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Effectiveness of ATM withdrawal forecasting methods under different market conditions

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ABSTRACT

This study aims to test the forecasting accuracy of recently implemented econometric tools as compared to the forecasting accuracy of widely used traditional models when predicting cash demand at ATMs. It also aims to verify whether the pandemic-driven change in market conditions impacted the predictive power of the tested models. Our conclusions were derived based on a data set that consisted of daily withdrawals from 61 ATMs of one of the largest European ATM networks operating in Krakow, Poland, and covered the period between January 2017 and April 2021.

The results proved that the recently implemented methods of forecasting ATM withdrawals were more accurate as compared to the traditional ones, with XGBoost providing the best forecasts in the majority of the tested cases. Moreover, it was found that the pandemic-driven change in market conditions affected the predictive power of the models. Both of these results seem particularly useful for improving the efficiency of ATM networks.

1. Introduction

Located in close proximity to almost all human settlements, automated teller machines (ATMs) play a major role in the process of satisfying society's demand for cash, with estimates indicating that there are now more than three million of them worldwide. From a theoretical point of view, one may distinguish between two main strategies of cash management in the ATM network – the reactive approach, and the proactive approach (Yang et al., 2005; Henttu-Aho, 2018; Poll et al., 2018). The reactive method is based on loading (unloading) cash in ATMs when the amount of cash at a given cash point drops to a certain level (exceeds a defined upper limit). The advantage of this approach is the lack of excess cash deposits in the ATMs, which in turn minimizes the costs of “freezing” the cash. However, this method simply leads to more periods with insufficient cash levels in ATMs since transports that are ordered in an ad hoc manner may not always arrive on time.

Given the above, an alternative management strategy (called the proactive approach) is usually adopted by practitioners; it is based on predicting deposits and withdrawals, which allows one to plan cash transports in advance so as to ensure adequate amounts of money in cash centers and to adapt to the transport capacity of the transporting company. This solution is not only free from the disadvantages of the reactive method but is even more cost-effective than its counterpart, as the synchronization of transports to neighboring points allows us to reduce transportation costs (since scheduled orders are much cheaper than ad hoc transports).

To prevent the ATMs from running out of cash, managers often decide to deliver and store significantly more cash in a device than usually needed (Simutis et al., 2007a). However, such a strategy simply leads to higher operating costs that result from the need to prepare the cash, “freeze” it, and transport it (Batı and Gözüpek, 2017; Ekinci et al., 2015, 2021). Those activities that generate costs that are related to cash management (which mainly consist of the preparation and transport of cash, “freezing” the cash, and returning any undisbursed cash) may account to up to 50 % of the total costs of operating an ATM network (Simutis et al., 2007a; Suder, 2015; Arnfield, 2017). In addition, these estimates do not include those costs that are difficult to determine; e.g., costs that are related to the loss of potential commissions on withdrawals. From both the theoretical and practical points of view, a crucial question in this context is how to define an optimal cash-management process that ensures an appropriate level of cash at ATMs and allows us to maintain operational efficiency while minimizing the risk of theft and fraud. The first step to answering this question requires us to select the most accurate methods of forecasting ATM withdrawals.

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The methodology of forecasting that is used in proactive management is a well-developed field of science. The selection of forecasting methods and the assessment of their potential applicability are to some extent based on a visual inspection of the historical data on the demand for cash (although many systems that are used by network operators take additional factors into account, such as local events, urban plans, and even weather forecasts). The historical data reflects information on those regularities that are related to the use of ATMs by network customers that are usually driven by calendar effects and special days or periods of a year. This data also includes information about the individual preferences and habits of consumers who use a given ATM or a set of ATMs in a given network. Thus, it is not surprising that ATM network operators usually rely on the use of traditional forecasting tools (usually, SARIMA-based techniques) – possibly extending them with calendar or 'special day' effects.

However, a change in market conditions or the emergence of new environmental factors may significantly affect the behaviors of ATM users, which hinders the process of data analysis and, consequently, reduces the predictive power of time-series-based models. Due to the associated total or partial lockdowns, the COVID-19 pandemic had a significant impact on patterns of cash demand and withdrawals. The outbreak of the pandemic caused a shock to global demand for cash in ATMs, which was reflected in the huge rise of volatility of withdrawals and sharp changes in the withdrawal patterns of different countries (Cronin and McInerney, 2022; Suder et al., 2023). The market conditions during the pandemic could have also significantly reduced the accuracy of the forecasting models that were used in ATM network management systems.

The latter allows one to locate a significant research gap in the literature, as analyzing the forecasting accuracy of various econometric techniques under different market conditions has not been given sufficient attention thus far. Conducting such an analysis is both timely and necessary, as it could efficiently support cash-management systems – especially during periods of rapid changes.

The main aim of this study is to test the forecasting accuracy of two recently implemented econometric tools (i.e., the machine-learning-based XGBoost technique [Wade and Glynn, 2020], and the two-dimensional Bayesian VAR model [Karlsson, 2013]) and compare them to the accuracy the traditional models that are widely-used in practice (namely, SARIMA-based models [Box et al., 2015]) when predicting cash demand at ATMs. The motivation behind the choice of the two alternative models is rather straightforward. The financial industry has already witnessed the successful application of XGBoost in tasks such as forecasting and time series analysis (Sirignano and Cont, 2019; Jiang et al., 2017); surprisingly, however, the forecasting accuracy of the tool has not been thoroughly tested for ATM withdrawal data up until now.[1] Given the well-documented performance of XGBoost in other areas of financial econometrics, it seems fully justified to test whether the method can also turn out to be an effective tool in the particular case of forecasting ATM withdrawals. To the best of the authors' knowledge, the second mentioned method (i.e., BVAR) has not been used in forecasting the sizes of withdrawals from ATMs. Compared to the one-dimensional time-series models, this novel approach is based on the two-dimensional vector approach that additionally uses the data from the numbers of withdrawals from ATMs to forecast the sizes of the withdrawals. From the point of view of ATM network operators, data on the numbers of withdrawals is fully available; this makes the application of the two-dimensional approach effortless.

A comparison of the forecasting accuracy of the models was made during both a stable period (i.e., the period before the outbreak of the COVID-19 pandemic) and a period of market turmoil (i.e., the period that covered the start of the COVID-19 pandemic). In addition, this article verifies whether market conditions differentiate the structure of ATM withdrawals (especially when it comes to the presence and intensity of seasonal and calendrical effects in time series of daily withdrawals) as well as the predictive power of the tested models.

The empirical research was based on analyzing the daily withdrawals of one of the largest operators of ATM networks in Europe. The analyzed time series came from 61 ATMs that were installed in Krakow, Poland. The data covered the period from January 2017 through April 2021.

The remainder of this paper is organized as follows. The literature review section provides an overview of former studies on the topic. The methodology section presents details on the methods and processes that were used. The empirical results section outlines the main results and provides the respective interpretation. Finally, the concluding section summarizes the results and indicates the main directions for future research.

2. Literature review

As underlined in the introductory section, the accurate forecasting of withdrawals from ATMs plays an important role in cash management. These predictions depend on mapping the structures and patterns in time series of withdrawals (e.g., calendrical and seasonal effects) that are driven by the behaviors and preferences of consumers as well as the events that essentially impact market conditions. Therefore, we focused on two aspects when reviewing the literature: payment behavior and its impact on both the structure of ATM withdrawals (including COVID-19-specific effects), and the methods and models that are applied in forecasting ATM withdrawals.

2.1. Consumer cash withdrawal behavior

Regarding cash and cashless transactions, consumer behavior has exhibited contradictory trends over the past decades. Initially, there was a decline in cash demand with the growing popularity of cashless payment methods and e-commerce transactions (Pietrucha and Maciejewski, 2020). However, cash demand has remained surprisingly resilient in recent years (Jiang and Shao, 2020), resulting in a paradoxical persistence of high cash demand (Jiang and Shao, 2020; Pietrucha and Maciejewski, 2020); this in turn has led to an increase in ATM withdrawals. These contrasting dynamics highlight the intricate and evolving nature of payment preferences in contemporary society. Bruno and Faggini (2022) explained that consumer preference for handling cash was influenced by various factors, but the primary driving force behind cash usage was the precautionary reserve motivation (which serves as a storage function). Pietrucha and Maciejewski (2020) found that consumers often perceived a certain level of risk that was associated with card and mobile payments, leading them to maintain cash reserves for precautionary purposes. The decision to hold cash reserves was influenced by factors such as the consumer's level of trust in electronic payments, attitude toward risk, income, and age. Overall, the significance of perceived risks in elucidating a consumer's choice of payment instruments has been emphasized in the literature. Karoubi et al. (2016) stressed the crucial role of cash unavailability risk in shaping consumer behavior with respect to payment methods, which explained the prevalence of cash withdrawals over time.

Moreover, the roles of perceived unavailability risks and precautionary reserve motivations have become particularly prominent during crises. The financial crises in the early decades of the 21st century were accompanied by a decline in trust in financial institutions, resulting in a greater preference for cash (Bátiz-Lazo et al., 2014; Jiang and Shao, 2020). This can lead to a hoarding behavior, as individuals choose to accumulate cash reserves in order to enhance their perceived security and mitigate potential issues that arise from disruptions in the financial system (such as the temporary unavailability of cash in ATMs). Bátiz-Lazo et al. (2014) suggested that this trend tended to be reversed as the economy recovered and confidence in the banking system was restored.

[1] In the literature, we could not find any application of XGBoost in forecasting ATM withdrawals.

Accordingly, there was an increased inclination for ATM withdrawals during crisis periods, which gradually returned to normal levels afterward.

Studies on consumers' broader payment habits and behaviors during the COVID-19 crisis have highlighted the decline in physical cash usage (Cevik, 2020; Lu and Kosim, 2022) and the accelerated adoption of digital technologies (Cevik, 2020; Das et al., 2020), which led to a general reduction in ATM withdrawals. These changes were often fostered by cashless initiatives undertaken by several governments and central banks across the globe as a measure for reducing contact with

Table 1
Methodology of forecasting withdrawals from ATMs – literature review.

