Conceptualization of Machine Learning in Economic Forecasting

Harish Paruchuri

Senior AI Engineer, Department of Information Technology, Anthem, Inc., **USA**

*E-mail for correspondence: harishparuchuri9999@gmail.com

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ABSTRACT

Economic forecasting is a very important aspect that policymakers in the financial and corporate organization rely on because helps them to determine future events that might infringe some hardship on the economy and the citizens at large. However, the principal statistical pointers that are available to the public domain provide numerous reservations and doubts for their economics estimates as it is later released with frequent issues to major revisions and also it shows a great lag in decision making for an incoming event. To this effect, the expansion of the latest forecasting patterns was important to address the gaps. Hence, this paper examines the conceptualization of Machine learning in economic forecasting. To achieve this, the Italian economy was used as the dataset, and machine learning controlled tools were used as the method of analysis. The result obtained from this study shows that machine learning is a better model to use in economic forecasting for quick and reliable data to avert future events.

Key words: Machine Learning, Economic Forecasting, decision making, Italian Economy

INTRODUCTION

In 2008 the greatest nightmare caught the world economy unaware and since that recession, economists have been on a course for the strategy reactions functioned better and the one that is not working (Cicceri et al. 2020). This gives rise to two findings. The first finding is the fiscal strategy, which is an essential instrument to combat a recession, while the second one is vital to possess a rapid and operative response design to a recession in an attempt to reduce its most serious and long-lasting impacts. In the light of this current crisis in the world's economy, the issue of gross domestic product (GDP) forecasting is the most trending debate today (Gavin, 2011).

In the last decade, Italy witnessed 2 economic catastrophes, in 2008 and 2011. It was truly living a dormancy (Cicceri et al. 2020). During that period of economic recession in Italy, their real gross domestic product dwindles gradually the second quarter of the year under review with a dumpy drib-in the fourth quarter of that year (Nyman and Ormerod, 2017). With all the effort that was put in, the growth was insignificant until the last quarter of 2009. However, the cumulative fall from the first quarter of 2008 until the fourth quarter of 2009 peak stood at 23.49%. Furthermore, they were hit with a national debt disaster in the 2011 fiscal year. Their real gross domestic product began dwindling another time in the fourth quarter of 2011 and it took them approximately two years to grow the GDP and that occurs in the fourth quarter of 2013. The cumulative peak for this period stood at 19.34% according to the third quarter peak in 2011. Largely, Italy lost 30.6% of its real gross domestic product within a decade (Gavin, 2011; Breiman, 2001; Dolfin et al., 2017; Dolfin et al., 2019a&b; Cicceri et al., 2020).

Statement of Problem

Policymakers from time to time have created rapid selections and everyday methods to notice the result of a lack of in-depth knowledge on the recent economy in the world (Dolfin et al., 2019a). However, if the fall in output can be discovered on time by the decision-makers, some kind of adjustment on financial strategy could be taken with the fiscal strategy to avert the recession or better still reduce the impacts on the real economy (Vadlamudi, 2019). The principal statistical pointers that are available to the public domain provide numerous reservations and doubts for their economics estimates as it is later released with frequently issue to major revisions (Cicceri et al., 2020). The expansion of the latest forecasting patterns is trending and is a very significant tool to address the gaps. Also, the latest methods frequently do not have the capacity to forecast the result of the recession on time and competent way. According to the NBER's methodology, at least two successive quarters are needed with a drop in growth for them to broadcast the commencement of a recession (Mullainathan and Spiess, 2017). This shows a great lag in decision-making for an incoming event. However, a swift insight would have averted the negativity (Mullainathan and Spiess, 2017; Cicceri et al., 2020).

Due to this great shortcoming in the prediction of a future event that has to do with the economy, new technologies were explored and these include machine learning (ML) and the artificial intelligence (AI) approaches, which can be used to handle composite economic structure with big data (Vadlamudi, 2020b). The machine learning patterns have been certified by many experts in the field to a sure and dependable tool to manage big data and make available great securities in relation to the precision of the inference. Machine learning signifies an essential tool to design policies proficient in linking all information from several economic bases and vigorously responding to diverse complications, deprived of the benefit of human beings (McCracken and Ng, 2016).

The objective of this study is to conceptualize machine learning in forecasting gross domestic product changes, using different enhanced machine learning approaches. We investigate if machine learning algorithms can increase estimating precision and attempt economic recovery as well as estimate recession.

