The use of correlation networks in parametric portfolio policies*

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ABSTRACT

Correlation networks reveal a rich picture of market risk structure dynamics. A rather compact and well-organized sector correlation network is indicative of a healthy market, whereas a widely spread sector correlation network characterizes a more fragile market environment. Intuitively, some characteristics of the correlation network can serve as natural measures of systemic risk. Pursuing an equity market timing strategy we document the predictive content of these measures to translate into a meaningful portfolio utility. Moreover, this result continues to hold when controlling for common predictors of the equity risk premium. Not only can correlation networks be useful as an aggregate market timing signal but also in navigating the cross-section of equity sectors. We especially document a significant outperformance of peripheral versus central equity sectors that cannot be explained by momentum or low volatility effects. Finally, we implement a parametric portfolio policy that comprises the complete information content of the sector network topology conditional on a given level of risk aversion.

Keywords: Correlation Networks, Parametric Portfolio Policies, Market Timing, Sector Allocation

JEL Classification: G11; G12; G14

Following the global financial crisis in 2008 the description and modelling of systemic risk has been of utmost importance to market participants. Given that market turbulence typically induces high volatility and asset correlations close to one, the variance-covariance matrix (VCV) of asset returns is a natural anchor for any measure of systemic risk. For instance, Kritzman, Li, Page, and Rigobon (2011) extract the main drivers of a given asset universe using a rolling principal components analysis throughout time. Fixing the most relevant principal components they track the associated fraction of total variance that is explained (or absorbed) by these factors, and thus label this measure the absorption ratio. The intuition is straight forward: Calm periods are characterized by a relatively low absorption ratio because markets are determined by quite a large menu of factors. Conversely, turbulent periods are characterized by a high absorption ratio indicating that markets are relying on the evolution of few factors and are thus less resilient to digesting shocks. In a related vein, we seek to provide a rich picture of the prevailing market risk structure. However, we do not focus on the most relevant components of the VCV but rather consider the complete topology of the correlation network associated with the VCV. We believe that this application of network theory in finance will prove to be a very illustrative and meaningful exercise to generate more resilient portfolios.

Network Theory is a subset of Graph Theory that concerns itself with the study of graphs as a representation of general asymmetrical relations between elements. A network is simply a graph with associated properties. The main premise of Network Theory is to connect single entities under consideration, represented by nodes (or points or vertices) using lines, called edges (for undirected links) and arcs (for directed links). A simple network can be constructed as a Minimum Spanning Tree (MST) which connects nodes in decreasing order of connectedness such that there is only one path between any given pair of nodes. Thus, the resulting network is acyclic. Mantegna (1999) pioneered the utilization of networks in financial markets and observed the hierarchical structure of stocks in the DJIA and S&P500 indices by constructing the minimum spanning tree of the underlying stock returns' correlation matrix. Tumminello, Aste, Di Matteo, and Mantegna (2005) presented an alternative technique to filter complex data sets, called the Planar Maximally Filtered Graph (PMFG), which preserves the hierarchical structure of the MST but contains a larger amount of information. Pozzi, Aste, Rotundo, and Di Matteo (2008) studied the use of dynamic correlation matrices in the MST- and PMFG-based analysis and conducted stability and robustness checks with regards to these two topological network filtering techniques. Di Matteo, Pozzi, and Aste (2010) extend this work to the detection of hierarchical organization of stock market sectors under the dynamic network approach.

In the finance literature, only recently did we observe efforts that seek to exploit the rewards of analyzing networks in financial markets. The objective is most often to infer the degree of systemic risk by examining the degree of connectedness among different market constituents. Unsurprisingly, following the global financial crisis the focus has been on analyzing interdependencies prevalent among financial companies. For instance, Billio, Getmansky, Lo, and Pelizzon (2012) use econometric concepts like Granger causality to describe the connectedness of hedge funds, banks, broker dealers and insurance companies. Moreover, an increase in interrelatedness can be indicative of an upcoming crisis period. Unlike this work, most of the existing literature focuses on describing the market risk structure that unfolds when visualizing the correlation network as a minimum spanning tree or as an alternative representation. With regards to network applications in portfolio management Papenbrock and Schwendner (2014) present a framework that aims for regime classification to pinpoint risk on or risk off environments. Also, the authors depict the implicit emerging state dependencies for a multi-asset portfolio. However, there are not many studies seeking to exploit the correlation network properties in an ex-ante fashion. A notable exception is Pozzi, Di Matteo, and Aste (2013) who use a sample of AMEX stocks to document that investing in peripheral stocks generates consistently better performance than investing in more central stocks. In a related vein, Ahern (2013) operationalizes the idea of network centrality applied to a network built from intersectoral trade data for some 500 U.S. industries. Ahern finds that more central industries earn higher returns than less central ones. He rationalizes this finding with a diversification argument that central industries have greater systematic risk and earn higher returns because they are more heavily exposed to idiosyncratic shocks transmitting from one industry to another by way of intersectoral trade.

We seek to exploit the potential out-of-sample benefits embedded in a given correlation network. In our study we build on the correlation matrix of European sector returns to visualize the connectedness of the equity market over time. We argue that correlation networks provide a rich picture of market risk structure dynamics. A rather close correlation network could characterize a compact market in which shocks might propagate more quickly because of a tight connection of market constituents. Conversely, a wide correlation network could characterize a less fragile market environment. Interestingly, it turns out that the above rationale does not apply to the analysis of sector correlation networks. Dense sector correlation networks usually characterize a healthy market structure catalyzing positive future equity returns. On the other hand, wider sector correlation networks are indicative of destabilizing changes in the underlying market structure. Intuitively, the average centrality of the correlation network is a natural measure of systemic risk where low general network centrality is a warning signal. In this vein, we pursue an equity market timing strategy using the parametric portfolio policy framework of Brandt and Santa-Clara (2006) and document that the predictive content of network centrality is also translating into a meaningful portfolio utility. Moreover, this result continues to hold when controlling for common predictors of the equity risk premium.