Family of methods	Authors	Methods used	Different market conditions	Data set
Parametric methods	Gurgul et al. (2023)	TBATS models	Not examined	Data from 74 ATMs from January 1, 2017, through December 31, 2019
	Gurgul and Suder (2016)	ARIMA	Not examined	Euronet data of 222 ATMs; January 2010 through December 2012
	Ding et al. (2018)	Similarity-enhanced collaborative filtering and ARIMA model	Not examined	4532 distributed services from 142 computers in 57 countries
	Wadi et al. (2018)	ARIMA	Not examined	Non-stationary data, becoming stable after 1200th observation
	Barrow et al. (2020)	Automatic robust estimation for exponential smoothing	Not examined	Multiple real-world data sets
	Lim and Zohren (2020)	Deep learning	Not examined	Survey
	Broda et al. (2014)	ARIMA, exponential smoothing	Not examined	Three-year data from bank in Serbia
	Baker et al. (2013)	Heuristic combination of parametric methods	Not examined	Cash withdrawal data from 21 ATMs owned and operated by financial institution
	Tadesse and Fayera (2021)	Multinomial and ordered logit model	Not examined	Commercial Bank of Ethiopia; 168 ATM holders interviewed; data collected from January through February 2019
Non-parametric methods	Ekinci et al. (2015)	Machine learning	Not examined	Aggregated ATM and time-interval data from Turkey
	Ekinci et al. (2021)	Machine learning	Not examined	Location, demographic, and withdrawal amounts from single ATM in Turkey
	Canser and Doseyen (2018)	Machine learning	Not examined	Data from 307 branches and 378 ATMs in Turkey; January 2015 through June 2016
	Simutis et al. (2007b)	Levenberg–Marquard algorithm, artificial neural network	Not examined	Simulated and experimental data from 15 ATMs in Lithuania
	Simutis et al. (2008)	Artificial neural network, support vector regression	Not examined	Simulated and experimental data from 15 real ATMs in Lithuania was used
	Crone (2008)	Artificial neural networks, computational	Not examined	ATM withdrawal data in Turkey; July 31, 2012, through August 1, 2013
	Onur (2019)	Computational intelligence	Not examined	ATM data including withdrawal amounts and transaction dates from July 31, 2012, through August 1, 2013, in Turkey
	Andrawis et al. (2011)	Computational intelligence	Not examined	Daily time series with strong day-of-the-week, moderate day-of-the-month, and moderate month-of-the-year seasonality
	Ramírez and Acuña (2011)	Multi-layered perceptron neural network	Not examined	Data from NN5 competition; 30 series of ATM withdrawals for training, and additional 11 series for benchmarking
	Coyle et al. (2010)	SOFNN (self-organizing fuzzy neural network)	Not examined	One hundred and eleven daily empirical time series of cash-machine withdrawals from competition data set
	Wichard (2011)	Hybrid model (neural network ensemble, ensemble of nearest trajectory models, 7-day cycle model)	Not examined	One hundred and eleven daily time series of cash money withdrawals from ATMs from different locations in England
	Jadwal et al. (2017)	Neural networks	Not examined	NN5 reduced data set, 11 time series from total of 111
	Teddy and Ng (2011)	Local learning	Not examined	One hundred and eleven daily time series from NN5 competition
	Taieb et al. (2012)	Multiple-output strategies	Not examined	One hundred and eleven series from NN5 forecasting competition
	Venkatesh et al. (2014b)	General regression neural networks	Not examined	NN5 timeseries competition, daily cash withdrawals over 2 years from 111 ATM centers in UK
	Sarveswararao and Ravi (2020)	Chaos theory, deep learning, machine learning	Not examined	Forty ATMs in India, missing values input with median
	Arabani and Komleh (2019)	Statistical Tools, ANN, SVM, CNN	Not examined	Daily withdrawal data from Iranian banking network
	Kamini et al. (2014)	Chaotic time series analysis combined with neural networks	Not examined	One hundred and eleven daily time series representing daily withdrawal amounts
	Makridakis et al. (2018)	Machine learning vs. statistical tools	Not examined	Survey
	Nemeshaev and Tsyganov (2016)	Neural networks	Not examined	Daily cash withdrawal data from Yekaterinburg, Russia, from July 1, 2014, through March 1, 2015
	Żylius (2015)	Computational intelligence	Not examined	Data from 8 different ATMs; historical data from up to 990 days
	Larrain et al. (2017)	Mixed-integer programming	Not examined	ATM withdrawals in Santiago, Chile
	Seyedeh et al. (2020)	CRISP-DM (cross industry standard process for data mining)	Not examined	Data gathered from ATM manufacturing company
	Denstad et al. (2021)	Multi-objective mathematical programming	Not examined	Data based on coordinates of each ATM; retrieved from Google Maps
	van der Heidea et al. (2020)	Mixed integer programming	Not examined	Two data sets of actual withdrawals from Geldmaat, operator of ATMs of three major banks in The Netherlands
	Fallahtafti et al. (2022)	Machine learning vs ARIMA/SARIMA	Examined (COVID-19)	Daily cash withdrawal data from ATMs from various districts in Tehran, Iran (March 21, 2017, through March 19, 2020) split by COVID-19 observation period

cash and, hence, reducing the probability of spreading the virus (Bruno and Faggini, 2022; Cevik, 2020; Fallahtafti et al., 2022; Lu and Kosim, 2022; Suder et al., 2023). Lu and Kosim (2022) found that, during a crisis, consumers showed a higher behavioral intention to adopt cashless payments.

However, consumers may exhibit a preference for keeping cash readily available at home as a dependable alternative – particularly during periods of uncertainty (such as during the COVID-19 pandemic) (Karoubi et al., 2016). This preference arises from the perceived risk of potential disruptions or the unavailability of digital payment systems during times of crisis. Consequently, individuals prioritize cash as a quick and consistently accessible payment instrument, ensuring transactional security and reliability (Karoubi et al., 2016). In line with this, Suder et al. (2023) uncovered the volatility of ATM withdrawals during the pandemic by showing that, despite the overall decrease in cash demand during the pandemic, its initial phase was characterized by uncertainty and witnessed a substantial rise in the total daily value of withdrawals. The authors suggested that the crisis generated a sense of insecurity among the public, leading to a preference for cash and the subsequent ATM withdrawals (Suder et al., 2023); hence, this resulted in cash hoarding. However, this initial rise in withdrawals was followed by a significant decline in both the total value and the number of transactions (which was in line with the suggestions of Bátiz-Lazo et al., 2014). Factors such as the accumulation of cash reserves, imposed restrictions, and the growing prevalence of cashless payments likely contributed to this decline (Suder et al., 2023).

It is interesting to note that the previous research has demonstrated that ATM withdrawals have exhibited notable calendrical effects and seasonal patterns. This was illustrated by Rodrigues and Esteves (2010), who examined the day-of-the-week, week-of-the-month, and month-of-the-year effects as well as the influence of holidays in Portugal. This evidence was further supported by a study that was conducted by Gurgul and Suder (2016), which revealed that ATM withdrawals varied significantly based on the day of the week. Fridays consistently exhibited higher cash withdrawals as compared to the other days, while Saturdays and Sundays experienced the lowest levels of withdrawals. Additionally, money withdrawals were found to be influenced by the weeks when people typically received their wages (such as the beginnings or ends of each month). Furthermore, seasonal factors also contributed to the withdrawal patterns, with the largest amounts being withdrawn in July, August, and December. This increased demand for cash could be attributed to the summer holidays and the Christmas season. However, these studies demonstrated that, when considering calendrical and seasonal effects, ATM withdrawal behavior tended to remain stable over time, which allowed for the possibility of forecasting.

2.2. Modeling and forecasting of withdrawals from ATMs

When forecasting ATM withdrawals, two general classes of methods are usually applied: parametric techniques, and non-parametric techniques. In this section, we seek to elucidate the originality of our research as it is related to previous studies. We summarized the key literature in Table 1, focusing on studies that have made significant contributions to the field as indicated by citation metrics and the availability and quality of full papers.

Our criteria for inclusion also emphasized the practical applicability of novel forecasting methods and examinations of the impacts of different market conditions on forecasting accuracy. It is essential to understand how adaptable these models are in the face of rapid and unprecedented changes in consumer behavior and market dynamics.

Table 1 provides a detailed review that highlights the methodologies, used data, key findings, and limitations of each study. This allowed for a comprehensive understanding of the current landscape of ATM withdrawal forecasting and identified gaps that our study aimed to fill – particularly in the context of machine-learning applications and the influence of market disruptions like the COVID-19 pandemic.

Two major conclusions can be drawn from the review of methods that were used in the previous studies on forecasting ATM withdrawals: 1) despite a thorough review of the literature, we only found a single study by Fallahtafti et al. (2022) that addressed the COVID-19 period. This underscores a gap in the literature regarding the forecasting of ATM withdrawals during significant market changes, thus highlighting the relevance and timeliness of this paper; and 2) a review of the references in Table 1 reveals the absence of a consensus on a single method or group of methods that can be unequivocally recommended for forecasting ATM withdrawal time series. In this context, exploring new or rarely used methods can significantly contribute to the body of research concerning the management of ATM networks. In this study, we turned our attention to two such methods (XGBoost and BVAR), with their selections justified in the sections below. Time series data comprised a sequence of observations that were collected at regular intervals, often characterized by temporal dependencies, seasonality, and trends (Prado and West, 2010; Hyndman and Athanasopoulos, 2018). The accurate forecasts of financial variables such as stock prices, economic indicators, or credit default rates are crucial for informed decision-making in areas like investment, risk management, and policy planning. XGBoost's effectiveness in time series forecasting stems from its capacity to capture complex nonlinear relationships among variables and its ability to process noisy high-dimensional data (Sirignano and Cont, 2019; Jiang et al., 2017). By engineering features that incorporate historical data, temporal dependencies, and external factors, XGBoost can identify intricate patterns and dependencies within data, leading to more-accurate forecasts (Prado and West, 2010; Hyndman and Athanasopoulos, 2018). Moreover, the algorithm's built-in regularization techniques help prevent overfitting – a common challenge in time series analysis where models may become excessively specialized to training data and fail to generalize well to new data (Prado and West, 2010; Hyndman and Athanasopoulos, 2018). Consequently, XGBoost has emerged as a valuable resource for financial practitioners who seek to make data-driven decisions based on reliable and precise forecasts. Given its popularity in financial econometrics, one may claim that XGBoost can also turn out to be an effective tool in the particular case of forecasting ATM withdrawals.

