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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Cyclical patterns in risk indicators based on financial market infrastructure transaction data*

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Abstract

This paper studies cyclical patterns in risk indicators based on TARGET2 transaction data. These indicators provide information on network properties, operational aspects and links to ancillary systems. We compare the performance of two different ARIMA dummy models to the TBATS state space model. The results show that the forecasts of the ARIMA dummy models perform better than the TBATS model. We also find that there is no clear difference between the performances of the two ARIMA dummy models. The model with the fewest explanatory variables is therefore preferred.

Keywords: ARIMA, TBATS, Time Series, TARGET2, Cyclical Patterns.
JEL classifications: E42, E50, E58, E59.

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1 Introduction

Financial market infrastructures (FMIs) play a crucial in the well-functioning of the economy. They facilitate the clearing, settlement, and recording of monetary and other financial transactions. Disruptions to or outages of these systems can seriously damage the economy, as this means financial actors cannot fulfil their obligations in time. Therefore, these infrastructures have to meet high standards defined by Principles for Financial Market Infrastructures (PFMIs, CPSS (2012)). FMI transaction data can provide relevant information on the well-being of these FMIs and the financial actors in these FMIs. This information can be useful 1) to overseers and operators who have an interest in the well-functioning of the FMI itself, to 2) prudential supervisors who are interested in the well-being of a single financial institution (e.g. commercial bank or insurance company), 3) to financial stability experts who have an interest in the well-being of the financial system as a whole and 4) monetary policy experts who are interested in the well-functioning of the money markets. Examples of how FMI transaction data has been used are Berndsen and Heijmans (2017) who develop risk indicators for the most important euro-denominated large-value payment system (TARGET2), Arciero et al. (2016) who identify unsecured interbank money market loans from TARGET2 and Baek et al. (2014) who define network indicators for monitoring intraday liquidity in the Korean large value payment system (BoK-wire).

Indicators or time series based on transaction level data often contain cyclical patterns, which have to be corrected for. This paper studies the performance of different models to extract cyclical patterns from time series based on transaction data.[1] By extracting patterns from the times series, we distinguish between normal patterns over time and potential stressful or notable patterns. We investigate two different ARIMA models with dummies and a state space model, which is a more advanced method. The dummy variables we include in the ARIMA models relate to the day of the week, months and decision by the Governing Council (with respect to the reserve maintenance period). The state space models are introduced by De Livera et al. (2011) and Hyndman and Athanasopoulos (2013). They study forecasting time series with complex seasonal patterns using exponen-

[1] These time series are the basis of the risk indicator development by Berndsen and Heijmans (2017).

tial smoothing. The time series we investigate in this paper are based on daily figures of network indicators, operational indicators and indicators providing information on liquidity flows between TARGET2 and other FMIs. We first fit three different models to the first part of the data (train data). Then we produce forecasts for the last part of the data (test data). By comparing the forecasts we determine which model performs best. Our paper is closely related to earlier work of Van Ark and Heijmans (2016). They compare the performance of a state space model to a Fourier ARIMA model and ARIMA dummy models for data that is aggregated per 10 minutes and per hour. They find that the state space model outperforms the ARIMA models. Our paper adds to the literature by setting up a model to correct for cyclicality in indicators based on FMI transaction level data. Triepels et al. (2017) provides a completely different method of looking at patterns or features in the data by using a machine learning technique.

Massarenti et al. (2012) study the timing of TARGET2 payments. They find that most value is transferred in the last business hour of the day. This implies that a disruption at this time can have serious consequences: 1) as the value is large, a disruption can seriously harm liquidity flows, 2) as it is the last hour of the business day, there is little time to solve the disruption and fulfill payment obligations. Baek et al. (2014) describe the network properties of the Korean interbank payment system BOK-Wire+. They apply existing methodologies for identifying systemically important banks and develop a new intraday liquidity indicator that compares banks' expected resources for settling payments in the remainder of the day with their expected liquidity requirements. Squartini et al. (2013) show early-warning signals for topological collapse in interbank networks. They study quarterly interbank exposures among Dutch banks between 1998 and 2008. The outcome of their research is relevant for bank regulators. One of their findings is a well-defined core-periphery structure. In contrast to our paper they use highly aggregated data instead of granular data.

The outline of this research is as follows. Section 2 provides a description of the studied data. Section 3 explains the models which have been tested for their forecast performance. The results of model performance are presented in section 4. Section 5 concludes.

2 Data

This section describes the transaction data and the time series that are used for this research. Section 2.1 provides general information on the most important euro denominated large value payment system (TARGET2). Section 2.2 describes the types of transactions that are settled in TARGET2. The time series that are used in this research are described in section 2.3.

2.1 TARGET2

TARGET2 is the real-time gross settlement (RTGS) system for euro-denominated payments, which is owned and operated by the Eurosystem.[2] It is one of the largest RTGS systems in the world. Payment transactions in TARGET2 are settled individually (gross) on a continuous real-time basis, in central bank money with immediate finality. TARGET2 settles approximately 350,000 transactions with a corresponding value of EUR 2,000 billion. In 2014 TARGET2 had approximately 1000 direct participants and $\pm$ 800 indirect participants.[3] Most of the participants are commercial banks located in the euro area. Besides commercial banks, central banks of the European Union and Ancillary Systems (AS) also participate in TARGET2. Ancillary Systems are systems that process clearing and settlement of payments. Non-EU banks acting through a subsidiary in the EU can also obtain direct access to TARGET2.[4]

2.2 Transaction data

The data consist of settled transactions in the range of June 2008 to December 2015. TARGET2 transactions can be divided into four main categories, see Table 2 in Appendix B. Category 1 are the transactions between commercial banks. Category 2 consists of transactions in which national central banks (NCB) are involved on the receiving and/or submitting side (or both) of the transaction. The third category consists of transactions that are submitted to TARGET2 by Ancillary Systems (ASs). Category 4 transactions are trans-

[2] TARGET2 stands for Trans-European Automated Real-Time Gross settlement Express Transfer system.

[3] https://www.ecb.europa.eu/paym/t2/html/index.en.html

[4] For a complete overview of TARGET2 access criteria, see the TARGET2 guideline https://www.ecb.europa.eu/ecb/legal/1003/1349/html/index.en.html

actions that are related to liquidity transfers. Transactions of sub-category 4.4 (so called technical transfer) are excluded in our research as these are transfers of liquidity between accounts of the same legal entity.