Not only is network centrality useful as an aggregate market timing signal but also in navigating the cross-section of equity sectors. Using the parametric portfolio policy framework of Brandt, Santa-Clara, and Valkanov (2009) we document a significant outperformance of peripheral versus central equity sectors that cannot be explained by momentum or low volatility effects. Finally, we implement a combined parametric portfolio policy that comprises the complete information content of the network topology conditional on a given level of risk aversion.

The paper is organized as follows. Section I is concerned with the construction of correlation networks using minimum spanning trees. Section II outlines the methodological framework of parametric portfolio policies along the lines of Brandt and Santa-Clara (2006) and Brandt, Santa-Clara, and Valkanov (2009). Section III blends the extracted network characteristics into the latter framework in terms of market timing, sector allocation as well as a combined strategy. Section IV concludes.

I. Correlation Networks

A Minimum Spanning Tree (MST) is one of the most fundamental types of topologically filtered networks and is easy to construct and interpret. The full representation of a variance-covariance matrix (VCV) as a network will have every point connected to every other point. We can, during the construction of this full network, impose a constraint that any two vertices are connected by exactly one path only. Graphs constructed with such a constraint are called "trees", see Cayley (1857). If all vertices are connected, it is a spanning tree. A network can have many different spanning trees. For n vertices, a spanning tree has $n-1$ edges connecting them. This is substantially lower than the $n(n-1)/2$ edges that are present in the full representation of a network making MSTs a convenient way of visualizing information.

A minimum spanning tree is simply the spanning tree that minimizes the sum of lengths of all edges. For correlation networks, as is the case here, we define the length of an edge between vertices i and j in terms of the correlation between them as

$$D(i,j) = \sqrt{2(1-\rho_{ij})} \tag{1}$$

This is a common choice; e.g. see Mantegna (1999). By construction, smaller distances between vertices indicate higher correlation.[1]

The construction of an MST is quite straight-forward. One starts with arranging the non-diagonal elements of the VCV in increasing order of D_{ij} (or, equivalently, decreasing order of ρ_{ij}). The algorithm of Kruskal (1956) then progressively links those vertices which have not already been linked. Linking vertices in this way results in a spanning tree, while arranging the non-diagonal elements as described above ensures that the spanning tree will be an MST. Many algorithms already exist for creating MSTs. For instance, the algorithm of Prim (1957), which we use, is always a tree and differs from Kruskal's algorithm only in terms of the procedure followed. It starts with an arbitrary vertex and constructs a tree by inserting edges of minimum weights for each vertex. Both algorithms result in the same output.

Studying an MST is a very powerful way of building intuition about the behavior of the underlying elements, in our case the equity market sectors. Figure 1 depicts two examples of sector correlation networks.[2] The upper chart gives the network based on 6 months daily return data from October 2002 to March 2003. The ensuing network is typical of a well-organized market structure. At the center, we find banks with most of the remaining sectors organized in a star-like fashion around the center. On the other hand, the lower chart of Figure 1 shows a widely spread

[1] Note that correlation cannot be used directly as it lacks properties of a metric.

[2] The MST visualization has been accomplished using the Asset Monitor of Financial Network Analysis, see `http://www.fna.fi`.

out network pertaining to the time period May 2008 to October 2008. Given the turmoils of the unravelling global financial crisis in 2008 we observe a network of sectors that are aligned in a chain-like fashion with banks having moved to the periphery. On similar lines, relative position and characteristics of a sector within the network can tell us how influential it is in driving the behavior of the overall market.

[Figure 1 about here.]

Extraction of such information from the correlation network, we argue, should be beneficial from an investment point of view. There are several characteristics or parameters that can be computed for a network. These characteristics help to describe the features and properties of the nodes or the network as a whole. One such property of a network is the notion of geodesic paths. A geodesic path between any two vertices is the shortest path connecting them in the network. As there is only one path connecting any two points in an MST, all paths in an MST are geodesic paths. In our strategy, we make use of two network characteristics—network diameter and node betweenness. The network diameter is a property of the network as a whole and is defined as the longest geodesic path of the network. The diameter measure captures the density of the network with a small value for a concentrated network and a large value for a more spread-out network. Node betweenness, on the other hand, is a property associated with every node. The node betweenness for a node i is the total number of geodesic paths passing through that node. It is a good measure to use for determining the centrality of every node within the network. Intuition suggests that the diameter could help in the market-timing strategy while the node betweenness could add value to a cross-sectional sector allocation strategy.

II. Parametric Portfolio Policies

To judge the relevance of the above correlation network characteristics for portfolio management we resort to the parametric portfolio policy framework introduced by Brandt and Santa-Clara (2006) and Brandt, Santa-Clara, and Valkanov (2009). Brandt and Santa-Clara (2006) augment the asset space by adding simple active portfolios that invest in certain base assets (like equities or bonds) proportionally to one or more conditioning variables, like dividend yield, term or default spreads. In essence, the classic static Markowitz solution in this augmented asset space turns out to be the optimal dynamic trading strategy.[3] While this approach is geared at timing a few distinct asset classes, the follow-up paper of Brandt, Santa-Clara, and Valkanov (2009) adopts the general idea of a parametric portfolio policy to manage security selection within a given asset class according to a set of asset characteristics.