To the best of authors' knowledge, the second method that was mentioned (i.e., BVAR) has not been used in the forecasting of the sizes of withdrawals from ATMs. The reason behind choosing the Bayesian framework follows from the fact that previous studies have suggested that, if a set of data is of low quality, then traditional maximum-likelihood VARs are often over-parameterized and imprecisely estimated (Doan et al., 1984). This explains why the approach that is based on the application of Bayesian techniques has recently become increasingly popular – mainly thanks to its good forecasting performance (c.f. Banbura et al., 2010, Canova and Ciccarelli, 2013, Giannone et al., 2015, Gneiting and Raftery, 2007, Schorfheide and Song, 2016, Villani, 2009, and Waggoner and Zha, 1999, among others). What matters most, the Bayesian approach takes not only the information that is stored in a given dataset into account but also the prior knowledge and expectations of the researcher (this is contrary to the frequentist approach). Technically, the main principle of Bayesian analysis is to mix the knowledge that an analyst has about the distribution for the parameters of a given VAR (the prior distribution) with the information that is present in the data (the likelihood function) in order to obtain the posterior (updated) distribution.

To summarize, the review of the forecasting methods that were used in the previous literature suggested that there was not a single forecasting method that would exhibit the best performance in the cases of alltime series of ATM withdrawals. In particular, the above claim implies that there is a strong need for testing the forecasting performance of the BVAR and XGBoost methods in the case of ATM withdrawal data during both stable and unstable periods. In particular, one could expect that the accuracy of the forecasts of ATM withdrawals was lower during the COVID-19 subperiod than it was during the period that preceded the outbreak of the pandemic.

3. Methodology

To enhance the accuracy of the forecasting of cash withdrawals, we explored and compared various methods. Our focus was on the traditional tool that was used by the data provider (i.e., the SARIMA model), ML-based techniques that were rarely used in the forecasting of ATM withdrawals (such as tree-based models – primarily XGBoost), and a novel approach that was based on a two-dimensional Bayesian VAR model. Apart from utilizing data on the sizes of withdrawals, the VAR innovative model also incorporates easily accessible data on the numbers of ATM withdrawals.

3.1. Data and sample collection

In the conducted research, data from ATMs that were managed by one of the largest independent ATM network operators in Poland was utilized. At the time of this writing, this operator also operated in 17 other countries worldwide. The operator provided data on the daily withdrawals from 78 ATMs that were located throughout the city of Krakow. Due to the fact that some of the ATMs experienced longer breaks during the pandemic period, a total of 61 time series of ATM withdrawals were ultimately analyzed (from January 2017 through April 2021). The research also used time series of the total cash demand from the selected ATMs. The withdrawal data currency that was used in this research was in Polish Zloty (PLN).

The top panel in Fig. 1 displays a time series of the cumulative daily cash demands in all of the ATMs during the considered period. On the other hand, the middle and bottom panels in Fig. 1 present the time series of two specific ATMs (ATMs 36 and 46 in the data set). Due to the objective of the study (which was focused at comparing the withdrawal patterns before COVID-19 and during the pandemic), the data sets from the periods of January 2017 through February 2019 and March 2019 through April 2020 were marked in different colors.

The withdrawal data from the two ATMs that are shown in Fig. 1 was carefully selected based on contrasting characteristics of the ATMs: ATM 36 represented an average ATM with its mean cash withdrawal being close to the overall dataset median, while ATM 46 exhibited the highest mean cash withdrawal. By focusing on these diverse ATMs, we aimed to provide valuable insights into the impact of the COVID pandemic on cash withdrawal patterns.

To provide an overview of the data distribution that represented the daily cash demand, Fig. 2 displays boxplots for the withdrawals from all of the ATMs combined, while Fig. 3 presents box plots for each individual ATM separately.

The boxplots in Fig. 3 offer a comprehensive view of the cash withdrawal trends across all of the ATMs; they also compare the pre-COVID and COVID periods. By examining the distribution of withdrawals from each ATM, we can easily identify changes in the patterns and demand levels during these two distinct timeframes.

The data set encompasses 61 ATMs, revealing varying cash-withdrawal patterns across numerous locations. While some ATMs exhibited high average daily withdrawal amounts, others showed relatively lower demand. The standard deviations of these ATMs also differed, suggesting a variation in the consistency of the withdrawal behaviors. Additionally, the minimum withdrawal amounts across all of the ATMs were predominantly zero, while the maximum withdrawal amounts displayed significant discrepancies.

Furthermore, noticeable differences could be observed among the 25th, 50th (median), and 75th percentiles; these indicated diverse withdrawal patterns at different ATMs. In general, the data highlighted a wide range of ATM withdrawal behaviors, reflecting diverse customer preferences and usage patterns.

Focusing on the differences between the pre-COVID and COVID periods, it is important to investigate the impact of the pandemic on ATM cash withdrawal trends. This could involve examining changes in the means, medians, and standard deviations of the withdrawals as well as identifying any potential seasonal effects or shifts in the withdrawal patterns across the selected ATMs during these periods.

A comparison of the pre-COVID and COVID summary statistics revealed some noticeable differences in the ATM withdrawal data across the various ATMs.

During the COVID-19 pandemic, the average daily ATM withdrawal level decreased from 52,067 to 37,900 PLN, which indicated that the customers were generally withdrawing less money from the ATMs during the pandemic as compared to the preceding period. This decrease could be attributed to reduced income, changed spending habits, or the increased use of digital payments.

The standard deviation of the mean withdrawals also decreased from 22,058 to 17,629 PLN, suggesting that the variations in the withdrawal amounts among the ATMs became smaller during the pandemic. This might imply that the customer withdrawal behaviors became more uniform across the different locations.

The minimum values for the mean and standard deviation statistics were also lower during the pandemic. The minimum mean withdrawal amount dropped from 2918 to 2526 PLN, while the minimum standard deviation decreased from 4863 to 3268 PLN. This indicated that the lowest withdrawal amounts and variations among the ATMs were even lower during the pandemic as compared to pre-COVID times.

The 25th percentile values for the mean and standard deviation also showed a decrease during the pandemic. The 25th percentile for the mean dropped from 36,836 to 26,480 PLN; for the standard deviation, this quartile decreased from 9238 to 7192 PLN. These changes suggested that the lower quartile of ATMs experienced more-pronounced reductions in their withdrawal amounts and variation.

On the other hand, the maximum values for the mean and standard deviation were higher during the pandemic. The maximum mean increased from 138,822 to 146,007 PLN, and the maximum standard deviation rose from 40,262 to 52,261 PLN. This might have indicated that a few ATMs experienced increases in withdrawal amounts and variations during the pandemic; this was possibly due to changes in customer behavior or location-specific factors.

Overall, the comparison of the pre-COVID and COVID ATM withdrawal data highlighted a general decrease in the withdrawal amounts and variation among the ATMs in Poland (with some exceptions for the maximum values).

3.2. Seasonal and calendrical effects

As previously mentioned, seasonal and calendar effects reflect the behaviors of ATM users. The skillful detection, analysis, and subsequent incorporation of these effects into econometric models are important elements in the entire process of the forecasting of ATM withdrawals. At the initial stage, primary attention is paid to determining which seasonal and calendrical effects should be considered. Based on the suggestions from the literature review as well as the types of specific and cyclical events in Poland (including holidays), the following seasonal and calendrical effects were considered in this study:

I. Day of the week: this effect assumes that ATM withdrawals significantly differed for different days of the week.
II. Month of the year: this implies that withdrawals may significantly increase in certain months.
III. Special days (SD) in the year: this effect assumes that specific calendar days (such as holidays, long weekends, and commemorative events) have significant impacts on the volumes and levels of ATM withdrawals. These events can cause variations in withdrawal patterns, and their inclusion in a predictive model can significantly enhance the accuracy and quality of the forecasts. In this study, ten such special events were considered: work-free holidays like Easter and Christmas (henceforth denoted

