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Co-movements in Market Prices and Fundamentals: A Semiparametric Multivariate GARCH Approach

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Co-movements in Market Prices and Fundamentals :

A Semiparametric Multivariate GARCH Approach

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Abstract In this paper we investigate on Multivariate GARCH models to assess the co-movements between stock prices of american firms listed on main markets and fundamentals. Co-movements can be seen as correlations. The latter are usually estimated via standard GARCH models such as the Dynamic Conditional Correlation (Engle, 2002) or the Baba-Engle-Kraft-Kroner (Baba et al., 1990). Nevertheless more flexible models such as the Orthogonal GARCH of Alexander (2001) can be used as well. We also introduce a new Semi-parametric Orthogonal GARCH as a natural non-linear extension of the Orthogonal GARCH. A Montecarlo simulation is conducted to evaluate finite sample performance of each model before applying them to the data. Empirical results show evidence that during crises, prices are less correlated with fundamentals that in normal periods:

Keywords Non-parametric · Multivariate GARCH · DynamicCorrelation · PCA

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1 Motivations

Market prices are very complex time series. Relating them to corporate finance involves the modelling of agents' expectations and understandings. Starting from the theory, the market price of a company is determined by its ability to generate future profits. Their movements are driven by demand and supply, themselves being driven by economic activity. It means that investors are the fundamental cause of asset price changes. On the stock exchange they are remunerated by dividends, the profits of the company distributed to equity holders. But actual earnings of a firm can be reinvested in the firm instead of being redistributed, in order to make future profits and finally be distributed as dividends. The relation between expected profits and prices movements is highly complex and time plays a key role. Indeed a company that is not distributing dividends because of major investments can be expected to be highly profitable. Moreover psychological considerations can influence investors' decisions. This field, named Behavioral Finance, has been more recently developed (Kahneman and Tversky, 1979; De Long and Shleifer, 1991; Barberis et al., 1998; Daniel et al., 2001; Rubinstein, 2001) than corporate finance models on market prices. For a complete review see Barberis and Thaler (2003) or Huang et al. (2016).

Market prices have bad statistical properties as time series, they have unit roots and stochastic trends (Fama and Malkiel, 1970). Because of that but also, because there are too many factors driving their changes it should not be possible to measure quantatively any effect from fundamentals. At least this is true for the first moment of prices, but maybe we can observe something in the second moment. For some periods we may observe that if fundamentals are getting higher then market prices also and vice versa, this would imply that they are positively correlated. We can call this relation a co-movement.

From finance theory we should observe a positive correlation, and from behavioral finance we expect it to vary over time. There may exist some events or news where fundamentals are less taken into account.

Co-movements are often estimated as dynamic correlations (Kearney and Potì, 2006; Lebo and Box-Steffensmeier, 2008; Yiu et al., 2010) in finance but also in other fields. In the case of market prices and fundamentals it has never been used, only dynamic correlations between assets in order to manage risks can be found in the literature. Regression analysis is often prefered (Jindrichovska, 2001; Jatoi et al., 2014) even for time variations (Ebrahimi and Chadegani, 2011) but we do not expect any effect in the first moment so this method is not suitable. The main models to estimate these co-movements are the well-known Multivariate Volatility Models and more specifically the Multivariate Generalized AutoRegressive Conditional Heteroskedasticity models (M-GARCH).

In this paper, more than using a different method on very recent data to answer the problem in a new fashion, we will also introduce a new estimator for dynamic correlations. Because many assumptions come into play when modelling time series, we will relax some of them by improving an existing class of M-GARCH with non-parametric methods to build a semi-parametric M-GARCH. It allows for more general specification of unpredictable shocks on prices but also for non-linear interactions through time.