A. Market Timing

Brandt and Santa-Clara (2006) consider an investor with quadratic utility and risk aversion γ. With r_{t+1} as future excess returns of the portfolio assets the investor seeks to derive optimal portfolio weights x_t by maximizing quadratic utility at time t:[4]

$$\max_{x_t} E_t \left[x_t^{'} r_{t+1} - \frac{\gamma}{2} x_t^{'} r_{t+1} r_{t+1}^{'} x_t \right] \tag{2}$$

The trick of Brandt and Santa-Clara is to assume the optimal portfolio strategy to be linear in the vector z_t of the K conditioning variables:

$$x_t = \theta z_t \tag{3}$$

where θ is an $N \times K$ matrix. Thus replacing x_t by its parametric function in (2) one obtains

$$\max_{x_t} E_t \left[(\theta z_t)^{'} r_{t+1} - \frac{\gamma}{2} (\theta z_t)^{'} r_{t+1} r_{t+1}^{'} (\theta z_t) \right] \tag{4}$$

For further simplifications, the authors use the fact that

$$(\theta z_t)^{'} r_{t+1} = z_t^{'} \theta^{'} r_{t+1} = \underbrace{\mathrm{vec}(\theta)^{'}}_{=:\tilde{x}} \underbrace{(z_t \otimes r_{t+1})}_{=:\tilde{r}_{t+1}} \tag{5}$$

The optimization problem then becomes

$$\max_{\tilde{x}} E_t \left[\tilde{x}^{'} \tilde{r}_{t+1} - \frac{\gamma}{2} \tilde{x}^{'} \tilde{r}_{t+1} \tilde{r}_{t+1}^{'} \tilde{x} \right] \tag{6}$$

[3] See the seminal work of Markowitz (1952) on the mean-variance paradigm.

[4] Note that $x_t^{'}$ and $r_{t+1}^{'}$ denote the transpose of the original weight and return vectors.

Because $\tilde{x}$ maximizes the conditional expected portfolio utility at all times, it also maximizes the unconditional expected portfolio utility:

$$\max_{\tilde{x}} E\left[\tilde{x}'\tilde{r}_{t+1} - \frac{\gamma}{2}\tilde{x}'\tilde{r}_{t+1}r_{t+1}'\tilde{x}\right] \tag{7}$$

In a nutshell, the original optimization problem (2) is thus equivalent to determining unconditional portfolio weights $\tilde{x}$ in the augmented asset space $\tilde{r}_{t+1}$. The optimal solution is computed analogous to the Markowitz solution:

$$\tilde{x} = \frac{1}{\gamma}E\left(\tilde{r}_{t+1}\tilde{r}_{t+1}'\right)^{-1} E\left(\tilde{r}_{t+1}\right) = \frac{1}{\gamma}E\left[(z_t z_t') \otimes (r_{t+1}r_{t+1}')\right]^{-1} E\left[z_t \otimes r_{t+1}\right] \tag{8}$$

For the practical implementation we use sample averages:

$$\tilde{x} = \frac{1}{\gamma}\left[\sum_{t=0}^{T}(z_t z_t') \otimes (r_{t+1}r_{t+1}')\right]^{-1}\left[\sum_{t=0}^{T} z_t \otimes r_{t+1}\right] \tag{9}$$

Note that $\tilde{x}$ are the optimal weights in the augmented asset space. To infer the optimal base asset weights, one simply adds the corresponding products of the elements of $\tilde{x}$ and z_t. The beauty of this approach is: The (static) Markowitz solution within the augmented asset space is equivalent to the optimal dynamic strategy. Intuitively, this optimization approach implicitly translates the predictive power embedded in the conditioning variables into robust portfolio performance. Moreover, given this framing of the dynamic portfolio optimization problem, any extension of the Markowitz model is readily available for use, viz. constraints, shrinkage, Black-Litterman, etc.

B. Sector Allocation

In a vein similar to the market timing approach of the preceding subsection, the follow-up paper of Brandt, Santa-Clara, and Valkanov (2009) tackles the issue of cross-sectional portfolio optimization in a utility-driven framework. Their approach is especially suitable for optimizing portfolios consisting of many assets within a specific asset class. Portfolio weights are modeled as linear functions of a few asset characteristics and the optimal portfolio weights derive from a utility optimization with respect to the transfer coefficients of these characteristics. Brandt, Santa-Clara, and Valkanov (2009) demonstrate the mechanics of their approach optimizing a

U.S. equity portfolio along classic company characteristics like size, book-to-market, and price momentum. In essence, their approach thus operationalizes known asset pricing anomalies but according to a specific risk profile inherent in the underlying utility function.

Brandt, Santa-Clara, and Valkanov (2009) consider an investor who seeks to optimize

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u(r_{p,t+1})\right] = E_t\left[u\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}\right)\right] \tag{10}$$

with $w_{i,t}$ the weight in asset i and N_t the number of assets at time t. Again, it is crucial to parameterize portfolio weights as a linear function of the asset characteristics $x_{i,t}$:

$$w_{i,t} = f(x_{i,t}; \phi) = \overline{w_{i,t}} + \frac{1}{N_t}\phi' \hat{x}_{i,t} \tag{11}$$

with benchmark weights $\overline{w_{i,t}}$, standardized asset characteristics $\hat{x}_{i,t}$, and coefficient vector ϕ. Modeling portfolio weights in this way corresponds to benchmark-relative management, in which deviations result only due to differences in asset characteristics. The cross-sectional standardization of asset characteristics gives stationary $\hat{x}_{i,t}$, an attribute that does not necessarily apply to the original variables $x_{i,t}$. Also, the cross-sectional mean of $\hat{x}_{i,t}$ is 0 making benchmark deviations equivalent to a zero-investment portfolio. Further scaling portfolio weights by the number of assets, N_t, avoids more aggressive allocations that could otherwise result from simply expanding the asset universe. Note that the portfolio weights parameterization is solely dependent on asset characteristics but not on historical returns. Implicitly, this modeling of portfolio weights assumes that the distribution of asset returns is fully explained in terms of the chosen asset characteristics. As a result, assets with similar characteristics will have similar portfolio weights. Computationally, the approach of Brandt, Santa-Clara, and Valkanov (2009) entails a strong reduction of the optimization problem's dimensionality. While the classic Markowitz approach builds on modeling N first moments and $(N^2 + N)/2$ second moments, one simply has to model N portfolio weights through the estimation of a manageable set of coefficients ϕ.

To further simplify the optimization problem one notes that the coefficients that maximize the conditional expected utility of the investor at a given time t are the same for all points in time.

