Network-Based Financial Forecasting: A Statistical and Economic Analysis

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Abstract

One of the main challenges facing researchers and industry professionals for decades is the successful prediction of asset returns. This paper enriches this endeavor by an in-depth analysis of topological metrics of correlation networks applied to financial forecasting. While academic research often focuses on statistical performance metrics, industry professionals are more interested in the economic value-added of competing forecasting approaches. Since statistical significance does not automatically imply economic significance, this article devotes attention to both types of performance metrics. We show that the benchmark mean model is indeed difficult to beat when it comes to statistical performance metrics. However, considering economic metrics, network-based predictors generate a clear value-added, which also applies to the multi risky asset allocation dimension.

Keywords: correlation networks, financial networks, network-based forecasting, minimum spanning trees, centrality, forecasting, asset allocation, investment strategy

JEL Classification: G10, G11, G17, C22, C32, C53.

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1 Introduction

This paper introduces the concept of network-based analysis to stock market prediction. Specifically, we extract network-based information from stock markets returns and extensively examine their predictive power concerning the same stock market returns. Hence, the predictors are not externally given, instead, like in the case of technical indicators, they are internally derived from the target variables.

Financial markets easily qualify as complex systems with many interactions and information exchanges between the various submarkets. Despite this apparent chaotic complexity, these kinds of systems tend to organize in a clear hierarchical manner, comprised of a few dominant and many subordinate submarkets (Simon (1962)). Consequently, given this type of organization, network-based analysis tools that aim to unveil hierarchical network or clustering patterns are the appropriate choice (Anderberg (1973)). We extract the hierarchical network structure of financial markets by building so-called financial networks[1] from the respective returns time series. For this purpose, the respective correlation-distances matrix is filtered with the minimum spanning tree method. This approach performs a so-called hierarchical clustering analysis, which results in a financial network. This financial network is the origin of various holistic and asset-specific network-based characteristics, which are utilized in predictive regressions.

Academic literature regarding financial forecasting with network-based predictors is almost non-existent, making this paper an early pioneer in this field. The specific contribution of this article is as follows. Starting with an in-sample analysis, we demonstrate the potential of network-based metrics in predictive regressions. To get a clearer picture, the study mainly focuses on univariate regressions, augmented by one best subset selection regression for each target variable. The target variables are represented by long-run return time series for ten US industry portfolios. We show that some network-based predictors exhibit statistically signifi-

[1]Most authors use the terms "financial networks" and "correlation networks" interchangeably because in most cases financial networks are derived from correlation-distances. For the sake of clarity, we stick with the more broader term "financial networks", since similarity metrics are not confined to correlations only.

cant in-sample forecasting power. Even better results are achievable if we broaden the pool of network-based predictors. Next, we extend the analysis by the out-of-sample (OOS) setting and contrast the results with the in-sample world. The first part of the OOS study deals with the statical analysis of network-based predictors. As expected, the strong in-sample results are not achieved in the OOS setting. Nevertheless, the overall OOS results are still highly promising, especially when using a broader set of network-based predictors. The second part of the OOS analysis deals with the economic analysis of network-based predictors. In the stock-bond asset allocation analysis, conditional (network-based) forecasting models in many instances have the edge over the unconditional (mean) model. Similar promising results are achieved in the multi risky asset allocation exercise by setting up network-based investment strategies. Furthermore, we show that the cross-sectional volatility of network-based return forecasts conveys important risk-information leading to superior risk-adjusted returns of the respective network-based investment strategy.

The remainder of the article is structured as follows. Section 2 provides a literature review on financial forecasting and connects the present article with related academic endeavors. The dataset and methodology of the paper are discussed in section 3. Section 4.1 is by far the biggest part of the paper and comprises all in-sample and OOS studies. Finally, the article is concluded in section 5.

2 Literature Review

Forecasting stock returns or the so-called equity risk premium is the supreme discipline of empirical financial research comprising numerous studies. Merton (1980) describes any forecasting endeavor as a "fool's errand" considering the fact that equity risk premium could be changing throughout time. On the other hand, Cochrane (2008) provides theoretical support for return predictability by jointly analyzing the forecastability of stock returns and dividends. Existing return predictability does not necessarily contradict the efficient market hypothesis, as argued by Campbell and Cochrane (1999) and Bansal and Yaron (2004). They derive general equilibrium models in which asset returns may still be predictable. Similarly, Cochrane (2011) develops theoretical arguments in favor of the predictive power of macroeconomic variables with regard to the time-varying equity risk premium.

The literature on stock market predictability is enormous. Hence, any survey attempt can only provide a small glimpse on the existing work. Early studies on return predictability by Fama and French (1988) and Campbell and Shiller (1988a,b) outline that dividend yields can predict stock market returns. Pesaran and Timmermann (1995) highlights that "true" return predictability should not only show up in-sample but must also prevail in an out-of-sample setting. This implies that the evidence of predictability should be exploitable in real-time, leading to a profitable investment strategy. In this vein, Goyal and Welch (2003) report that the out-of-sample predictability power of dividend yields is nonexistent for most of the time. The predictability discussion was reignited once again by the seminal paper of Goyal and Welch (2008). For a broad set of predictors proposed by the academic literature, they suggest that in an out-of-sample setting, all of them can not beat the (unconditional) historical average predictor consistently. Referring to these results, Campbell and Thompson (2008) argue that the out-of-sample evidence for predictability can be significantly improved by imposing plausible economic restrictions on the predictive regressions and the fitted values. A similar conclusion is also drawn by Pettenuzzo et al. (2014). The more recent literature proves out-of-sample predictability by relying on approaches that include (i) (sophisticated) pooling of forecasts or predictors (Rapach et al. (2010), Baetje (2017), Gargano et al. (2017), Hull and Qiao (2017)), (ii) harnessing technical analysis in predictive regressions (Neely et al. (2014)), (iii) machine learning techniques (Cavalcante et al. (2016), Zhong and Enke (2017), Rapach et al. (2018)) and (iv) regime-based forecasting (Hammerschmid and Lohre (2018)).

On the other side, academic research applying network-based analysis to forecasting asset returns is scant. Using Spanish stock market data, Peralta (2015) demonstrates that network-based measures predict unstable (adverse) market phases by estimating probit models. Kim and Sayama (2017) predicts S&P 500 returns by, besides others, network-based information from mutual information networks. They show that the explanatory power of ARIMA models increases when network-based metrics are added. Lastly, Baitinger and Maier (2019) prove the explanatory power of network-based information concerning future hedge fund returns. However, all cited papers demonstrate successful in-sample predictability, which is not necessarily equal to (exploitable) out-of-sample predictability. Furthermore, they focus on small subsets of network-based metrics. We tackle these shortcomings in the current paper by extensively analyzing in-sample and out-of-sample stock market predictability using a broad set of network-based predictors.

3 Dataset and Methodology

The dataset underlying our studies utilizes monthly returns for 10 US industry portfolios retrieved from the Kenneth R. French Data Library. Detailed information on the dataset is outlined in table 1. Even though the time series is available from 1927, we focus on the post-war period, due to data quality issues. Specifically, our analysis begins in January 1950. Note that the predictive regressions discussed below aim to model future returns of these time series (target variables) with predictors that are based on network metrics (network-based predictors):

$$R_{i,t+h} = \alpha + \beta N_{j,t} + \epsilon_{t+h}. \tag{1}$$

$R_{i,t+h}$ is the return of the i-th industry portfolio (or asset) at time $t+h$, whereby h stands for the forecasting horizon and is set to $h+1$ throughout all empirical studies. $N_{j,t}$ is the j-th network-based metric at time t. Note that these network-based metrics themselves, however, are extracted from financial networks of the target variables.

The basic methodology of the paper is schematically illustrated in figure 1. First, for a given dataset spanning from $t-tw$ to t (t=time, tw=time window), we build a financial

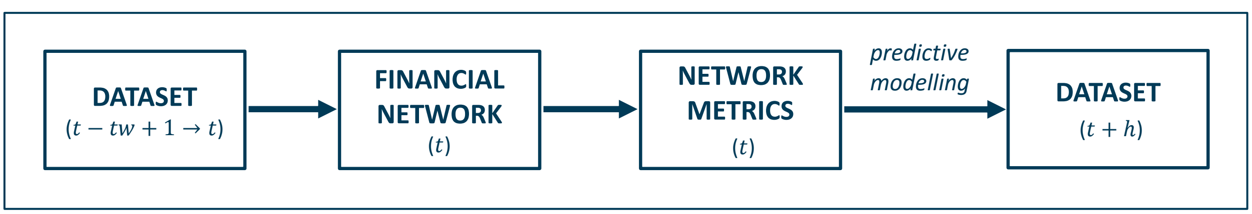
Table 1: Utilized Dataset, 10 Industry Portfolios

#	Abbreviation	Description
1	*NoDur*	Consumer Non-Durables – Food, Tobacco, Textiles, Apparel, Leather, Toys
2	*Durbl*	Consumer Durables – Cars, TV's, Furniture, Household Appliances
3	*Manuf*	Manufacturing – Machinery, Trucks, Planes, Chemicals, Office Furniture, Paper, Commercial Printing
4	*Enrgy*	Energy – Oil, Gas, Coal Extraction and Products
5	*HiTec*	Business Equipment – Computers, Software, Electronic Equipment
6	*Telcm*	Telephone and Television Transmission
7	*Shops*	Wholesale, Retail, Laundries, Repair Shops
8	*Hlth*	Healthcare, Medical Equipment, and Drugs
9	*Utils*	Utilities
10	*Other*	Mines, Construction, Building Materials, Tranportation, Hotels, Bussiness Services, Entertainment, Finance

Source: Kenneth R. French Data Library;
`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_ind_port.html`
We use monthly value weighted total returns. The full sample dataset spans from January 1947 to February 2018 resulting in 854 monthly data points for each industry portfolio. However, the first 36 months are reserved for the calculation of the first financial network. Hence, the effective full sample size spans from January 1950 to February 2018 leading to 818 monthly data points. The out of sample (backtesting) period spans from May 1958 to February 2018 comprising 718 monthly returns for each industry portfolio.This means that the first estimation window for the first out of sample return forecast spans from January 1950 to April 1958 which is exactly 100 monthly data points. Note that for the estimation of financial networks and out of sample return predictors a rolling window approach is utilized.

network. This financial network and the derived network-based metrics are consequently based on the available information up to time t. Finally, we model future monthly returns $(t + h)$ with these network metrics. When constructing financial networks, we follow the

Figure 1: Basic Methodology Schema



common approach and choose the linear (Pearson) correlation as our dependence measure[2]. However, the original correlation coefficients are not appropriate distance metrics and need

[2]The Pearson correlation coefficient is not the only option for dependence measurement. For example, Fiedor (2014), Kaya (2015) and Baitinger and Papenbrock (2017b) estimate the dependence structure of asset returns by information-theoretic concepts.

to be modified as follows (Gower (1966) and Mantegna (1999)):

$$d_{ij}^t = \sqrt{2(1-\rho_{ij}^t)}, \tag{2}$$

where d_{ij}^t is the (correlation-)distance index between the i-th and j-th asset at time t, ρ_{ij}^t is the respective correlation coefficient. This distance index exhibits an intuitive appeal. A strong linkage between two assets (high correlation coefficient) gives a small distance metric, implying that these assets are close to each other in the metric space and *vice versa*. The distance matrix is then filtered by the minimum spanning tree (MST) technique to retrieve the financial network. The MST connects all nodes or vertexes (i.e. assets) with the smallest possible sum of distances[3]. Once all nodes are connected to the network by at least one edge, the MST algorithm stops. It thus leads to the most radical filtered network, always consisting of exactly $N-1$ edges (N=amount of assets/nodes). This radical filtering technique yields a clear network picture which is not blurred by numerous edges[4].

Having constructed the network structure of the given dataset at time t, the next step is to extract network-based measures from the financial network. To be precise, the network-based metrics are retrieved from the so-called adjacency matrix, which is the mathematical representation of the financial network. Table 2 shows the network-based metrics that are utilized for prediction purposes in this paper. There are two basic types of network-based measure.

The upper part of the table outlines the so-called centrality scores. Each node (asset) has a specific position or centrality in the considered network. This relative position or embeddedness intensity can be objectively quantified by the centrality score. Since the centrality score is defined for each node, we get 60 (5 centrality metrics $\times$ 10 assets = 60)

[3]A non-mathematical illustration of the MST approach is provided by Mantegna (1999). An integer programming representation of the MST problem is demonstrated by Kaya (2015).

[4]The Planar Maximally Filtered Graph (PMFG) is a less drastic alternative to the MST, see Tumminello et al. (2005). However, Baitinger and Papenbrock (2017a) contrast network-based information provided by MSTs and PMFGs. They come to the conclusion that both network types convey qualitatively similar information.

Table 2: Overview of centrality scores and holistic network-based measures.