In order to illustrate the problem a simulation is conducted under many different assumptions. Results suggest that it will be better suited than the parametric M-GARCH in our specific analysis. Three models are applied to the data. The first one is fully parametric: BEKK-GARCH of Engle (1995).This model is the multivariate extension of univariate GARCH models. One major problem in Econometrics is the so called Curse of Dimensionality: this happens when the number of parameters to be estimated in the model is exponentially increasing with the dimension of the problem. This issue arises in the BEKK because parameters are matrices of sizes of the number of series. If one tries to model the correlations between 2 assets then there are two matrices of size 2×2 and a upper triangular matrix of constants 2×2 but with only 3 parameters which make in the end 11 parameters. But if one wants to estimate it with 10 series then there are 255 parameters to estimate. There are 5 times more series but 23 times more parameters Such a thing can be avoided in two ways. The first one is to keep the BEKK model but to restrict the matrices of parameters such that it has a lower number of parameters, but it is still exponentially increasing, just in a slower way. The other method is to change the framework and subset the multivariate problem into univariate problems, and this is achieved by the eigendecomposition offered in the other models. The second model is parametric but relies on the assumption that there exist some factors driving the whole volatility of the observables: Orthogonal-GARCH of Alexander (2001). This assumption allows to decompose the multivariate covariance matrix into univariate variances. However it still estimates variances from parametric univariate GARCH models. The curse of dimensionality is avoided since the number of parameters is now linear in the number of series, not exponential. This allows the O-GARCH to be more flexible because there are less parameters but decomposed and then recomposed, creating a quite complex mixture in the model. This is convenient, but it could be even more flexible with very little changes. The last model is our new semi-parametric counterpart of the second: Semi-Parametric Orthogonal GARCH. It introduces non-linear volatility functions. Instead of using parametric models as in the O-GARCH we rely on a non-parametric procedure described in Bühlmann and McNeil (2002) to estimate univariate volatilities. This results in a very complex combination of non-linearities through the eigenvalue decomposition. It should allow this model to better capture fast changing correlations and to work in more general frameworks.

2 Model the Co-Movements

Co-movements are modelled in most studies as time varying correlations (Kearney and Potì, 2006; Lebo and Box-Steffensmeier, 2008; Yiu et al., 2010). The latter can be measured by Multivariate GARCH models. They assume that

the variables of interest move stochastically but still relate somehow, not in the first moment (the mean) but in the second (the variance). These facts are modelled by specific dynamics: movements of variables are impacted by random shocks Z_t and by their dynamic covariance matrix H_t. This allows variables to move according to some unkown and unpredictable process (in mean) but still have some related components. Shocks (or noise) may be distributed accorded to any distribution. Most M-GARCH models assume they are independently and identically distributed Gaussian innovations.
The specification for the Multivariate GARCH is:

$$r_t = H_t^{-1/2} Z_t, \tag{1}$$

$$Z_t | \Omega_{t-1} \sim Normal(0, I), \tag{2}$$

$$\mathbf{E}_{t-1}[r_t r_t'] = H_t, \tag{3}$$

$$R_t = D_t^{-1/2} H_t D_t^{-1/2}, \tag{4}$$

where r is the matrix of returns, Ω_{t-1} the set of all available information at the previous period, Z is a multivariate noise and H is the conditional covariance matrix of variables, D is the diagonal matrix of standard deviations and R is the correlation matrix at time t.

2.1 BEKK

There exist a lot of M-GARCH specifications, within the parametric ones the BEKK-M-GARCH model is very popular. It was developed by Baba et al. (1990). The modelling lies in the parameterization of the dynamics in the conditional variance covariance matrix H_t:

$$H_t = CC' + \sum_{k=1}^{K} \sum_{i=1}^{q} A_{i,k} \varepsilon_{t-i} \varepsilon_{t-i}' A_{i,k}' + \sum_{k=1}^{K} \sum_{i=1}^{p} B_{i,k} H_{t-i} B_{i,k}', \tag{5}$$

where C is the constant lower triangular matrix, A is the ARCH-effect coefficient matrix containing the shock impact and B the GARCH-effect coefficient matrix measuring the volatility persistence. Different parameterization of the matrices A and B have been proposed. One of the most popular is the diagonal-BEKK where the matrices are diagonal, cross-effects are constrained to zero, which is obviously not suitable for our study. Another one is the scalar-BEKK where the matrices are replaced by a single coefficient on the diagonal so cross-effects are removed, but also all variable share the same parameter which is even more restrictive. In our case we are interested in correlations and how the accounting variables affect the returns, therefore the BEKK will be estimated with full parameter matrices.

2.2 Orthogonal Garch

The literature is still focused on multivariate GARCH and is seeking for a new parameterization. The Orthogonal MGARCH of Alexander (2001) is a variant of this model, replicating the matrices R_t and H_t using Principal Component Analysis (Pearson, 1901). The variance-covariance matrix, contrary to the previous method, is first estimated individually and then decomposed into orthogonal factors. This method allows to decompose the multivariate problem into univariate problems. This is much less computationally expensive because there are less parameters to estimate, this is the reason why it has become quite popular.