Thus, they also maximize the unconditional expected value. The original optimization problem (10) can hence be written in terms of coefficients ϕ.

$$\max_{\phi} E\left[u(r_{p,t+1})\right] = E\left[u\left(\sum_{i=1}^{N_t} f(x_{i,t};\phi) r_{i,t+1}\right)\right] \tag{12}$$

The estimation of ϕ builds on the corresponding sample moments:

$$\max_{\phi} \frac{1}{T}\sum_{t=0}^{T-1} u(r_{p,t+1}) = \frac{1}{T}\sum_{t=0}^{T-1} u\left(\sum_{i=1}^{N_t}\left(\overline{w_{i,t}} + \frac{1}{N_t}\phi' \hat{x}_{i,t}\right) r_{i,t+1}\right) \tag{13}$$

III. Exploiting Correlation Networks Characteristics in Parametric Portfolio Policies

A. Market Timing

We pursue a market timing strategy based on correlation networks for 15 European sector indices of DJ STOXX for the time period from January 1987 to October 2013. For investigating the value of network centrality in timing equity markets we use the correlation network's diameter as a conditioning variable in the dynamic portfolio selection paradigm of Brandt and Santa-Clara (2006). The diameter is computed for sector correlation networks derived from a rolling 6-month window of daily returns. We use the DJ Euro STOXX 50 as equity investment and 3-month European interest rates as cash investment. The equity investment ranges between 0% and 100%. To benchmark the predictive content embedded in the correlation network's centrality we additionally feed the optimization with common predictors of the equity risk premium. In particular, we include dividend yield, term spread, default spread, and the TED spread. Also, we control for the simple average correlation of the equity sectors which is computed using a 6-month window of daily sector returns. The coefficients θ pertaining to the optimal portfolio strategy are determined using an initial window of 60 months which is expanded for subsequent optimizations. Concerning the model's backtest, we can thus compute out-of-sample portfolio performance starting January 1992. Given that we use monthly data the implicit portfolio rebalancing frequency is monthly, too. Note that the optimal strategy is governed by a risk aversion parameter of $\gamma = 10$.

To assess the relevance of the conditioning variables we plot the corresponding θ-coefficients over time in Figure 2. Notably, we find the theta coefficient for the network's diameter to be significant. The coefficient's sign is negative which supports our intuition that a spreading of the network is indicative of a destabilizing economy and prompts a decrease in the equity weight. Among the classic predictor variables we observe dividend yield and term spread to also exhibit negative and significant theta coefficients while the TED spread's coefficient is significantly positive. The default spread is not deemed to be relevant. Interestingly, using average correlation as a conditioning variable is marginally meaningful, however, the corresponding theta's sign is unexpected. All else equal, an increase in average correlation relative to its preceding 12 months' mean leads to a reduction in the equity weight.

[Figure 2 about here.]

The economic significance of the correlation network's diameter is best visualized by means of an optimal weights decomposition as given in Figure 3. Therein, the optimal equity weight results from simply adding the products obtained by multiplying the associated elements of θ and z_t. Integrating over this decomposition one captures a considerable contribution of network centrality to the optimal equity portfolio weight. We note that the diameter's realization typically helps reducing equity weight during severe market setbacks. Especially, the market timing strategy is quite successful in navigating the global financial crisis that unfolded around the collapse of Lehman. At that time, the interaction of four conditioning variables brought the equity weight down to 0%: diameter, dividend yield, term spread and default spread. The ensuing market timing strategy has an average equity weight of 53.2% over time but still gives rise to an equity-like return of 10.0% p.a. Given a portfolio volatility of 10.9% the risk-adjusted return amounts to a Sharpe Ratio of 0.57.

[Figure 3 about here.]

B. Sector Allocation

Not only can network centrality be useful as an aggregate market timing signal but also in navigating the cross-section of equity sectors. Using the parametric portfolio policy framework of

Brandt, Santa-Clara, and Valkanov (2009) we investigate the return behaviour associated with the centrality characteristic of given stock sectors. As laid out in Section I we compute the node betweenness to determine the centrality of sectors for any given month within the sample period January 1987 to October 2013. Given that the node betweenness ultimately builds on the variance-covariance matrix one might argue that sectors simply stand out in this ranking because of a return history characterized by extremely high or low returns and/or volatility. Then, any anomalous return pattern related to differences in sectors' centrality might potentially be traced back to momentum or low volatility effects in the sector returns. Therefore, we simultaneously control for two further sector characteristics, 1-month price momentum and sector volatility as computed from 1-month daily sector returns.

As before, the determination of the optimal coefficients ϕ initially builds on a 5-year window of monthly data which is expanded for subsequent optimizations. The first optimal portfolio to be used in the backtest is thus obtained for January 1992. Each of the three sector characteristics is being standardized cross-sectionally in every month. Standardization makes characteristic stationary and ensures that active sector weights will add up to 0%. We benchmark the sector strategy relative to an equal-weight portfolio consisting of the 15 Dow Jones Euro STOXX sectors. Due to the specification of the weight function the resulting portfolio weights will then add up to 100%. While the optimal strategy coefficients ϕ are governed by the risk aversion parameter $\gamma = 10$, we scale portfolio weights such that the optimal strategy obeys an ex-ante tracking error of 5% relative to the $1/N$ benchmark. Figure 4 gives the ϕ-coefficients for the three characteristics over time. First, we observe that there is a negative sign for sectors' centrality which implies that peripheral sectors are to be preferred over more central ones. For volatility, we also uncover a negative coefficient which relates to a low-volatility rationale that seems to apply for stock sectors as well. Finally, the positive coefficient or 1-month momentum is evidence of a short-term price momentum effect inherent in European sector returns.

[Figure 4 about here.]

The corresponding sector portfolio weights are depicted in the upper chart of Figure 5. Note that the associated strategy performance is considerably superior to the naive $1/N$ benchmark and to the standard Markowitz mean-variance strategy. Tilting towards peripheral sectors, positive momentum and low volatility results in a highly favorable strategy performance of 15.2% return p.a. at an annualized volatility of 15.7%. The ensuing Sharpe ratio is 0.72.

