Forecasting Bank Capital Ratios Using the Prophet Model by Facebook

James Kolari and Ivan Pastor Sanz

Abstract

This study investigates the efficacy of the Prophet model by Facebook with respect to forecasting bank capital ratios. Bank financial ratios and macroeconomic information are combined to forecast total risk-adjusted capital ratios for 19 large U.S. banks. Using a sample period from March 2005 to December 2020, in-sample results show that the model accurately estimates bank capital ratios over time. As validation, out-of-sample tests indicate that forecasting errors are smaller for Prophet models compared to benchmark ARIMAX models. Based on these and other results, we conclude that the Prophet model does a good job of forecasting bank capital ratios. By implication, it provides a practical forecasting tool for bank regulatory supervisors, management, and investors.

JEL Classification: G17, G28, C53

Keywords: risk-adjusted capital ratios, stress tests, financial condition, Prophet model

I. Introduction

An extensive literature exists on the use financial ratios and other measures of financial distress in regression models to predict nonfinancial corporate and bank failures.[1] In these models, the dependent variable is usually a binary indicator of whether a firm failed within a specific time horizon (e.g., one or two years) based on firm-specific financial ratios as regressors. Different techniques have been used on a spectrum from traditional statistical models, such as logistic regression, to more sophisticated algorithms as well as combinations of different techniques.[2] A diverse list of financial ratios are employed, including (for example) equity capital ratios, nonperforming assets coverage ratio, nonaccrual loans to total assets, net-charge offs to total assets, return on equity and assets, short-term deposit ratios, among others.

An important lesson from the bank failure literature is that inadequate capitalization is an indicator of incipient bank distress and possible later failure.[3] In this regard, failure is a process that normally is preceded by losses that deteriorate equity

James Kolari (j-kolari@tamu.edu), corresponding author, Texas A&M University, USA; Ivan Pastor Sanz (ivanpastorsanz@gmail.com), School of Business and Economics, Universidad Internacional de La Rioja (UNIR), Spain.

[1] See studies by Altman (1968), Altman and McGough (1974), Meyer and Pifer (1975), Sinkey (1975), Altman, Haldeman, and Narayanan (1977), Korobrow and Stuhr (1985), Whalen and Thomson (1988), Kolari, Glennon, Shin, and Caputo (2000), and others.
[2] For example, see Tam and Kiang (1992), Martínez (1996); Vellido, Lisboa and Vaughan (1999), Arena (2008), Boyacioglu, Kara and Baykan (2009), Betz, Oprică, Peltonen, and Sarlin (2014), López-Iturriaga and Sanz (2015), Berger, Imbierowicz, and Rauch (2016), Chiaramonte, Liu, Poli, and Zhou (2016), Chiaramonte and Casu (2017), Ekinci and Erdal (2017), Iwanicz-Drozdowska, Laitinen, and Suvas (2018), Jing and Fang (2018), and others.
[3] For example, see Coats and Fant (1993), DeAngelo and DeAngelo (1990), and Johnsen, and Melicher (1994), Gilbert, Meyer, and Vaughn (1999), Jagtiani, Kolari, Lemiux, and Shin (2000), Cole and Wu (2009), Acharya, Engle, and Richardson (2012), Chapel, Killgo, and Klemme (2021), and others.

capital over time. Recognizing this process, regulatory officials have implemented stress test methodologies to better anticipate problems in banks. Stress tests are forward-looking exercises that aim to evaluate the impact of severe but plausible adverse scenarios on the capital ratios of financial firms (Schuermann, 2020). They take into account not only individual financial ratios but macroeconomic variables, qualitative information, and action plans of banks.

Stress test methodologies can be categorized as either top-down based on only publicly available bank-level data or bottom-up using detailed account and loan-level data for each bank (Covas and Driscoll, 2014; Kapinos and Mitnik, 2015; and Hirtle, Kovner, Vickery, and Bhanot, 2016).[4] Although stress tests are valuable to regulatory authorities and banking organizations, they have some important limitations. For example, the definition of an adverse scenario itself is not an easy task. If a scenario does not change much over time, it could become very predictable, thereby training banks to be well prepared for a rather narrow set of scenarios (Glasserman and Tangirala, 2016; and Schuermann, 2020). Another challenge is that stress tests are complex with high computational costs and difficulties in terms of capturing counterparty and liquidity risks. Despite these potential issues, bank regulatory supervisors emphasize capital ratios as a key benchmark in determining interventions to assist troubled banks.

Given the importance of capital ratios in assessing bank condition, researchers have proposed alternative models to forecast bank capital. For example, Jagtiani, Kolari, Lemiux, and Shin (2000) applied logit regression in combination with neural-network methods to predict whether banks' capital ratios would fall below an adequate level one year ahead of time. Another study by Acharya, Engle, and Richardson (2012) proposed an SRISK measure to estimate the expected capital shortfall of a financial firm conditional on a systemic event.[5] While SRISK takes advantage of readily available public information, it depends heavily on bank equity values that can be influenced by other factors than the financial condition of individual institutions (Homar, Kick and Salleo, 2016; and Iyengar, Luo, Rajgopal, Venkatasubramanian and Zhang, 2017). Further work by Kolari, López-Iturriaga, and Sanz (2019) developed an early warning system based on multiple strategy ensemble methods to predict whether European banks would pass their capital ratio stress tests. Bank financial ratios and macroeconomic variables in different countries were able to predict approximately 90 percent of stress test capital results in out-of-sample validation analyses. Finally, Chapel, Killgo, and Klemme (2021) developed a model that, given a loan loss scenario, estimates whether a bank's capital ratio will fall below regulatory requirements.

This paper contributes to the aforementioned literature by testing the efficacy of the Prophet model with respect to forecasting total bank capital. Designed by Facebook and released in 2017, Prophet is a decomposable time series model with three components – namely, trend, seasonality, and holidays. Taylor and Letham (2018) proposed the Prophet model with a configurable modular design to flexibly adjust parameters to take

[4] Not surprisingly, studies have shown that stress tests can affect bank behavior, equity performance, and CDS spreads. See studies by Alves, Mendes and Pereira da Silva (2015), Georgescu, Gross, Kapp and Kok (2017), Neretina, Acharya, Berger, and Roman (2018), Sahin, and De Haan (2020), and Goel and Agarwal (2021).

[5] See also Acharya and Steffen (2014a,b).

into account a wide variety of time series forecasting problems. [6] Due to its open source software programs (viz., Python and R codes) and powerful forecasting tools, Prophet is becoming increasingly popular among researchers in a variety of different fields of study. For instance, it has been applied to predicting future sales in the retail sector (Kumar, Chauhan, and Dubey, 2019), sales in supermarkets (Jha and Pande 2021), and Brent crude oil trends (Güleryüz and Özden 2020). More recently, researchers have used it to predict the evolution of COVID-19 cases in different countries (Mahmud, S., 2020; Mahanty, Swathi, Teja, Kumar, and Sravani., 2021; and Shradha, Mareedu, Kim, and Woo, 2021). Relevant to the present study, Prophet has been employed to forecast equity prices in the stock market (Fang, Lan, Lin, Chang, Chang, and Wang, 2019; and Madhuri, Chinta, and Kumar, 2020). In our finance application of the model, we assume that the equity capital ratio of an individual bank is highly dependent on previous capital ratios as well as the macroeconomic environment. Based on different scenarios, and conditioned on projections of macroeconomic variables, sensitivities to model predictors are utilized to estimate bank capital values.

Our empirical tests show that the proposed Prophet model provides fairly accurate estimates of the future evolution of bank capital ratios for individual banks. In the sample period March 2004 to December 2020, total risk-based capital ratios for 19 large U.S. banks are estimated using banks' individual financial ratio and macroeconomic variables. Hence, 19 different models are trained. We find that in-sample estimates of fitted bank capital ratios accurately estimate actual capital ratios over time. Turning to out-of-sample tests, one-year-ahead forecasts are generated on a rolling basis in the sample period. We conduct validation tests by comparing the forecast errors for Prophet vis-à-vis well-known ARIMAX models. Because Prophet models consistently outperform ARIMAX models in terms of forecasting ability, we conclude that the Prophet model does a good job of forecasting bank capital ratios. An important implication of our findings is that the Prophet model could be used to supplement bank stress tests by regulatory agencies to increase supervisory effectiveness and thereby enhance bank safety and soundness. Also, in their compliance activities, banks can use Prophet to help manage regulatory capital requirements. Finally, due to its ease of access and usage, investors could implement the Prophet model to evaluate banks' capital ratios.

II. Empirical Methods

We employ the Prophet model to predict the total capital ratios of large U.S. banks. Developed by Facebook (Taylor and Letham, 2018), the Prophet model identifies non-linear trends in the time series, such as yearly, weekly, daily seasonality, and holiday effects, and then combines them to produce an estimated value of the dependent variable.

The underlying model features a decomposable time series with three components: trend, seasonality, and holidays (if they exist). According to Hastie and Tibshirani (1987), in its simplest form, Prophet is represented as follows:

$$y(t) = g(t) + s(t) + \mathcal{E}(t), \tag{1}$$

[6] According to Facebook, Prophet provides a forecasting tool that can be tweaked by users to produce customized forecasts, thereby combining automatic processes with researcher judgement. It has the advantage that even users with little formal knowledge of statistics can generate reasonable and accurate forecasts. Also, it is robust to missing data, outliers, and shifts in time series data. For further information including download and installation, see https://facebook.github.io/prophet/. The authors are not affiliated with Facebook and have no conflict of interest to declare.

where *y*(*t*) represents the time series under analysis (i.e., the total risk-based capital ratio of a bank), *g*(*t*) is a nonlinear saturating trend function that models nonperiodic changes of the series, *s*(*t*) represents the seasonality component fitting only yearly periodic changes in the trend and holiday effects which capture sudden events that are predictable over time, and the last term $\mathcal{E}$(t) corresponds to any unusual changes that cannot be explained by the model. Regarding to the first term, the nonlinear trend function is defined as:

$$g(t) = \frac{C(t)}{1+e^{-k(t-m)}}, \tag{2}$$

where *C*(*t*) is a time-varying capacity that, in this case, represents the maximum capital ratio of each bank in each quarter, *k* denotes the time-varying growth rate, and *m* is an offset parameter.