2.3 Time series

We investigate the performance of our models on different types of time series derived from TARGET2 transaction data. Table 1 provides an overview of investigated time series. The time series are divided into 4 groups: A) operational, B) network properties, C) links to other ancillary systems and D) HHIs. A common factor is that they are all daily aggregates.

Table 1: Time series based on TARGET2 transaction data.

Time series number	Description
A	**Operational indicators**
1	Relative performance TARGET2
2	Throughput at 12.00
3	Throughput at 14.30
B	**Network properties**
4	Edge density undirected
5	Edege density directed
6	Degree
7	Reciprocity
8	Transitity
9	Eigenvector centrality
10	Hub centrality
11	Authority centrality
C	**Links to AS**
12	Turnover to AS (absolute)
13	Turnover to AS (relative)
D	**HHI**
14	HHI turnover
15	HHI degree
16	HHI Eigenvector centr
17	HHI Hub centr.
18	HHI Authority centr.

2.3.1 A: operational

The time series with respect to operational aspects are relatively straightforward. We look at 1) the relative usage of the system and 2) on the throughput of liquidity at certain times of the business day. The relative usage is measured by dividing the actual number of transactions settled on a given day by the amount guaranteed by the service level agreement of the payment system. This guaranteed amount has been laid down in the service level agreement.

The throughput guidelines look at the cumulative value settled over the day. These guidelines are intraday deadlines by which individual banks are required to send a predefined proportion of the value of their daily payments. CHAPS, the UK large value payment system, enforces these guidelines, see Ball et al. (2011).

The throughput guidelines set up by CHAPS for each participants are as follows:

$$\text{Transferred value before 14.30} <= 75\% \tag{1}$$

$$\text{Transferred value before 12.00} <= 50\% \tag{2}$$

It is of course possible to set different percentages and cut off times.

2.4 B: Network Properties

The literature describes the use of many network properties for payment systems, see e.g. Pröpper et al. (2013) or Soramäki et al. (2007). Edge density (which is also known as connectivity) is the ratio of number of actual links and total number of possible links between nodes, see Appendix A.1. Degree is the number of links of each node per day, see Appendix A.2 Reciprocity is the fraction of links with a link in the opposite direction, see Appendix A.3. Transitivity (also known as clustering coefficient) measures the probability that neighbors of a node are also connected to each other, see Appendix A.4

Eigenvector centrality captures the importance of connected nodes and elaborates the concept of degree, see Appendix A.5 for a definition. The eigenvector centrality not only captures the amount of links for each node (like degree), but also captures how important each connected node is. This means that a node can have links to many other nodes (high degree), but in order to also have a high eigenvector centrality, the connected nodes must also have many connections to other nodes. Hub and authority centrality show whether the in- and outgoing links of nodes are going to or coming from important nodes. Hub nodes are nodes that point to many useful (high authority) nodes and nodes with high authority scores are nodes pointed to by nodes with high hub scores.

The literature often also looks at the diameter of the network. This number is very stable (between 5 and 7) over time. Therefore, we do not investigate this indicator further.

2.4.1 C: Links to Ancillary Systems

TARGET2 settles many transactions going from and to other FMIs (also called ancillary systems in the context of TARGET2). Therefore, there is a liquidity dependency between TARGET2 and these Ancillary systems (ASs). Time series number 12 describes the development of the absolute turnover of ancillary systems in TARGET2. Series 13 gives the relative development of the ancillary system turnover relative to the total turnover of TARGET2.

2.4.2 D: HHI

The normalized Herfindahl-Hirschman Index (HHI) denotes the distribution of relative turnover of participants. If there is one large bank with all turnover of the whole market then the normalized HHI is 1. When turnover is equally distributed amongst participants, this number is zero. The normalized HHI is calculated by using the following formula:

$$HHI_{normalized} = \frac{\sum_{i=1}^{N} M_i^2 - 1/N}{1 - 1/N} \tag{3}$$

for $N > 1$, where M_i is the market share of bank N.

We apply the HHI not only to the outgoing turnover of banks but also to the network properties degree, eigenvector centrality, hub centrality and authority centrality. The HHI is a measure that in contrast to the median takes the distribution of each node (bank) into account. However, the largest node has the largest contribution to the HHI.

3 Method

We compare three different models that can capture cyclical variation. The first two models are based on the simple ARIMA model:

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4}$$

The optimal number of included lags of the Auto Regressive parts p and Moving Average parts q are found based on the minimization of the Akaike Information Criterion (AIC). To detect seasonality, the simple ARIMA model is often extended by Fourier's series, as explained in Hyndman and Athanasopoulos (2013). The main idea of this method is to write a periodic function as a combination of sines and cosines. However, this method requires equal cycle lengths. Since the number of business days differs across months, this model is not suitable for detecting monthly seasonality. This paper considers the following models to detect cyclicality:

1. ARIMA with dummy variables for days of the week and first, middle and last three days of the month (Dummy model 1).

2. ARIMA with the dummy variables as used in the first dummy model extended by governing council meetings decisions (Dummy model 2).

3. TBATS: Trigonometric, Box-Cox transformation, ARMA errors, Trend and Seasonality.

3.1 Dummy model 1: DM1

Dummy Model 1 extends the standard ARIMA model by adding dummy variables for the day of the week and month:

$$Y_t = \mu + \sum_{i=1}^{M} \sum_{j=1}^{P_i - 1} \gamma_{i,j} D_{i,j,t} + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{5}$$

where $D_{i,j,t}$ is a matrix containing the dummy variables for the day of the week and month. This means that for each business day of the week and month a dummy variable is created.[5] As it was found that the Tuesdays usually did not show any significant changes in payment behavior, this day is the omitted variable to avoid the dummy variable trap. Figure 1 shows how the monthly dummy variables are constructed for months with 20 business days.

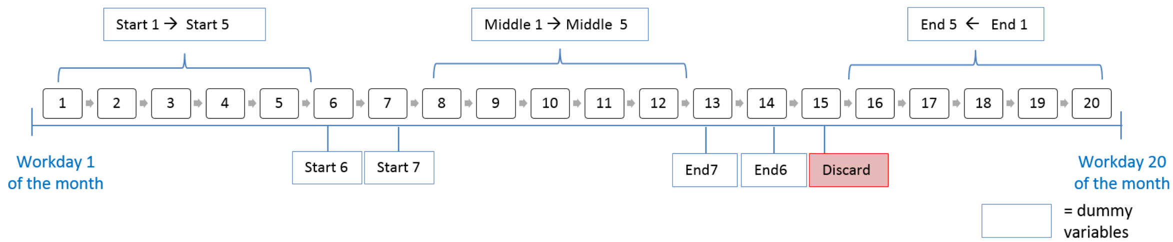


Figure 1: Dummy variable construction for a month with 20 business days.