[Figure 5 about here.]

To shed some light on the mechanics and characteristics of the parametric sector portfolio policy we decompose a few selected sector weights by the three sector characteristics in Figure 6. In particular, the left hand side features three sectors that are typically considered to be more peripheral in the sector correlation network and are thus overweighted in the sector allocation strategy. Notably, Health Care as well as Food & Beverages happen to belong to the network periphery throughout the whole sample period. The ensuing overweight for these two sectors is attenuated because of their additional low volatility characteristic. As for Automobiles & Parts, one can observe more variability in the sector weight profile over time. Starting out at the center of the sector correlation network the sector is first being underweighted. Moving to the periphery in the last decade this underweight is being dissolved. Conversely, the right hand side of Figure 6 gives the sector weights of the three most central sectors in the sample. Industrial Goods & Services is the prime example of a central sector which is therefore constantly underweighted in the sector allocation strategy—volatility and momentum effects hardly play a role in its weights decomposition. The two other quite central sectors we portray are Banks and Insurance. Banks have been central within the sector correlation network until the global financial crisis started to unfold in 2008. As a result, the strategy has been underweight Banks (and Insurance) prior 2008. However, with Banks moving towards the periphery the sector weight increased. Given the negative momentum and high volatility of bank stocks in late 2008 these two asset characteristics prevented the strategy from becoming unduly overweight in Banks at the worst of times.

To summarize, we document an outperformance of peripheral versus central equity sectors that cannot be explained by momentum or low volatility effects. We rationalize this observation as follows. A central sector (e.g. Banks) with a high node betweenness value will be closely connected to all other sectors in the network. This means that central sectors will be more vulnerable to other sectors as compared to peripheral structures (e.g. Automobiles and Food & Beverages) which have a high correlation with few other sectors. Thus, there is a lower degree of risk associated with peripheral sectors. This makes them a more attractive investment option compared to central sectors.

[Figure 6 about here.]

C. Combining Market Timing and Sector Allocation

Having documented market timing and sector allocation strategies to extract significant portfolio utility from sector correlation network characteristics it is natural to pursue a combined strategy that blends market timing and sector allocation strategies to one. Moreover, we implement a combined parametric portfolio policy that comprises the complete information content of the network topology conditional on a given level of risk aversion. The combined strategy simply maps the sector allocation of Subsection B into the equity position of the market timing strategy of Subsection A. Especially, the sector allocation strategy is scaled down whenever the market timing is cautious with regards to investing in equity. As a result, the weakening profitability of the sector allocation strategy in times of equity market setbacks is considerably smoothed because of the market timing overlay. The combination strategy has a volatility of 10.9% and an annualized return of 14.3% giving rise to a Sharpe ratio of 0.96, see Figure 7.

[Figure 7 about here.]

IV. Conclusion and Outlook

Identifying the prevailing market risk structure is highly relevant for meaningful portfolio management. Still, it is less obvious whether the knowledge of the current risk structure is adding value over and above fundamental or technical variables when predicting asset risk premia. In this vein, our benchmarking of network indicators in the framework of Brandt and Santa-Clara (2006) is highly adequate for assessing their economic relevance vis-à-vis the common set of risk premia predictors.

Indeed, the diameter of the sector correlation networks proves to be a meaningful conditioning variable for pursuing equity market timing. Moreover, the relative positioning of sectors within the network is a useful characteristic to describe the cross-section of sector returns. In particular, we document a notable outperformance of peripheral versus central equity sectors. Central sectors are generally more prone to shocks spilling over from various sectors while peripheral sectors are more resilient in that regard. Finally, we demonstrate how to operationalize the benefits of the sector correlation network in a combined parametric portfolio policy that blends market timing and sector allocation.

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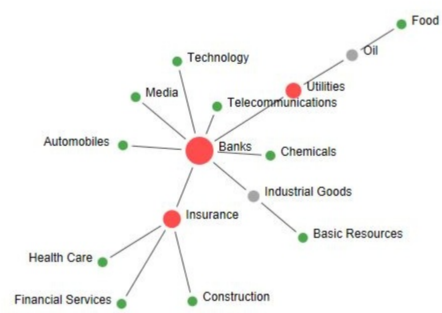
Figure 1. Minimum Spanning Tree

The figure depicts the correlation network as a minimum spanning tree for European equity sectors. The node size corresponds to each sector's centrality and the three most central sectors are highlighted in red, while the peripheral sectors are highlighted in green. The upper plot builds on the variance-covariance matrix using daily data from the six-months period from October 2002 to March 2003. The lower plot is for the time period May 2008 to October 2008.

October 2002 to March 2003



May 2008 to October 2008

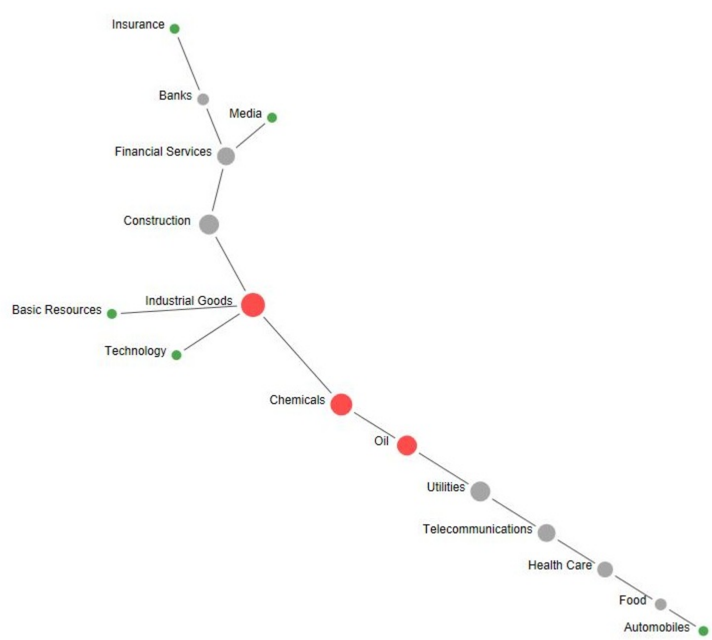


Figure 2. Theta Coefficients

The figure depicts the θ-coefficients that obtain in the parametric portfolio policy. The θ-coefficients have a solid line while the corresponding 95% confidence interval is marked by a dashed line. The time period is from January 1993 to August 2013.