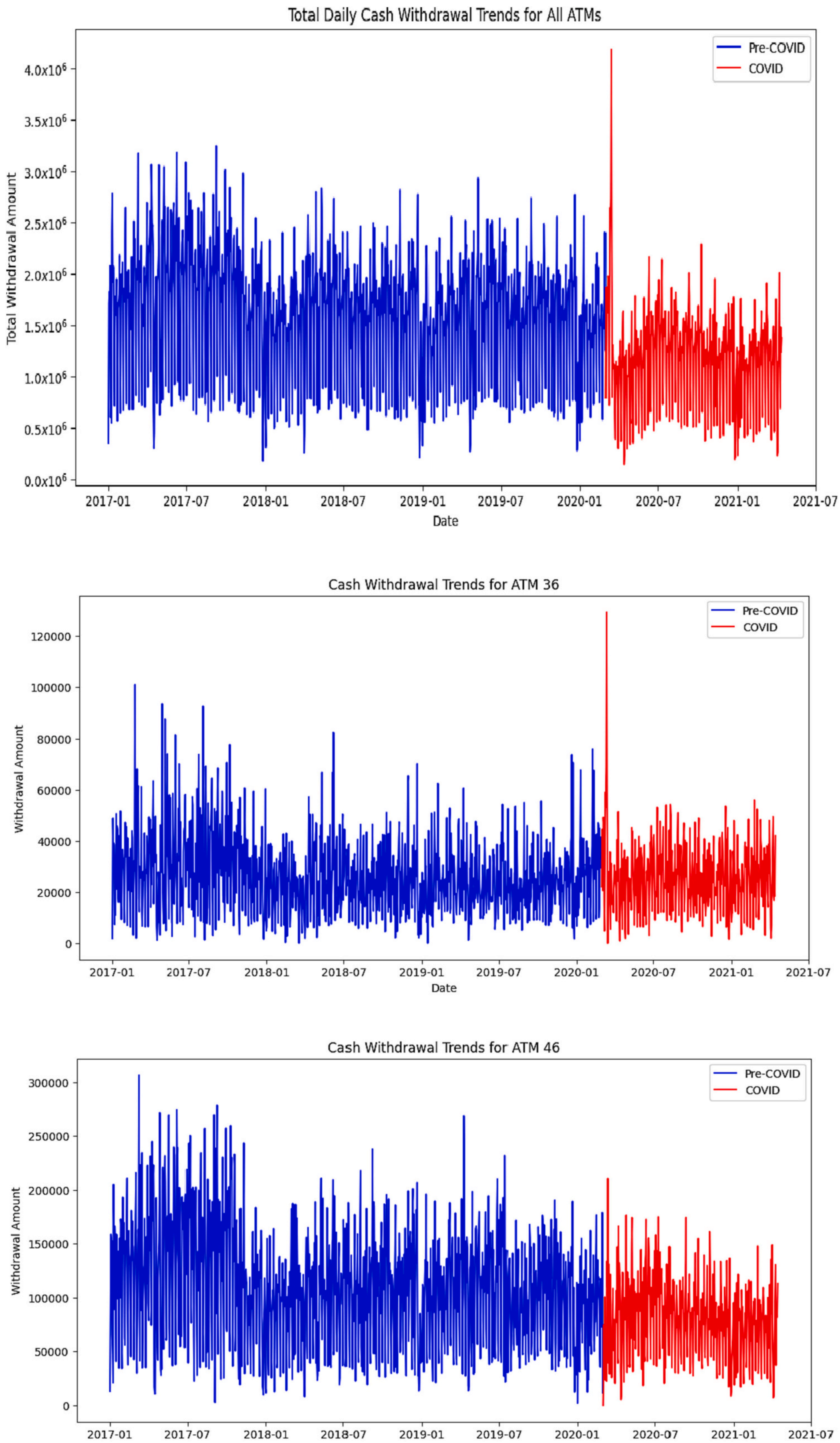

Fig. 1. Cash withdrawal trends for all ATMs, ATM 36, and ATM 46 during pre-COVID and COVID periods.

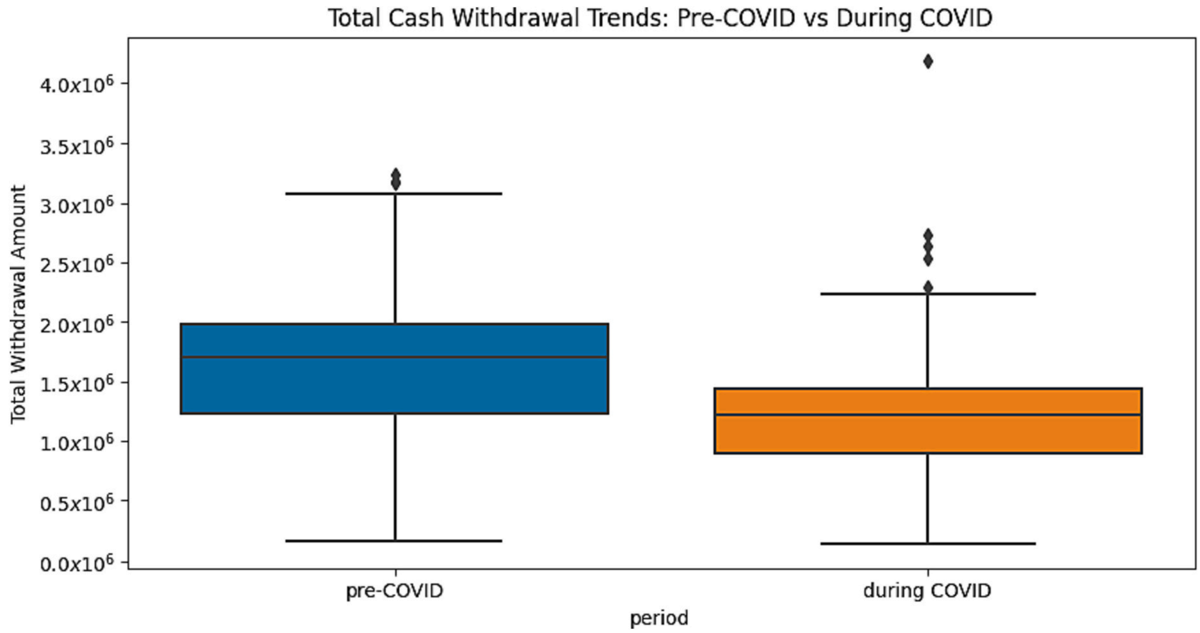

Fig. 2. Comparison of total cash withdrawal distributions for all ATMs: pre-COVID vs. COVID periods.

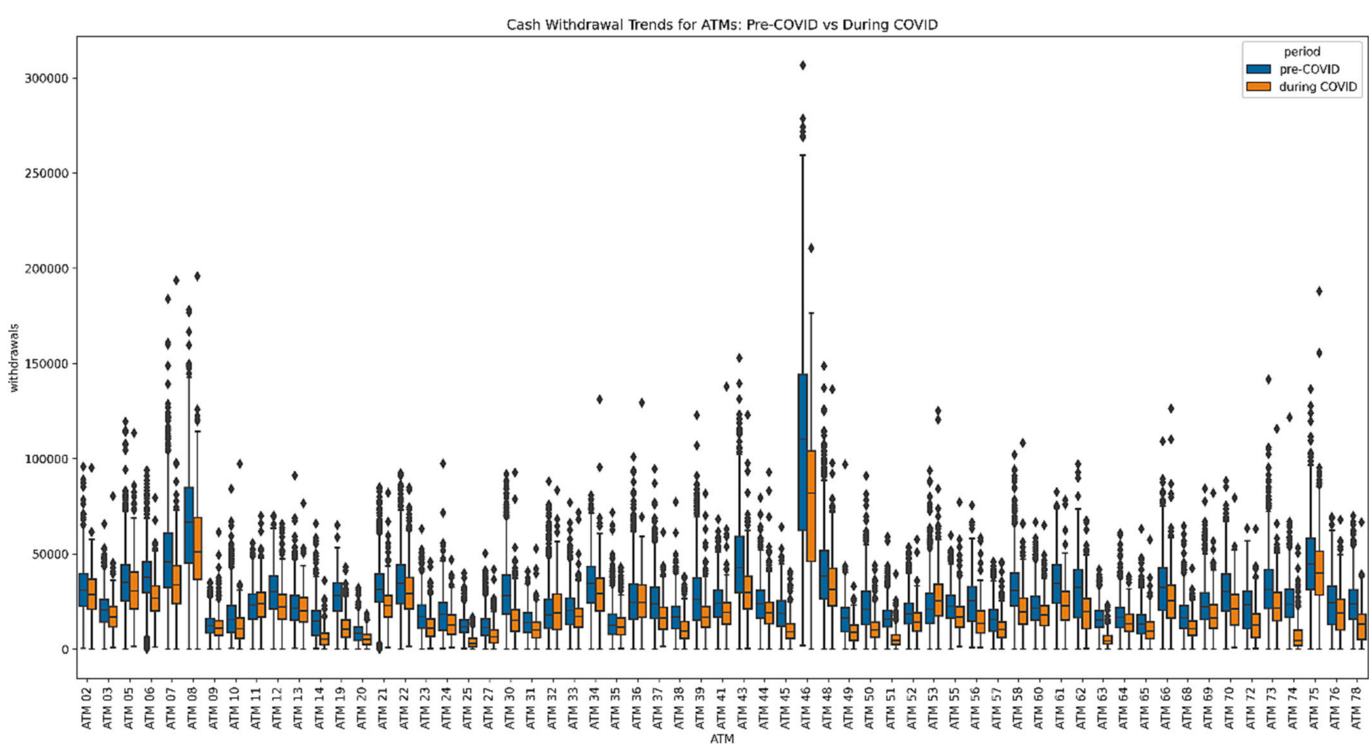

Fig. 3. Comparison of cash withdrawal distributions across all ATMs: pre-COVID vs. COVID periods.
Note: Each boxplot represents distribution of cash withdrawals for specific ATM (pre-COVID periods in blue, and COVID periods in orange) highlighting differences in demand levels and patterns between two timeframes.

as SD1); the tenth day of each month, when wages and salaries are commonly paid in Poland (SD2); the first day of each month (SD3); the last day of each month (SD4); trading Sundays (SD5); the starts of long weekends (SD6); the ends of long weekends (SD7); the days before the starts of long weekends (SD8); the days after the ends of long weekends (SD9); and special occasions such as Valentine's Day, Mother's Day, and St. Nicholas Day (SD10).

3.3. Methods and procedures

To investigate the temporal variations in the ATM withdrawals during the COVID and pre-COVID periods, we employed a statistical approach that involved a two-sample *t*-test, followed by a Bonferroni correction for multiple testing (Bland and Altman, 1995). For each ATM, we computed the average withdrawals for each day of the week. A two-sample t-test (a widely used procedure for comparing two population means (Crawley, 2005)) was then performed for each ATM and day of the week pairing – contrasting the withdrawals on the specific day against the withdrawals on the remaining days.

Given the multiple comparisons made – one t-test for each ATM and day of the week pairing – we addressed the risk of Type I errors (false positives) through the application of the Bonferroni correction (Dunn, 1961). This procedure adjusted the significance level by the number of comparisons that were made, thus effectively controlling the familywise error rate. The significant results were identified based on an adjusted p-value of <0.05.

To reach the second main goal of the study (i.e., to forecast the ATM withdrawals with the highest possible accuracy), we used a triple of forecasting methods that have shown great promise for the application of predicting ATM cash withdrawal demand: the SARIMA model (often used to forecast ATM withdrawals), XGBoost (an ML-based technique), and BVAR (a two-dimensional VAR approach that has never been applied in the context of ATM withdrawal-forecasting problems).

3.3.1. SARIMA method

SARIMA, or seasonal autoregressive integrated moving average, is a well-established model in time series forecasting; it remains a standard choice for its proficiency in identifying linear patterns, trends, and seasonality (Shumway and Stoffer, 2010). In our computations, we used open-source R and IDE RStudio statistical software. In order to estimate the SARIMA models, we used the SARIMA function in the core stats package. What is noteworthy, this function allows one to use dummy variables that reflect calendrical effects and special day effects.