Irrespective of the length of the month we always use the first five, last five, and middle five business days. The first five dummy variables correspond to the first five business days of the month, and are referred to as 'Start1,...,Start5' in Figure 1. The last and middle five days are referred to as 'End1, ... ,End5' and 'Middle1, ... ,Middle5' respectively. If the middle number is not an integer, it is rounded up to the nearest integer number. We look at the first, middle and last days of the month to investigate where seasonality is the strongest.

We find that for the dummy model, the optimum number of first, middle and last days of the month to include is three, which means that we include nine dummy variables for day of the month. Furthermore, this model includes dummy variables for the business days of the week (except Tuesday). Hence in total 13 dummy variables are used. This model will be referred to as DM1.[6] Since parsimonious models are preferred, we determine whether the week and/or month dummy variables could be omitted without significantly lowering the performance of Dummy model 1 by applying the Likelihood Ratio (LR) test:

$$LR = -2[\mathcal{L}(\tilde{\theta}) - \mathcal{L}(\hat{\theta})] \tag{6}$$

[5]For example one column in the $D_{i,j,t}$ matrix is the Monday dummy variable, which is equal to one for each Monday and zero otherwise. Another column in $D_{i,j,t}$ is for example the 'Last day of the month' variable, which is equal to 1 for each last day of the month, and zero otherwise. The length of these columns is equal to the total number of business days in the full dataset.

[6]We also applied a model that includes all week and all monthly dummy variables. However, even though many variables are added to the model, it did not improve the fit or forecast. Therefore, the model that includes all monthly dummy variables is not discussed further in this paper.

where $\mathcal{L}(\tilde{\theta})$ is the log-likelihood of the restricted model (fewer variables) and $\mathcal{L}(\hat{\theta})$ the log-likelihood of the more unrestricted model (more variables). Under the null hypothesis, the Likelihood Ratio statistic follows approximately a χ^2_n distribution (see Wilks (1938)) where degrees of freedom n is equal to the difference of the estimated parameters between the two nested models. H_0 is rejected in case $LR \geq \chi^2_{n;1-\alpha}$ which means that the unrestricted (full) model fits the data significantly better than the model with fewer variables, corrected for the fact that adding more variables should always lead to a better fit. In case the LR test concludes that the month or week dummy variables do not significantly improve the model, these variables are excluded from $D_{i,j,t}$. [7]

3.2 Dummy model 2: DM2

The decisions by the Eurosystem's Governing Council may affect behavior of market participants. The second model extends Dummy model 1 by including the Governing Council meetings, which have an impact on the Reserve Maintenance Period (RMP). Besides the week and month dummies as used in DM1, we also include the first and last three business days of the Reserve Maintenance Periods. Therefore, DM2 includes six more dummy variables than DM1. This version of the ARIMA-dummy model will be referred to as (DM2, or Dummy model 2). Both DM1 and DM2 are estimated by Maximum Likelihood Estimation (MLE).

3.3 TBATS

The last model is a state space model with a level component l_t and is extended with M trigonometric seasonal cycles s_t^i and ARIMA errors d_t. The TBATS model is introduced by De Livera et al. (2011) as an extension of conventional Innovation State Space Models in order to include less restricted cyclical patterns and to deal with correlated errors. The TBATS model uses a transformation of the data $Y_t^{(\omega)}$, which is the Box-Cox transformed data Y_t, in order to allow for some types of nonlinearity. As extensively discussed in De Liv-

[7] This changes the number of columns in $D_{i,j,t}$ from 13 to 4 or 9 respectively

era et al. (2011) the TBATS model is defined by:

$$Y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-1}^{(i)} + d_t \tag{7a}$$

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha d_t \tag{7b}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t \tag{7c}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{7d}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\left(\frac{2\pi jt}{m_i}\right) + s_{j,t-1}^{*(i)} \sin\left(\frac{2\pi jt}{m_i}\right) + \gamma_1^{(i)} d_t \tag{7e}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1}^{(i)} \sin\left(\frac{2\pi jt}{m_i}\right) + s_{j,t-1}^{*(i)} \cos\left(\frac{2\pi jt}{m_i}\right) + \gamma_2^{(i)} d_t \tag{7f}$$

From line 7a it can be seen that the data is decomposed into level, trend and seasonal components. The ith seasonal component has (possible non-integer) length m_i and is written as a sum of k harmonics. The stochastic level of the ith seasonal component is denoted by $s_{j,t}^{(i)}$, and the stochastic growth in the level of the ith seasonal component allows the seasonal periods to slightly change over time, and is denoted by $s_{j,t}^{*(i)}$.

De Livera et al. (2011) state that estimation of the TBATS model is done by minimizing equation (8) with respect to θ which is a vector that contains the Box-Cox parameter ω, the smoothing parameters and ARMA coefficients:

$$\mathcal{L}^* = n\log(\mathrm{SSE}^*) - 2(\omega-1)\sum_{t=1}^{n} \log Y_t \tag{8}$$

where $\mathcal{L}^*$ is the optimal log-likelihood and SSE^* is the sum of squared errors that is optimized for given parameter values.

The advantage of the ARIMA dummy model is that the model itself is quite intuitive and if the dummy variables are constructed in the proposed way it does not matter whether lengths of periods are varying. Contrary to the periods in the TBATS model, the end of the month can be always taken into account in the ARIMA dummy model, irrespective of the length of the month. The TBATS model on the other hand has an outcome that is very intuitive since this model decomposes the time series into different components such as level, trend and seasons, which easily results in a visual output.

3.4 Model comparison

3.4.1 Out-of-sample fit

We assume that the model with the best out-of-sample fit is also the model that captures cyclical variation best. In order to avoid over-fitting of the data, model performance of the TBATS and ARIMA dummy models is compared based on out-of-sample fit. The model estimation is based on July 2008 - June 2014 and the fit of each model is based on July 2014 - Dec 2015, which are the train data and the test data respectively. The output of the estimation that is based on the train data is used to determine forecasts for the test period. Two different forecasts are produced; 5 and 20 period(s) ahead, which means that for each forecast it is assumed that all data up until 5 or 20 days ago is known. Reason for this is that 5 periods correspond to a week and 20 periods correspond approximately to a month.