Full Name	Abbreviation	Definition/Comment
closeness *(centality of the i-th node)*	***cls***	reciprocal of the sum of the minimal distances between node i and all other nodes
betweenness *(centality of the i-th node)*	***btw***	total number of geodestic paths (each weighted by reciprocal distances) passing through node i
eccentricity *(centality of the i-th node)*	***ecc***	greatest geodestic path (weighted by reciprocal distance) of node i to any other node
degree *(centality of the i-th node)*	***deg***	number of edges, which are connected to node i; edges are weighted by reciprocal distances
eigenvector *(centality of the i-th node)*	***evc***	the i-th value of the first eigenvector of the graph adjacency matrix
diameter *(of the network)*	***diam***	the unweighted length of the longest geodestic path pertaining to the newtork
weighted diameter *(of the network)*	***diamw***	the distance-weighted length of the longest geodestic path pertaining to the newtork
radius *(of the network)*	***rad***	the smallest unweighted eccentricity among the network vertices
weighted radius *(of the network)*	***radw***	the smallest distance-weighted eccentricity among the network vertices
mean degree (T20%) *(of the network)*	***tdeg***	the average degree of vertices with the highest 20% degree centralities
mean weighted degree (T20%) *(of the network)*	***tdegw***	the average weighted degree of vertices with the highest 20% highest weighted degree centralities
mean distance *(of the network)*	***mdist***	average distance calculated using all edge distances
similarity ratio *(of the network)*	***sim***	similarity of network at time t to the previous period network (from t-1)

Geodestic path = shortest path between two vertices/nodes in a given financial network; graph adjacency matrix = matrix representation of a financial network. Eccentricity centrality is multiplied by -1 to yield the same interpretation as the remaining centrality metrics. Centrality scores are always node-specific and quantify the centrality/interconnectedness risk of the considered node. The higher the centrality score, the higher the centrality/interconnectedness risk or network embeddedness intensity of the specific node. The remaining metrics, except the similarity ratio, convey holistic network-based information by quantifying the shape or concentration level of the complete network. The similarity ratio compares graph adjacency matrices across the time dimension. All predictors are standardized ($\sigma = 1$, $\mu = 0$). This enables the comparability of coefficients.
Parts of the table are adopted from Baitinger and Papenbrock (2017a) and Baitinger and Maier (2019).

centrality data points for each network at time t. Therefore, network-based analysis is very data intensive, especially for larger portfolios.

The lower part of table 2 illustrates holistic network-based metrics. In contrast to centrality scores, holistic network-based measures assess the complete network and not solely the individual nodes. These metrics, except the similarity ratio, objectively quantify the overall shape (i.e., concentration level) of the financial network. The similarity ratio compares the current network (set of edges) to the $t-h$ network.[5] A drastic increase in the dissimilarity (i.e., crash in the similarity ratio) between neighboring networks across the time dimension can signify a major regime shift in financial markets (compare Onnela et al. (2003b) and Nobi et al. (2014)).

Table 3: Label examples of derived network-based metrics.

Full Name	**Abbreviation**	**Definition/Comment**
first principal component	***PC1***	first principal component of the network information matrix
differenced closeness	***Dcls***	first-order differenced (D) closeness centrality score of the i-th asset
differenced diameter	***Ddiam***	first-order differenced (D) betweenness diameter of the network
closeness of the first asset	***cls1***	closeness centrality score of the first asset/node, i.e., *NoDurb*
betweenness of the fourth asset asset	***btw4***	betweenness centrality score of the fourth asset/node, i.e., *Enrgy*
differenced betweenness of the fourth asset	***Dbtw4***	first-order differenced (D) betweenness centrality score of the fourth asset/node, i.e., *Enrgy*

Since we intend a broad analysis of network-based metrics in predictive models, the pool of predictors is further enlarged. The additional metrics are derived from the primary metrics that are outlined in table 2. Firstly, the original metrics are analyzed in a time-dynamic fashion. For this purpose, the primary metrics are first-order differenced and the original label is marked by a bold ***D***. In this way, we can analyze whether the change in centrality or holistic scores is indicative for future stock returns. Secondly, we condense network-based information (original and dynamic) by principal component analysis, whereby the first 6

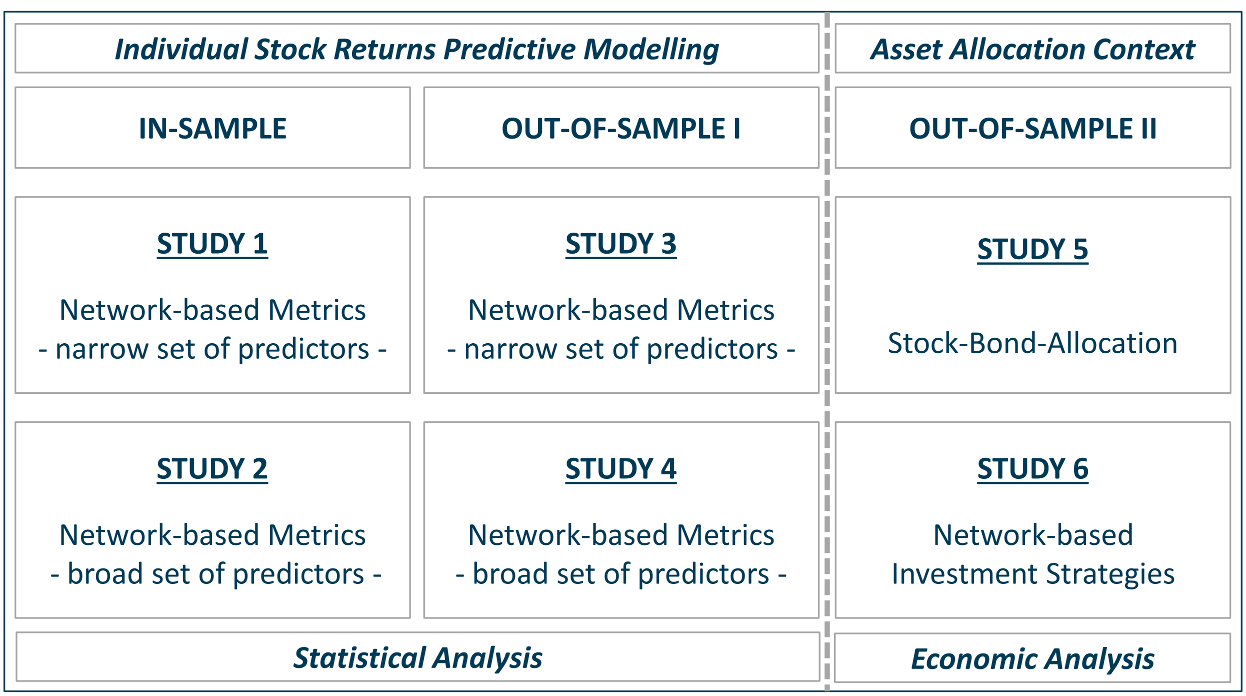
[5]For the sake of simplicity, we exclusively focus on neighboring networks in the time dimension (h=1).

principal components (**PC1**, **PC2** and so on) are considered. For the sake of clarity, some label examples of the derived metrics are outlined in the upper part of table 3. Summing up, the pool of network-based predictors for a given target variable (asset) consists of 32 variables: 13 original metrics (table 2), 13 first-order differenced original metrics and 6 principal components. We refer to this pool of predictors as "narrow set of predictors".

In addition, the predictors base for a considered target variable is further broadened by the direct inclusion of centrality scores of other assets. Note that in the narrow set of predictors exclusively centrality scores of the same asset are considered. The inclusion of other asset specific centrality scores in their original and their dynamic version adds 90 (9 assets $\times$ 5 centrality scores $\times$ 2 versions) additional variables to the predictors pool. We refer to this pool of predictors as "broad set of predictors".

A schematic overview of all empirical studies is presented in figure 2. The first two sub-studies are conducted in an in-sample environment. Since in-sample results are not necessarily indicative of achievable out-of- sample (OOS) performance, the resulting 4 sub-

Figure 2: Schematic Overview of the Empirical Studies



studies (3-6) exclusively rely on the OOS setting. The first four sub-studies perform a statical analysis of network-based predictors, while the economic perspective is considered in sub-studies 5 and 6. Note that the economic analysis inevitably necessitates assistance from asset allocation exercises. In study 5, we perform a one-period stock-bond-allocation to quantify the economic value-added of network-based predictors. In study 6, we construct comprehensive (multi-risky-asset) network-based investment strategies that yield an economic analysis of predictors in a holistic fashion[6].

4 Empirical Studies

4.1 In-Sample Analysis with the Narrow Set of Predictors

Table 4 outlines the results of the univariate in-sample study using the complete data sample comprising 818 monthly returns for each industry portfolio. Due to space constraints, we state only the most significant results.[7] In this sub-study, future returns ($R_{i,t+1}$) are modeled by the centrality scores of the same asset and holistic network-based metrics. With regard to table 4 several findings are noteworthy: Firstly, the results demonstrate that network-based metrics can predict future stock returns in-sample, as indicated by the significant t-test statistics. Secondly, the results are clearly dominated by holistic network metrics. Thirdly, on average more concentrated networks are associated with higher or positive future returns. Concentrated networks are indicated by low/lower ***diam***, ***diamw*** and ***mdist*** and high/higher ***tdeg*** and ***tdegw***.

The sign of each coefficient for the respective holistic metric comply with the statement in the third remark. Especially, ***mdist*** and ***tdeg*** are significant for all industry portfolios. Fourthly, centrality scores are underrepresented in table 4 indicating their limited ability to

[6]To manage the scope of the paper, the last two sub-studies (5 and 6) focus exclusively on the broad set of predictors.

[7]Throughout the paper, we present always the most significant results. Detailed results containing all predictors are available upon request.

Table 4: Univariate Predictive Regression Results, Jan1950 to Feb2018, $h = 1$

Predictors	Target Variables									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
cls										
coeff	0.0030	0.0064	0.0052	0.0071	0.0086	0.0036	0.0046	0.0049	0.0038	0.0034
t-stat	*1.87	*1.87	***2.76	***3.02	**2.10	**2.09	**2.34	***2.60	**2.14	**1.94
a-rsq	0.30%	0.69%	0.62%	0.95%	0.54%	0.47%	0.66%	0.63%	0.49%	0.29%
diam										
coeff	-0.0013	-0.0039	-0.0034	-0.0058	-0.0028	-0.0009	-0.0021	-0.0002	-0.0034	-0.0040
t-stat	-0.90	*-1.69	**-2.08	***-3.31	-1.37	-0.53	-1.25	-0.09	**-2.35	**-2.17
a-rsq	-0.02%	0.28%	0.37%	1.05%	0.09%	-0.08%	0.06%	-0.12%	0.65%	0.49%
diamw										
coeff	-0.0024	-0.0060	-0.0034	-0.0054	-0.0035	-0.0039	-0.0037	-0.0018	-0.0037	-0.0041
t-stat	*-1.91	***-2.95	**-2.18	***-3.03	*-1.54	**-2.35	**-2.43	-1.14	***-2.59	***-2.53
a-rsq	0.22%	0.83%	0.36%	0.90%	0.18%	0.63%	0.45%	0.01%	0.80%	0.53%
tdeg										
coeff	0.0023	0.0032	0.0037	0.0046	0.0045	0.0029	0.0022	0.0003	0.0038	0.0042
t-stat	*1.89	1.41	**2.31	***2.52	**2.11	*1.83	*1.48	0.23	***2.95	***2.54
a-rsq	0.21%	0.16%	0.45%	0.60%	0.41%	0.31%	0.08%	-0.12%	0.82%	0.56%
tdegw										
coeff	0.0045	0.0084	0.0055	0.0071	0.0060	0.0061	0.0064	0.0040	0.0043	0.0068
t-stat	***2.76	***3.07	***2.77	***3.44	**2.01	***2.97	***3.29	**2.08	***2.52	***3.23
a-rsq	0.65%	1.11%	0.73%	1.03%	0.48%	1.10%	0.99%	0.32%	0.67%	1.02%
mdist										
coeff	-0.0036	-0.0067	-0.0036	-0.0043	-0.0047	-0.0061	-0.0052	-0.0039	-0.0028	-0.0043
t-stat	**-2.35	***-2.76	**-2.04	**-2.34	*-1.61	***-3.15	***-2.78	**-2.27	*-1.69	**-2.23
a-rsq	0.52%	0.88%	0.35%	0.43%	0.35%	1.49%	0.84%	0.42%	0.30%	0.46%
Decc										
coeff	0.0043	0.0137	0.0050	0.0068	0.0037	0.0079	0.0059	0.0024	0.0079	0.0132
t-stat	1.30	***2.69	*1.47	*1.51	0.73	**2.19	*1.65	0.44	***2.79	**2.43
a-rsq	0.10%	0.68%	0.12%	0.26%	-0.04%	0.54%	0.15%	-0.08%	0.82%	0.94%
Dradw										
coeff	-0.0080	-0.0151	-0.0103	-0.0095	-0.0062	-0.0091	-0.0070	-0.0059	-0.0064	-0.0122
t-stat	**-2.07	***-2.85	***-2.53	*-1.88	-1.19	**-2.32	*-1.57	-1.25	*-1.88	***-2.64
a-rsq	0.48%	0.84%	0.59%	0.37%	0.03%	0.56%	0.21%	0.11%	0.31%	0.79%
Dtdeg										
coeff	0.0020	0.0033	0.0023	0.0038	0.0025	0.0030	0.0033	0.0001	0.0017	0.0025
t-stat	1.29	1.42	1.24	*1.87	0.96	*1.72	*1.67	0.05	1.08	1.25
a-rsq	0.05%	0.09%	0.04%	0.25%	0.00%	0.21%	0.20%	-0.12%	0.03%	0.06%
PC1										
coeff	-0.0014	-0.0031	0.0022	0.0036	0.0021	-0.0019	-0.0022	0.0015	-0.0021	0.0022
t-stat	**-2.20	***-2.56	***3.10	***4.21	*1.93	**-2.38	***-2.80	*1.88	***-3.08	***2.68
a-rsq	0.40%	0.93%	0.81%	1.64%	0.33%	0.64%	0.72%	0.23%	1.07%	0.68%

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: coeff = coefficient; t-stat = Student's t-test statistic; a-rsq = adjusted r-squared. The remaining abbreviations are explained in table 1, 2 and 3. Significant coefficients are marked by a bold font. This table shows a selection of the best in-sample predictors. The complete predictive regression results are available upon request. A bootstrapped-based stability analysis of these results is outlined in table 13 in the appendix.

predict future stock returns. Solely ***cls*** is characterized by significant coefficients for all industry portfolios. Lastly, the first principal component of all predictors (***PC1***) demonstrates a superior predictive ability, which is also stable across different time frames[8].

