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# Predicting economic growth with stock networks

Raphael H. Heiberger

*University of Bremen, Institute for Sociology, Bremen, 28205, Germany*

## HIGHLIGHTS

- Combining Econophysics with Machine Learning techniques.
- Utilizing Bayes classifiers to predict economic growth with stock networks.
- Correctly forecasting critical (and prosperous) economic developments in the US up to one year ahead.
- Derivation of the future status of whole networks based on the present local positions of nodes.

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ABSTRACT

Networks derived from stock prices are often used to model developments on financial markets and are tightly intertwined with crises. Yet, the influence of changing market topologies on the broader economy (i.e. GDP) is unclear. In this paper, we propose a Bayesian approach that utilizes individual-level network measures of companies as lagged probabilistic features to predict national economic growth. We use a comprehensive data set consisting of Standard and Poor's 500 corporations from January 1988 until October 2016. The final model forecasts correctly all major recession *and* prosperity phases of the U.S. economy up to one year ahead. By employing different network measures on the level of corporations, we can also identify which companies' stocks possess a key role in a changing economic environment and may be used as indication of critical (and prosperous) developments. More generally, the proposed approach allows to predict probabilities for different overall states of social entities by using local network positions and could be applied on various phenomena.



## 1. Introduction

The development of financial markets and overall economic growth are closely connected. Already Joseph Schumpeter [1] emphasized the central role of the financial sector for business cycles. Since then, economists explore the finance-growth nexus in various manners (for an review see Levine [2]). The perspective taken by the majority of economists focuses on the intermediaries of the financial system and is highly influential in powerful institutions like the International Monetary Fund or the World Bank [3,4]. Within this paradigm, the financial structure of a country is thought of as either bank or market-based with the tendency that national financial systems becoming more market-oriented as economies evolve. The set of relationships and interactions of financial institutions, however, is rarely investigated from a network perspective, since "economists are relative latecomers to this project" [5]. It is a rather new development that economists use nodes and edges to explore questions in regard to debt, the complexity of a nation's economy or consequences of environmental volatility for agents [6–8].

*E-mail address:* raphael.heiberger@uni-bremen.de.

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An interdisciplinary challenger of the economic paradigm, often dubbed econophysics [9], also relies on the statistical investigation of stock interaction networks and their dynamics. This kind of analysis was first conducted by Mantegna [10] using the correlation between price fluctuations of single stocks to construct networks and reproduce the topological properties of a market. The main idea is to decrease the immense complexity of financial markets to facilitate investigation, and, at the same time, retain its core information in order to reveal structural dynamics [11–13]. It has been shown that such networks are very useful to predict financial crises and economic shocks [14–17].

Despite the huge scientific and institutional efforts to illuminate the interplay between financial markets and economic growth, there exists no research on the connection between market topologies as understood in econophysics and the evolution of business cycles as investigated by many economists. In this paper, we propose a naïve Bayes model in order to link both statistically. Classifying data with Bayes' theorem is a common task in machine learning [18]. For instance, almost all spam-filters use Bayesian classifiers. More generally, the categorization of large data can be effectively achieved with that approach, as Hagenau and colleagues [19] demonstrate for the prediction of individual stock prices by automated news reading. Naïve Bayes models are often compared to multinomial logistic regressions [20]. However, as shown by Ng and Jordan [21], Bayesian models converge to its asymptotic error rate more quickly with $O(log(n))$ compared to $O(n)$ for multinomial logit models in a model with $n$ variables. This property is especially apparent if we work with long forecast horizons and lagged Bayesian models in order to predict recessions [20].

Here, we bridge the separated research areas of econophysics and "mainstream" economics [13] by proposing a model based on individual stock network positions that anticipates periods of crisis and prosperity in the U.S. economy.

## 2. Data and methods

### 2.1. Construction of stock networks

The raw data consists of 491 companies listed in the Standard and Poor's 500 in October 2016. The S & P 500 is based on large and well established blue chips of the United States and their stock prices are publicly available. We retrieved them from Yahoo [22]. They start in January 1988 and end in the third quarter 2016. The basic information consists of $N$ assets with price $P_{it}$ for asset $i$ at time $t$. The logarithmic return between two points in time is calculated with $r_{it} = ln(P_{it}) - ln(P_{it-1})$. In order to investigate the dynamics of the stock market, we divide the individual stock data into $M$ windows, denominated $t = 1, 2, \ldots, M$ of width $T$, that is, the number of returns in $M$. We use one year (i.e., 250 trading days) as window width. The windows overlap and shift further at length $\omega T$.