3.4.2 RMSE

For each forecast (5 and 20 periods ahead for each risk indicator) the out-of-sample Root Mean Square Error (RMSE) is calculated, which indicates the magnitude of the difference between the predicted observations and the real observations. Contrary to most accuracy measures, the RMSE penalizes the error for forecasted observations that deviate considerably from the actual data while penalizing overestimations and underestimations equally. However, since the RMSE is not scale invariant it cannot be used to compare the fit across different indicators. An accuracy measure that can be used across risk indicators is the Mean Average Percentage Error (MAPE). However, since the MAPE penalizes overestimations more than underestimations, the RMSE is a more appropriate measure to determine the fit of each forecast.

4 Results

4.1 Cyclical patterns

For each risk indicator we determine if cyclical patterns (month and/or week) are present. We conclude that for the 1.1 and 1.2 transactions combined all risk indicators contain significant week and month patterns, except for the turnover to AS (time series 12 and 13 in

Table 1) for which the TBATS model cannot recognize a month or week pattern.[8] However, when all transactions (except 4.4) are included, the ARIMA dummy models still determines significant cyclical patterns, but the TBATS model does not recognize any cyclical pattern for the relative turnover to AS, the HHI eigenvector and hub centrality. Table 3 in Appendix C provides an overview of cyclical variations for the dummy model and the TBATS model.

4.2 Forecast accuracy

The out-of-sample fit is compared based on the RMSEs of the 5 and 20 periods ahead forecasts. Since the absolute value of the RMSE depends on the scale of the risk indicator, it is hard to interpret the magnitude. In order to provide some referential framework to the RMSE of the Dummy and TBATS models, they are compared to the RMSEs of naive models. The 5 periods ahead forecasts are compared to the naive model where each value at time t is set equal to the value at time $t-5$. The 20 periods ahead forecasts are compared to the naive model where each value at time t is set equal to the value at time $t-20$. For each risk indicator we normalized the RMSE with respect to the naive model and subtracted 1. Therefore, a positive value means that the forecast of a certain model performs better than the naive forecasts, and a negative value implies that the forecast of a certain model performs worse than the naive forecasts. Since the RMSEs are normalized, the magnitudes can be interpreted as a percentage increase or decrease with respect to the naive model. For example a value of 0.3 implies that the RMSE of a model is 30 % lower (better) than the RMSE of the naive model.

[8] We also modeled 1.1 and 1.2 transactions separately, however, we did not find significant differences compared to the patterns that are found when both 1.1 and 1.2 transactions are included.

Figure 2: Out-of-sample fit of all indicators for 1.1 and 1.2 transactions with respect to the naive model.

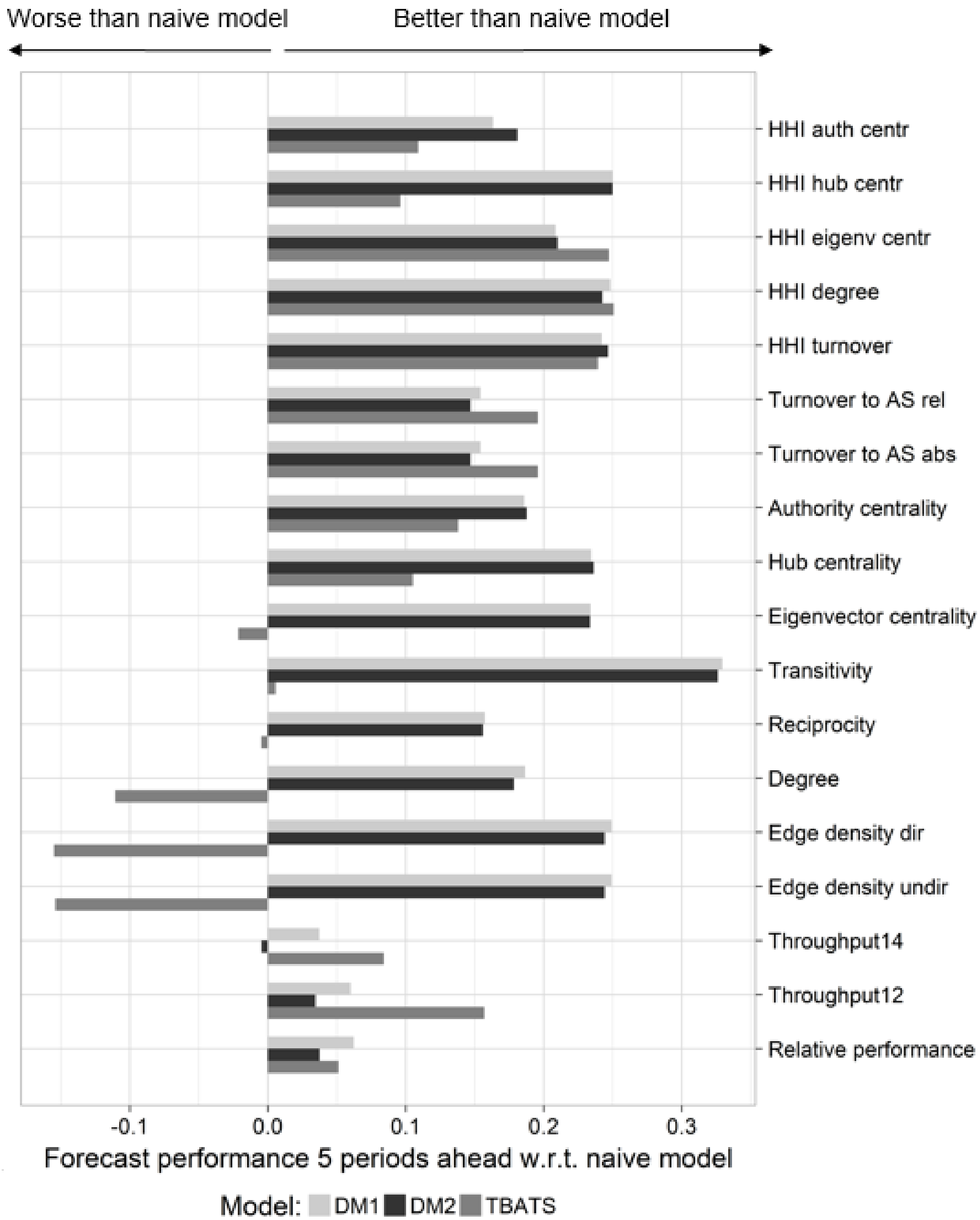


Figure 3: Out-of-sample fit of all indicators for 1.1 and 1.2 transactions with respect to the naive model.

