_{t_1} - \phi^d_{t_2}|$ is maximized, see Table 2.

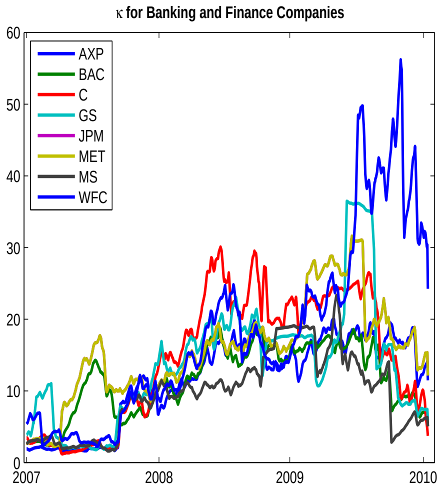


(a) Ξ_t: BANK SECTOR

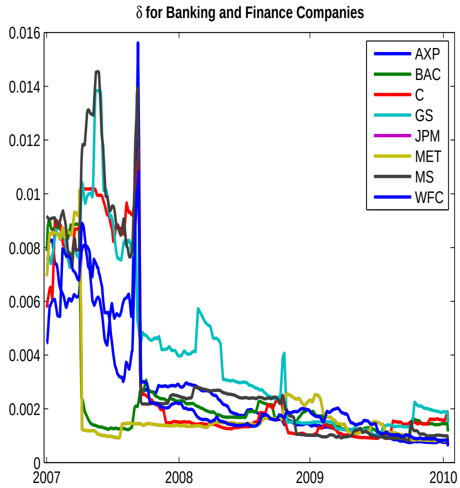


(b) Ξ_t: OTHERS

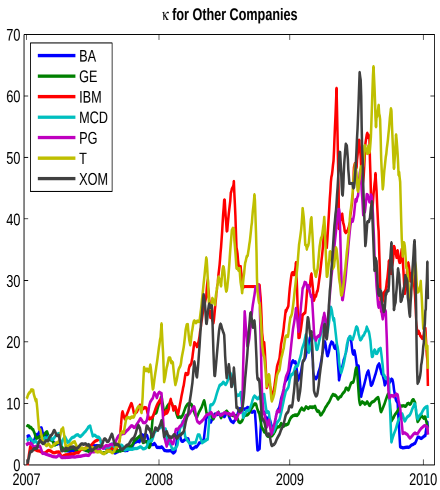
Figure 3: Ξ_t criterion for the two-factors model. Panel (a) reports Ξ_t for the stocks belonging to the bank-financial sector, while Panel (b) reports the Ξ_t distance for the stocks belonging to the other sectors of US economy.



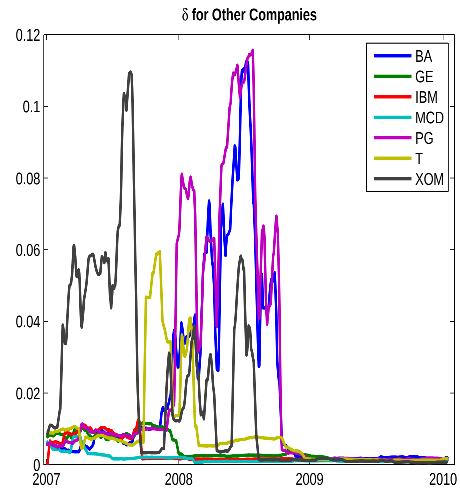
(a) κ: BANK SECTOR



(b) δ: BANK SECTOR

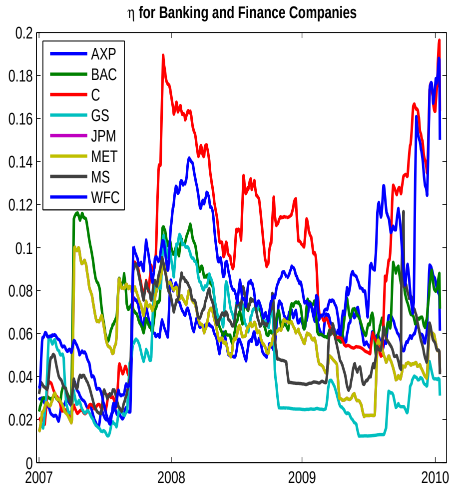


(c) κ: OTHERS

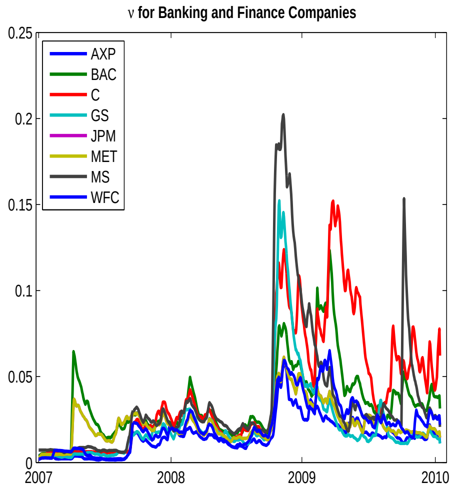


(d) δ: OTHERS

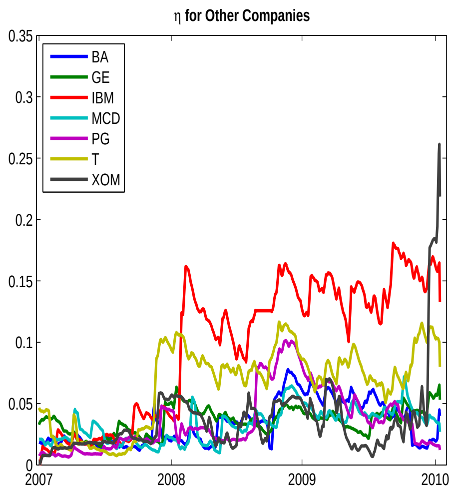
Figure 4: Estimated parameters κ and δ of the two-factors model. Panel (a) and (c) report the estimates of the parameter κ for the stocks belonging to the bank-financial sector and the other sectors of US economy respectively. Panel (b) and (d) report the estimates of the parameter δ for the stocks belonging to the bank-financial sector and the other sectors of US economy respectively.



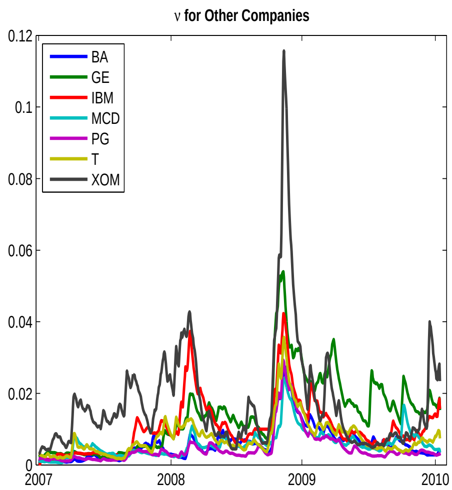
(a) η: BANK SECTOR



(b) ν: BANK SECTOR

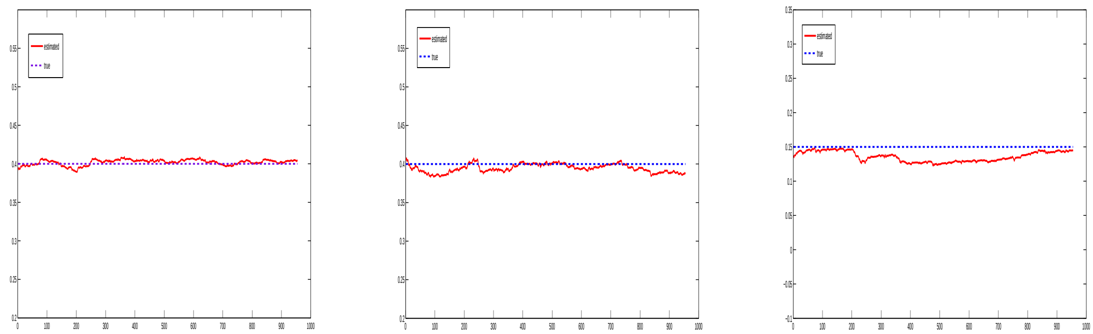


(c) η: OTHERS

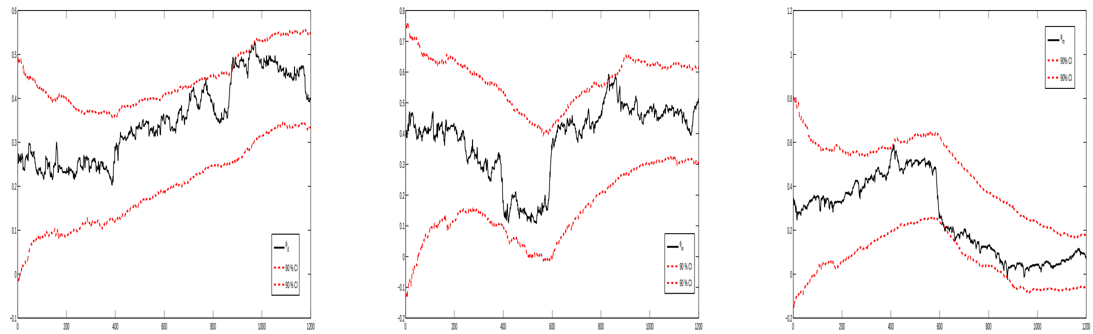


(d) ν: OTHERS

Figure 5: Estimated parameters ν and η of the two-factors model. Panel (a) and (c) report the estimates of the parameter η for the stocks belonging to the bank-financial sector and the other sectors of US economy respectively. Panel (b) and (d) report the estimates of the parameter ν for the stocks belonging to the bank-financial sector and the other sectors of US economy respectively.

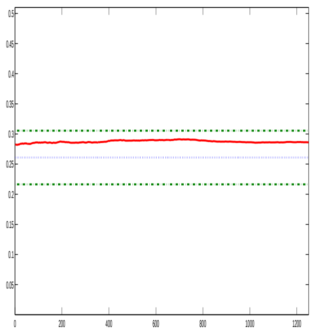


(a) ϕ^d (b) ϕ^w (c) ϕ^m

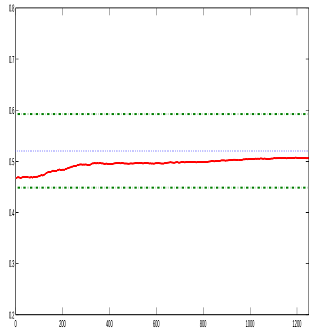


(d) ϕ^d_t with 90% CI (e) ϕ^w_t with 90% CI (f) ϕ^m_t with 90% CI

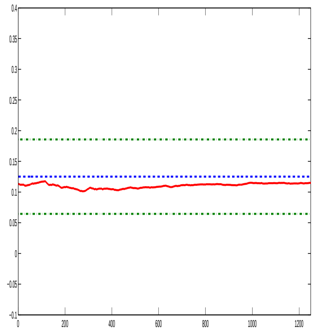
Figure 6: Estimates of the TV-HAR parameters with the *on-line* method. Panels a)-c) report the TV-HAR estimates when the DGP is a constant HAR model. The dashed blue line is the true parameter, while the solid red line is the *on-line* estimate. Panels d)-f) report the true parameter (solid black line), and the 90% Monte Carlo confidence band (dashed red lines) when the DGP is a TV-HAR with time-varying parameters.



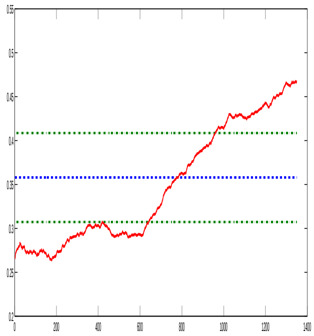
(a) ϕ_t^d estimates



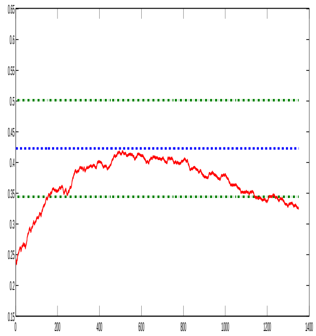
(b) ϕ_t^w estimates



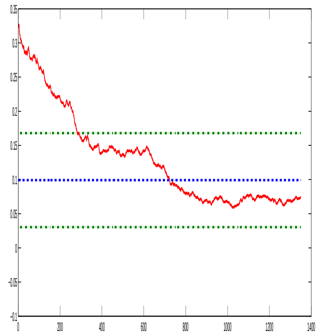
(c) ϕ_t^m estimates



(d) ϕ_t^d estimates



(e) ϕ_t^w estimates



(f) ϕ_t^m estimates

Figure 7: Estimates of the TV-HAR parameters with the *on-line* method. Panels a)-c) report the estimates of the TV-HAR parameters when the volatility series is generated from a TFSV model with constant parameters. The red solid line is the average for each $t \in [1 : T]$ of the *on-line* estimates, while the dotted blue line is the average of the OLS estimates based on the full sample. The green dashed lines correspond to the 90% confidence bands of the OLS estimates. Panels d)-f) report the estimates of the TV-HAR parameters when the RV is generated from a TFSV model with time-varying parameters. The red solid line is the average for each $t \in [1 : T]$ of the *on-line* estimates. The dotted blue line is the average of the OLS estimates based on the full sample, while the green dashed lines correspond to the 90% confidence bands of the OLS estimates..

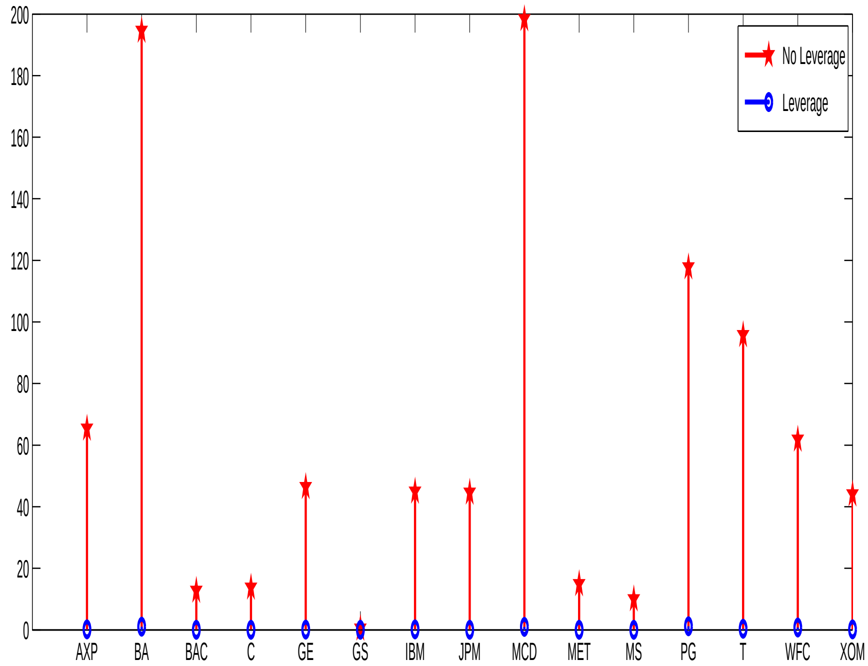


Figure 8: Determinants of the matrix $\Delta = \frac{\partial \Theta(\Psi)}{\partial \Psi}\Big|_{\hat{\Psi}}$ for the TFSV model with and without leverage, when the auxiliary models are the HAR-L and the HAR respectively. The blue dots represent the absolute value of the determinant of the matrix Δ for the TFSV model with leverage and HAR-L as auxiliary model. The red stars represent the absolute value of the determinant of the matrix Δ with the TFSV model without leverage effect and the baseline HAR model as auxiliary. The matrix Δ is obtained evaluating the partial derivative in correspondence of the estimates of the parameters obtained with OLS based on the full sample.