ИКОНОМИЧЕСКИ ИЗСЛЕДВАНИЯ
ECONOMIC STUDIES
Volume 32(8), 2023

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APPLICATION OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN THE CONDUCT OF MONETARY POLICY BY CENTRAL BANKS[2]

Over the past few years, artificial intelligence (AI) and machine learning (ML) have become increasingly important in central banks' policy-making and monetary policy-making processes. The global financial crisis of 2008-2009, the COVID-19 pandemic, as well as various other episodes of high economic uncertainty since the turn of the millennium have adjusted central banks to a number of serious challenges and have led to the expansion of these mandates and emerging and exploiting new and extensive data. The study briefly notes on this as a big database (big data) and applications of AI/ML-based techniques that can provide support on monetary policy decisions, especially during times of uncertainty in the economy, referring to the latest research in this area. Also, concrete examples based on the creation of big data and AI/ML techniques applied in the activities of the European Central Bank and other central banks in Europe and the rest of the world are considered and analyzed. The analysis reveals that big data and AI/ML methods have demonstrated successful utility in conducting monetary policy by central banks. Although useful as a complement, these tools cannot be regarded as replacements for conventional data and methods due to issues related to statistics, the ability to interpret outcomes and ethical dilemmas.
Keywords: artificial intelligence; big data; machine learning; central banks; monetary policy; economic uncertainty
JEL: E52; E58; D81; C55

Introduction

In the past, central banks, particularly the European Central Bank (ECB), focused primarily on maintaining price stability, utilizing conventional monetary policy instruments to achieve this goal. However, following the onset of the global financial crisis in 2008-2009, and especially in response to overcoming the adverse effects of the COVID-19 pandemic, the

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[2] This scientific article is funded by scientific project with contract № KP-06-M45/4 in 2020/12.07.2021 entitled *"Fiscal and Monetary Instruments for Regulating Uncertainty in the Economy"* from the Competition for Financial Support for Project of Junior Basic Researchers and Postdocs – 2020 of The Bulgarian National Science Fund.
This paper should be cited as: *Georgieva, S. (2023). Application of Artificial Intelligence and Machine Learning in the Conduct of Monetary Policy by Central Banks. – Economic Studies (Ikonomicheski Izsledvania), 32(8), pp. 177-199.*

toolkit of central banks evolved to include “non-traditional instruments” of monetary policy, such as additional asset purchases, quantitative easing, targeted longer-term refinancing operations, and others. Additionally, central banks are assigned various new responsibilities, including assessing systemic risk, banking regulation and supervision, digital currencies, and addressing climate change.[3] These expanded responsibilities are partly a response to the presence and utilization of new sources of data, often referred to as big data, which provide valuable information to central banks (Chakraborty, Joseph, 2017). In their project at the Frankfurt School of Finance and Management, Kinywamaghana & Steffen (2021) examine the important role of big data and AI/ML in supporting the decision-making activities of central banks in the conduct of monetary policy, with an emphasis on the improvement and refinement of statistical information and analytical capacity, preparation of macroeconomic analyzes and forecasts, monitoring of financial markets and assessment of financial risk.

What is big data?

While in engineering sciences and statistics, there are clear definitions of what big data is, in the field of economics there is still no comprehensive definition of the concept. The study approach, proposed by Goldstein et al. (2021), serves as a conditional definition that helps to understand the main characteristics of this type of information. Big data has great potential for economic analysis and decision-making, but its use requires special skills and tools for processing and analysis. According to their perspective, big data is characterized by three main properties (Kinywamaghana, Steffen, 2021). **First**, a large size in terms of sample size, which involves a significantly larger amount of data than the size of the usual data samples that are used in traditional statistics. This data can be collected from various sources, such as sensors, websites, social media, and other sources. **Second**, high dimensionality (high frequency of data), which refers to the number of variables (parameters) compared to the sample size. Big data often covers a significant number of variables, allowing for more detailed analyses and the discovery of complex relationships and dependencies. This aspect is also discussed by Martin & Nagel (2019). **Third**, big data is characterized by great variety and complex structure. They contain different forms of information such as text, photos, or audio, and very often this data is unstructured. This means that the data is not organized in traditional tables or databases, which causes the need to use new methods to analyze and process the information.

What is the source of big data?

Different data sources contributing to the generation of big data used by central banks in decision-making processes encompass various categories. Among the most prevalent sources

[3] Central banks increasingly recognize the potential risks that climate change poses to price stability, such as the impact of weather-related events leading to increased inflation. For example, on January 25th, 2021, the ECB has made important announcements regarding initiatives aimed at addressing climate change. These initiatives include the establishment of a climate change center. More information about this announcement is on https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210125_1~3fc4ebb4c6.en.html.

are internet-based indicators primarily obtained from web-based platforms. Additionally, datasets related to trade, financial market indicators, and administrative records are also used.[4] According to a study by Doerr et al. (2021), approximately 80% of central banks have incorporated big data into their operations by 2020, representing a significant increase of 30% compared to 2015. Furthermore, about 40% of central banks have specifically utilized big data for announcing their policy decisions. However, it is important to note that, compared to the private sector, only a limited number of central banks have fully embraced big data (Tissot, 2018). This may be attributed to various factors, including the complexities of implementing new technologies and the specific requirements of central banks when processing and analyzing financial information. Nonetheless, the growing interest and involvement of central banks in big data demonstrate their significant potential for improving and optimizing economic analyses and decision-making in the future.

One of the crucial questions is how to make the analysis of big data as effective as possible (Kinywamaghana, Steffen, 2021). Financial experts often face the challenge of extracting information from high-frequency or unstructured data (Goldstein et al., 2021). Furthermore, financial big data is frequently characterized by challenges such as white noise, fat-tailed distributions, non-linear models, and time dependencies, rendering traditional econometric methods inapplicable for such analysis (Petropoulos et al., 2018). In response to the challenges posed by the complexity of big data, AI and ML have emerged, often applied in combination with other approaches.

According to the 2018 European Artificial Intelligence Strategy[5], AI is the concept of creating computer systems capable of exhibiting intelligent behaviours, which involves analyzing their surroundings and taking actions, to some extent independently, to achieve specific objectives. (AI) has the potential to function in two primary ways. It can exist as software within the digital realm, examples of which include voice assistants, image analysis software, search engines, and systems for speech and face recognition. Alternatively, AI can be seamlessly incorporated into hardware devices, giving rise to sophisticated robots, self-driving cars, drones, and applications within the context of the Internet of Things (IoT). People interact with AI regularly in their daily lives, such as using language translation services, generating subtitles for videos, or blocking email spam. Moreover, AI goes beyond just easing day-to-day activities; it plays a vital role in addressing some of the world's most significant challenges, including in areas like health care, road safety, combating climate change, predicting cyber security threats, conducting economic policy, and many more.

As Chakraborty & Joseph (2017) postulate, machine learning (ML) can be described as an algorithmic approach to solving problems, which automatically optimizes itself through experience, primarily derived from data, and requires minimal to no human intervention (FSB[6], 2017). ML algorithms are a subset of AI techniques and are commonly classified into

[4] An illustrative example of big data used by central banks is credit registries. These registries are widely utilized in academic research, as evident from studies such as Altavilla et al. (2020). Credit registries provide valuable information that can be used by central banks for a better understanding of credit dynamics and risk assessment within the financial system.

[5] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2018:237:FIN.

[6] Financial Stability Board (FSB) is an international body that monitors and makes recommendations about the global financial system. https://www.fsb.org/.

four main types: supervised, unsupervised, reinforcement, and deep learning (Wibisono et al., 2019). These ML techniques have seen increasing adoption in academic and practical settings within the economic and financial domains, and central banks have also embraced their application. A key factor behind this trend is the availability of extensive and intricate databases (Israël, Tissot, 2021) and the advancement of big data analytics, which have empowered central banks to leverage ML tools to aid their policymaking, especially in the realms of monetary and financial stability, as well as in associated statistical, analytical, and communication tasks (Chakraborty, Joseph, 2017; Doerr et al, 2021; Bruno, Marcucci, 2021).

Undoubtedly, the fact is that AI and ML become increasingly significant in improving the database used by central banks in decision-making during monetary policy implementation. The application of AI- and ML-based techniques offers several potential advantages:

Expansion of existing macroeconomic indicators: AI and ML can complement traditional macroeconomic indicators by providing additional insights through the inclusion of more comprehensive and detailed real-time information. This helps central banks gain a deeper understanding of economic conditions and potential risks. Although big data has the capacity to enhance GDP and other macroeconomic predictions, their complete potential can be fully harnessed by utilizing ML algorithms. In numerous instances, the enhancement in forecasting accuracy is tied to particular scenarios, like when conventional monthly indicators for the relevant quarter are not yet accessible.

Utilization of new data sources: AI and ML enable central banks to leverage non-traditional data sources such as Google searches, real estate data, online consumer prices, or social media activity.[7] These alternative data sources can offer valuable information for assessing economic trends, consumer sentiments, and market dynamics.

Introduction of innovative data collection techniques: AI and ML techniques facilitate the adoption of advanced data collection methods, including web scraping, text mining, and integration of multiple data sources. These techniques allow central banks to gather and analyze data more efficiently, enhancing the timeliness and quality of information used in decision-making processes, but also have the capability to address specific problems. Additionally, ML tools are primarily focused on forecasting issues and have the ability to discover overarching patterns in data (Mullainatha, Spiess, 2017). These techniques are designed to identify predictive models that can effectively forecast outcomes based on the models and relationships found in the data. This transition from parameter estimation to forecasting is a key distinction between traditional approaches and the application of ML in economics.

[7] The advent of smartphones and cloud computing has led to the generation of vast volumes of data, providing valuable opportunities for the financial sector and central banks to enhance their decision-making processes. An example is the ability of market participants to monitor information dissemination through social media platforms. Wibisono et. al. (2018) offer a comprehensive review of the application of AI/ML in the context of central banking. Their work provides valuable insights into the utilization of AI/ML techniques and their potential impact on central bank operations.

1. Application of AI/ML in Supporting Decision-Making Processes by Central Banks in the Conduct of Monetary Policy

The use of AI/ML by central banks raises significant questions about their role in supporting monetary policy decision-making. This study examines four key questions, discussed also in Kinywamaghana & Steffen (2021), related to the use of AI/ML in central banks' monetary policy-making activities, addressing issues like opportunities for AI/ML to improve policy-making; monetary policy decisions; AI/ML application areas; way of applying AI/ML in practice; potential risks and challenges associated with the use of AI/ML. These questions aim to explore the benefits, applications, current practices, and potential pitfalls of integrating AI/ML into central bank decision-making processes.

AI/ML play a critical role in enhancing the capabilities of collecting, processing, and analyzing data for central banks. AI/ML contribute to more precise and timely data collection by enabling regulators to extract real-time data from firms' systems at various levels of granularity. Additionally, they can leverage third-party sources to gather data on consumer behaviour, including spending and saving patterns (Proudman, 2020). Furthermore, AI enhances and refines analytical abilities by efficiently identifying non-linear models within the data. According to Genberg & Karagedikli (2021), the strength of ML lies in its predictive power, enabling the discovery of data patterns that are not pre-defined. Techniques like aggregating models from online ML can be employed to obtain the most accurate predictor for systemic financial crises in scenarios beyond the sample data (Fouliard et al., 2020).

AI/ML contribute to reducing operational costs by automating repetitive tasks, thereby freeing supervisors from performing these tasks manually. This automation helps to minimize the occurrence of human errors in the process. AI and ML technologies lead to reduced application processing times for banks, offering them improved transparency in the decision-making process. By using online application forms with mandatory fields, supervisors receive more comprehensive applications, thereby minimizing the need for additional document requests after the initial submission (Hakkarainen, 2020).

Central banks face various responsibilities like ensuring price stability, assessing systemic risk, regulating commercial banks, overseeing digital currencies, and addressing climate change. To address these challenges, central banks have embraced AI/ML techniques, offering promising prospects for future research in financial economics. Kinwamaghana & Steffen (2021) identify the areas where AI/ML can support and improve decision-making in the conduct of monetary policy by central banks.

Improving the communication of the central bank

Text analytics can be used to create metrics to measure central bank communication and examine the conveyed information and used channels, and analyze market reactions and responses to these signals. Central banks use a variety of communication channels, including press conferences, meetings, social media platforms, and future guidance and recommendations to continue their attempts to strengthen communication with the public (Haldane, McMahon, 2018). For example, Schmeling & Wagner (2019) show that changes in the tone of the central bank communication have a significant effect on asset prices. The tone captures how the central bank sets economic fundamentals and its monetary policy. When the tone turns more positive, stock prices rise, especially for stocks with high systematic risk, while credit spreads and volatility risk premia decline. Using Twitter data, Ehrmann & Wabitsch (2021) examine English and German Twitter traffic for the ECB. The results show that Twitter traffic is responsive to the ECB's communication. In another paper, Ehrmann & Talmi (2020) examine the extent to which central bank reporting similarity affects financial market volatility. They show that similar press releases generate less volatility in markets, and more substantial textual changes following a series of very similar announcements lead to much more volatility.

Improving banking supervision

The ECB actively uses various projects under the umbrella of Supervisory Technologies (SupTech)[8], which include advanced data analysis and text analysis[9]. SupTech refers to the application of innovative technologies to support financial supervision, such as cloud computing and ML techniques. For example, Hannes et al. (2018) propose a model derivation framework for early warning of impending European banking shocks. Goldsmith-Pinkham et al. (2016) utilize a computational linguistics strategy to gauge banking oversight. This approach involves analyzing a database of supervisory concerns, referred to as “matters requiring attention” or “immediate attention”, which are identified by Federal Reserve examiners in relation to banking institutions.

Development of assessments to increase financial stability

Network analysis proves to be an effective tool for examining the interrelationships between financial and non-financial services, thus identifying potential sources of systemic risk. This approach offers an improvement over other “small data” methods, as described in Cai et al. (2018). Applying a new measure of bank interconnectedness, the authors conclude that diversification ignores negative externalities in an interconnected financial system and underlies its enhanced financial stability. A recent illustrative case where high-frequency data could be valuable is GameStop’s January 2021 episode[10] involving retailers coordinating via social media. The interplay between these retail traders and sophisticated investors leads to significant market volatility and breeds concerns about financial stability.

[8] SupTech refers to the use of technology to facilitate and improve supervisory processes from the perspective of the supervisors, https://www.bankingsupervision.europa.eu/press/publications/newsletter/ 2020/html/ssm.nl200812_3.en.html.

[9]https://www.bankingsupervision.europa.eu/press/publications/newsletter/2021/html/ssm.nl210217_3.en.html.

[10] A 2022 documentary about the history of GameStop Corp, the world’s largest American retailer of video games, consumer electronics, and games headquartered in Grapevine, Texas. The documentary chronicles GameStop‘s brief decline in 2021, which saw GameStop stock soar more than 2500% amid rampant volatility. This story is told mostly from the perspective of a few value investors who have been involved in sharing their due diligence on social media, https://www.wsj.com/articles/melvin-capital-lost-53-in-january-hurt-by-gamestop-and-other-bets-11612103117.

Improving credit rating and scoring analysis

According to a speech by Enria (2019), big data and AI can effectively serve many purposes, including overcoming information asymmetries in credit rating and scoring. These new tools can help banks assess the credit ratings of customers with limited credit and history, helping them eliminate human bias, all at a low cost. Using natural language processing to analyze reports and social media can offer valuable information about the creditworthiness of businesses' customers. In their study, Khandani et al. (2010) apply ML techniques to predict consumer credit risk using non-linear non-parametric models. They suggest that this technique may have important applications in predicting systemic risk in the banking system.

Improving investigations against financial crimes and money laundering

The application of AI can improve efficiency and effectiveness in financial crime investigations and risk management in both financial and non-financial institutions. Proudman (2018) believes that the growth of AI techniques opens up the prospect of supporting ML or "cyborg" supervision of banks. There is a shift from a rules-based approach to anti-money laundering monitoring to ML methods that use customer data and publicly available information from the Internet to identify suspicious activities and detect the flow of funds.

Improving complaint handling

In his speech on November 30th, 2020, Hakkarainen (2020) points out that ML-based tools could perform supervisory tasks previously performed by humans, such as answering and resolving customer complaints. Also, by applying AI that mimics human thinking, insights can be extracted from unstructured data and actionable models can be suggested. Institutions like the Central Bank of Italy use AI techniques to streamline the handling of customer complaints. Similarly, the Central Bank of France develops an algorithm that can automatically assess the compliance of banks' regular supervisory reports and other submissions, as well as assess the quality of information using natural language processing.

Enhance decision-making processes and expand the customer base for goods and services

AI-based models can be utilized by banks to reach a broader customer base, including individuals who are underserved and have limited access to banking services. Blumenstock et al. (2015) and Blumenstock (2016) explore the possibilities of inferring the socio-economic status of mobile phone users through their usage patterns. In countries around the world with limited resources, where household surveys and studies are rare, this approach offers the opportunity to gather localized and timely information at a significantly lower cost than the traditional methods. This initiative can be seen as a potential contribution to addressing poverty.

Improving economic forecasting and nowcasting

Big data, along with AI/ML techniques, are used to forecast business cycles, including key components such as gross domestic product (GDP), inflation, and monetary aggregates. According to Tissot (2018), by observing consumer durables (such as cars) and analyzing job advertisements, we could for example model real economic indicators such as economic activity, unemployment created in the economy as a whole, or specific sectors (such as tourism). ML methods are particularly well-suited to predictive analytics, which are extremely attractive in predicting returns on financial assets and measuring risk premiums. Gu et al. (2020) perform a benchmarking analysis based on ML methods to measure activity risk premiums. They double large economic gains for investors by driving out with the help of ML, in some cases the performance of the leading strategies based on regression from the literature.

Improving the Quantitative Measurement of Uncertainty in Economics

Baker et al. (2016) created an index to measure economic uncertainty (Economic Policy Uncertainty – EPU) based on text analysis and ML of business news in newspapers. Using firm-level data, they find that political uncertainty is associated with greater stock price volatility and reduced investment and employment in politically sensitive sectors such as defence, health, finance, and infrastructure construction. At a macro level, innovation in policy uncertainty predicts declines in investment, output, and employment in the US and 12 major economies over the period 1900-2015. Bybee et al. (2021) developed an approach to measure the economy's performance through a textual analysis of 800,000 articles in the Wall Street Journals for the period 1984-2017 to forecast macroeconomic performance. Using a standard vector auto-regression VAR, they show that the attention a publication attracts to a particular topic contains meaningful information about future economic performance beyond the standard indicators.

2. Application of AI/ML in the Conduct of Monetary Policy by Central Banks – Practical Examples

In conducting monetary policy, policymakers act in real-time, based on limited information about current economic conditions. In recent years, political institutions have explored a large number of new data sources and alternative statistical methods to assess economic activity in real-time (Appendix 1). Here are presented examples of how central banks use AI, ML techniques, and big data to analyze the business cycle. These new data sources and tools are primarily used to improve forecasts of economic activity and short-term forecasting of real GDP. In addition, they provide valuable insights for assessing cyclical trends and creating an objective description of a series of events. Discussed here are two illustrative examples presented in Hirschbühl, et al. (2021), namely: indicators of economic sentiment for the euro area derived from newspaper articles and the application of big data analytics and ML to measure uncertainty using textual data.

2.1. Nowcasting euro area real GDP growth with newspaper-based sentiment

Here are presented the main findings in a study by Ashwin, et al. (2021). Economic sentiment indicators for the euro area, drawn from newspaper articles in the four largest euro area countries known as the Big Four (Germany, France, Italy, and Spain) in their main national languages, are examined here. The dataset includes a massive collection of 5 million articles spanning the period from January 1998 to December 2020, originating from 15 different newspapers[11], retrieved through the Dow Jones Factiva DNA database. Specifically, they focus on articles categorized as economic, corporate, or financial markets to minimize irrelevant information such as sports and lifestyle topics. These indicators are available on a daily basis and contain timely economic signals that can be compared to well-known sentiment indicators such as the Purchasing Managers' Index (PMI[12]). Moreover, they may substantially improve current forecasts for real GDP growth in the euro area.

In the literature, two approaches are most often used to construct sentiment indicators from textual data. The predominant approach involves utilizing a straightforward word count technique based on predefined collections of words, often referred to as dictionaries or lexicons. Nonetheless, a significant portion of these dictionaries was designed for the English language. Given the multilingual context within the Eurozone, addressing this requires either devising new dictionaries for other languages or translating texts into English. Alternatively, more resource-intensive model-based techniques such as semantic clustering or topic modelling can extract subjects that can be likened to emotions and their triggers. The sentiment indicators outlined in this context rely on the word count from news articles, which are translated into English. This translation process employs the Google Translate API (Application Programming Interface) for converting news articles into English. To ensure accuracy, the methodology has undergone validation checks that encompass comparing it against dictionaries in national languages and even translating these dictionaries into English. In general, the translation of articles into English shows the most reliable and stable results. Only the sentiment indicators referring to the Financial Stability Based Dictionary (taken from Correa et al., 2017) and the VADER[13] General Purpose Dictionary (taken from Hutto, Gilbert, 2014) are presented here.

Regardless of the used vocabulary and despite the presence of some noise, sentiment indicators that are based on newspaper articles are highly correlated with the composite PMI over the period 2000-2019 (Figure 1a). This is evidence that these measures actually capture the sentiment. When it comes to detecting turning points, however, the choice of vocabulary matters. The first sentiment indicator captures the Global Financial Crisis very well, which is not surprising given the financial nature of this crisis. But on the other hand, this indicator

[11] In France – Les Echos, Le Figaro, Le Monde; in Germany – Die Welt, Suddeutsche Zeitung, Der Tagesspiegel, German Collection; in Italy – Corriere della Sera, La Repubblica, Il Sole 24 Ore, La Stampa; in Spain – Expansi´on, El Mundo, El Pa´ıs, La Vanguardia.

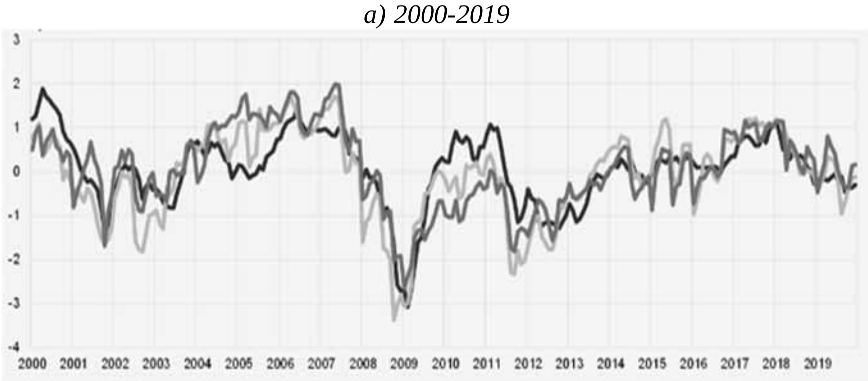
[12] Purchasing Managers' Index (PMI) is an index of the prevailing direction of economic trends in the manufacturing and service sectors. It consists of a diffusion index that summarizes whether market conditions are expanding, staying the same, or contracting as viewed by purchasing managers. The purpose of the PMI is to provide information about current and future business conditions to company decision-makers, analysts, and investors. https://www.investopedia.com/.

[13] The VADER (Valence Aware Dictionary and sEntiment Reasoner).

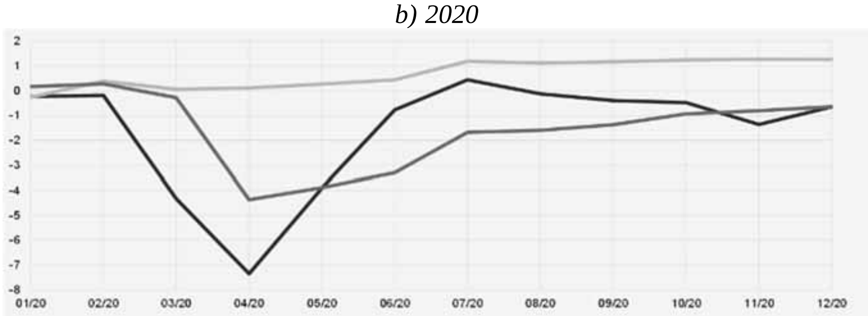
fails to capture the COVID-19 crisis (Figure 1b), though its development is consistent with the behaviour of financial markets and funding conditions, which have remained favourable in the context of a very strong policy response. In contrast, general-purpose vocabulary is more consistent and stable over time. This, therefore, shows that in identifying the most appropriate text dictionary to use, the nature of economic shocks may play an important role.

Figure 1. PMI and newspaper-based sentiment indexes for the "Big Four" in the euro area

a) 2000-2019



b) 2020

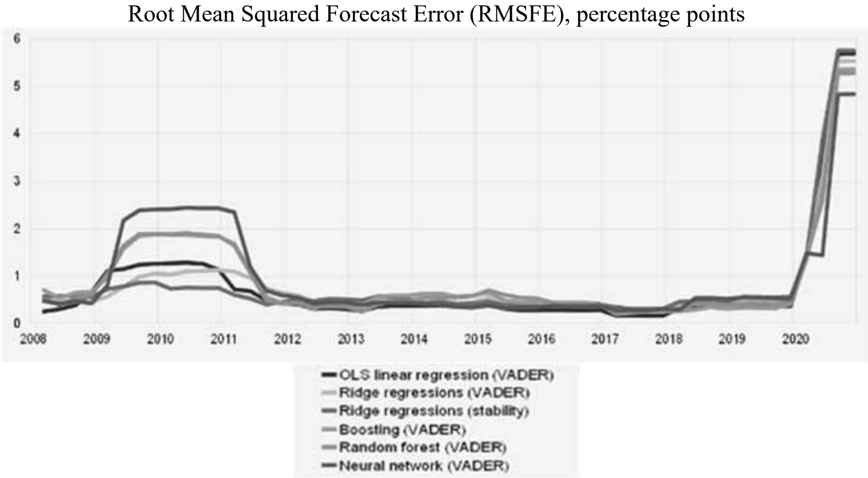


Source: Ashwin, J. et al., 2021; Factiva; IHS Markit; Eurostat.

Several studies in the field, including those by Thorsrud (2020), Larsen & Thorsrud (2019), and Kalamara et al. (2020), have identified that text analytics can substantially enhance the accuracy of forecasts for important macroeconomic indicators. Notably, improvements in forecast precision are observed for real-time GDP forecasts utilizing the PMI composite index and text sentiment indicators as pivotal predictors (specific improvements are not displayed). These enhancements tend to be most prominent in current forecasts generated during the initial half of the quarter (first six weeks), a period when various other indicators for estimating current GDP are yet to be available. This outcome aligns with findings from existing literature. It's essential to underscore that the effectiveness of leveraging text-based information in a timely manner depends on the model utilized. Traditional linear methods like the Least Squares Regression Method, such as ordinary least squares linear regression, prove effective during stable economic conditions with minimal alterations in the economic outlook. However, during periods of significant economic shocks, Machine Learning (ML) models come into play by capturing nonlinearities and filtering out noise (depicted in Figure 2). Ridge regressions[14] , for instance, outperformed other methods during the financial crisis, as evidenced by the lowest Root Mean Square Error (RMSFE)[15], particularly when incorporating the sentiment indicator derived from the Financial Stability Dictionary. Interestingly, during the pandemic, neural networks emerged as the most effective models, despite being the least effective models during the financial crisis. This divergence is attributed to the fact that there were no comparable crises in the training data prior to the financial crisis, hence limiting the neural networks' ability to learn. This underscores a drawback of more complex ML models: their requirement for substantial training data (in other words, they are "data hungry").

Figure 2. Forecast accuracy

Root Mean Squared Forecast Error (RMSFE), percentage points



Notes: Figure 2 reports Root Mean Squared Forecast Error (RMSFE) for a Rolling-window[16] of 8 quarters. Forecasts are revised by the conclusion of the initial month in the quarter of reference. The variable under consideration is the representation of actual growth in real Gross Domestic Product (GDP) as of March 24, 2021.

Source: Ashwin, et al., 2021; Factiva; IHS Markit; Eurostat.

[14] Ridge Regression is a specialized technique used to analyze multiple regression data that is multicollinear in nature. It is a fundamental regularization technique, but it is not used very widely because of the complex science behind it. https://www.engati.com/.

[15] Root Mean Square Error (RMSE) measures the average difference between a statistical model's predicted values and the actual values. Mathematically, it is the standard deviation of the residuals. Residuals represent the distance between the regression line and the data points. RMSE quantifies how dispersed these residuals are, revealing how tightly the observed data clusters around the predicted values. https://statisticsbyjim.com/.

[16] Rolling-window analysis of a time-series model is expressed relative to the delivery date and automatically shifts forward with the passage of time. For example, a customer with a 5-year Rolling window who gets a delivery on 04.05.2016 would receive data covering the period from 04.05.2016 to 04.05.2021. https://www.mathworks.com/.

2.2. Sources of uncertainty in economic policies within the euro area and how they affect various demand elements

Economic policy uncertainty arises from a variety of sources that affect consumer and firm decisions differently. As an illustration, heightened uncertainty surrounding forthcoming tax adjustments and customs tariffs can influence a company's deliberation on constructing a new manufacturing facility or venturing into a new market for exports. This stems from the fact that future circumstances significantly impact weighty, unalterable investment choices. In contrast, uncertainty pertaining to the forthcoming direction of monetary policy holds significance for both business entities and consumers when it comes to making spending determinations. This is because it influences their projections concerning forthcoming economic shifts and the availability of funding.

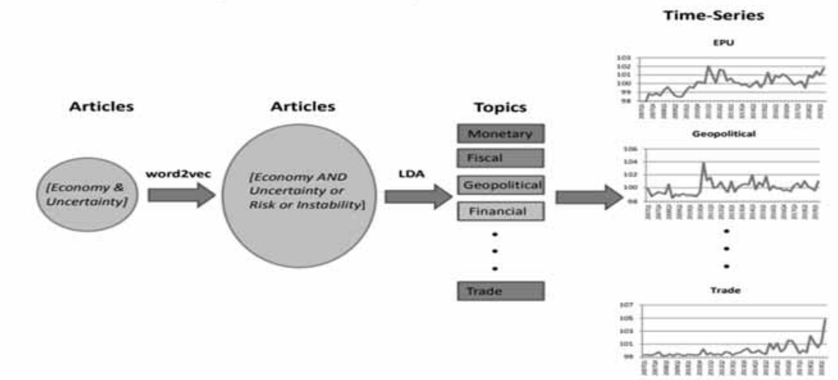
In recent years, the euro area has been affected by an unprecedented number of episodes of uncertainty, including the Great Recession (2008-2014); the euro area sovereign debt crisis (2010-2012); the sanctions imposed on Russia by the European Union (EU) following the crisis in Ukraine (March 2014); the Brexit vote (June 2016); the COVID-19 pandemic (2020); unprecedented levels of inflation (2021-2022); the military conflict between Russia and Ukraine (2022); the sanctions imposed against Russia (2022-2023); the recession in the economy (2023) and the subsequent disruptions in the global supply chains of goods and services. These instances have played a role in fostering elevated levels of political uncertainty within the Eurozone. Grasping the origins and the dynamic nature of uncertainty that impacts the economy holds substantial importance for decision-makers, including central banks. Companies are particularly attuned to this uncertainty factor while deliberating their investment choices. When confronted with shocks of uncertainty, they might curtail their investments, employment opportunities, or dealings with foreign intermediaries, which can then result in a trade deceleration and a reduction in overall investment activities. Subsequently, consumers might react to heightened uncertainty by deferring their spending and increasing precautionary savings, as exemplified by the increase in household savings rates during 2018 and 2021. Briefly examined here is how the capabilities of big data and ML are applied in the practice to measure the effect of different episodes of policy uncertainty on investment in the euro area for the period January 2000 to May 2019 (Azqueta-Gavaldón et al., 2019; Azqueta-Gavaldón et al., 2020). For this purpose, the Economic Uncertainty Index (EPU) of the four largest economies in the Eurozone (The Big Four) is modelled using a pre-selected set of keywords in newspaper articles.[17] The EPU is constructed by aggregating various components (sub-indices) such as political; monetary policy; fiscal policy; trade policy; geopolitical policy; European regulation; domestic regulation and energy policy.

Figure 3 illustrates the procedure of transforming news articles into time series data for modelling individual components of uncertainty. The process involves several straightforward steps: a) gathering all news articles containing the terms “economy” and

[17] *German newspapers:* Handelsblatt, Frankfurter Allgemeine Zeitung, Die Welt, S¨uddeutsche Zeitung; *French newspapers:* Le Figaro, Le Mond; *Italian newspapers:* Corriere della Sera, La Repubblica, La Stampa; *Spanish newspapers:* El Pa´ıs, El Mundo, La Vanguardia. From January 2000 to May 2019, the total number of news articles containing any form of the word “economy” and “uncertainty” is 14 695 in Germany, 11 308 in France, 30 346 in Italy, and 32 289 in Spain.

"uncertainty"; b) broadening the selection of articles related to economic uncertainty by incorporating words that are semantically most similar to the aforementioned terms in each language, using the "word2vec" algorithm[18]; c) utilizing Latent Dirichlet Allocation (LDA) topic modelling algorithms to identify distinct economic uncertainty topics; d) constructing time series based on these identified themes.

Figure 3. Converting news into time series



Note: The gray circles represent the hull, i.e. the aggregate of all news articles; "word2vec" stands for the continuous bag-of-words model[19] developed by Mikolov et al. (2013); LDA stands for Latent Dirichlet Allocation Algorithm, developed by Blei, Ng, and Jordan (2003).
Source: Azqueta-Gavaldón et al., 2020.

The primary benefit of employing this approach lies in its versatility across various languages, negating the need for reliance on particular keywords. This characteristic enhances its resistance to selection bias. Furthermore, this method identifies overarching themes that underpin broader economic policy uncertainties (such as fiscal, monetary, or trade policy uncertainties) within newspaper articles. This attribute proves particularly advantageous in constructing narratives and conducting economic analyses (Azqueta-Gavaldón et al., 2019).

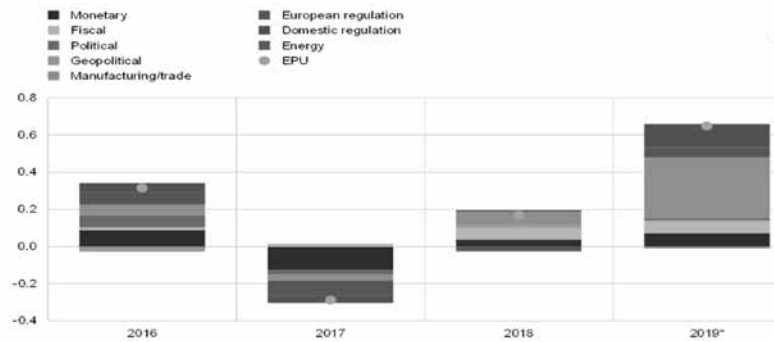
Following the standard procedure in the literature, Azqueta-Gavaldón et al. (2019) use a structural vector autoregression (SVAR) model to document the relationship between business investment through investment in machinery and equipment and the created EPU index and eight sub-indices (Figure 4).

[18] Word2vec is a technique for natural language processing (NLP) published in 2013. The word2vec algorithm uses a neural network model to learn word associations from a large corpus of text. Word2vec is not a singular algorithm, it is rather a family of model architectures and optimizations that can be used to learn word embeddings from large datasets. Embeddings learned through word2vec have proven to be successful on a variety of downstream natural language processing tasks, https://www.tensorflow.org/.

[19] The bag-of-words model is a way of representing text data when modeling text with machine learning algorithms. The bag-of-words model is simple to understand and implement and has seen great success in problems like language modeling and document classification, https://machinelearningmastery.com/.

The various components of the index indicate that trade, domestic regulation, and fiscal policy have been the primary sources of policy uncertainty since 2016. The contributions of individual uncertainty components to overall economic policy uncertainty have been quite dynamic during this period. In 2016, during the Brexit referendum year, the main drivers of policy uncertainty in the euro area were linked to monetary policy, European regulation, and trade. However, in 2017, the reduction in policy uncertainty is mainly due to a significant decrease in uncertainty related to monetary policy. This decrease is attributed to the clarity provided by the ECB on the future interest rate policy for an extended period after cutting interest rates in 2016.

Figure 4. Sources of uncertainty in economic policies within the euro area (average annual percentage changes and percentage point contributions)



* from January to May

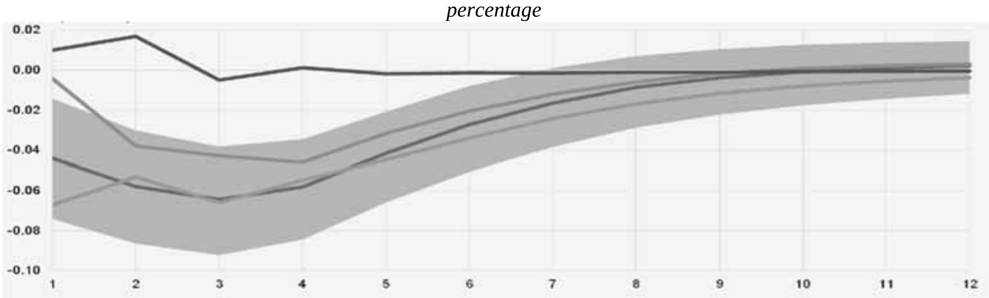
Source: Azqueta-Gavaldón et al., 2019.

Moving on to 2018 and up to 2019, a consistent and notable increase in the euro area Economic Policy Uncertainty (EPU) index can be observed. This increase is primarily driven by uncertainty related to trade, influenced by global trade disputes involving the United States and China, which are likely to impact the euro area exports and imports. Additionally, uncertainties surrounding the Brexit negotiations and concerns regarding domestic and fiscal policies in some euro area countries contribute to this rise in uncertainty. These concerns are connected to factors like the uncertain effects of new emission standards in domestic regulation and the enforcement of EU budget rules in certain member states. It is worth noting that these increased uncertainties are not associated with the conduct of monetary policy.

The impulse responses, presented in Figures 5a and 5b when applying structural vector autoregression (SVAR) in the study by Azqueta-Gavaldón et al. (2020), confirm that the EPU increases based on ML have a significant negative shock on private consumption and business investment as expressed by machinery and equipment investment in the euro area. The effect on investment is more pronounced compared to consumption, implying that uncertainty might exert a larger influence on supply factors. This observation aligns with the research of Born & Pfeifer (2014). Addressing the sources of economic policy uncertainty, the scope is confined to energy, trade, and monetary policy uncertainties due to space limitations. As anticipated, shocks stemming from uncertainties in monetary policy exert a clearly negative impact on both investment and consumption. Conversely, an escalation in trade policy uncertainty demonstrates an inconsequential effect in both instances. Moreover, amplifications in energy policy uncertainty lead to a more substantial reduction in consumption compared to other sources, while their influence on investment, though less intense, sustains over a longer period. While these findings are based on aggregate outcomes, Economic Policy Uncertainty (EPU) is likely to exert a more substantial role in capital investment at the firm level as opposed to the aggregate level.

Figure 5a. Impulse responses of consumption

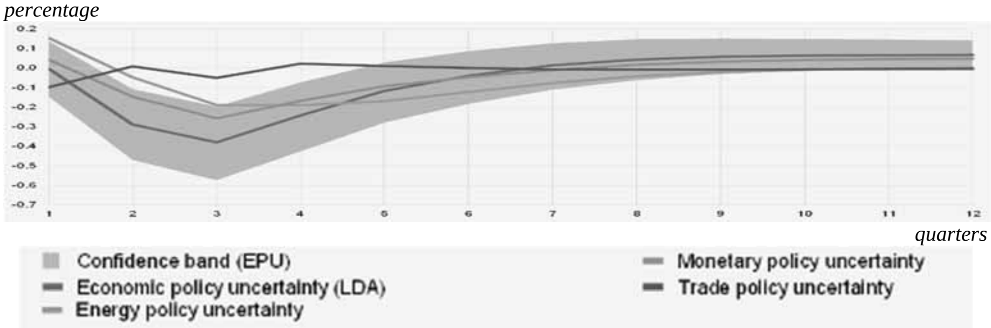
percentage



quarters

Figure 5b. Impulse responses of consumption

percentage



Source: Azqueta-Gavaldón et al., 2020.

Supporting the aforementioned findings, Gulen & Ion (2016) present evidence that the connection between political uncertainty and capital investment is not consistent across the board. Instead, it is notably more pronounced for companies characterized by greater investment irreversibility and those with heightened reliance on government expenditure. In a similar vein, Husted et al. (2020) offer documentation indicating that monetary policy uncertainty distinctly hampers investment at the firm level in the United States. Studies by Baker et al. (2016); Gulen & Ion (2016); and Meinen & Roehe (2017) report a strong relationship between investment and overall political uncertainty.

3. Potential Challenges in the Use of AI/ML in the Conduct of Monetary Policy by Central Banks

It is clear that the applications of AI/ML are undeniably leading to positive transformations in the process of conducting monetary policy by central banks, but these innovations also come with inherent risks. These challenges can be categorized into four main areas: data risks, methodological risks, interpretive risks, and ethical risks (Kinywamaghana, Steffen, 2021).

Data risks (data challenge)

Significant risks are related to the availability and quality of the used data. The challenges come from the limited access to data that is both timely and suitable for analysis, as well as from the existence of the so-called "knightian uncertainty"[20]. In his speech on October 23rd, 2018, Marc Carney, Bank of England Governor, points out that AI relies on well-defined questions and historical data to draw conclusions, such as in the case of detecting fraud or abuse in insurance valuations (Carney, 2018). Additionally, the presence of bias in the data combined with heightened correlations between them can lead to potentially procyclical behaviour, as AI/ML systems may inadvertently perpetuate existing biases.

According to Tissot (2018), highly granular and detailed data may contain confidential and personal information, which increases the risk of potential misuse by unauthorized parties. As a result, it is essential that robust procedures and safeguards are in place to protect data security. According to Santor (2021), to ensure responsible use of data it is critical that central banks establish clear standards and a governance framework. Di Castri et al. (2019) believe that the use of reliable data is essential to maintain the integrity of AI/ML-based analytics and decision-making processes. For example, samples of data collected from social media platforms may not always be representative or reliable. To address this, economists and researchers should use validation checks and apply quality control to ensure the accuracy and reliability of the information obtained.

Challenges concerning the used methodology

Integrating AI-collected data into a comprehensive information model poses challenges due to its diverse sources, formats, and structures. Ensuring seamless integration requires careful thought and complex technical processes. Establishing robust data integration frameworks and methodologies becomes critical to effectively incorporate AI-generated data into existing information models (Di Castri et al., 2019). According to Danielsson et al. (2021), AI is effective in assessing exogenous risks that are of limited relevance to macro institutions. On the other hand, endogenous risks arise from the interactions between market participants, such as regulators and financial institutions, as they pursue their goals. These are interactions with vague goals and data, established statistical techniques, and repetitive events that serve

[20] In economics, Knightian uncertainty is the absence of any quantifiable knowledge about some possible event, as opposed to the presence of quantifiable risk (e.g. that in statistical noise or the confidence interval of a parameter), https://www.learnsignal.com/.

small purposes. Periods of stress can constrain the behaviour of agents, causing behavioural synchronization and eventually major stress events or crisis.

The application of ML creates prerequisites for the emergence of reputational risk, as algorithms have stronger predictive capabilities and weak explanatory ones. As such, they can be exposed to public criticism when the gained insights are used to justify policy decisions. This situation may invite public scrutiny if the insights obtained from ML are used to justify policy decisions, as noted by Wibisono et al. (2019). Another challenge is in the so-called biased algorithms. The reason is that they tend to reproduce biases present in the underlying data. The way the data is collected can affect the results, leading to potential bias. Moreover, ML predictions can generate biased estimates of causal effects (Athey (2017).

Interpretability of models

AI-based models often lack transparency[21], making it difficult to understand how and why they reach specific conclusions. Users cannot see the inner workings of the model, only the final result (black box effect). Also, in a number of cases, complex calculations can be challenging to understand.[22] Wibisono et al. (2019) emphasize on the need for specialized expertise to work with AI systems. Specialists from private and public institutions need to possess different skills to manage an effective supervision, risk, and control environment. According to Danielsson et al. (2020), overreliance on AI by supervisory staff can have detrimental consequences. Contingency planning and preventive regulatory measures can be underestimated, leading to a false sense of security. This highlights the importance of maintaining a balanced approach and relying not only on AI for decision-making and risk management.

Ethical challenges (discrimination)

According to Prince & Schwarcz (2020), the advent of big data and AI has brought about a revolution in how companies, governments, and employers categorize individuals. This transformation presents a lot of complex challenges for anti-discrimination regulations. An evident concern is that poorly designed algorithms or flawed data can disproportionately harm specific groups of the population. Even when algorithms are well-programmed and utilize accurate data, they may still perpetuate historical discriminatory patterns. Surprisingly, however, the existing legal literature largely overlooks or misunderstands one of the most critical threats posed by big data and AI to anti-discrimination efforts. This threat involves the possibility that modern AI systems may lead to “proxy discrimination”.

Proxy discrimination refers to a harmful form of disparate impact, where a seemingly unbiased practice unfairly affects individuals belonging to a protected class. While disparate

[21] Bank to the future: supervisors take on fintech innovation - https://www.bankingsupervision.europa.eu/press/publications/newsletter/2019/html/ssm.nl191113_1.en.html.

[22] Bringing artificial intelligence to banking supervision - https://www.bankingsupervision.europa.eu/press/publications/newsletter/2019/html/ssm.nl191113_4.en.html.

impact involves practices that have unintentional unequal outcomes, proxy discrimination occurs when a second condition is met. This condition demands that the discriminator gains some advantage or benefit from the fact that the facially neutral practice produces unequal effects. This advantage can be either the intentional desire to impact the protected group disproportionately or when a legally prohibited characteristic predicts the discriminator's goals in ways that cannot be accurately represented by non-suspect data.

Conclusion

Highlighted here is how big data and AI/ML methods can complement traditional economic analysis and support central banks in conducting monetary policy. The financial crisis of 2008-2009 and the COVID-19 pandemic have accelerated the adoption and refinement of AI/ML and big data techniques. These extraordinary shocks to the economy have demonstrated the value of alternative data sources, which can provide more timely insights into the state of the economy and help monitor economic activity. Moreover, these major shocks have introduced non-linearities in the economy, necessitating adjustments to existing statistical models or the development of new approaches. ML methods are particularly well-suited to handle such non-linearities, offering advantages over traditional methods in this regard. By leveraging big data and AI/ML techniques, central banks can gain a more comprehensive and dynamic understandings of economic conditions. This, in turn, enables them to make more informed and effective monetary policy decisions, responding more proactively to economic challenges and supporting economic stability and growth.

In addition, the adoption of new data sources and methods in central banks brings forth certain challenges as well. While big data enable the use of a broader array of timely indicators like text-based or Internet-based data, they may result in duplication and reporting problems. Text-based sentiment indicators, though valuable due to their higher frequency and cost-effectiveness compared to survey-based indicators, can present unique challenges as well. The main challenge comes from the fact that alternative data sources are not primarily collected for economic analysis and lack the standardized procedures followed in conventional economic data collection. As a result, their extraction and validation are not carried out by independent statistical offices, raising concerns about the reliability and comparability of the data. The application of such alternative data in decision-making processes exposes central banks to various risks, as the reproducibility of results and accountability might be compromised. Alternative data, such as credit card transactions or news articles from digitized newspapers, often exhibit high levels of noise and require meticulous treatment. Additionally, data availability issues and restrictions on data sharing can further hinder the reproducibility of results. These risks necessitate careful consideration when investing resources in software development, addressing legal issues, and customizing IT infrastructure. To mitigate these challenges, central banks should be vigilant in ensuring data quality, implementing rigorous data validation processes, and addressing issues related to data privacy and sharing. Proper methodologies for handling noisy data and handling data discrepancies should be devised. Collaborations with relevant stakeholders, such as industry partners and academic institutions, can also enhance data credibility and reproducibility. While embracing big data and AI/ML methods offers significant benefits, it is crucial to approach their integration thoughtfully, keeping in mind the potential risks and challenges that come with using alternative data sources.

Although, while big data and ML methods offer significant advantages and can enhance economic forecasting, they cannot currently replace standard data and traditional statistical methods. ML methods can help address some of the limitations of big data and unlock its full potential. When combined with large datasets, ML methods often outperform traditional statistical techniques, providing more accurate insights into economic developments. However, the complexity of ML models can hinder their interpretability, making it difficult to understand forecast revisions and communicate them effectively. Communicating complex ML-driven forecasts to policymakers and the public clearly and understandably remains a challenge. Another significant limitation of ML methods is their original lack of focus on identifying causal relationships, which are crucial for policymakers. Improving ML techniques' ability to capture causality is currently a major area of research, and addressing this challenge could make ML methods more promising complements and alternatives to established methods. While big data and ML methods have the potential to revolutionize economic analysis, it is essential to continue refining these techniques to ensure their accuracy, interpretability, and ability to identify causal relationships effectively (Joseph, 2019). By overcoming these challenges, ML can become a valuable tool for policymakers and central bankers, providing them with more robust and actionable insights to support their decision-making processes (Farrell et al., 2021).