We can then quantify the degree of similarity between assets $i$ and $j$ for the given window around $t$ with the correlation coefficient

$$\rho_{ijt} = \frac{\overline{r_{it} r_{jt}} - \overline{r_{it}}\,\overline{r_{jt}}}{\sqrt{(\overline{r_{it}^2} - \overline{r_{it}}^2)(\overline{r_{jt}^2} - \overline{r_{jt}}^2)}} \tag{1}$$

where $\overline{r_{it}}$ indicates a time average over the consecutive trading weeks $t$ that are contained in the return vector $r_{it}$. Finally, we can derive the $N * N$ correlation matrix $C_t$, which is completely characterized by $N(N-1)/2$ correlation coefficients. To mirror changes in the stock networks, $C_t$ is shifted by $\omega T$. The derived networks are matched to national economic growth rates in the United States as measured by the gross domestic product (expenditure approach, seasonally adjusted). The most disaggregated temporal level for official data provided by the U.S. Bureau of Economic Analysis is by quarters, i.e., each growth rate is compared to the previous quarter. Correspondingly, the shift $\omega T$ of the correlation matrix $C_t$ is set to three months (i.e., 60 trading days).

From the moving stock price correlation matrices, we construct dynamic networks by using the winner-take-all-approach discussed by Tse et al. [12]. Therefore, only those correlations between stocks are used that lie above a certain connection criterion $z$. To be part of the stock network the correlation (i.e., the weight of the relation) between stock $i$ and $j$ has to satisfy the condition $\rho_{ijt} > |z|$. Here, the condition is set to 0.7, as a lower bound of strong correlations. Please note that different levels of correlations have no impact on the network structure [15,12]. There exist two major advances of the threshold approach compared with other proposed reduction techniques like minimal spanning trees [11] or planar graphs [23]: (a) The constructed networks lose no essential information. Both alternatives remove edges with high correlation if the respective nodes fit certain topological conditions and are, on these grounds, already within the reduced graph. (b) There is no fixed upper bond, i.e., the number of nodes included in the network is not mandatory but dependent on the specific period and its topology.

### 2.2. Network measures

To describe individual positions of nodes in networks, there exists a wide range of measures. In this paper, we employ the following:

- *Weighted Degree* of one node is represented by the strength of the tie between stock $i$ and all it neighbors $j$, being equivalent to $s_i = \sum_{j=1}^{N} \rho_{ij}$.

- *Generalized Degree* is defined as $s_{gen}(i) = d_i^{(1-\alpha)} * s_i^{\alpha}$ with $d_i$ being the (unweighted) number of ties of $i$ and $\alpha$ as a scaling parameter set to 1. The advantage according to Opsahl et al. [24] is that, other than with the "pure" weighted degree $s_i$, $s_{gen}$ also considers the number of degrees.
- *Triangles* are simply the number of triads between $i, j, k$ involving node $i$.
- *Clustering Coefficients* can be written as $CC(i) = \frac{1}{d_i*(d_i-1)}\sum_{j,k}(\hat{\rho}_{ij}\hat{\rho}_{ik}\hat{\rho}_{jk})^{1/3}$ with $\hat{\rho}_{ij} = \rho_{ij}/\max(\rho)$ [25]. Thus the edge weights $\rho$ are normalized by the maximum weight in the network so that the contribution of each triangle $i, j, k$ depends on all of its edge weights.
- *Modularity* is defined as $Q = 1/2w\sum_{i,j}[\rho_{ij} - \frac{d_i d_j}{2w}]f(c_i, c_j)$ with $w = 1/2\sum_{ij}\rho_{ij}$ and $c_i$ being the community of node $i$. The function is 1 if $c_i = c_j$ and 0 otherwise. The resulting community assignments are used as features. We calculated the modularity for each dynamic network by using the algorithm of Blondel et al. [26].

Finally, we include the probably most common measures in social network analysis [27]:

- *Betweenness Centrality* is $C_{bet}(i) = \sum_{i\neg j\neg k}\frac{\sigma_{jk}(i)}{\sigma_{jk}}$ where $\sigma_{jk}$ denotes the number of shortest paths between $j$ and $k$. Let then $\sigma_{jk}(i)$ be the number of paths a node $i$ lies on. The measure was computed by using the algorithm of Brandes [28].
- *Closeness Centrality* is $C_{close}(i) = \frac{N-1}{\sum_{j=1}^{N-1} di_{ij}}$ with $di_{ij}$ being the shortest-path distance between $i$ and $j$ (i.e., the number of paths between them).
- *Degree Centrality* simple is the normalized number of degrees, i.e., $C_{deg}(i) = \frac{d_i}{N-1}$.