Table 5: Best Subset Selection Results, Jan1950 to Feb2018, $h = 1$

NoDur	Intercept	ecc	evc	Decc	Ddeg	a-rsq
coeff	0.0119	-0.0064	0.0053	0.0103	-0.0120	3.08%
t-stat	***7.89	***-3.75	***3.36	***2.88	***-2.95	
Durbl		tdegw	Ddeg	Dradw	Dmdist	
coeff	0.0119	0.0086	0.0065	-0.0116	0.0240	2.20%
t-stat	***5.20	***3.19	1.21	**-2.20	*1.69	
Manuf		mdist	Drad	Dradw	PC2	
coeff	0.0125	-0.0084	0.0049	-0.0124	0.0033	1.40%
t-stat	***6.77	***-2.95	**1.97	***-2.52	**2.04	
Enrgy		Dcls	Devc	PC1		
coeff	0.0108	0.0081	-0.0057	0.0032		1.91%
t-stat	***6.00	1.16	-1.41	***3.55		
HiTec		evc	radw	mdist	PC6	
coeff	0.0136	0.0055	-0.0073	-0.0109	-0.0037	1.51%
t-stat	***5.56	**1.94	**-1.98	***-2.98	*-1.52	
Telcm		mdist	Decc	Devc	Drad	
coeff	0.0107	-0.0064	0.0131	-0.0065	0.0039	3.18%
t-stat	***7.10	***-3.39	***3.37	***-2.72	**1.95	
Shops		tdegw	Dcls	Decc	PC6	
coeff	0.0121	0.0065	-0.0147	0.0137	-0.0029	2.05%
t-stat	***6.67	***3.38	***-2.64	***2.65	*-1.63	
Hlth		ecc	radw	mdist	PC3	
coeff	0.0131	-0.0115	-0.0111	-0.0065	0.0046	1.43%
t-stat	***6.98	**-2.27	**-2.25	***-2.88	***2.84	
Utils		btw	deg	tdeg	Decc	
coeff	0.0103	-0.0124	0.0126	0.0029	0.0072	2.86%
t-stat	***7.69	***-3.04	***2.63	**2.41	***2.51	
Other		tdegw	Dbtw	Decc	Drad	
coeff	0.0115	0.0065	-0.0110	0.0230	0.0036	2.59%
t-stat	***5.95	***3.30	***-2.75	***3.16	1.42	

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: coeff = coefficient; t-stat = Student's t-test statistic; a-rsq = adjusted r-squared. The remaining abbreviations are explained in table 1, 2 and 3. Significant coefficients are marked by a bold font. This table shows the best predictive regression for each target variable according to the a-rsq metric. For the best subset selection, predictive regressions based on all non-repeating permutations of up to four predictors were evaluated.

To illustrate the predictive potential of network-based metrics in a multivariate context, we present predictive equations for each industry portfolio based on the best subset selec-

[8] In table 13, which is placed in the appendix, we perform a bootstrapped-based stability analysis of the results from table 4.

tion in table 5. The best subset selection utilizes a brute force approach that evaluates all non-repeating combinations of up to for predictors and selects predictive regressions with the highest adjusted r-squared. Table 5 suggests that the multivariate predictive potential of network-based metrics is considerable, but varies strongly across the different industry portfolios. In this regard, the predictive regression modeling $t+1$ returns of *Manuf* exhibits the lowest adjusted r-squared (1.40%) whereas *Telcm* is more predictable with an in-sample adjusted r-squared of 3.08%. Analyzing the specific predictors reveals that holistic network metrics are slightly more present in the forecasting equations, especially ***mdist*** and ***tdegw***. Furthermore, table 5 demonstrates that some predictors can exhibit strong predictive power when combined with other predictors. For example, ***evc*** and ***ecc*** are characterized by higher absolute t-test statistics in the *NoDur*-equation (table 5) than in the respective univariate predictive regressions[9] highlighting the merit of multivariate forecasting. Lastly, some predictive equations in table 5 comprise principal factors beyond ***PC1***. This observation once again stresses the advantage of multivariate forecasting. Principal factors beyond ***PC1*** or ***PC2*** usually convey residual network-based information. However, in combination with other network metrics, this residual information can have a clear value-added.

4.2 In-Sample Analysis with the Broad Set of Predictors

In this sub-study we repeat the analysis from section 4.1, using an enlarged pool of predictors. Now centrality scores of any asset (and their dynamic version) can be part of the predictive modeling of the considered target variable. Table 6 illustrates univariate predictive regression results, while 7 show multivariate best subset section results. In line with the previous section, we perform a stability analysis of the results from table 6. For the sake of brevity, these results are placed in the appendix[10].

The results in table 6 reveal that the relative network position or embeddedness intensity of certain assets convey important predictive information for all other assets. In this regard,

[9] ***evc***=1.74, ***ecc***=-2.17, see the detailed results which are available upon request.

[10] See table 14.

the ***cls*** metric of various assets predicts significantly future returns of all other assets. For example, ***cls8***, which is the closeness centrality index for *Hlth*, not only significantly predicts the $t+1$ returns of the health care industry portfolio, but in addition $t+1$ returns of all other industry portfolios. In some cases, the predictive ability of the closeness centrality index for *Hlth* (***cls8***) is even higher for foreign sectors. The general phenomenon that certain assets or sectors structurally dominate a considered financial network is already recorded in numerous studies (see Mantegna (1999), Onnela et al. (2003a) andPeralta (2015)). The results in table 6 add to this academic endeavor by proving that this phenomenon also applies to predictive network-based modeling.

Best subset selection results in table 7 confirm as well the value-adding of considering centrality information of all nodes when setting up predictive equations. Compared to the previous section, the adjusted r-squared is in many cases greatly enhanced, whereby asset-specific centrality metrics now dominate the predictive equations. In some instances, the predictive regression is entirely made up of asset-specific centrality indices from other industry portfolios. For example, the best regression for $t+1$ returns of *Durbl* completely relies on centrality information from other assets. Summing up, table 7 makes clear that network-based interdependencies can be enormous and should be taken into account when constructing network-based forecasting models.

4.3 Out-of-Sample Analysis with the Narrow Set of Predictors

From a practitioners point of view, the above in-sample results are of limited value as they do not guarantee out-of-sample (OOS) outperformance of network-based predictors. However, OOS outperformance is necessary to make sure that the information content of the respective network-based predictors can be exploited in profitable investment strategies. Therefore, all subsequent sub-studies exclusively focus on OOS analysis. We start by outlining how OOS forecasts are generated.

Table 6: Best In-Sample Predictors, Univariate Predictive Regression Results, Broader Set of Predictors, Jan1951 to Feb2018, $h = 1$

Predictors	**Target Variables**									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
cls8										
coeff	0.0041	0.0079	0.0053	0.0054	0.0061	0.0065	0.0068	0.0049	0.0030	0.0070
t-stat	***2.55	***3.45	***2.97	***2.79	**2.23	***3.40	***3.57	***2.60	*1.86	***3.83
a-rsq	0.66%	1.19%	0.79%	0.66%	0.61%	1.57%	1.35%	0.63%	0.33%	1.35%
tdegw										
coeff	0.0045	0.0084	0.0055	0.0071	0.0060	0.0061	0.0064	0.0040	0.0043	0.0068
t-stat	***2.76	***3.07	***2.77	***3.44	**2.01	***2.97	***3.29	**2.08	***2.52	***3.23
a-rsq	0.65%	1.11%	0.73%	1.03%	0.48%	1.10%	0.99%	0.32%	0.67%	1.02%
cls3										
coeff	0.0043	0.0089	0.0052	0.0060	0.0058	0.0059	0.0058	0.0033	0.0042	0.0056
t-stat	***2.75	***3.21	***2.76	***2.86	**2.05	***3.09	***3.02	**1.94	***2.64	***2.73
a-rsq	0.58%	1.27%	0.62%	0.71%	0.43%	1.03%	0.80%	0.17%	0.65%	0.66%
cls5										
coeff	0.0057	0.0111	0.0071	0.0089	0.0086	0.0084	0.0076	0.0042	0.0064	0.0072
t-stat	***2.51	***3.14	***2.67	***3.08	**2.10	***3.21	***2.82	*1.63	***2.75	***2.48
a-rsq	0.54%	1.03%	0.63%	0.84%	0.54%	1.14%	0.72%	0.13%	0.83%	0.58%
deg3										
coeff	0.0040	0.0078	0.0049	0.0042	0.0055	0.0051	0.0054	0.0039	0.0031	0.0051
t-stat	***2.70	***2.99	***2.67	*1.89	**2.04	***2.84	***3.02	**2.38	**2.09	***2.57
a-rsq	0.49%	0.94%	0.54%	0.29%	0.38%	0.76%	0.67%	0.28%	0.31%	0.52%
Decc9										
coeff	0.0072	0.0103	0.0074	0.0128	0.0050	0.0132	0.0086	0.0079	0.0079	0.0115
t-stat	**2.08	***2.49	**1.99	***3.08	*1.00*	***3.51	**2.33	*1.82*	***2.79	***3.00
a-rsq	0.57%	0.52%	0.40%	1.16%	0.02%	1.87%	0.58%	0.46%	0.82%	1.02%
mdist										
coeff	-0.0036	-0.0067	-0.0036	-0.0043	-0.0047	-0.0061	-0.0052	-0.0039	-0.0028	-0.0043
t-stat	**-2.35	***-2.76	**-2.04	**-2.34	*-1.61	***-3.15	***-2.78	**-2.27	*-1.69	**-2.23
a-rsq	0.52%	0.88%	0.35%	0.43%	0.35%	1.49%	0.84%	0.42%	0.30%	0.46%
diamw										
coeff	-0.0024	-0.0060	-0.0034	-0.0054	-0.0035	-0.0039	-0.0037	-0.0018	-0.0037	-0.0041
t-stat	*-1.91	***-2.95	**-2.18	***-3.03	*-1.54	**-2.35	**-2.43	*-1.14*	***-2.59	***-2.53
a-rsq	0.22%	0.83%	0.36%	0.90%	0.18%	0.63%	0.45%	0.01%	0.80%	0.53%
PC2										
coeff	0.0007	0.0023	0.0016	0.0024	0.0019	0.0009	0.0010	0.0006	0.0015	0.0018
t-stat	1.22	***2.70	***2.51	***3.88	***2.53	*1.40*	*1.54	*0.92*	***3.01	***2.69
a-rsq	0.07%	0.88%	0.60%	1.31%	0.54%	0.15%	0.16%	-0.03%	0.95%	0.75%
cls4										
coeff	0.0035	0.0067	0.0047	0.0071	0.0043	0.0038	0.0047	0.0033	0.0041	0.0055
t-stat	**2.04	**2.37	**2.22	***3.02	***1.67	**1.95	**2.34	*1.63	**2.41	***2.50
a-rsq	0.31%	0.61%	0.45%	0.95%	0.17%	0.32%	0.43%	0.15%	0.54%	0.58%

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: coeff = coefficient; t-stat = Student's t-test statistic; a-rsq = adjusted r-squared. The remaining abbreviations are explained in table 1, 2 and 3. Significant coefficients are marked by a bold font. This table shows a selection of the best in-sample predictors. The complete predictive regression results are available upon request. A bootstrapped-based stability analysis of these results is outlined in table 14 in the appendix.

Table 7: Best Subset Selection Results, Broader Set of Predictors, Jan1950 to Feb2018, $h = 1$

	Intercept	evc1	cls7	Decc6		Adj-Rsqr
NoDur	0.0117 ***7.751	0.0055 ***3.465	0.0047 ***3.043	0.0106 ***2.924		3.35%
	Intercept	cls3	btw8	Ddeg6	Decc10	
Durbl	0.0122 ***5.362	0.0093 ***3.646	0.0049 ***2.740	-0.0097 ***-2.380	0.0143 ***2.846	3.54%
	Intercept	cls2	evc8	Decc6	Ddeg6	
Manuf	0.0117 ***6.351	0.0064 ***2.940	0.0043 ***2.744	0.0098 ***2.640	-0.0062 ***-1.859	2.48%
	Intercept	tdegw	evc7	ecc10	Decc9	
Enrgy	0.0106 ***5.409	0.0099 ***4.144	-0.0038 ***-2.008	0.0085 ***3.033	0.0098 ***2.223	3.25%
	Intercept	evc5	cls8	Ddeg6	Devc7	
HiTec	0.0141 ***6.293	0.0061 ***2.438	0.0072 ***2.630	-0.0098 ***-2.300	-0.0073 ***-2.072	2.24%
	Intercept	mdist	btw8	Decc9		
Telcm	0.0106 ***7.190	-0.0058 ***-3.129	0.0027 ***1.749	0.0148 ***4.227		5.27%
	Intercept	cls5	btw8	Dbtw10	Decc10	
Shops	0.0135 ***7.093	0.0082 ***3.053	0.0049 ***3.103	-0.0117 ***-3.239	0.0150 ***2.995	3.05%
	Intercept	evc1	ecc6	Decc6		
Hlth	0.0131 ***7.018	0.0064 ***3.519	-0.0055 ***-2.429	0.0130 ***2.775		2.40%
	Intercept	cls9	btw9	Devc5	Decc9	
Utils	0.0103 ***8.248	0.0062 ***3.491	-0.0054 ***-3.312	0.0044 ***1.682	0.0070 ***2.534	2.90%
	Intercept	evc1	tdegw	Decc9		
Other	0.0120 ***6.263	0.0056 ***2.784	0.0070 ***3.601	0.0127 ***3.283		3.22%

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: coeff = coefficient; t-stat = Student's t-test statistic; a-rsq = adjusted r-squared. The remaining abbreviations are explained in table 1, 2 and 3. Significant coefficients are marked by a bold font. This table shows the best predictive regression for each target variable according to the a-rsq metric. For the best subset selection, predictive regressions based on all non-repeating permutations of up to four predictors were evaluated.