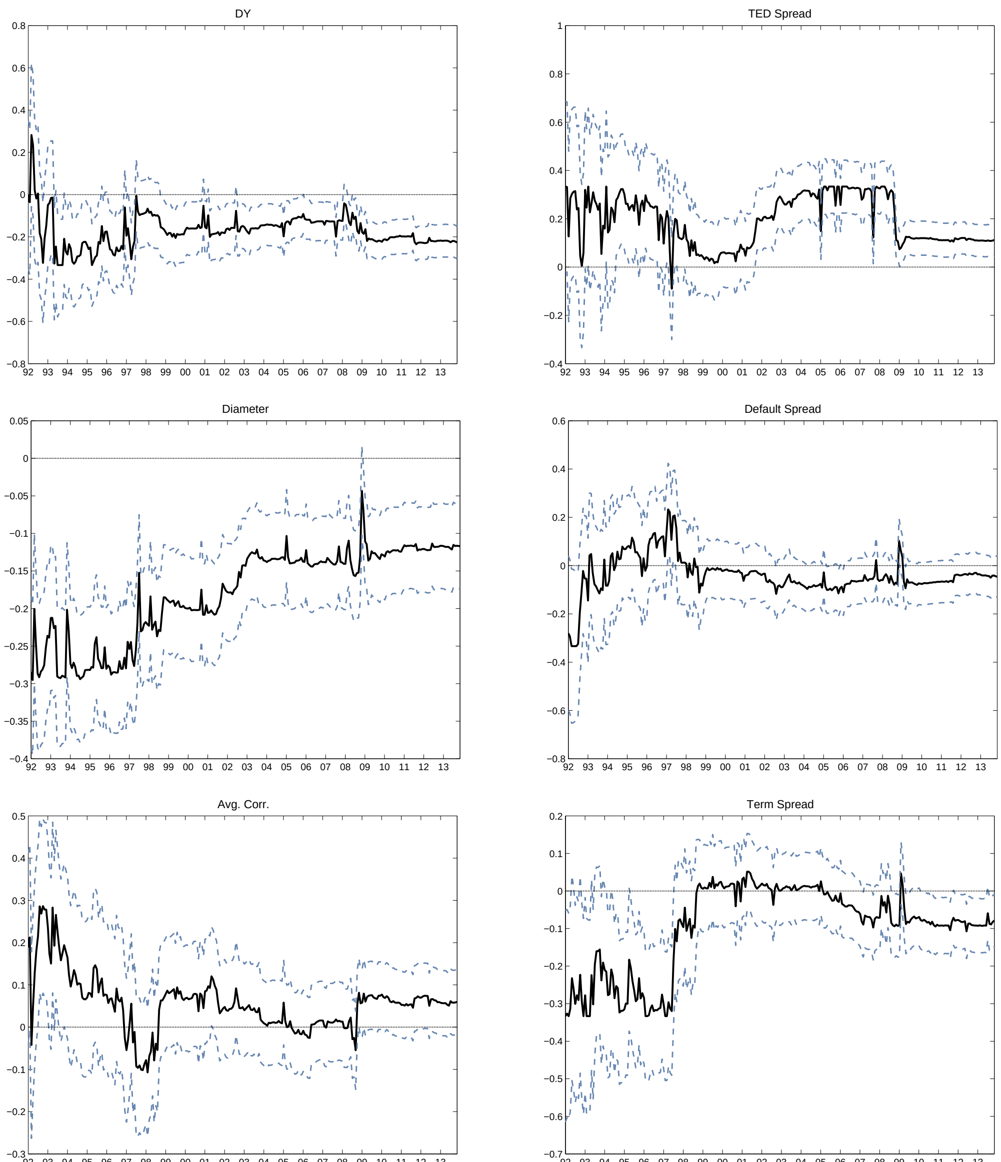


Figure 3. Parametric Portfolio Policy: Market Timing

The figure depicts the weights of the parametric portfolio policy for market timing in the upper chart and the corresponding performance in the lower chart. The time period is from January 1993 to August 2013.