$$V_t = diag(\sigma^2_{t,1}, \ldots, \sigma^2_{t,K}), \tag{6}$$

where $\sigma^2_{t,i}$ are empirical variances, fitted with individual GARCH models. The standardized returns are:

$$u_t = V_t^{1/2} \varepsilon_t, \tag{7}$$

with the properties: $\mathbf{E}[u_t] = 0$ and $\mathbf{E}[u_t u_{t'}] = C$.
The unconditional correlation matrix C can be decomposed as

$$C = P \Lambda P', \tag{8}$$

with P the orthogonal eigenvectors matrix and Λ the matrix of ranked eigenvalues in descending order.
Let's define $L = P\Lambda^{1/2}$, then $R = P\Lambda^{1/2}\Lambda^{1/2}P' = LL'$ and we can write the principal components as:

$$F_t = L^{-1} u_t, \tag{9}$$

if we assume the covariance matrix of principal components $\mathbf{E}_{t-1}[F_t F_t] = Q_t$ to be diagonal:

$$Q_t = diag(\sigma^2_{t,F_1}, \ldots, \sigma^2_{t,F_K}). \tag{10}$$

These variances can be estimated individually using GARCH models. And so $\mathbf{E}_{t-1}[u_t u_{t'}] = LQ_tL'$ and:

$$H_t = \mathbf{E}_{t-1}[\varepsilon_t \varepsilon_{t'}] = V_t^{1/2} L Q_t L' V_t^{1/2}. \tag{11}$$

2.2.1 Parametric

In the standard O-GARCH, individual variances for both observables and components are estimated under the usual parametric GARCH(1,1) process. It is defined as:

$$\varepsilon_t = \sigma_t Z_t \tag{12}$$

$$\sigma_t^2 = \gamma + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1} \tag{13}$$

The parameters are usually estimated via Maximum Likelihood under the assumptions that shocks Z_t are normally distributed.

2.2.2 Semi-parametric

The standard specification of individual variances in the O-GARCH may somewhat restrict the flexibility of the model. Introducing non-linear variances can be seen as a natural extension with very few differences. Indeed since we are working with a eigen decomposition, all variances to be estimated are univariate problems. To the best of our knowledge this model has never been defined or used in the literature before, but it has very low differences with the previous model. A non-linear garch model can be described as (12) where:

$$\sigma_t^2 = f(\varepsilon_{t-1}, \sigma_{t-1}^2). \tag{14}$$

The unknown functional form f is fitted by a recursive procedure described in Bühlmann and McNeil (2002) First a parametric GARCH is fitted to get a first estimate of σ_t^2 then a non-parametric procedure, which here is a local-linear regression, is used to estimate f by regressing ε_t^2 against σ_{t-1}^2 and ε_{t-1}. This procedure is repeated until a stopping criteria is met and the final result is the average of the few lasts estimates of the repetition. No major assumptions are made on the distribution of Z_t nor on the functional form of $f(.)$. They only have zero mean, finite variance and fourth moment existence, also $f(.)$ has to be continuous.

The model is said to be semi-parametric because univariate variances are estimated non-parametrically but the eigen decomposition is fully parametric and linear. The Principal Component Analysis method used assumes a linear decomposition of the multivariate problem. The Principal Components are linear combinations of individual variances.

3 Simulation

To check the finite sample performance of our estimator, a bivariate process is simulated, estimated and evaluated by Montecarlo techniques.

The simulation is made under several assumptions about shocks distribution and linkage functions. The returns follow a multivariate GARCH process:

$$r_t = H_t^{-1/2} Z_t, \tag{15}$$

$$H_t = D_t^{1/2} R_t D_t^{1/2}. \tag{16}$$

The variances of each series follow either a standard GARCH or a non-linear GARCH process following the simulation design in Bühlmann and McNeil (2002):

$$D_{i,i,t} = h_{i,i,t} = 0.01 + 0.2 r_{i,t}^2 + 0.75 h_{i,i,t-1}, \tag{17}$$

$$D_{i,i,t} = h_{i,i,t} = 0.8 r_{i,t-1} + \exp(-0.2 \left| r_{i,t-1} \right| h_{i,i,t-1})(5 + 0.2 r_{i,t-1}^2). \tag{18}$$

Shocks are either distributed as Gaussian or as Student with 5 degrees of freedom, such that they have some extreme values (fat tails). This is equivalent as simulating a situation which has same type of shocks all the time, and another with severe shocks in some rare periods:

$$Z_t|\Omega_{t-1} \sim Normal(0,1), \tag{19}$$

$$Z_t|\Omega_{t-1} \sim Student(5). \tag{20}$$

The correlation matrix is changing over time following a dynamic that is not specific to each of the models, this in order not to give advantage to any of them. The first is time varying and the second is constant and equal to zero. This is in order to check if the models capture a quite strong effect evolving through time not too fast nor too slow, but also if they can detect a constant correlation and if there is none. The processes are the following:

$$R_t = -0.7\sin(10\frac{t}{T}), \tag{21}$$

$$R_t = 0. \tag{22}$$

Simulated process is repeated 1000 times. Because the sample of the study has a limited number of observations, we test it on different sample sizes. We have 20 years of quarterly data, this means 80 observations. Fundamentals are not reported by companies more often. Other sizes are taken into consideration. If we had monthly data over 20 years this would have been 240 observations, and 960 if we had weekly data.
The mean squared error metric is used as performance measure and is defined as:

$$MSE = \sum_{t=1}^{T}\left(\widehat{R}_t - R_t\right)^2 \tag{23}$$

As a benchmark, we take the Pearson correlation coefficient. In case of the dynamic correlation it will be the worst possible estimator, in the case of constant correlation it will be the best possible estimator. If the models we used are good estimators they should have low MSE. When there is a dynamic correlation they should have much lower MSE than the Pearson estimator, otherwise they should be close to it. MSE accross each repetitions are given in Table 1.