### 2.3. Recursive feature elimination

One crucial task using Bayesian classifiers is to find the right number and types of features in order to avoid overfitting, i.e., using too many (or few) features from array $X$ in order to predict $P(Y_k|X_i)$. As can be seen in Fig. 3, the optimum number of features providing the highest forecast quality is far from including all available features and the quality of prediction would decline sharply, if doing so. To extract the most feasible number of features, we utilize an approach from machine learning known as "recursive feature elimination" [29]. Stemming from gene selection, the algorithm eliminates information redundancy and yields more compact subsets of features. As all others models and results used in this paper, the implementation of the recursive feature elimination process is based on the *scikit* package in Python.

## 3. Results

The main aim of this paper is to model the relationship between individual network positions of stocks and the overall state of the economy. We approximate the development of the financial market by stock networks derived from 491 companies listed in the Standard & Poor's 500. Fig. 1 demonstrates the evolution of the *overall* network structure and the respective economic growth in the United States. Besides strong deflections around the financial crisis starting in summer 2007 (low modularity, high correlation and declining entropy), all three global network measures exhibit no clear and consistent connection to boom and bust periods in the overall economy, since we observe relatively low modularity, high correlation and low entropy values during the boom period in 2003. Yet, the *individual* network positions during periods of prosperity are clearly distinguishable from those in recessions as Fig. 2 shows in greater detail. We will use these changing network positions on the micro-level to predict periods of prosperity and recessions as indicated by the GDP growth of the U.S. economy within a Bayesian framework.

### 3.1. Predicting economic growth with stock networks

Naïve Bayes classifier are widely used in machine learning procedures [18,19]. The eponymous theorem states that

$$P(Y_k|X) = \frac{P(Y_k)P(X|Y_k)}{P(X)} \tag{2}$$

where $Y_k$ is the $k$th class (i.e., the explanandum) and $X = x_1, \ldots, x_n$ are $n$ observed variables (i.e., the explanans, often called features). Assuming independence of the variables, $P(Y_k)P(X|Y_k)$ can be written as the joint probability

$$P(Y_k)P(x_1|Y_k)\ldots P(x_n|Y_k) = P(Y_k)\prod P(x_i|Y_k) \tag{3}$$

The "naı̈ivety" of the approach stems from the assumed independence of observations. Practically, its violation has only little impact on the predictive ability of Bayesian models. It has even been shown that functional dependence between the elements of $X$ provides the best results [33]. Network positions exhibit such a dependency by design. Accepting this assumption, we derive from (1) and (2) the decision rule how to assign a class $\hat{Y}$ to a set of observations $X$ with

$$\hat{Y} = argmax_{k\in(1,\ldots,k)}P(Y_k)\prod P(X_i|Y_k). \tag{4}$$

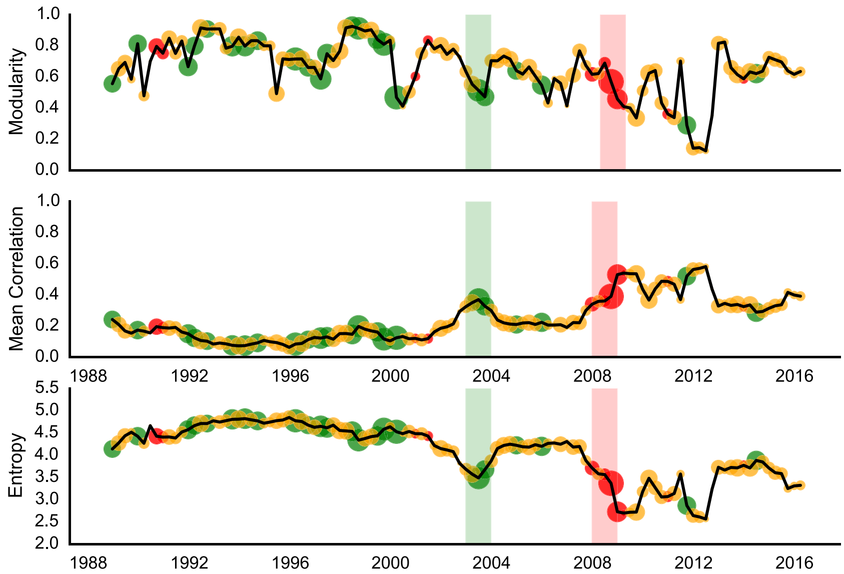



**Fig. 1.** Development of network structure and economic growth. The lines indicate global network measures over time: modularity [30], mean correlation [31], and singular value decomposition entropy [32]. The dots represent quarterly economic growth, their size is according to its extent. Quarter-to-quarter growth that is larger than one is marked green (prosperity), negative periods are depicted in red (recessions), and every growth rate in-between is shown in orange. Two especially prosperous (weak) economic periods are highlighted with a light green (red) bar. The network structure is displayed in Fig. 2 for each of those. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