The effects of possible changes in the growth trend are explicitly examined by introducing *S* change points in the model. In this respect, the vector of rate adjustments is defined by:

$$\delta \in \mathbb{R}^S, \tag{3}$$

where δ_j represents the rate of change at a time s_j. This rate of change corresponds to the base rate *k* plus the rate of change of adjustments that happened until that time, which can be represented as follows:

$$\delta_t = k + \sum_{j:t>s_j} \delta_j, \tag{4}$$

Defining a vector that can be represented as:

$$a_j(t) = \begin{cases} 1, \text{if } t \geq s_j \\ 0, \text{otherwise} \end{cases}, \tag{5}$$

the rate of change at time *t* can be defined as $k + a(t)^{T\delta}$. Using *k* and the offset parameter *m*, the correct adjustment at change points *j* can be computed as:

$$\gamma_j = \left(s_j - m - \sum_{l<j} \gamma_l\right)\left(1 - \frac{k+\sum_{l<-j}\delta_l}{k+\sum_{l\leq j}\delta_l}\right). \tag{6}$$

The trend will be described as a non-linear function with saturated logistic growth as follows:

$$g(t) = \frac{C(t)}{1+e^{(-(k+a(t)^T\delta)(t-(m+a(t)^T\gamma)))}}. \tag{7}$$

The logistic growth model is a special case of the generalized logistic growth curve, which is a type of sigmoid curve.

The seasonality model is constructed with the standard Fourier series that takes into account arbitrary smooth seasonal effects. Hence, seasonality can be modelled as:

$$s(t) = \sum_{n=1}^{N}\left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right). \tag{8}$$

Here P is the regular period expected for the time series; for instance, P takes the value of 365.25 for a year. In our case, given quarterly information, this value is fixed to 91.31. Parameters $a_n$and b_n need to be estimated to fit the seasonability, i.e., the estimation has the format $\beta = [a_1, b_1, \dots, a_N, b_N]^T$.

The Prophet model allows the inclusion of extra regressors to enhance forecast results. In our case, past values of the capital ratio of each bank are augmented with other variables. The latter macroeconomic variables are treated as supporting terms in equation (7). Hence, these variables are added in the linear component of the model.

III. Data

Our sample consists of large U.S. banks that participated in the Dodd-Frank Act stress test exercise (DFAST) released in 2021. From a total of 23 banks that participated in the DFAST exercise, data is available to obtain a robust model for 19 financial institutions.[7] All banks are holding companies with \$100 billion or more in total consolidated assets. Financial information for each bank is gathered from March 2004 to December 2020 using quarterly bank holding company (BHC) data on form FR Y-9C Consolidated Reports of Condition and Income. Table 1 lists our sample banks as well as their total assets and total risk-based capital ratios as of year-end 2020.

Different applications of the Prophet algorithm are possible. In predictive and machine learning models, data is usually split into training and test sets. The model is fit to the training set and then validated on the test set. However, in time series forecasting tests, training on a "fixed origin" can give misleading information about performance. Hence, a rolling window approach is recommended for time series (Svetunkov, 2020).

In the rolling window strategy, the sample size used to estimate the model is fixed and the start and end dates move forward by rolling one year at a time. Hence, the start and end dates move one year ahead with a fixed sample size, wherein the oldest observations are dropped and the newest ones are added. Subsequently, observations in the development period are applied to forecast the following four quarters of total risk-based capital ratios. In this manner, the fixed rolling window is updated one year at a time to produce one-step-ahead forecasts. This approach estimates and keeps parameters updated for each rolling window. In turn, it avoids the stability parameter drift problem of estimated parameters that are updated for each fixed rolling window estimate. Also, it has been shown to be an effective approach in modern financial markets characterized by rapidly changing business conditions (Cheung, Chinn, and Pascual, 2005).

As mentioned earlier, the total sample period spans the period March 2004 to December 2020. We estimate19 different models, one for each individual bank in the sample. The financial information for each bank is based on their previous values for the respective bank. Yearly rolling forecasting is carried out to predict the capital ratios of each bank. Each rolling sample contains a total of 48 quarters. This sample size is a trade-off between model robustness and data availability. The selected number of quarters is equal to the minimum number of quarters available for Morgan Stanley and Goldman Sachs, which are systemically important financial institutions (SIFIs) that are salient

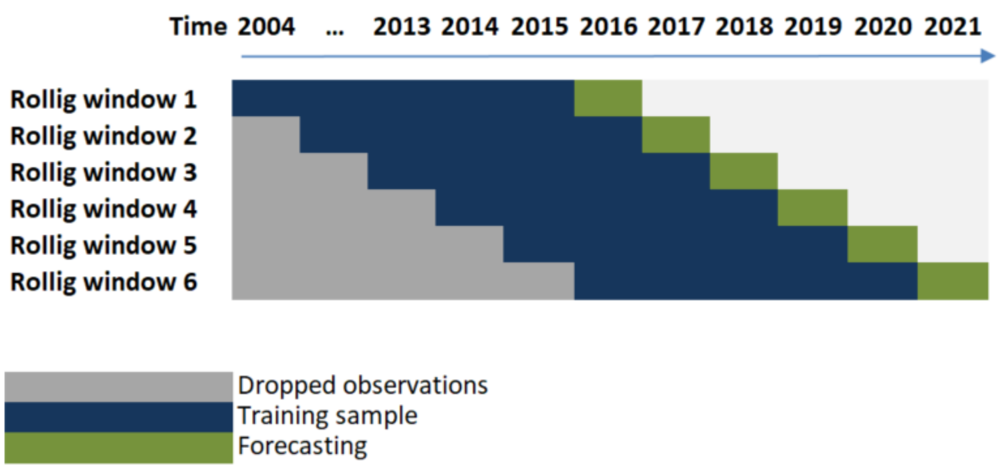
[7] The following banks were excluded from our analyses: RBC US Group Holdings LLC, DB USA Corporation, Credit Suisse Holdings (USA) Inc., and UBS Americas Holding LLC. These banks only had financial information for the last 18 quarters in the sample period, which is insufficient to build a robust time series prediction model.

Table 1. Sample banks

Bank name	Qtrs	Initial date	End date	Risk-based capital ratio	Total assets (MM $)
Morgan Stanley	48	31/03/2009	31/12/2020	21,45%	1,115,862,000
The Goldman Sachs Group, Inc.	48	31/03/2009	31/12/2020	19,52%	1,163,040,000
Barclays US LLC	65	31/12/2004	31/12/2020	22,18%	161,286,000
Capital One Financial Corporation	65	31/12/2004	31/12/2020	17,72%	421,602,066
Regions Financial Corporation	66	30/09/2004	31/12/2020	13,56%	147,598,000
HSBC North America Holdings Inc.	68	31/03/2004	31/12/2020	21,40%	241,536,144
MUFG Americas Holdings Corporation	68	31/03/2004	31/12/2020	16,29%	167,845,574
Northern Trust Corporation	68	31/03/2004	31/12/2020	15,56%	170,003,912
BMO Financial Corp.	68	31/03/2004	31/12/2020	15,60%	184,653,995
State Street Corporation	68	31/03/2004	31/12/2020	15,34%	314,706,000
The PNC Financial Services Group, Inc	68	31/03/2004	31/12/2020	15,61%	466,864,739
The Bank of New York Mellon Corporation	68	31/03/2004	31/12/2020	17,11%	469,633,000
TD Group US Holdings LLC	68	31/03/2004	31/12/2020	18,25%	507,327,229
Truist Financial Corporation	68	31/03/2004	31/12/2020	14,51%	509,228,000
U.S. Bancorp	68	31/03/2004	31/12/2020	13,36%	553,905,000
Wells Fargo & Company	68	31/03/2004	31/12/2020	16,47%	1955163000
Citigroup Inc.	68	31/03/2004	31/12/2020	16,77%	2260090000
Bank of America Corporation	68	31/03/2004	31/12/2020	16,08%	2819627000
JPMorgan Chase & Co	68	31/03/2004	31/12/2020	17,30%	3386071000

participants in the financial system. The first rolling process for estimating model parameters is obtained using information from March 2004 to December 2015. The estimated model is used to forecast the capital ratios in the following four quarters ending December 2016. In the next rolling window, model parameters are estimated based on data from March 2005 to December 2016, and capital ratios in the following four quarters are predicted using the new estimated parameters. Thus, the rolling process is repeated six times with the last rolling window from March 2006 to December 2020. This forecasting process is summarized graphically in Figure 1. To simplify matters, only one year is observed for projections instead of four quarters.

Figure 1. Rolling origin process with constant holdout size



Prophet requires the specification of customizable parameters, which are known as *hyperparameters* in the field of machine learning. These parameters are higher level than other parameters, which are set before training the model and tuned based on dataset features (Agrawal, 2021). For Prophet, the most important parameters are the following: change points that define trend changes; seasonality that defines periodic functions which can affect the time series; and the Fourier order of the seasonality function that determines how fast the seasonality can change and adapt.

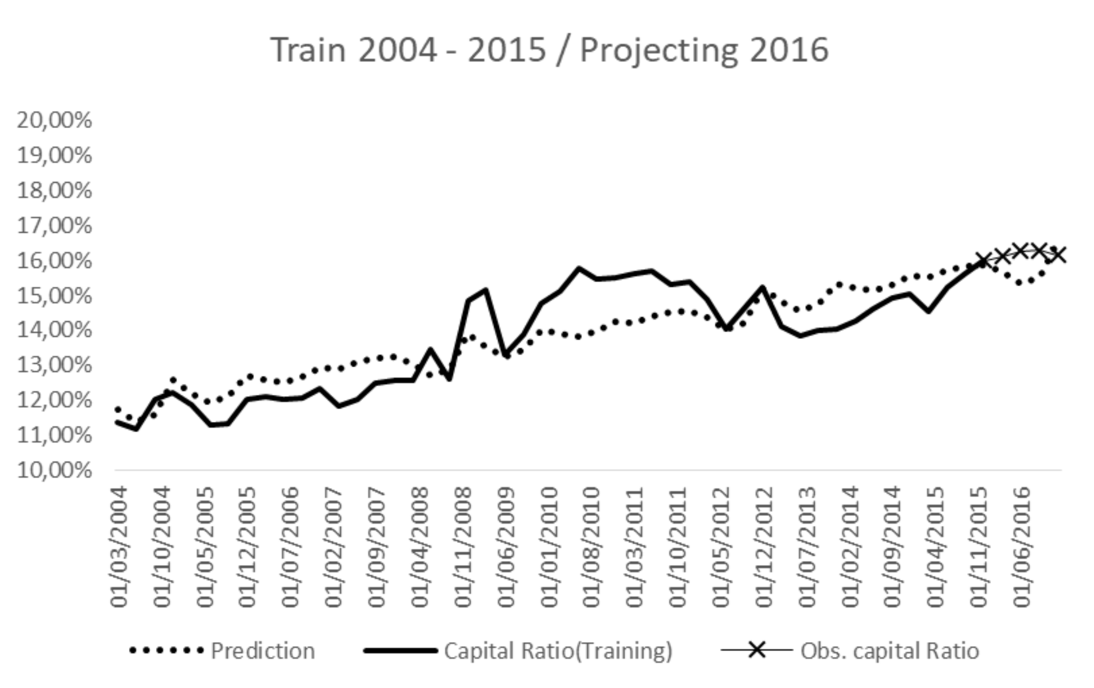
The default configuration of Prophet is not necessarily well suited for all time series problems. For this reason, it needs to be tuned to obtain the best model for each bank and rolling window. Hyperparameters are selected by calculating several possible combinations and storing the ones that achieve the lowest error between the observed and estimated values. Table 2 summarizes the 18 different combinations of hyperparameters tested in this paper. Thus, a total of 108 different models are performed for each bank (i.e., the number of rolling windows multiplied by the combinations of different parameters).