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Appendix 1

Participants in the conduct of monetary policy	Application of AI/ML in conducting monetary policy by central banks
European Central Bank	Truffle Analytics is a ML-based tool integrated into the Supervisory Review and Evaluation Process (SREP)[23]. Its purpose is to examine SREP procedures and decisions, enabling the ECB to recognize common patterns and trends in the operations of different banks, as well as to identify and highlight emerging trends in the industry (Hakkarainen, 2020).
	ECB collects daily data from MTS Market[24] to generate daily yield curves for the euro area. Additionally, the ECB utilizes Google data to evaluate economic indicators in real time.
	To perform volatility and resilience assessments, data from Prisma[25] are specifically utilized. The analysis conducted on specific categories within the product basket primarily centers on commodity prices.
	Joint project with Factiva[26] on text mining that enables banks to analyze qualitative data. This includes analysis of various textual sources like news articles, financial contracts, social media content, supervisory reports, market intelligence and other relevant reports.
Bank of Mexico	Joint project with the UK's Financial Conduct Authority (FCA) on web scraping and text mining audits advertising material and financial advice documents provided by financial institutions.
	Cutting-edge AI/ML system is developed to create a risk index utilizing sentiment analysis of Twitter messages. This index effectively captures the reactions of Twitter users to positive or negative shocks impacting the Mexican financial sector. Research indicates that when there are shocks affecting the index, there is a positive correlation with an escalation of financial market risk, higher stock market volatility, increased sovereign risk, and greater exchange rate volatility.
Bank of Canada	Using ML techniques, the Bank performs sentiment analysis in surveys and monetary policy reports. The application of this tool aims to improve forecasting capabilities and identify any anomalies in the data.
Bank of Greece	Bank of Greece conducts an analysis of data collected from corporate and small and medium-sized enterprise (SME) loans using data mining algorithms. The primary goal is to reduce data complexity through dimensionality reduction and enhance the accuracy of predicting the future behavior of corporate loans. This approach enables making more informed decisions, gaining deeper insights into lending patterns, and better assessing potential risks associated with corporate borrowers.
Central Bank of Sweden	Sveriges Riksbank uses ML algorithms to build the index, which includes research on fruit and vegetable prices collected daily from the internet. The main objective of this initiative is to assess whether the inclusion of these data can improve the precision of short-term inflation forecasts.
Reserve Bank of New Zealand	The Bank applies ML techniques to analyze vast real-time datasets that consist of around 550 macroeconomic indicators. The primary objective is to enhance the existing forecasting of GDP growth, including predicting the current or near-term state of the economy. Initial findings from

[23] Supervisors assess the risks banks face and check that banks are equipped to manage those risks properly. This activity is called the Supervisory Review and Evaluation Process (SREP) and its purpose is to allow banks' risk profiles to be assessed consistently and decisions about necessary supervisory measures to be made, https://www.bankingsupervision.europa.eu/.

[24] MTS is one of Europe's leading e-commerce fixed income markets, with over 500 unique counterparties and an average daily volume of over EUR 130 billion, https://www.mtsmarkets.com/.

[25] Prisma is a server library that helps developers read and write data to the database in an intuitive, efficient and safe way, https://www.prisma.io/.

[26] Factiva is a business information and research tool owned by Dow Jones & Company. Factiva aggregates content from both licensed and free sources. Providing organizations with search, alert, distribution and other information management capabilities, https://www.dowjones.com/professional/factiva/.

Participants in the conduct of monetary policy	Application of AI/ML in conducting monetary policy by central banks
	their ML experiments have shown encouraging outcomes, surpassing the performance of traditional statistical metrics commonly employed for such predictions.
Bank of Italy	An advanced monitoring system is developed to monitor consumer inflation expectations in real time. This system utilizes ML techniques and conducts text analysis on millions of Italian Twitter posts each day. The indicators derived from Twitter data exhibit a robust correlation with conventional statistical measures, indicating their reliability. They outperform other available sources in predicting monthly survey-derived inflation expectations and demonstrate an exceptional ability to accurately forecast consumer expectations.
Bank Indonesia	Bank Indonesia carries out experiments to assess the efficacy of ML techniques in identifying stakeholder expectations concerning the central bank interest rate. This entails collecting and analyzing information from publicly available news articles to gauge the anticipated stance on the interest rate. The objective is to offer valuable insights for the monthly meetings of the Board of Governors, thereby enhancing the decision-making process through better-informed inputs.
Central Bank of Chile	AI/ML system is deployed to generate a daily economic uncertainty index for Chile. This index is built through the analysis of Twitter feeds and quantifies the level of general disagreement among users, acting as a proxy for economic uncertainty regarding economic development and policies. The index displays significant spikes that align with instances of pronounced economic uncertainty arising from both domestic and international factors. This illustrates the promising use of social media data for capturing and monitoring real-time economic uncertainty effectively.
Central Bank of the Netherlands	AI utility is employed to identify liquidity challenges in banks as a preemptive measure against potential deposit withdrawals. The objective is to determine whether AI can efficiently detect early signs of liquidity issues and enhance the bank's capacity to address such problems promptly.
Central Bank of Spain	AI tool is developed to categorize banknotes as fit or unfit for circulation based on their condition. The use of this tool leads to greater efficiency and accuracy in banknote evaluation, ensuring that only suitable and quality banknotes are used in circulation, while unfit ones are dealt with appropriately.
Federal Reserve System	Big Data and ML-based tool is constructed to generate the Week Economic Index (Lewis et al., 2020), which consolidates seven weekly indicators representing the US economy. This tool effectively combines and analyzes these indicators to provide a comprehensive and timely assessment of economic health and performance on a weekly basis. This allows policymakers, businesses and analysts to make informed decisions and gain a deeper understanding of the current state of the US economy.
German Federal Bank	Big data and ML-based tool is developed for modeling the Week Activity Index.
Swiss National Bank	Through the application of ML techniques, a specialized algorithm is developed to examine the correlation between central bank independence and the evolution of inflation.
Bank of Portugal	Bank of Portugal utilizes data from the Portuguese credit register. This source is distinguished by its remarkably extensive and detailed information, comprising over 200 attributes, resulting in a large number of intricate observations.
Central Bank of Ecuador	Development of neural networks, specifically autoencoders, is employed to detect outliers in a vast volume of transactions. The primary objective is to identify unusual transactions that may warrant further investigation by the payment system oversight team. This application has proven to be highly effective in identifying a diverse range of payment transaction anomalies.
Bank of Thailand	The bank implements a ML-based anomaly detection and classification technique for banknote printing. This approach is designed to tackle the challenges of identifying defective banknotes and understanding the reasons behind their issues. The tool is built on a Convolutional Neural Network (ResNet-101), a powerful type of artificial neural network commonly used for image analysis.