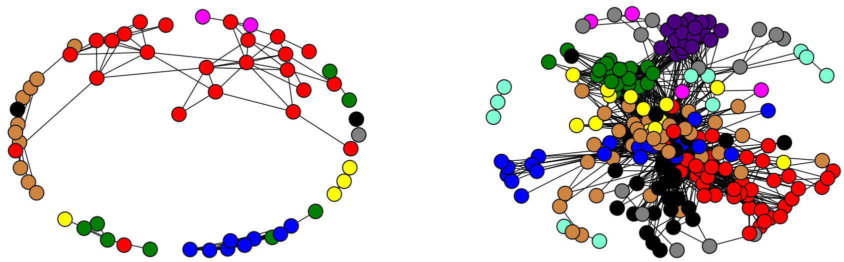


**Fig. 2.** Stock networks in prosperity and recession. The graph on the left side corresponds to the prosperity period highlighted in Fig. 1 with a light green bar (), the graph on the right side to the light red bar. The nodes are collocated by a spring embedding layout. Each color is related to a sector of the Global Industry Classification Standard: Consumer Discretionary = black, Consumer Staples = gray, Financials = red, Health Care = aquamarine, Industrials: brown, Information Technology = blue, Materials = yellow, Telecommunications Services = magenta, Utilities = indigo, Energy = green. Please note that in both graphs sectors are highly clustered which is often seen as evidence for the empirical significance of the constructed stock networks [13]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In our case, categories $P(Y_k)$ reflect the state of the economy and are assumed to be conditioned by the individual network positions of the S & P 500 corporations in array $X$. Assigning multiple classes as $k$ allows us to examine three different economic states as dependent variable: Prosperity (quarterly growth $>$ 1%), recession (negative GDP growth $<$ 0%) and "business as usual" (quarterly GDP growth between 0 and 1%). To *predict* business cycles, we have to add time lags. The decision function then becomes

$$\hat{Y}_{t+h} = argmax_{k \in (1,\ldots,k)} P(Y_{k,t+h}) \prod P(X_{i,t} | Y_{k,t+h}) \quad (5)$$

where $h$ is the recession forecasting horizon with $h = 0, 3, 6, 9, 12$ months. For instance, with $h = 6$ the model provides a prediction of the economic state six months ahead conditional on the available stock data at time $t$.

The remaining question for the implementation of the model is the composition of array $X$, i.e., which features should be included. Utilizing all available features would most likely lead to an overfitted model. Fortunately, machine learning enables us to extract the most predictive features for a condition $Y_k$ by removing features with low explanatory values and thus maximizing the fit of the model via the above mentioned recursive feature elimination. To evaluate the accuracy of each model we use the F-score