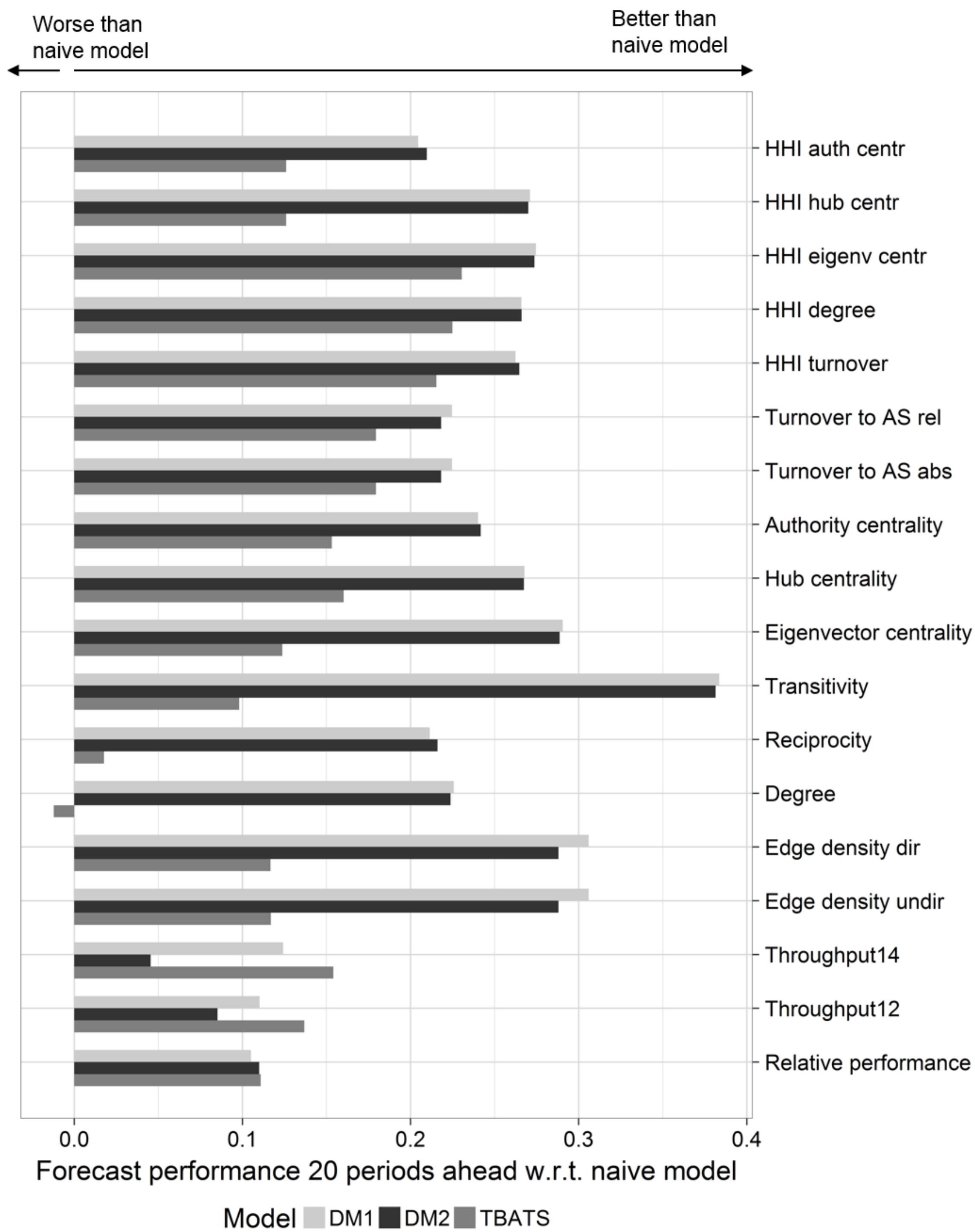


Figure 2 and 3 show the normalized RMSE for 5 and 20 days ahead forecasting for the 1.1 and 1.2 transactions. For nearly all indicators, the ARIMA dummy and TBATS model perform better than the naive model as virtually all bars are positive. Also, ARIMA dummy models produce more accurate forecasts than the TBATS model. We expect that this difference between the ARIMA dummy models and the TBATS model is due to the varying month lengths. Even though the TBATS model can capture cycles that change slightly, we expect that the month lengths vary too much across months. From Figure 2 and 3 we can also conclude that the difference in performance between DM1 and DM2 is very small. This implies that adding the governing council decisions does not significantly improve the model, and therefore we conclude that the RMP effect is not significant. Figure 6 and 7 in Appendix D show the normalized RMSE for 5 and 20 days ahead forecasting for all transactions.

4.3 Visualized forecasts

Figure 5 visualizes the 20 days (roughly 1 calendar month) ahead forecasting of the reciprocity indicator. The figure shows the difference between the predicted values (dashed red line) and the actual observations (solid blue line) for the degree indicator, using dummy model 1. The light, medium and dark gray area correspond to the 90, 95 and 99% confidence intervals, respectively. The errors can be approximated by a normal distribution. Figure 4 shows an example of the error distribution compared to the normal distribution. The errors, however, have fatter tails than a normal distribution. As a result the number of times the predicted value lies outside e.g. the 99% interval is more than 1%.

Figure 4: Histogram of errors of Throughput at 12.00 indicator of 1.1 and 1.2 transactions, produced by Dummy model 1.