The $t+h$ out-of-sample (conditional) return forecast for the i-th industry portfolio, based on the j-th network-based metric, is given by:

$$\hat{R}_{i,t+h} = \hat{\alpha}^i_{j,t} + \hat{\beta}^i_{j,t} N_{j,t}, \tag{3}$$

where $\hat{\alpha}^i_{j,t}$ and $\hat{\beta}^i_{j,t}$ are the OLS estimates from regressing $\{R_{i,s}\}^t_{s=t-rw+2}$ on a constant and $\{N_{i,s}\}^{t-1}_{s=t-rw+1}$. rw is the rolling window length. Using this setup yields a return forecast that utilizes only the data available up to the time at which the forecast is made and by this complying with the strict rules of an OOS setup. We use a rolling window approach of 100 months ($rw = 100$) for the estimation of the forecasting model parameters. This will ensure that the model always captures the most recent dynamics. The benchmark approach is the (unconditional) mean model, which is often very hard to beat (Goyal and Welch (2008)):

$$\hat{R}^B_{i,t+h} = rw^{-1} \sum_{s=t-rw+1}^{t} R_{i,s} \tag{4}$$

For the sake of consistency with the conditional forecasting model, the benchmark model relies as well on a rolling window of 100 months. When testing for statistical significance, we follow the methodology of Goyal and Welch (2008) and McCracken (2007). First, we define the difference of the rooted mean squared forecasting errors between the benchmark model and the conditional (active) model as:

$$\Delta RMSE = \sqrt{MSE_B} - \sqrt{MSE_A}, \tag{5}$$

where MSE_B and MSE_A is the mean squared forecasting error of the benchmark model and the conditional (active) model, respectively. The statistical significance of $\Delta RMSE$ (null hypothesis $\Delta RMSE = 0$) is measured by the McCracken (2007) F-statistic defined by:

$$MSE - F = (T - h + 1) \times \left(\frac{MSE_B - MSE_A}{MSE_A} \right). \tag{6}$$

In this case, T represents the length of the OOS period. Similarly to Goyal and Welch (2008), we bootstrap the critical thresholds of the $MSE - F$ statistics and indicate the significance levels in the tables if necessary. In addition, we measure the hit ratios of competing models and quantify the statistical significance[11] by bootstrapping the critical thresholds.

Table 8 analyzes the best in-sample predictors, which are outlined in table 4, in an OOS framework. Considering the r squared numbers in table 8 makes clear that in-sample results cannot be directly transferred to the OOS case, as the respective OOS values are much smaller than their in-sample counterparts. However, the r squared metrics in table 8 are still throughout positive implying a decent OOS explanatory power of the predictors in focus. Hit ratios and $\Delta RMSE$ marked by a bold font represent instances where the conditional model outperforms the respective unconditional benchmark. As can be seen from the table, such instances are a rare phenomenon highlighting the difficulty of beating the mean model. Additionally, none of these instances are statistically significant.

In general, the (unconditional) mean model forecasts exhibit by construction a small variation leading to a bias-variance tradeoff which is dominated by low variance. This characteristic makes the mean model hard to beat with regard to the MSE and rooted MSE. Furthermore, the mean model by construction replicates the empirical observation that positive stock returns outnumber the negative counterparts. This feature makes the mean model also hard to beat in terms of the hit ratio.[12]

In the last column of table 8, we calculate the average OOS performance metrics for each predictor. This analysis underscores once again the superiority of holistic network-based metrics. With regard to r squared, ***tdegw*** and ***mdist*** are in the lead, while ***Dradw*** produces the highest average hit ratio. Lastly, the highest average $\Delta RMSE$ value is exhibited by ***diam*** and ***tdeg***. All of the mentioned metrics are holistic meaning they quantify the shape of the complete network.

[11] The null hypothesis is: $hit\ ratio\ of\ conditional\ model - hit\ ratio\ of\ unconditional\ model = 0$.

[12] On the other side, the inelasticity of the mean model makes it an easy target when it comes to the r squared metric. The active models mostly dominate the mean model benchmark in terms of r squared. For the sake of clarity, we refrain from marking almost all r squared metrics in table 8 by a bold font.

Table 8: Predictors from Table 4 in an OOS Setup, all numbers are in %

Predictors	**Target Variables**										**Avrg**
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*	
cls											
R^2	0.138	0.007	0.051	0.361	0.160	0.024	0.093	0.684	0.122	0.079	0.172
Hit Ratio	*61.89*	*54.94*	*60.08*	*58.83*	***57.86***	*58.41*	*60.08*	*59.53*	*60.08*	*58.55*	*59.03*
$\Delta RMSE$	-0.025	-0.078	-0.033	-0.027	-0.033	-0.038	-0.034	**0.001**	-0.020	-0.013	-0.030
diam											
R^2	0.273	0.317	0.096	0.265	0.003	0.573	0.026	0.005	0.347	0.271	0.217
Hit Ratio	*62.17*	*55.77*	*58.41*	*57.58*	*55.08*	*58.97*	*59.67*	***60.50***	*60.78*	*60.08*	*58.90*
$\Delta RMSE$	-0.015	-0.005	-0.026	-0.007	-0.041	-0.008	-0.030	-0.031	-0.005	-0.007	-0.017
diamw											
R^2	0.020	0.167	0.007	0.238	0.000	0.057	0.012	0.161	0.098	0.059	0.082
Hit Ratio	*62.17*	*55.77*	*59.94*	*58.28*	*56.75*	*59.53*	*60.64*	***60.50***	*60.22*	*59.81*	*59.36*
$\Delta RMSE$	-0.036	-0.025	-0.052	-0.030	-0.064	-0.038	-0.048	-0.054	-0.024	-0.036	-0.041
tdeg											
R^2	0.065	0.037	0.014	0.180	0.094	0.192	0.014	0.002	0.138	0.055	0.079
Hit Ratio	*62.31*	*54.66*	*59.81*	*58.97*	*55.63*	*59.53*	*61.61*	***62.03***	*60.08*	*58.55*	*59.32*
$\Delta RMSE$	-0.017	-0.033	-0.015	-0.002	-0.011	-0.021	-0.026	-0.028	-0.012	-0.010	-0.017
tdegw											
R^2	0.592	0.486	0.344	0.692	0.366	0.718	0.637	0.071	0.321	0.515	0.474
Hit Ratio	***62.59***	*56.19*	*59.53*	*57.16*	*56.47*	***61.20***	*60.36*	*59.53*	*58.97*	*58.97*	*59.10*
$\Delta RMSE$	-0.005	-0.019	-0.023	-0.007	-0.041	-0.012	-0.006	-0.033	-0.021	-0.009	-0.018
mdist											
R^2	0.378	0.246	0.394	0.553	0.551	0.783	0.403	0.006	0.063	0.457	0.384
Hit Ratio	*60.50*	*55.22*	*59.94*	*58.69*	***58.28***	*60.22*	*60.22*	*59.94*	*59.81*	*59.39*	*59.22*
$\Delta RMSE$	-0.025	-0.036	-0.029	-0.022	-0.032	-0.013	-0.033	-0.044	-0.032	-0.023	-0.029
Decc											
R^2	0.036	0.823	0.010	0.055	0.004	0.365	0.006	0.304	0.150	0.128	0.188
Hit Ratio	*62.17*	*56.33*	*59.39*	*58.69*	*56.47*	***60.92***	*60.50*	*61.47*	*61.06*	*58.55*	*59.56*
$\Delta RMSE$	-0.027	**0.008**	-0.017	-0.025	-0.045	-0.013	-0.017	-0.050	-0.015	-0.028	-0.023
Dradw											
R^2	0.044	0.268	0.105	0.156	0.000	0.136	0.040	0.032	0.098	0.085	0.097
Hit Ratio	***63.00***	*56.47*	***60.50***	***59.53***	***57.16***	***60.64***	*61.20*	*61.06*	***61.61***	*59.11*	*60.03*
$\Delta RMSE$	-0.026	-0.005	-0.021	-0.031	-0.037	-0.020	-0.040	-0.044	-0.010	-0.029	-0.026
Dtdeg											
R^2	0.047	0.118	0.015	0.020	0.026	0.103	0.002	0.003	0.161	0.002	0.050
Hit Ratio	*62.03*	*55.08*	*60.22*	*58.55*	*57.02*	*59.81*	*61.06*	***62.03***	*60.78*	*57.86*	*59.44*
$\Delta RMSE$	-0.017	-0.040	-0.023	-0.008	-0.029	-0.021	-0.027	-0.020	-0.032	-0.027	-0.024
PC1											
R^2	0.016	0.152	0.003	0.156	0.006	0.002	0.070	0.271	0.158	0.000	0.083
Hit Ratio	*60.92*	*55.77*	*59.67*	***59.53***	*56.19*	*58.14*	*59.81*	*61.34*	***61.75***	*57.72*	*59.08*
$\Delta RMSE$	-0.031	-0.059	-0.033	-0.043	-0.017	-0.060	-0.030	**0.006**	-0.009	-0.037	-0.031

Legend: Avrg = average of the respective row; R^2 = coefficient of determination (r squared); $\Delta RMSE$ = rooted mean squared forecasting error of the benchmark model MINUS rooted mean squared forecasting error of the conditional model. The remaining abbreviations are explained in table 1, 2 and 3. This table analyzes the performance of the best in-sample predictors from table 4 in an OOS framework. Instances of OOS conditional model outperformance in terms of hit ratio and $\Delta RMSE$ are marked by a bold font. However, none of these instances are statistically significant. The complete OOS results are available upon request.

The main findings from table 8 can be summarized as follows: Firstly, the performance of the best in-sample predictors is reduced in the OOS setup, but the explanatory power is still modestly positive. Secondly, the mean model proves to be a tough benchmark as it is difficult to beat when it comes to statistical performance metrics ($\Delta RMSE$ and hit ratio). Finally, holistic network metrics show superior forecasting power in the OOS framework. This impression is confirmed when looking at the overall best OOS predictors, which are presented in the appendix (table 15).

4.4 Out-of-Sample Analysis with the Broad Set of Predictors

In table 9, we repeat the above exercise with a broader set of predictors and present a selection of the best results. Like in the in-sample case, the performance metrics can be strongly improved by adding asset specific centrality scores to the set of predictors. In some instances, the outperformance of the conditional model is even statistically significant. However, the mean model is still a hard-to-beat benchmark, especially in terms of $\Delta RMSE$. Furthermore, similarly to the in-sample case, we observe that some assets convey important network-based information, which well predicts stock returns of other network constituents (assets). For example, centrality metrics of *Durbl* (***cls2***, ***deg2*** and ***Decc2***) are strong predictors for many other network constituents. Interestingly, centrality metrics of *Durbl* often predict future stock returns of other industry portfolios even better than *Durbl* returns.

For the sake of completeness, we analyze the best in-sample predictors from the broader dataset (table 6) in an OOS setup. The respective results are placed in the appendix (table 16), as they do not convey any new information. Similarly to the previous section, the strong in-sample performance even for the broader dataset is not achieved in the OOS setting. Therefore, in-sample results should always be analyzed with a healthy dose of skepticism.