- INSERT TABLE 1 HERE -

From Table 1 all models were able to detect the correlation more or less correctly. Among all cases the best estimator is always the SP-O-GARCH. Surprisingly it seems that the O-GARCH is not doing so bad, especially in large sample where it is close to SP-O-GARCH even if there was non-linearities involved and non-gaussian shocks.
Relative to the Benchmark the O-GARCH and SP-O-GARCH are performing well in large but also in small samples. With good assumptions the BEKK has also strong results but the parametrization allows too much variance in the correlation dynamics. Remember that all models are assuming that the dynamic

correlation is a time series, therefore it cannot be as smooth as what is simulated. But because the dynamics over this time series are much restricted in BEKK, its MSE is higher. This metrics penalizes more very volatile estimates around the true value.

Anyway this suggests that in a more general framework (with no gaussian innovations and non-linear functional forms) the O-GARCH and SP-O-GARCH may perform better than BEKK, whatever the correlation process (constant or not).

4 Application

4.1 Dataset

The database comes from stockpup.com who freely offers quarterly regularized data of 734 U.S. securities. Databases are individual reports of companies. These are very recent data, going from 30 Sept. 1993 to 30 Sept. 2016. The variables we will focus on are listed and described below:
Revenue - Total revenue for a given quarter.
Earnings - Earnings or Net Income for a given quarter.
EPS - Basic earnings per share for a given quarter.
Dividend per share - Common stock dividends paid during a quarter per share.
Price - The medium price per share of the company common stock during a given quarter.
ROE - Return on equity is the ratio of Earnings (available to common stockholders).
ROA - Return on assets is the ratio of total Earnings to average Assets.
Price to Book ratio - The ratio of Price to Book value of equity per share as of the previous quarter.
Price Earnings ratio - The ratio of Price to EPS diluted as of the previous quarter.
We provide some simple statistics of the most important variables to describe the database in Table 2.

- INSERT TABLE 2 HERE -

As we can see through Table 2, there is a strong heterogeneity in firms. There are big firms with billions of shares and smaller ones with millions. Some are performing well, with very high earnings but other experienced huge losses, but in average all firms are making profits. Return on Asset and Return on Equity show that profitability can be very different depending on the measure used. Short term investors may only care about dividends and ROE, but the profitability adjusted for the risk (ROA) points out there is less performance, indicating most firms are leveraged. PER and Price to Book distributions also provide information on the valuation of the firm on the market. We can see strongly over-valued companies, the maximum PER is in billions, but the distribution has high kurtosis (fat tails), only few companies have extreme PER.

Net Margins are heavily skewed, this is due to the fact that only positive margins are reported.
For analysis purposes the dataset will be merged by sectors, weighting each variable by the relative market capitalisation of each firm in each quarter. The merged results are reported in Table 3.

- INSERT TABLE 3 HERE -

In the end because of missing data only 405 companies are retained. The most important sector is Consumer Services. Therefore the conclusion drawn from greater sectors will be more general while those from smaller sectors will be more firm specific. We expect bigger groups to give more interpretable results because statistical behavior is usually observable at the population level rather than at the individual level.

4.2 Results

Co-movements can now be estimated and compared among each model. The dynamics are very interesting and have fairly intuitive interpretation. However results seem to be very sector specific, there is no general conclusion we can state for one variable in particular. Obviously there are 12 sectors and 10 variables so there is a lot to analyze. We will only focus on the most interesting estimates in terms of model comparison and of economic interpretation. Let's start with the Consumer Services ROE correlation estimates.

