PressAcademia
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JEFA
ISSN 2148-6697
Journal of Economics, Finance and Accounting YEAR 2023 VOLUME 10 ISSUE 2

THE IMPACT OF THE US EMPLOYMENT REPORT ON THE GOLD SPOT RATE

DOI: 10.17261/Pressacademia.2023.1733
JEFA- V.10-ISS.2-2023(5)-p.108-120

Nima Niyazpour[1], Kaya Tokmakcioglu[2]
[1]Istanbul Technical University, Management Engineering, Ayazağa, Istanbul, Turkey.
niyazpour18@itu.edu.tr, ORCID: 0000-0001-7369-4945
[2]Istanbul Technical University, Management Engineering, Ayazağa, Istanbul, Turkey.
tokmakcioglu@itu.edu.tr, ORCID: 0000-0002-5981-299X

Date Received: April 17, 2023 **Date Accepted:** June 11, 2023

To cite this document
Niyazpour, N., Tokmakcioglu, K., (2023). The impact of the US employment report on the gold spot rate. Journal of Economics, Finance and Accounting (JEFA), 10(2), 108-120.
Permanent link to this document: http://doi.org/10.17261/Pressacademia.2023.1733

ABSTRACT
Purpose- Considering the various financial markets, it can be observed that macroeconomic events such as announcement releases might affect the volatility and the direction of price movements in the related markets. While some announcements might play a substantial role in this subject, some might be categorized as unessential announcements in the economic calendars. Reports related to the employment situation, inflation, growth of the domestic product, and commodity reservations of a country are crucial points on the schedule of investors and traders all around the globe. However, reports coming from countries with a major economic share have a much more significant effect on the market. In that regard, researchers are more interested in the evaluation of economic events of countries like the United States, United Kingdom, Germany, and China. In that regard, this study focuses on the impact of the U.S. employment situation report on the XAU/USD spot exchange rate.
Methodology- In the first part of the study, the significance of relevant factors of the announcement has been evaluated to specify the importance of the elements included in the employment report. In that interest, an OLS regression model has been developed in the first step. Furthermore, the face and statistical validity phases have been controlled to improve the efficiency of the model. The second part of the study focuses on the direction of the price movement respectively after specific periods from the report's release. To satisfy the desired goal of the study, two various models have been applied to the data to evaluate the two models and their performances. The first model is based on logistic regression approaches while the second model benefits from XGboost regression. Accuracy metrics have been evaluated for both models to decide on the healthiness of the performances.
Findings- Findings demonstrate that the gold spot exchange rate reacts strongly to the announced nonfarm payroll employment figure, while the market takes its revision of the prior month and unemployment rate as additional data around the release of the announcement. Results suggest that employment reports labeled as "bad news" for the U.S. economy caused an increase in the exchange rate of the gold spot. Price discovery for different time intervals after the announcement release shows that the first 10 minutes are the most crucial. Time intervals before the announcement release imply that exchange rate changes are regular and there is not any recognizable pattern for price movements before the announcement release, while abnormal returns start to show up just after the release of the announcement.
Conclusion- To sum up, the impact of the announcement report on the price movement of the gold spot is undeniable. However, uncertainties increase before the announcement, and volatility increases after the announcement. Various statuses lead to specific movements in the market. While the uncertainties are lower before the announcement, the price movement of the gold spot would be diverse to the status of the announcement.

Keywords: U.S. Nonfarm payrolls, employment report, macroeconomic event study, gold spot, machine learning, decision tree
JEL Codes: F31, F62, G15