Table 9: Best Predictors in an OOS Setup, Broader Set of Predictors, all numbers are in %

Predictors	Target Variables										Avrg
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*	
cls2											
R^2	0.479	0.007	0.222	0.429	0.091	0.180	0.194	0.026	0.005	0.343	0.198
Hit Ratio	**62.73**	54.94	*62.03	58.14	**57.16**	**60.92**	**62.03**	61.89	59.39	**60.92**	59.79
$\Delta RMSE$	-0.025	-0.078	-0.047	-0.011	-0.048	-0.018	-0.041	-0.057	-0.042	-0.048	-0.041
deg2											
R^2	0.012	0.208	0.003	0.038	0.026	0.000	0.001	0.200	0.000	0.035	0.052
Hit Ratio	61.61	54.94	**60.50**	**59.25**	56.61	60.22	60.50	61.20	59.94	**59.67**	59.44
$\Delta RMSE$	-0.048	-0.137	-0.084	-0.056	-0.077	-0.057	-0.068	-0.070	-0.049	-0.073	-0.072
cls5											
R^2	0.426	0.131	0.059	0.089	0.160	0.502	0.093	0.003	0.335	0.172	0.197
Hit Ratio	62.03	54.94	59.67	58.83	**57.86**	**61.06**	60.50	61.34	60.92	**59.53**	59.66
$\Delta RMSE$	-0.009	-0.020	-0.027	-0.024	-0.033	-0.013	-0.026	-0.051	-0.005	-0.013	-0.022
btw7											
R^2	0.092	0.213	0.132	0.004	0.060	0.310	0.075	0.042	0.000	0.097	0.103
Hit Ratio	61.75	**57.16**	59.94	58.83	**57.72**	59.67	59.25	60.50	60.08	**59.67**	59.46
$\Delta RMSE$	-0.057	-0.023	-0.039	-0.025	-0.023	-0.030	-0.049	-0.034	-0.036	-0.044	-0.036
ecc8											
R^2	0.037	0.016	0.040	0.069	0.001	0.000	0.016	0.013	0.005	0.118	0.032
Hit Ratio	61.47	55.22	**61.34**	57.58	**57.86**	59.53	**62.03**	60.50	59.11	58.55	59.32
$\Delta RMSE$	-0.032	-0.054	-0.045	-0.049	-0.066	-0.037	-0.034	-0.038	-0.039	-0.044	-0.044
Dcls											
R^2	0.158	0.115	0.000	0.279	0.013	0.039	0.036	0.002	0.000	0.044	0.069
Hit Ratio	**62.59**	55.77	59.53	58.69	**58.00**	59.67	60.78	61.75	60.36	**59.53**	59.66
$\Delta RMSE$	-0.016	-0.009	-0.026	-0.011	-0.042	-0.025	-0.022	-0.036	-0.024	-0.018	-0.023
Ddiamw											
R^2	0.006	0.090	0.030	0.000	0.130	0.020	0.205	0.076	0.000	0.003	0.056
Hit Ratio	62.45	**56.88**	**60.64**	58.28	56.75	59.67	61.20	61.20	61.34	**59.94**	59.83
$\Delta RMSE$	-0.021	-0.032	-0.024	-0.032	-0.038	-0.024	-0.037	-0.042	-0.018	-0.025	-0.029
Dradw											
R^2	0.044	0.268	0.105	0.156	0.000	0.136	0.040	0.032	0.098	0.085	0.097
Hit Ratio	**63.00**	56.47	**60.50**	**59.53**	**57.16**	**60.64**	61.20	61.06	**61.61**	59.11	60.03
$\Delta RMSE$	-0.026	-0.005	-0.021	-0.031	-0.037	-0.020	-0.040	-0.044	-0.010	-0.029	-0.026
Decc2											
R^2	0.276	0.823	0.368	0.059	0.047	0.302	0.272	0.189	0.005	0.836	0.318
Hit Ratio	**62.59**	56.33	**61.34**	**59.81**	**57.30**	59.94	59.94	61.61	**61.75**	**61.47	60.07
$\Delta RMSE$	-0.015	**0.008**	-0.010	-0.051	-0.029	-0.020	-0.010	-0.003	-0.025	**0.008**	-0.015
Dcls7											
R^2	0.036	0.181	0.057	0.013	0.071	0.002	0.081	0.078	0.023	0.152	0.069
Hit Ratio	**62.59**	55.63	**60.92**	58.41	**57.30**	60.08	60.64	**62.31**	61.20	59.11	59.82
$\Delta RMSE$	-0.056	-0.032	-0.029	-0.037	-0.033	-0.046	-0.035	-0.050	-0.027	-0.045	-0.039

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: Avrg = average of the respective row; R^2 = coefficient of determination (r squared); $\Delta RMSE$ = rooted mean squared forecasting error of the benchmark model MINUS rooted mean squared forecasting error of the conditional model. The remaining abbreviations are explained in table 1, 2 and 3. This table shows the best predictors in the OOS framework using a broader set of predictors. Instances of OOS conditional model outperformance in terms of hit ratio and $\Delta RMSE$ are marked by a bold font. The complete OOS results are available upon request.

4.5 Out-of-Sample Analysis: Asset-specific Asset Allocation Exercise

The above study analyzes OOS predictability from a statistical perspective, which is only of limited relevance for the economic value-added of predictors. To tackle this shortcoming, we perform a certainty equivalent return (CER) analysis, whereby we adopt the methodology of Campbell and Thompson (2008), Ferreira and Santa-Clara (2011) and Neely et al. (2014). We start by assuming an investor with a single-period horizon and mean-variance preferences who allocates between a risky asset and risk-free bills. For this investor, the optimal portfolio weight in the risky asset is given by:

$$w_t^* = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{R}_{i,t+h}}{\hat{\sigma}_{i,t+h}}\right), \tag{7}$$

where $\hat{R}_{i,t+h}$ and $\hat{\sigma}_{i,t+h}$ is the one-period ($h = 1$) forecast of the asset return and its variance, respectively. γ is the risk aversion parameter of the investor, which we set to $\gamma = 5$[13]. The optimal risky asset weight w_t^* is confined to 0% and 150% implying a short-sale constraint and a leverage limit of 50%. For reasons of consistency, we assume that the investor empirically estimates $\hat{\sigma}_{i,t+h}$ by using a rolling window of 100 monthly returns for the i-th asset[14]. Hence, the return and variance estimates are based on the same estimation window. Having determined the optimal weight in the risky asset, the total portfolio return of the analyzed investment strategy is given by:

$$R_{p,t+h} = w_t^* R_{i,t+h} + (1 - w_t^*) R_{f,t+h}, \tag{8}$$

[13] The variation of γ leads to qualitatively similar findings.

[14] Note that we deviate in this aspect from the methodology of Campbell and Thompson (2008) and Neely et al. (2014) who estimate variance using a rolling five-year window of monthly returns.

where $R_{f,t+h}$ is the return on Treasury bills[15]. After calculating the OOS portfolio return series, the CER for the mean-variance investor is defined as:

$$CER_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}_p^2, \tag{9}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the empirical mean and variance for the investor's portfolio, respectively. Note that the portfolio mean and variance are annualized. Therefore the CER is stated in *p.a.* terms. On a standalone basis the CER can be interpreted as the maximum *p.a.* fee the investor is willing to pay to get exposure to the respective investment strategy. The results we present in table 10 and 11 show the delta between the CER of the active (conditional) model and the benchmark (mean/unconditional) model:

$$\Delta CER = CER_A - CER_B. \tag{10}$$

Precisely, CER_A is the certainty equivalent return of the asset allocation exercise that relies on a univariate (one predictor) return forecasting model. The same logic applies to CER_B, where the return prediction is based on the simple mean model. We test the null hypothesis H_0: $CER_A - CER_B = 0$ by the bootstrap-based methodology of Ledoit and Wolf (2008). In addition, we calculate in table 10 and 11 ΔCER after trading costs assuming transaction costs of 40 basis points per unit of absolute turnover volume. Lastly, both tables show the average monthly turnover volumes of each investment strategy.

For the sake of brevity, we start by discussing the results that are based on the broader set of predictors and hence skipping the narrow dataset analysis[16]. Table 10 outlines the results of the OOS asset allocation exercise when using the best in-sample predictors (broader dataset). Table 11 presents the overall best predictors analyzed in the OOS asset allocation setting. The main findings from these tables can be summarized as follows: Firstly, from

[15] We downloaded Treasury bills return data from the homepage of Amit Goyal (`http://www.hec.unil.ch/agoyal/`).

[16] The findings for the broader dataset also apply to the narrow set of predictors.

Table 10: Predictors from Table 6 and 16 in an OOS Asset Allocation Setup, all numbers are in %

Predictors	Target Variables									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
cls8										
ΔCER	0.75	***2.91	*1.84	*1.62	**2.60	*1.72	***3.29	**3.11	0.01	***2.91
ΔCER a. TC	0.36	**2.45	1.32	1.07	*2.12	1.32	**2.72	**2.59	-0.31	**2.37
Mean Turn.	*10.15*	*12.35*	*13.86*	*14.43*	*12.22*	*10.23*	*13.92*	*13.29*	*9.11*	*13.64*
tdegw										
ΔCER	**1.90	**3.16	**2.75	***3.56	**2.98	***3.46	***3.26	1.59	1.13	**3.14
ΔCER a. TC	*1.49	**2.65	*2.14	**2.95	*2.49	**2.97	**2.70	1.09	0.66	*2.51
Mean Turn.	*10.52*	*13.14*	*15.11*	*14.86*	*12.25*	*11.80*	*13.70*	*13.18*	*11.66*	*15.14*
cls3										
ΔCER	0.21	***3.47	1.27	*1.96	*2.00	*2.05	1.31	0.24	0.33	1.87
ΔCER a. TC	-0.38	**2.88	0.62	1.26	1.49	1.43	0.64	-0.35	-0.28	1.26
Mean Turn.	*13.86*	*14.65*	*16.19*	*17.07*	*12.81*	*14.13*	*15.95*	*14.94*	*14.38*	*15.04*
cls5										
ΔCER	0.52	***3.05	*2.25	1.57	**3.16	*1.97	1.17	-0.33	0.60	*1.99
ΔCER a. TC	-0.03	**2.53	1.66	0.98	*2.64	1.41	0.55	-0.79	0.08	1.45
Mean Turn.	*12.99*	*13.53*	*14.98*	*15.08*	*12.96*	*13.27*	*15.16*	*12.50*	*12.81*	*14.02*
deg3										
ΔCER	0.20	*2.47	0.69	0.32	1.09	*1.69	1.02	0.24	0.80	1.51
ΔCER a. TC	-0.39	1.86	0.04	-0.37	0.61	1.18	0.35	-0.27	0.29	0.80
Mean Turn.	*13.80*	*15.34*	*16.43*	*17.05*	*12.31*	*12.25*	*16.21*	*13.69*	*12.47*	*16.90*
Decc9										
ΔCER	0.13	0.88	*1.43	*1.69	*1.57	**1.85	0.72	*1.51	0.32	*1.76
ΔCER a. TC	-1.34	-0.48	-0.16	-0.03	0.26	0.32	-0.77	-0.03	-1.02	0.20
Mean Turn.	*29.70*	*29.94*	*34.26*	*36.64*	*28.11*	*31.40*	*31.45*	*32.59*	*28.34*	*33.30*
mdist										
ΔCER	0.39	***3.58	1.80	**2.77	*3.10	1.43	1.70	0.84	-0.59	*2.05
ΔCER a. TC	0.13	**3.31	1.48	**2.52	*2.80	1.08	1.41	0.53	-0.94	1.76
Mean Turn.	*7.63*	*8.58*	*9.83*	*8.47*	*8.89*	*9.10*	*8.96*	*9.90*	*9.63*	*9.21*
diamw										
ΔCER	-0.05	*1.87	0.99	***3.09	1.27	0.59	0.64	-0.65	0.47	1.29
ΔCER a. TC	-0.51	1.37	0.49	**2.53	0.79	0.17	0.20	-1.15	0.02	0.77
Mean Turn.	*11.51*	*13.09*	*13.32*	*14.20*	*12.54*	*10.57*	*11.86*	*13.65*	*11.43*	*13.43*
PC2										
ΔCER	-0.28	0.48	-0.13	-0.07	0.15	0.72	-0.01	-1.19	-0.66	0.68
ΔCER a. TC	-0.84	-0.13	-0.81	-0.82	-0.49	0.08	-0.65	-1.91	-1.24	0.03
Mean Turn.	*13.39*	*15.54*	*16.92*	*18.29*	*15.61*	*14.77*	*15.65*	*17.78*	*14.09*	*16.14*
cls4										
ΔCER	0.08	**2.78	*1.38	**2.52	0.73	0.77	0.91	0.14	0.85	**2.30
ΔCER a. TC	-0.37	*2.33	0.96	**2.12	0.32	0.37	0.48	-0.21	0.51	*1.84
Mean Turn.	*11.19*	*12.16*	*11.94*	*11.36*	*11.37*	*10.39*	*11.61*	*10.64*	*9.24*	*12.34*

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: ΔCER = certainty equivalent return (CER) differential/CER of the investment strategy based on the conditional return forecasting model MINUS CER of the investment strategy based on the unconditional return forecasting model; ΔCER a. TC = CER differential after trading costs, whereby we assume a transaction cost of 40 basis points per 1% of absolute turnover volume; Mean Turn. = average monthly portfolio turnover of the active investment strategy. The remaining abbreviations are explained in table 1, 2 and 3. This table shows the best in-sample predictors from table 6 (broader set of predictors) in the OOS asset allocation framework. Instances of conditional model outperformance in terms ΔCER and ΔCER a. TC are marked by a bold font. The complete OOS results are available upon request.

Table 11: Best Predictors in an OOS Asset Allocation Setup, Broader Set of Predictors, all numbers are in %

Predictors	Target Variables									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
tdegw										
ΔCER	****1.90**	****3.16**	****2.75**	*****3.56**	****2.98**	*****3.46**	*****3.26**	**1.59**	**1.13**	****3.14**
ΔCER a. TC	***1.49**	****2.65**	***2.14**	****2.95**	***2.49**	****2.97**	****2.70**	**1.09**	**0.66**	***2.51**
Mean Turn.	*10.52*	*13.14*	*15.11*	*14.86*	*12.25*	*11.80*	*13.70*	*13.18*	*11.66*	*15.14*
cls8										
ΔCER	**0.75**	*****2.91**	***1.84**	***1.62**	****2.60**	***1.72**	*****3.29**	****3.11**	**0.01**	*****2.91**
ΔCER a. TC	**0.36**	****2.45**	**1.32**	**1.07**	***2.12**	**1.32**	****2.72**	****2.59**	-0.31	****2.37**
Mean Turn.	*10.15*	*12.35*	*13.86*	*14.43*	*12.22*	*10.23*	*13.92*	*13.29*	*9.11*	*13.64*
btw7										
ΔCER	-0.36	*****3.30**	****2.77**	**1.14**	***1.61**	**0.09**	****1.95**	***1.37**	**0.01**	***1.67**
ΔCER a. TC	-0.78	****2.90**	****2.28**	**0.70**	**1.19**	-0.20	**1.48**	**0.94**	-0.33	**1.23**
Mean Turn.	*10.69*	*11.10*	*13.12*	*12.18*	*11.42*	*8.15*	*12.46*	*12.29*	*9.43*	*12.11*
mdist										
ΔCER	**0.39**	*****3.58**	**1.80**	****2.77**	***3.10**	**1.43**	**1.70**	**0.84**	-0.59	***2.05**
ΔCER a. TC	**0.13**	****3.31**	**1.48**	****2.52**	***2.80**	**1.08**	**1.41**	**0.53**	-0.94	**1.76**
Mean Turn.	*7.63*	*8.58*	*9.83*	*8.47*	*8.89*	*9.10*	*8.96*	*9.90*	*9.63*	*9.21*
cls3										
ΔCER	**0.21**	*****3.47**	**1.27**	***1.96**	***2.00**	***2.05**	**1.31**	**0.24**	**0.33**	**1.87**
ΔCER a. TC	-0.38	****2.88**	**0.62**	**1.26**	**1.49**	**1.43**	**0.64**	-0.35	-0.28	**1.26**
Mean Turn.	*13.86*	*14.65*	*16.19*	*17.07*	*12.81*	*14.13*	*15.95*	*14.94*	*14.38*	*15.04*
cls5										
ΔCER	**0.52**	*****3.05**	***2.25**	**1.57**	****3.16**	***1.97**	**1.17**	-0.33	**0.60**	***1.99**
ΔCER a. TC	-0.03	****2.53**	**1.66**	**0.98**	***2.64**	**1.41**	**0.55**	-0.79	**0.08**	**1.45**
Mean Turn.	*12.99*	*13.53*	*14.98*	*15.08*	*12.96*	*13.27*	*15.16*	*12.50*	*12.81*	*14.02*
deg4										
ΔCER	**0.42**	****2.03**	***1.68**	***2.20**	***1.85**	***1.32**	**1.11**	**1.17**	**0.28**	****2.21**
ΔCER a. TC	**0.10**	****1.75**	**1.40**	***1.94**	**1.59**	**1.10**	**0.83**	**0.88**	**0.04**	***1.90**
Mean Turn.	*9.00*	*9.09*	*9.48*	*8.87*	*8.42*	*6.89*	*8.82*	*9.38*	*7.48*	*9.52*
cls9										
ΔCER	**0.09**	***1.98**	**1.12**	****2.42**	***2.19**	**1.16**	-0.23	-0.47	**0.48**	**1.37**
ΔCER a. TC	-0.34	**1.53**	**0.71**	***1.96**	***1.74**	**0.75**	-0.67	-0.78	**0.03**	**0.92**
Mean Turn.	*10.93*	*12.29*	*11.79*	*12.52*	*11.80*	*10.56*	*12.06*	*10.02*	*11.47*	*12.20*
PC1										
ΔCER	-0.28	***1.58**	**1.08**	*****2.79**	**0.57**	-0.51	**0.66**	**0.28**	**0.17**	***1.30**
ΔCER a. TC	-0.72	**1.20**	**0.68**	****2.34**	**0.21**	-0.89	**0.25**	-0.12	-0.30	**0.89**
Mean Turn.	*11.13*	*10.99*	*11.60*	*12.20*	*10.09*	*9.88*	*11.51*	*11.49*	*11.77*	*11.50*
deg6										
ΔCER	**0.05**	**1.35**	***1.71**	-0.22	**0.69**	-0.27	**0.21**	-0.11	-0.62	**1.20**
ΔCER a. TC	-0.29	**1.04**	**1.42**	-0.60	**0.35**	-0.48	-0.11	-0.37	-1.00	**0.89**
Mean Turn.	*9.32*	*9.55*	*9.44*	*11.10*	*9.88*	*6.84*	*9.78*	*9.07*	*10.26*	*9.60*

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: ΔCER = certainty equivalent return (CER) differential/CER of the investment strategy based on the conditional return forecasting model MINUS CER of the investment strategy based on the unconditional return forecasting model; ΔCER a. TC = CER differential after trading costs, whereby we assume a transaction cost of 40 basis points per 1% of absolute turnover volume; Mean Turn. = average monthly portfolio turnover of the active investment strategy. The remaining abbreviations are explained in table 1, 2 and 3. This table shows the best predictors in the OOS asset allocation framework analyzing the broader set of predictors. Instances of conditional model outperformance in terms ΔCER and ΔCER a. TC are marked by a bold font. The complete OOS results are available upon request.

an economic perspective, network-based predictors mostly outperform the mean model. In many instances, the CER differentials are statistically significant. In contrast to statistical performance measures like $\Delta RMSE$, economic performance metrics cannot be boosted by the low variance of the mean model return forecasts. On the contrary, the small variance of the mean model return forecasts (and therefore low R^2) makes the mean model inflexible. This shortcoming explains its underperformance in dynamic investment strategies. Secondly, asset allocation models based on conditional return forecasting generate a noticeable amount of portfolio turnover. However, even when accounting for transaction costs, the economic value-added mostly persists. Finally, the results in table 11 reveal that closeness centrality (***cls***) is on average the most potent predictor from the group of asset-specific network metrics. From the group of holistic network metrics, ***tdegw*** is in the lead.

4.6 Out-of-Sample Analysis: Holistic Asset Allocation Exercise

The previous empirical study analyzed predictors in a narrow asset allocation framework, whereby each risky asset was allocated separately in a stock-bond portfolio. In this section, we extend the asset allocation perspective by modeling all risky assets (from table 1) simultaneously. This approach yields a holistic view on the economic value-added of network-based predictors. Note that when using the given OOS return forecasts and the empirical covariance matrix, we have all ingredients to set up an investment strategy that dynamically manages all risky assets. Using the broader set of predictors, we end up with 123 return forecasts[17] for each asset and OOS time point. This enables us to construct monthly return forecasts for each asset under a single-period optimization model. Since the investor can not know ex ante the best predictor for each asset, we assume that she calculates the mean from the current 123 return forecasts and uses it as her respective return forecast[18]. Additionally, the existence of many return forecasts enables us to determine forecast uncer-

[17]The interested reader is referred to the appendix (table 17), where we list every single predictor or forecasting model.

[18]Precisely, we use a trimmed mean methodology that ignores the most extreme positive and negative forecasts.

tainty for every time point and target variable (risky asset). This is achieved by calculating the cross-sectional standard deviation of the return forecasts. The optimizations problems of the implemented single-period investment strategies are given as follows:

$$\text{Benchmark-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_B - \lambda_1[\boldsymbol{w}^\top \boldsymbol{V}\boldsymbol{w}]\right), \tag{11}$$

$$\text{1. Active-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_A - \lambda_1[\boldsymbol{w}^\top \boldsymbol{V}\boldsymbol{w}]\right), \tag{12}$$

$$\text{2. Active-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_A - \lambda_2[\boldsymbol{w}^\top \boldsymbol{\sigma(\mu_A)}]\right), \tag{13}$$

$$\text{3. Active-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_A - \lambda_1[\boldsymbol{w}^\top \boldsymbol{V}\boldsymbol{w}] - \lambda_2[\boldsymbol{w}^\top \boldsymbol{\sigma(\mu_A)}]\right), \tag{14}$$

$$\text{4. Active-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_{tdegw} - \lambda_1[\boldsymbol{w}^\top \boldsymbol{V}\boldsymbol{w}]\right), \tag{15}$$

$$\text{5. Active-Strategy:} \qquad \boldsymbol{w}^* = arg\max_{\boldsymbol{w}} \left(\boldsymbol{w}^\top \boldsymbol{\mu}_{cls8} - \lambda_1[\boldsymbol{w}^\top \boldsymbol{V}\boldsymbol{w}]\right). \tag{16}$$

$\boldsymbol{w}$ is the portfolio weights vector, which is optimized on a monthly basis. $\boldsymbol{\mu}_B$ is the vector of return estimates from the benchmark (mean) model, whereas the $\boldsymbol{\mu}_A$ vector contains return forecasts from the conditional (active) models. As mentioned above, each element of $\boldsymbol{\mu}_A$ is a cross-sectional mean of the return forecasts from the broader set of predictors. $\boldsymbol{\sigma(\mu_A)}$ is the vector of cross-sectional standard deviations of return forecasts for each asset and quantifies forecast uncertainty. $\boldsymbol{V}$ is the (simple) empirical covariance matrix which represents our portfolio risk estimator in combination with $\boldsymbol{w}$. λ_1 is the well known risk aversion parameter of the mean-variance investor. We introduce a second risk aversion parameter, λ_2, which measures the aversion towards forecast uncertainty.

While the first active strategy is the active counterpart of the benchmark strategy, the second active strategy relies solely on the forecast uncertainty metric. The third active strategy combines both type of risks: portfolio variance and forecast uncertainty. The fourth and the fifth active strategy are hypothetical as they assume that the investor knows ex ante the results from table 11. The investor implementing the former investment strategy relies solely on return forecasts based on the ***tdegw*** predictor ($\boldsymbol{\mu}_{tdegw}$), while the investor of the latter strategy relies on return forecasts based on the ***cls8*** ($\boldsymbol{\mu}_{cls8}$) predictor.

Table 12 shows the OOS performance metrics of the respective investment strategies for various risk aversion parameter combinations. Once again, we observe that from an economic perspective the simple mean model is easy to beat. In most constellations, the mean returns

Table 12: OOS Performance Metrics of Investment Strategies Based on Network Information

PANEL A: $\lambda_1 = 1,\ \lambda_2 = 3$						
	Benchmark	1. ActStr	2. ActStr	3. ActStr	4. ActStr	5. ActStr
μ_P	13.12%	14.21%	14.01%	12.63%	14.30%	15.18%
σ_P	19.08%	18.78%	15.95%	14.84%	18.62%	18.21%
SR	0.688	****0.757**	***0.878**	0.851	0.768	0.834
CER	11.30%	***12.45%**	12.74%	11.53%	12.57%	13.52%
Mean Turn.	*20.29%*	*42.63%*	*78.77%*	*71.17%*	*46.63%*	*45.73%*
PANEL B: $\lambda_1 = 2.5,\ \lambda_2 = 1.5$						
μ_P	12.38%	12.91%	13.60%	12.26%	13.65%	14.78%
σ_P	15.81%	16.02%	18.03%	14.33%	16.71%	16.10%
SR	0.783	0.806	0.754	0.856	0.817	***0.918**
CER	9.26%	9.70%	9.54%	9.69%	10.16%	****11.54%**
Mean Turn.	*18.75%*	*37.46%*	*68.48%*	*53.88%*	*43.03%*	*44.81%*
PANEL C: $\lambda_1 = 4,\ \lambda_2 = 2$						
μ_P	11.86%	12.19%	13.52%	11.85%	12.92%	14.48%
σ_P	14.23%	14.43%	17.00%	13.35%	15.10%	14.79%
SR	0.833	0.845	0.795	0.887	0.856	****0.979**
CER	7.81%	8.03%	7.74%	8.28%	8.36%	*****10.10%**
Mean Turn.	*16.46%*	*31.80%*	*71.16%*	*47.51%*	*40.39%*	*41.38%*
PANEL D: $\lambda_1 = 2,\ \lambda_2 = 4$						
μ_P	12.64%	13.35%	11.70%	11.84%	13.78%	14.94%
σ_P	16.71%	16.86%	15.29%	13.73%	17.39%	16.78%
SR	0.757	0.792	0.765	0.862	0.792	***0.890**
CER	9.85%	10.51%	9.36%	9.96%	10.75%	***12.12%**
Mean Turn.	*19.70%*	*40.01%*	*73.73%*	*64.18%*	*44.48%*	*45.58%*

*** Significant at 1%-, ** 5%-, and * 10% level.
Legend: CER = certainty equivalent return;

or/and risk-adjusted return metrics (CER and Sharpe Ratio) of the active strategies surpass the ones of the benchmark strategy. In some cases, the return advantage of active strategies is even statistically significant.

As already mentioned above, the first active strategy is the active equivalent of the benchmark model and thus directly comparable. For every risk aversion parameter (λ_1), the first active strategy outperforms the benchmark with regard to mean return and risk adjusted returns (CER and Sharpe Ratio). This performance edge is the higher, the lower the risk aversion of the investor. This outcome is plausible since a lower risk aversion leads to a greater weighting of $\boldsymbol{\mu}_A$ in the objective function and hence allows the conditional forecasts to play out their advantage.

The second strategy relies solely on the cross-sectional standard deviation of return forecasts which represents forecast uncertainty. Thus it is a close relative of strategy 1, which relies on the traditional empirical variance metric for the estimation of portfolio risk. According to the objective function 13, assets with higher return uncertainty cause a higher penalization of the objective function and vice versa. Therefore, assets with higher return forecast uncertainty are ceteris paribus disliked and vice versa. Indeed, table 12 demonstrates that $\boldsymbol{\sigma(\mu_A)}$ conveys valuable information with regard to portfolio risk. Moreover, panel A reveals that given an appropriate weighting (λ_2), $\boldsymbol{\sigma(\mu_A)}$ can even beat the classic risk measure ($\boldsymbol{w}^\top \boldsymbol{V} \boldsymbol{w}$) in terms of risk adjusted returns. Note that risk adjusted return measures (Sharpe Ratio and CER) of strategy 2 in panel A dominate the equivalent counterparts of strategy 1 regardless of the λ_1-parameter. However, the appropriate weighting of $\boldsymbol{\sigma(\mu_A)}$ is crucial. Higher or lower (panel B to D) λ_2-values result in suboptimal risk-return ratios.