As an illustrative example of model results, Figure 2 displays a comparison between the actual and estimated risk-based capital ratio for JP Morgan Chase, the largest U.S. bank in terms of total assets in December 2020. Results are displayed only for the first rolling window. Three time series are plotted. First, the historical observed total risk-based capital ratio is marked as a continuous line, which is the actual value used to train the model in each window. Second, quarterly fitted values of the model are shown as a dotted line. Third, and last, projections or forecasts are obtained for the sample used to train each model in the following four quarters and displayed as xxxx hash marks. In this case, the Prophet algorithm only utilizes the past values of the total risk-based capital ratio for the bank to fit the model. The figure shows that past values of capital ratio are not sufficient to obtain accurate forecasts.

Table 2. Combinations of different hyperparameters tested in each Prophet model

Combination ID	Number of change points	Seasonality function	Fourier order
1	5	multiplicative	3
2	10	multiplicative	3
3	15	multiplicative	3
4	5	additive	3
5	10	additive	3
6	15	additive	3
7	5	multiplicative	5
8	10	multiplicative	5
9	15	multiplicative	5
10	5	additive	5
11	10	additive	5
12	15	additive	5
13	5	multiplicative	10
14	10	multiplicative	10
15	15	multiplicative	10
16	5	additive	10
17	10	additive	10
18	15	additive	10

Figure 2. JP Morgan Chase projections using past values of risk-based capital ratio



To improve forecasts, we augment capital ratio information with macroeconomic variables. By fitting models using macroeconomic indicators, capital adequacy can be assessed in the context of different projected macroeconomic scenarios, thereby enabling the observation of their impact on model projections. Therefore, for each of the 19 banks, one model is fitted combining past information of the capital ratio and a set of macroeconomic variables. The list of useful macroeconomic variables can be considerable. As an example, during DFAST 2021 supervisory scenarios, 28 key variables describing U.S. economic activity and asset prices were projected and subsequently used to identify banks that lacked sufficient capital to comply with minimum required capital ratios over nine quarters. The list of these macroeconomic variables is shown in Table 3. Historical macroeconomic data and scenarios are provided by the Federal Reserve. In this paper, we use the same set of macroeconomic variables to enrich our models. Therefore, macroeconomic variables are added as additional regressors in our Prophet specifications.

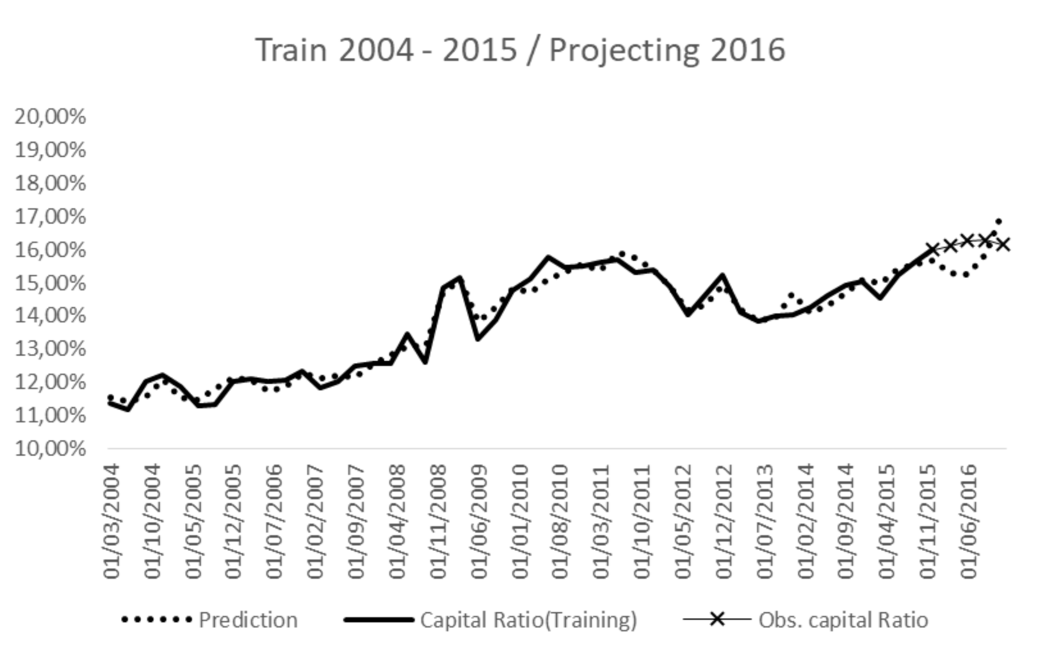
Due to numerous macroeconomic variables and sample data for a maximum of 68 quarters of information for each bank, we selected the five most correlated variables with the capital ratio for each bank to develop our models[8]. Consequently, the list of variables used for one bank may be different from those used for another bank; hence, our models are bank-specific. Figure 3 shows the projections for the same model displayed in Figure 2 for JP Morgan Chase after augmentation with macroeconomic information. Comparing Figures 2 and 3, we see that this trained model, which incorporates macroeconomic information, is much more accurate than with only financial ratios.

[8] Other alternatives incorporating the top two-to-seven most correlated macroeconomic variables were tested with no material changes in the results. To conserve space, the list of most correlated variables for each bank is not reported but is available upon request.

Table 3. List of macroeconomic variables

Variable description	
Real GDP growth	Euro area bilateral dollar exchange rate (USD/euro)
Nominal GDP growth	Developing Asia real GDP growth
Real disposable income growth	Developing Asia inflation
Nominal disposable income growth	Developing Asia bilateral dollar exchange rate (F/USD index)
Unemployment rate	Japan real GDP growth
CPI inflation rate	Japan inflation
3-month Treasury rate	Japan bilateral dollar exchange rate (yen/USD)
5-year Treasury yield	U.K. real GDP growth
10-year Treasury yield BBB corporate yield	U.K inflation
Mortgage rate	U.K. bilateral dollar exchange rate (USD/pound)
Prime rate	
Dow Jones Stock Market Index	
House Price Index	
Commercial Real Estate Price Index	
Market Volatility Index	
Euro area real GDP growth	
Euro-area inflation	

Figure 3. JP Morgan Chase projections using past values of the risk-based capital ratio and macroeconomic information



IV. Empirical Results

As shown in the Appendix, Figure 3 is repeated for the five largest U.S. banks by assets in December 2020. Six different graphs are displayed for each bank related to each of the six rolling samples used to train the different models. To conserve space, the analyses of other sample banks are not shown but are available upon request from the authors.

Actual values of capital ratios are not shown after December 2020, which was the last information accessed for this paper. During the DFAST 2021 stress test, this date represents the starting date for projections. Therefore, only projected values are displayed after this date.

Because each bank model is dependent on macroeconomic variables, projections require the use of future values or trajectories of the macroeconomic variables. In regulatory stress test exercises, baseline and adverse scenarios are used to evaluate the capital adequacy of major banks and the banking system itself. Baseline scenarios depict a future state of the society and/or environment in which no new policies are implemented. On the other hand, severely adverse scenarios are not forecasts but rather hypothetical scenarios designed to assess the strength of banking organizations and their resilience to unfavorable economic circumstances.

Our projections are based on the severely adverse scenario proposed in the DFAST 2021 stress test. Under this scenario, for the year 2021, U.S. real GDP declined by 4 percent from the fourth quarter of 2020, the rate of unemployment increased to 6.75 percent, and the annualized consumer price inflation rate fell to about 1 percent in the second quarter of 2021. Additionally, the 10-year Treasury rate declined to a low of about 0.25 percent in the first quarter of 2021 and remained at that level through the first quarter of 2022. The evolution of these macroeconomic variables impacted stock market prices, which declined by approximately 55 percent through the end of the third quarter of 2021, and home prices declined by about 23.5 percent.

Table 4 displays the forecasted values of capital ratios for each bank applying the adverse macroeconomic scenario for the year 2021. The average capital ratio of samplebanks was 17.06% at the beginning of the period and ended at 17.01% in December 2021. The minimum average ratio at 16.41% occurred in March 2021. This decline suggests that aggregate capital ratios can fluctuate considerably over time. Also, some banks display more variations than others over time. Morgan Stanley, TD Group US Holdings, Goldman Sachs, Bank of America, and Capital One exhibited the largest intertemporal fluctuations in capital ratios. For these five banks, our projections indicate sharp quarterly declines in their capital ratios. For instance, the capital ratio of JP Morgan Chase dropped precipitously from 21.45% in December 2020 to 13.51% in March 2021 due to application of the adverse scenario. This bank has never experienced a quarterly reduction in its capital ratio of this magnitude in its entire history. A similar situation is observed in the case of Bank of America.