3.3.2. XGBoost method

XGBoost is a cutting-edge machine-learning algorithm that is based on gradient-boosted decision trees; it is known for its ability to capture intricate nonlinear relationships and adeptly manage high-dimensional data. In recent years, the XGBoost algorithm has emerged as a powerful and efficient machine-learning tool, gaining considerable attention in various fields (including finance) (Chen and Guestrin, 2016). Developed by Tianqi Chen and Carlos Guestrin, XGBoost builds upon the principles of gradient-boosted decision trees, which have shown remarkable proficiency in handling diverse types of structured and unstructured data (Chen and Guestrin, 2016). The XGBoost algorithm employs a technique that is known as boosting, which combines multiple weak learners – individual decision trees with limited predictive power – into a single robust model that is capable of making accurate predictions of complex problems.

The intuition behind XGBoost revolves around iteratively constructing a series of decision trees, with each subsequent tree aiming to correct any errors that were made by its predecessors (Chen and Guestrin, 2016). This is accomplished by optimizing an objective function that quantifies the differences between true target values and the model's predictions. By minimizing this objective function, the algorithm adjusts the weights of individual trees, resulting in improved overall predictive accuracy. One of the strengths of XGBoost is its customizability, as users can fine-tune various hyperparameters (such as tree depth, learning rate, and regularization terms) in order to tailor the model to specific problems (Chen and Guestrin, 2016).[2]

3.3.3. BVAR method

If one wants to take not only the location- and client-related specificity of an examined ATM into account but also the possible links between number and size of the ATM's withdrawals, a specific class of quantitative tools seems especially appropriate for the purpose of econometric modeling – vector autoregressive (VAR) models. BVAR, or Bayesian vector autoregression, is an innovative extension of the VAR model that employs Bayesian techniques to impose shrinkage on the parameters, making it especially fitting for situations with limited data and numerous variables.

Five different prior formulations of Bayesian VARs (BVAR) were examined for each two-dimensional model: the Minnesota prior, normal-Wishart prior, independent normal-Wishart prior, normal-diffuse prior, and dummy observation prior. All of the BVAR models were constructed using the latest release of the Bayesian estimation, analysis, and regression (BEAR) toolbox. Developed at the European Central Bank, BEAR is a MATLAB-based toolbox that allows non-technical users to understand, augment, and adapt Bayesian VAR models for various purposes (including policymaking). The GUI version of BEAR includes a user-friendly graphic interface that allows the tool to be used by country desk economists. For the purpose of this paper, however, we used the advanced developer version of BEAR that gives the user access to complete MATLAB codes with implementations of the five Bayesian identification schemes that are listed above. When accompanied with the possibility of programming in MATLAB, this feature opens a way for conducting professional analyses on a large number of BVAR models. In order to choose the hyperparameters in all of the examined BVAR models, we followed the procedure of Giannone et al. (2012), which allowed us to optimize the values of the hyperparameters by maximizing the value of the marginal likelihood for each given BVAR model.

Each of the described methods offers unique advantages and can be customized for the specific task of ATM cash-withdrawal forecasting, thus providing valuable insights for decision-makers in the banking and financial sectors.

3.4. Methods of forecast comparison

In order to compare the accuracy of the examined methods in predicting ATM cash withdrawal demand, we conducted a respective analysis across eight distinct two-week periods: four before the onset of the COVID-19 pandemic, and four during the pandemic. These time windows were selected in such a way that allowed for the inclusion of various calendrical effects and special days.

The analyzed periods were as follows:

Pre-pandemic:
- April 26 – May 10, 2019;
- August 1–14, 2019;
- October 11–24, 2019;
- December 15–28, 2019.

During the pandemic:
- April 26 – May 10, 2020;
- August 1–14, 2020;
- October 11–24, 2020;
- December 15–28, 2020.

To assess the forecast accuracy of ATM withdrawal amounts in the available publications, the most commonly compared metric is MAPE. On the other hand, the operator of an ATM network that provided the data for this study relies on the SMAPE measure. Therefore, both of these forecast quality measures were used in this study. The formulas for calculating these measures are as follows (Makridakis et al., 1998):

- mean absolute percentage error – MAPE:

$$MAPE(X_t, t_0, h) = \sum_{i=0}^{h-1} \left| \frac{X_{t_0+i} - \widehat{X}_{t_0+i}}{X_{t_0+i}} \right|, \tag{1}$$

- symmetric mean absolute percentage error – SMAPE:

[2] The authors have provided the implementation of this methodology in respective code, which is accessible for reference at the following GitHub repository: https://github.com/amachno/bankomaty_2022.

$$SMAPE(X_t, t_0, h) = \sum_{i=0}^{h-1} \left| \frac{X_{t_0+i} - \widehat{X}_{t_0+i}}{\frac{1}{2}\left(X_{t_0+i} + \widehat{X}_{t_0+i}\right)} \right|, \quad (2)$$

where

X_{t_0+i} – actual value at time $t_0 + i$;
$\widehat{X}_{t_0+i}$ – forecasted value at time $t_0 + i$;
h – forecast horizon;
t_0 – start of forecast window.

4. Analysis of results

The research results will be presented in two subsections. In the first part, the results of the analyses and comparisons regarding the occurrence of the calendrical and seasonal effects in the time series of payouts before and during the pandemic are presented. In the second part, the results of the forecasts that were obtained by the selected methods are included, and a comparison of the effectiveness of using each method for the considered periods is made.

4.1. Seasonal and calendrical effects in ATM withdrawals – comparison of before and during COVID-19

This section presents the results of the study on the occurrence of the calendrical and seasonal effects; the analysis was carried out for the pre-COVID and COVID periods. This identified any significant trends and changes that occurred during the COVID-19 pandemic.

4.1.1. Day-of-week effect

Fig. 4 shows a box chart for the total cash demands on particular days of the week.

The day-of-the-week seasonality analysis (Fig. 4) highlights distinct patterns in the ATM cash withdrawals. During the pre-COVID period, total withdrawals increased from Monday through Friday, with the highest numbers of withdrawals occurring on Fridays. The withdrawals then decreased sharply over the weekend, with Sunday having the lowest total number of withdrawals.

During the COVID period, a similar pattern could be observed; however, the overall total numbers of withdrawals were significantly lower as compared to the pre-COVID period. The increase in the number of withdrawals from Monday through Friday was less pronounced, and the highest numbers of withdrawals still occurred on Fridays (but with a smaller difference as compared to the other weekdays). The decrease in the numbers of withdrawals over the weekends was more significant, with Sunday experiencing an even lower total number of withdrawals when compared to the pre-COVID period. Despite the differences in the levels of ATM withdrawals before and during COVID-19, there were significant differences in the levels of withdrawals for each day of the week during both of the studied periods.

A similar analysis was carried out separately for the withdrawals from the 61 analyzed ATMs. Table 2 reveals the distribution of the ATMs that exhibited significant differences in withdrawal amounts for specific days of the week during the COVID and pre-COVID periods.

During the pre-COVID period, the number of ATMs that displayed significant variations was relatively high across all days of the week. The greatest differences in the withdrawal amounts were noted on Fridays and Saturdays (61 ATMs), followed by Sundays (60 ATMs). This pattern could reflect traditional banking habits where people tend to withdraw money at the end of each week for weekend expenditures.

Conversely, the number of ATMs that showed significant variations in withdrawals dramatically reduced during the COVID period; in particular, 15 of the ATMs showed significant differences on Mondays. This suggests a shift in consumer behavior, which was possibly due to changes in work patterns, stay-at-home orders, or other behavioral changes that were induced by the pandemic.

This comparison indicates the impact of the COVID-19 pandemic on the public's banking behavior as was reflected by ATM withdrawal patterns. Further research could delve into the underlying factors that caused these shifts, such as changes in shopping habits, employment statuses, or financial insecurities during the pandemic.

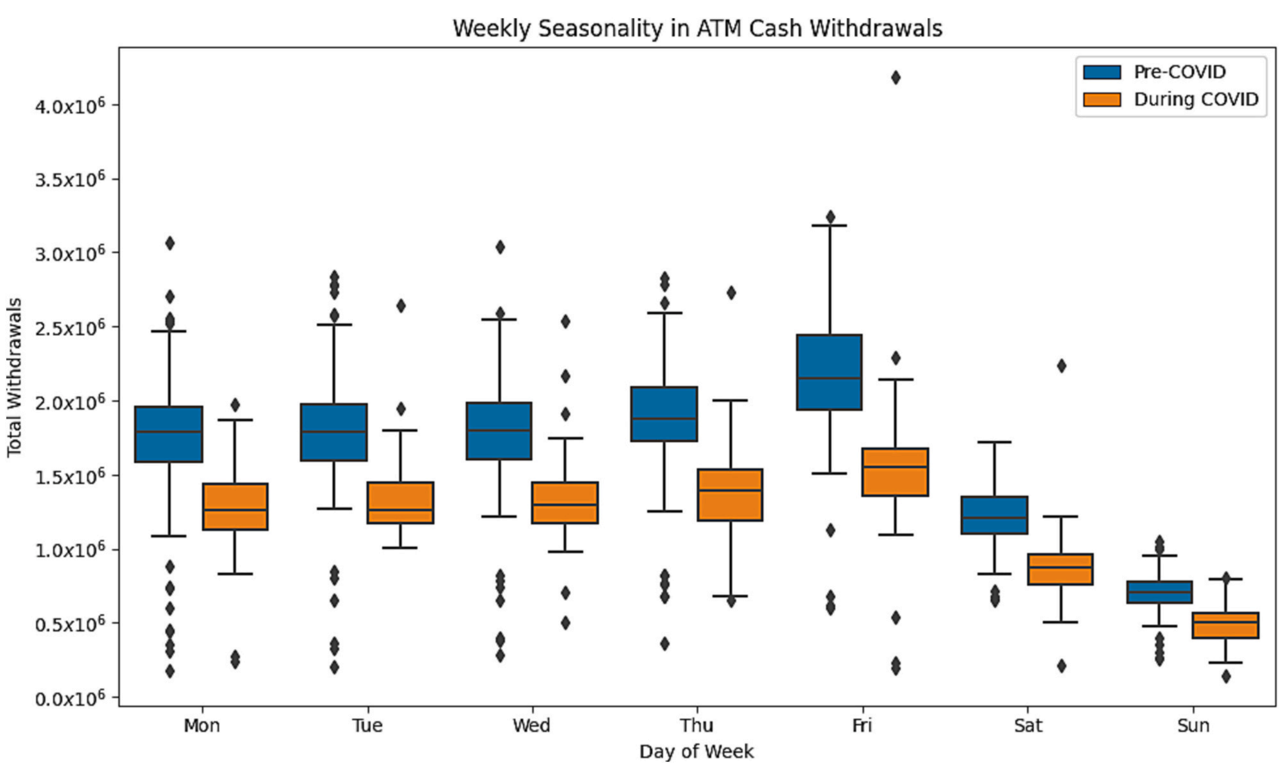

Fig. 4. Weekly seasonality: distribution of ATM cash withdrawals across days of week (comparing pre-COVID and COVID periods).