$$F = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (6)$$

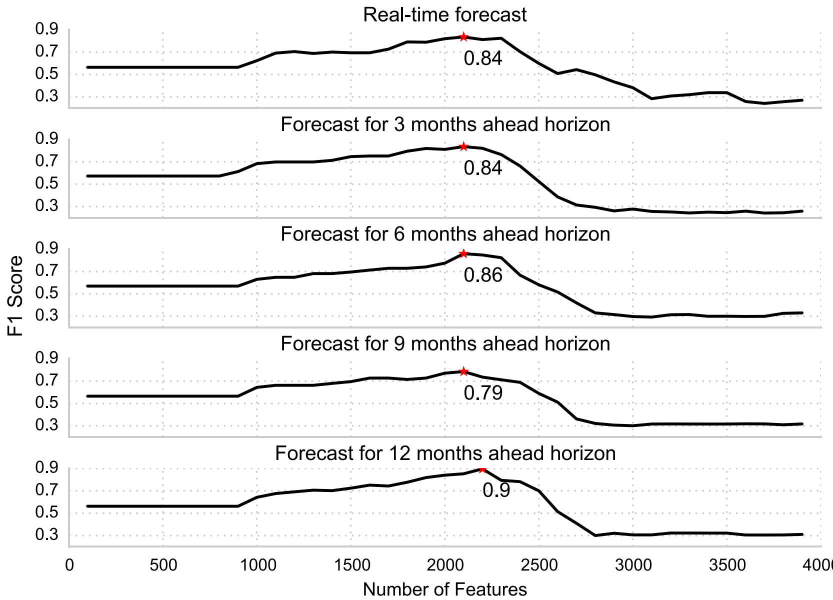



**Fig. 3.** Comparison of the quality of models with different number of features. Each model starts with all variables. By recursive feature elimination a given number of most predictive features (x-axis) is derived. The respective F-score of the model is displayed on the $y$-axis for different forecast horizons.

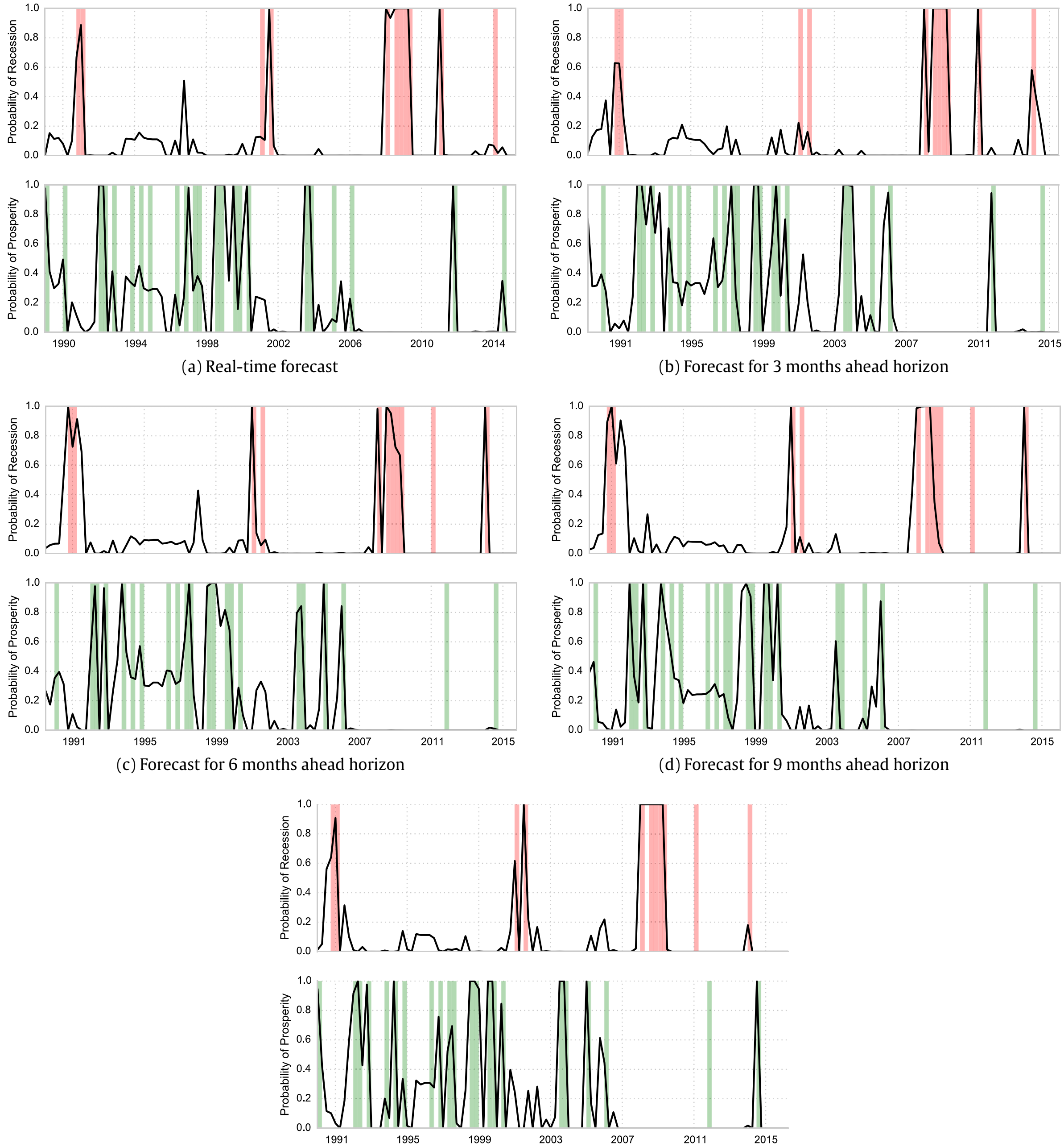
where precision is the fraction of positive predictions that are truly positive, and recall tells us the fraction of truly positive observations that were predicted positive. The differences between the forecast horizons in the optimal number of features are minimal (Fig. 3), differing only slightly when predicting the economic status 12 months ahead. We therefore set the number of features maximizing the F-score for all models to 2100, with the exception of the one year forecast horizon in which 2200 features maximize the F-score.