Strategy 3 combines both risk metrics, return forecast uncertainty and empirical variance, in the objective function. Since both metrics convey valuable risk information, strategy 3 is characterized by far the smallest realized standard deviation across all panels. However, for this reduction in risk, the investor disproportionately pays with lower mean returns leading to slightly uncompetitive CER-values. The last two strategies (4 and 5) rely on single model return forecasts instead of a cross-sectional mean across all return forecasts. In this regard, two observations are noteworthy: Firstly, the use of single model return forecasts does not lead to higher realized portfolio volatility relative to the multi-model mean forecasts (strategy 2). Since multi-model mean forecasts should be more smooth across the time dimension, this observation is somewhat surprising. Secondly, strategy 5 clearly outperforms strategy 4 and all other strategies in table 12. Interestingly, in the single risky asset allocation analysis (table 11) the ***tdegw***-predictor on average dominates the ***cls8***-predictor. In the holistic multi-asset allocation exercise however, the ranking is the complete opposite. Hence a single risky asset allocation analysis of a considered predictor is not necessarily indicative of its holistic multi risky asset performance!

Lastly, the attentive reader may have noticed that all active strategies in table 12 incur significantly more transaction volumes than the benchmark strategy. This observation is not surprising, as the active forecasts - even after the cross-sectional averaging - exhibit higher variation in the time dimension than the slowly adapting benchmark forecasts. Hence, practical implementations of network-based active strategies should consider professional transaction volume management which "intelligently" limits the incurred implementation costs.

5 Concluding Remarks

This paper presents the first in-depth analysis of network-based metrics in the predictive modeling context and by this connects two deeply researched academic paths: network-based analysis and financial forecasting. The main message from this article is that the discussed network-based methodology is not only useful for contemporaneous analyses but also when it comes to the prediction of financial markets. In this regard our paper demonstrates the difficulty of proper performance measurement of prediction models: Firstly, statistical performance measures should be treated with caution as they are only weakly related to the economic performance of the respective predictors. Secondly, even economic performance metrics can convey contracting messages. As we have shown in the last two empirical sub-studies, asset-specific economic performance of network-based predictors can be completely unrelated to its performance in multi-risky-asset investment strategies.

Furthermore, the paper demonstrates the advantages of thick modeling, i.e., creating many forecasting models by broadening the set of predictors. The first advantage is the improvement of forecasting performance by considering centrality metrics of other network constituents. The second advantage is the derived forecasting uncertainty (or model uncertainty) from the cross-sectional volatility of the various forecasts. This metric conveys important risk information which results in superior network-based investment strategies.

Since network-based forecasting is a relatively empty academic field, numerous future research projects can arise from here of which we discuss only a small fraction. Our methodology is based on the plain linear predictive modeling, but this can be just the first step towards more sophisticated prediction models. The toolkit of predictive modeling contains numerous non-linear and non-parametric methods, which all can be utilized to increase the degree of sophistication of network-based prediction models. In this regard, an interesting research question could be, whether machine learning algorithms can improve the performance of network-based predictors. Moreover, the network-based investment strategies presented in the final sub-study are mostly based on network-based predictors and "classical" (second moment) risk estimators. Future research can bring this endeavor to "the next level" by constructing truly holistic network-based investment strategies, which are based on simultaneous network-based return and risk modeling. Summing up, this paper marks the early beginning of network-based predictive modeling and active network-based investment strategies. Hopefully, more research will fill this almost blanc academic space.

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Appendix: Further Empirical Results

Table 13: Stability Analysis of Results from Table 4 via P-Values Bootstrapping

Predictors	**Target Variables**									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
cls										
95th P. p-val.	0.6877	0.4005	0.1870	0.2267	0.4262	0.4555	0.3223	0.4738	0.2637	0.7546
5th P. p-val.	0.0005	0.0023	0.0000	0.0000	0.0007	0.0003	0.0001	0.0000	0.0009	0.0001
% significant	*60.70%*	*69.52%*	***89.78%***	***89.26%***	***74.45%***	***71.49%***	***80.85%***	***79.67%***	***80.31%***	*59.43%*
diam										
95th P. p-val.	0.9126	0.8649	0.8228	0.1131	0.8991	0.9198	0.8879	0.9347	0.6228	0.7810
5th P. p-val.	0.0005	0.0001	0.0000	0.0000	0.0004	0.0022	0.0004	0.0109	0.0000	0.0000
% significant	*35.41%*	*52.21%*	*62.95%*	***94.30%***	*42.70%*	*28.89%*	*40.56%*	*20.16%*	***72.28%***	*63.83%*
diamw										
95th P. p-val.	0.6944	0.1946	0.4610	0.0667	0.8310	0.5938	0.3134	0.9018	0.2003	0.4720
5th P. p-val.	0.0005	0.0000	0.0003	0.0000	0.0015	0.0000	0.0001	0.0051	0.0001	0.0000
% significant	*60.37%*	***90.20%***	***74.35%***	***97.06%***	*48.58%*	***72.99%***	***82.00%***	*31.16%*	***88.57%***	***78.28%***
tdeg										
95th P. p-val.	0.6724	0.8755	0.4535	0.4652	0.6421	0.7149	0.7995	0.9539	0.1942	0.3231
5th P. p-val.	0.0007	0.0035	0.0002	0.0000	0.0005	0.0011	0.0053	0.0728	0.0000	0.0001
% significant	*61.42%*	*39.84%*	***76.25%***	***79.48%***	*67.18%*	*58.81%*	*43.56%*	*7.04%*	***90.22%***	***83.03%***
tdegw										
95th P. p-val.	0.1570	0.0824	0.1228	0.0319	0.6223	0.3333	0.0394	0.6567	0.1809	0.0816
5th P. p-val.	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0001	0.0001	0.0000
% significant	***91.42%***	***96.15%***	***93.19%***	***98.90%***	*68.29%*	***86.36%***	***98.36%***	*67.51%*	***89.76%***	***96.00%***
mdist										
95th P. p-val.	0.2661	0.0902	0.3521	0.4330	0.8147	0.1874	0.0720	0.4973	0.5520	0.3591
5th P. p-val.	0.0002	0.0001	0.0006	0.0000	0.0019	0.0000	0.0001	0.0001	0.0025	0.0002
% significant	***83.70%***	***95.72%***	***75.42%***	***77.45%***	*51.75%*	***91.26%***	***97.00%***	***75.16%***	*57.44%*	***77.86%***
Decc										
95th P. p-val.	0.8783	0.5472	0.8435	0.8776	0.9342	0.6689	0.7206	0.9541	0.3280	0.5481
5th P. p-val.	0.0018	0.0000	0.0028	0.0004	0.0183	0.0000	0.0025	0.0602	0.0000	0.0001
% significant	*36.12%*	***79.44%***	*42.28%*	*44.61%*	*19.01%*	*66.92%*	*48.98%*	*8.81%*	***85.24%***	***75.09%***
Dradw										
95th P. p-val.	0.5240	0.1875	0.4941	0.7738	0.8967	0.3515	0.7540	0.8894	0.7036	0.3956
5th P. p-val.	0.0002	0.0000	0.0000	0.0002	0.0010	0.0002	0.0025	0.0034	0.0008	0.0000
% significant	*67.76%*	***90.46%***	***78.66%***	*58.67%*	*36.04%*	***78.21%***	*46.10%*	*34.99%*	*60.65%*	***82.32%***
Dtdeg										
95th P. p-val.	0.8892	0.8484	0.8746	0.6736	0.9154	0.7008	0.7663	0.9450	0.8810	0.8839
5th P. p-val.	0.0033	0.0041	0.0048	0.0007	0.0242	0.0020	0.0018	0.0367	0.0254	0.0030
% significant	*36.02%*	*40.30%*	*34.32%*	*60.92%*	*19.61%*	*54.23%*	*50.29%*	*12.66%*	*21.81%*	*35.16%*
PC1										
95th P. p-val.	0.6116	0.2998	0.2226	0.0087	0.7512	0.6590	0.1406	0.7619	0.1207	0.3787
5th P. p-val.	0.0001	0.0001	0.0000	0.0000	0.0002	0.0000	0.0000	0.0003	0.0000	0.0000
% significant	***70.50%***	***85.73%***	***89.97%***	***99.39%***	*62.54%*	***71.29%***	***92.59%***	*58.91%*	***93.90%***	***81.86%***

Legend: 95th P. p-val. = bootstrapped p-value lying at the 95th percentile; 5th P. p-val. = bootstrapped p-value lying at the 5th percentile; % significant = percentage of bootstrapped p-values that are smaller than 0.1. Percentage values exceeding 70% are marked by a bold font. The remaining abbreviations are explained in table 1, 2 and 3. This table shows block bootstrapped p-values (Politis and Romano (1994)) from the estimated in-sample coefficients outlined in table 4. The complete p-value bootstrapping results are available upon request.

Table 14: Stability Analysis of Results from Table 6 via P-Values Bootstrapping

Predictors	Target Variables									
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*
cls8										
95th P. p-val	0.4081	0.0531	0.1030	0.1814	0.5797	0.2096	0.0278	0.5073	0.5307	0.0245
5th P. p-val	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0018	0.0000
% significant	***81.33%***	***97.58%***	***94.87%***	***90.65%***	***72.51%***	***90.90%***	***98.68%***	***79.01%***	*63.63%*	***99.07%***
tdegw										
95th P. p-val	0.1479	0.0872	0.1206	0.0297	0.6243	0.2987	0.0396	0.6470	0.1725	0.0816
5th P. p-val	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0001	0.0001	0.0000
% significant	***91.93%***	***95.71%***	***93.66%***	***99.14%***	*67.92%*	***86.95%***	***98.49%***	*67.68%*	***90.06%***	***95.95%***
cls3										
95th P. p-val	0.2613	0.1066	0.1891	0.1223	0.6131	0.2920	0.1268	0.7524	0.1616	0.2712
5th P. p-val	0.0000	0.0000	0.0000	0.0000	0.0003	0.0000	0.0000	0.0002	0.0001	0.0000
% significant	***86.77%***	***94.80%***	***89.42%***	***93.67%***	***70.15%***	***87.76%***	***93.38%***	*60.74%*	***90.86%***	***86.16%***
cls5										
95th P. p-val	0.3071	0.0955	0.1740	0.0798	0.4187	0.1221	0.1510	0.7818	0.1322	0.2606
5th P. p-val	0.0001	0.0000	0.0000	0.0000	0.0006	0.0000	0.0001	0.0014	0.0000	0.0001
% significant	***83.48%***	***95.23%***	***90.65%***	***96.25%***	***74.90%***	***93.84%***	***92.06%***	*50.74%*	***92.50%***	***84.80%***
deg3										
95th P. p-val	0.4023	0.2461	0.3744	0.5848	0.6381	0.5100	0.2229	0.5389	0.4513	0.3965
5th P. p-val	0.0000	0.0000	0.0000	0.0006	0.0004	0.0000	0.0000	0.0000	0.0005	0.0000
% significant	***81.28%***	***88.43%***	***82.39%***	*65.72%*	*67.29%*	***80.47%***	***89.54%***	***73.37%***	***71.05%***	***80.84%***
Decc9										
95th P. p-val	0.6179	0.4445	0.7522	0.2154	0.9149	0.0871	0.4544	0.7181	0.3173	0.2699
5th P. p-val	0.0002	0.0000	0.0001	0.0000	0.0030	0.0000	0.0001	0.0008	0.0000	0.0000
% significant	*67.17%*	***79.61%***	*61.68%*	***89.73%***	*30.60%*	***95.56%***	***76.15%***	*57.29%*	***85.54%***	***87.59%***
mdist										
95th P. p-val	0.2535	0.0911	0.3576	0.4123	0.8122	0.1793	0.0727	0.4911	0.5381	0.3360
5th P. p-val	0.0003	0.0001	0.0007	0.0000	0.0019	0.0000	0.0001	0.0001	0.0022	0.0002
% significant	***84.35%***	***95.59%***	***75.31%***	***78.61%***	*51.94%*	***91.11%***	***97.05%***	***75.56%***	*57.24%*	***78.27%***
diamw										
95th P. p-val	0.6794	0.2033	0.4595	0.0642	0.8549	0.5923	0.3280	0.8993	0.1830	0.4610
5th P. p-val	0.0005	0.0000	0.0003	0.0000	0.0016	0.0000	0.0001	0.0054	0.0001	0.0000
% significant	*60.96%*	***89.71%***	***74.15%***	***97.15%***	*48.84%*	***73.08%***	***81.01%***	*31.96%*	***89.66%***	***78.47%***
PC2										
95th P. p-val	0.8921	0.5790	0.6783	0.0299	0.5762	0.8803	0.8651	0.9133	0.3437	0.6016
5th P. p-val	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0014	0.0000	0.0000
% significant	*45.13%*	***77.15%***	***72.80%***	***98.59%***	***75.95%***	*44.24%*	*49.00%*	*32.64%*	***86.24%***	***76.80%***
cls4										
95th P. p-val	0.8001	0.6393	0.7330	0.2460	0.8583	0.8590	0.6122	0.8455	0.5210	0.6805
5th P. p-val	0.0000	0.0000	0.0001	0.0000	0.0003	0.0000	0.0000	0.0003	0.0000	0.0000
% significant	*60.84%*	***71.01%***	*66.95%*	***89.05%***	*51.08%*	*57.06%*	***71.41%***	*48.36%*	***74.99%***	***71.97%***

Legend: 95th P. p-val. = bootstrapped p-value lying at the 95th percentile; 5th P. p-val. = bootstrapped p-value lying at the 5th percentile; % significant = percentage of bootstrapped p-values that are smaller than 0.1. Percentage values exceeding 70% are marked by a bold font. The remaining abbreviations are explained in table ??? and table ???. This table shows block bootstrapped p-values (Politis and Romano (1994)) from the estimated in-sample coefficients outlined in table 6. The complete p-value bootstrapping results are available upon request.