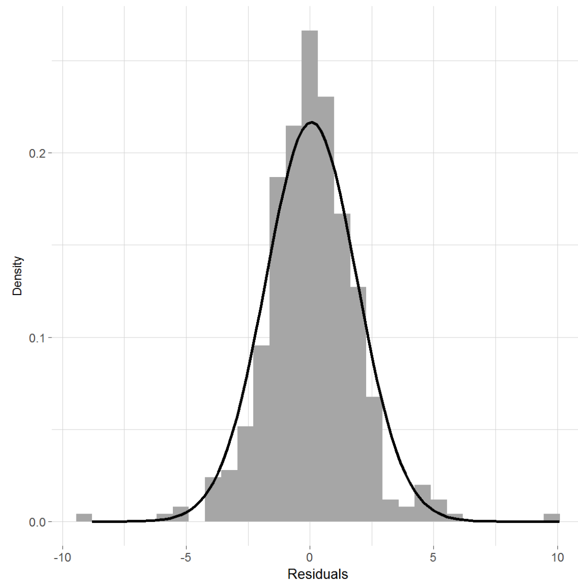
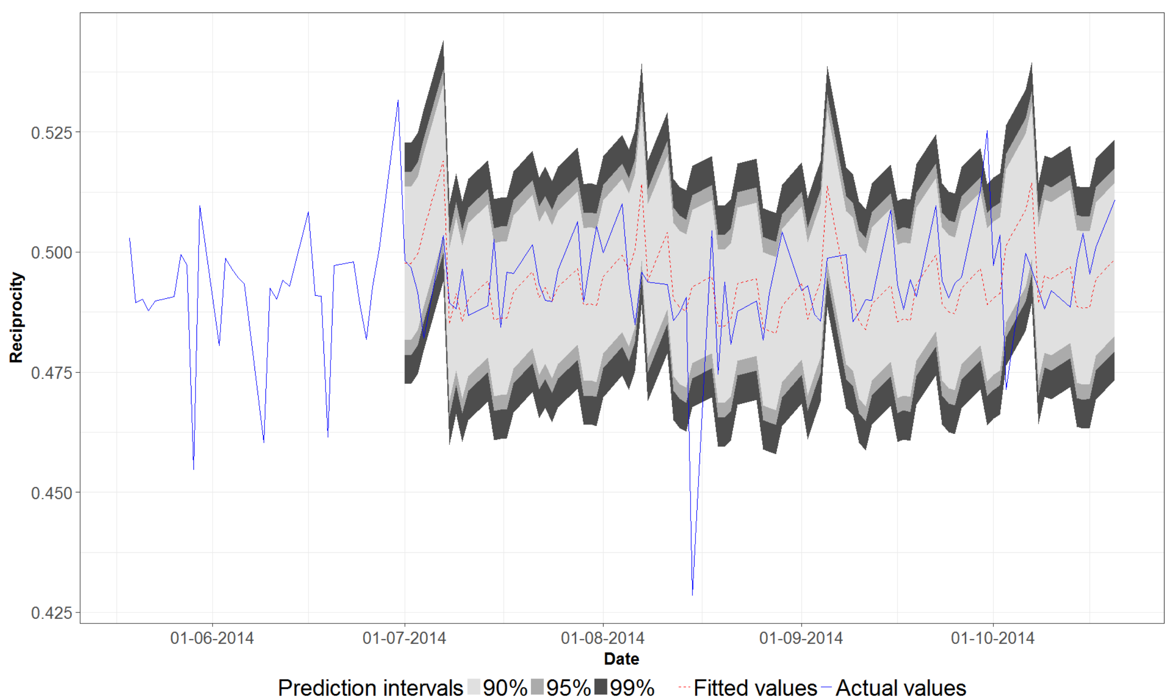


Figure 5: 20 days ahead forecast example: Reciprocity predicted 20 periods ahead by Dummy model 1.



FMI experts monitoring indicators often use a signaling for automatically identifying changes that should be considered abnormal. For signaling there is a tradeoff between giving alarms too often (false positive) or too few (false negative). Depending on the preference of the expert, the confidence intervals outside of which alarms should be given can be chosen to be wider or narrower. Also, experts can adjust the number of times they are warned by changing the threshold for the number of times the real value lies outside the prediction interval in a given month.

5 Conclusion

This paper examined cyclical patterns in FMI risk indicators using TARGET2 transaction data ranging from 2008 up to 2015. We investigate three different cyclical patterns as input to the models; 1) week, 2) month and 3) reserve maintenance period. All three models are able to detect multiple cyclical patterns. The ARIMA dummy models are flexible in varying period lengths. The ARIMA models can generally handle cycle length better than the TBATS model, which is an important feature for the month pattern since the number of business days in a month varies between 19 and 23. On the other hand, the output of the TBATS model is more intuitive. This output visualizes the amplitude of each cycle (i.e. week and month) individually and combined.

Significant cyclical patterns are found by both the ARIMA models and the TBATS models for nearly all risk indicators based on interbank (1.1 and 1.2) transactions. When all transactions (excluding technical transfers, category 4.4) are included in the risk indicators, the TBATS model does not find significant cyclical patterns in some (3 out of 18) risk indicators. We find that the forecasts from the ARIMA dummy models are more accurate than the TBATS forecasts. Moreover, there is not much difference between the RMSEs of the two ARIMA dummy models. Hence, we do not include the governing council decision in our model. FMI or central bank experts, such as policy advisors, FMI overseers and financial stability experts, could use our forecasting method to determine whether a risk indicator deviates significantly from the normal pattern.

A Time series explanation

A.1 Edge density

The edge density is calculated in the following way:

$$c = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij}}{N(N-1)} \tag{9}$$

where a_{ij} is the adjacency matrix that contains a 1 if two nodes have a link on a day and zero otherwise.

A.2 Degree

Degree is the number of links of each node per day and is calculated by the following formula:

$$k_i = \sum_{j=1}^{N} a_{ij} \tag{10}$$

where a_{ij} is as defined in A.1

The average degree is defined as follows:

$$k_{avg} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij}}{N} \tag{11}$$

A.3 Reciprocity

Reciprocity is the fraction of links with a link in the opposite direction. Garlaschelli and Loffredo (2004) define it as follows:

$$\rho = \frac{\sum_{i \neq j}(a_{ij} - c)(a_{ji} - c)}{\sum_{i \neq} j(a_{ij} - c)^2} \tag{12}$$

where a_{ij} and c are as defined in equation (9).

A.4 Transitivity

The transitivity for each single node is calculated as follows:

$$Tran_i = \frac{2z_i}{k_i(k_i - 1)} \tag{13}$$

where k_i refers to the degree as defined in equation (10) and z_i denotes the number of links between neighbors of node i. Note that the maximum number of possible connections that the neighbors of node i can have is equal to $(k_i * (k_i - 1))/2$

The transitivity for the whole network is the average of the transitivity of the nodes in the full network, which is shown in the following formula:

$$Tran_{avg} = \frac{\sum_{i=1}^{N} Tran_i}{N} \tag{14}$$

A.5 Eigenvector centrality

The eigenvector centrality of node v_i can be written as a function of the eigenvector centrality of its neighbors ($c_e(v_j)$) in the following way, as explained by Zafarani et al. (2014):[9]

$$c_e(v_i) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{j,i} c_e(v_j) \tag{15}$$

where $A_{j,i}$ denotes the transpose of adjacency matrix A and λ corresponds to an eigenvalue of $A_{j,i}$. The eigenvector centrality of all nodes can be written as $\mathbf{C_e} = (C_e(v_1), C_e(v_2), ..., C_e(v+n))^T$ so equation (15) can be written in matrix notation as follows:

$$\lambda \mathbf{C_e} = A^T \mathbf{C_e} \tag{16}$$

where $\mathbf{C_e}$ is an eigenvector of adjacency matrix A_T and λ the eigenvalue corresponding to $\mathbf{C_e}$. Note that A^T is equal to A for all undirected networks.

A.6 Hub and authority centrality

The equation for hub centrality are as follows:

$$h_i = \sum_{i \to j} a_j = \sum_j A_{ij} * a_j = A * a \tag{17}$$

$$a_i = \sum_{j \to i} h_j = \sum_j A_{ji} * h_j = A^T h$$

[9] http://dmml.asu.edu/smm/chapters/SMM-ch3.pdf

where a and h denote the vector of the authority and hub scores of all nodes, A_{ij} denotes the adjacency matrix and A_{ji} the transpose of the adjacency matrix. Hence, $h = (AA^T)h$ and $a = (A^T A)a$ are the eigenvectors corresponding to eigenvalues of AA^T and $A^T A$ respectively

A.6.1 Interdependency indicator

n. Turnover relative to AS

This turnover relative to AS indicator measures liquidity in the whole system and calculates the percentage of the liquidity that originates from Ancillary Systems.

B Transaction categories in TARGET2

Table 2: Categories of transactions in TARGET2.

Description	Category
1. Main transactions	
Customer payments	1.1
Interbank payments	1.2
2. Transactions with central bank	
Cash operation	2.1
Intraday repo and similar transactions	2.2
Payments sent and/or received on behalf of customers	2.3
Inter NCB payments	2.4
Other transactions	2.5
3. Transactions with AS	
Trade by trade settlement of SSS	3.1
Other settlement operations	3.2
EBA EURO1	3.3
CLS	3.4
EBA Step2	3.5
4. Liquidity transfers	
Intraday transfers with LVPS	4.1
Intraday transfers with retail systems	4.2
Intraday transfers with SSS	4.3
Internal transfers between different accounts of the same participant	4.4
Commercial transfer between different account of same participant	4.5
Transfers T2S	4.6
Transfers back to TARGET2 from T2S	4.7

C Cyclical variation

Table 3: Cyclical variation presence.

Risk indicator	1.1 and 1.2 transactions				All transactions			
	ARIMA dummy		TBATS		ARIMA dummy		TBATS	
	Week	Month	Week	Month	Week	Month	Week	Month
Operational indicators								
Relative performance TARGET2	✓	✓	✓	✓	✓	✓	✓	✓
Throughput at 12.00	✓	✓	✓	✓	✓	✓	✓	✓
Throughput at 12.00	✓	✓	✓	✓	✓	✓	✓	✓
Network properties								
Edge density undirected	✓	✓	✓	✓	✓	✓	✓	✓
Edge density directed	✓	✓	✓	✓	✓	✓	✓	✓
Degree	✓	✓	✓	✓	✓	✓	✓	✓
Reciprocity	✓	✓	✓	✓	✓	✓	✓	✓
Transitivity	✓	✓	✓	✓	✓	✓	✓	✓
Eigenvector centrality	✓	✓	✓	✓	✓	✓	✓	✓
Hub centrality	✓	✓	✓	✓	✓	✓	✓	✓
Authority centrality	✓	✓	✓	✓	✓	✓	✓	✓
links to AS								
Turnover to AS (absolute)	✓	✓	✓	✓	✓	✓	✓	✓
Turnover to AS (relative)	✓	✓	✗	✗	✓	✓	✗	✗
HHI								
HHI turnover	✓	✓	✓	✓	✓	✓	✓	✓
HHI degree	✓	✓	✓	✓	✓	✓	✓	✓
HHI eigenvector centrality	✓	✓	✓	✓	✓	✓	✗	✗
HHI Hub centrality	✓	✓	✓	✓	✓	✓	✗	✗
HHI authority centrality	✓	✓	✓	✓	✓	✓	✓	✓

checkmark ✓indicates that the model recognizes a significant pattern

D RMSE forecasting all transactions

Figure 6: Out-of-sample fit of all indicators for all transactions (except category 4.4) with respect to the naive model.