V. Robustness Check

In this section, we conduct a robustness check that comparatively benchmarks the forecasted results based on Prophet to those generated from an ARIMAX model. This well-known model is based on the auto-regressive integrated moving average (ARIMA) model (Box, Jenkins, and Reinsel, 2011). ARIMAX can be considered an extended version of the ARIMA model that utilizes multivariate time series of lagged moving averages of exogenous variables to forecast the dependent variable. An auto ARIMA function is commonly used in the literature[9] to select the best model by automatically generating a set of optimal parameters. To do this, all possible combinations of ARIMA parameters are tested to find the model with the lowest Akaike information criterion (AIC) and Bayesian Information Criterion (BIC) values. In the present case, the macroeconomic variables used to develop each Prophet model are added to be the models. Forecasted values of the test data are evaluated using three widely-used metrics: mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square

[9] For example, see Hyndman and Khandakar (2008), Oliveira and Oliveira (2018); and Maldonado, González, and Crone (2019).

error (RMSE). The root mean square error (RMSE) measures the accuracy of the models. This metric considers the residuals between actual and predicted values penalizing large errors and scaling the scores in the same units as the forecast values. It is calculated as follows:

Table 4. Prophet projections for the year 2021

Bank Name	2020Q4	2021Q1	2021Q2	2021Q3	2021Q4	Min ratio	Max decline
JPMorgan Chase & Co	17.30%	16.64%	16.75%	16.86%	17.23%	16.64%	-0.66%
Bank of America Corporation	16.08%	13.80%	14.03%	13.84%	13.42%	13.42%	-2.28%
Citigroup Inc.	16.77%	16.34%	16.26%	16.22%	15.88%	15.88%	-0.43%
Wells Fargo & Company	16.47%	16.49%	16.68%	16.60%	16.37%	16.37%	-0.23%
The Goldman Sachs Group	19.52%	17.84%	15.17%	19.96%	20.11%	15.17%	-2.67%
Morgan Stanley	21.45%	13.51%	17.00%	18.72%	17.57%	13.51%	-7.94%
U.S. Bancorp	13.36%	13.22%	12.95%	13.06%	13.06%	12.95%	-0.27%
Truist Financial Corporation	14.51%	14.,36%	14.20%	14.89%	14.82%	14.20%	-0.16%
TD Group US Holdings LLC	18.25%	16.19%	12.45%	13.02%	11.74%	11.74%	-3.74%
The Bank of New York Mellon	17.11%	16.33%	16.60%	16.42%	17.02%	16.33%	-0.78%
The PNC Financial Services	15.61%	14.35%	14.49%	14.82%	14.97%	14.35%	-1.26%
Capital One Financial	17.72%	15.72%	15.51%	15.95%	15.59%	15.51%	-2.00%
State Street Corporation	15.34%	15.57%	15.71%	16.26%	17.50%	15.57%	0.14%
HSBC North America	21.40%	24.04%	26.91%	27.40%	27.37%	24.04%	-0.03%
BMO Financial Corp.	15.60%	15.72%	16.26%	16.32%	16.50%	15.72%	0.06%
Northern Trust Corporation	15.56%	15.61%	15.73%	15.80%	15.78%	15.61%	-0.02%
MUFG Americas Holdings	16.29%	16.73%	16.69%	16.61%	15.87%	15.87%	-0.74%
Barclays US LLC	22.18%	25.70%	28.01%	27.55%	28.37%	25.70%	-0.46%
Regions Financial	13.56%	13.72%	13.27%	13.46%	13.97%	13.27%	-0.45%
Average	**17.06%**	**16.41%**	**16.56%**	**17.04%**	**17.01%**	**16,41%**	**-0,66%**

$$RMSE = \sqrt{\frac{1}{n}\sum|a_t - f_t|}\ , \tag{10}$$

where a_t is the actual value, and f_t is the forecasted value. The mean absolute error (MAE) measures the average of the absolute error values. It is calculated as:

$$MAE = \frac{\sum_{i=1}^{n}|a_t - f_t|}{n}\ . \tag{11}$$

Finally, MAPE represents the average of absolute percentage errors:

$$MAPE = \frac{1}{n}\sum\frac{|a_t - f_t|}{a_t}\ . \tag{12}$$

Its main strengths are scale-independence and ease of interpretation (Byrne, 2012). These aforementioned metrics were calculated for each bank and rolling sample using the data not used to train the different models. Given six different rolling windows, the average of the metrics is calculated to obtain an overall measure of the forecast accuracy for each bank.

Table 5 summarizes the forecasting accuracy results for Prophet and ARIMAX models. On a consistent basis, Prophet models that allow for change points or shifts in trends have lower errors across all metrics than the ARIMAX models. For most of the banks, the difference in errors is very significant. For banks with more limited data, such as the Goldman Sachs Group, Prophet models still outperformed the ARIMAX models. Similar conclusions were reached when comparing the Prophet and ARIMA models in their simpler versions, wherein no external regressors were considered but only past values of the capital ratios. When only financial ratios are present in the model, the error increases but in approximately the same proportion for both approaches. Thus, similar to findings in Taylor and Letham (2018), the flexibility of the Prophet approach with respect to fitting trend and seasonal components generates more accurate forecasts. We further infer from these results that automatic fitting with default parameters is suitable for most applications, including the prediction of total capital risk-based capital ratios of U.S. banks.

Table 5. Average performances metrics on the test set (RMSE, MAE and MAPE) for the ARIMAX and Prophet models

Bank Name	RMSE		MAE		MAPE	
	Prophet	ARIMAX	Prophet	ARIMAX	Prophet	ARIMAX
JPMorgan Chase & Co	0,005	0,006	0,004	0,005	0,027	0,031
The PNC Financial Services Group, Inc	0,008	0,008	0,007	0,008	0,052	0,058
Bank of America Corporation	0,005	0,006	0,004	0,005	0,026	0,033
Truist Financial Corporation	0,005	0,008	0,004	0,007	0,029	0,052
State Street Corporation	0,009	0,015	0,007	0,012	0,043	0,073
U.S. Bancorp	0,003	0,004	0,002	0,004	0,018	0,032
Wells Fargo & Company	0,006	0,006	0,005	0,005	0,032	0,033
Northern Trust Corporation	0,007	0,010	0,006	0,009	0,039	0,064
BMO Financial Corp.	0,006	0,007	0,005	0,006	0,035	0,040
MUFG Americas Holdings Corporation	0,009	0,014	0,007	0,013	0,042	0,074
Citigroup Inc.	0,006	0,006	0,005	0,005	0,029	0,031
Morgan Stanley	0,009	0,013	0,007	0,011	0,034	0,048
Capital One Financial Corporation	0,008	0,014	0,008	0,013	0,051	0,095
The Goldman Sachs Group, Inc.	0,008	0,016	0,007	0,014	0,036	0,080
HSBC North America Holdings Inc.	0,020	0,023	0,018	0,021	0,083	0,094
Regions Financial Corporation	0,006	0,010	0,005	0,022	0,028	0,041
The Bank of New York Mellon Corporation	0,006	0,016	0,005	0,014	0,035	0,109
TD Group US Holdings LLC	0,012	0,020	0,011	0,017	0,082	0,129
Barclays US LLC	0,015	0,037	0,012	0,035	0,072	0,224

VI. Conclusion

In this paper we used the Prophet model by Facebook to predict the total risk-based capital ratios of U.S. banks. Prophet is an increasingly popular open source software program for the purpose of forecasting business time series that offers flexible, reliable, and practical tools for developing modular regression models. Our sample consisted of 19 banks that participated in the last Dodd-Frank Act stress test exercise released in 2021. Predictive models were constructed based on historical capital ratios for each bank as well as macroeconomic variables for the period March 2004 to December 2020. In-sample results showed that the fitted values for our Prophet models closely approximated actual bank capital ratios. Also, we found that one-year-ahead forecasts for individual banks improved considerably upon augmenting financial ratios with macroeconomic variables.

To assess the validity of Prophet models, we compared their forecasting performance to conventional ARIMAX models. Our comparisons utilized three forecasting metrics, including MSE, RMSE, and MAPE. For all banks under study, we found that Prophet models outperformed ARIMAX models. Based on these findings, we conclude that the Prophet model provides accurate forecasts of bank capital ratios. By implication, it could be used to supplement bank stress tests by regulatory agencies as well as the supervisory process to enhance bank safety and soundness. Additionally, banks subject to regulatory capital requirements can use the Prophet model as a risk management tool in their compliance activities. Finally, investors can readily implement the Prophet model to assess banks' capital ratios as measures of bank condition.

The main strengths of Prophet are the flexibility in fitting the trend and seasonal components, low sensitivity to outliers, simplicity plus ease of use, and the ability to incorporate various sources of expert knowledge. A number of directions for future research are recommended. First, our U.S. bank analyses could be replicated for European banks as a further validity test. Second, enhancements in our Prophet model specifications could be investigated. For example, Prophet could be used to predict the capital adequacy of U.S. or European banks by incorporating not only past values of each bank's information but the overall capital adequacy of the entire financial system also. In this way the sensitivity of individual banks to changes in the financial system could be evaluated. Third, and last, our analyses using the Prophet model could be extended to alternative techniques, such as deep learning methodologies that detect nonlinear patterns in the data. In this regard, approaches such as long short-term memory (LSTM) and convolutional neural networks (CNNs) are well suited for time series problems.

References

Acharya, V. V, and Steffen, S. (2014a). Benchmarking the European Central Bank's asset quality review and stress test: A tale of two leverage ratios. VOX CEPR's Policy Portal.

Acharya, V. V, and Steffen, S. (2014b). Making sense of the comprehensive assessment. Working paper, CEPR, NYU Stern, and ESMT European School of Management and Technology.

Acharya, V. V., Berger, A. N., and Roman, R. A. (2018). Lending implications of U.S. bank stress tests: Costs or benefits? *Journal of Financial Intermediation* 34, 58–90.

Acharya, V., R. Engle, and M. Richardson (2012). Capital shortfall: A new approach to ranking and regulating systematic risks. *American Economic Review*102, 59–64.

Agrawal, T. (2021). *Hyperparameter Optimization in Machine Learning: Make Your Machine Learning and Deep Learning Models More Efficient.* Apress, Springer Nature: Berlin, Germany.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23, 189–209.

Altman, E., Haldeman, R., and Narayanan, P. (1977). ZETA analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance* 1, 29–54.

Altman, E. I., and McGough, T. P. (1974). Evaluation of a company as a going concern. *Journal of Accounting* 138, 50–57.

Alves, C., Mendes, V., and Pereira Da Silva, P. (2015). Do stress tests matter? A study on the impact of the disclosure of stress test results on European financial stocks and CDS markets. *Applied Economics* 47, 1213–1229.

Arena, M. (2008). Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data. *Journal of Banking and Finance* 32, 299–310.

Berger, A. N., Imbierowicz, B., and Rauch, C. (2016). The roles of corporate governance in bank failures during the recent financial crisis. *Journal of Money, Credit and Banking* 48, 729–770.

Betz, F., Opricǎ, S., Peltonen, T. A., and Sarlin, P. (2014). Predicting distress in European banks. *Journal of Banking and Finance* 45, 225–241.

Bovenzi, J. F., Marino, J. A., and McFadden. E. F. (1983). Commercial bank failure prediction models. *Economic Review*, Federal Reserve Bank of Atlanta, 186–195.

Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (2011). *Time Series Analysis, Forecasting and Control*, 4th ed. Wiley: Hoboken, NJ.

Boyacioglu, M. A., Kara, Y., and Baykan, M. K. (2009). Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey. *Expert Systems with Applications* 36, 3355–3366.

Chapel, A., Killgo, K., and Klemme, K. (2021) Banks face new challenges as Texas rebounds from COVID-19 shock. *Southwest Economy*, Federal Reserve Bank of Dallas, 14–17.

Chernykh, L., and Cole, R. A. (2015). How should we measure bank capital adequacy for triggering prompt corrective action? A (simple) proposal. *Journal of Financial Stability* 20, 131–143.