- INSERT FIGURE 1 HERE -

Figure 1 suggests a strong shift in correlation over some periods. We recall that Consumer Services is the greatest sector in terms of number of firms in our dataset. For companies in that sector it means that Return on Equity is of importance for asset pricing, and that investors pay attention to it, at least in normal periods. We see that up to 2000 the correlation is estimated between 0.5 and 1 depending on the model, meaning a strong positive correlation, as it was expected. However during 2000 up to 2003 correlation sharply decreased, this fact may be due to the 2001 crisis and the explosion of the Internet Bubble. During this event, and for several months after ROE became less correlated with market prices. This phenomenon lasted until 2004 according to the BEKK but earlier for the two others. Correlation came back faster to its previous value in O-GARCH and SP-O-GARCH. For the SP-O-GARCH it seems that it not only came back but also a little bit higher than previously, which is not observed in the parametric models. Then in 2007, just before the 2008 crisis, this fundamental became once again decorrelated. This time it even goes negative, something that is very counter-intuitive from an economic point of view. It means that investors were mispricing assets, in terms of what the theory expect from them. This peak can be viewed as a signal to the crisis. We measured that prices were going the other way with respect to firms' performance, the market is not considering only economic activity of firms as it should and so deviates from equilibrium. This time recovery in correlation is

faster in every model, around 2009. At that time another event started in the market but with different effects depending on the model. O-GARCH suggests a little decorrelation while BEKK exhibits strong and fast shifts. The SP-O-GARCH has the same magnitude but goes smoothly. After that things gets back to what we can call a normal period up to now.
An interesting thing is that this effect is also measured for Return on Equity for the sector of Capital Goods.

- INSERT FIGURE 2 HERE -

Figure 2 shows the dynamic correlation estimates in this sector. The same conclusion can be drawn, periods of decorrelation are barely the same. The interpretation may change because during the abnormal periods correlation did not go merely zero but near to -1. However in the SP-O-GARCH it tends to be more around -0.5 than -1, this is more realistic from an economic point of view.
For some variables in some sectors correlation appears to change significantly over time. But it may be possible that it is not the case for all variables in all sectors, there may be some constant correlation or even no correlation. These static co-movements should be also well measured by our dynamic correlation models. From simulation we have highlighted the fact that in small samples the BEKK tends to behave erraticaly. It has too much variance around the true correlation, its average mean squared error was about 0.08 or 0.12 when the other perfomed 4 times better. This implies that correlation estimates seem to move over time while in fact the relationship is constant. Such a thing has been probably observed in several cases. One of them is in the sector of Transportation with respect to the earnings of firms.

- INSERT FIGURE 3 HERE -

Figure 3 shows that according to the BEKK co-movements are fast changing. Correlation fluctuates between 0.2 and 0.7 almost every quarter. In the two other models correlation is estimated to be constant around 0.5 over the whole sample. Such a thing happens because of the constrained parametric structure in BEKK. Fully parametric models are not robust to heavy tailed shocks or non-linear dynamics, they are less flexible. Surprisingly the O-GARCH seems not subject to this problem in this example, we recall that it performed quite well in simulation in the same case. However it also sometimes has some drawbacks.
Another example of this phenomenon can be observed in the sector of Technology with respect to Dividend per Share:

- INSERT FIGURE 4 HERE -

In Figure 4 according to the SP-O-GARCH it is fairly easy to conclude that there is no co-movements anywhere in time, dynamic correlation is around zero. In the BEKK again correlation moves pretty fast in a high range. O-GARCH suggests the same as SP-O-GARCH but its estimate does not look like an estimated time series. In fact these are true zeros all the way. This is because when there is no correlation O-GARCH may estimate the eigen composition such that there is no common factor to individual variances. This has been observed during the simulation and is not a surprising behavior of

Table 1 Dynamic Correlation Models Performance

R_t	N.Obs	Residuals	Garch	BEKK	O-GARCH	SP-O-GARCH	Pearson
0	80	$Normal(0,1)$	Linear	0.08	0.02	0.01	0.00
0	240	$Normal(0,1)$	Linear	0.02	0.004	0.004	0.00
0	960	$Normal(0,1)$	Linear	0.01	0.001	0.001	0.00
0	80	$Student(5)$	Non-linear	0.12	0.03	0.02	0.00
0	240	$Student(5)$	Non-linear	0.06	0.02	0.02	0.00
0	960	$Student(5)$	Non-linear	0.05	0.01	0.01	0.00
$-0.7\sin(10\frac{t}{T})$	80	$Normal(0,1)$	Linear	0.18	0.12	0.11	0.22
$-0.7\sin(10\frac{t}{T})$	240	$Normal(0,1)$	Linear	0.15	0.11	0.09	0.22
$-0.7\sin(10\frac{t}{T})$	960	$Normal(0,1)$	Linear	0.07	0.05	0.04	0.22
$-0.7\sin(10\frac{t}{T})$	80	$Student(5)$	Non-linear	0.20	0.14	0.13	0.22
$-0.7\sin(10\frac{t}{T})$	240	$Student(5)$	Non-linear	0.14	0.12	0.11	0.22
$-0.7\sin(10\frac{t}{T})$	960	$Student(5)$	Non-linear	0.12	0.05	0.04	0.22

the model. However in the case that correlation would have had some non-zero value at some point in time, the O-GARCH would have encounetered issues in estimating it. It is not as flexible as our new model. This does not happen when we let individual variances in the beginning being non-linear.