1. INTRODUCTION

In general, Gold is viewed as a safe-haven asset, particularly during uncertain economic periods. As a result, a variety of variables, including macroeconomic updates like the US nonfarm payroll report, can affect changes in the price of Gold. The effect of scheduled macroeconomic events in the U.S. and other countries on foreign exchange markets has been studied in several papers. These studies include the impact of announcements such as employment situation reports, gross domestic product, producer price index, customer price index, and trade surplus or deficit on different features of exchange markets such as price changes, market volume, and market volatility. Based on numerous studies, the U.S. employment situation report can be called one of the most effective announcements on the gold market. Instead of studying various events, this paper will focus on the U.S. employment situation announcement to comprehensively evaluate its impact on the Gold spot exchange rate. U.S. employment report includes the total number of nonfarm payroll employment, unemployment rate, and revisions of the previously announced figures in the preceding month. First, this study aims to answer questions about the effect of each figure during the time of the announcement on exchange rate changes. What will be the direction of changes in the exchange rate regarding the effect of each figure? Which figure has more effect on exchange rate changes? Most studies evaluate the impact of the U.S. employment situation based on the total number of nonfarm payroll employment statistics, which can be addressed as the announcement's headline. In contrast, some other studies make this evaluation based on unemployment statistics (K. P. Evans & A. E. Speight, 2010), and eventually, some studies evaluate each of them separately (Chatrath et al., 2014). This study focuses on measuring the effect of the U.S. employment report based on all predictor variables together to achieve more reliable results. Furthermore, the standard procedure suggested by (Ederington et al., 2019) is followed, which is based on the differences between announced figures and the median of forecasted numbers compiled by Bloomberg and MMS. This difference is labeled as "Surprise" for the announced figures. It is mandatory to mention that economic events can affect pre-market so that after evaluating the effect of each figure on exchange rate changes, the reaction of the gold spot exchange before the announcement is evaluated to see if there is the existence of abnormal returns before the release of announcement or not. Abnormal returns are defined as the difference between exchange rate changes and expected exchange rate changes. The advent of high-frequency data has inspired an explosion of writing on a wide range of financial market concerns, so in this study, high-frequency data are used to inspect intraday price movement with high precision. In this case, one day before the announcement in one-minute time intervals are examined, and likewise, after the announcement, one day afterward, the announcement in one-minute intervals using data from January 2011 to March 2020 are explored. Reasonably more than forecasted amounts for the total number of nonfarm payroll and its revision for the preceding month are considered good status for the U.S. economy, so they strengthen the value of the U.S. Dollar. In contrast, more than the forecasted unemployment rate is considered a bad status for the U.S. economy. Hence, it weakens the value of the U.S. Dollar. Based on this logic, more than forecasted amounts for the total number of nonfarm payroll and its revision weakens Gold, while more than forecasted unemployment rate strengthens Gold. Three distinct regression techniques have been taken into consideration for this: XGboost regression, logistic regression, and linear regression. The same independent variables and dependent variables are specified for each of these techniques. For logistic regression and XGboost regression, the dependent variable is a binary variable that indicates whether the exchange rate increased or decreased over a given time frame. The dependent variable for linear regression is the change in the XAU/USD exchange rate. The purpose of this research is to compare the findings from various regression techniques and to comprehend how these independent variables affect the dependent variable. The strength and direction of the relationships between these variables using linear regression can be determined, and the direction and size of changes in the XAU/USD exchange rate using logistic regression and XGboost regression can be predicted. The effect of US nonfarm payroll report releases on spot exchange rates can be understood more thoroughly and useful inferences about the variables that influence changes in the price of Gold can be made by employing multiple regression methods. Investors, decision-makers, and anyone else interested in comprehending the intricacies of the gold market may find the findings to be of interest. The statistical technique of linear regression involves fitting a linear equation to the observed data to model the connection between a dependent variable and one or more independent variables. Finding the link between the dependent variable and the independent variables and estimating its strength and direction are the goals of linear regression. According to the assumptions of linear regression, the dependent variable must be continuous, normally distributed, and have a linear connection to the independent variables. Contrarily, logistic regression is a statistical technique used to simulate the relationship between a binary dependent variable and one or more independent variables. A binary dependent variable has only two possible values, 0 or 1. Based on the values of the independent variables, logistic regression aims to forecast the likelihood of the binary outcome. Given that the relationship between the dependent variable and the independent factors is not always linear, logistic regression assumes that the dependent variable has a logistic distribution. To determine the strength and direction of the link between the change in the XAU/USD exchange rate and the independent variables, linear regression is utilized in this research work. On the other hand, to anticipate the course of changes in the exchange rate, logistic regression is used to estimate the likelihood of the XAU/USD exchange rate increasing or decreasing depending on the values of the independent variables. In summary, this study hypothesizes that the gold spot exchange reacts negatively to "surprise" amounts on the total number of nonfarm payroll and its revision, while it reacts positively to the "Surprise" amount in the unemployment rate. Other sections of this paper are organized as follows. Section 2 describes previously studied literature. Section 3 explains the data and relevant methodology. In section 4 results are included. Moreover, section 5 includes the conclusion of this study.

2. LITERATURE REVIEW

The classification of price discoveries, and studies about the effect of macroeconomic fundamentals on asset prices included in various financial markets, are essential concerns of market efficiency models and market microstructure theoretical literature. Investors worldwide are interested in the movements of the U.S. economy as the leading economy in the world. As a result, the economic news of the U.S. is unquestionably one of the most important topics of discussion among investors throughout the world (Nikkinen et al., 2006), so any economic event in the U.S. can be assumed as a potential opportunity in financial markets. Also, evidence from Gau & Wu (2017) suggests that New York's trading time is one of the most dominant trading times in the financial markets. That is why the effect of macroeconomic events on the U.S. has been studied in numerous papers. These events usually cause abnormal exchange rate changes between various financial markets regarding the importance of these events. The advent of high-frequency data plays a vital role in the development of literature related to price discoveries (Cai et al., 2001). Some of these studies focus on classifying jumps in exchange rate changes corresponding to macroeconomic events. (Chatrath et al., 2014) focuses on intra-day jump distributions of currency returns, which extends the microstructure analysis. Similarly, Andersen & Bollerslev (1998) and Andersen et al., (2001) suggest that the most significant returns are related to public information announcements and, in particular, specific macroeconomic reports. Moreover, Andersen et al. (2001) focus on spikes in volatility to develop a structure for the identification of jumps where they extend this identification by including features from realized bi-power variation (Barndorff-Nielsen & Shephard, 2004). It should be noted that the impact of macroeconomic events is not only limited to abnormal returns and jumps on exchange rate changes but also affects volatility, volume, and buy/sell spread. Numerous papers particularly evaluate the impact of macroeconomic announcements on the volatility of different markets (DeGennaro & Shrieves, 1997), (Melvin & Yin, 2000), and (Evans & Lyons, 2002). (K. Evans & A. Speight, 2010) evaluates the price movement and market volatility regarding macroeconomic news announcements in the short run. Likewise, Sun et al., (2011) propose a new volatility estimator based on wavelet analysis and demonstrate that Intraday volatility clusters grow as we get closer to the release date and then dissipate exponentially afterward. Few papers discover the effect of macroeconomic announcements on market volume, so it is theoretically ambiguous. Fleming & Remolona (1999) is one of the studies which considers the effects of macroeconomic announcements on Treasury securities market volume. They illustrate that the release of the announcements causes an immediate jump in the market return, and subsequently, market volatility and volume increase and remain steady for several hours. Congruently, Chaboud et al. (2004) find that trade activity surges around the time of scheduled macroeconomic data releases, as well as at other periods of the day when trading volume is often higher for institutional reasons. This study focuses more on literature, studying the effect of macroeconomic announcements on commodities such as gold. Cai et al. (2001) is one of the essential studies which addresses abnormal volatilities on gold futures to related macroeconomic events and ranks them by their importance. They examine the impact of 23 regularly released macroeconomic announcements in the U.S. and find that only 4 of them significantly affect the volatility of the gold market. Their findings display that employment reports turn out to be the most important announcement for the Gold market, followed by GDP, CPI, and personal income. Christie–David et al. (2000) applies a regression model between the unemployment rate and price movements of Gold and Silver using four-year intra-day data. Results demonstrate that Gold strongly reacts to the release of CPI, unemployment rate, and gross domestic product. And the PPI. Similarly, Smales & Yang (2015) studies the reaction of Gold futures during the announcement releases where they distinguish the status of the received announcement as "good" economic news and "bad" economic news. Their findings show that news relating to the unemployment rate significantly affects the gold market, and Gold reacts positively to unexpectedly "bad" economic reports and negatively to "good" reports. Eventually, Chen & Gau (2010) compares the behavior of price movements around announcements between spot and future rates and identifies the characteristics of each market. According to their findings, the foreign exchange spot market has a more significant influence on price discovery, although futures returns are more susceptible to announcements than spot returns.

Dezhkam & Manzuri (2023) use extreme gradient boost (XGBoost) to predict shifting stock price trends. The model outperforms benchmark methods and exhibits superior performance metrics when it comes to portfolio creation. In a similar work (Abu-Doush et al., 2023) used a multilayer perceptron neural network and an archive-based Harris Hawks optimization algorithm, to introduces a new framework for forecasting Gold prices. The framework examines several feature selection strategies and uses a variety of input datasets to show how well the proposed algorithm predicts gold prices when compared to other optimization algorithms and traditional machine learning approaches. In contrast to prior models, (Hajek & Novotny, 2022) proposes a fuzzy rule-based prediction system for Gold prices that takes into account past financial data as well as news sentiment. The results emphasize the significance of news effects in short-term forecasts and point to the possibility for fuzzy rule-based systems to beat current strategies while providing investors with clear trading guidelines. However, (Yun et al., 2021) describes an improved feature engineering approach and a stock price prediction system based on the GA-XGBoost algorithm. The study highlights the value of feature engineering in enhancing prediction precision and striking a balance between the benefits and drawbacks of dimensionality in predicting stock price direction. The analysis presented in (Han et al., 2023) suggests a brand-new labeling technique for predicting stock price trends termed N-Period Min-Max (NPMM). The study shows that by focusing on instance selection and lowering data size, the NPMM labeling method outperforms other labeling methods in terms of trading performance. Also, the Post-Earnings-Announcement Drift (PEAD) phenomenon in the stock market is examined in (Ye & Schuller, 2021) using a machine learning strategy, specifically XGBoost. It exhibits the capability of XGBoost to estimate PEAD direction and the potential for creating portfolios with higher positive returns and smaller negative returns based on the model's predictions.

3. DATA AND METHODOLOGY

3.1. Data

For this study, related data of U.S. employment situation report is collected from the Bureau of Labor Statistics (BLS), which is usually issued on the first Friday of each month at 8:30 AM Eastern Time to illustrate the employment situation of the preceding month, from January 2011 to March 2020 giving 139 observations. This data includes (1) the total number of U.S. nonfarm payroll employment for the preceding month, (2) the revision of previously announced nonfarm payroll employment figures, (3) the unemployment rate for the preceding month, (4) The median of most recent analyst forecasts of the total number of U.S. nonfarm payroll and unemployment before to the announcement. To study the impact of the employment situation, report on the gold spot exchange rate more accurately and avoid data adjustment error in this study, data that are precisely released on the announcement time should be studied. U.S. nonfarm employment and unemployment “surprises” are calculated as the difference between the announced BLS figure, and the median of analyst forecasts compiled by Bloomberg to follow the most recent studies approach. On behalf of calculating changes on the gold spot exchange rate, historical data of the Gold spot exchange in one-minute frequency are collected from Histdata.com for U.S. employment situation report days from January 2011 through March 2020. Cumulative price changes from one before to the release of the announcement through market close time on announcement days are calculated. The observation window is defined from 8:30 AM open price to 8:40 AM open price interval and extended each 10 minutes up to 9:30 AM open price to cover one hour after the announcement release. Furthermore, 6:00 AM open price through 8:29 AM open price is defined as observation window for pre-market reaction. This approach aims to test various intervals before and after the release of the announcement to interpret more precise results. Time intervals are not extended beyond the observation windows to evade effects on exchange rate changes by factors other than the U.S. employment situation report. In addition, to observe any abnormal exchange rate changes, data in the same frequency are collected to include the announcement window on U.S. employment report days from January 2011 through March 2020. Table 1 includes descriptive statistics for data included in this study. Furthermore, figure 1 and figure 2 exhibit the changes in the level of the essential figures of the announcement. As can be seen, the median of forecasts collected by Bloomberg can vary from the actual announced number for total nonfarm figure. In contrast, the actual figure for unemployment experiences less deviation to the forecasted figure from Bloomberg side. Additionally, for the period of study, the unemployment ratio has a steady trendline. Necessary to mention that some announcement dates include simultaneous events which might affect the price movement in a particular time interval. All simultaneous events have been considered for data period of this study and eliminated in order to achieve more reliable results based on pure impact of variables included in this study.

Table 1: Descriptive Statistics

	Mean	**Median**	**Standard Deviation**
Panel A - U.S nonfarm payroll employment statistics (All numbers in 1000 of jobs)			
Announced Change	137.39	162.00	147.37
Median analyst forecast change	136.46	139.95	139.95
Nonfarm payroll surprise	0.93	1.00	65.04
Revision of prior month	7.51	10.00	31.23
Panel B – U.S Unemployment rate (all in percentage)			
Announced Change	6.43%	5.90%	2.19%
Median analyst forecast change	6.47%	6.10%	2.21%
Unemployment surprise	-0.04%	0.00%	0.14%
Panel C – XAU/USD Cumulative exchange rate changes following the release of the employment report (all in percentage)			
8:30 - 8:40	0.03%	0.06%	0.61%
8:30 - 8:50	0.01%	0.02%	0.66%
8:30 - 9:00	0.01%	0.04%	0.70%
8:30 - 9:10	0.04%	0.07%	0.72%
8:30 - 9:20	0.04%	0.08%	0.75%

8:30 - 9:30	0.07%	0.12%	0.79%

Figure 1: Actual Versus Forecasted Total Number of Nonfarm Payrolls

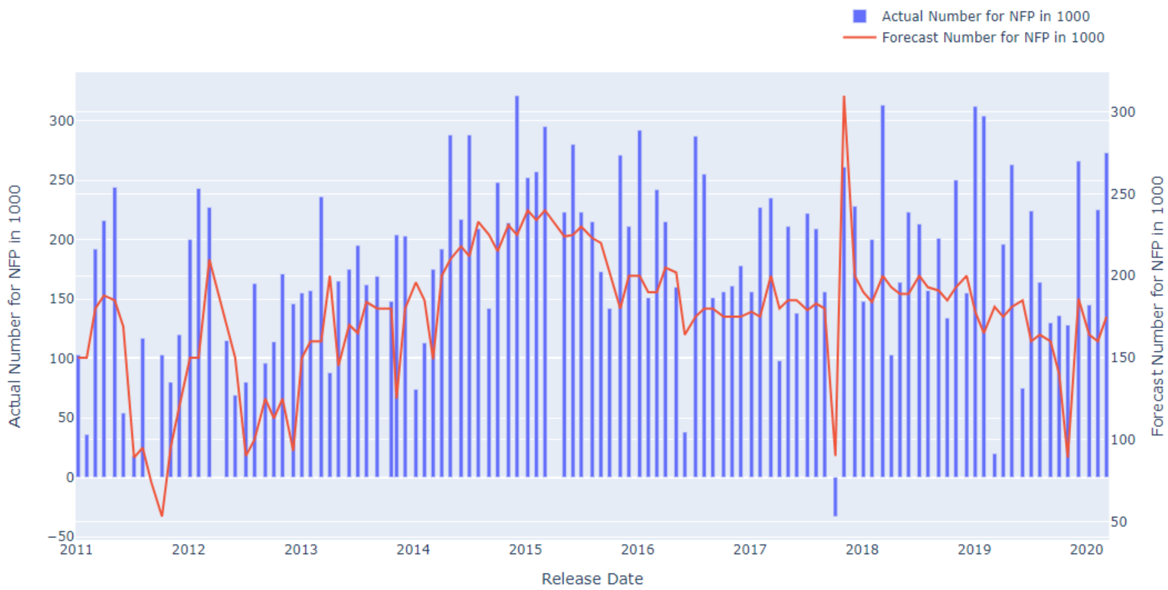
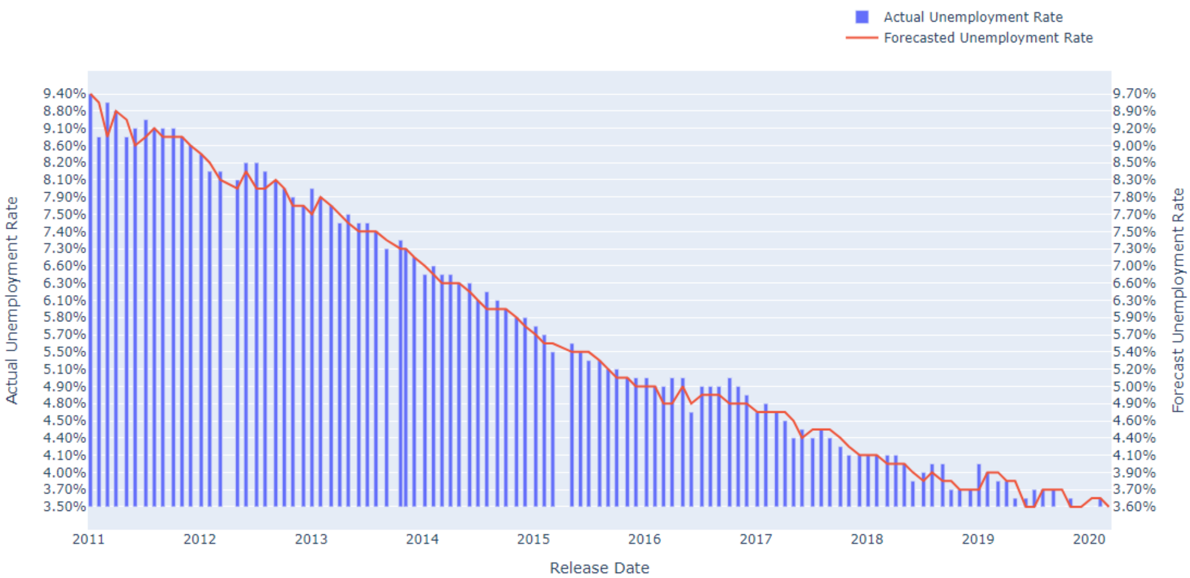


Figure 2: Actual Versus Forecasted Unemployment Rate



3.2. Methodology

The objective of this study is to determine whether the U.S. Nonfarm Payrolls announcement affects the spot price of Gold. Linear regression will be used to examine the relationship between changes in the XAU/USD rate, which is the dependent variable, and the number of Nonfarm Payrolls surprises, unemployment rate surprises, and preceding month revision surprises, which are the independent variables. In addition, for model estimation and evaluation, logistic regression and XGBoost regression are used to predict the direction of the dependent variable based on the independent variables.

3.2.1. The Reaction of Gold Spot Exchange Rate to the U.S. Nonfarm Payroll Report

First, essential predictor variables are identified to study market reaction to U.S. nonfarm payroll reports. Following most recent studies, the total number of U.S. nonfarm payroll employment, unemployment rate, the median of most recent analyst forecasts, and revision of the previous month's payroll number are the essential predictor variables. Based on the typical procedure in literature, the difference between the announced level of U.S. nonfarm payroll employment and the median analyst forecast, which Bloomberg compiles, is recognized as the "surprise" change in employment levels. To make more accurate analyses and understandable results, employment level "surprises" are standardized to the mean of zero and variance of one for the data period from January 2011 through March 2020 and named "Employment surprise." Similarly, the same practice is applied for the unemployment rate, and the standardized difference between the unemployment rate and the median of analyst forecast change is named "Unemployment Surprise." Also, the standardized difference between the revised number of nonfarm employment and the previously announced nonfarm employment number is named "Employment Revision." Multiple regression methods are applied for both samples to discover the relationship between predictor variables and changes in the gold spot exchange rate during the release of the U.S. employment situation. The multiple regression method helps find coefficients relevant to each predictor variable, so it is mandatory to prevent any possibility of multicollinearity. Before applying multiple regression for exchange rate changes, Pearson correlation coefficients between predictor variables are calculated and shown in table 2. Results in correlation analysis show a low correlation between independent variables of the model, which indicates a low possibility of multicollinearity in the regression model. Additionally, in order to achieve robust results variance inflation factor for independent variables of the study has been considered to conclude the possibility of multicollinearity shown in table 3. Since variance inflation factor for all variables is approximately equal to 1, it can be concluded that there is no possibility of multicollinearity in the OLS model.

Table 2: Correlation Matrix for Independent Variables

	Total NFP Surprise	Unemployment Surprise	Revision
Total NFP Surprise	1		
Unemployment Surprise	0.2113	1	
Revision	0.0358	-0.0636	1

Table 3: Variance Inflation Factor Metrics

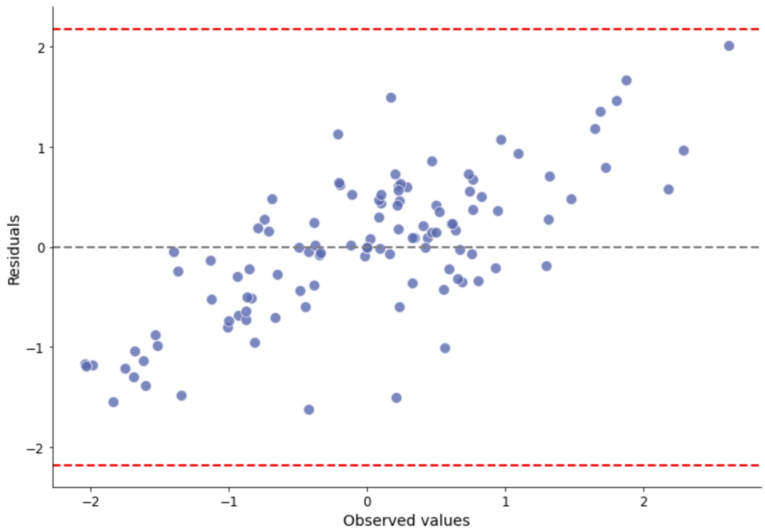
Variable	VIF
Total NFP Surprise	1.0494
Unemployment Surprise	1.0523
Revision	1.0066

Estimations for cumulative exchange rate change ($Exchange\_Change\ \%_t$) in equation (1) for different time intervals following the release of announcement has been considered for OLS model.

$$Exchange\_Change\%_t = \beta_0 + \beta_1\, Total\_Nonfarm\_Surprise_t + \beta_2\, Unemployment\_Surprise_t + \beta_3\, Revision_t + \varepsilon_t \qquad (1)$$

Necessary to mention, residuals for OLS model have been considered in order to evaluate the possibility of heteroskedasticity in the residuals of the model. In that regard, figure 3 represents the distribution of the residuals for the initial model.

Figure 3: Distribution of Residuals



However, distribution of residuals presented on the graph might not provide accurate understanding of the residual's variance. To evaluate this issue more adequately, alternative tests have been applied on the initial model in case of presence of heteroskedasticity. Alternative tests according to the evaluation of this phenomenon are presented in Table 4.

Table 4: Heteroskedasticity Tests

Test	Test Metric	P-value	Hypotheses
Goldfeld-Quandt test	F-statistic: 1.1308	0.3295	Null hypothesis: homoscedasticity
Breusch-Pagan test	Chi-squared statistic: 1.1753	0.7589	Null hypothesis: homoscedasticity
White test	Chi-squared statistic: 13.5276	0.1401	Null hypothesis: homoscedasticity

The Goldfeld-Quandt test, the Breusch-Pagan test, and the White test were the three tests used to determine heteroskedasticity. These tests' findings indicate that there isn't much evidence of heteroskedasticity in the model. The results of the Goldfeld-Quandt test showed that there was no significant difference in variance between the two groups of data, with a test statistic of 1.1308 and a p-value of 0.3296. The Breusch-Pagan test, which had a test statistic of 1.1753 and a p-value of 0.7589, also revealed no indication of heteroskedasticity. The White test resulted in a test statistic of 13.5276 and a p-value of 0.1401, indicating that the homoskedasticity null hypothesis cannot be rejected. Overall, the findings of the three tests have agreed, showing that presence of heteroskedasticity is rejected. However, considering homoscedasticity, GLS model has been applied to compare findings in both models.

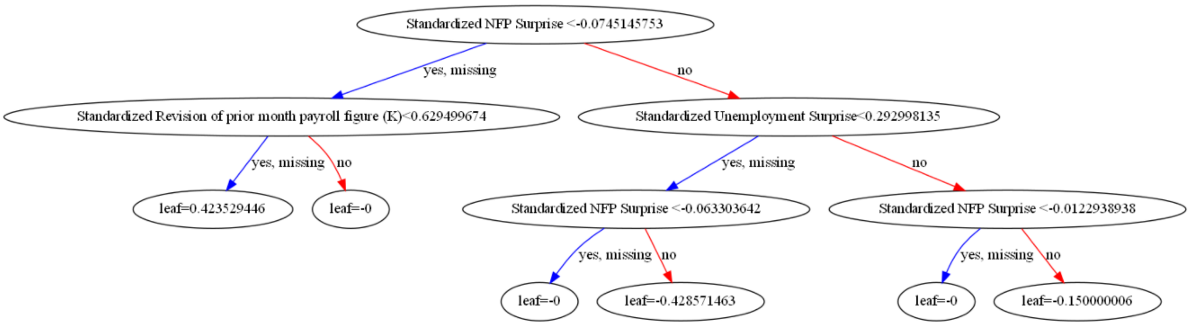
Furthermore, fixing predictors, dependent variable has been considered for various time intervals following the announcement release.

3.2.2. The Direction of Exchange Rate Movement After Announcement Release

Since the impact of announcement release is observable, it is appealing to predict the behavior of the movement following the announcement release. In that regard two feasible behaviors have been considered for price movement. Based on the status of the announcement the movement can be either ascending or descending. While the outcome is binary, decision tree approaches can be beneficial to be practiced in this regard. In this case, movement direction has been evaluated based on the same predictors of this study. Two separate models based on logistic regression and XGboost regression developed and accuracy metrics for both models has been compared in order to select a model with more accuracy metrics.

The effectiveness of the XGboost and logistic regression models has been assessed using a variety of criteria. These binary classification models are often evaluated using two metrics: accuracy and AUC-ROC (Area Under the Receiver Operating Characteristic Curve). The percentage of instances that were correctly classified out of all instances has been utilized to calculate accuracy. However, accuracy alone might not be adequate to judge model performance in scenarios when the classes are unbalanced. In order to test the model's capability to distinguish between positive and negative cases across all potential threshold values, AUC-ROC has also been used. The confusion matrix has also been looked at in order to total up the number of true positives, false positives, true negatives, and false negatives in addition to these metrics. Other helpful metrics, including precision, recall, and F1-score, have been computed from the confusion matrix. The fraction of real positives among all instances projected to be positive has been measured using precision. The proportion of true positives among all real positive cases has been calculated using recall. The harmonic mean of recall and precision has been calculated using the F1-score, which offers a fair evaluation of both measurements. Figure 4 represents the decision tree structure for XGboost model.

Figure 4: Decision Tree Structure



3.2.3. The Reaction of Pre-Market to Release of U.S. Nonfarm Payroll Report on The Gold Spot Exchange Rate

The efficient market hypothesis (EMH) suggested by (Fama et al., 1969) remains the dominant theory to interpret market behavior. It implies that prices movements in financial markets should be formed in a random walk without any discernible patterns that can be analyzed to extract potential profits (Caporale & Plastun, 2021). Based on this hypothesis, it is assumed that price movements prior to the release of the U.S. Employment should follow a random walk if there is no existence of information leakage. Abnormal returns on the gold spot exchange rate changes 150 minutes before the announcement release and 10 minutes after the announcement release are calculated for data from January 2011 through March 2020.

Abnormal returns for time are calculated as follows:

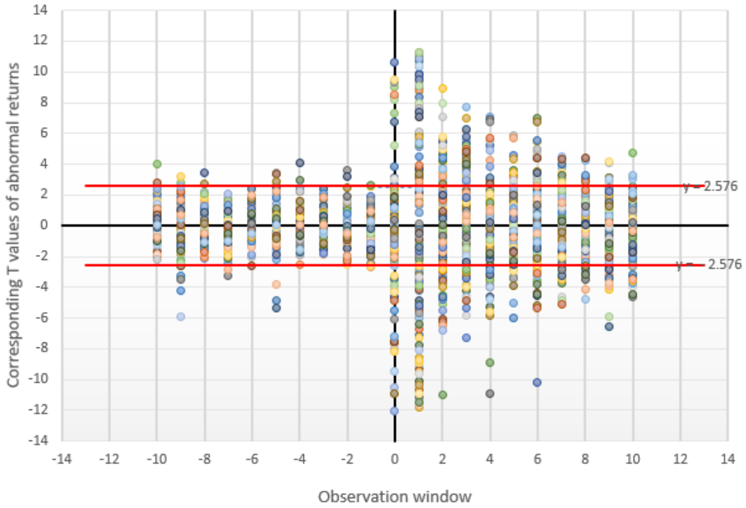
$$AR_t = R_t - E(R)_t \tag{2}$$

Where R_t is return at time t, and $E(R)_t$ is expected return which is corresponding average return for sample period, and it is calculated as follows:

$$E(R)_t = (\frac{1}{T}) \sum_{i=1}^{T} R_i \tag{3}$$

In this formula, t is the sample size, and for this study, it equals 131, including 150 minutes before the announcement release and 10 minutes after. In the following, T-Statistics for abnormal returns are calculated figure5. The observation window includes 10 minutes before the announcement release and 10 minutes after the announcement release.

Figure 5: Corresponding T-Values of Returns



4. FINDINGS AND DISCUSSIONS

Standardized variables provide a better understanding of results. In this case, each coefficient measures the movement of one standard deviation change in the predictor variable on cumulative changes of the exchange rate before and after the release of the announcement. In order to evaluate the presence of heteroskedasticity, GLS model has been performed. Results coming from GLS model approve the robustness of the OLS model while coefficients show no deviation between two approaches shown in table 5.

Table 5: OLS and GLS Regression Results

	Dependent variable: Exchange Rate	
	OLS Model	**GLS Model**
Standardized NFP Surprise	-9.458*** (1.059)	-9.458*** (1.059)
Standardized Revision	-0.355*** (0.118)	-0.355*** (0.118)
Standardized Unemployment Surprise	0.347** (0.302)	0.347** (0.302)
Intercept	-0.880*** (0.128)	-0.880*** (0.128)
Observations	112	112
Adj. R-squared	44.51%	44.51%
Residual Std. Error	0.738 (df=108)	0.738 (df=108)
F Statistic	30.684*** (df=3; 108)	30.684*** (df=3; 108)
Note:	*p<0.1; **p<0.05; ***p<0.01	

For the sample of this study, employment surprise coefficient is significantly different from zero at 5% level for all time intervals, so it can infer that one standard deviation increase in employment surprise tends to origin decreases between 0.34% through 0.14% in exchange rate changes 30 minutes following the release of the announcement. Likewise, the employment revision coefficient is significantly different from zero at a 5% level for all time intervals, indicating that one standard deviation increase in employment revision tends to origin decreases almost 0.035% through in exchange rate 30 minutes following the release of the announcement. In contrast, the unemployment surprise coefficient is different from zero at 5% level for all time intervals, representing that one standard deviation increase in unemployment surprise tends to origin increase between 0.034% through 0.014% in exchange rate 30 minutes following the announcement.

The statistics show that positive employment surprise weakens Gold, consistent with previous studies and the hypothesis of this study. Additionally, coefficients show the relative importance of each predictor variable. The results on Wald tests at 5% level can infer that the coefficient of employment surprise is significantly greater than the coefficient of employment revision and unemployment surprise, indicating that it has more impact relative to employment revision and unemployment surprise on the exchange rate changes. Coefficients for predictor variables in different time intervals 30 minutes following the release of announcement stay consistent, indicating that the impact of announcement release is completed in the first 30 minutes following the release of the announcement. In summary, it can infer from results on multiple regression model that at the time of announcement release, market presumes surprise on nonfarm payroll employment number as the most deciding variable and strictly reacts to this variable and views the employment revision and unemployment surprise as variables which contain additional information regarding the release of the announcement. Moreover, a multiple regression model for time intervals included one hour prior to the release of the announcement is applied to see if there are significant coefficients for predictor variables or not. Results show that coefficients of predictor variables are not significantly different from zero, indicating no information leakage prior to announcement release. The market does not react to the release of the U.S. nonfarm payrolls report one hour before the release of the announcement. Results for T-Statistics of abnormal returns specifies that 2.12% of abnormal returns through 8:20 to 8:30 interval is out of confidence level, and an expansion in T-statistics of abnormal returns happens just after the release of the U.S. nonfarm payrolls report where 28.64% of abnormal returns are out of desired range. Results on abnormal returns are in line with results achieved by the multiple regression method because both indicate the existence of jumps in exchange rate changes after the U.S. nonfarm payrolls report release. At the same time, both reject the reality of exchange rate changes caused by the U.S. nonfarm payrolls report for time intervals before the release of the announcement. Table 6 represents results for various time intervals following the announcement release. While first time window includes 5 minutes after the announcement, the largest observation time window presents 30 minutes following the announcement.

Table 6: OLS Regression for Each Cumulative Intervals

	Dependent variable: Exchange Rate					
	Cum 5	**Cum 10**	**Cum 15**	**Cum 20**	**Cum 25**	**Cum 30**
Standardized NFP Surprise	-3.4581*** (1.052)	-2.3782*** (1.119)	-2.1040*** (1.125)	-1.8755*** (0.168)	-1.7664*** (1.173)	-1.4254*** (1.201)
Standardized Revision	-0.355*** (0.118)	-0.3606*** (0.125)	-0.4154*** (0.125)	-0.3849*** (0.130)	-0.3918*** (0.131)	-0.3516*** (0.134)
Standardized Unemployment Surprise	0.3475** (0.302)	0.1692** (0.319)	0.3242** (0.321)	0.3075** (0.334)	0.2712** (0.336)	0.1207** (0.343)
Intercept	-0.8803*** (0.128)	-0.7861*** (0.135)	-0.7858*** (0.136)	-0.7379*** (0.141)	-0.7239*** (0.142)	-0.6737*** (0.145)
Observation	112	112	112	112	112	112
Adj. R-squared	44.51%	38.10%	37.46%	32.51%	31.97%	28.63%
Residual Std. Error	0.738 (df=108)	0.749 (df=108)	0.786 (df=108)	0.820 (df=108)	0.893 (df=108)	0.941 (df=108)
F Statistic	30.684*** (df=3; 108)	23.771*** (df=3; 108)	23.160*** (df=3; 108)	18.821*** (df=3; 108)	18.386*** (df=3; 108)	15.842*** (df=3; 108)
Note:	*p<0.1; **p<0.05; ***p<0.01					

Note: Each column represents cumulative exchange rate change 5 to 30 minutes following the announcement release.

Up to this point, it has been shown that gold spot exchange rate reacts negatively to a positive status of employment report especially to the headline of the announcement and other features included in the announcement gives additional information related to the announcement. In order to predict the direction of the movement, it is necessary to evaluate findings on decision tree approaches. Table 7 shows measurement metrics for two models of this study.

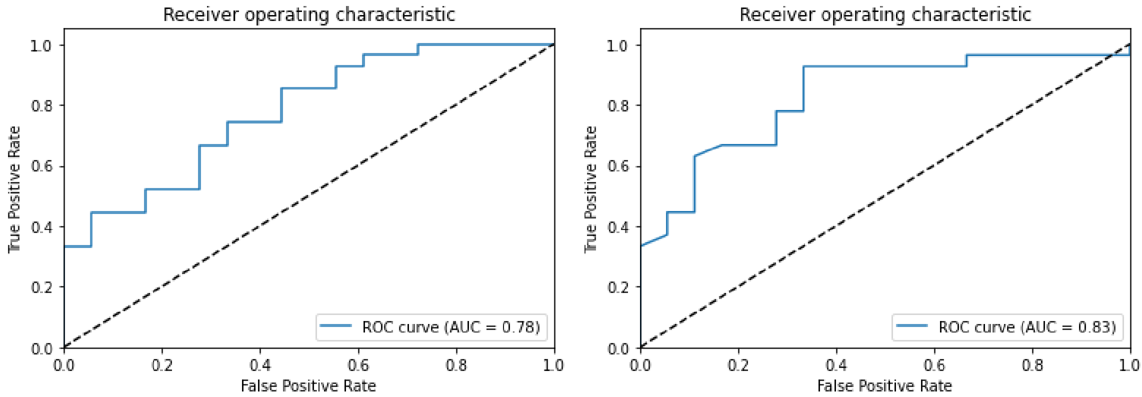
The goal was to evaluate how the release of the U.S. employment data affected the direction of the movement of the spot gold exchange rate. Logistic regression and XGboost decision tree methods were used, and 70% of the data was used to train the models. At a 5% level of significance, the logistic regression model produced coefficients for the standardized NFP surprise, standardized unemployment surprise, and standardized revision, respectively, of -1.00201, 0.3286, and -0.2388. The logistic regression model's accuracy, precision, recall, F1 score, and AUC score were discovered to be 0.7111, 0.6845, 0.9627, 0.8, and 0.7757, respectively. The study's findings show that the standardized NFP surprise, standardized unemployment surprise, and standardized revision all significantly affect the spot price of gold after the announcement is made. The direction of the movement in the exchange rate was reasonably well predicted using the logistic regression model, which is a widely used decision tree approach in binary outcome prediction. The model had an accuracy of 0.7111, which means that 71.11% of the time it predicted the movement's direction accurately. The accuracy of the logistic regression model was 0.6845, which indicates that 68.45% of the positive cases that the model predicted were in fact true. The model's recall was 0.9627, which indicates that 96.27% of all positive cases in the dataset were accurately predicted by the model. The model's F1 score was 0.8, which represents the harmonic mean of precision and recall and offers a single indicator of the model's general effectiveness. The model's AUC score was 0.7757, which shows that it is more accurate than random guessing in differentiating between positive and negative cases. Overall, the study's findings show that decision tree methods can be used to foretell how economic announcements will affect the spot price of gold. To increase the models' precision and investigate additional variables that can influence the exchange rate, more research is nonetheless required.

The effect of the U.S. employment data on the spot price of gold after the announcement has been predicted using the XGboost decision tree approach. The same features as in the logistic regression model were utilized, and for the standardized NFP surprise, standardized unemployment surprise, and standardized revision, respectively, the relevance of each feature was found to be 0.4388, 0.3286, and 0.2325. The accuracy of the XGboost model was 0.7777, which is somewhat better than the accuracy of the logistic regression model. The model's accuracy was 0.7931, which indicates that 79.31% of the positive cases it predicted were in fact positive. The model's recall was 0.8518, which indicates that it accurately predicted 85.18% of the positive cases in the dataset. The harmonic mean of precision and recall for the model was 0.8214, which is known as the F1 score. The model's AUC score was 0.8271, indicating that it performs better than random guessing in differentiating between positive and negative cases. The findings of this study show that the XGboost decision tree approach is a good technique for forecasting how economic announcements will affect the spot price of gold. The NFP surprise, followed by the unemployment surprise and revision, has the greatest influence on the exchange rate, according to the relevance of each component in the XGboost model. Figure 6 shows ROC curves for both model and corresponding AUC scores. In conclusion, the XGboost model fared better in predicting the movement of the exchange rate than the logistic regression model. According to the study's findings, decision tree methods can be a useful tool for forecasting how economic announcements will affect the financial markets. The accuracy of the models can be increased by conducting additional research to examine additional variables that may impact the exchange rate.

Table 7: Measurement Features for Decision Tree Models

Model	Accuracy	Precision	Recall	F1 score	AUC score
Logistic Regression	0.7111	0.6842	0.9630	0.8000	0.7757
XGboost	0.7778	0.7931	0.8519	0.8214	0.8272

Figure 6: ROC Curve for Logistic Regression and XGboost Regression



Note: graph in the right side represents ROC curve of logistic regression approach with AUC of 78%, while graph in the right side represents ROC curve of XGboost approach with AUC of 83%.

5. CONCLUSION AND IMPLICATIONS

The release of the U.S. jobs report has a considerable impact on gold spot exchange rates, the study's findings show. According to the analysis, a high number of nonfarm payrolls has the most bearing on the announcement, while the unemployment rate and the revision from the previous month also add to the picture. It has been discovered that an upbeat job report weakens gold spot exchange rates. Additionally, the research has demonstrated that abnormal returns occur immediately following the announcement, indicating that the market is responding fast to the fresh information. The study's decision tree methods, such as logistic regression and XGboost, have shown great precision and accuracy in forecasting the direction of gold spot exchange rates depending on the timing of the release of the U.S. employment report. Overall, the analysis emphasizes the significance of the release of the U.S. employment data as a significant factor influencing gold spot exchange rates. For traders and investors who are interested in forecasting the direction of gold spot exchange rates after the release of the U.S. jobs report announcement, the findings and models created in this study may be helpful.

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