Table 2
Numbers of ATMs showing significant differences (two sample *t*-test, $p < 0.05$) in withdrawal amounts on different days of week (COVID and pre-COVID periods).

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
COVID	15	46	43	53	59	52	59
pre-COVID	48	56	57	57	61	61	60

4.1.2. *Month-of-year effect*

Fig. 5 shows a box chart for the total cash demand during particular months of the year.

In the analysis of the monthly seasonality of ATM cash withdrawals, it was evident that the COVID pandemic significantly impacted the withdrawal patterns. Prior to the pandemic, the withdrawals exhibited a relatively higher volume, with noticeable peaks in the months of April, May, and June as well as a smaller peak in October. During the COVID period, however, the withdrawal patterns transformed. The overall withdrawal amounts were reduced across all of the months, with the highest volumes being observed in March, June, and July. This observation highlights the influence of the pandemic on the financial behavior of individuals that resulted in altered monthly patterns of ATM cash withdrawals.

As displayed in Table 3, significant variations in withdrawal amounts could be observed across several months during the pre-COVID period. Using a two-sample t-test that compared January to all of the other months collectively, January notably featured 52 ATMs with significantly different withdrawal amounts pre-COVID.

The COVID-19 pandemic seemed to introduce modifications in this pattern. Table 3 illustrates that, during the COVID period, the number of ATMs that exhibited significant variations in their withdrawal amounts changed. January saw 30 ATMs that showed significant differences, while April and May featured 29 and 26 such ATMs, respectively.

Additionally, we observed significant differences in several specific instances via the t-test analysis that compared the mean total number of withdrawals per month. During the 'pre-COVID' period, January displayed a significant deviation in mean total withdrawals as compared to the other months. Within the 'COVID' period, significant differences could be observed for January, April, and July, suggesting the potential impact of the pandemic on ATM withdrawal behavior.

These findings might suggest that the severity of the lockdown measures during the COVID-19 pandemic influenced ATM withdrawal patterns during certain months. The increase in the number of ATMs that showed significant variations during those months with stricter lockdowns indicated changes in consumer behavior, which was possibly due to limited access to physical bank branches or increased reliance on digital banking services. Further research is necessary for understanding the specific factors that drove these changes as well as their implications for financial forecasting models during periods of significant disruption and restrictive measures.

4.1.3. *Special-day effect*

Fig. 6 shows a boxplot for the total cash demand on particular special days vs. normal days.

On normal days (which had the highest numbers of observations), the boxplots display a range of withdrawal amounts. During the COVID period, there was a decrease in withdrawal amounts as compared to the pre-COVID period.

The boxplots for special days (SD) demonstrate variations in the withdrawal patterns during the COVID period. Across different special days, there was a decrease in withdrawal amounts as compared to the pre-COVID period. However, the extent of this decrease varied depending on the specific special day.

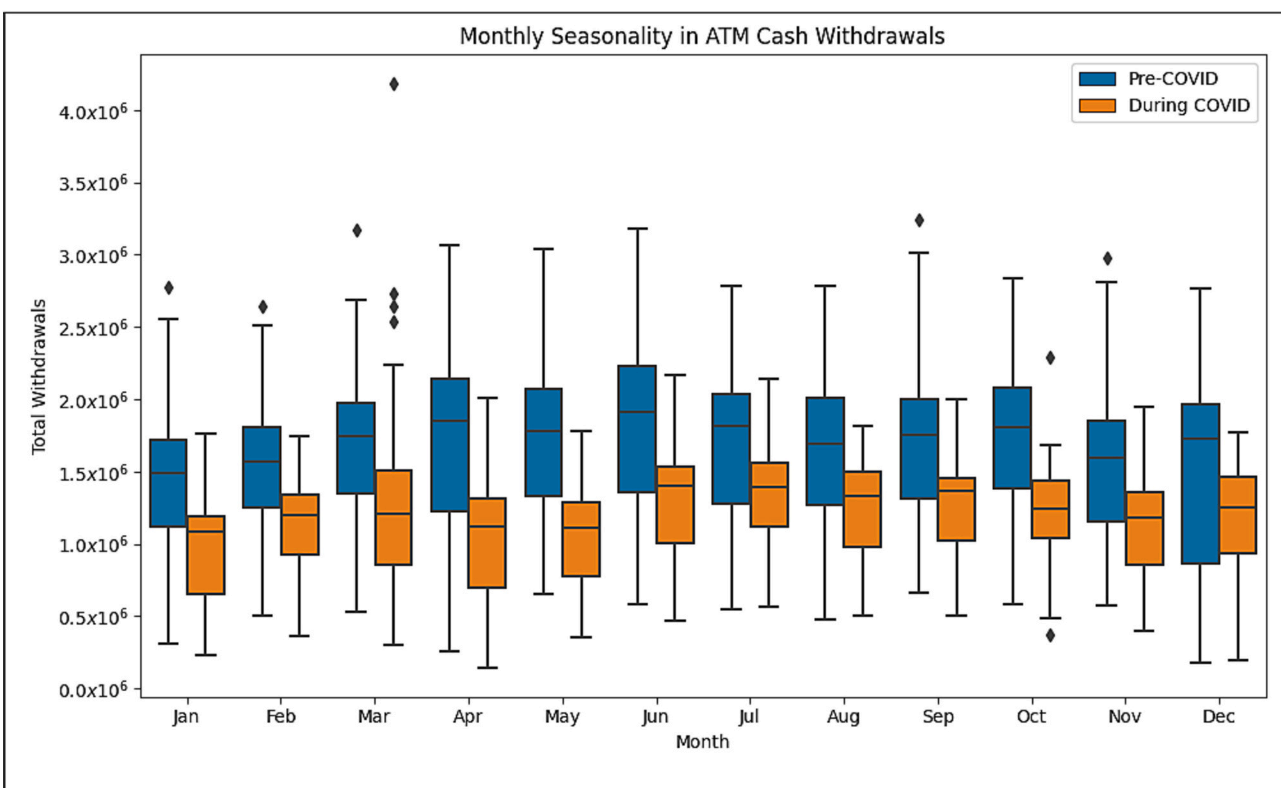

Fig. 5. Monthly seasonality: distribution of ATM cash withdrawals per month (comparing pre-COVID and COVID periods).

Table 3
Numbers of ATMs showing significant differences (two sample *t*-test, $p < 0.05$) in withdrawal amounts during different months (COVID and pre-COVID periods).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
COVID	30	8	17	29	26	10	21	10	17	3	10	6
pre-COVID	52	19	4	4	8	29	11	10	8	14	13	15

Note: This table presents monthly ATM withdrawal patterns during COVID and pre-COVID periods.

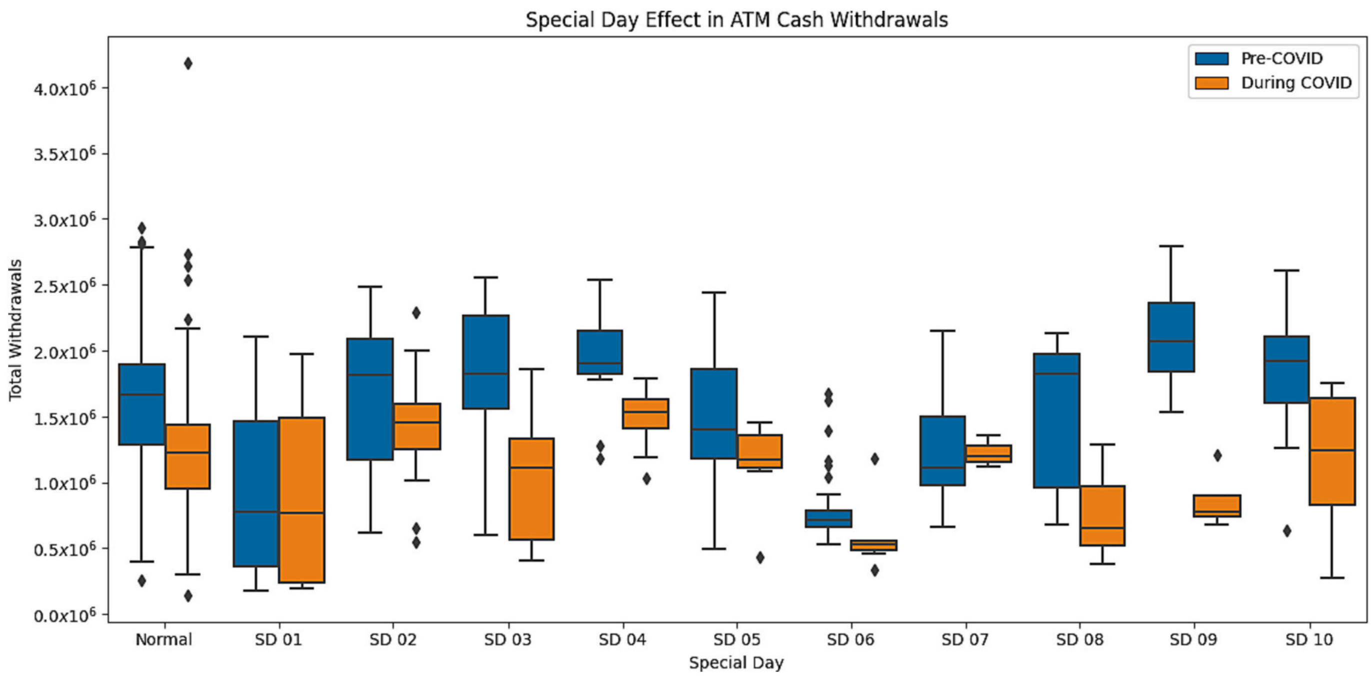

Fig. 6. Comparison of cash withdrawal distributions across all ATMs: pre-COVID vs. COVID periods; each boxplot represents distribution of cash withdrawals for specific special days, with pre-COVID periods marked as blue and COVID periods as orange.

On SD 01, for example, the boxplot shows a range of withdrawal amounts, with a decrease in the median value during the COVID period. Similarly, the boxplot indicates decreases in withdrawal amounts on SD 04 when compared to the pre-COVID period.

Notably, there was an increase in the minimum withdrawal amounts during the COVID period on certain special days (like SD 05 and SD 07). This suggests that, despite the challenging circumstances, these special days exhibited a consistent level of ATM usage.

The boxplot visualization provides insights into the distributions of withdrawal amounts during different types of days as well as the impact of the COVID-19 pandemic. As is indicated by the interquartile range and outliers, the variability in the withdrawal amounts reflected changes in consumer behavior that were influenced by the pandemic.

Upon examining the statistical significance of the withdrawals on special days (SDs) during both the pre-COVID and COVID periods, the findings revealed distinct patterns. During the pre-COVID period, the days marked as SD 01, SD 04, SD 06, and SD 09 show a significant difference in withdrawal patterns compared to non-special days. However, during the COVID period, only SD 04 and SD 06 maintained this significant difference, while SD 01 and SD 09 no longer stood out significantly. The rest of the special days did not exhibit significant differences in withdrawals during either period, which indicated that their impacts on the withdrawal behaviors was relatively consistent regardless of the pandemic circumstances.

Table 4 illustrates the distribution of ATMs that exhibited significant differences in withdrawal amounts on different special days as compared to non-special days during the COVID and pre-COVID periods.

During the pre-COVID period, several ATMs showed significant variations in their withdrawal amounts on certain special days. Specifically, 58 ATMs displayed significant differences on the tenth day of each month (SD1), while 57 ATMs exhibited variations at the starts of long weekends (E6).

In contrast, the number of ATMs that showed significant variations decreased during the COVID period. On the sixth special day (SD 06), 59 ATMs exhibited significant differences in their withdrawal amounts.

These findings suggested that the COVID-19 pandemic had a substantial impact on the withdrawal patterns on special days. The reduced number of ATMs that showed significant variations during the COVID period indicated changes in consumer behavior and preferences. Further investigation is warranted in order to understand the underlying reasons for these changes and their implications for financial forecasting models during periods of disruption.

Summing up this part of the results, it can be stated that, to a large extent, the calendrical and seasonal effects during the pandemic (verified by means of the average level of payments) were to be less noticeable than during the pre-pandemic period.

Table 4
Number of ATMs showing significant differences (two sample *t*-test, $p < 0.05$) in withdrawal amounts on different special days (COVID and pre-COVID periods).

Period	SD 01	SD 02	SD 03	SD 04	SD 05	SD 06	SD 07	SD 08	SD 09	SD 10
COVID	13	9	4	18	0	59	2	7	12	0
Pre-COVID	58	0	12	38	4	57	18	1	36	4

5. Forecasting results and model performance comparison

In this section, we present the performances of the three modeling approaches – XGBoost, SARIMA, and BVAR. By examining the performance of each model before and during the pandemic, we aimed to identify which models excelled under different circumstances and whether any trends or stability patterns emerged across the periods. Additionally, we investigated the influence of the potential impact of the pandemic on the models' forecasting capabilities.

We analyzed the performance of the three forecasting models (BVAR, SARIMA, and XGB) at the ATM and period levels using both MAPE and SMAPE as evaluation metrics. The results of the analysis are presented in Tables 5 and 6.

The performance of the three models (BVAR, SARIMA, and XGB) varied significantly across the different periods and evaluation metrics. Overall, the XGB model consistently outperformed the BVAR and SARIMA models in terms of both MAPE and SMAPE. In particular, the XGB model exhibited lower error rates for all of the periods, with its performance remaining relatively stable throughout the entire time span. In contrast, the BVAR model demonstrated the highest number of errors (particularly in terms of MAPE), while the SARIMA model showed a mixed performance, with some periods exhibiting lower numbers of errors than the BVAR model did and others showing higher numbers.

Comparing the pre-COVID and COVID periods, it was evident that the XGB model's performance remained robust despite the challenges that were posed by the pandemic. While the error rates of the BVAR and SARIMA models tended to increase during the COVID period (particularly in terms of MAPE), the XGB model maintained relatively low error rates. This suggested that the XGB model was better-suited to adapt to unforeseen events and changing market conditions. In summary, the XGB model demonstrated superior performance and resilience as compared to the BVAR and SARIMA models; this makes it a preferable choice for forecasting in the face of uncertain and dynamic environments. However, an interesting finding emerged when we focused on the performance of the models during the winter festive season. Despite XGB's consistent superior performance across most of the year, the SARIMA model took precedence during this specific seasonal period.

To gain deeper insights into the models' performance, we generated ranking tables for each metric that indicate the rank of each model for each ATM and period combination. In addition, we provided summary tables that show the frequency of how many times each model achieved a specific ranking (1, 2, or 3) across all of the ATMs and periods.

As shown in Table 7, the results of the model rankings based on both the MAPE and SMAPE metrics provided interesting insights into their performance at the ATM and period levels. For the MAPE metric, the XGB model clearly outperformed the other models, achieving a 1 ranking in 285 cases (compared to 186 cases for SARIMA and 17 cases for BVAR). Conversely, the BVAR model had the most occurrences of 3 rankings, with 337 instances; this indicated that it was the least-accurate model according to the MAPE metric.

When considering the SMAPE metric, the XGB model still performed the best, achieving 1 rankings in 291 cases, followed by SARIMA (with 171 instances) and BVAR (with 26). Similar to the MAPE results, the BVAR model had the highest number of 3 rankings (307 instances).

Overall, the results that are presented in Table 7 indicated that the XGB model consistently demonstrated superior performance across both of the MAPE and SMAPE metrics, while the BVAR model consistently underperformed. The SARIMA model exhibited a moderate performance, ranking somewhere between the XGB and BVAR models8.

The transition matrices that are presented in Table 8 and Table 9 compare the best-performing models based on the MAPE and SMAPE metric for the specific pre-COVID and COVID periods. The findings suggested that the XGB model consistently outperformed the BVAR and SARIMA models across the majority of the ATMs for both the pre-COVID and COVID periods. The performance of BVAR and SARIMA as the best models during the pre-COVID period generally shifted toward the XGB model during the COVID period, which indicated that XGB was more resilient to the changes that were brought about by the pandemic. In contrast, SARIMA's performance as the best model during the pre-COVID period tended to decline in the number of ATMs for which it remained the best model during the COVID period (particularly for the last two time periods). Overall, the results highlighted the robustness of the XGB model in handling the impact of the COVID period (maintaining its performance across most of the ATMs), while the performances of the BVAR and SARIMA models declined for the same period.

The empirical investigation substantiated the claim that there was no single forecasting method that would consistently outperform the others for all-time series of ATM withdrawals. Among the three models tested – SARIMA, XGBoost, and BVAR – XGBoost generally exhibited the most robust performance. However, this superiority was not universal; there were certain periods and specific ATMs for which SARIMA or BVAR delivered superior results. Thus, this finding substantiated the supposition that the selection of an optimal forecasting method may require consideration of specific time series or ATM attributes rather than adopting a one-size-fits-all approach.

The analysis also corroborated the hypothesis that stated that the quality of the forecasts deteriorated during the COVID-19 period as compared to the pre-pandemic period. This degradation could be observed across all of the models and time periods; this was evidenced by the increased values of both the mean and median MAPE. The observed rise in MAPE during the pandemic indicated a greater average discrepancy between the forecasted and actual numbers of ATM withdrawals, thus reflecting a decrease in the predictive accuracy of the models during this tumultuous period. Thus, it was verified that the COVID-19 crisis had negative impacts on the forecasting capabilities of all of the employed models.

Table 5
MAPE statistics.

Period	Model	Pre-COVID			During COVID			Total		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
26.04–5.05	BVAR	74.31	69.85	16.29	258.00	73.78	784.78	166.15	70.40	560.39
	SARIMA	73.84	49.32	110.82	59.53	53.43	40.66	66.69	49.94	83.43
	XGB	53.68	31.38	103.27	74.23	37.00	108.90	63.96	34.30	106.19
1–14.08	BVAR	54.94	48.14	31.40	93.34	53.95	174.48	74.14	50.95	126.32
	SARIMA	35.25	29.28	26.91	53.39	42.09	43.00	44.32	33.27	36.86
	XGB	31.09	26.44	18.20	46.18	29.82	87.82	38.63	28.50	63.61
11–24.10	BVAR	61.04	51.20	44.17	115.20	82.51	116.86	88.12	66.73	92.08
	SARIMA	96.82	64.71	87.18	98.36	79.58	82.56	97.59	71.90	84.55
	XGB	32.21	25.50	21.38	44.22	35.31	25.72	38.22	32.02	24.31
15–28.12	BVAR	100.98	66.04	87.20	104.00	82.66	85.09	102.47	77.33	85.81
	SARIMA	33.32	31.18	12.68	53.34	32.75	96.12	43.33	32.07	69.01
	XGB	70.50	42.75	77.99	64.72	48.29	53.44	67.61	45.15	66.64

Table 6
SMAPE statistics.

Period	Model	Pre-COVID			During COVID			Total		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
26.04–5.05	BVAR	123.56	120.14	13.34	63.28	55.39	31.83	93.42	113.12	38.81
	SARIMA	37.93	36.00	12.15	65.04	55.85	34.14	51.48	41.12	28.92
	XGB	34.88	33.58	10.44	39.26	34.99	13.97	37.07	33.94	12.48
1–14.08	BVAR	35.54	35.41	11.16	37.29	36.45	9.83	36.42	35.71	10.51
	SARIMA	26.53	25.13	8.14	34.36	31.73	11.84	30.45	29.09	10.85
	XGB	26.99	25.63	8.31	29.75	28.99	8.97	28.37	26.85	8.73
11–24.10	BVAR	35.71	35.05	7.66	47.98	44.40	14.82	41.84	39.85	13.26
	SARIMA	43.36	42.03	11.21	49.39	47.34	12.98	46.38	43.96	12.45
	XGB	26.29	24.14	8.40	32.16	30.63	8.31	29.22	28.17	8.83
15–28.12	BVAR	46.76	44.85	11.10	48.14	47.73	11.47	47.45	46.04	11.26
	SARIMA	30.90	29.97	8.37	37.41	34.45	17.01	34.15	30.49	13.75
	XGB	37.51	36.71	10.12	41.34	39.16	13.21	39.42	37.92	11.88

Table 7
Summary of ranking frequencies for each model (based on MAPE and SMAPE).