5 Discussion

Our results suggest that estimated co-movements between accounting variables and markets returns are varying through time and seemingly according to some crash events. This was found using the multivariate GARCH analysis with some studies (Ebrahimi and Chadegani, 2011). Accounting variables are less taken into account during crisis periods, this is supportive for theories of behavioral finance. Market prices may be formed with other considerations. The panel dataset has allowed for a deeper analysis accross sectors. The results suggest that co-movements between fundamentals and market prices are sector dependent. Depending on the activity of the companies investors may be looking at different fundamentals. Because of many reasons the sample is small and therefore there might be some selection bias. Same analysis should be performed on another dataset to validate empirical findings of the study. The list of companies can be extended but also the number of periods. Also the study omits a lot of variables which are either non observable or out of sync with fundamentals. Not controlling for these effects may change the magnitude of estimated correlation.

Moreover the paper introduced a new Multivariate GARCH model and finite sample performance were tested on simuation with great results. Its robusteness to non-gaussian shocks and non-linear time relationships allows for more flexibility and more realistic situations. This model should be investigated more deeply as an extension to the Orthogonal GARCH.

Table 2 Descriptive Statistics

	Moments		Extremes		Quantiles		
	Mean	St.Dev.	Min	Max	1st Q.	Median	3rd Q.
Shares	$4.5e8$	$1e9$	$2e6$	$3e10$	$8e7$	$1.6e9$	$4e9$
Earnings	$2.3e8$	$9e8$	$-6e10$	$2e10$	$2e7$	$7e8$	$2e9$
Market price	37.39	67.18	0.05	1938.2	14.38	26.11	43.26
ROE	0.15	0.18	−0.99	1.19	0.08	0.15	0.22
ROA	0.06	0.10	−4.09	0.75	0.02	0.05	0.10
Price/Book	4.28	17.42	0.00	2232.00	1.77	2.78	4.45
PER	$5e15$	$8.8e16$	0.01	$5e8$	12.84	18.22	26.85
Net Margin	0.11	0.12	0.00	3.62	0.04	0.08	0.14

Table 3 Sector List

Sector	Number of Companies
Finance	43
Basic Industries	22
Technology	46
Health Care	44
Energy	28
Consumer Services	64
Capital Goods	39
Consumer Non-Durables	34
Miscellaneous	4
Public Utilities	23
Consumer Durables	13
Transportation	11