Cheung, Y. W., Chinn, M. D., and Pascual, A. G. (2005). What do we know about recent exchange rate models? In-sample fit and out-sample performance evaluated. In *Exchange Rate Modelling: Where Do We Stand*? DeGrauwe P., Ed.. MIT Press: Cambridge, MA, 239–276

Chiaramonte, L., and Casu, B. (2017). Capital and liquidity ratios and financial distress. Evidence from the European banking industry. *The British Accounting Review* 49, 138–161.

Chiaramonte, L., Liu, F. H., Poli, F., and Zhou, M. (2016). How accurately can Z-score predict bank failure? *Financial Markets, Institutions and Instruments* 25, 333–360.

Coats, P. K., and Fant, L. F. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management* 22, 142–155.

Cole, R. A., and Wu, Q. (2009). Predicting bank failures using a simple dynamic hazard model. Paper presented at 22nd Australasian Finance and Banking Conference, Sydney, Australia.

Covas, R., and Driscoll, J. C. (2014). Bank liquidity and capital regulation in general equilibrium, Working paper 2014-85, Federal Reserve Board, Washington, D.C.

DeAngelo, H., and DeAngelo, L. (1990). Dividend policy and financial distress: An empirical investigation of NYSE firms. *Journal of Finance* 45, 1415–1431.

Ekinci, A., and Erdal, H. E. (2016). Forecasting bank failure: Base learners, ensembles and hybrid ensembles. *Computational Economics* 49, 677–686.

Facebook. (2017). Facebook Prophet documentation. https://facebook.github.io/prophet.

Fang, W. X., Lan, P. C., Lin, W. R., Chang, H. C., Chang, H. Y., and Wang, Y. H. (2019). Combine Facebook prophet and LSTM with BPNN forecasting financial markets: The Morgan Taiwan Index. *Proceedings of the 2019 International Symposium on Intelligent Signal Processing and Communication Systems*, Taipei, Taiwan, 1–2.

Georgescu, O. M., Gross, M., Kapp, D., and Kok, C. (2017). Do stress tests matter? Evidence from the 2014 and 2016 stress tests. Working paper no. 2054, European Central Bank.

Gilbert, R. A., Meyer, A. P., and Vaughn, M. D. (1999). The role of supervisory screens and econometric models in off-site surveillance. *Review*, Federal Reserve Bank of St. Louis (November/December), 31–56.

Glasserman, P., and Tangirala, G. (2016). Are the Federal Reserve's stress test results predictable? *Journal of Alternative Investments* 18, 82–97.

Goel, T., and Agarwal, I. (2021). Limits of stress-test based bank regulation. BIS Working paper no. 953, Monetary and Economic Department, Bank for International Settlements.

Güleryüz, D., and Özden, E. (2020). The prediction of brent crude oil trend using LSTM and facebook Prophet. *Avrupa Bilim ve Teknoloji Dergisi* 20, 1–9.

Hastie, T., and Tibshirani, R. (1986). Generalized additive models. *Statistical Science* 1, 297–310.

Hirtle, B., Kovner, A., Vickery, J., and Bhanot, M. (2016). Assessing financial stability: The capital and loss assessment under stress scenarios (CLASS) model. *Journal of Banking and Finance* 69, 35–55.

Homar, T., Kick, H., and Salleo, C. (2016). Making sense of the EU wide stress test: A comparison with the SRISK approach. Working paper no. 1920. European Central Bank.

Hyndman R., and Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. *Journal of Statistical Software* 27, 1-22.

Iyengar, G., Luo, Y., Rajgopal, S., Venkatasubramanian, V., and Zhang, Z. (2017). Towards a financial statement based approach to modeling systemic risk in insurance and banking. Working paper no. 17–77, Columbia Business School.

Iwanicz-Drozdowska, M., Laitinen, E. K., and Suvas, A. (2018). Paths of glory or paths of shame? An analysis of distress events in European banking. *Bank i Kredyt* 49, 115–144.

Jagtiani, J. A., Kolari, J. W., Lemieux, C. M., and Hwan Shin, G. H. (2000). Predicting inadequate capitalization: Early warning system for bank supervision. Emerging Market Series (S&R-2000-10R), Federal Reserve Bank of Chicago (September).

Jha, B. K., and Pande, S. (2021). Time series forecasting model for supermarket sales using FB-Prophet. Paper presented at the *2021 5th International Conference on Computing Methodologies and Communication*, Erode, India, 547-554.

Jing, Z., and Fang, Y. (2017). Predicting US bank failures: A comparison of logit and data mining models. *Journal of Forecasting* 37, 235–256.

Johnsen, T., and Melicher, R. W. (1994). Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. *Journal of Economics and Business* 46, 269–286.

Kapinos, P., and Mitnik, O. A. (2016). A top-down approach to stress-testing banks. *Journal of Financial Services Research* 49, 229–264.

Kolari, J., Glennon, D., Shin, H., & Caputo, M. (2002). Predicting large US commercial bank failures. *Journal of Economics and Business* 54, 361–387.

Kolari, J. W., López-Iturriaga, F. J. L., and Sanz, I. P. (2019). Predicting stress tests in European banks. *Global Finance Journal* 39, 44–57.

Korobrow, L., and Stuhr, D. (1985). Performance measurement of early warning models: Comments on West and other weakness/failure prediction models. *Journal of Banking and Finance* 9, 267–273.

Kumar, N., Chauhan, R., and Dubey, G. (2019). Applicability of financial system using deep learning techniques. *Proceedings of the 2019 International Conference on Recent Advancement in Computer, Communication and Computational Sciences*. Springer: Berlin, Germany.

López-Iturriaga, F. J., and Sanz, I. P. (2015). Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks. *Expert Systems with Applications* 42, 2857–2869.

Madhuri, C., Chinta, M., and Kumar, V. (2020). Stock market prediction for time-series forecasting using Prophet upon ARIMA. Paper presented at the *7th International Conference on Smart Structures and Systems (ICSSS),* Chennai, India, 317–321.

Mahanty, M., Swathi, K., Teja, K. S., Kumar, P. H., and Sravani, A. (2021). Forecasting the spread of COVID-19 pandemic with Prophet. *Revue d'Intelligence Artificielle* 35, 115–122.

Mahmud, S. (2020). Bangladesh COVID-19 daily cases time series analysis using Facebook Prophet model. Working paper, Shahjalal University of Science and Technology.

Maldonado, S., Gonzalez, A., and Crone, S. (2019). Automatic time series analysis for electric load forecasting via support vector regression. *Applied Soft Computing* 83, 105616.

Martínez, I. (1996). Forecasting company failure: neural approach versus discriminant analysis: An application to Spanish insurance companies. In *Intelligent Systems in Accounting and Finance.* Sierra Molina, G., and Bonsón Ponte, E. (Eds.). Huelva: Spain, 169–185.

Meyer, P. and Pifer, H. (1970). Prediction of bank failures. *Journal of Finance* 25, 853–868.

Oliveira, E. M., and Oliveira, F .L. (2018). Forecasting mid-long term electric energy consumption through bagging ARIMA and exponential smoothing methods. *Energy* 144, 776–788.

Ömer Faruk D. (2010). A hybrid neural network and ARIMA model for water quality time series prediction. *Engineering Applications of Artificial Intelligence* 23, 586–594.

Pritsker, M. (2014). Stress-testing US bank holding companies: A dynamic panel quantile regression approach: A comment. *International Journal of Forecasting* 30, 714–716.

Sahin, C., de Haan, J., and Neretina, E. (2020). Banking stress test effects on returns and risks. *Journal of Banking and Finance* 117, 1–19.

Schuermann, T. (2020). Capital adequacy pre- and postcrisis and the role of stress testing. *Journal of Money, Credit and Banking* 52, 87–105.

Shradha S., Joshi, J., Mareedu, S., Kim, Y. P., and Woo, J. (2021). Scalable predictive time-series analysis of COVID-19: Cases and fatalities. Working paper, Cornell University.

Sinkey, J. E., Jr. (1975). A multivariate statistical analysis of the characteristics of problem banks. *Journal of Finance* 20, 21–36.

Svetunkov, I. (2020). *Time Series Analysis and Forecasting with ADAM*. *URL: openforecast.org/adam* (April 2021).

Tam, K.Y., and Kiang, M. (1992). Predicting bank failures: A neural network approach. *Decision Sciences* 3, 926–947.

Taylor, S. J., and Letham, B. (2018). Forecasting at scale. *The American Statistician* 72, 37–45.

Valencia, F., and Laeven, L. (2008). Systemic banking crises: A new database. *IMF* Working paper no. 08(224).

Vellido, A. (1999). Neural networks in business: a survey of applications (1992–1998). *Expert Systems with Applications* 17, 51–70.

Whalen, G., and Thomson, J. B. (1988). Using financial data to identify changes in bank condition. *Economic Review*, Federal Reserve Bank of Cleveland, 17–26.

Appendix: Model projections for the five largest US banks by assets.

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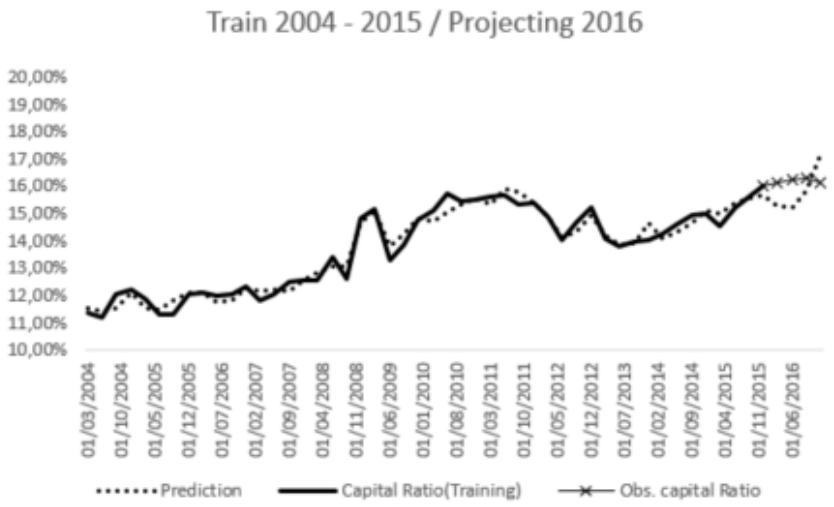