The final model estimates boom and bust probability for different forecast horizons that are shown in Fig. 4. The model captures the three grave crises of the overall economy in the last 28 years: the recession in the succession of the fall of the Iron Curtain in the early 1990s, the New Economy Bubble around the millennium and, most recently, the financial crisis and its aftermath. Even more, the model also predicts periods of prosperity in almost all cases. This is also the case when the stock market measures precede the GDP by as much as one year. The results underline the future-oriented modus operandi of financial markets, i.e., the changes in market topology anticipate developments in the broader economy. Therefore, the network positions in the financial market of U.S. companies are well-suited as features in a Bayesian model to predict the overall economic state in the future.

To be sure, there are differences in the quality of the model dependent on the forecast horizon. Taking the recent financial crisis as example (2008–2010), we see that only the forecasts in Fig. 4a (real-time) and Fig. 4b (3 months ahead) include the last bump of the crisis in early 2011. The longer horizons though still get the main part of the recession in 2008 and 2009. The lower precision of larger forecast horizons is in accordance with other papers on economic growth prediction [34,35]. Comparing the proposed model to the cited economic approaches is not directly possible, however, since economists do not utilize properties of stock networks (so far) but rely on regressions with "leading-indicator" variables. This approach goes back to [36]. Turning to the econophysics literature, the studies there mostly concentrate on the prediction of aggregated market dynamics (not product-market GDP) with global network measures (instead of local measures). For instance, [14] uses singular value decomposition to predict the state of the market. In accordance to what can be seen in Fig. 1, [32] find that the singular value decomposition entropy is declining during the financial crisis. Other studies reveal higher correlations between stock prices during the financial turmoil [15,37], in accordance with results for former crisis [16]. Our findings present, however, the first approach to bridge the streams of thought of economists and econophysicists on economic crises and growth, and provides strong evidence for the predictive potential of local network measures for recessions *and* prosperity of the overall economy.

### 3.2. Which features and companies possess the highest explanatory power?

The conditional probabilities $P(Y_{kt}|X_{it})$ can be ranked by their explanatory power. Combined with the recursive feature elimination process, we get a tool to extract the most influential individual positions consisting of the measures and companies. As shown in Fig. 5, the most predicting network measures are $C_{bet}$ and $C_{deg}$ (indicated in shades of blue). The least influential features are the generalized degree $s_{gen}$ and the community assignments $c_i$. Thus, the "classic" centrality measures proposed by Freeman [27] provide the vast majority of the most useful features. It is also important to note that none of the




(a) Real-time forecast
(b) Forecast for 3 months ahead horizon
(c) Forecast for 6 months ahead horizon
(d) Forecast for 9 months ahead horizon
(e) Forecast for 12 months ahead horizon

**Fig. 4.** Prosperity and recession probability predictions at various forecast horizons. Each plot shows the probability $Y_{kt}$ for a recession in the upper box and for a period of prosperity in the lower. The phases of prosperity (quarterly growth $>$ 1%) are shaded with a green bar, recessions (negative quarterly growth $<$ 0%) with a red one. All three major crises are predicted correctly up to one year ahead. The same is true for the vast majority of "boom"-periods in the U.S. economy.

widely used global measures depicted in Fig. 1 (modularity, mean correlation and entropy) is among the selected features, although we included them in the initial vector $X_{it}$. This underlines the predictive potential of local network measures [38].