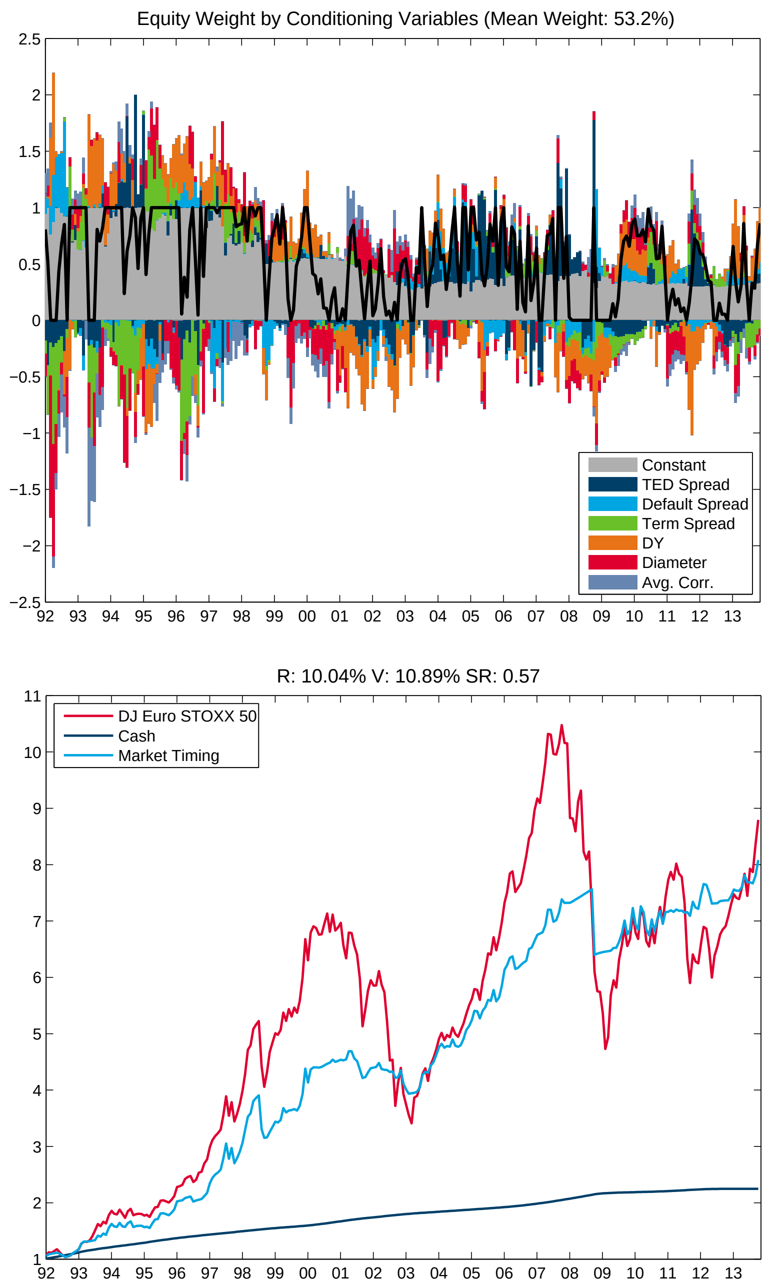


Figure 4. ϕ-Coefficients over Time

The figure depicts the ϕ-coefficients that obtain in the parametric portfolio policy. The time period is from January 1993 to August 2013.

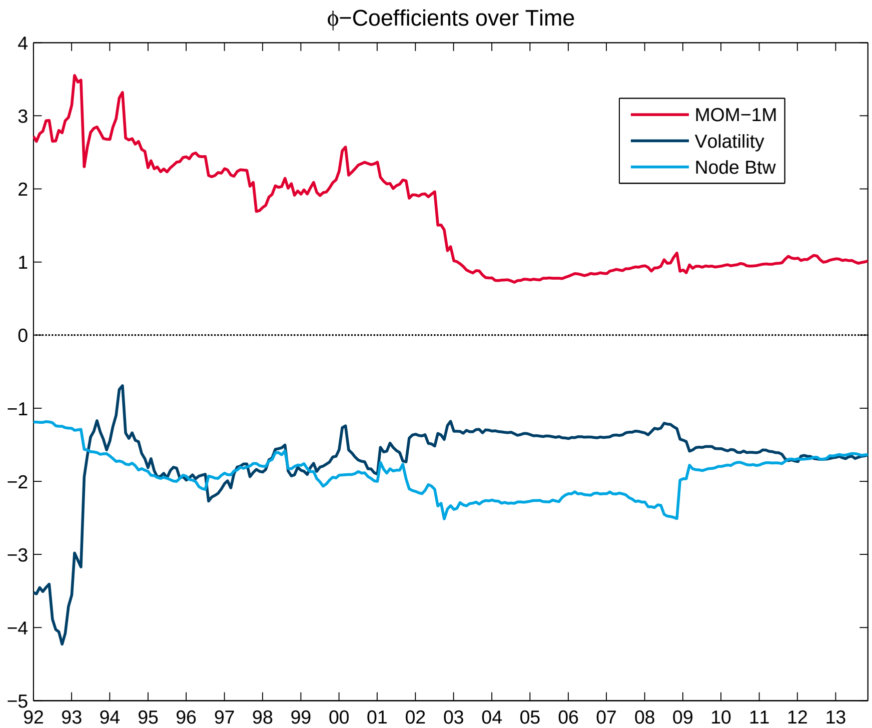
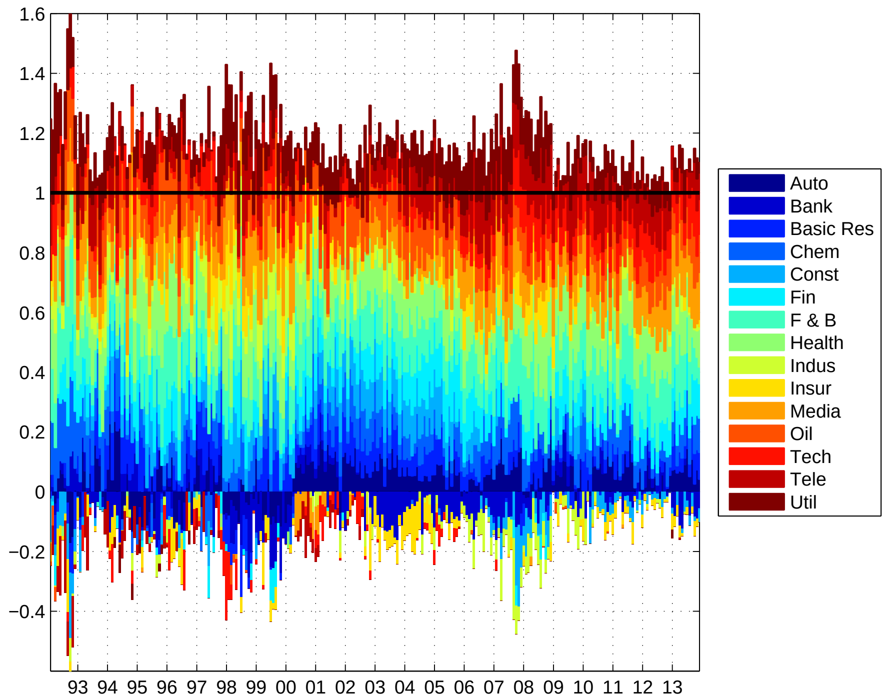


Figure 5. Parametric Portfolio Policy: Sector Allocation

The figure depicts the weights of the parametric portfolio policy for sector allocation in the upper chart and the corresponding performance in the lower chart. The time period is from January 1993 to August 2013.