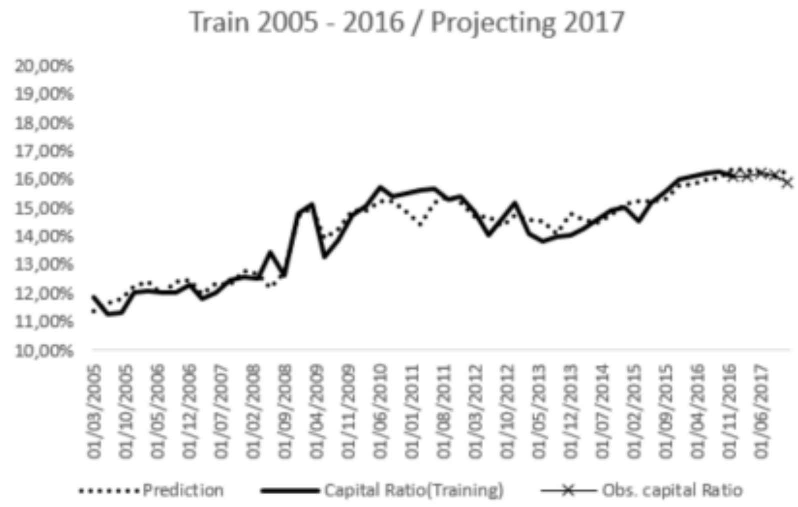

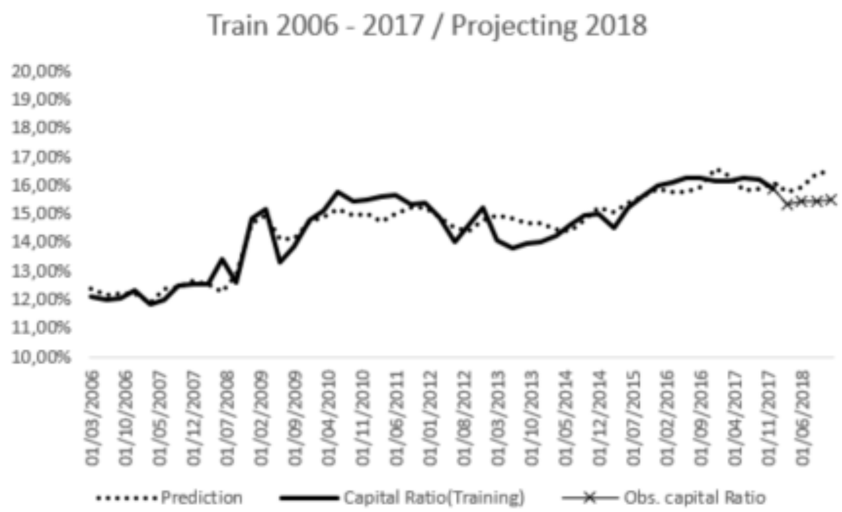

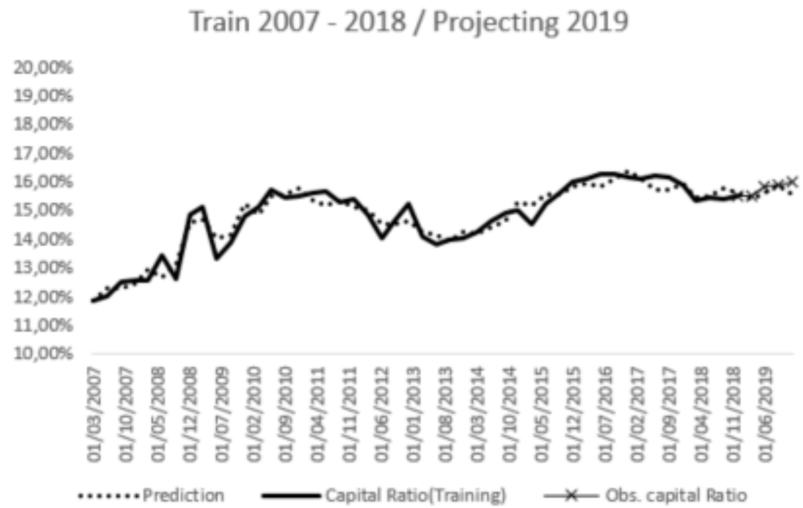

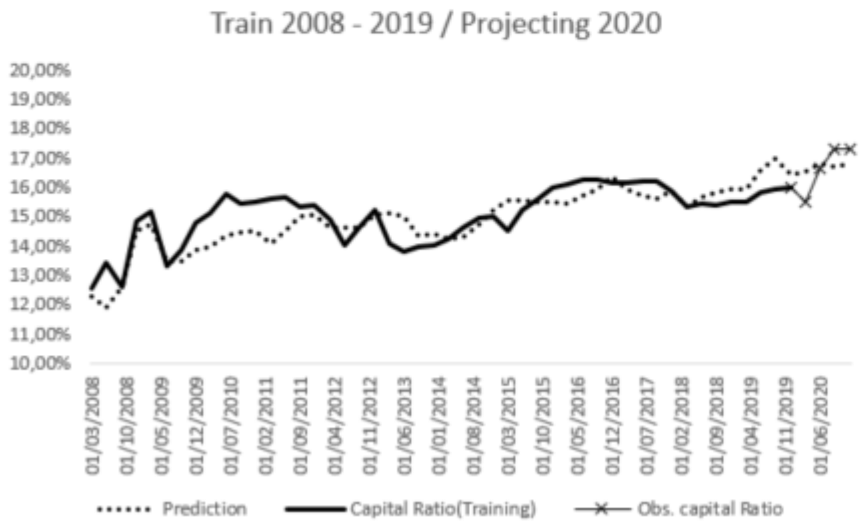

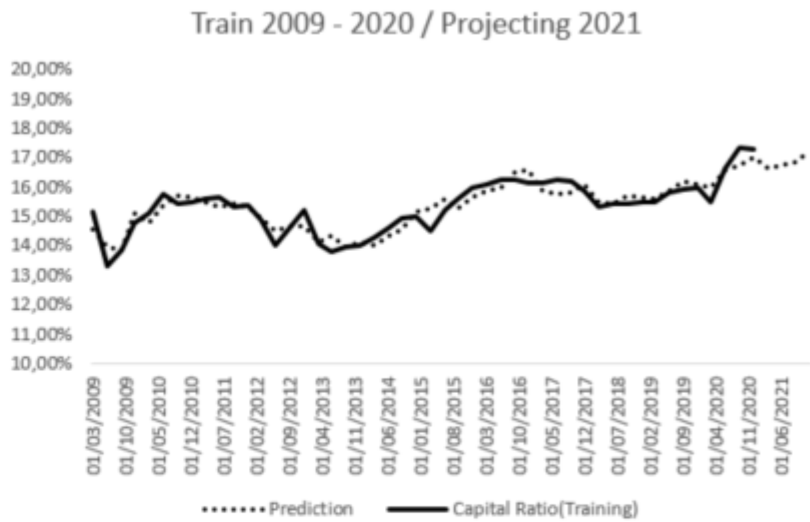

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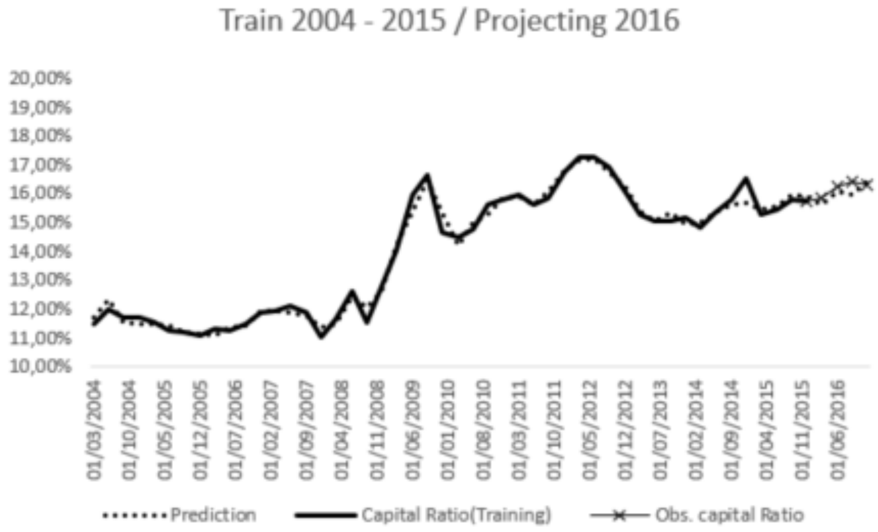
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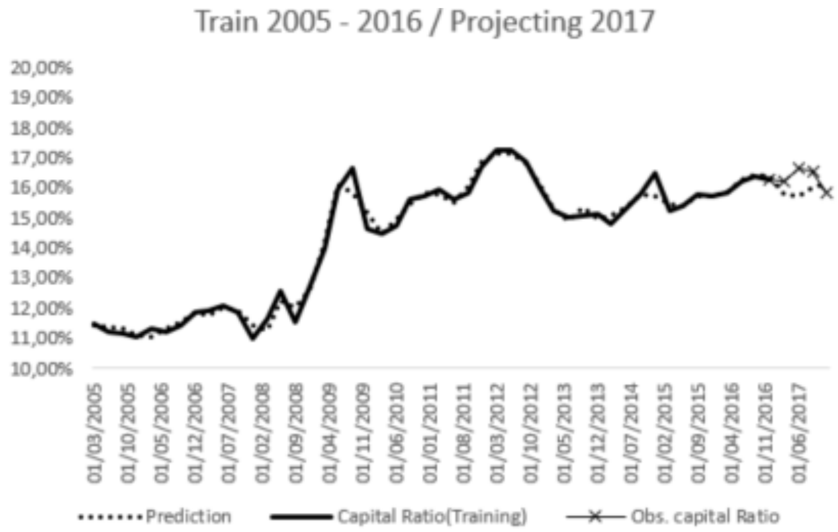
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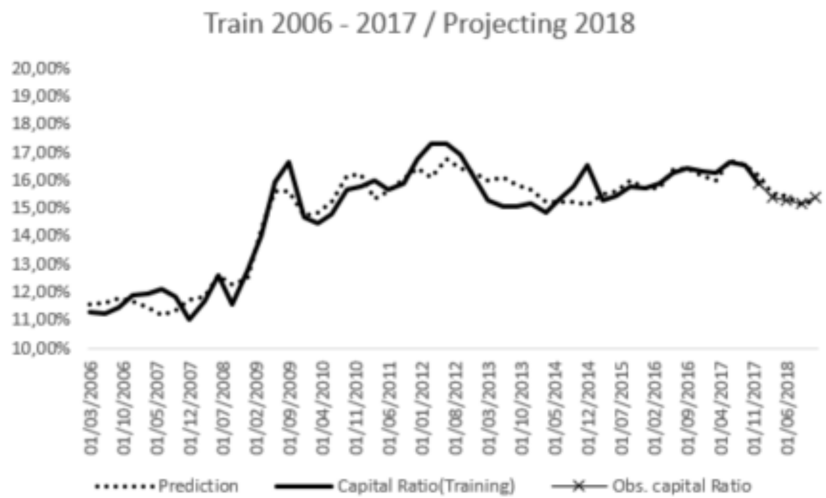
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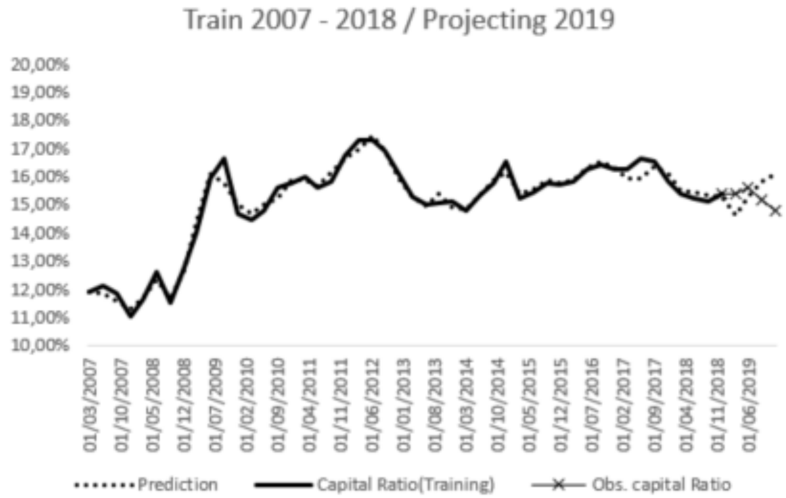
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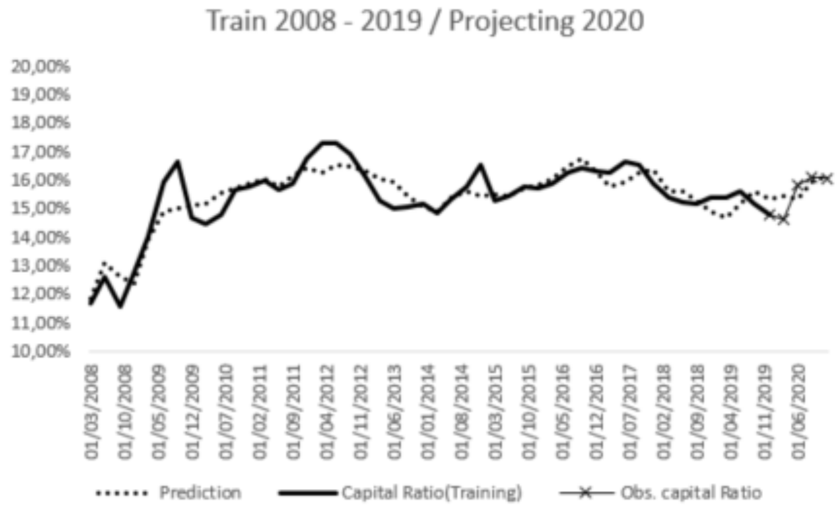