Measure	Model	Pre-COVID			COVID			Total		
		1	2	3	1	2	3	1	2	3
MAPE	BVAR	9	78	157	8	56	180	56	180	337
	SARIMA	97	73	74	89	96	59	96	59	133
	XGB	138	93	13	147	92	5	92	5	18
SMAPE	BVAR	12	61	171	14	94	136	26	155	307
	SARIMA	103	78	63	68	87	89	171	165	152
	XGB	129	105	10	162	63	19	291	168	29

Note: table shows number of times each model achieved 1, 2, or 3 rankings across all ATMs and periods (1 represents best MAPE results, while 3 represents worst).

Table 8
Transition matrices comparing best-performing models based on MAPE metric for four pairings of pre-COVID and COVID periods.

		Best during 26.04–10.05.2020					Best during 1–14.08.2020		
		BVAR	SARIMA	XGB			BVAR	SARIMA	XGB
Best during 26.04–10.05.2019	BVAR	0	0	1	Best during 1–14.08.2019	BVAR	1	3	1
	SARIMA	1	6	9		SARIMA	2	8	18
	XGBoost	1	16	27		XGBoost	1	5	22

		Best during 11–24.10.2020					Best during 15–28.12.2020		
		BVAR	SARIMA	XGB			BVAR	SARIMA	XGB
Best during 11–24.10.2019	BVAR	0	0	2	Best during 15–28.12.2019	BVAR	1	0	0
	SARIMA	0	1	5		SARIMA	0	36	11
	XGBoost	1	5	47		XGBoost	0	9	4

Note: each matrix shows the number of ATMs for which a specific model (BVAR, SARIMA, or XGBoost) was the best performer for the earlier pre-COVID period (rows) and the later COVID period (columns). The matrices provide insights into the performance shifts and the resilience of the models in adapting to the changes that were brought about by the pandemic.

6. Discussion

In addition to the direct implications of this research (which are related to improving the forecasting of ATM withdrawals), one may go beyond the scope of the study and illuminate the broader relevance of the obtained outcomes. As mentioned in the introduction, ATM withdrawals represent one of the crucial elements of the cash-management process from the perspective of cost-optimization forecasting. As shown in this study, the effective forecasting of ATM withdrawals requires us to not only conduct continuous optimizations of parameters of well-known analytical methods but also to seek innovative methods. In other words, the process of cash management (including the forecasting of cash levels) requires us to use smart and innovative solutions. One of the major preconditions for achieving such a desired managerial strategy is to rely on experienced and open-minded decision-makers. In this context, the results of our research should be interpreted in reference to the arguments of Yang and Yang (2023), who found solid evidence of the positive role that external parachuted executives have for enterprise innovation investments. When building innovative managerial strategies for ATM networks, one could use the concept of open innovation (Saura et al., 2023), which seems to be constantly gaining importance in the era of digitalization and artificial intelligence.

7. Conclusions

There are two main conclusions that have resulted from this study. First, the results of the conducted analysis have proven that, during periods of market turmoil, one needs to use alternative forecasting tools more than he/she does during "business as usual" periods. To be more precise, the operators of ATM networks should look at the COVID-19 data as a potential source of unique knowledge. Carefully studying the properties of the data could help to efficiently train forecasting models and elaborate a respective analytical framework that reflects pandemic-specific consumer behavior. Second, the study shows that, regardless of

Table 9
Transition matrices comparing best-performing models based on SMAPE metric for four pairings of pre-COVID and COVID periods.

		Best during 26.04–10.05.2020					Best during 1–14.08.2020		
		BVAR	SARIMA	XGB			BVAR	SARIMA	XGB
Best during 26.04–10.05.2019	BVAR	0	0	0	Best during 15–28.12.2019	BVAR	2	3	1
	SARIMA	1	2	22		SARIMA	2	8	19
	XGBoost	2	7	27		XGBoost	3	7	16

		Best during 11–24.10.2020					Best during 15–28.12.2020		
		BVAR	SARIMA	XGB			BVAR	SARIMA	XGB
Best during 11–24.10.2019	BVAR	0	0	5	Best during 15–28.12.2019	BVAR	0	1	0
	SARIMA	0	0	5		SARIMA	1	29	14
	XGBoost	3	2	46		XGBoost	0	9	7

Note: Each matrix shows the number of ATMs for which a specific model (BVAR, SARIMA, or XGB) was the best performer for the earlier pre-COVID period (rows) and the later COVID period (columns). The matrices provide insights into the performance shifts and the resilience of the models in adapting to the changes that were brought about by the pandemic.

the current market regime, it is worth seeking innovative forecasting solutions as in comparison to SARIMA-based approach the two procedures that have been used in this study but not by a data-providing company (i.e., XGBoost and BVAR) provided significant gain in forecasting accuracy at a minimal operational cost. Looking from a broader perspective, open innovations and the growing popularity of AI have set solid grounds for the straightforward and efficient application of various quantitative methods in ATM withdrawal forecasting. However, the efficient forecasting of ATM withdrawals cannot be solely based on a purely technocratic approach, as expert knowledge seems irreplaceable in managing the major drawbacks of the mathematical methods (especially overfitting). In order to avoid such problems, one should seek innovative solutions that go beyond focusing on historical patterns and, additionally, take the locations and habits of the local community that use any examined ATMs into account.

7.1. Theoretical implications

This study adds value to the theoretical deliberations on the forecasting of ATM withdrawals and, more broadly, the cash-management process in two particular areas. First, the empirical results confirmed the presence of calendrical and seasonal effects in the data set – especially the effects of the day of the week and selected special effects. These results were consistent with the studies by Simutis et al. (2008), Rodrigues and Esteves (2010), and Gurgul and Suder (2016). In addition, the novel result that is presented in the study was proof of the fact that, during the COVID-19 pandemic, the structures of withdrawals changed, and the number of ATMs for which the examined effects occurred in the series of withdrawals decreased. Both of these outcomes seem important for further discussions on deriving theoretical patterns of ATM withdrawals that, in turn, are essential for defining more-effective cash management strategies.

7.2. Practical implications

When it comes to forecasting ATM withdrawals, the obtained results showed that, out of the three proposed methods (i.e., the frequently used SARIMA method as well as the innovative XGBoost and BVAR methods), XGBoost showed the best overall forecasting performance. This method also turned out to be the least sensitive to changes under the environmental conditions that were caused by the COVID-19 pandemic. However, the conducted research showed that this method was not the most effective tool for all of the analyzed periods. It turned out that, for the period with the greatest accumulation of holidays (i.e., the end of the year), the SARIMA model showed better forecasting accuracy. In addition, the BVAR model turned out to be the most effective forecasting tool for several ATMs even though it showed the lowest general performance. In other words, these results are consistent with those of Parmezan et al. (2019), who suggested that there was no single model that could be used in the process under consideration nor under all conditions. Instead, the use of a bunch of preselected forecasting tools seems to be a reasonable strategy. From the perspective of practical applications, the outcomes of this study seem useful for ATM network operators, as they have provided detailed reports on the forecasting accuracy of particular methods in different market regimes. This is especially important in the case of the results that were obtained for the COVID-19 period, as the risk of market turmoil in upcoming years cannot be neglected.

7.3. Limitations and future research directions

It should be noted that the conducted research had some limitations. First, the data set that was used was provided by a single operator and contained time series that were collected from a single geographical location (the city of Krakow). The possibility of testing the models on ATM data that is provided by different operators and/or collected from different geographical locations would give a more complete picture of the examined issues. Second, the missing data in the examined time series was replaced with a value of "0" by the data provider. This approach meant that this value could not be unambiguously interpreted in the series; i.e., the zero withdrawal could be caused by the fact that there were no actual withdrawals, the ATM was broken, or there was no communication with the ATM for some time even though it was dispensing cash correctly. It would be advisable to obtain such information from ATM network operators. Third, the obtained data lacked access to information about the infrastructural location of the ATMs (shops, bank branches, gas stations, etc.). According to the research by Gurgul and Suder (2016, 2018), the structures of payments (particularly regarding the occurrence of calendrical effects) may depend on the infrastructural locations of the ATMs. As a consequence, the proper choices of forecasting models may be determined by such information.

Due to the fact that the management of an ATM network is a multistage process, there are several main directions for future research in this field. The first one is the application of the proposed forecasting methods for a large sample of ATM withdrawal data. This would provide an opportunity to evaluate the usefulness of these methods in real problems. Another possible path would be to try to focus on the two-dimensional vector approach and use the data on the numbers of withdrawals from ATMs to forecast the sizes of the withdrawals. As shown with the example of the BVAR models, such an approach can improve the quality of a forecast. It is also worth paying attention to the intensive development of deposit & withdrawal machines. Analyses of the structures of cash in such devices and attempts to forecast their levels could be milestones for research in this area.

Further research on forecasting ATM withdrawals and, more broadly, cash-management processes should also take the rapidly changing environment into account. The development of digital banking (Martínez-Navalón et al., 2023), the growth of green banking (Moslehpour et al., 2023), this rise in the popularity of split loyalty (Szopiński, 2023), the role of AI for the future of customer-relationship management and whole B2B ecosystems (Saura et al., 2021), and the factors that drive the internalizations of firms (Masango and Marinova, 2014) are but a few of the concepts that are worthy of attention in further research in the discussed area.

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CRediT authorship contribution statement

Marcin Suder: Conceptualization, Data curation, Methodology, Project administration, Software, Supervision, Writing – original draft, Writing – review & editing, Formal analysis. **Henryk Gurgul:** Funding acquisition, Writing – original draft, Writing – review & editing, Methodology, Supervision, Validation. **Belem Barbosa:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision, Formal analysis, Project administration. **Artur Machno:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing, Data curation. **Łukasz Lach:** Data curation, Formal analysis, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

The data that has been used is confidential.

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