LITERATURE REVIEW

There are numerous theories associated with the working of the economy, and the right variable to be analyzed just to maintain rapid economic movement insight. So many investigators have been debated about the right approach to carry out forecasting study in macroeconomics and this debate resulted in two fundamental clusters, according to the accepted investigation procedure. Nyman and Ormerod (2017) conducted a study that we considered as the primary case study on the accepted procedure in this work. They pay more attention to a short-term estimate of actual gross domestic product growth for the US and UK both with the statistical method by employing Ordinary Least Square (OLS) regression as well as Random Forest (RF) machine learning approach by showing in what way the previous warranty exact precision, particularly in the prodigious recession of 2008/09. The primary class accepts a statistical technique, supposing that information can be described by stochastic patterns, and others have a great machine-driven process according to the manipulation of algorithms and handling information as tools to comprehend unidentified instruments (Zhu et al., 2021; Paruchuri, 2019; Breiman, 2001).

Other debates in topical investigation observe the prevalence of techniques not as much shared, like the Kinetic Theory for Active Particles (KTAP) method to the patterning of economic structures (Dolfin et al., 2017; Dolfin et al., 2019a). Dolfin et al. (2019b) recommend a pattern for credit risk taint on the activities of financial systems over the addition of septic elements, the distinctive methodic risk from characteristic risk, and analyzing it in diverse topological systems with diverse ranks of networking. It is observed that economics papers are not willing to accept any investigations or studies short of the acceptance of approaches with official assets which include large sample potential of forecasters and analysis on the subject of routine, uniformity, and competence (Cicceri et al., 2020). Moreover, the improvement in the understanding in controlled and uncontrolled machine learning methods are contestable, having seen the use of this technology in the model, pictures or audio identification, on the other hand, is important in the tropical work in the area of economics, statistics and econometrics (Vadlamudi, 2019).

Mullainathan and Spiess (2017) propose the application of machine learning in the econometric area and the concept is that machine learning is capable to identify the composite system in the dataset and the instincts are that fresh frontline in the field can offer instruments that will stun the confines in the forecast, most especially in gross domestic product growth. Mullainathan and coworker back their finding with many machine learning methods used on the estimation of asset worth by using random forest and collaborative algorithms by presenting a twofold or dual precision ability than the conventional econometrics methods like ordinary least square regression. In the light of this debate, Vadlamudi et al., (2021) add by suggesting that one design a forecasting approaches of a Lyapunoy-oriented economic pattern forecasting control in the area of economic optimization by representing its economic optimality and secure loop firmness via a collaborative of recurrent neural networks and a k-fold cross-confirmation used in a nonlinear structure. other articles by Vadlamudi (2020a) and Wu et al. (2018) apply a similar Lyapunoy-oriented system, respectively, to provide a solution to the issue of forecasting mechanism pattern development of the data-oriented economic on a nonlinear chemical procedure structure and to address the issue of mechanistic structure policy for chemical procedures to warranty economic streamline and approach working safekeeping in stochastic nonlinear structure.

Also, Prüser (2019) validated the application of the Bayesian additive regression tree pattern, which forecasts applying a great number of forecasters provide more precision in a small macroeconomic time sequence. In the same vein, Paruchuri (2017) emphasize the use of the nonlinear autoregressive method of neural connection for the estimation of phase sequence according to the Levenberg-Marquardt approach, employed for the administration of connection factors, and presenting a heuristic law that controls the learning procedure and adapts the topology of the network. The simulation stage of the forecast of the estimation has been used via the Monte Carlo approach together with the addition of Gaussian noise. On the other hand, Jansen et al. (2016) liken the short-term estimating abilities of different statistical techniques applying a dataset with many monthly pointers inserted with minute but very important data, displaying that this prediction model is the best rather than those centered on only one pointer. Jansen and his coworkers added Europe and the 5 biggest nations from 1996 to 2011.

Ahmed et al. (2021) uses an automatic regressive integrated moving average pattern to forecast forthcoming time sequence via the Box-Jenkins method, highlighting the significance of gross domestic product as an integral pointer for economic growth of a nation and deliberate that the right forecast of this pointer is ultimate in central bank policy-making for all the nations. All though there is no perfect data about in what way machine learning can improve predicting correctly in the forecast generated. In several research papers, numerous examples confirming how predicting correctly possibly will be increased by these tools. More so, there is clear data that shows how simple univariate linear patterns are more vigorous than multivariate.

METHODS

Analysis Approaches

For us to achieve our objectives of this study, we selected some patterns that will address both the machine learning and the statistical approaches. We adopted a machine learning controlled method, with a categorized dataset. Work-out data are linked to the novel standards by the macroeconomic values that are feedback data and give out the outcome, which is gross domestic product values. This approach gives rise to quick output and generally, the result produced is very correct. For us to detect the correlation between the variable, we apply a multivariate regression test. Machine learning structural design plays an essential part in the economic information and can be applied to fit very composite non-linear systems with a large volume of data by increasing short-term predicting correctly and forecasting duration of recessions. At the initial stage, a descriptive and relationship analysis to ascertain the environment and the performance of the variable selected on a theoretical source. It was then that we carry out the strength check just to perform structural authentication analysis, thus confirming in what way forecasts of the early regression factor act when the regression term is adapted with injecting or ejecting regressors.

At that point, outputs were compared by applying the 5 regression forecasting approaches mentioned below:

- Ordinary Least Squares regression (OLS);
- Nonlinear Auto-regression models (NAR);
- Nonlinear Autoregressive with exogenous variables model (NARX);
- Support Vector Regression (SVR);
- Boosted Trees (BT).

Ordinary least square regression is the best approach suitable for forecasting the factor of a linear regression pattern. We selected this method because it can choose the factor of the linear utility just to reduce the error of sum squares, which is the dissimilarity between forecasting and reality. All the structures to forecast the outcome were considered to satisfy the regression goal. More so, to realize that it is not a non-linear issue, then just run the fit utility on the sampled data and high error will be the output.

Nonlinear Autoregressive with exogenous variables pattern is a NAR coupled with exogenous feedbacks values, hence this model take in cognition of bot the current value and past value of a time sequence of the exogenous parameters. NARX and NAR with exogenous factors patterns were forecasted employing the Levenberg-Marquardt algorithm (Gavin, 2011). Levenberg-Marquardt was created to elucidate nonlinear least-square difficulties and applies the slope parentage technique and the Gauss-Newton (GN) techniques to curtail the inaccuracies. The Gauss-Newton technique is best and comes together much faster for small-size data than slope parentage techniques. Though, the Levenberg-Marquardt approach is much alike to the slope percentage techniques especially when the variables are outlying from their ideal value. Virtually, Levenberg-Marquardt adaptively revises variable modernizes among slope parentage and Gauss-Newton update (Gavin, 2011).

$$\left\lfloor \int_{.}^{T} W \int_{.}^{\cdot} + \lambda \right\rfloor him = \int_{.}^{T} W \left(Vt - \acute{\upsilon}t\right) \qquad 1$$

Where $\int_{.}^{T} W \left(Vt - \acute{\upsilon}t\right)$ represent a standard equation for Gauss-Newton (GN) technique, and λ denotes the restraining factor which is typically adjusted to a huge rate to tolerate you moving little phases in the track of the vertical slope parentage. The merits of realizing Levenberg-Marquardt methods is that nearby are 2 likely possibilities for the algorithm's route at each repetition and also is more vigorous than GN approaches (Donepudi et al., 2020b; Paruchuri, 2020).

Nonlinear support vector regression, one of the widespread nonparametric machine learning approaches that centered on kernel utilities was employed. Here the yield is an actual integer, thus it is problematic to forecast the data that has immensity prospect values. We fix a margin of tolerance (epsilon) in estimate to the SVM which would have previously entreated from the tricky. A nonlinear support vector regression utility is charity to forecast new standards:

$$y = \sum_{t=1}^{N} (\alpha n - \alpha^{*}_{n}) \,.\, \mathrm{G(xn,x)} + \mathrm{b},$$

$(\alpha - \alpha_n^*)$ equal to the variance among two Lagvariety multipliers of SV, G called Gram matrix is an n-by-n matrix that comprises basics G(xn, x) and b is the bias.

To curtail inaccuracies or miscalculations, it controls the hyperplane which makes the best use of the boundary, so the utilities, of kernel kind, alter the information into an interplanetary to great measurement, consenting learning recovering of nonlinear patterns (Donepudi et al., 2020a). For the activities assessment of the patterns, adjusted R^2 is employed as an index of precision of the patterns applied. This determines the portion of the adjustment of the dependent factor conveyed by the forecasters. The mean square error was used as a forecaster that processes the average of the actual values. We ensured that our patterns were trained on a time window by selecting the default variable structure for each algorithm. The precision of the forecasting of each pattern was measured by computing mean square error and R^2

Dataset use in this study

In an attempt to conceptualize machine learning in economic forecasting, we selected an Italian economic dataset existing from many sources as the source of data we are using in this study. We try to introduce the major markers of credit and actual economic movement. According to the study carried out by Fildes and Stekler (2002) that states there is no actual approach that determines the precision of one pattern well than the other or that it is better throughout the period, we then choose data on both sides ranging from the first quarter of 1995 to second quarter of 2015. These data were extracted from the ISTAT database. Also, we considered the modified four times a year Italian gross domestic product as the dependent parameter. This characterizes the volume of the product carried out in each quarter with any modification for inflation and seasonality. These parameters were selected to keep in our pattern all data and all the impact as a result of other economic parameters. The decision-makers were capable to forecast the usefulness of their strategy and bringing together new procedures based on the modified gross domestic product. It is important to underlined or emphasized that the source of data considered in this study has been designed according to our theoretical information and short of any pre-evaluation to which extent the parameters are related to gross domestic product growth. For the construction of the dataset, parameters from many official bases by requiring for each number from the source.

Immediately we demarcated the risk and construct the dataset, no statistical investigation or characteristic production effort to try to excerpt significant features from the uncooked data and thus increase the routine of machine learning algorithms on macroeconomic time-sequence forecasting. The following economic parameters were selected from Italian data as clarifying parameters: Unemployment rate (Appendix 1), inflation rate (Appendix 2), the stock market (appendix 3), the yield curve (appendix 4 and 5), cross debt (appendix 6 and 7) and balance payment (appendix 8).

Results and Discussion

The result obtained in respect to best fit with the methods and test of the regression patterns estimated in the methods. Our result shows that the machine learning approach can provide reliable data for better forecasting of the recession eras than statistical approaches. The machine learning approach gives rise to a lower mean square error and a higher degree of R^2 than the Autoregressive statistical method. For the period under review in this study, all approaches applied were capable to estimate the 2 major disasters, missing a momentous negative revolving that for a quarter. The most efficient approach that we applied in this study appears to be the Nonlinear Autoregressive with exogenous variables model.

The machine learning that extrapolates the AR method applying the exogenous parameters gives astonishing output. This study was not only able to produce the lowest error as shown in Figures 1 and 2. Figures 3 and 4 show the accurate forecasting of the recession-era in the early 2000 and the 2 disasters. To be specific, concerning the 2 disasters, the method predicts the approaching recession that is at the 2018 and 2011 quarters prior that they occur.

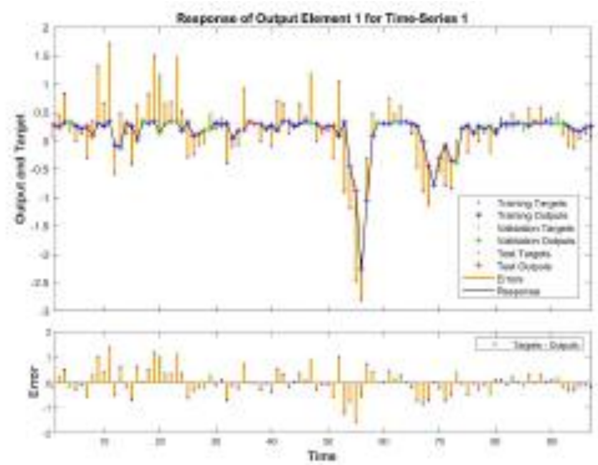

Figure 1: Italian gross domestic product growth rate from the first quarter of 1995 to the second quarter of 2015 forecast with NARX approaches and predicted errors (OECD Stat, 2019).

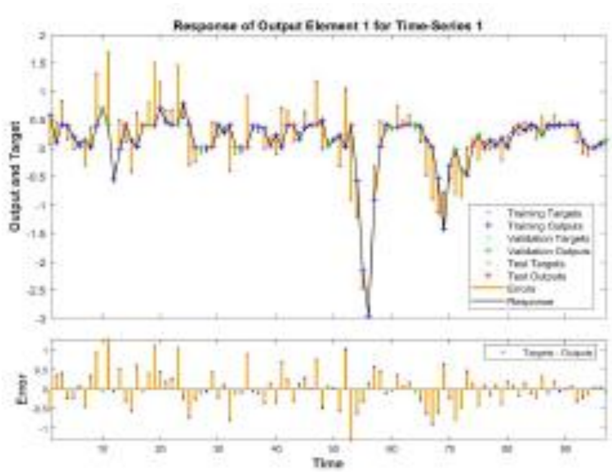

Figure 2: Italian gross domestic product growth rate from the first quarter of 1995 to the second quarter of 2015 forecast with NAR approaches and predicted errors (OECD Stat, 2019).

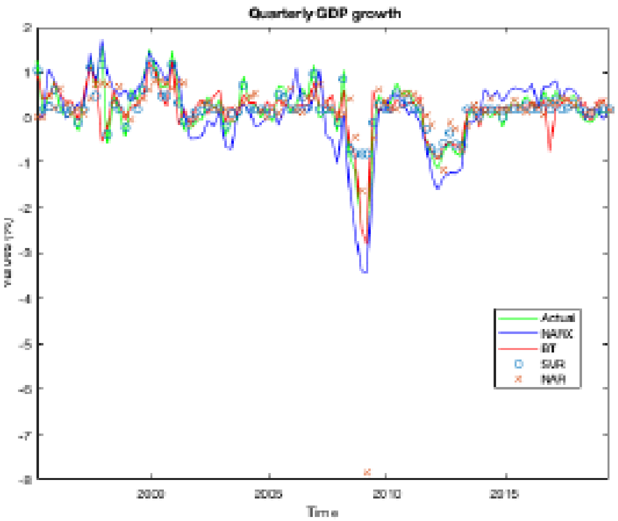

Figure 3: Italian gross domestic product growth rate from the first quarter of 1995 to the second quarter of 2015 predicted by NAR, NARX, BT, SVR approaches and predicted errors (OECD Stat, 2019).

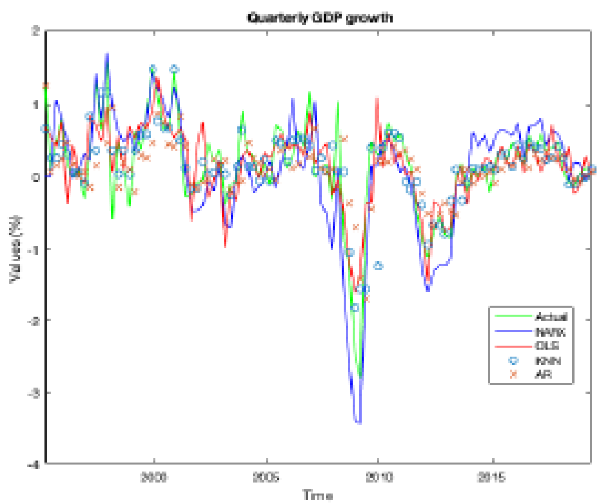

Figure 2: Italian gross domestic product growth rate from the first quarter of 1995 to the second quarter of 2015 predicted by AR, NARX, OLS approaches, and predicted errors (OECD Stat, 2019).

The value of the actual gross domestic product is presented in Table 1 as available by OECD and forecasted correlated values by our approaches for the comparative session of the 2 disasters by merging the predictions of all the machine learning approaches with the recent gross domestic product value. Among all the models employed in this study, it is only the NARX approach is capable of forecasting gross domestic product trends correctly 1 or 2 quarters before the commencement of recession. Also, it was observed that this model is capable of averting wrong positives that is momentary periods of the downturn for at least a quarter. Contrarily, it was observed that auto regression was unable to forecast the upcoming event that is the trend of gross domestic product and also for forecasting gross domestic product difference and it was far behind the development of the economic series.

Table 1. Actual Gross Domestic Product growth rate (OECD Stat, 2019).

Duration	Actual GDP	NARX	SVR	AR	OLS	NAR	BT
2007:Q1	-0.003	1.044	0.174	0.656	0.181	0.727	0.0266
2007:Q2	0.118	-0.370	0.174	0.11	0.367	0.360	0.217
2007:Q3	0.179	-0.508	0.174	0.062	0.460	0.199	0.501
2007:Q4	-0.319	-1.020	-0.119	0.106	-0.253	0.096	-0.102
2008:Q1	1.043	0.103	0.843	-0.150	-0.029	-0.029	0.074
2008:Q2	-0.899	-1.563	-0.100	0.516	-0.495	0.409	-0.604
2008:Q3	-1.189	-2.547	-0.826	-0.371	-0.127	-0.404	-0.845
2008:Q4	-2.471	-3.33	-0.826	-0.711	-1.617	-1.629	-2.471
2009:Q1	-2795	-3.435	-0.826	-1.412	-1.373	-7.836	-2.795
2009:Q2	-0.315	-1.305	-0.115	-1.706	-0.372	-0.4544	0.5872
2011:Q2	0.1196	-0.118	0.174	0.237	0.068	0.342	0.475
2011:Q3	-0.470	-0..627	-0.270	0.096	-0.313	0.031	-0.511
2011:Q4	-0.883	-1.296	-0.683	-0.235	-0.652	-0.166	-0.765
2012:Q1	-1.127	-1.601	-0.826	-0.509	-1.460	-0.879	-0.937
2012:Q2	-0.774	-1.325	-0.574	-0.677	-0.334	-1.176	-0.648
2012:Q3	-0.548	-1.222	-0.348	-0.515	-0.407	-0.100	-0.631
2012:Q4	-0.800	-1.230	-0.647	-0.362	-0.764	-0.248	-0.630
2013:Q1	-0.847	-1.153	-0.647	-0.473	-0.710	-0.723	-0.631
2013:Q2	0.006	-0.105	0.174	-0.522	-0.071	-0.187	0.168

Conclusion

The approaches employed in this study try to duplicate the real prediction of the Italian economy from the first quarter of 1995 to the second quarter of 2015. Different economic parameters were used to aid in successful forecasting of the economic situation. The result shows that machine learning is the best tool to employ in forecasting because it provides reliable and correct prediction and NARX was seen to be more promising in forecasting, giving at least 1 or 2 quarter warning before the occurrence of the event. The major input of this investigation is that machine algorithms provide superior performance in predicting economic recession than the classical statistical methods generally employed. Also, this model enables the use of raw clarification parameters with no adjustments still gives a good output, indicating that machine learning an ideal model for economic predictions.

References

Ahmed, A. A. A., Aljarbouh, A., Donepudi, P. K., & Choi, M. S. (2021). Detecting Fake News using Machine Learning: A Systematic Literature Review. Psychology and Education, 58(1), 1932–1939. https://zenodo.org/record/4494366. https://doi.org/10.5281/zenodo.4494366

Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Stat. Sci.* 16, 199–231.

Cicceri, G., Inserra, G. and Limosani, M. (2020). A Machine Learning Approach to Forecast Economic Recessions—An Italian Case Study. *Mathematics*, *8*(24), 1-20.

Dolfin, M., Knopoff, D., Limosani, M. and Xibilia, M. G. (2019a). Credit Risk Contagion and Systemic Risk on Networks. *Mathematics*, 7, 713.

Dolfin, M., Leonida, L. and Muzzupappa, E. (2019b). Forecasting Efficient Risk/Return Frontier for Equity Risk with a KTAP Approach—A Case Study in Milan Stock Exchange. *Symmetry*, 11, 1055.

Dolfin, M., Leonida, L. and Outada, N. (2017). Modeling human behavior in economics and social science. *Phys. Life Rev*., 22, 1–21.

Donepudi, P. K., Ahmed, A. A. A., Hossain, M. A., & Maria, P. (2020b). Perceptions of RAIA Introduction by Employees on Employability and Work Satisfaction in the Modern Agriculture Sector. International Journal of Modern Agriculture, 9(4), 486–497. https://doi.org/10.5281/zenodo.4428205

Donepudi, P. K., Banu, M. H., Khan, W., Neogy, T. K., Asadullah, ABM., & Ahmed, A. A. A. (2020a). Artificial Intelligence and Machine Learning in Treasury Management: A Systematic Literature Review. International Journal of Management, 11(11), 13–22. https://doi.org/10.5281/zenodo.4247297

Fildes, R. and Stekler, H. (2002). The state of macroeconomic forecasting. *J. Macroecon*., 24, 435–468.

Gavin, H. (2011). The Levenberg-Marquardt Method for Nonlinear Least Squares Curve-Fitting Problems. Ph.D. Thesis, Department of Civil and Environmental Engineering, Duke University, Durham, NC, USA, pp. 1–15.

Jansen, W. J.; Jin, X. and de Winter, J. M. (2016). Forecasting and nowcasting real GDP: Comparing statistical models and subjective forecasts. *Int. J. Forecast*., 32, 411– 436.

McCracken, M. W. and Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business and Economic Statistics*, *34*(4):574–589.

Mullainathan, S. and Spiess, J. (2017). Machine learning: An applied econometric approach. *J. Econ. Perspect*, 31, 87–106.

Nyman, R. and Ormerod, P. 2017. Predicting Economic Recessions Using Machine Learning Algorithms. *ArXiv:* 1701.01428.

OECD Stat. (2019). https://stats.oecd.org/

Paruchuri, H. (2017). Credit Card Fraud Detection using Machine Learning: A Systematic Literature Review. *ABC Journal of Advanced Research*, *6*(2), 113-120. https://doi.org/10.18034/abcjar.v6i2.547

Paruchuri, H. (2019). Market Segmentation, Targeting, and Positioning Using Machine Learning. *Asian Journal of Applied Science and Engineering*, *8*(1), 7-14. Retrieved from https://journals.abc.us.org/index.php/ajase/article/view/1193

Paruchuri, H. (2020). The Impact of Machine Learning on the Future of Insurance Industry. *American Journal of Trade and Policy*, *7*(3), 85-90. https://doi.org/10.18034/ajtp.v7i3.537

Prüser, J. (2019). Forecasting with many predictors using Bayesian additive regression trees. *J. Forecast*., 38, 621–631.

Sahm, C. (2019). Direct Stimulus Payments to Individuals. In Recession Ready: Fiscal Policies to Stabilize the American Economy; Boushey, H., Nunn, R., Shambaugh, J., Eds. The Hamilton Project and the Washington Center for Equitable Growth: Washington, DC, USA,

Vadlamudi, S. (2019). How Artificial Intelligence Improves Agricultural Productivity and Sustainability: A Global Thematic Analysis. *Asia Pacific Journal of Energy and Environment*, *6*(2), 91-100. https://doi.org/10.18034/apjee.v6i2.542

Vadlamudi, S. (2020a). Internet of Things (IoT) in Agriculture: The Idea of Making the Fields Talk. *Engineering International*, *8*(2), 87-100. https://doi.org/10.18034/ei.v8i2.522

Vadlamudi, S. (2020b). The Impacts of Machine Learning in Financial Crisis Prediction. *Asian Business Review*, *10*(3), 171-176. https://doi.org/10.18034/abr.v10i3.528

Vadlamudi, S.; Paruchuri, H.; Ahmed, A. A. A.; Hossain, M. S.; & Donepudi, P. K. (2021). Rethinking Food Sufficiency with Smart Agriculture using Internet of Things. Turkish Journal of Computer and Mathematics Education, 12(9), 2541–2551. https://turcomat.org/index.php/turkbilmat/article/view/3738

Wu, Z.; Durand, H. and Christofides, P.D. (2018). Safeness Index-Based Economic Model Predictive Control of Stochastic Nonlinear Systems. *Mathematics*, 6, 69.

Zhu, Y., Kamal, E. M., Gao, G., Ahmed, A. A. A., Asadullah, A., Donepudi, P. K. (2021). Excellence of Financial Reporting Information and Investment Productivity. International Journal of Nonlinear Analysis and Applications, 12(1), 75-86. https://doi.org/10.22075/ijnaa.2021.4659

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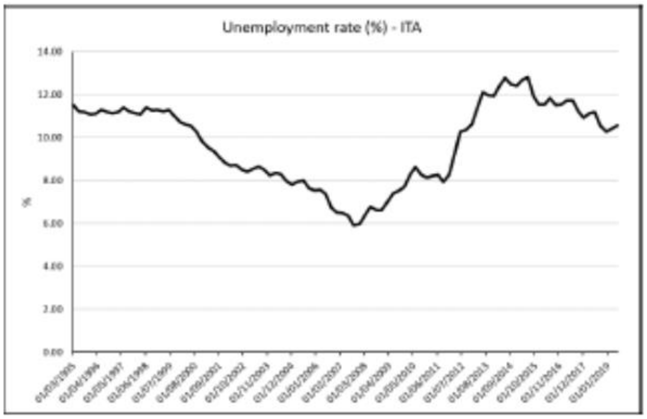
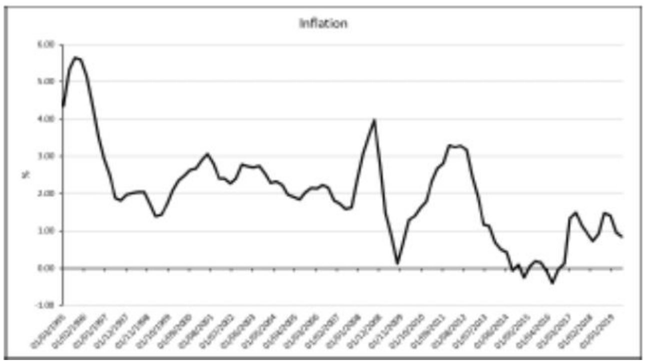
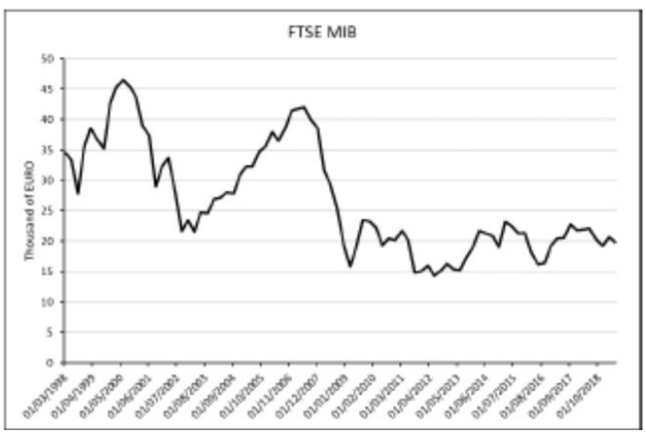
Appendices



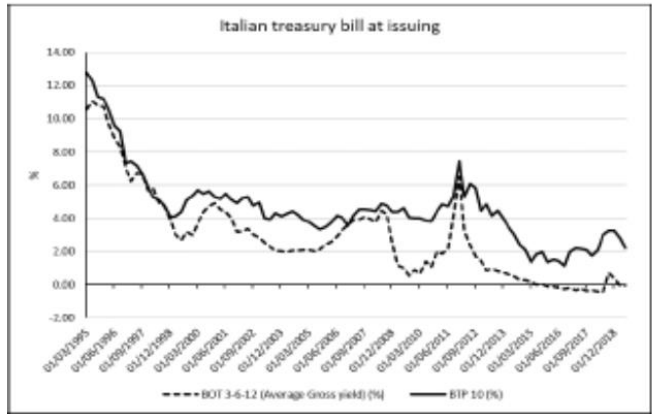
Appendix 1: The unemployment rate (Eurostat, 2019 as cited by Sahm, 2019)



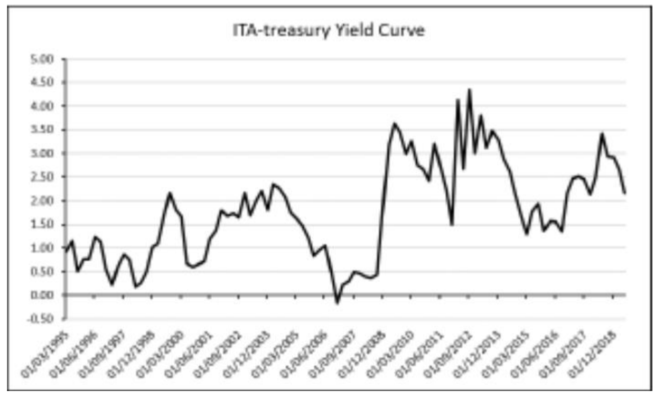
Appendix 2: The Inflation rate (Eurostat, 2019 as cited by linov, 2017; Cicceri et al., 2020)



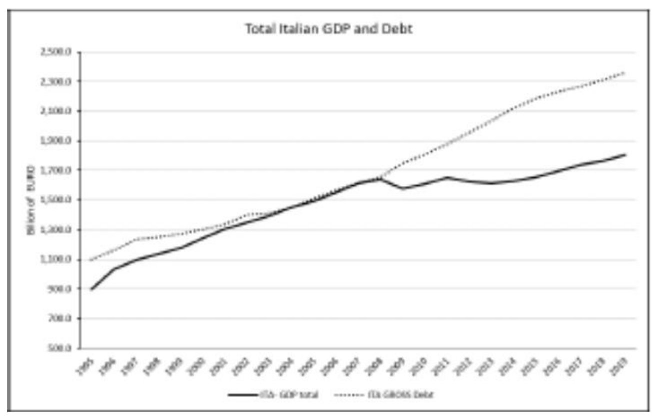
Appendix 3: The Stock index (Cicceri et al., 2020)



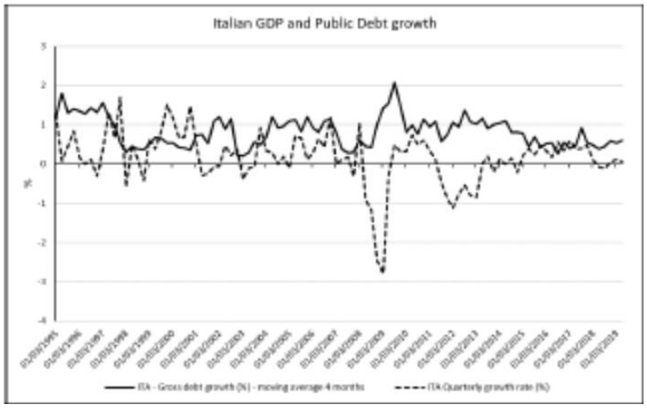
Appendix 4: Italian Treasury bill showing the yield curve (Bank of Italy, 2019 as cited by Cicceri et al., 2020)



Appendix 5: Yield curve extracted by the difference between long-term and short-term Treasury bill maturity (Bank of Italy, 2019 as cited by Cicceri et al., 2020)



Appendix 6: Gross Debt (Bank of Italy, 2019 as cited by Cicceri et al., 2020)



Appendix 7: Debt growth rate and gross domestic product growth (Bank of Italy, 2019 as cited by Cicceri et al., 2020)

Appendix 8: Payment balance (Bank of Italy, 2019 as cited by Cicceri et al., 2020).

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