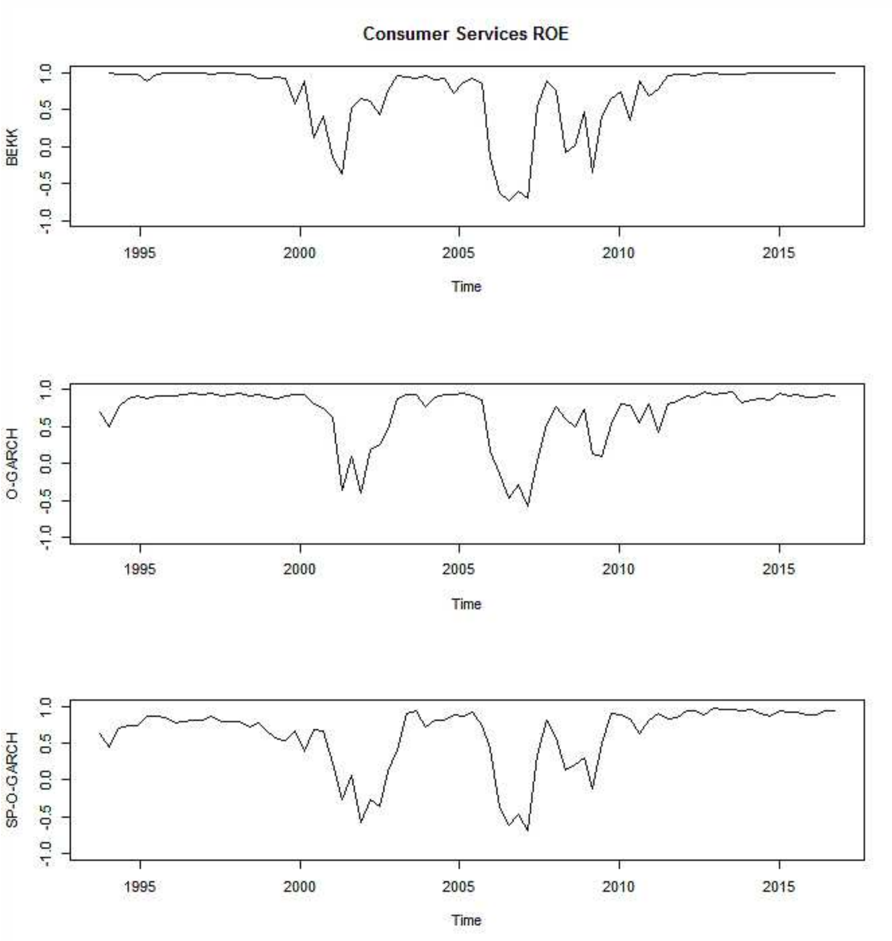

Fig. 1 Dynamic Correlation Estimates $\widehat{R}_t$: Consumer Services ROE over 1993-2016

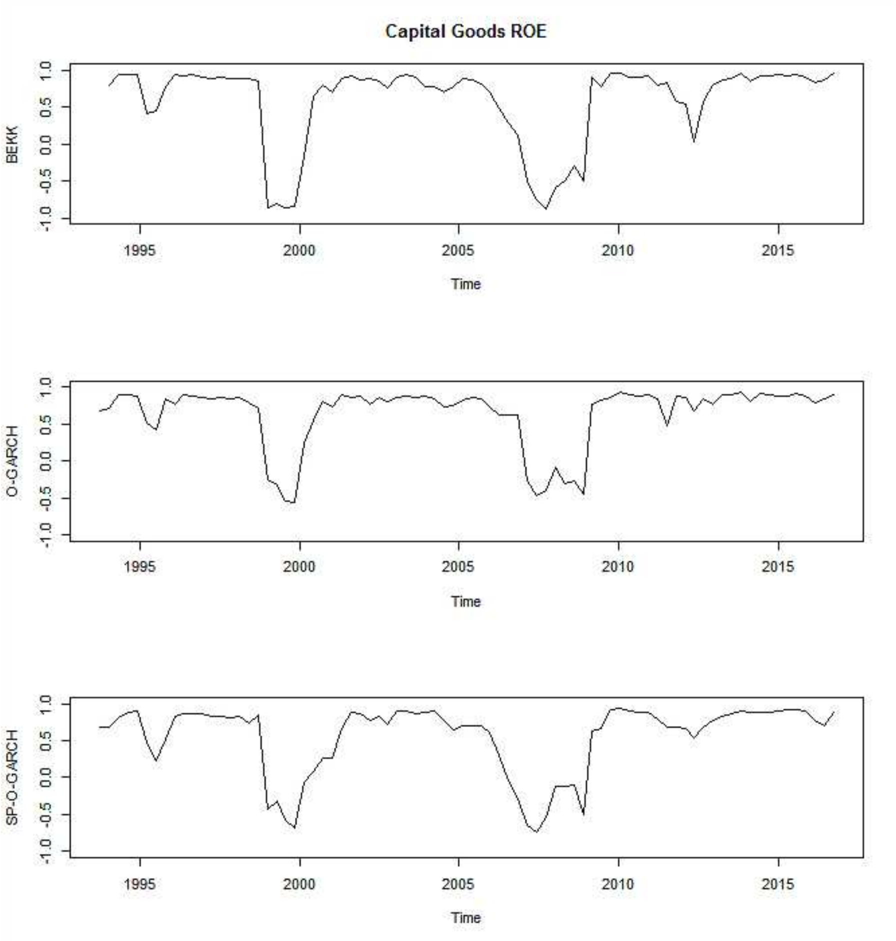

Fig. 2 Dynamic Correlation Estimates $\widehat{R}_t$: Capital Goods ROE over 1993-2016