With regard to the influence of individual stocks, we can also see how often which of them appear in the features. The corporations whose stock network positions are used in all different measures are, surprisingly, not the most central nodes in the network. Rather, all of them are located in the periphery. Fig. 6 clearly shows that corporations, which are present in all features, have both low values of betweenness ($C_{bet}$) and degree centrality ($C_{deg}$). For all forecast horizons, these stocks are among the lowest of each centrality measure. The corporations included in the features are also not the most prominent

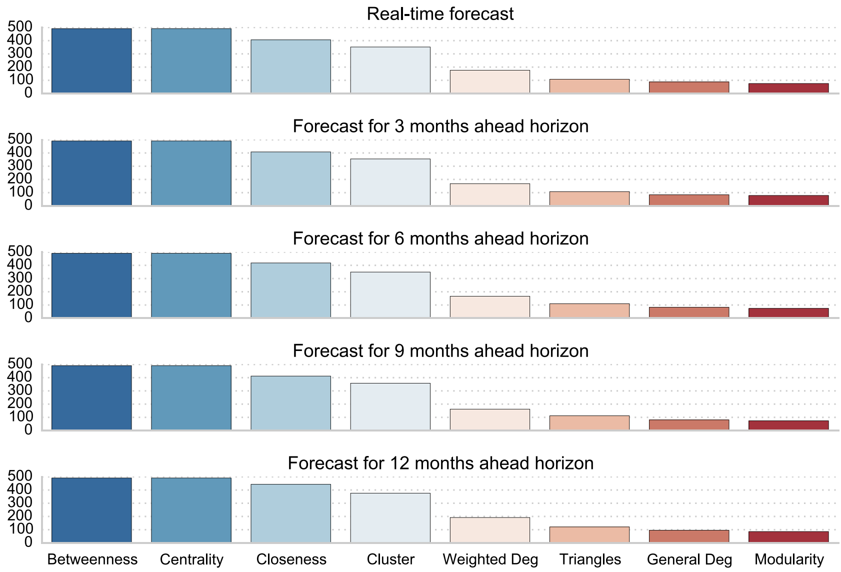



**Fig. 5.** Comparison of the included features in the models for different forecast horizons. The maximal number how often a positional network measure can be included as a feature is equal to the number of nodes, i.e., at the most 491.

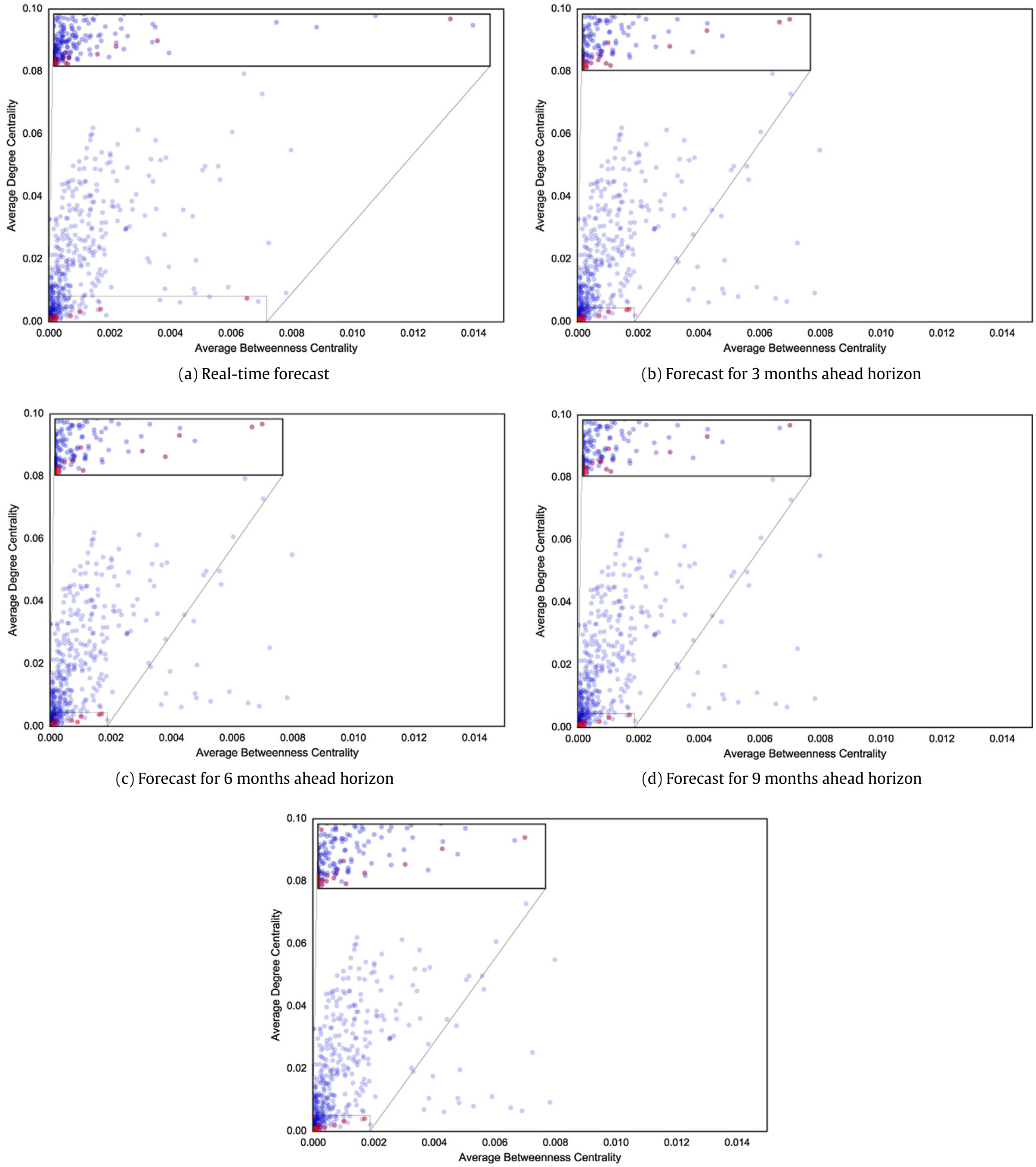
ones in the S & P 500 (see *Table S1* for a full list of corporations that are incorporated as features in all measures). Yet, their peripheral positions are decisive for forecasting economic growth in our model since they are most likely to appear in the networks during recessions or prosperity, and less often during regular economic episodes. The decisive firms to detect boom and busts are therefore *not* the most central and prominent stocks, but those found in the periphery of the S & P 500.

## 4. Discussion

In this paper, we propose a Naïve Bayes model that uses stock network data as a forecasting tool for economic development. The dynamic network topology predicts all recessions and almost all prosperity periods of the last 28 years in the United States up to one year ahead. The model relies solely on publicly available stock prices for the corporations of the S & P 500 index, which is a great advantage given the limited amount of free information on financial systems [39]. By utilizing Bayes' theorem our approach differs from most econometric approaches, although the Federal Reserve of Kansas has very recently applied it in a comparable manner [20]. An additional contrast to other studies about forecasting economic developments is that we are not concentrating on predicting single stock prices [40,41] or behavior of individuals [42,43]. Instead, we derive our model directly from the network topology, which does not only matter when markets are illiquid [44] ("bust" periods), but shows to be highly predictive for "boom" periods too. Thus, network complexity in financial markets not only leads to higher default risks [45], but can be used to extract information about positive developments. In particular, our results provide further evidence that local network measures possess predictive power [38] and opportunities to find switching processes in complex systems [46].

In addition, this paper reveals the role of individual corporations within dynamic stock networks. Surprisingly, not the most central stocks are decisive to detect signals for economic growth or recessions, but those at the periphery. This finding is in compliance with Pozzi et al. [47] who find that corporations in the periphery of networks are less volatile then central stocks. Investors and institutional regulators should therefore include seemingly less important corporations in their observations and not only focus on the center of stock networks.

Finally, the formulation of the proposed model is very general and could be applied to various network phenomena. For instance, the approach may be eligible for positions in school friendship networks, in order to derive the kind of attended schools (e.g. charter or public schools), or networks between co-workers to identify the organization they are working in (e.g. ties could be differentiated by department, industry or profitability). Furthermore, collaboration networks of scientists could be used to predict the universities at which they get appointed, and networks produced by interlocking directorates may be linked to their occurrence in certain economic systems (i.e., liberal or conservative regimes [48]). At the moment, the predictive potential of networks is only feasible with regard to individual tie formation for which highly restricted techniques are used, particularly exponential random graph models [49] and stochastic actor-based models [50]. These two de facto standards in social network analysis are based on strong assumptions in terms of network types, change rates and time periods. The proposed Bayes approach has none of these limitations and therefore allows the derivation of the future status of whole networks solely based on the present positions of nodes. Here, we provide first evidence for the usefulness of




(a) Real-time forecast

(b) Forecast for 3 months ahead horizon

(c) Forecast for 6 months ahead horizon

(d) Forecast for 9 months ahead horizon

(e) Forecast for 12 months ahead horizon

**Fig. 6.** Weighted degree plotted against number of triangles. The most predictive corporations are marked red and shown in the inset. For each forecast horizon, the most predictive companies are among the lowest in both network measures.

such a combination of Bayes classifier and individual network measures by applying the model on a long-lasting economic question.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.physa.2017.07.022.

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