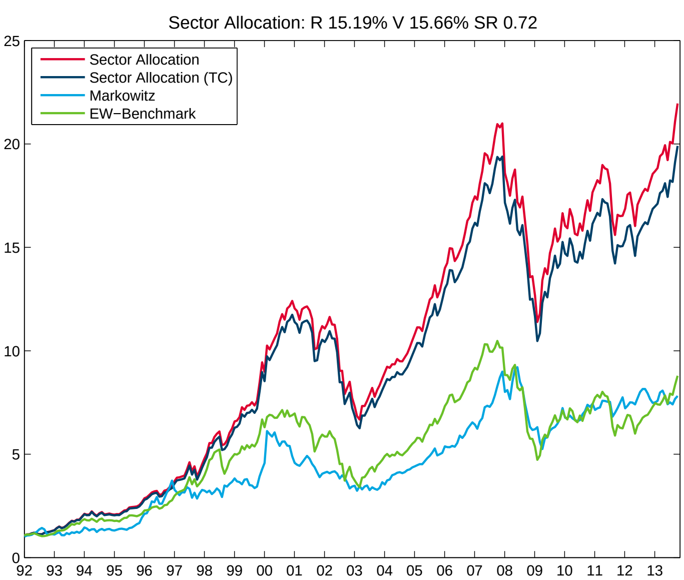


Figure 6. Sector Weight Decomposition

The figure depicts the sector weights of the parametric portfolio policy for six exemplary stock sectors. The time period is from January 1993 to August 2013.

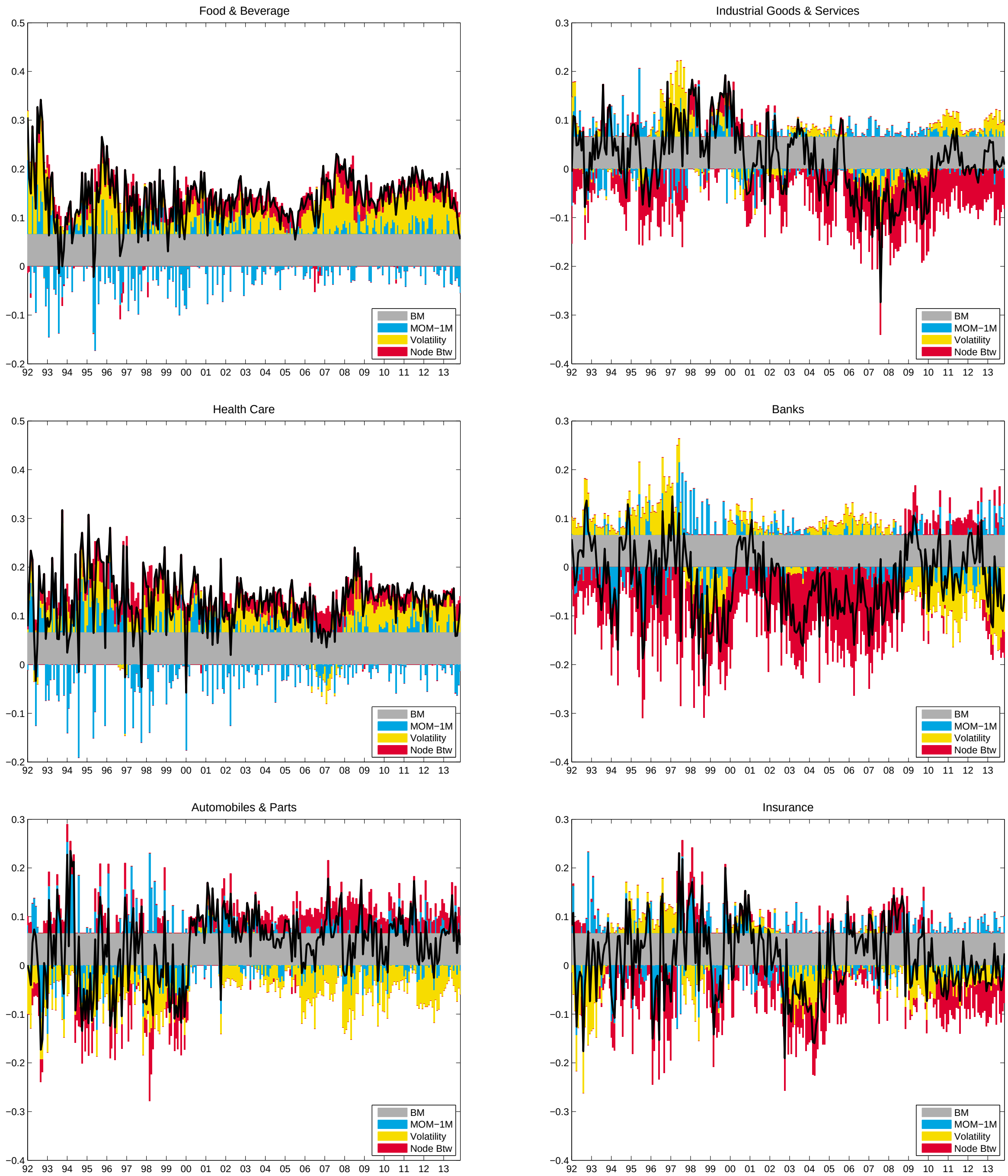


Figure 7. Combination Strategy

The figure depicts the weights of the combined parametric portfolio policies in the upper chart and the corresponding performance in the lower chart. The time period is from January 1993 to August 2013.