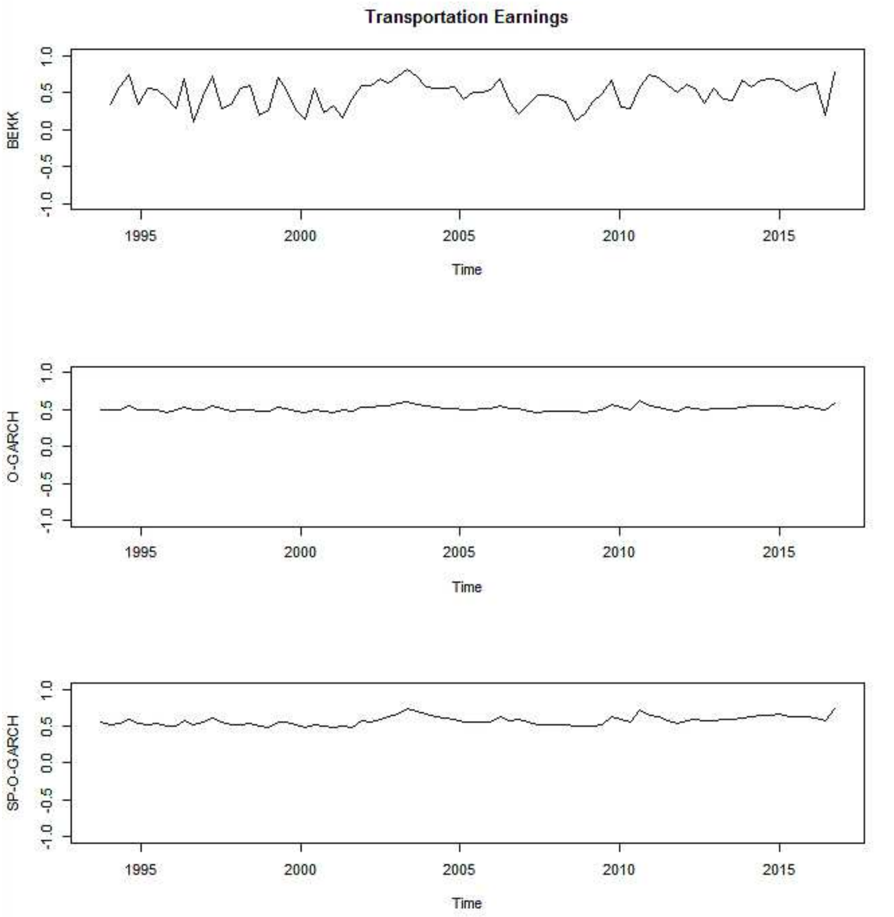

Fig. 3 Dynamic Correlation Estimates $\widehat{R}_t$: Transportation Earnings over 1993-2016

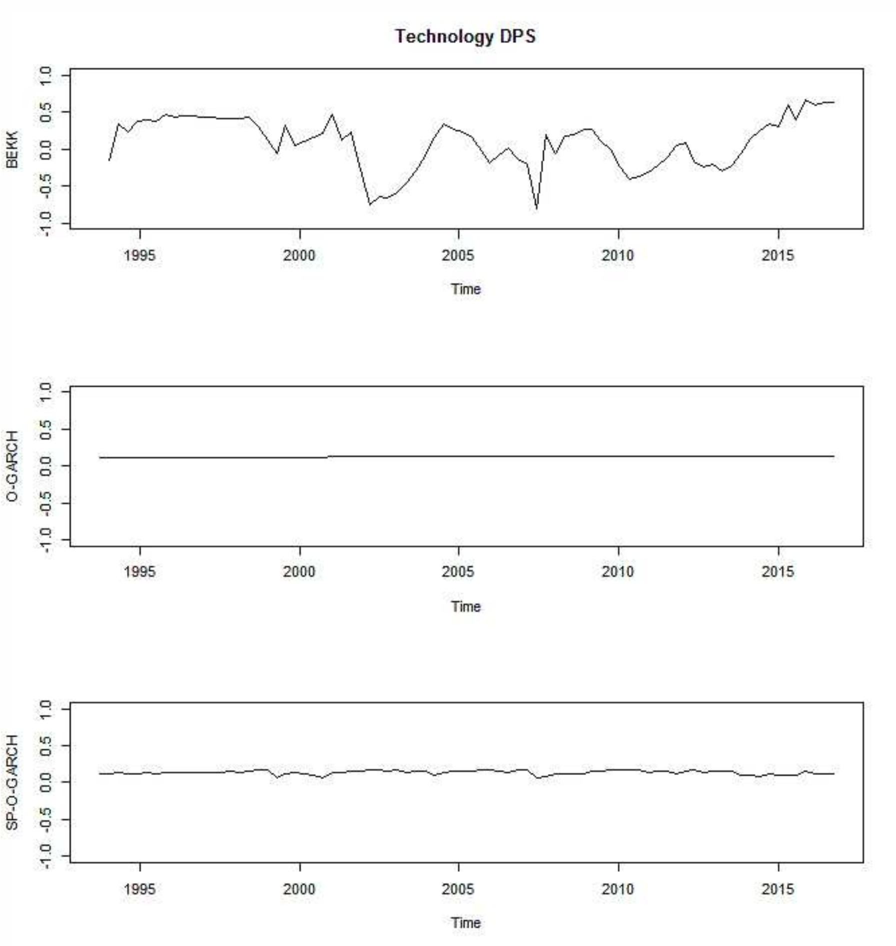

Fig. 4 Dynamic Correlation Estimates $\widehat{R}_t$: Technology DPS over 1993-2016

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