Table 15: Best Predictors in an OOS Setup, all numbers are in %

Predictors	Target Variables										Avrg
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*	
cls											
R^2	0.138	0.007	0.051	0.361	0.160	0.024	0.093	0.684	0.122	0.079	0.172
Hit Ratio	61.89	54.94	60.08	58.83	**57.86**	58.41	60.08	59.53	60.08	58.55	59.03
$\Delta RMSE$	-0.025	-0.078	-0.033	-0.027	-0.033	-0.038	-0.034	**0.001**	-0.020	-0.013	-0.030
deg											
R^2	0.002	0.208	0.030	0.213	0.007	0.000	0.059	0.444	0.068	0.001	0.103
Hit Ratio	61.47	54.94	58.55	**59.11**	56.75	59.25	60.08	**62.03**	61.34	58.55	59.21
$\Delta RMSE$	-0.038	-0.137	-0.047	-0.041	-0.052	-0.043	-0.052	-0.031	-0.043	-0.018	-0.050
tdegw											
R^2	0.592	0.486	0.344	0.692	0.366	0.718	0.637	0.071	0.321	0.515	0.474
Hit Ratio	**62.59**	56.19	59.53	57.16	56.47	**61.20**	60.36	59.53	58.97	58.97	59.10
$\Delta RMSE$	-0.005	-0.019	-0.023	-0.007	-0.041	-0.012	-0.006	-0.033	-0.021	-0.009	-0.018
Ddiamw											
R^2	0.006	0.090	0.030	0.000	0.130	0.020	0.205	0.076	0.000	0.003	0.056
Hit Ratio	62.45	**56.88**	**60.64**	58.28	56.75	59.67	61.20	61.20	61.34	**59.94**	59.83
$\Delta RMSE$	-0.021	-0.032	-0.024	-0.032	-0.038	-0.024	-0.037	-0.042	-0.018	-0.025	-0.029
Drad											
R^2	0.231	0.001	0.131	0.350	0.028	0.124	0.013	0.128	0.035	0.062	0.110
Hit Ratio	60.78	55.77	59.94	**59.53**	**57.72**	58.55	60.08	61.06	**61.61**	58.55	59.36
$\Delta RMSE$	-0.017	-0.031	-0.022	-0.001	-0.031	-0.028	-0.031	-0.027	-0.020	-0.038	-0.025
Dradw											
R^2	0.044	0.268	0.105	0.156	0.000	0.136	0.040	0.032	0.098	0.085	0.097
Hit Ratio	**63.00**	56.47	**60.50**	**59.53**	**57.16**	**60.64**	61.20	61.06	**61.61**	59.11	60.03
$\Delta RMSE$	-0.026	-0.005	-0.021	-0.031	-0.037	-0.020	-0.040	-0.044	-0.010	-0.029	-0.026
Dtdegw											
R^2	0.009	0.003	0.057	0.301	0.228	0.083	0.215	0.145	0.213	0.051	0.131
Hit Ratio	61.61	**57.44**	60.22	**60.22**	56.19	59.94	60.78	61.20	59.25	59.11	59.60
$\Delta RMSE$	-0.044	-0.042	-0.030	**0.001**	-0.059	-0.034	-0.055	-0.046	-0.009	-0.043	-0.036
Dmdist											
R^2	0.016	0.001	0.038	0.236	0.330	0.009	0.010	0.003	0.020	0.000	0.066
Hit Ratio	62.45	**57.30**	59.67	**59.11**	56.19	58.97	60.64	60.78	61.34	58.00	59.44
$\Delta RMSE$	-0.047	-0.016	-0.019	-0.041	-0.057	-0.052	-0.039	-0.034	-0.023	-0.030	-0.031
PC1											
R^2	0.016	0.152	0.003	0.156	0.006	0.002	0.070	0.271	0.158	0.000	0.083
Hit Ratio	60.92	55.77	59.67	**59.53**	56.19	58.14	59.81	61.34	**61.75**	57.72	59.09
$\Delta RMSE$	-0.031	-0.059	-0.033	-0.043	-0.017	-0.060	-0.030	**0.006**	-0.009	-0.037	-0.031
PC4											
R^2	0.877	0.012	0.095	0.016	0.045	1.033	0.019	0.018	0.322	0.157	0.260
Hit Ratio	61.89	54.10	59.11	58.28	**57.16**	**62.03**	58.97	61.47	59.67	**60.08**	59.28
$\Delta RMSE$	**0.008**	-0.126	-0.038	-0.026	-0.034	**0.018**	-0.066	-0.028	-0.055	-0.034	-0.038

Legend: Avrg = average of the respective row; R^2 = coefficient of determination (r squared); $\Delta RMSE$ = rooted mean squared forecasting error of the benchmark model MINUS rooted mean squared forecasting error of the conditional model. The remaining abbreviations are explained in table 1, 2 and 3. This table shows the best predictors in the OOS framework. Instances of OOS conditional model outperformance in terms of hit ratio and $\Delta RMSE$ are marked by a bold font. However, none of these instances is statistically significant. The complete OOS results are available upon request.

Table 16: Predictors from Table 6 in an OOS Setup, all numbers are in %

Predictors	**Target Variables**										**Avrg**
	NoDur	*Durbl*	*Manuf*	*Enrgy*	*HiTec*	*Telcm*	*Shops*	*Hlth*	*Utils*	*Other*	
cls8											
R^2	0.890	0.404	0.182	0.140	0.289	0.699	0.828	0.684	0.028	0.493	0.464
HitRatio	*61.34*	*55.63*	*59.67*	*58.97*	*56.61*	*60.50*	*60.08*	*59.53*	*60.08*	***59.67***	*59.21*
$\Delta RMSE$	-0.005	-0.016	-0.037	-0.043	-0.014	-0.018	**0.002**	**0.001**	-0.031	-0.011	-0.017
tdegw											
R^2	0.592	0.486	0.344	0.692	0.366	0.718	0.637	0.071	0.321	0.515	0.474
HitRatio	***62.59***	*56.19*	*59.53*	*57.16*	*56.47*	***61.20***	*60.36*	*59.53*	*58.97*	*58.97*	*59.10*
$\Delta RMSE$	-0.005	-0.019	-0.023	-0.007	-0.041	-0.012	-0.006	-0.033	-0.021	-0.009	-0.018
cls3											
R^2	0.252	0.408	0.051	0.159	0.111	0.661	0.251	0.004	0.134	0.096	0.213
HitRatio	*62.45*	*54.80*	*60.08*	*58.97*	***57.16***	*60.08*	*60.50*	*60.50*	*59.25*	*59.11*	*59.29*
$\Delta RMSE$	-0.013	-0.026	-0.033	-0.017	-0.039	-0.001	-0.017	-0.035	-0.018	-0.032	-0.023
cls5											
R^2	0.426	0.131	0.059	0.089	0.160	0.502	0.093	0.003	0.335	0.172	0.197
HitRatio	*62.03*	*54.94*	*59.67*	*58.83*	***57.86***	***61.06***	*60.50*	*61.34*	*60.92*	***59.53***	*59.67*
$\Delta RMSE$	-0.009	-0.020	-0.027	-0.024	-0.033	-0.013	-0.026	-0.051	-0.005	-0.013	-0.022
deg3											
R^2	0.312	0.329	0.030	0.001	0.019	0.549	0.182	0.000	0.060	0.039	0.152
HitRatio	*60.92*	*53.96*	*58.55*	*58.28*	*54.66*	*59.81*	*61.06*	*60.22*	*61.34*	***59.81***	*58.86*
$\Delta RMSE$	-0.013	-0.040	-0.047	-0.051	-0.029	-0.006	-0.014	-0.020	-0.026	-0.046	-0.029
Decc9											
R^2	0.028	0.001	0.008	0.084	0.005	1.119	0.006	0.005	0.150	0.176	0.158
HitRatio	***62.59***	*56.05*	*59.53*	*58.83*	***57.44***	*60.36*	*60.50*	*61.47*	*61.06*	*59.25*	*59.71*
$\Delta RMSE$	-0.039	-0.038	-0.041	-0.023	-0.057	**0.008**	-0.036	-0.037	-0.015	-0.025	-0.030
mdist											
R^2	0.378	0.246	0.394	0.553	0.551	0.783	0.403	0.006	0.063	0.457	0.384
HitRatio	*60.50*	*55.22*	*59.94*	*58.69*	***58.28***	*60.22*	*60.22*	*59.94*	*59.81*	*59.39*	*59.22*
$\Delta RMSE$	-0.025	-0.036	-0.029	-0.022	-0.032	-0.013	-0.033	-0.044	-0.032	-0.023	-0.029
diamw											
R^2	0.020	0.167	0.007	0.238	0.000	0.057	0.012	0.161	0.098	0.059	0.082
HitRatio	*62.17*	*55.77*	*59.94*	*58.28*	*56.75*	*59.53*	*60.64*	*60.50*	*60.22*	***59.81***	*59.36*
$\Delta RMSE$	-0.036	-0.025	-0.052	-0.030	-0.064	-0.038	-0.048	-0.054	-0.024	-0.036	0.041
PC2											
R^2	0.000	0.031	0.263	0.597	0.035	0.075	0.003	0.203	0.141	0.017	0.137
HitRatio	*62.03*	*55.35*	*59.67*	*57.30*	*56.61*	*59.25*	*61.47*	*60.08*	*60.50*	*58.14*	*59.04*
$\Delta RMSE$	-0.055	-0.077	-0.112	-0.135	-0.084	-0.043	-0.054	-0.095	-0.049	-0.076	-0.078
cls4											
R^2	0.253	0.562	0.358	0.361	0.036	0.603	0.159	0.000	0.157	0.569	0.306
HitRatio	***63.14***	*55.49*	*59.67*	*58.83*	*56.61*	*58.83*	*60.22*	*61.06*	*61.20*	*59.39*	*59.44*
$\Delta RMSE$	-0.019	-0.011	-0.023	-0.027	-0.034	-0.011	-0.017	-0.037	-0.021	-0.002	-0.020

Legend: Avrg = average of the respective row; R^2 = coefficient of determination (r squared); $\Delta RMSE$ = rooted mean squared forecasting error of the benchmark model MINUS rooted mean squared forecasting error of the conditional model. The remaining abbreviations are explained in table 1, 2 and 3. This table analyzes the performance of the best in-sample predictors from table 6 in an OOS framework. Instances of OOS conditional model outperformance in terms of hit ratio and $\Delta RMSE$ are marked by a bold font. However, none of these instances are statistically significant. The complete OOS results are available upon request.

Table 17: Overview of the Broader Set of Predictors

#	Predictor Abb.	#	Predictor Abb.	#	Predictor Abb.	#	Predictor Abb.
1	*cls1*	32	*evc5*	63	*Devc*	94	*Ddeg6*
2	*btw1*	33	*cls6*	64	*Ddiam*	95	*Devc6*
3	*ecc1*	34	*btw6*	65	*Ddiamw*	96	*Dcls7*
4	*deg1*	35	*ecc6*	66	*Drad*	97	*Dbtw7*
5	*evc1*	36	*deg6*	67	*Dradw*	98	*Decc7*
6	*diam*	37	*evc6*	68	*Dtdeg*	99	*Ddeg7*
7	*diamw*	38	*cls7*	69	*Dtdegw*	100	*Devc7*
8	*rad*	39	*btw7*	70	*Dmdist*	101	*Dcls8*
9	*radw*	40	*ecc7*	71	*Dcls2*	102	*Dbtw8*
10	*tdeg*	41	*deg7*	72	*Dbtw2*	103	*Decc8*
11	*tdegw*	42	*evc7*	73	*Decc2*	104	*Ddeg8*
12	*mdist*	43	*cls8*	74	*Ddeg2*	105	*Devc8*
13	*cls2*	44	*btw8*	75	*Devc2*	106	*Dcls9*
14	*btw2*	45	*ecc8*	76	*Dcls3*	107	*Dbtw9*
15	*ecc2*	46	*deg8*	77	*Dbtw3*	108	*Decc9*
16	*deg2*	47	*evc8*	78	*Decc3*	109	*Ddeg9*
17	*evc2*	48	*cls9*	79	*Ddeg3*	110	*Devc9*
18	*cls3*	49	*btw9*	80	*Devc3*	111	*Dcls10*
19	*btw3*	50	*ecc9*	81	*Dcls4*	112	*Dbtw10*
20	*ecc3*	51	*deg9*	82	*Dbtw4*	113	*Decc10*
21	*deg3*	52	*evc9*	83	*Decc4*	114	*Ddeg10*
22	*evc3*	53	*cls10*	84	*Ddeg4*	115	*Devc10*
23	*cls4*	54	*btw10*	85	*Devc4*	116	*Dsim*
24	*btw4*	55	*ecc10*	86	*Dcls5*	117	*PC1*
25	*ecc4*	56	*deg10*	87	*Dbtw5*	118	*PC2*
26	*deg4*	57	*evc10*	88	*Decc5*	119	*PC3*
27	*evc4*	58	*sim*	89	*Ddeg5*	120	*PC4*
28	*cls5*	59	*Dcls*	90	*Devc5*	121	*PC5*
29	*btw5*	60	*Dbtw*	91	*Dcls6*	122	*PC6*
30	*ecc5*	61	*Decc*	92	*Dbtw6*	123	*BSS*
31	*deg5*	62	*Ddeg*	93	*Decc6*		

Legend: Abb. = abbreviation; BSS = best subset selection model. The remaining abbreviations are explained in table 2 and 3.