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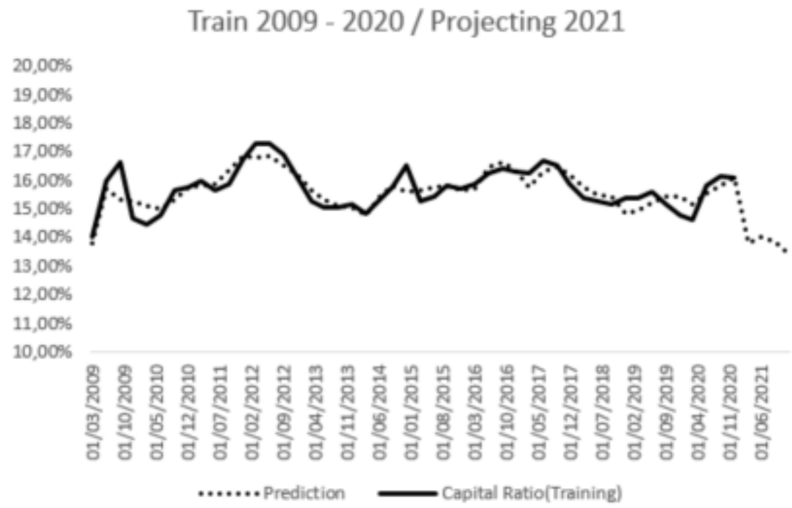
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Prediction
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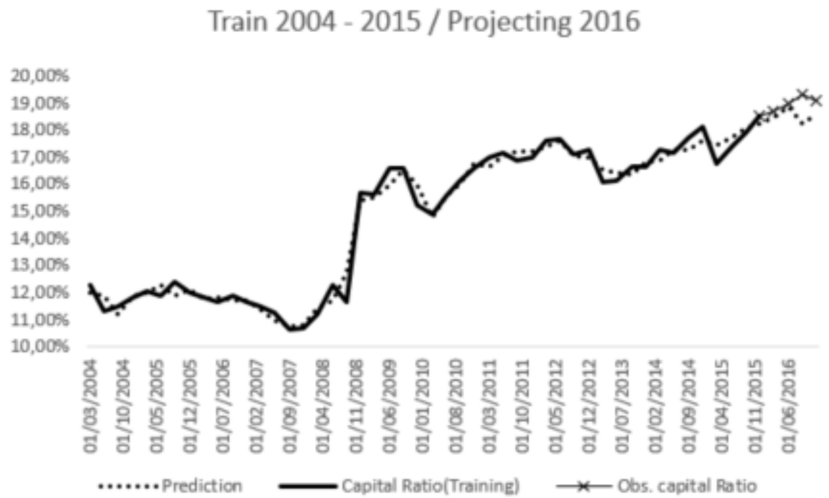
Citigroup: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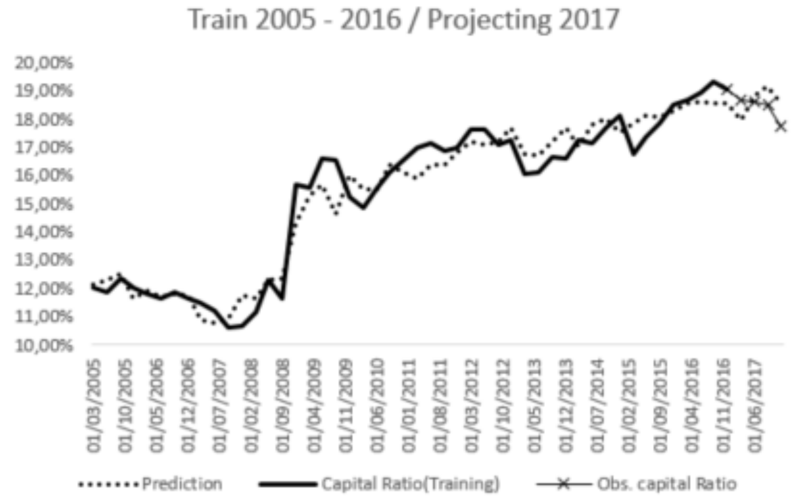
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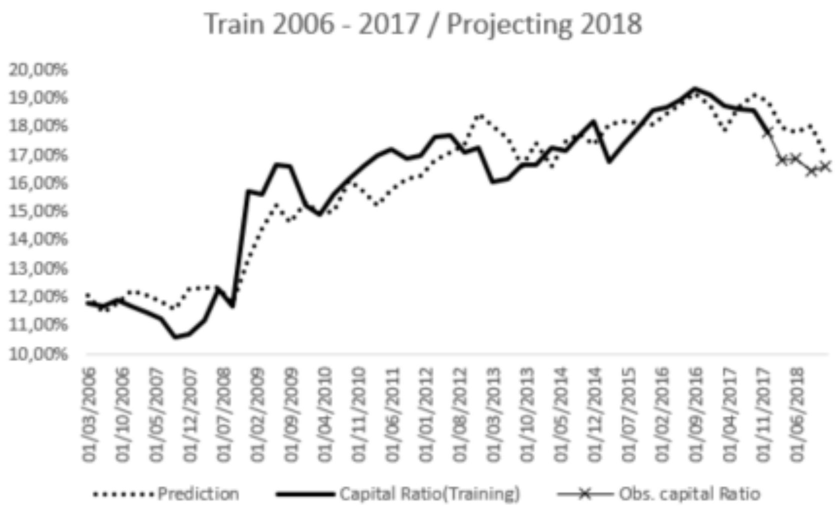
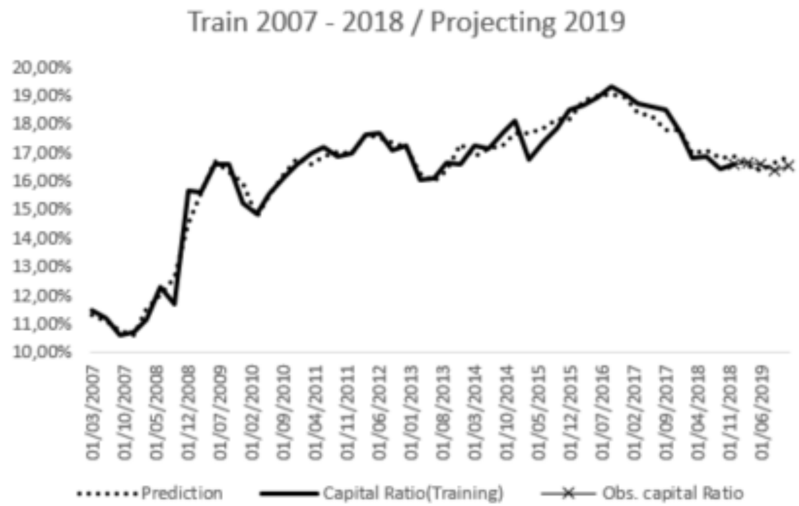
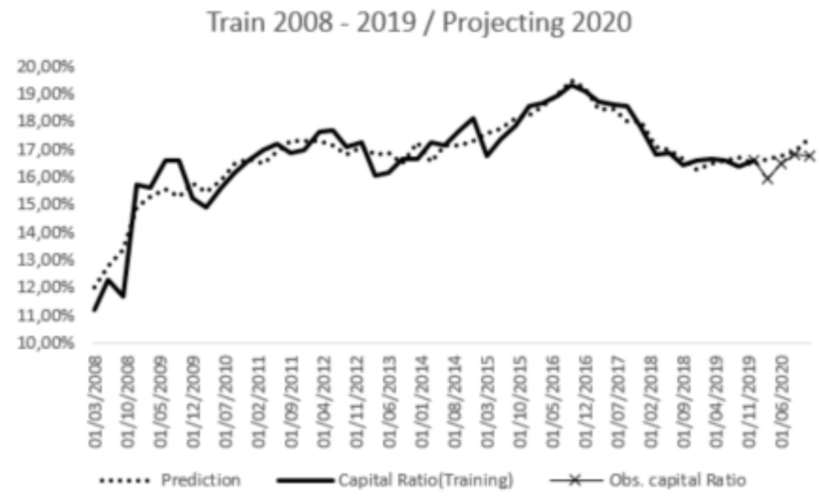
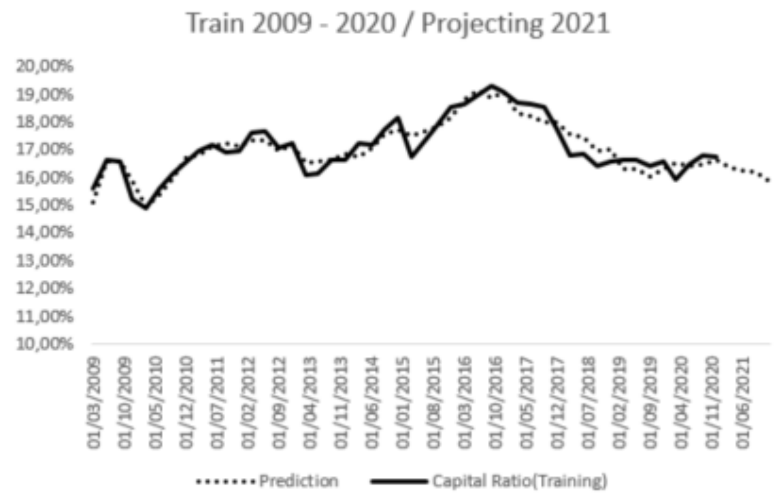
Capital Ratio(Training)
Obs. capital Ratio