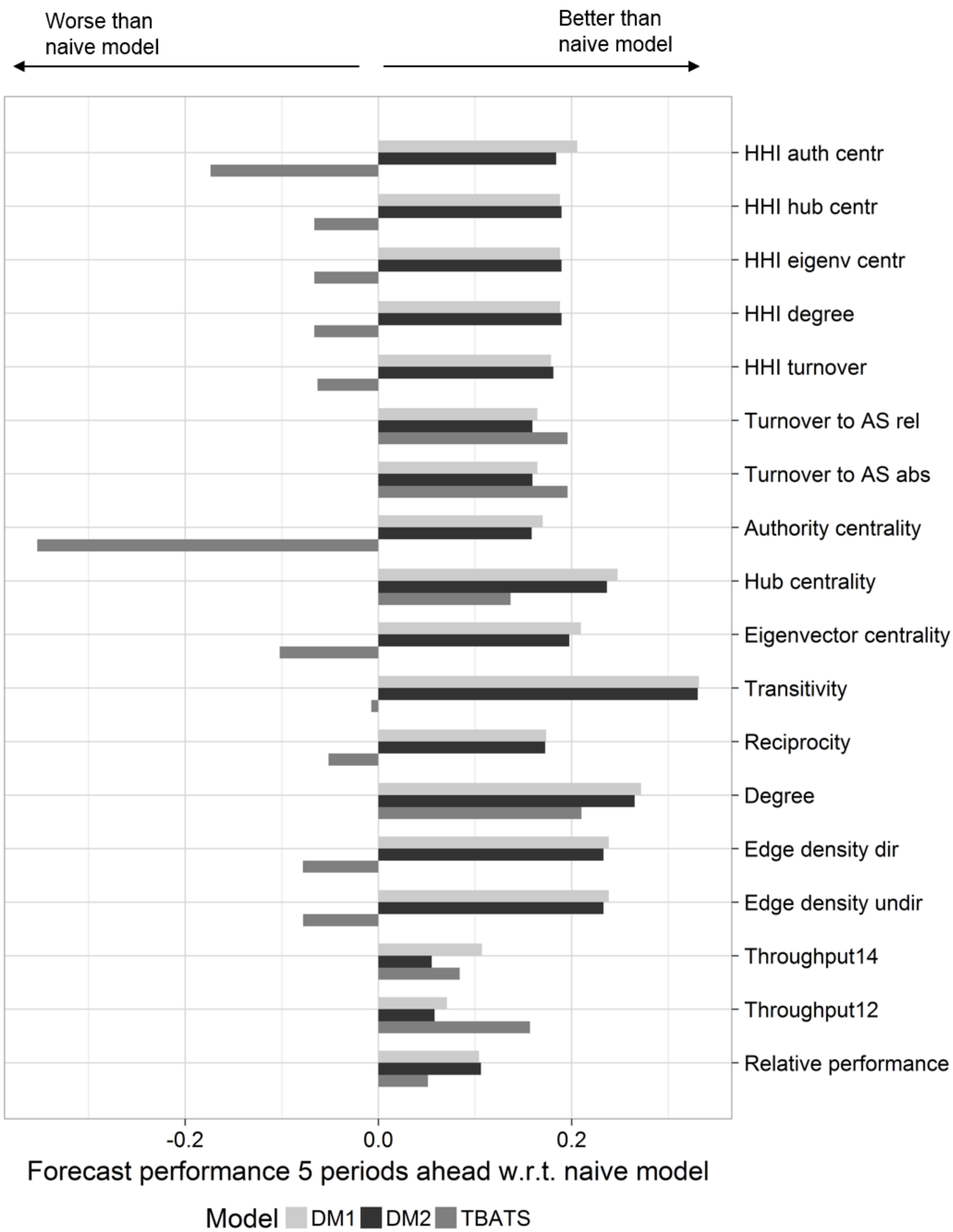
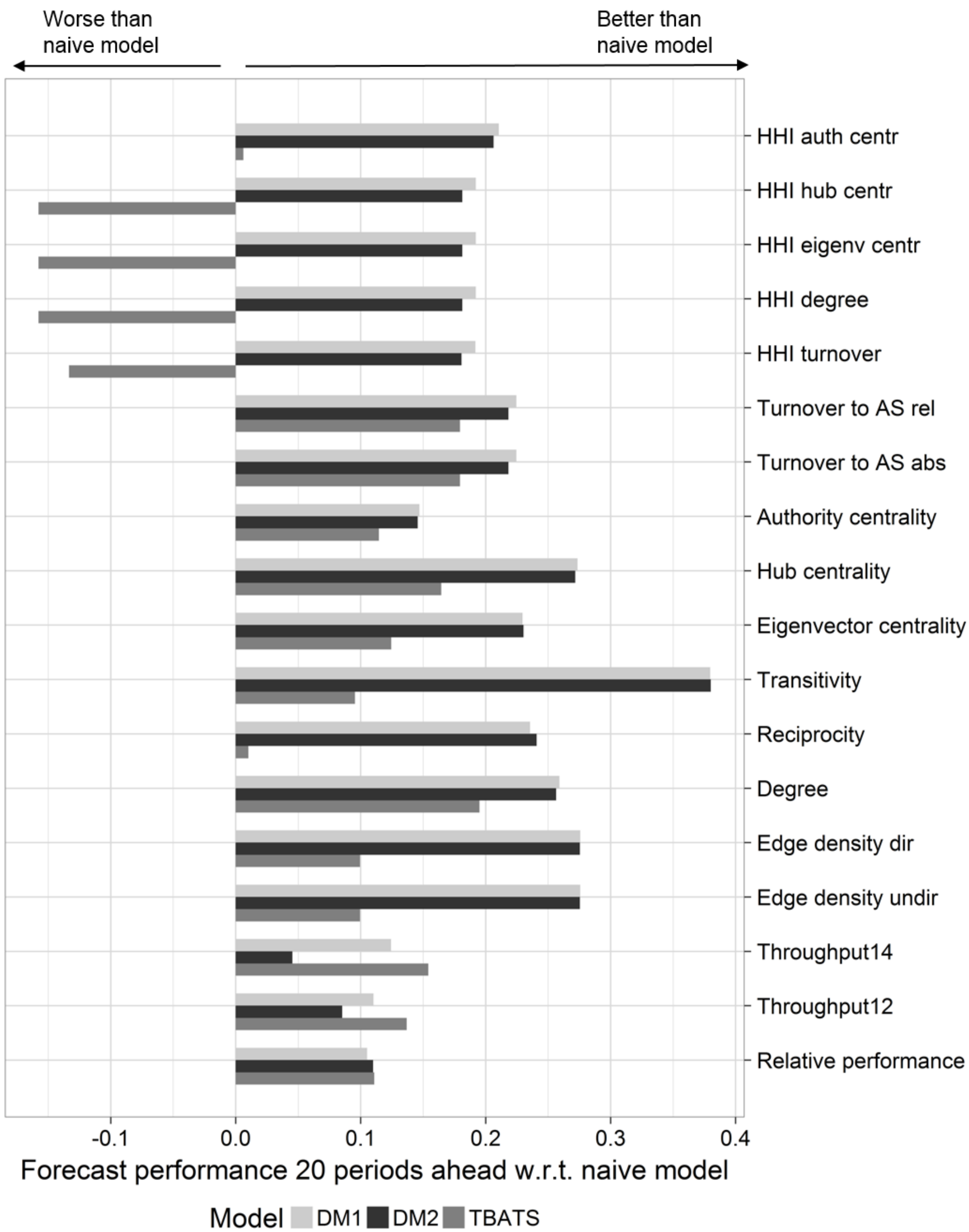


Figure 7: Out-of-sample fit of all indicators for all transactions (except category 4.4) with respect to the naive model.



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