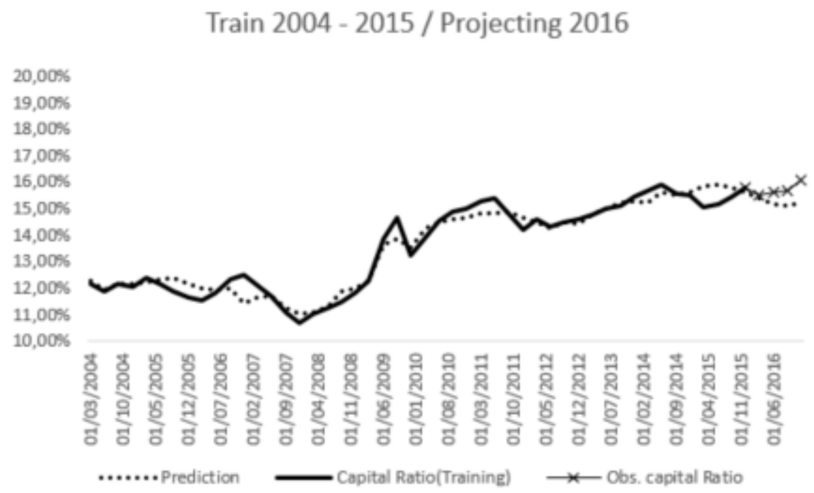

Train 2006 - 2017 / Projecting 2018
Prediction
Capital Ratio(Training)
Obs. capital Ratio

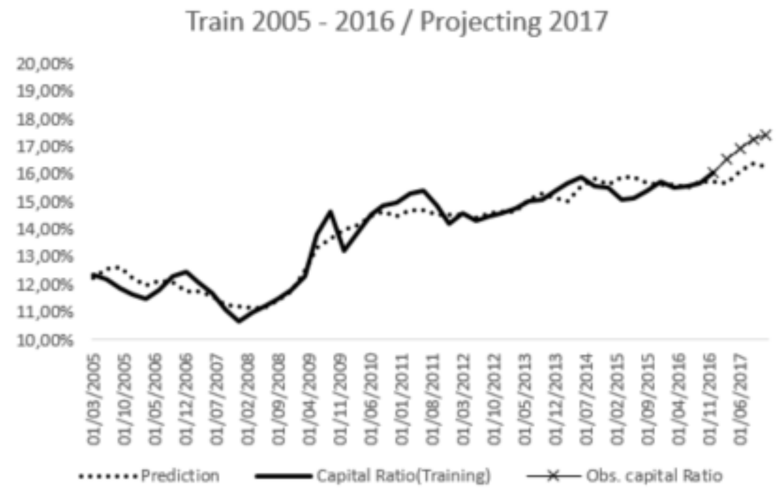

Train 2007 - 2018 / Projecting 2019
Prediction
Capital Ratio(Training)
Obs. capital Ratio

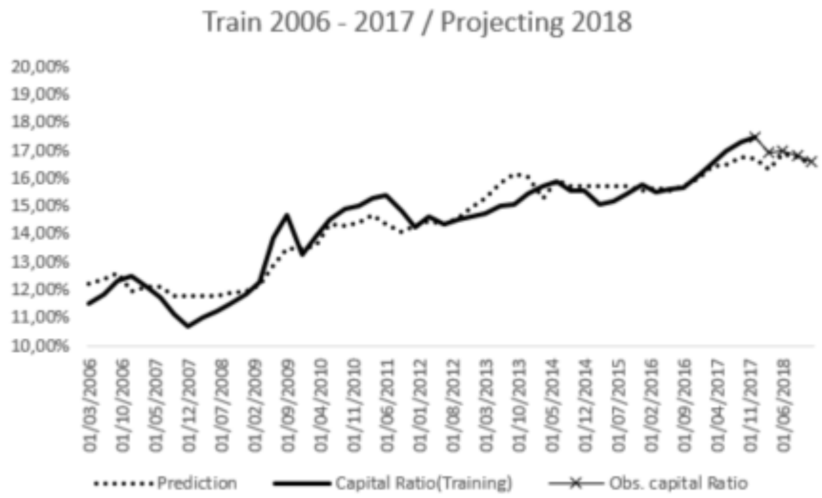

Train 2008 - 2019 / Projecting 2020
Prediction
Capital Ratio(Training)
Obs. capital Ratio

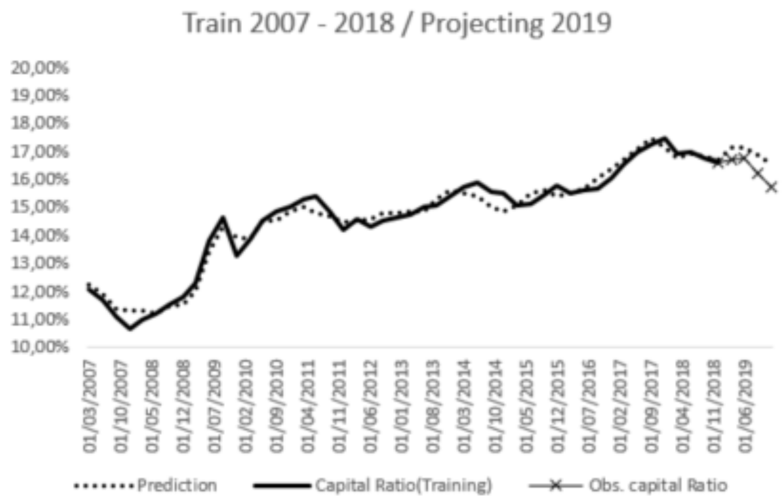

Train 2009 - 2020 / Projecting 2021
Prediction
Capital Ratio(Training)

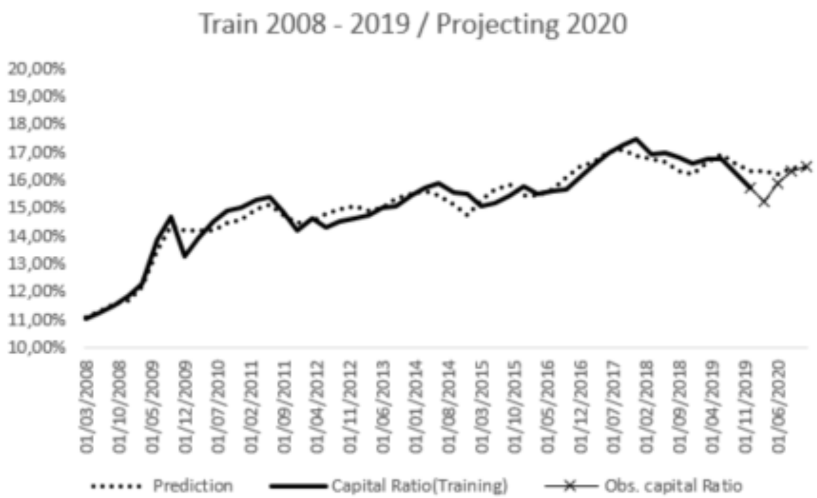
Wells Fargo:

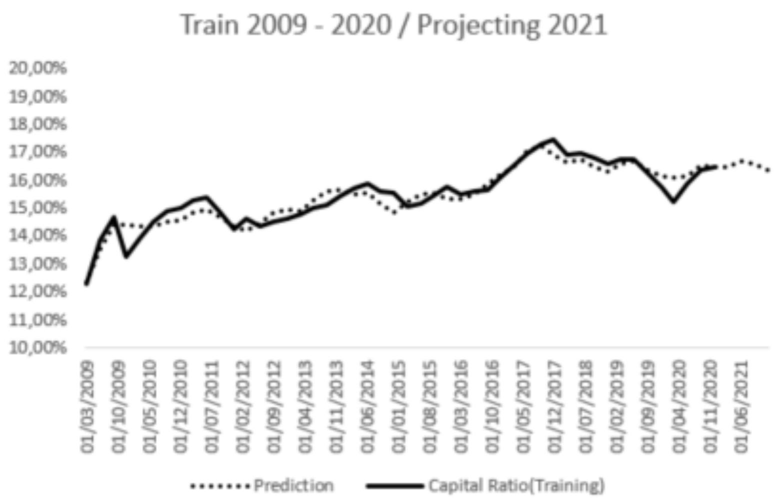

Train 2004 - 2015 / Projecting 2016
Prediction
Capital Ratio(Training)
Obs. capital Ratio


Train 2005 - 2016 / Projecting 2017
Prediction
Capital Ratio(Training)
Obs. capital Ratio


Train 2006 - 2017 / Projecting 2018
Prediction
Capital Ratio(Training)
Obs. capital Ratio


Train 2007 - 2018 / Projecting 2019
Prediction
Capital Ratio(Training)
Obs. capital Ratio


Train 2008 - 2019 / Projecting 2020
Prediction
Capital Ratio(Training)
Obs. capital Ratio


Train 2009 - 2020 / Projecting 2021
Prediction
Capital Ratio(Training)

Goldman Sachs: