



To my grandfather

ESSAYS ON FOREIGN EXCHANGE

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

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ESSAYS ON FOREIGN EXCHANGE

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ABSTRACT

ESSAYS ON FOREIGN EXCHANGE

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This thesis investigates the foreign exchange market dynamics by using high frequency data. There is a vast literature on currency markets. However, we aimed to bring a new light on the foreign exchange market dynamics by investigating high frequency data for a set of mostly traded currencies, that includes both developed and emerging market currencies. In the first chapter, we focus on the commonality in liquidity in the foreign exchange market where we are able to contribute to the literature by using a comprehensive data set (14 currencies) with high frequency analysis. Our findings indicate that commonality in liquidity exist for foreign exchange markets even beyond crisis periods and also monetary policy meetings of Federal Reserve (FOMC) have significant effect on commonality in liquidity. In the second chapter, we study the foreign exchange market for a large data set (14 currencies) where we analyzed the predictability of jumps in the foreign exchange market. We showed that different machine learning methodologies can be used for jump prediction as well as prediction of the direction of jumps in foreign exchange market where Multi Layer Perceptron (MLP), Support Vector Machine (SVM) and Random Forest methodologies have the highest accuracy rates. In our analysis, we are able to predict the occurrence of jumps as well as the direction of jumps in the foreign exchange market using state of art machine learning methodologies

for high frequency data even for the Covid Pandemic period where volatility in the foreign exchange market is very high.

Keywords: Commonality in Liquidity, Foreign Exchange, High-Frequency Analysis, Jump Prediction, Machine Learning



ÖZET

DÖVİZ KURU ÜZERİNE MAKALELER

Uzun, Sevcan
Doktora, İşletme
Tez Danışmanı: Doç. Dr. Ahmet Şensoy

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Bu tez, yüksek frekans veri kullanarak döviz piyasası dinamiklerini araştırmaktadır. Döviz piyasası üzerine yazılan literatür gün geçtikçe büyümektedir. Diğer yandan, bu çalışma ile en çok işlem yapılan gelişmiş ve gelişmekte olan ülke para birimleri incelenerek yüksek frekans verileri yardımıyla, döviz piyasası dinamiklerine yeni bir bakış açısı getirilmeye çalışılmıştır. Çalışmanın ilk bölümünde, 14 farklı para birimini içeren yüksek frekanslı ve kapsamlı bir veri seti kullanılarak, döviz piyasalarındaki likidite eşzamanlılığına katkıda bulunmaktadır. Araştırmanın sonuçları ayrıca, döviz piyasalarındaki likidite eşzamanlılığının kriz dönemleri dışında da devam ettiğini ve FOMC toplantılarının, piyasadaki sistemik likidite üzerinde önemli etkileri bulunduğunu göstermektedir. Çalışmanın ikinci bölümünde, yine gelişmiş ve gelişmekte olan 14 farklı ülkenin para birimleri yüksek frekanslı veri setiyle incelenerek döviz piyasasındaki sıçramaların tahmin edilebilirliği araştırılmıştır. Çalışmanın bu kısmında, döviz piyasalarındaki sıçramaların tahmin edilebilirliğinin yanı sıra, bu sıçramaların yönünün tahmin edilebilirliği de incelenmiştir. Multi Layer Perceptron (Çok Katmanlı Algılayıcı), Support Vector Machine (Destek Makineleri) ve Random Forest (Rasgele Orman) yöntemleri, çalışmada en yüksek tahmin edilebilirlik skorlarını vermiştir. Çalışma, Covid pandemisi gibi, yüksek volatilité dönem-

lerinde de makine öğrenmesi yöntemlerinin yardımıyla döviz piyasasındaki sıçramaların ve yönlerinin tahmin edilebileceğini göstermiştir.

Anahtar Kelimeler: Döviz Piyasası, Likiditede Eşzamanlılık, Makine Öğrenmesi, Sıçrama Tahmini, Yüksek Frekanslı Analiz



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CHAPTER I

INTRODUCTION

1.1. Overview

By incorporating high frequency exchange rate data, this thesis contributes to the existing literature by examining the commonality in liquidity in the foreign exchange market first.

Commonality in liquidity is defined as the co-movements of foreign exchange rate liquidities over time, where the foreign exchange liquidity is driven largely by shocks that affect the whole foreign exchange market. Commonality in liquidity can arise from both supply side and demand side factors. Some studies have shown evidence for the supply-side determinants of liquidity commonality driven by funding constraints faced by market participants and some studies show evidence for the demand-side sources of liquidity commonality related to the correlated trading activity, level of institutional ownership. Commonality in liquidity implies diminishing liquidity across all foreign exchange rates and it can not be diversified easily. Furthermore, commonality in foreign exchange, equity and bond markets suggests liquidity risk impairs the efficacy of international and cross asset class diversification. Given the increasing interconnectedness of the global markets, it has become more and more important to understand commonality in liquidity. Foreign exchange market liquidity and commonality has

started to receive attention especially in the aftermath of the global financial crisis. Our analysis contributes to the literature by using a comprehensive data set where we are able to provide recent evidence for the commonality in liquidity in the foreign exchange market. We show that commonality in liquidity is prevalent in the foreign exchange market when high frequency data is used. We are covering a data set from 2014 to 2018 where both developed and emerging market currencies are included (AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDCHF, USDHUF, USDJPY, USDMXN, USDNOK, USDPLN, USDSEK, USDTRY, USDZAR). We cover a time period beyond global financial crisis and show that liquidity commonality in the foreign exchange market persists even after the global financial crisis. Furthermore, we analyzed the effects of the monetary policy meetings of Federal Reserve (FOMC) and European Central Bank (ECB).

After analyzing commonality in liquidity in the foreign exchange market, we focus on another characteristic of the foreign exchange market. While there are studies that try to link the relation between exchange rate levels and uncertainty, we investigate the large discontinuities in the foreign exchange market which are identified as jumps. In particular, we analyze jumps for each of the exchange rates and develop a forecasting model using different machine learning methodologies. Our data set covers a sample period from 2018 to 2021 where again 14 different developed and emerging exchange rates (AUDUSD, USDCAD, USDCHF, USDCZK, EURUSD, GBPUSD, USDHUF, USDJPY, USDMXN, USDNOK, NZDUSD, USDPLN, USDSEK, USDZAR) are included. Our empirical results show that we are able to predict the occurrence of jumps in the foreign exchange market by using Multilayer perceptron, Support Vector Machine and Random Forest methodologies and furthermore we are able to predict the direction of jumps in the foreign exchange market by using the before mentioned methodologies. Our

results are robust to different sizes of the training and test data, which we show in our robustness section. Also we further analyzed the effects of Covid pandemic on the jump detection process in the foreign exchange market and our empirical results show that, although our prediction accuracy has decreased, we are able to predict the occurrence of jumps as well as their direction in the foreign exchange market using machine learning methodologies.



CHAPTER II

COMMONALITY IN FOREIGN EXCHANGE LIQUIDITY: HIGH FREQUENCY ANALYSIS

2.1. Introduction

Liquidity is important for all financial markets, whether it is stock market, bond market or foreign exchange market. Commonality in liquidity according to [Brockman, Chung, and Pérignon \(2009\)](#) refers to the impact of a common or market-wide liquidity factor on an individual firm in terms of bid-ask spreads and depths whereas [Mancini, Rinaldo, and Wrampelmeyer \(2013\)](#) define commonality in liquidity as co-movements of foreign exchange rate liquidities over time, that is foreign exchange liquidity is driven largely by shocks that affect the whole foreign exchange market. From earlier papers related to market micro-structure research, transaction and liquidity naturally refer to the repeated trading of a single asset. Traditional micro-structure research suggests that individual trading volume, volatility and price are strong determinants of liquidity. With the work of [Chordia, Roll, and Subrahmanyam \(2000\)](#), [Pástor and Stambaugh \(2003\)](#) and [Sadka \(2006\)](#), interest has moved to the market-wide exploration of liquidity. [Chordia et al. \(2000\)](#) suggest that liquidity is more than just an attribute of a single asset and individual liquidity measures co-move with

each other. [Chordia et al. \(2000\)](#) show how portfolio managers are facing more challenges in terms of changing their portfolio holdings when the market-wide forces affect liquidity. By accepting the existence of commonality in liquidity, [Chordia et al. \(2000\)](#) show inventory risks and asymmetric information both affect individual stock liquidity. [Pástor and Stambaugh \(2003\)](#) demonstrate how the common momentum strategy of buying winning stocks and selling losing stocks becomes less attractive given liquidity risk plays a role in pricing anomalies in financial markets. [Mancini et al. \(2013\)](#) provide first foreign exchange liquidity commonality analysis and show that from a central bank perspective, when liquidity is provided for an exchange rate, there may be positive spillovers to other currencies. Furthermore, providing liquidity in local currency could mitigate liquidity strains in other investment currencies and constraint sudden appreciation of funding currencies. Thus, understanding commonality in liquidity is beneficial not only for investors but also market and policy makers as well. Commonality in liquidity matters as even when the fundamental value of the exchange rate does not change, volatility of nominal and real exchange rates may increase. For individual firms this may lead to the need for better exchange rate risk management whereas for households it may lead to a loss in the purchasing power and quality of life.

Commonality in liquidity can arise from both supply side and demand side factors. Some studies have shown evidence for the supply-side determinants of liquidity commonality driven by funding constraints faced by market participants and some studies show evidence for the demand-side sources of liquidity commonality related to the correlated trading activity, level of institutional ownership. Commonality in liquidity implies diminishing liquidity across all foreign exchange rates and it can not be diversified easily. Furthermore, commonality in foreign exchange, equity and bond markets suggests liquidity risk

impairs the efficacy of international and cross asset class diversification. Given the interconnectedness of the global markets, it has become more and more important to understand commonality in liquidity.

Most of the studies on commonality in liquidity has investigated stock market dynamics whereas only a few have focused on bond markets and foreign exchange markets. Foreign exchange market liquidity and commonality has started to receive attention especially after the global financial crisis.

Foreign exchange market has different characteristics as being decentralized and over the counter, where trades takes place 24 hours a day for 5.5 days a week and it is world's most traded asset class. According to BIS (2009) Triannual Survey, daily trading volume of foreign exchange is 6.6 trillion USD. Around 80 percentage of trading that takes place in the foreign exchange market is algorithmic trading. This paper contributes to the existing literature by providing some recent evidence on commonality in foreign exchange market liquidity where a more extensive data set (14 currency pairs) is used.

Our contribution with this paper is twofold: First of all, by using an extensive data set we are able to provide recent evidence for the commonality in liquidity in the foreign exchange market. Our results show that commonality in liquidity exists for foreign exchange market when using high frequency data as well. Furthermore, we investigate whether the monetary policy meetings of Federal Reserve (FOMC) and European Central Bank (ECB) have affect on market-wide foreign exchange liquidity and demonstrate that FOMC meetings have a direct effect on systemic market liquidity.

Rest of this section is organized as follows: Section 2 gives information on the relevant literature whereas section 3 provides information on data, analysis and

results where conclusion draws upon the results of the section and provides suggestions for further studies.

2.2. Related Literature

Liquidity is a broad concept and there is no unique definition for it. [Grossman and Miller \(1988\)](#) model market liquidity as determined by the demand and supply of immediacy. An asset is liquid if it can be sold quickly, at low cost, without causing any significant price change. To this definition, [Pástor and Stambaugh \(2003\)](#) adds ability to trade large quantities quickly. [Brockman et al. \(2009\)](#) define commonality in liquidity as the impact of a common or market wide liquidity factor on an individual firm, in terms of bid-ask spreads and depths. From earliest papers related to market microstructure research, transaction and liquidity naturally pertain to the repeated trading of a single homogeneous asset. With the work of [Chordia et al. \(2000\)](#) the interest has been shift to the market-wide exploration of liquidity. Traditional microstructure literature suggests individual trading volume, volatility and price are influential determinants of liquidity. [Chordia et al. \(2000\)](#) suggest that liquidity is more than just an attribute of a single asset and individual liquidity measures co-move with each other. Controlling for volume, price and volatility, authors find there are common influences in the market that are significant. The quoted spreads, quoted depth and effective spreads move together with the market and industry wide liquidity. Furthermore, [Brunnermeier and Pedersen \(2008\)](#) also show that when fundamental volatility increases, market liquidity declines, in line with the empirical findings of [Benston and Hagerman \(1974\)](#), [Amihud and Mendelson \(1989\)](#) and [Vayanos \(2004\)](#) where liquidity premiums increase in volatile times. [Brunnermeier and Pedersen \(2008\)](#) suggest that asymmetric information and

inventory costs are the two primary sources of commonality in liquidity related to the market microstructure effects.

While most of research on liquidity has focused on stock markets, there are a few that has focused on bond markets, foreign exchange markets and in commodity markets. Foreign exchange liquidity affects traders in the market but also every company and investor that has assets denominated in foreign currencies is affected from foreign exchange liquidity. Furthermore, it affects and is affected from other financial markets, including bond, stock and derivative markets. Especially in recent years, after the global financial crisis, with the new financial reforms, the structure and liquidity of foreign exchange markets have changed. Electronic trading has increased, as stated by [King, Osler, and Rime \(2013\)](#) transparency has increased, with the introduction of new traders in the market trading behaviors of existing traders changed, and with advances in technology, transaction speeds have also increased. [Banti, Phylaktis, and Sarno \(2012\)](#), develop a measure for common liquidity to test whether liquidity of individual currencies are dependent on the global foreign exchange liquidity. They find that global liquidity measure explains a fraction of liquidity fluctuations in individual currencies. Furthermore, the global foreign exchange liquidity measure has strong variation through time.

[Mancini et al. \(2013\)](#), present one of the first studies of systematic liquidity in the foreign exchange market. In contrast to the commonly held view that foreign exchange markets are liquid all the time, authors show that there are variations in currency liquidities. Furthermore, they also show that there are comovements of foreign exchange liquidity. They also look at the comovements of liquidities in foreign exchange, US equity and bond market and found strong comovements which suggests the liquidity risks may actually affect diversification. Theoretically, during times of distress, different asset markets have stronger illiquidity linkages.

A study by [Banti \(2016\)](#) also investigates the illiquidity channel links in stock markets and foreign exchange markets. During financial crisis periods, small firm stocks are strongly correlated to currencies when compared to large firm stocks. [Banti \(2016\)](#) found that stock market illiquidity affects the liquidity of all currencies but it is restricted to small stocks in the crisis episodes. Furthermore, investing currencies are more linked with small stock compared to funding currencies in the last financial crises whereas funding currencies were stronger in the dot-com bubble. [Karnaukh, Ranaldo, and Söderlind \(2015\)](#) use low frequency data (daily) and illustrate variations in currency liquidity using a data set for 30 years, for 20 currencies, compared to [Mancini et al. \(2013\)](#) where they use 9 currencies for 3 years. [Karnaukh et al. \(2015\)](#) demonstrate that foreign exchange liquidity is weakened during crisis periods and foreign exchange liquidity reacts to exogeneous demand and supply liquidity shocks. They found that commonality in foreign exchange liquidity is strong and there are periods of systematic liquidity and illiquidity for the time period analyzed. They further confirm the previous findings of [Mancini et al. \(2013\)](#) and [Banti et al. \(2012\)](#) where commonality in foreign exchange liquidity is found to be stronger for developed market currencies.

2.3. Data and Results

The bid-ask spread is the most widely used measure of liquidity in the literature starting with the early work of [Demsetz \(1968\)](#) in which he claims that under competitive conditions the bid-ask spread, or markup will measure the cost of making transactions without delay. In an illiquid market, buy orders tend to push transaction prices up, while sell orders tend to do the opposite. In this setting, the best price at which a security can be bought (ask price) is considerably above the

best price at which it can be sold (bid price). For this reason, the difference between these two prices – the bid-ask spread – is a common measure of liquidity conditions. The aim of this research is to analyze the extent of commonality in liquidity in foreign exchange market. In this study, proportional bid-ask spread (proportional quoted spread) is going to be used as the cost aspect of illiquidity, following [Mancini et al. \(2013\)](#) and [Fong, Holden, and Trzcinka \(2017\)](#). Liquidity is proxied by means of quoted bid-ask spreads. Bid-ask spreads have the implicit cost of trading but they do not cover other aspects of liquidity. Classic theories of liquidity indicate that bid-ask spreads should rise with market risk or volatility, with the expected time between trades, with adverse selection risk, rate of information arrival, trade size, dealers' risk aversion. Spreads, as a proxy for liquidity, are based on asymmetric information and inventory considerations of market makers. A market is regarded as liquid if the proportional quoted bid-ask spread is low. Data worked on is unique in the sense that it is high frequency data on bid-ask spreads for a long period of time, for many countries with different characteristics. The data is taken from Gain Capital, a USA based firm, with average monthly volume of 501.2 Billion USD and with over 140,000 traders worldwide, 1200 institutional partners.

In this study, the tick data is used. [Goyenko, Holden, and Trzcinka \(2009\)](#) show the effect of added value of intraday data when measuring liquidity.

Approximately there is around 1 observation per each 5 second interval. The data set covers every hour, for every day, for 5.5 days for every week, for 52 weeks and for the time period from December 15, 2014 to April 27, 2018. Data set covers both developed markets and developing markets. Given a pegged exchange rate implies different liquidity dynamics, pegged currencies are removed from data set which leads to a total of 14 floating and free-floating currencies (AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDCHF, USDHUF, USDJPY, USDMXN,

USDNOK, USDPLN, USDSEK, USDTRY, USDZAR) to be included in the analysis. Throughout the analysis, all quotations are USD based, including reverse quoted currencies. The currencies selected account for approximately 76 percentage of all daily trades in the foreign exchange market (BIS, 2019).

For each of the observations, that is tick data, mid-quote price P_m , and spread P_s is calculated such that

$$P_m = \frac{P_A + P_B}{2} \quad (2.1)$$

whereas

$$P_s = P_A - P_B. \quad (2.2)$$

We exclude observations that take place between Friday midnight and Sunday midnight because the trading activity observed during these non standard trading hours are minimal. Tick data is aggregated for 5-minute intervals for each of the currencies. Within each of these 5-minute intervals, opening and closing, high and low mid prices and opening, closing, highest and lowest spreads are reported and calculated. The liquidity measure that is used in the analysis is the relative spread (defined as last quoted spread over last mid price for each of the 5-minute interval):

$$L_{i,t} = P_{S,i,t} / P_{M,i,t} \quad (2.3)$$

When the proportional quoted bid-ask spread ($L_{i,t}$) is low, the market is regarded as liquid. The percentage change in individual currency liquidity is calculated as follows:

$$\Delta L_{i,t} = \left(\frac{L_{i,t} - L_{i,t-1}}{L_{i,t-1}} \right) \quad (2.4)$$

As an alternative measure, individual currency liquidity (first difference) is also

measured over quoted spreads as following:

$$\Delta L_{i,t} = L_{i,t} - L_{i,t-1} \quad (2.5)$$

The overall liquidity measure for market is calculated following [Mancini et al. \(2013\)](#) by excluding each of the currency and averaging the individual liquidity of remaining currencies for each set of pairs such that

$$\Delta L_{M,t} = \sum_{i=1; j \neq i}^{14} \Delta L_{j,t} \quad (2.6)$$

The first hypothesis to be tested is as follows: there is commonality in liquidity in foreign exchange markets that is foreign exchange liquidity is driven by shocks that affect the foreign exchange market as a whole rather than individual rates. The following regression is estimated for each of the currencies,

$$\begin{aligned} \Delta L_{i,t} = & \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \\ & \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} \end{aligned}$$

Where $\Delta L_{i,t}$ is the measure of an individual liquidity for currency i , at time t , $\Delta L_{M,i,t}$ is the equally-weighted cross sectional average of the liquidity variable for all currencies at time t , excluding currency i . The reason for excluding each currency when calculating market liquidity is to eliminate the effect of individual currency i 's own variation on the market average. In order to capture the effect of non-concurrent adjustments in liquidity variation at the currency and market level, following [Chordia et al. \(2000\)](#), the lag and lead variables for market liquidity are also included in the regressions. $R_{M,i,t}$ is the return for the market for the currency i , excluding currency i , in calculating market return for that

exchange rate. Return for each currency is calculated using $P_{MC,i,t}$ such that $P_{MC,i,t}$ is the closing mid-price for each of the 5 minute intervals. Market return for each of the currencies is calculated by excluding each of the currency and taking cross sectional average of the remaining currency returns for that interval. $V_{i,t}$ is the volatility for currency i , at time t . Volatility for currencies is estimated following Garman and Klass (1980), where lowest and highest prices for the spesific time interval are also used in addition to the opening and closing prices. Empirical studies show that Garman-Klass volatility estimation is 8 times better than the classical volatility estimation methodologies. The volatility is estimated with the following formula where highest and lowest prices of the interval is normalized with respect to the opening prices:

$$V_{i,t} = \sqrt{0.5(\log(P_{M,i,t}^H) - \log(P_{M,i,t}^L))^2 - (2\log(2) - 1)(\log(P_{M,i,t}^C) - \log(P_{M,i,t}^O))^2} \quad (2.7)$$

With these regressions, it is aimed to show the extent of liquidity commonality in foreign exchange market and to analyze whether the liquidity commonality is robust to changes in return in the market and volatility of the individual currencies.

To test for commonality, for each exchange rate i , we regress the time series of liquidity measure $\Delta L_{i,t}$ on the market liquidity measures $\Delta L_{M,i,t}$ including lead and lag market liquidity, return $R_{M,i,t}$, including lag and lead return for the market and volatility $V_{i,t}$ of the exchange rate i for 5-minute intervals. We begin with the main regression results for the each of the liquidity change measures. Same liquidity measure, quoted bid-ask spread is used throughout the study, however, the change is calculated by first difference and then also for a percentage change in liquidity variable. The results of the main regressions for first difference of liquidity is reported for high frequency analysis . Table 2.1 results show that

the liquidity of each foreign exchange rate depends on the market-wide liquidity. As expected, individual volatility has a positive and highly significant effect on the cost of trading. Another interesting finding is that market return does not have a significant effect on the liquidity. The market measures reported is calculated using an equally-weighted index, the results are also robust to a volume-weighted index, that is calculated using BIS daily trading foreign exchange volume data.

While the previous regressions have used high frequency data (tick data aggregated to 5 minute intervals), another set of analysis is done to test whether commonality changes when data is aggregated to daily data frequencies. The reason for testing for different frequencies is that high frequency (tick data) may not adjust to information very quickly whereas daily data shows more adjustment. In order to examine daily data, first of all, 5 minute data is aggregated to daily frequency. The minimum of the lowest spread for the calendar day for each of the five minute intervals is recorded as the lowest spread for the day and the lowest mid-price for the calendar day for each of the five minute intervals is recorded as the lowest mid-price for the day. In a similar manner, the highest of the highest spread and highest mid-price for the 5 min-interval for the calendar day is recorded as the highest spread and highest mid-price for the day. The opening spread and opening mid-price of the first 5 min-interval is the opening spread and mid-price for the calendar day whereas the closing spread and closing mid-price for the last 5 min-interval is the closing spread and closing mid-price for the day. Aggregating data to daily frequency leads to 869 days of observations for 14 different currencies. The same set of regression is done, this time over daily measures. For each exchange rate i , we regress the time series of daily liquidity measure $\Delta L_{i,t}$ on the market liquidity measures $\Delta L_{M,i,t}$, including lag and lead market liquidity as well as return $R_{M,i,t}$ including lag and lead returns and

Table 2.1: Liquidity Sensitivity to Changes in Market-Wide FX Liquidity, High Frequency

*Panel	A:	Liquidity	Sensitivity	to	Changes	in	Market-Wide	FX	Liquidity
	$\Delta L_{M,i,t-1}$	$\Delta L_{M,i,t}$	$\Delta L_{M,i,t+1}$	$R_{M,i,t-1}$	$R_{M,i,t}$	$R_{M,i,t+1}$	$\Delta V_{i,t-1}$	$\Delta V_{i,t}$	$\Delta V_{i,t+1}$
AUD	-0.007*** (-3.86)	0.040*** (17.20)	0.016*** (8.58)	0.003** (2.08)	-0.002 (-1.62)	0.000 (0.36)	0.009*** (5.48)	0.035*** (20.26)	0.003** (2.11)
CAD	-0.017*** (-8.05)	0.040*** (15.21)	0.014*** (6.87)	0.002 (1.51)	-0.006*** (-3.74)	0.004*** (2.60)	0.009*** (4.95)	0.052*** (26.50)	0.002 (0.95)
CHF	-0.008*** (-6.48)	0.026*** (16.26)	0.013*** (10.40)	-0.003*** (-2.96)	-0.001 (-0.62)	0.001 (1.30)	0.002 (1.64)	0.024*** (19.79)	0.001 (0.60)
EUR	-0.023*** (-10.72)	0.062*** (23.60)	0.025*** (11.58)	0.000 (-0.05)	0.001 (0.92)	-0.001 (-0.44)	0.004** (2.24)	0.020*** (9.96)	0.000 (-0.07)
GBP	-0.007*** (-4.29)	0.030*** (14.99)	0.015*** (9.58)	-0.001 (-0.61)	-0.002 (-1.44)	0.001 (0.55)	0.003*** (2.31)	0.032** (20.95)	0.000 (-0.28)
HUF	-0.008*** (-7.20)	0.020** (13.73)	0.010** (8.32)	0.002** (2.04)	-0.001 (-1.04)	0.001 (0.75)	0.002** (2.31)	0.015*** (13.45)	0.002 (1.87)
JPY	-0.007*** (-3.27)	0.042*** (17.05)	0.024*** (11.86)	0.000 (0.28)	0.002 (1.02)	-0.002 (-1.45)	0.006*** (3.68)	0.027*** (14.42)	0.004** (2.49)
MXN	-0.010** (-5.00)	0.036*** (15.30)	0.014*** (7.11)	-0.001 (-0.86)	-0.001 (-0.60)	0.000 (-0.29)	-0.001 (-0.76)	0.083*** (46.62)	0.009*** (5.44)
NOK	-0.015*** (-11.64)	0.030*** (18.93)	0.012*** (9.05)	-0.001 (-0.91)	0.000 (-0.05)	-0.001 (-1.06)	0.009*** (8.32)	0.047*** (39.95)	0.001 (0.83)
NZD	-0.011*** (-6.47)	0.027*** (12.70)	0.007*** (4.03)	0.002* (1.66)	0.003** (2.01)	-0.004*** (-2.84)	0.011*** (7.31)	0.053*** (32.81)	0.006*** (3.84)
PLN	-0.009*** (-6.47)	0.023*** (13.29)	0.009*** (6.52)	-0.002 (-1.51)	0.002 (1.55)	-0.001 (-1.00)	0.005*** (4.47)	0.036*** (27.13)	0.001 (1.18)
SEK	-0.011** (-7.94)	0.035*** (19.78)	0.014*** (10.10)	0.000 (0.44)	-0.002** (-2.29)	0.001 (0.66)	0.008*** (6.78)	0.040*** (30.24)	0.003 (2.12)
TRY	-0.009*** (-6.18)	0.021*** (12.40)	0.007*** (5.32)	0.002* (1.85)	-0.002* (-1.86)	0.001 (0.79)	-0.008*** (-6.69)	0.056*** (44.48)	0.013*** (10.81)
ZAR	-0.007*** (-4.37)	0.029*** (14.26)	0.016*** (9.79)	-0.002 (-1.34)	-0.002 (-1.32)	0.001 (1.07)	-0.003*** (-2.45)	0.077*** (50.41)	0.015*** (11.08)

For each exchange rate i , high frequency individual liquidity is regressed on average market-wide foreign exchange liquidity, market return and individual volatility:

$$\Delta L_{i,t} = \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

Liquidity of the foreign exchange rate i is excluded before computing $\Delta L_{M,i,t}$, return of the foreign exchange rate i is excluded before computing $R_{M,i,t}$. The standard errors are Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. The frequency is for 5 minutes for each of the variables where the sample is from December 15, 2014 to April 27, 2018 in which non-trading days are excluded. The number of observations is 237.467.

Panel B: Test for Population Mean for High Frequency Analysis p-value 0.00 t-stat 9.98***

$\bar{\beta} = \beta_1 + \beta_2 + \beta_3$. By using high frequency $\bar{\beta}$ liquidity, the population is tested for whether the mean is equal to zero. t-stat is significant, meaning the population has a zero mean. The sample is from December 15, 2014 to April 27, 2018. * Statistical significance at the 10 % level., ** Statistical significance at the 5 % level., *** Statistical significance at the 1 % level.

volatility $V_{i,t}$ of the exchange rate i for daily frequency.

$$\begin{aligned}\Delta L_{i,t} = & \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 \Delta R_{M,i,t-1} \\ & + \beta_5 \Delta R_{M,i,t} + \beta_6 \Delta R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}\end{aligned}$$

The results reported in Table 2.2 show that commonality in liquidity increases when data is aggregated to daily frequency. Individual currency liquidity is affected from concurrent market wide foreign exchange liquidity. Using a volume weighted portfolio instead of equally weighted portfolio also shows that the results are robust to different choice of portfolio formation. All estimated slope coefficients are positive and statistically significant for the concurrent market liquidity which implies that as the market liquidity increases, currency liquidity also increases. Furthermore, this also implies that foreign exchange rates are affected by funding liquidity. However, the significance of the effect of lag market liquidity on individual foreign exchange liquidity disappears when compared to high frequency data. We think this happens because foreign exchange liquidity adjusts quickly to shocks to market wide liquidity and thus we are not able to see the effect of previous observations' market wide liquidity when data is aggregated.

Another analysis to be done is to check for the time variation in commonality in liquidity. For each trading day, the following main regression is estimated for each of the currency i .

$$\begin{aligned}\Delta L_{i,t} = & \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} \\ & + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} \quad (2.8)\end{aligned}$$

We also test whether the $\bar{\beta}$'s are statistically different from zero. We further test the hypothesis that are coming from a population with mean equal to zero.

Table 2.2: Liquidity Sensitivity to Changes in Market-Wide FX Liquidity, Daily Frequency

*Panel	A:	Liquidity	Sensitivity	to	Changes	in	Market-Wide	FX	Liquidity
	$\Delta L_{M,i,t-1}$	$\Delta L_{M,i,t}$	$\Delta L_{M,i,t+1}$	$R_{M,i,t-1}$	$R_{M,i,t}$	$R_{M,i,t+1}$	$\Delta V_{i,t-1}$	$\Delta V_{i,t}$	$\Delta V_{i,t+1}$
AUD	-0.013 [*] (-1.73)	1.003 ^{***} (56.40)	0.003 (0.49)	-0.008 (-0.79)	0.000 (0.01)	-0.005 (-0.44)	-0.006 (-0.55)	-0.011 (-0.93)	-0.004 (-0.37)
CAD	-0.001 (-0.07)	1.102 ^{***} (35.72)	0.010 (1.13)	-0.013 (-0.84)	-0.004 (-0.26)	0.012 (0.69)	-0.007 (-0.42)	-0.011 (-0.63)	-0.007 (-0.40)
CHF	-0.008 (-0.96)	0.837 ^{***} (32.02)	-0.001 (-0.15)	-0.010 (-0.72)	0.003 (0.21)	-0.002 (-0.13)	-0.011 (-0.80)	-0.013 (-0.56)	0.002 (0.09)
EUR	-0.017 ^{***} (-2.59)	1.006 ^{***} (52.40)	0.005 (0.76)	-0.013 (-1.53)	0.012 (1.42)	0.003 (0.33)	-0.012 (-1.44)	-0.013 (-1.22)	0.001 (0.10)
GBP	-0.007 (-1.02)	0.989 ^{***} (77.90)	0.003 (0.48)	-0.003 (-0.36)	0.010 (1.27)	0.002 (0.21)	-0.016 (-1.50)	-0.006 (-0.58)	0.003 (0.26)
HUF	0.003 (0.23)	0.993 ^{***} (50.24)	0.005 (0.43)	0.011 (0.83)	-0.012 (-1.00)	0.009 (0.74)	-0.016 (-0.88)	-0.020 (-1.07)	-0.004 (-0.26)
JPY	-0.015 ^{**} (-1.68)	1.035 ^{***} (48.87)	0.002 (0.24)	-0.010 (-1.16)	0.006 (0.64)	-0.010 (-0.82)	-0.026 ^{**} (-2.03)	-0.011 (-0.85)	-0.012 (-0.70)
MXN	-0.004 (-0.23)	0.933 ^{***} (42.26)	-0.017 (-1.08)	0.011 (0.62)	0.028 ^{**} (2.07)	-0.019 (-1.24)	-0.024 (-1.19)	0.012 (0.75)	0.027 (1.52)
NOK	-0.005 (-0.56)	0.984 ^{***} (59.18)	-0.003 (-0.24)	-0.011 (-1.07)	0.012 (1.15)	0.002 (0.21)	-0.005 (-0.44)	0.006 (0.46)	0.022 (1.45)
NZD	-0.007 (-0.70)	0.992 ^{***} (41.24)	-0.002 (-0.26)	-0.011 (-1.00)	0.009 (0.76)	-0.006 (-0.46)	-0.008 (-0.66)	0.005 (0.31)	-0.001 (-0.04)
PLN	-0.016 (-0.43)	0.712 ^{***} (22.01)	0.016 (0.51)	0.002 (0.09)	-0.036 (-1.40)	0.002 (0.09)	0.059 ^{**} (2.02)	0.038 (1.18)	0.020 (0.58)
SEK	-0.002 (-0.16)	0.985 ^{***} (45.55)	0.025 ^{**} (2.04)	-0.017 (-1.60)	0.009 (0.70)	-0.007 (-0.46)	-0.011 (-0.60)	-0.010 (-0.69)	-0.012 (-0.60)
TRY	0.014 (0.64)	0.843 ^{***} (28.97)	-0.033 [*] (-1.75)	0.013 (0.72)	-0.012 (-0.64)	-0.026 (-1.40)	-0.009 (-0.44)	0.004 (0.20)	-0.021 (-0.90)
ZAR	0.014 (0.62)	0.896 ^{***} (35.99)	0.005 (0.25)	0.002 (0.10)	0.011 (0.62)	0.004 (0.19)	-0.002 (-0.09)	-0.002 (-0.10)	0.015 (0.71)

For each exchange rate i , daily frequency individual liquidity is regressed on average market-wide foreign exchange liquidity.

$$\Delta L_{i,t} = \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

Liquidity of the foreign exchange rate i is excluded before computing $\Delta L_{M,i,t}$, return of the foreign exchange rate i is excluded before computing $R_{M,i,t}$. The standard errors are Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. The frequency is daily for each of the variables where the sample is from December 17, 2014 to April 27, 2018. The number of observations is 869.

*Panel B: Test for Population Mean for Daily Frequency Analysis **p-value** 0.00 **t-stat** 34.92^{***}

$\bar{\beta} = \beta_1 + \beta_2 + \beta_3$. By using daily frequency $\bar{\beta}$ liquidity, the population is tested for whether the mean is equal to zero. t-stat is significant, meaning the population has a zero mean. The sample is from December 15, 2014 to April 27, 2018. The number of observations is 869.

* Statistical significance at the 10 % level., ** Statistical significance at the 5 % level., *** Statistical significance at the 1 % level.

Table 2.3 shows that $\bar{\beta}$'s are statistically significantly different from zero with high t-stats and low p-values. The mean and median of the estimated $\bar{\beta}$'s are used as a proxy for the the systematic liquidity factor. The basic OLS results for mean β variation are reported in Table 2.3 show that while there is a deterministic trend in mean β , that is there is a systematic liquidity factor that affects the liquidity of the individual currencies there does not exist a stochastic trend for mean β . The analysis done with median $\bar{\beta}$'s also lead to similar results which are not reported here.

Table 2.3: Trends in Systemic Liquidity

Panel A: Deterministic Trend Exploration			
	Estimate	t-stat	p-value
α	-0.16	-2.46	0.01
t	0.003 ***	2.84	0.00
Panel B: Stochastic Trend Exploration			
	Estimate	t-stat	p-value
α	-0.165	-2.44	0.01
t	0.003 ***	2.82	0.00
$\bar{\beta}_{t-1}$	-0.006	-0.19	0.85

$\bar{\beta} = \beta_1 + \beta_2 + \beta_3$ where $\beta_1, \beta_1, \beta_1$ are coefficients from regressions that are done daily for each of the currencies.

$$\Delta L_{i,t} = \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} \quad (2.9)$$

By using $\bar{\beta}$ coming from daily regressions, the population is tested for whether there is a trend in the β 's . $\bar{\beta}_L = \alpha_0 + \alpha_1 t + \epsilon_t$ t for deterministic trend exploration and $\bar{\beta}_L = \alpha_0 + \alpha_1 t + \alpha_2 \bar{\beta}_{L,t} + \epsilon_t$ T-statistics is significant for a deterministic trend, where the lag β_2 is not significant implying there is not a stochastic trend The sample is from December 15, 2014 to April 27,2018. The number of observations is 878.

* Statistical significance at the 10 % level

** Statistical significance at the 5 % level

*** Statistical significance at the 1 % level

We further test for whether monetary policy meetings have affect on foreign exchange liquidity. At this stage, we limit ourselves with the announcement days made by the FOMC and European Central Bank (ECB) due to their relatively

strong impact on world-wide monetary policy determination. First of all, we identify days where there are FOMC and ECB monetary policy meetings. FOMC meetings run for 2 days, the decision of the meetings are announced on the last day of the meetings. During data period from December 15th 2014 to April 27th 2018, there are 26 FOMC meetings and 27 ECB monetary policy meetings. Throughout the whole sample period, ECB and FOMC meetings never overlap, there is always at least 5 days difference between ECB and FOMC meetings except only for December 2017 meetings where day difference is 1. We run the following regression to assess the impact of monetary policy meetings on systemic liquidity. The results of these regressions is shown in Table 2.4. Results show that, on the day of an FOMC meeting announcement, market liquidity is affected where as ECB monetary policy meetings does not have such an effect on overall foreign exchange market liquidity. This may be because USD is the major trade currency, around 80 percentage of all foreign exchange trades according to BIS (2019). Results are robust to different lag selections as well. Results show that, FOMC announcements create a highly significant positive impact on commonality, increasing the high frequency co-movement of liquidity in the foreign exchange market. On the other hand, even though the sign is positive, we don't observe such a significant impact of ECB monetary policy decisions.

Another interesting aspect of monetary policy announcements is their pre-announcement impact on commonality in addition to their post-announcement effect. Therefore, we expand our analysis to see if the commonality changes some periods before the monetary policy announcements. For this part, we perform an analysis similar to those of [Morck, Yeung, and Yu \(2000\)](#) and [Sensoy \(2016\)](#). In particular, we average daily cross-sectional mean $\bar{\beta}$ first on only those trading days in the event windows that cover five trading days prior to the monetary policy announcements. Then we repeat the same procedure

on whole days except those that belong to the event windows. The mean comparison of the whole sample and the event window is based on a one-tail, two-sample t-test for differences in means. Further, the t-statistics are corrected for unequal variances whenever appropriate using the [Satterthwaite \(1941\)](#) approximation. Accordingly, we find that for both central bank announcements, daily average beta is higher for event windows (ECB: 0.063 & FOMC: 0.051) compared to non-event periods (ECB: 0.049 & FOMC: 0.050). However, the difference is only significant in the case of ECB announcement. We believe that there are two potential explanations for this situation: i) an information leakage before ECB announcements, or ii) a better signalling communication with regard to future monetary policy by the ECB so that market participants can position themselves better collectively prior to the ECB announcements. In fact, the latter argument is supported by the recent study of [Bennani, Fanta, Gertler, and Horvath \(2020\)](#) where authors find that ECB communication related to conventional measures explain the future monetary policy well. Overall, we face with an interesting picture where commonality in FX liquidity significantly increases before ECB announcements and after FOMC announcements.

$$\beta_{L,i,t}^- = \alpha + \alpha_1 Dummy_{ECB} + \alpha_2 Dummy_{FOMC} + \alpha_3 t + \epsilon \quad (2.10)$$

While the previous regressions have used liquidity measure as the dependent variable, we also look at the return as the dependent variable. In line with the previous section, first of all the following regression for high frequency data is estimated:

Table 2.4: Sensitivity of Foreign Exchange Liquidity to Monetary Policy Meetings

	$Dummy_{ECB}$	$Dummy_{FOMC}$	t
Estimates	0.016	0.0383***	0.011**
t-stats	(1.28)	(2.91)	(2.28)

By using liquidity $\bar{\beta}$ coming from daily regressions, $\bar{\beta}$ is regressed on dummy variables. $Dummy_{FOMC}$ is a dummy variable that takes 1 on the day when the FOMC meeting ends, $Dummy_{ECB}$ is a dummy variable that takes 1 on the day when the ECB meeting is made. The estimation regressed is as follows:

$$\bar{\beta}_{L,i,t} = \alpha + \alpha_1 Dummy_{ECB} + \alpha_2 Dummy_{FOMC} + \alpha_3 t + \epsilon \quad (2.11)$$

The frequency is daily for each of the variables where the sample is from December 15, 2014 to April 27, 2018. The number of observations is 878.

* Statistical significance at the 10 % level

** Statistical significance at the 5 % level

*** Statistical significance at the 1 % level

$$R_{i,t} = \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

where $R_{M,i,t}$ is the return for the market for the currency i , excluding currency i , in calculating market return for that exchange rate. Return for each currency is calculated using $P_{M,i,t}$ such that $P_{M,i,t}$ is the closing mid-price for each of the 5 minute intervals. Market return for each of the currencies is calculated by excluding each of the currency and taking cross sectional average of the remaining currency returns for that interval. $\Delta L_{M,i,t}$ is the equally-weighted cross sectional average of the liquidity variable for all currencies at time t , excluding currency i . The reason for excluding each currency when calculating return and market liquidity is to eliminate the effect of individual currency i 's own variation on the market average. In order to capture the effect of non-concurrent adjustments in liquidity variation at the currency and market level, following [Chordia et al. \(2000\)](#), the lag and lead variables for market liquidity are also

included in the regressions. $V_{i,t}$ is the volatility for currency i , at time t . Volatility for currencies is estimated following Garman-Klass (1980), where lowest and highest prices are also used in addition to the opening and closing prices for the specified interval.

The results reported in Table 2.5 show that return of the individual currency is highly influenced by the return of the market as a whole although market liquidity $\Delta L_{M,i,t}$, that excludes currency i does not play a significant role in return of the individual currency. The market measures reported is calculated using equally-weighted index, the results are also robust to a volume-weighted index, that is calculated using BIS daily trading foreign exchange volume data (2019).

While the previous regressions have used high frequency data (tick data aggregated to 5 minute intervals), another set of analysis is done to test whether commonality changes when data is aggregated to daily data frequencies. The reason for testing for different frequencies is that high frequency (tick data) may not adjust to information very quickly whereas daily data shows more adjustment. In order to examine daily data, first of all daily data is aggregated in a similar manner, as the previous aggregation methodology. The same set of regression is done, this time over daily measures. For each exchange rate i , we regress the time series of daily return measure $R_{i,t}$ on the market return $R_{M,i,t}$ including lag and lead returns as well as market liquidity measures $\Delta L_{M,i,t}$, including lag and lead market liquidity and volatility $V_{i,t}$ of the exchange rate i for daily intervals. The results reported in Table 2.6 show that commonality in return increases when data is aggregated to daily frequency.

Another analysis to be done is to check for the time variation in return. For each trading day, the following main regression is estimated for each of the currency i .

Table 2.5: Return Sensitivity to Changes in Market-Wide Return, FX Liquidity and Volatility, High-Frequency

	$R_{M,i,t-1}$	$R_{M,i,t}$	$R_{M,i,t+1}$	$\Delta L_{M,i,t-1}$	$\Delta L_{M,i,t}$	$\Delta L_{M,i,t+1}$	$\Delta V_{i,t-1}$	$\Delta V_{i,t}$	$\Delta V_{i,t+1}$
AUD	0.011*** (7.78)	0.649*** (45.08)	-0.012*** (-8.65)	0.000 (0.05)	0.000 (0.02)	0.000 (0.06)	0.005*** (3.35)	-0.001 (-0.59)	0.000 (0.25)
CAD	0.010*** (6.65)	0.568*** (38.76)	0.000 (-0.07)	-0.002 (-0.85)	-0.002 (-0.91)	0.000 (-0.14)	0.000 (-0.18)	-0.003* (-1.68)	0.000 (0.02)
CHF	-0.008*** (-5.64)	0.587*** (43.45)	-0.012*** (-8.60)	0.002 (1.05)	0.003 (1.13)	0.000 (0.15)	-0.004*** (-2.50)	-0.007*** (-4.20)	-0.005*** (-3.58)
EUR	-0.011*** (-9.80)	0.783*** (67.67)	-0.023*** (-20.29)	0.005*** (3.05)	0.000 (-0.11)	0.000 (-0.01)	-0.006*** (-4.28)	-0.009*** (-6.49)	0.000 (0.09)
GBP	0.002 (1.52)	0.521*** (36.00)	-0.009*** (-6.03)	0.003 (1.32)	-0.001 (-0.32)	-0.002 (-1.08)	0.000 (0.04)	-0.003* (-1.67)	-0.002 (-1.21)
HUF	-0.007*** (-5.91)	0.677*** (56.39)	-0.002* (-1.84)	0.004*** (2.70)	0.002 (0.79)	0.001 (0.61)	-0.004*** (-2.57)	-0.015*** (-9.83)	-0.004*** (-2.77)
JPY	0.000 (-0.19)	0.351*** (21.07)	-0.004** (-2.45)	0.001 (0.57)	-0.001 (-0.23)	0.001 (0.24)	-0.026*** (-13.77)	-0.022*** (-10.15)	-0.015*** (-7.83)
MXN	0.009*** (6.04)	0.371*** (25.81)	0.018*** (12.82)	0.000 (-0.02)	0.002 (1.02)	0.000 (-0.18)	0.008*** (4.85)	0.013*** (6.99)	0.000 (-0.03)
NOK	-0.003** (-2.07)	0.629*** (51.57)	-0.008*** (-6.33)	0.001 (0.48)	-0.002 (-1.18)	-0.002 (-1.34)	0.006*** (4.02)	0.004*** (2.81)	0.001 (1.06)
NZD	0.008*** (5.39)	0.612*** (40.93)	-0.011*** (-7.45)	0.003 (1.31)	-0.001 (-0.50)	0.001 (0.51)	-0.002 (-1.38)	-0.004** (-2.39)	0.001 (0.38)
PLN	-0.008*** (-6.63)	0.675*** (54.71)	0.000 (-0.40)	0.002 (1.14)	0.003 (1.58)	0.002 (1.45)	-0.005*** (-3.47)	-0.005*** (-2.99)	-0.002 (-1.36)
SEK	-0.008*** (-6.47)	0.658*** (51.05)	-0.010*** (-7.42)	0.002 (1.10)	0.003 (1.32)	0.005 (2.63)	0.001 (0.93)	-0.003** (-2.14)	-0.003** (-2.26)
TRY	0.012*** (9.40)	0.315*** (23.98)	0.022*** (16.41)	0.000 (-0.02)	0.000 (-0.14)	0.000 (0.11)	0.005*** (3.18)	0.011*** (6.90)	0.002 (1.20)
ZAR	0.018*** (13.09)	0.333*** (24.16)	0.025*** (18.14)	-0.002 (-0.89)	-0.001 (-0.32)	0.002 (0.89)	0.000 (-0.04)	-0.003* (-1.82)	-0.001 (-0.71)

For each exchange rate i , high frequency individual return is regressed on average market-wide foreign exchange return. Return of the foreign exchange rate i is excluded before computing $\Delta R_{M,i,t}$.

$$R_{i,t} = \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

The frequency is for 5 minutes for each of the variables where the sample is from December 15, 2014 to April 27, 2018. The number of observations is 237.467.

* Statistical significance at the 10 % level.

** Statistical significance at the 5 % level.

*** Statistical significance at the 1 % level.

Table 2.6: Return Sensitivity to Changes in Market-Wide Return, FX Liquidity and Volatility, Daily-Frequency

*Panel	A:	Return	Sensitivity	to	Changes	in	Market-Wide	Return	and	FX	Liquidity
	$R_{M,i,t-1}$	$R_{M,i,t}$	$R_{M,i,t+1}$	$\Delta L_{M,i,t-1}$	$\Delta L_{M,i,t}$	$\Delta L_{M,i,t+1}$	$\Delta V_{i,t-1}$	$\Delta V_{i,t}$	$\Delta V_{i,t+1}$		
AUD	-0.023 (-0.94)	0.725*** (28.77)	-0.051** (-2.01)	0.021 (0.59)	0.081 (1.50)	0.008 (0.17)	0.002 (0.07)	-0.021 (-0.53)	0.012 (0.30)		
CAD	0.047* (1.80)	0.649*** (24.62)	-0.041 (-1.51)	-0.085** (-2.11)	-0.075 (-1.40)	-0.012 (-0.29)	0.038 (1.15)	0.056 (1.34)	0.019 (0.50)		
CHF	0.064** (2.32)	0.618*** (20.77)	0.060** (2.18)	-0.013 (-0.30)	-0.057 (-1.03)	-0.025 (-0.60)	-0.041 (-1.01)	-0.070* (-1.65)	-0.064* (-1.80)		
EUR	0.018 (0.78)	0.738*** (27.57)	-0.027 (-1.12)	-0.019 (-0.54)	-0.001 (-0.02)	0.006 (0.17)	-0.039 (-1.46)	-0.034 (-0.77)	-0.004 (-0.09)		
GBP	-0.015 (-0.49)	0.581*** (18.44)	-0.024 (-0.75)	-0.076* (-1.76)	-0.021 (-0.35)	-0.030 (-0.67)	-0.035 (-0.92)	-0.045 (-1.23)	-0.021 (-0.60)		
HUF	-0.004 (-0.19)	0.750*** (30.17)	0.013 (0.57)	-0.015 (-0.38)	-0.009 (-0.17)	-0.010 (-0.26)	0.007 (0.20)	0.015 (0.31)	0.017 (0.55)		
JPY	0.035 (1.01)	0.394*** (7.98)	0.025 (0.69)	0.030 (0.66)	-0.025 (-0.36)	-0.031 (-0.64)	-0.075** (-2.00)	-0.150*** (-2.82)	0.009 (0.23)		
MXN	-0.017 (-0.59)	0.534*** (14.32)	-0.062** (-2.04)	0.019 (0.44)	-0.098* (-1.67)	-0.092* (-1.97)	0.079* (1.89)	0.198*** (3.56)	0.128*** (3.40)		
NOK	-0.023 (-0.98)	0.767*** (31.33)	0.014 (0.56)	-0.064* (-1.77)	-0.079 (-1.79)	0.005 (0.16)	0.030 (0.94)	0.089*** (2.72)	0.018 (0.64)		
NZD	-0.018 (-0.63)	0.703*** (26.41)	-0.042 (-1.63)	-0.030 (-0.75)	-0.029 (-0.48)	-0.005 (-0.12)	0.004 (0.12)	-0.032 (-0.82)	0.004 (0.14)		
PLN	0.021 (1.00)	0.764*** (32.53)	0.032 (1.43)	0.013 (0.39)	0.022 (0.46)	0.018 (0.46)	-0.005 (-0.16)	0.052 (1.39)	0.031 (0.89)		
SEK	0.017 (0.68)	0.727*** (27.87)	-0.002 (-0.09)	-0.039 (-1.05)	0.015 (0.32)	0.027 (0.68)	-0.041 (-1.35)	0.037 (1.03)	-0.014 (-0.50)		
TRY	-0.021 (-0.76)	0.552*** (16.76)	-0.064** (-2.24)	-0.030 (-0.67)	-0.091 (-1.42)	-0.093** (-2.23)	0.061 (1.44)	0.217*** (4.24)	0.104** (2.32)		
ZAR	-0.020 (-0.78)	0.62*** (21.50)	0.018 (0.75)	-0.003 (-0.09)	-0.006 (-0.10)	-0.016 (-0.37)	0.043 (0.85)	0.099* (1.86)	0.081** (2.06)		

For each exchange rate i , daily frequency individual return is regressed on average market-wide foreign exchange return, liquidity and volatility.

$$R_{i,t} = \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

Return of the foreign exchange rate i is excluded before computing $R_{M,i,t}$. The frequency is daily for each of the variables where the sample is from December 18, 2014 to April 27, 2018. The number of observations is 866.

* Statistical significance at the 10 % level.

** Statistical significance at the 5 % level.

*** Statistical significance at the 1 % level.

*Panel	B:	Test	for	Population	Mean	for	Daily	Frequency	Analysis	p-value 0.00	t-stat 3.63
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By using daily frequency return $\bar{\beta}$, the population is tested for whether the mean is equal to zero. t-stat is significant, meaning the population has a zero mean. The sample is from December 18, 2014 to April 27, 2018. The number of observations is 866.

$$R_{i,t} = \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t} \quad (2.12)$$

The mean and median of the estimated $\bar{\beta}$'s are used as a proxy for the the systematic return factor. The basic OLS results for mean β variation are reported in Table 2.7 show that there is a deterministic trend in mean $\bar{\beta}$, that is there is a factor that affects the return of the individual currencies there does not exist a stochastic trend for mean $\bar{\beta}$. The analysis done with median sum $\bar{\beta}$'s also lead to similar results which are not reported here.

Table 2.7: Trends in Systemic Return

Panel A: Deterministic trend exploration			
	Estimate	t-Stat	p-Value
α	0.559	127.56	0.00
t	-0.003***	-4.13	0.00
Panel B: Stochastic trend exploration			
	Estimate	t-Stat	p-Value
α	0.273	18.55	0.00
t	-0.002**	-2.22	0.00
$\bar{\beta}_{t-1}$	0.51***	19.61	0.76

$\bar{\beta} = \beta_1 + \beta_2 + \beta_3$ where $\beta_1, \beta_1, \beta_1$ are coefficients from following equation for daily aggregated data.

$$R_{i,t} = \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1}$$

By using daily frequency $\bar{\beta}$ return, the population is tested for whether there is a trend in the β 's . $\bar{\beta} = \alpha + \beta_1 t$ for deterministic trend exploration and $\bar{\beta} = \alpha + \beta_1 t + \beta_2 \bar{\beta}_{t-1} t - \text{statissignificant for a deterministic trend, where the lag } \beta_2$ is also significant implying there is a stochastic trend. The sample is from December 15, 2014 to April 27, 2018. The number of observations is 878.

* Statistical significance at the 10 % level.

** Statistical significance at the 5 % level.

*** Statistical significance at the 1 % level.

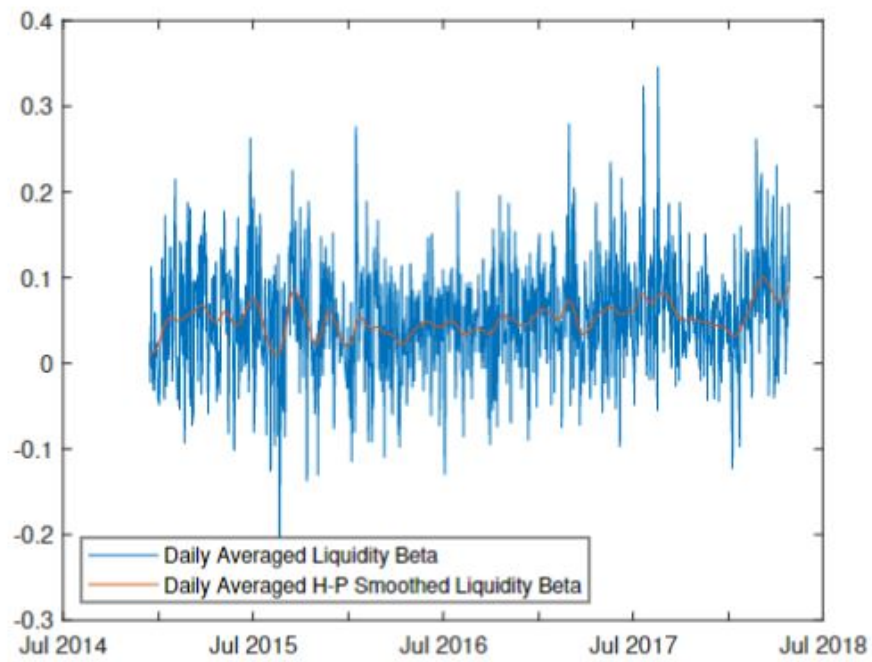


Figure 2.1: Values of liquidity $\bar{\beta}$ over time

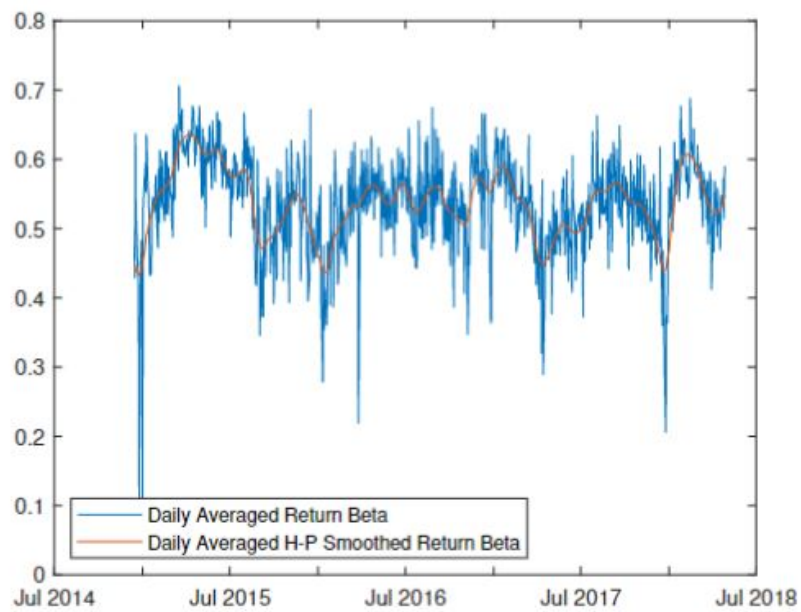


Figure 2.2: Values of return $\bar{\beta}$ over time

2.3.1 High Frequency relation between systematic liquidity and systematic return risks

After estimating for time-varying return and liquidity betas, we calculate the mean betas for return and liquidity on each day for the whole time period. One aspect that would be of interest to market participants, policy makers and academics would be the interaction between commonality in liquidity and the common movements in exchange rate levels. This has been studied in detail by [Brunnermeier and Pedersen \(2008\)](#) for asset markets and it has been shown that in turbulent times, the situation evolves into a worsening return-liquidity spiral. [Akyildirim, Nguyen, and Sensoy \(2018\)](#) examine this concept for eurozone sovereign bond markets and show that commonality in bond liquidity has a strong impact on the commonality in yield changes, but not vice versa. [Kamara, Lou, and Sadka \(2008\)](#) find that these two commonalities have common drivers in the US equity market. However, to the best of our knowledge, this concept has not been studied for the FX market in an empirical setup.

Figure 2.2 and Figure 2.1 displays the time-varying return and liquidity measures. We show both the actual value and normalized values in the figures ¹. We further report the smoothed trend in Figure 2.3.

To better understand the dynamics between return and liquidity in the foreign exchange market, we apply an unrestricted Vector Auto Regression Model (VAR(p)) applied on normalized liquidity and return beta where optimal lag selection is found to be 3. The estimated parameters for the VAR system is given in Table 2.8 and impulse responses are given in Figure 2.4,. As seen from Table 2.8, return is affected from its previous values. However, liquidity does not have a significant effect on return and vice versa. Liquidity commonality is

¹We apply [Hodrick and Prescott \(1997\)](#) filter to our measures to eliminate noise and extract the trends.

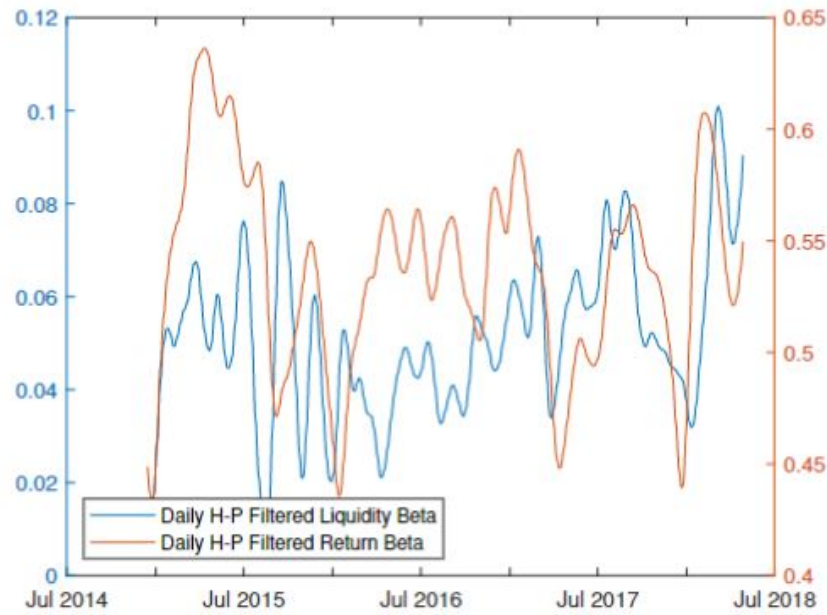


Figure 2.3: Liquidity and Return Daily Betas(smoothed trend)

strongly affected from its previous values as well. While we were expecting to see the extreme market movements causing a change in liquidity commonality, our results do not indicate such a result. Any shock to return is reversed in roughly 3 periods whereas reversal for a shock to liquidity is much longer, around 8 periods as seen from impulse response analysis. Accordingly, we see that commonality in liquidity has a weak yet significant positive effect on commonality in return series. The explanatory power of 1 and 2 day lagged liquidity commonality terms shows us that an increase in the systematic FX liquidity risk most likely increases the systematic return risk in FX markets. However, we do not see a reverse relationship. This evidence is similar to that found by [Akyildirim et al. \(2018\)](#) for eurozone sovereign bond markets and it emphasizes the increased importance of liquidity conditions in recent years, even at the high-frequency level.

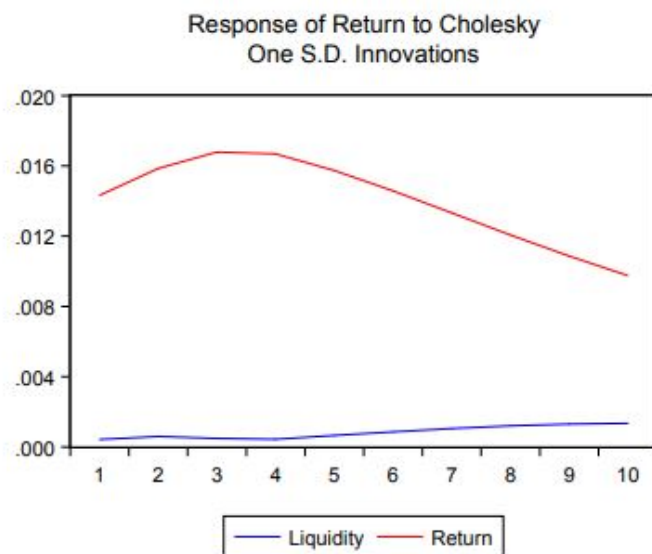
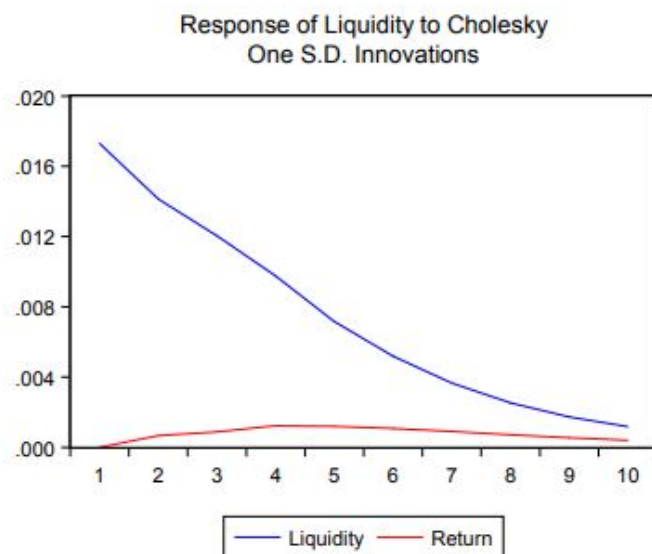


Figure 2.4: Impulse Response Graphs

Table 2.8: Parameter Estimates for VAR(3) Using Smoothed Values of Liquidity $\bar{\beta}$ and Return $\bar{\beta}$

	β_R		β_L	
	Coefficient	t-stats	Coefficient	t-stats
$\beta_{R,-1}$	2.821 ***	(>10)	0.015	(0.81)
$\beta_{R,-2}$	-2.680 ***	(<-10)	-0.025	(-0.66)
$\beta_{R,-3}$	-0.858 ***	(>10)	0.011	(0.55)
$\beta_{L,-1}$	0.038 *	(1.72)	2.610 ***	(>10)
$\beta_{L,-2}$	0.075	(1.73)	-2/282	(<-10)
$\beta_{L,-3}$	-0.030	(1.63)	0.664	(>10)
Constant	0.000	(0.39)	0.000	(0.53)

The sample is from December 15, 2014 to April 27, 2018. The number of observations is 878.

* Statistical significance at the 10 % level.

** Statistical significance at the 5 % level.

*** Statistical significance at the 1 % level.

2.4. Concluding Remarks

The uniqueness of this study comes from its data set coverage, for an extended period of time, post Global Financial crisis (from 2014 to 2018) while using tick data. While previous foreign exchange commonality studies have coverage that includes Global Financial Crisis and Eurozone Debt Crisis periods, this study covers a post-crisis period. With this data, it is possible to analyze liquidity commonality apart from major financial crisis and explore the commonality in liquidity, by including both developed and developing markets in analysis. In line with [Mancini et al. \(2013\)](#) time-series regression results, the R^2 increases in magnitude when tick data is aggregated from 5-minute intervals to daily data. Using high frequency data over 4 years for 14 currency pairs, from December 2014 to April 2018, we study foreign exchange liquidity in depth. Extending previous literature ([Mancini et al. \(2013\)](#) and [Karnaikh et al. \(2015\)](#)), we are able to demonstrate that commonality in liquidity exist for foreign exchange markets beyond a crisis period and it is prevalent. In line with previous findings in literature, we also demonstrate that liquidity commonality increases where one

aggregates the data. We show that, even controlling for the positive trend in commonality, Fed's monetary policy decisions have a significant positive impact on the high-frequency FX liquidity co-movement whereas ECB does not create such an effect. Results reveal the increased importance of the Fed's decisions on high-frequency trading activity in the FX markets, and stresses on the potential challenges to be faced by other central banks when one clearly dominates the others. However and interestingly, we observe a significant increase in commonality before ECB announcements whereas this is not the case for the announcements by Fed. We believe that this might be a sign of either information leakage prior to ECB announcements or a better signalling and communication policy by the ECB with regard to its future actions. Finally, we consider the bilateral relation between commonality in liquidity and commonality in return series in FX markets at the high-frequency level. We find that liquidity commonality has a positive explanatory power on return commonality, but not vice versa. This result points out to the increased importance of intraday liquidity conditions in FX markets for financial stability in recent years, especially with regards to cases like flash crashes.

CHAPTER III

JUMP FORECASTING IN FOREIGN EXCHANGE MARKETS: A HIGH FREQUENCY ANALYSIS

3.1. Introduction

Currency fluctuations are a normal phenomenon in foreign exchange markets with floating exchange rate regimes. After the breakdown of Bretton Woods system, each country decided to go with their own exchange rate regime whether floating or pegged ([Heller, 1978](#)), which has important implications both for the domestic as well as international economic policies. Law of one price and arbitrage, covered interest rate parity and uncovered interest rate parity, are the most popular models in the literature ([Engel, 2014](#)) to explain levels of exchange rates. There is a vast literature on the determinants of exchange rate. While some research on determinants of foreign exchange focused on the macroeconomic fundamentals ([Dornbusch, 2019](#); [Fratzscher, 2009](#); [Morana, 2009](#); [Pericoli & Taboga, 2012](#)) many studies have found an unstable relation between exchange rates and macroeconomic fundamentals ([Bacchetta & van Wincoop, 2013](#); [Beckmann & Czudaj, 2017](#); [Krol, 2014](#)). Some other studies investigated the levels of exchange rates where uncertainty also plays a role as in the case of Brexit ([Bartsch, 2019](#); [Nasir, 2020](#); [Nasir & Morgan, 2018](#)) or for emerging

markets ([Abid, 2020](#); [Bush & Noria, 2021](#)) as well as developed economies ([Grossmann, Love, & Orlov, 2014](#); [Murad, 2022](#); [Smales, 2021](#)). When the path of foreign exchange returns exhibit large discontinuities, jumps are said to be observed in the foreign exchange market. Jumps refer to a price change over a very short period of time that is related to a broad range of market phenomena that cannot be connected to a noisy Gaussian distribution ([Lahaye, Laurent, & Neely, 2011](#); [Lee, 2012](#); [Zheng & Shen, 2008](#)).

In this study, for the foreign exchange market, jumps are identified by taking into account the ratio of return to estimated volatility following [Lee and Mykland \(2008\)](#) so that even when the volatility is high, it is possible to distinguish whether the change on the nominal exchange rate is due to a jump or a result of the high volatility in the market. Current literature suggests two mainstream of explanations for these jumps: jumps are market reaction to unexpected information or jumps are caused by a lack of liquidity on the market ([Das, 2002](#); [Joulin, Lefevre, Grunberg, & Bouchaud, 2008](#); [Lahaye et al., 2011](#)).

No matter what the reason is, the presence of jumps in foreign exchange (FX) markets have uttermost importance for traders as well as financial risk managers. In particular, FX jumps make markets incomplete as the risk associated with them can not be hedged against easily. FX jumps also bring higher risks in the context of derivative pricing and asset allocation. From the policy makers' (such as central banks) and market makers' point of view, FX jumps create problems since these jumps make it harder for them to effectively inject liquidity to market when deemed necessary. Based on these arguments, it is clear that the ability of forecasting jumps in the FX markets would be a highly desirable skill in the world of modern finance.

Traditionally, financial market predictions have used classical algorithms such as linear regression, random walk models, moving average and combined

approaches such as ARMA, ARIMA and ARCH. With the development of modern mathematical tools, high performing computers as well as high frequency trading activities lead to new strategies for forecasting financial time series via techniques such as support vector machine (SVM), random forest (RF), artificial neural networks (ANN), convolutional neural networks (CNN) and deep neural networks such as long-short term memory (LSTM) algorithms. Overall, these machine learning algorithms are able to deal with and identify hidden patterns and complex relations in large data sets. Indeed, [Ryll and Seidens \(2019\)](#) suggest that machine learning algorithms offer superior predictive performance to stochastic models because of their ability to capture non-linear patterns in time series.

Whether it is individual stock or market index forecasting, several studies have used machine learning algorithms for the prediction of future price directions in the stock markets ([Albu & Lupu, 2020](#); [Chen, Leung, & Daouk, 2003](#); [Deepak, Uday, & Malathi, 2017](#); [Dingli & Fournier, 2017](#); [Hegazy, Soliman, & Salam, 2014](#); [Jang & Lee, 2019](#); [Kaczmarczyk & Hernes, 2020](#); [Kercheval & Zhang, 2015](#); [Moghaddam, Moghaddam, & Esfandyari, 2016](#); [Patel, Shah, Thakkar, & Kotecha, 2015](#); [Shen, Jiang, & Zhang, 2012](#); [Sirignano & Cont, 2019](#); [Tsantekidis et al., 2020](#)). Some other studies have focused on FX market prediction ([Galeshchuk & Mukherjee, 2017](#); [W. Huang, Lai, Nakamori, & Wang, 2004](#); [Jung & Choi, 2021](#); [Majhi, Panda, & Sahoo, 2009](#); [Maté & Jiménez, 2021](#); [Qian & Rasheed, 2010](#); [Sermpinis, Dunis, Laws, & Stasinakis, 2012](#); [Yao & Tan, 2000](#)). More recently, machine learning algorithms have even started to be used in forecasting the cryptocurrency market dynamics ([Akyildirim, Goncu, & Sensoy, 2021](#); [Alessandretti, ElBahrawy, Aiello, & Baronchelli, 2018](#); [Chowdhury, Rahman, Rahman, & Mahdy, 2020](#); [Jaquart, Dann, & Weinhardt, 2021](#)).

While machine learning models are able to provide effective results in terms of financial time-series forecasting, they are difficult to interpret and do not allow

for inference. However, the fact that these models have been able to produce accurate out-of-sample forecasting results suggests that these models are able to identify meaningful patterns in data.

Abovementioned studies show that machine learning algorithms have been well utilized in terms of forecasting asset price directions. However, although jumps are common anomalies and create serious problems in financial markets, the literature on predicting jumps in the same context has not been studied in detail yet, let alone the FX markets.¹ Even for stock market jump prediction, there are a limited number of studies that use state of art machine learning methodologies (Albu & Lupu, 2020; Kong, Zhu, & Azencott, 2021; Mäkinen, Kanninen, Gabbouj, & Iosifidis, 2019; Yeung, Wei, Chan, Lau, & Yiu, 2020). For example, Mäkinen et al. (2019) study the predictability of stock price jumps using high frequency data with machine learning techniques. While the authors are able to forecast the existence of jumps, they fail to predict the direction of the jump for the set of stocks analyzed. In another study, Kong et al. (2021) demonstrate that for Chinese stock market, jump occurrences as well as their direction can be predicted for the high frequency data. Using machine learning algorithms, Yeung et al. (2020) analyze the forecasting of jumps in major and developing stock market indices at the intraday level and test the effectiveness of these algorithms compared to other classical jump detection methods. By analyzing log-returns for 10 different stock exchange indices using neural networks, Albu and Lupu (2020) try to detect anomalies in daily returns and conclude that they are able to identify a period with potential disruptive dynamics. To the best of our knowledge, these

¹Even though prediction of jumps is a scarce field, there are several jump detection models in the literature including but not limited to the non-parametric jump test of Jiang and Oomen (2008), Barndorff-Nielsen Shepherd test (Barndorff-Nielsen & Shephard, 2006), Lee-Mykland test (Lee & Mykland, 2008), and Aït-Sahalia & Jacod test (Aït-Sahalia & Jacod, 2009). Dumitru and Urga (2012) perform a comprehensive comparison between available non-parametric jump detection procedures and state that the tests by Lee and Mykland (2008) and T. Andersen, Bollerslev, and Dobrev (2007) provide the best overall performance for jump detection at the intraday level.

studies are the only ones that consider forecasting jumps in the stock markets via machine learning. [Lee and Wang \(2020\)](#) study the predictability of jumps in the currency markets using a generalized jump regression methodology where they link intraday jumps with information variables observed at different frequencies. Interestingly, there is no study trying to predict the occurrence of jumps in the FX market using machine learning methodologies.

In this study, we try to forecast the occurrence and also the direction of jumps in the FX market using high frequency data with different machine learning algorithms. In doing so, we implement namely K nearest neighbourhood, decision trees, multi-layer perceptron, support vector machine and random forest algorithms on our sample data set. Accordingly, we show that it is possible to obtain (average) prediction accuracies around 78% (73%) with for the jump arrival and up to 70 % average accuracy for the predictability of jump directions. Among all the methods considered, multi-layer perceptron has the highest average accuracy for jump prediction overall, followed by support vector machine and random forest methodologies with slightly less average accuracy results.

We further implement different time frames to train and apply random under sampling procedures in order to increase our test and training samples as well as to test the robustness of our findings. The different sub-sampling of training and testing periods also leads to consistent results in terms of accuracy levels which are around 73% for the predictability of occurrence and up to 70% average accuracy for the predictability of jump direction. Although initially designed for analyzing low-frequency data, technical trading indicators (in combination with liquidity indicators) have been found to be successful to predict jump direction in our study.

Our contribution to the literature is manifold. First, we provide a forecasting methodology to identify jumps in the FX market using high frequency data. To the

best of our knowledge, there is no prior study trying to predict jumps in the FX market using machine learning methodology whereas there are only few studies focused on stock market jump predictions by using such algorithms (Albu & Lupu, 2020; Kong et al., 2021; Mäkinen et al., 2019; Yeung et al., 2020). Thus, we directly contribute to the forecasting literature on financial time-series. Second, while applications of machine learning in forecasting time-series in the FX market has mainly focused on predicting future prices or volatility (Galeshchuk & Mukherjee, 2017; Jung & Choi, 2021; Maté & Jiménez, 2021; Qian & Rasheed, 2010), we implement machine learning methodologies to detect jumps using both technical and liquidity indicators. Our approach combines both liquidity measures and technical indicators to enhance intraday foreign exchange jump prediction at the high frequency. Third, in addition to predicting the occurrence of jumps, we predict the direction of jumps in the FX market as well, which is crucial and has a potential to provide important and direct implications for market makers and liquidity providers as well as investors in the FX market.

In the rest of the section, Data Methodology section introduces our sample data and the features that we use in our machine learning algorithms. Afterwards, Jump Detection Methodology section presents the technique used to identify the jumps to be predicted by the machine learning algorithms and further explains how we split our time series data for out-of-sample forecasting. We also summarize the six main machine learning algorithm that we use to forecast pre-identified jumps in the FX market. We then present the results and conclude the chapter.

3.2. Data and Feature Selection

Our analysis is conducted on 14 exchange rates (AUDUSD, USDCAD, USDCHF, USDCZK, EURUSD, GBPUSD, USDHUF, USDJPY, USDMXN, USDNOK, NZDUSD, USDPLN, USDSEK, USDZAR). The dataset is obtained from Bloomberg and refers to the sub-second level tick-by-tick bid and ask quotations with time stamps. The sample is from January 1st, 2018 until April 30th, 2021. As stated earlier, only a few studies focus on high frequency jump prediction via machine learning in the literature, yet they either focus on a limited number of stocks, a specific stock market and a limited time frame, covering less than a year. We want our results to be widely applicable thus, we aim to make our data set to be as comprehensive as possible. In this respect, we include most popular developed and emerging market currencies in our study.² Moreover, the sample covers more than three years, which is one of the longest time frames in high frequency financial time series analysis.

[Jiang, Lo, and Verdelhan \(2011\)](#) state that tick data should be used carefully related to the concerns about market microstructure effects. Tick-by-tick data has more information but also induces higher market microstructure noise. In a recent study, [Liu, Patton, and Sheppard \(2015\)](#) find minimal evidence that the consensus 5-minute interval is surpassed by any other choice of sampling frequency in terms of volatility estimation. Therefore, we aggregate our ultra high frequency data for 5-minute intervals and obtain 248,256 intraday observations per exchange rate.

Although we have a rich sample to work on, an important step in our analysis is the indicators to be used in our algorithm. At this stage, two factors step up as the

²According to BIS Triannual Survey (2019), 88.3% of all daily transactions in the over-the-counter FX trades are USD based. Our coverage of currencies makes up to 78% of all trades for all USD currency pairs. More than a quarter of all USD currency pair trades are EURUSD, followed by USDJPY (15%) and GBPUSD (11%).

potential determinants, i.e., market liquidity and popular technical indicators. In financial markets, liquidity measures give information about the market status at a given time whereas technical indicators examine the market movement within a comparably longer time window. Although liquidity measures have been individually studied for predicting jump arrivals, a combination of both liquidity and technical indicators have been omitted for FX market jump forecasting.³

In our study, we have two problems at hand. One is to identify the occurrence of an FX jump in the next 5-minute interval (whether upwards or downwards) which is stated as a binary classification problem. The other is to identify the direction of the jump (upwards or downwards) as well as its occurrence for the upcoming 5-minute interval, hence stated as a trinary classification problem with machine learning algorithms. In the next part, we identify the features that are used for jump prediction.

3.2.1 Features Used in Jump Prediction

One of the major determinants of success in a machine learning setup is the selection of features since features that are not related to the target variable can lead to under performing models. In our work, features are selected both by the availability of data and following the recent literature on high frequency trading in financial markets ([Kong et al., 2021](#); [Mäkinen et al., 2019](#); [Ntakaris, Magris, Kanninen, Gabbouj, & Iosifidis, 2018](#)). [Ntakaris et al. \(2018\)](#) show that

³Current literature has focused on the importance of liquidity as a signal for jumps in asset prices. For example, [Boudt and Petitjean \(2014\)](#) analyze the 30 stocks of the Dow Jones Industrial Average Index and conclude that liquidity shocks in the effective spread and the number of trades are the key drivers behind the occurrence of a jump. [Jorion \(1988\)](#), by analyzing USD and German mark, investigates the discontinuities in exchange rates and find that exchange rates display significant jump components which are more pronounced than stock market. [Piccotti \(2018\)](#), by analyzing FX market, finds that before jumps and cojumps, exchange rates have greater illiquidity, greater jump-signed order flow, and greater jump-signed cumulative abnormal returns. [Serdengeecti, Sensoy, and Nguyen \(2021\)](#) analyze the return and liquidity jumps for the most traded emerging market FX rates and demonstrate that increase in the bid-ask spread reduces the duration between consecutive return jump.

incorporating both statistical features as well as technical indicators in financial time series prediction can help improve the performance of machine learning models. [Kong et al. \(2021\)](#) also show the importance of using both liquidity as well as technical indicators to improve the financial series forecasting using machine learning with high frequency data. Similarly, [Kercheval and Zhang \(2015\)](#) argue that adding features such as liquidity denoted by bid-ask spread can help improving the predictive performance of a machine learning model rather than using only price and volume variables. Accordingly, we present the details of our liquidity and technical indicators below.

Liquidity and Return Indicators

In addition to the (cumulative) return and realized volatility of the individual exchange rate series, we use two main liquidity measures (proportional quoted spread and regular spread).

Let LM be any liquidity measure, then its value computed in the i th interval of the day t is represented by $\{LM_{t,i} \quad i=1,2,\dots, n, \quad t=1,2,\dots,T\}$ where T is the total number of trading days. The return r and R are two types of returns where r is the return within the interval whereas R is the intraday cumulative return in the last one hour period. Let $p_{t,i}$ be the close price on day t for interval i . In the i th interval of day t , then $r_{t,i}$ and $R_{t,i}$ are defined as

$$r_{t,i} = \ln(p_{t,i}) - \ln(p_{t,i-1}) \quad (3.1)$$

$$R_{t,i} = \ln(p_{t,i}) - \ln(p_{t,i-12}) \quad (3.2)$$

Proportional quoted spread, $q_{s,i,t}$ is used to evaluate the trading cost where

$$q_{s,i,t} = p_{s,i,t} / p_{m,i,t} \quad (3.3)$$

where mid-quote price $p_{m,i,t}$ is presented as the following:

$$p_{m,i,t} = \frac{p_{A,i,t} + p_{B,i,t}}{2} \quad (3.4)$$

and the regular spread $p_{s,i,t}$ is

$$p_{s,i,t} = p_{A,i,t} - p_{B,i,t}. \quad (3.5)$$

where $p_{A,i,t}$ is the best ask price and $p_{B,i,t}$ is the best bid price at the end of the interval i in day t .

Realized volatility $rv_{t,i}$ is another variable that we use and it is defined as the sum of squared returns within the i th interval of day t in the following way:

$$rv_{t,i} = \sum_{j=1}^{N_{t,i}} rr_j^2 \quad (3.6)$$

where rr_j is the mid-price return on the j th tick record in the given interval i .

Similar to the returns, realized volatility is also calculated for the last one hour time period in order to cover a longer time frame.

Technical Indicators

In a given day, let O_k , H_k , L_k , C_k be the open price, highest price, lowest price, close price of interval k . To begin with, price rate of change $PROC(q)_k$ is a useful identity to identify the intraday trend of price change

$$PROC(q)_k = \left(\frac{C_k - C_{k-q}}{C_{k-q}} \right) \quad (3.7)$$

where $q = 5, 10, 20, 30$.⁴

The moving average (*MA*) and exponential moving average (*EMA*) are two indicators that determine the potential changes in price series. $MA(q)_k$ and $EMA(q)_k$ of prices over q lagged periods are defined by

$$MA(q)_k = \left(\frac{\sum_{i=1}^q C_{k-i+1}}{q} \right) \quad (3.8)$$

$$EMA(q)_k = \left(\frac{2}{q+1} C_k + \frac{q-1}{q+1} EMA(q)_{k-1} \right) \quad (3.9)$$

where $q = 5, 10, 20, 30$.

With respect to the two types of moving averages, two types of biases ($BIAS(q)_k$, $EBIAS(q)_k$) and two types of oscillators ($OSCP(q)_k$, $EOSCP(q)_k$) are defined to evaluate the deviation of the current market conditions from historical levels:

$$BIAS(q)_k = \left(\frac{C_k - MA(q)_k}{MA(q)_k} \right) \quad (3.10)$$

$$EBIAS(q)_k = \left(\frac{C_k - EMA(q)_k}{EMA(q)_k} \right) \quad (3.11)$$

$$OSCP(q)_k = \left(\frac{MA(q)_k - MA(q)_{k-1}}{MA(q)_{k-1}} \right) \quad (3.12)$$

$$EOSCP(q)_k = \left(\frac{EMA(q)_k - EMA(q)_{k-1}}{EMA(q)_{k-1}} \right) \quad (3.13)$$

The stochastic indicators, fast percent K (*fK*), fast percent D (*fD*) and slow percent

⁴This is similar to the cumulative log-return for one hour period, however this variable is calculated as the percentage change and covers alternative time frames.

D (sD) measure where the current price is in relation to the recent trading range. These indicators help identify oversold and overbought market conditions. In order to measure these variables, we define

$$HH(q)_k = \max\{H_k, H_{k-1}, \dots, H_{k-q+1}\} \quad (3.14)$$

$$LL(q)_k = \min\{L_k, L_{k-1}, \dots, L_{k-q+1}\} \quad (3.15)$$

then stochastic fast percent K $fK(q)_k$ is calculated as

$$fK(q)_k = \left(\frac{C_k - LL(q)_k}{HH(q)_k - LL(q)_k} \right) \quad (3.16)$$

Fast stochastic percent D $fD(q)_k$ and slow stochastic percent D $sD(q)_k$ are estimated by the following expressions:

$$fD(q)_k = \left(\frac{fK(q)_{k-2} + fK(q)_{k-1} + fK(q)_k}{3} \right) \quad (3.17)$$

$$sD(q)_k = \left(\frac{fD(q)_{k-2} + fD(q)_{k-1} + fD(q)_k}{3} \right) \quad (3.18)$$

Further technical indicators include accumulation/distribution oscillator ADO_k , true range TR_k and commodity channel index. These indicators use various price information to measure volatility of prices from different aspects. These indicators are calculated in the following way:

$$ADO_k = \left(\frac{(H_k - O_k) - (C_k - L_k)}{2 * (H_k - L_k)} \right) \quad (3.19)$$

$$TR_k = \max\{H_k - L_k, L_k - C_{k-1}, H_k - C_{k-1}\} \quad (3.20)$$

$$CCI(q)_k = \left(\frac{M_k - SM(q)_k}{0.015G(q)_k} \right) \quad (3.21)$$

where $M_k = (H_k + L_k + C_k)/3$, $SM(q)_k = (\sum_{i=1}^q M_{k-i+1})/q$ and $G(q)_k =$

$$(\sum_{i=1}^q |M_{k-i+1} - SM(q)_k|)/q.$$

After calculating the set of features for both liquidity and technical indicators, data needs to be normalized since some machine learning methods, such as RBF kernel of support vector machine, assume that all features are centered around the mean and have variance in the same order. Separate standardization is needed for features since there are different behaviors and scales among them. Therefore the features are standardized using z-score,

$$z = \left(\frac{x - u}{s} \right) \quad (3.22)$$

where u is the mean and s is the standard deviation of the training samples. Data is normalized using the last one hour of the sample data. The reason is that if data were to be normalized over the full sample period, the main differences between prices would have come from the long-term drift instead of the price changes in the recent past periods. The nature of the FX market activity strongly changes over the day, and it exhibits jumps are a result of the shorter term dynamics in the market rather than long term changes in prices. Furthermore, with this standardization methodology and using a sliding window where only historical values are used, we are able to eliminate the look-ahead bias (Tsantekidis et al., 2020; Wu, Wang, Su, Tang, & Wu, 2020). Following existing literature (Boudt & Petitjean, 2014; Kong et al., 2021), liquidity measures within a prior one hour window (12 number of 5-minute intervals) are calculated as candidate attributes. Furthermore, we also add the mean value of each liquidity measure over the prior one hour window as a new attribute. For the intraday technical indicators, although no standard exists, we include lags of $q = 5, 10, 20, 30$ to define technical indicator candidates, thus leading to a total of 116 candidate attributes for our study.

Following the nature of a classification problem for machine learning, we identify the attribute vector where the occurrence of a jump is represented by 0/1 (for binary classification) and -1/0/1 for trinary classification.

3.3. Jump Detection Methodology

While some formal jump detection tests have been developed especially to identify jumps, most of them are well suited for low frequency data. One of the earlier contributions to the jump detection tests using high frequency data is developed by [Barndorff-Nielsen and Shephard \(2006\)](#), where the authors develop a robust jump measure of integrated variance called realized bipower variation. Building on [Barndorff-Nielsen and Shephard \(2006\)](#) model, [Lee and Mykland \(2008\)](#) develop an alternative non-parametric test that gives both the direction and size of detected jumps at the intraday level data. This test enables for the identification of the exact timing of the jump as well. The exact timing and size of a price jump can be detected by using [Lee and Mykland \(2008\)](#) jump test. In the absence of jumps and after standardizing for the local volatility, instantaneous returns are increments of Brownian motion. Standard returns that are too extreme to come from a standard Brownian motion reflects jumps. In our study, we use the jump detection methodology of [Lee and Mykland \(2008\)](#). In this method, exchange rate volatility is decomposed into jumps and time-varying diffusion component as follows:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \quad (3.23)$$

where p_t is the log mid-quote exchange rate, $\mu(t)$ is the continuous locally bounded variation process, $\sigma(t)$ is a stochastic volatility process, $W(t)$ is the standard Brownian motion, $q(t)$ is a counting process independent of $W(t)$ and

taking binary values depending on whether there is a jump or not, and finally $k(t)$ is the jump size. Furthermore, the authors induce a test statistic for each return observation by comparing its absolute value with a rolling window local variation measure such as:

$$J_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i}} \quad (3.24)$$

With this framework, each trading day i consists of M equally spaced intraday returns where $r_{t,i}$ is the local 5 minute log return of the miq-quote spot exchange rate in the interval t of the day i and $\eta_{t,i}$ is the local variation measure calculated by the integrated volatility measure. [Barndorff-Nielsen and Shephard \(2004, 2006\)](#) show that under the price generation process, realized bi-power variation defined in equation (3.24) converges to integrated volatility and thus consistently estimates the integrated variance,

$$RBPV_t(M) = \mu^{-2} \frac{1}{M-2} \sum_{t=2}^M |r_{t,i}| |r_{t-1,i}| \quad (3.25)$$

where $\mu = \sqrt{2/\pi}$ and M is the number of observations in the local variation window. In order to take advantage of the bipolar variation, the window size should be smaller than the number of observation but it needs to be big enough so that the effects of jumps on estimating instantaneous volatility disappears. Even when the market volatility is high, the [Lee and Mykland \(2008\)](#) procedure allows for the detection of jumps accurately. [Lee and Mykland \(2008\)](#) suggest different optimal window sizes for different frequencies of data where taking into account the computational burden and also the marginal contribution is optimized. Following [Lee and Mykland \(2008\)](#) we use a window length of 270 data points for 5 minutes returns in our analysis. In a practical application, this would need a less than a day's data collection to be able to forecast a jump occurrence for an

upcoming period for 5 minute frequency data. If one wants to use a frequency of data of 1 hour for a jump identification, it would need almost 3.5 days of data and 16 days' worth of data for a daily frequency for the jump detection analysis outlined.

[Boudt, Croux, and Laurent \(2011\)](#) demonstrate the accuracy and robustness of the LM test and improve it by adding intra-week periodicity in volatility. A trading day is divided into 5-minute intervals and intraday jumps within each interval are detected using the methodology developed by [Lee and Mykland \(2008\)](#) and [Boudt et al. \(2011\)](#). Furthermore, intraday periodicity may have a deteriorating effect on $J_{t,i}$. [Boudt et al. \(2011\)](#) suggest to use an intraday periodicity adjustment factor to rescale the returns. Following [Boudt and Petitjean \(2014\)](#), we make the adjustment procedure and estimate the modified filtered jump statistic $\tilde{J}_{t,i}$ given in equation (3.26) below.

$$J_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i} \tilde{f}_{t,i}} \quad (3.26)$$

where $\tilde{f}_{t,i}$ is the intraday periodicity factor obtained by a flexible fourier specification as in [T. G. Andersen and Bollerslev \(1998\)](#).

[Lee and Mykland \(2008\)](#) demonstrate that the obtained jump statistic follows a standard Gumbell distribution. Hence, we reject the null hypothesis of no jump if the filtered $\tilde{J}_{t,i}$ statistic is greater than the value suggested by the Gumbell distribution:

$$\tilde{J}_{t,i} > G_{-1}(1 - \alpha)S_n + C_n \quad (3.27)$$

where $G_{-1}(1 - \alpha)$ is the $(1 - \alpha)$ quantile function of the standard Gumbell distribution and

$$C_n = (2\log n)^{0.5} - \frac{\log(\pi) + \log(\log n)}{2(2\log n)^{0.5}} \quad (3.28)$$

with

$$S_n = \frac{1}{2(2\log n)^{0.5}} \quad (3.29)$$

where n is the number of total observations and α is the significance of discontinuity in the local variation window at 5%. Total number of trading days is 1039 for the whole time period (January 1, 2018 until April 30, 2021), and according to our methodology, total number of jumps is 15,336 and median number of jumps per day is 11 as given in Figure 3.2 below. Table 3.1 summarizes the jump statistics for different currencies as well. The jumps are calculated over the average price of each of the 5 minute intervals following [Lee and Mykland \(2008\)](#) methodology. For illustrative purposes, an example of a positive and a negative jump for a selected currency AUD is given below in Figure 3.1.

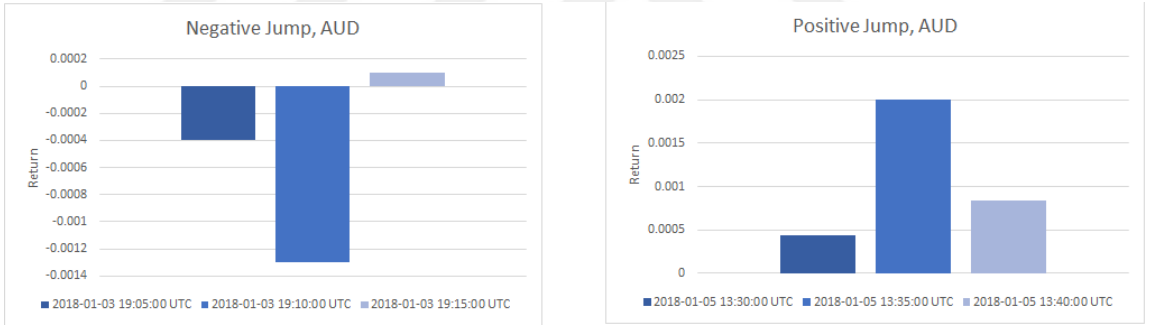


Figure 3.1: Positive and Negative Jump Example (AUD)

3.3.1 Class Balancing

When machine learning is applied in a static setting, a randomly selected test set can be used to identify the classifier accuracy. However, in time series data, the only way to get a fair estimate of a classifier accuracy is to select a test set that occurs after the training set. Our data is split such that 80 % of data covering from time period January 1, 2018 until August 31, 2020 is in the training set and 20 % of data from September 1, 2020 until April 30, 2021 is in the testing set.

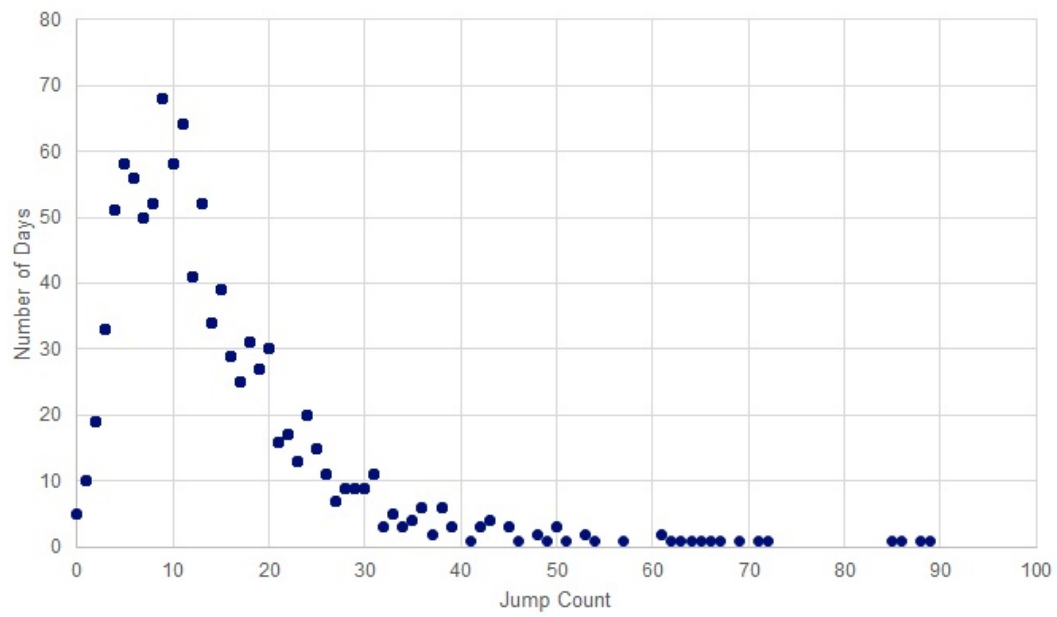


Figure 3.2: Daily Jump Distribution at the Aggregate Level

Table 3.1: Jump Statistics for Individual Currencies against the US Dollar

Panel A: Observed Number of Jumps						
	All Jumps		Negative Jumps		Positive Jumps	
	Jump Count	Jump Size	Jump Count	Jump Size	Jump Count	Jump Size
AUD	660	0.0024	341	-0.0023	319	0.0024
CAD	496	0.0017	239	-0.0017	257	0.0017
CHF	578	0.0014	271	-0.0014	307	0.0014
CZK	898	0.0017	430	-0.0017	468	0.0017
EUR	666	0.0015	319	-0.0014	347	0.0016
GBP	648	0.0021	314	-0.0021	334	0.0022
HUF	932	0.0017	439	-0.0017	493	0.0018
JPY	706	0.0015	325	-0.0015	381	0.0015
MXN	876	0.0024	487	-0.0023	389	0.0025
NOK	1065	0.0021	543	-0.0022	522	0.0021
NZD	597	0.0024	281	-0.0025	316	0.0024
PLN	896	0.0017	425	-0.0016	471	0.0017
SEK	837	0.0018	419	-0.0017	418	0.0018
ZAR	2523	0.0019	1268	-0.0019	1255	0.0018

Panel B: Test Statistics for Jump Sizes							
	Mean ($\times 10^6$)	Min	Max	Std. ($\times 10^4$)	Skew.	Kurt.	Obs.
AUD	-0.074	-0.032	0.014	3.990	-2.429	242.640	248256
CAD	0.133	-0.007	0.008	2.680	0.202	35.084	248256
CHF	0.193	-0.007	0.006	2.600	-0.044	18.464	248256
CZK	-0.054	-0.010	0.007	3.450	-0.200	29.545	248256
EUR	-0.068	-0.004	0.006	2.640	0.154	18.826	248256
GBP	0.087	-0.010	0.021	3.550	0.742	79.800	248256
HUF	-0.600	-0.007	0.008	3.630	0.098	22.143	248256
JPY	-0.001	-0.014	0.028	2.640	4.449	571.704	248256
MXN	-0.007	-0.019	0.020	5.700	0.253	51.224	248256
NOK	-0.038	-0.028	0.022	5.140	-0.532	113.030	248256
NZD	0.049	-0.015	0.013	3.870	-0.388	66.161	248256
PLN	-0.410	-0.007	0.007	3.670	0.027	17.315	248256
SEK	-0.130	-0.010	0.010	3.950	0.082	23.917	248256
ZAR	-0.550	-0.034	0.023	6.560	-0.724	72.663	248256

All jumps are calculated using [Lee and Mykland \(2008\)](#) jump test with adjusted [Boudt et al. \(2011\)](#) adjustment factor. The sample period covers from January 1, 2018 until April 30, 2021.

During the training and testing model, we assure there is no information leakage from test set to training set and vice versa.

Given the upward, downward and non-jumping classes are k , l and m for the training data set, there is an unbalance of data since non-jumping cases are in some cases hundred times larger than upward and downward jump classes. For the binary classification problem, to identify occurrence of jumps, the upward and downward jumping instances are grouped as one class ($k+l$) and the other class is m for the non-jumping instances. Since m is hundred times larger than ($k+l$), first we randomly oversample minority class hence doubling its size then we further adopt a random undersampling procedure on the non-jumping class to make its size equal to the minority class.

For the trinary classification problem where we are trying to identify the occurrence of an upward or a downward jump, there is also an imbalance between upward and downward jump classes as well as all jumping and non-jumping instances. Hence, to overcome this problem, we apply a two step procedure where we first use SMOTE (Synthetic Minority Oversampling Technique) to balance the minority classes of upward and downward jumps. After oversampling the minority classes, since non-jumping instances are still significantly larger than the minority class, we apply a random undersampling procedure on the majority class again, making the three class sizes equal for the training sets.

Given using only one test set is limited as the estimated results can vary widely depending on the training set, and in order to overcome the variation caused by class balancing, we replicate the same procedure to construct 50 different training sets for each of the algorithms that we are using. While some of the studies ([Akyildirim et al., 2021](#); [Mäkinen et al., 2019](#)) using machine learning for

financial market predictions have over sampled the minority class (mainly doubling), we do not see any benefit in terms of explanatory power with doubling our minority sample.

After splitting test and training data and balancing class sizes, we implement the feature selection methodology and then different model training procedures are applied on each of the 50 training sets for each of the currencies. The performance of each model is also analyzed on 50 different test sets that are also conducted by using class balancing procedures. Therefore, we are able to split the data set into 50 training and 50 test sets so that train and test cycles are carried on different combinations of these sets for each of the methodologies, for each of the currencies, hence making our results more robust with the help of sampling procedures.

Preprocessing and Feature Selection

High dimensional data analysis is a challenge for researchers in the field of machine learning. Feature selection algorithms help to overcome computation time problems, improve learning accuracy and facilitate a better understanding of the model. Plenty of feature selection models are available in the literature given the availability of data leading to hundreds of variables ([Chandrashekar & Sahin, 2014](#)). The goal of feature selection is to select a subset of variables from the input which can efficiently describe input while reducing the effects of noise or irrelevant variables and still provide efficient prediction results ([Guyon & Elisseeff, 2003](#); [Ladha & Deepa, 2011](#)).

Machine learning algorithms are very sensitive to the quality of input data. Hence, appropriate feature extraction methodologies are vital for the success and efficiency of the models. Furthermore, as the dimensionality of the data increases, the volume of space increases so fast that available data becomes sparse. After an

extensive analysis and executing different feature selection algorithms including Minimum redundancy- maximum relevance (mRMR) feature selection algorithm, in order to overcome dimensionality problems, Principal Component Analysis (PCA) is used to reduce the dimensionality in this study. The objective of PCA is to reduce the dimensionality of the data set while retaining as much as possible variation in the data set, and to identify new meaningful underlying variables (Ince & Trafalis, 2007). PCA, while reducing the dimensionality of the data, keeps the main essence of the original data set and allows for a better identification of patterns in the training data that which leads to a better generalization ability and a higher accuracy (Nobre & Neves, 2019).

Several studies in finance has used machine learning in combination with PCA and has demonstrated that using PCA, especially with technical indicators, has improved the average classification accuracy in the testing phase (Byun, Baek, Ahn, Oh, & Kim, 2015; Y. Huang, Bai, & Li, 2007; Ince & Trafalis, 2007; Li, 2021; Nobre & Neves, 2019; Tsai & Hsiao, 2010; Yu, Chen, & Zhang, 2014; Zhong & Enke, 2019). The PCA analysis leads to five principal components. For a demonstration, the plots of principal components for the binary classification and trinary classification cases for selected currency (AUD) are given in Figure 3.3 and Figure 3.4, respectively.

In our study, the data are first transformed using PCA, which leads to a diagonal covariance matrix, and then each dimension is normalized such that the covariance matrix is equal to the identity matrix (whitening). While PCA analysis linearly transforms the original inputs into uncorrelated features, we also add independent component analysis (ICA) to linearly transform inputs into statistically independent features (Cao, Chua, Chong, Lee, & Gu, 2003; Oja, Kiviluoto, & Malaroiu, 2000).

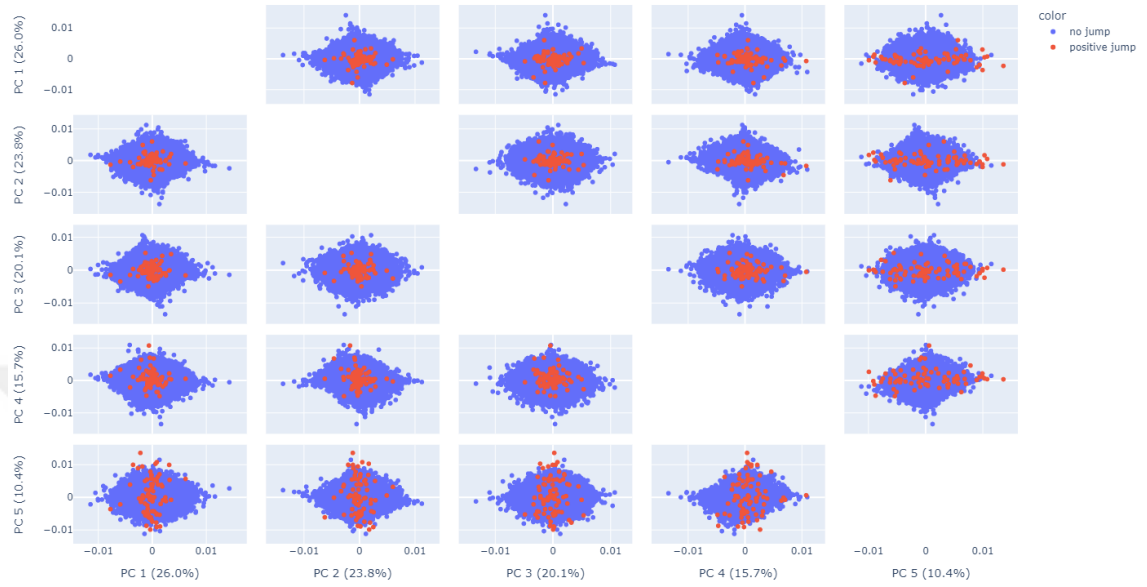


Figure 3.3: Binary Classification PCA Plot (AUD, KNN)

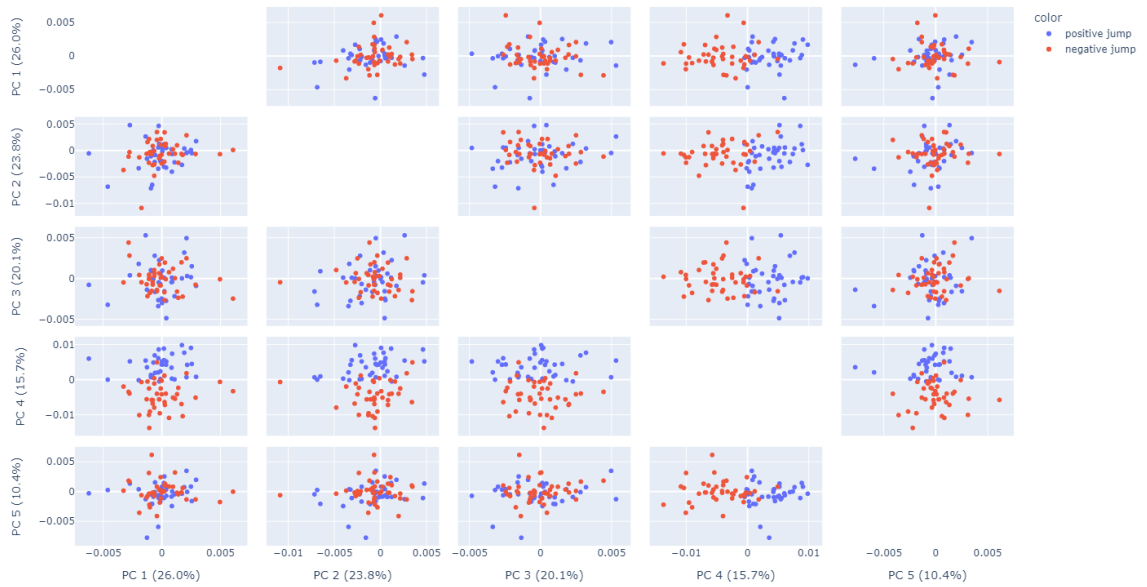


Figure 3.4: Trinary Classification PCA Plot (AUD, KNN)

3.4. Classification Algorithms

We use 5 different machine learning algorithms (K-Nearest Neighborhood, Support Vector Machine, Decision Tree, Random Forest, Multilayer Perceptron) to answer the binary classification (jump arrival in the following interval) and trinary classification (direction of the arriving jump in the following interval, as up or down) problems we have. Furthermore, we added ARIMA with AdaBoost classification methodology as a baseline econometric model in our analysis. For the binary classification, this would imply that using the previous data points, we are able to identify whether a jump is coming in the next 5 minute period and for the trinary classification problem, it would imply that we are able to predict not only the occurrence but also the direction of the jump for the coming 5 minute period. The Machine Learning algorithms studied enable us to compare the results of our models to the actual real life situations. The implementation of classification algorithms are done using Python's scikit-learning package. In this section, we briefly discuss the application of these algorithms and how they are implemented for our study.

3.4.1 K Nearest Neighbourhood

The K Nearest Neighbourhood (KNN) algorithm is a non-parametric classification methodology, simple yet effective in many applications from identifying the risk for cancer to recommendation systems used by streaming channels, from text mining to credit/loan analysis in finance. KNN is a supervised machine learning algorithm that works by finding distances between a query and the data by selecting the number of data points closest to the query and gives the most frequent label (in the case of classification) or averages (in the case of a regression). KNN algorithm assumes similarity between the new case/data and

available ones and classifies data into the category that is most similar to the available categories. Most KNN algorithms use euclidean distance to calculate the distance between the two points where the distance formula is given below:

$$d_{x,y} = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (3.30)$$

KNN model, for a given value of k , will find the k -nearest neighbors of the data point and then it will assign the class to the data point by having the class which has the highest number of data points out of all classes of the K neighbors. For the purposes of this study, neighbour values of 5, 7, 10, 20 and 30 are implemented using the grid search function of scikit. To save space, results reported in this paper are with neighbour values of 7 for both of the KNN classification problems.

3.4.2 Support Vector Machine

Support Vector Machine (SVM) is another supervised machine learning algorithm that can be used for classification or regression problems. SVM is based on the idea of finding a hyperplane that best divides dataset into classes. Support vectors are the data points nearest to the hyperplane. The effectiveness of the SVM depends on the selection of the kernel functions. SVM can accurately predict time series data even when the underlying system process is non-linear and non-stationary. The results of the SVM are dependent on the choice of kernel functions. In this study, exhaustive grid search is done, where all parameter combinations are considered. Grid search implements the usual estimator API: when “fitting” it on a dataset all the possible combinations of parameter values are evaluated and the best combination is retained. In this study, the Gaussian (rbf) kernel is used. The trade-off parameter c and the kernel scale parameter g are important parameters to be optimized. For the non-perfecet seperation

problem, the SVM classification algorithm solves the following problem where x_i for $i=1,2,\dots,N$ with a sample size of N observations.

$$\begin{aligned}
\min_{w,b,\xi} \quad & \frac{1}{2}w^t w + C \sum_{i=1}^N \xi_i \\
\text{s.t.} \quad & y_i(w\phi(x_i + b)) + \xi_i - 1 \\
& \xi \geq 0
\end{aligned} \tag{3.31}$$

The dual form of the equation is obtained by first forming a Lagrangian of the already obtained minimization problem with the help of a Lagrange Multiplier so that new constraints could be added to the objective function and then would be solved for the primal variable values that minimize the original objective function. The kernel by definition avoids the explicit mapping necessary to get linear learning algorithms to learn a nonlinear function. In this study, the value range for c (0.01, 1, 10, 100, 1000) and for g (0.00001, 0.0001, 0.001, 0.01, 1) are used for each of the research questions at hand. The optimal values for c and g are found to be 1 and 0.01 respectively where we use the Gaussian kernel (rbf).

3.4.3 Decision Tree

Decision tree also belongs to the family of supervised learning algorithms that can be used both for regression and classification problems. Decision trees start from the root of the tree and to some leaf/terminal node, with the node providing the classification example. Each node in the tree acts as a test case for some attribute, and each edge descending from the node corresponds to the possible answers to the test case. This process is recursive in nature and is repeated for every subtree rooted at the new node. For decision trees, attributes are also selected using criteria such as Gini index, entropy, gain ratio, chi-square. Decision trees are simple to understand and interpret however they can be unstable, which means a

small change in data can lead to a change in the optimal structure of the decision tree. In this study, to optimize decision tree, grid search is utilized. The output given by the decision tree uses Gini impurity criteria, and we allow the tree to go deeper to enable it to capture more information about the data but not too deep as it can lead to overfitting. Hence, after grid search, optimal max depth is found to be 3 for both binary and trinary classification problems we are investigating.

3.4.4 Random Forest

Random forest (RF) classifier is an integrated classifier that generates multiple decision trees using randomly selected subsets of training samples and variables. RF algorithm, proposed by [Breiman \(2001\)](#), is one of the most powerful methods when dealing with high dimensional data. For classification tasks, the output of the random forest is the class selected by most trees. The forest that is built within the model is an ensemble of decision trees, usually trained with the "bagging" method. The main idea behind a bagging method is that a combination of learning models increases the overall fit. By training multiple decision trees on different subspaces of feature spaces, RF decreases the variance of the model without increasing its bias. RF adds additional randomness to the model thus, instead of searching for the best feature among a subset of features, it searches for the best feature among a subset of random features. Given a training set $X = x_1, \dots, x_n$ with responses $Y = y_1, \dots, y_n$ bagging repeatedly (B times) selects a random sample with replacement of the training set and fits trees to these samples. For $b=1 \dots B$, n training samples from X, Y called X_b and Y_b , and train a classification tree f_b on X_b, Y_b . After training, predictions for the test data can be made by taking the majority vote in the case of classification trees. The parameter to be chosen for estimators can range and also the nodes for the tree are chosen looking for optimum split of features. Gini impurity is calculated using the

formula:

$$GiniIndex = 1 - \sum p_j^2 \quad (3.32)$$

where p_j is the probability of class j. The Gini impurity measures the frequency at which any of the dataset will be mislabeled when it is randomly labeled. The entropy is a measure of information that indicates the disorder of features with the target where

$$Entropy = - \sum p_j \cdot \log_2 p_j \quad (3.33)$$

where p_j is the probability of class j. Entropy is a measure of information that indicates the disorder of the features with the target. Similar to the Gini Index, the optimum split is chosen by the feature with less entropy. Computationally, entropy is more complex since it uses logarithms. In this study, both indexes are used for robustness and gini index is reported as they yield very similar results and Gini index is slightly computationally less expensive.

3.4.5 Artificial Neural Network

Multi-layer perceptron (MLP) is a type of artificial neural network with several single processing elements, called neurons developed first by [Bishop et al. \(1995\)](#). The neurons are connected to each other by a joint mechanism where a set of weights are assigned. MLP has three layer: input layer, output layer and hidden layer. Neuron takes the values of inputs parameters, sums them up according to their weights and adds a bias. Except for the input layer, each node is a neuron that uses a nonlinear activation function. By applying the transfer function, the value of outputs are determined. MLP uses backpropagation for training. With the use of multiple layers and non-linear activation, MLP can distinguish data that is not linearly separable. Learning occurs in the perceptron by changing

connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. Given there is more than one local minimum by definition, we are able to overcome the issue of getting stuck in a local minima by changing the learning parameters and also by identifying different number of hidden units following [Lek and Guégan \(2012\)](#). MLPs are universal approximators hence no standard exists for choosing the number of layers in the algorithm ([Goodfellow, Bengio, & Courville, 2016](#)). The number of hidden layers are chosen as (2,10,1) where input layer has two variables, one hidden layer with 10 nodes and an output layer with 1 node.

3.4.6 ARIMA and AdaBoost

In order to compare our Machine Learning Algorithm analysis with a classical econometric model, we also included ARIMA in our analysis. Autoregressive Integrated Moving Average (ARIMA) model is a generalization of an autoregressive moving average model. The model's goal is to predict the future value of stocks or financial markets by analysing the differences between the values in the series instead of through actual values. Given the high frequency nature of our problem, we used (0,1,0) a random walk with drift, in our analysis for series order. In the our research problem, since we have a classification problem, to predict the occurrence of jumps, we added adaboost as a classification model in addition to ARIMA estimations. AdaBoost model, first developed by [Freund and Schapire \(1997\)](#); [Freund, Schapire, et al. \(1996\)](#) is a supervised classifier algorithm that starts by fitting a classifier on the original data set and afterwards, additional copies of the classifier are fitted on the same data set but the weights of incorrectly classified instances are adjusted so that following classifiers focus on more difficult cases. The advantage of AdaBoost is that it can be applied to both binary and trinary classification problems.

3.5. Empirical Results

For the binary classification problem, recall is the number of true positive samples divided by the sum of the true positives and false negatives while precision is the number of true positives divided by the sum of true positives and false positives. The equation for precision would be thus

$$Precision = \frac{tp}{tp + fp} \quad (3.34)$$

and for recall we have

$$Recall = \frac{tp}{tp + fn} \quad (3.35)$$

where tp, tn, fp and fn stand for true positive, true negative, false positive and false negative respectively. F1 score is the harmonic mean of the precision and recall metrics.

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3.36)$$

where accuracy is given by following equation:

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \quad (3.37)$$

For the trinary classification problem that we investigate, the precision is calculated as

$$Precision = \left(\frac{\sum_{i=1}^q tp_i}{\sum_{i=1}^q (tp_i + fp_i)} \right) \quad (3.38)$$

where recall is:

$$Recall = \left(\frac{\sum_{i=1}^q tp_i}{\sum_{i=1}^q (tp_i + fn_i)} \right) \quad (3.39)$$

F1 score demonstrating the relations between data's positive labels and those given by a classifier based on per-class average,

$$F1 = \frac{(\beta^2 + 1)Precision * Recall}{(\beta^2)Precision + Recall} \quad (3.40)$$

Average accuracy is given by the equation below:

$$AverageAccuracy = \left(\frac{\sum_{i=1}^q \left(\frac{tp_i + tn_i}{tp_i + fp_i + fn_i + tn_i} \right)}{l} \right) \quad (3.41)$$

In the case of unbalanced classes, researchers focus on F1 score performance since its ability to be only affected in one direction of skewed distributions. After using class balancing techniques, we are able to use both F1 score and accuracy as indicators of performance of the models. All results are out-of-sample. In a data set with no stationary trend, a random forecast would lead an expected score of 50%. The brief summary results for binary and trinary classification problems are given below in Table 3.2 and Table 3.3 where detailed results for each of the different algorithms for each of the currencies with a more comprehensive summary are given in the Appendix Table 4.7 and Table 4.14 respectively.

As stated earlier, we aggregate tick data for 5-minute time intervals and then apply five different classification algorithms. The target variable for the binary classification methods is the class of the jump variable that takes value of 0 when there is no jump for the coming 5-minute period and 1 when there is a jump forecasted in the next 5-min period. For the trinary classification, we identify the occurrence as well as the direction (upward/downward) of the coming jump in the next 5-minute period.

The jumps are identified using the methodology of Lee and Mykland (2008) and adjusted with the intraday periodicity factor following Boudt et al. (2011) which helps us overcome the over (under)-detection of jumps in intraday intervals with high (or low) volatility. After identifying the jumps and using class-balancing

methodologies separately for the datasets that will be used for the binary and trinary classification problems, we split our data set as the training and testing set. The main results reported are for the 80% train and 20% test split. Our whole sample covers from January 1st, 2018 until April 30th, 2021 implying the train set covers period from January 1st, 2018 until August 31st, 2020 whereas the test set covers from September 1st, 2020 until April 30th, 2021. We conduct a PCA and fast ICA analysis on the training set and use the before discussed machine learning classification algorithms on each of the currencies individually.

In order to measure the performance of our models, we use the aforementioned F1 and accuracy rates. Each of the models for individual currencies are trained on their own sample and subsamples, and tested on their own subsamples. The model training and testing is repeated for 50 subsamples for each of the currencies and in Table 3.2 and Table 3.3, the average accuracy of 14 currencies for each of the algorithms are reported as well as the F1 scores. The data is separated such that the model is first developed that is trained on the 80% of the data and the remaining 20 % is reserved as the test set for out of sample forecasting. For additional robustness, we also did the same procedure where the model is trained on the 60% of the data and tested on the 40% of the data set. As stated in the class balancing section, there is no leakage from training data to testing data. Our results below demonstrate that, in general, predicting whether a foreign exchange jump is arriving is easier than predicting its direction. For all of our prediction problems, multi-layer perceptron and SVM are the most promising models whereas the performance of decision tree model is the lowest compared to others.

For the binary classification problem of identifying the occurrence of the jump in the next period, multi-layer perceptron and SVM lead to the best average

Table 3.2: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Binary Classification

		Mean	Median
KNN	F1 Score (No Jump)	0.73	0.73
	F1 Score (Jump)	0.66	0.66
	Accuracy	0.70	0.70
ML Perceptron	F1 Score (No Jump)	0.75	0.75
	F1 Score (Jump)	0.70	0.70
	Accuracy	0.73	0.73
Decision Tree	F1 Score (No Jump)	0.66	0.66
	F1 Score (Jump)	0.65	0.65
	Accuracy	0.65	0.65
SVM	F1 Score (No Jump)	0.76	0.76
	F1 Score (Jump)	0.69	0.69
	Accuracy	0.73	0.73
Random Forest	F1 Score (No Jump)	0.74	0.74
	F1 Score (Jump)	0.69	0.69
	Accuracy	0.72	0.72
ARIMA	F1 Score (No Jump)	0.63	0.63
	F1 Score (Jump)	0.60	0.60
	Accuracy	0.62	0.62

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is boldfaced. Train sample is 80% of data set.

Table 3.3: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Trinary Classification

		Mean	Median
KNN	F1 Score (No Jump)	0.59	0.59
	F1 Score (Positive Jump)	0.69	0.69
	F1 Score (Negative Jump)	0.71	0.71
	Accuracy	0.66	0.66
ML Perceptron	F1 Score (No Jump)	0.63	0.63
	F1 Score (Positive Jump)	0.72	0.72
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.70	0.70
Decision Tree	F1 Score (No Jump)	0.52	0.52
	F1 Score (Positive Jump)	0.64	0.64
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.60	0.60
SVM	F1 Score (No Jump)	0.64	0.64
	F1 Score (Positive Jump)	0.71	0.71
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.69	0.69
Random Forest	F1 Score (No Jump)	0.62	0.62
	F1 Score (Positive Jump)	0.72	0.72
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.69	0.69
ARIMA	F1 Score (No Jump)	0.51	0.51
	F1 Score (Positive Jump)	0.61	0.63
	F1 Score (Negative Jump)	0.58	0.60
	Accuracy	0.57	0.57

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is boldfaced. Train sample is 80 % of data set.

accuracy results, closely followed by random forest methodology (Table 3.2). The overall average accuracy of the multi-layer perceptron and SVM model across all currencies is 0.73 for both, closely followed by random forest model which has an overall accuracy of 0.72. While SVM is computationally expensive, multi-layer perceptron is slightly better in terms of identifying the occurrence of jumps in the binary classification problem overall. Random forest is also as efficient as SVM in identifying the jump instances. As for individual models reported in Appendix Table 4.1, Table 4.2, Table 4.3, Table 4.4 and Table 4.5, Table 4.6 the highest accuracy rate is 0.78 overall and lowest success rate is 0.62 overall. The highest F1 scores are also coming from the multi-layer perceptron and SVM models. Although they are very close, it is safe to say that our models are able to detect non-jump instances slightly better than jump instances when compared over average F1 scores. The average F1 score across different currencies for non-jump instances is 0.75 for multi-layer perceptron whereas it is 0.70 for jump instances for the same model. The lowest average accuracy ratios come from the decision tree model. Since decision trees can be unstable, that is a small change in data can lead to a large change in the structure of the optimal decision tree, they can be relatively inaccurate. Random forest reduces the variance part of error rather than bias part, hence on a test data that has not been used for the training of the model, it outperforms decision tree in terms of accuracy. ARIMA model with AdaBoost classification has the lowest accuracy score for our data set and research problem, we think it may be because we are investigating a classification problem rather than a regression problem and hence, the need to combine ARIMA with AdaBoost (for classification) given the characteristics of our data set and high frequency analysis led to a lower accuracy score. The scores for the binary classification imply that at least a part of the jumps in data are predictable within a reasonable level of confidence.

We also perform the whole analysis where the training set is 60% of data set instead of 80%. The summary results for a different sampling of train and test set are given in Table 3.4 below. Again, the multi-layer perceptron and SVM had the highest average accuracy results for the binary classification problem and also the average accuracy has not changed significantly compared to a larger training set. The results for a different selection of a train and test set also support the effectiveness our model composition.

Table 3.4: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Binary Classification

	Currency	Mean	Median
KNN	F1 Score (No Jump)	0.74	0.74
	F1 Score (Jump)	0.70	0.70
	Accuracy	0.71	0.71
ML Perceptron	F1 Score (No Jump)	0.75	0.75
	F1 Score (Jump)	0.70	0.70
	Accuracy	0.73	0.73
Decision Tree	F1 Score (No Jump)	0.66	0.66
	F1 Score (Jump)	0.65	0.65
	Accuracy	0.66	0.66
SVM	F1 Score (No Jump)	0.76	0.76
	F1 Score (Jump)	0.69	0.69
	Accuracy	0.73	0.73
Random Forest	F1 Score (No Jump)	0.75	0.75
	F1 Score (Jump)	0.70	0.70
	Accuracy	0.72	0.72
ARIMA	F1 Score (No Jump)	0.63	0.63
	F1 Score (Jump)	0.61	0.61
	Accuracy	0.62	0.60

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is boldfaced. Train sample is 60% of data set.

In order to identify the direction of the jumps, we use the same models and same

sample data. For the trinary classification identification, multi layer perceptron slightly outperforms SVM and random forest in terms of overall average accuracy. However, all three models are actually able to identify the occurrence of a negative jump with same average accuracy. Random forest and multi-layer perceptron models are slightly better than predicting accurately the occurrence of positive jumps compared to SVM. Decision tree is again the worst performing model for the trinary classification problem. The highest average accuracy for individual currencies are observed with multi-layer perceptron model, followed by SVM and random forest models with highest average accuracy being 0.76 for any exchange rate. The summary results are given in Table 3.3 whereas individual model results are given in Appendix Table 4.8, Table 4.9, Table 4.10, Table 4.11, Table 4.12 and a detailed summary table is given in Table 4.14 for the trinary classification problem. Multi-layer perceptron has the advantage of distinguishing data that is not linearly separable and also same accuracy ratios can be achieved with smaller data. Hence, even when we look at the individual currency average accuracy results, we can observe that regardless of the sample size of the training or test data, multi-layer perceptron can deliver consistently better results compared to other algorithms. For identifying the negative jumps in the next 5-minute period, all three methods of multi-layer perceptron, SVM and random forest achieve same average accuracy whereas KNN classification algorithm lag behind and decision tree algorithm is again the lowest performing model in terms of average accuracy. For identifying positive jumps, multi-layer perceptron and random forest slightly outperform SVM with average accuracy rates of 0.72. Multi-layer perceptron is an artificial neural network model whereas SVM models are also closely related to neural networks. SVM can map the input data to a higher dimensional space to assign a decision boundary. For SVM, it is done by using kernel tricks, whereas for multi-layer perceptron via non-linear activation

functions. Both classes of algorithms can approximate non-linear decision functions, with different approaches. Furthermore, random forest is also able to handle highly non-linear relations leading to better classification performance. Although all the algorithms used in this study can be used for non-linear classification functions, random forest, multi-layer perceptron and SVM provide the highest accuracy results.

Similar to the previous case, we perform the whole analysis where the training set is 60% of data set instead of the 80 % for the trinary classification. The summary results for the different sampling ratios are given in Table 3.5. Again, the multi-layer perceptron and SVM have the highest average accuracy results for the trinary classification problem when the train and test sample are changed, also the average accuracy do not change compared to a larger train set.

To understand the quality of the fit of the different models, we used RMSE (Root Mean Square Deviation) where the smaller the RMSE, the better fit is the model. We implemented Model confidence set (MCS) procedure developed by Hansen, Lunde, and Nason (2011). The main advantage of MCS procedure is that it does not assume a particular hypothesis rather all models are treated equally in terms of their sample performance and these models are evaluated on their out-of-sample predictive abilities. We used a 5 % confidence interval and did 1.000 bootstraps for each of the models. For the sake of space, results are reported in Appendix Table 4.15 and Table 4.16 where the results of the MCS analysis for binary and trinary classification problems are reported consecutively. For the binary classification problem, ML Perceptron and SVM models are able to fit data better compared to other algorithms. Also for the trinary classification problem, ML Perceptron, SVM and RF models also fit data better compared to KNN and Decision Tree models. In line with F1 and accuracy scores of the binary

Table 3.5: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Trinary Classification

		Mean	Median
KNN	F1 Score (No Jump)	0.60	0.60
	F1 Score (Positive Jump)	0.70	0.70
	F1 Score (Negative Jump)	0.71	0.71
	Accuracy	0.67	0.67
ML Perceptron	F1 Score (No Jump)	0.64	0.64
	F1 Score (Positive Jump)	0.73	0.73
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.70	0.70
Decision Tree	F1 Score (No Jump)	0.53	0.53
	F1 Score (Positive Jump)	0.65	0.65
	F1 Score (Negative Jump)	0.66	0.66
	Accuracy	0.60	0.60
SVM	F1 Score (No Jump)	0.65	0.65
	F1 Score (Positive Jump)	0.73	0.73
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.70	0.70
Random Forest	F1 Score (No Jump)	0.62	0.62
	F1 Score (Positive Jump)	0.73	0.73
	F1 Score (Negative Jump)	0.74	0.74
	Accuracy	0.70	0.70
ARIMA	F1 Score (No Jump)	0.48	0.48
	F1 Score (Positive Jump)	0.58	0.58
	F1 Score (Negative Jump)	0.51	0.52
	Accuracy	0.53	0.52

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is bold-faced. Train sample is 60 % of data set.

and trinary classification problems, results for MSC analysis also indicate that jump prediction problem for binary classification problem has a better fitting performance when compared to the trinary classification problem.

3.5.1 Robustness

In addition to using a different training and testing data set for robustness, we also analyzed the impact of Covid pandemic on foreign exchange market jump prediction, we first did the analysis only for the time period starting from December 1st, 2019 until end of the data set, which is April 30th, 2022. The initial regression results for both binary and trinary classification problems post covid era are given in below Tables 3.6 and 3.7 consecutively. As seen, the Multilayer Perceptron and SVM and also Random Forest models are again the best performing machine learning models. The detailed summary tables are provided in the Appendix Table 4.17 and Table 4.18. The performance of the models in terms of predicting a jump arrival and a classification of jump are similar to the whole sample period data. However, there is a decrease in the accuracy scores. This is in line with the findings in the literature where Covid pandemic has lead to a decline in the efficiency and increase in volatility of the foreign exchange market (Abedin, Moon, Hassan, & Hajek, 2021; Narayan, 2022; Zhang, Chen, & Shao, 2021) which also resulted in a decreased performance of the models compared to full sample.

We also did a rolling window analysis for the post Covid era, results of which are reported below in Table 3.8 and Table 3.9 for the binary and trinary classification problems respectively. Again, the Multilayer Perceptron and SVM and also Random Forest models are again the best performing machine learning models for the binary and trinary classification problems.

Table 3.6: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Binary Classification Results Post Covid Era

		Mean	Median
KNN	F1 Score (No Jump)	0.65	0.65
	F1 Score (Jump)	0.58	0.58
	Accuracy	0.62	0.62
ML Perceptron	F1 Score (No Jump)	0.68	0.68
	F1 Score (Jump)	0.62	0.62
	Accuracy	0.65	0.65
Decision Tree	F1 Score (No Jump)	0.58	0.58
	F1 Score (Jump)	0.58	0.58
	Accuracy	0.58	0.58
SVM	F1 Score (No Jump)	0.71	0.71
	F1 Score (Jump)	0.61	0.61
	Accuracy	0.67	0.67
Random Forest	F1 Score (No Jump)	0.66	0.66
	F1 Score (Jump)	0.61	0.61
	Accuracy	0.64	0.64
ARIMA	F1 Score (No Jump)	0.66	0.65
	F1 Score (Jump)	0.58	0.56
	Accuracy	0.62	0.61

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is bold-faced. Train sample is 80 % of data set for the time period December 1st, until April 30th, 2022

Table 3.7: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Trinary Classification Results Post Covid Era

		Mean	Median
KNN	F1 Score (No Jump)	0.53	0.53
	F1 Score (Positive Jump)	0.63	0.63
	F1 Score (Negative Jump)	0.61	0.61
	Accuracy	0.59	0.59
ML Perceptron	F1 Score (No Jump)	0.53	0.53
	F1 Score (Positive Jump)	0.68	0.68
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.62	0.62
Decision Tree	F1 Score (No Jump)	0.44	0.44
	F1 Score (Positive Jump)	0.57	0.57
	F1 Score (Negative Jump)	0.55	0.55
	Accuracy	0.52	0.52
SVM	F1 Score (No Jump)	0.56	0.56
	F1 Score (Positive Jump)	0.68	0.68
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.63	0.63
Random Forest	F1 Score (No Jump)	0.52	0.52
	F1 Score (Positive Jump)	0.67	0.67
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.61	0.61
ARIMA	F1 Score (No Jump)	0.49	0.49
	F1 Score (Positive Jump)	0.60	0.60
	F1 Score (Negative Jump)	0.59	0.60
	Accuracy	0.56	0.56

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is bold-faced. Train sample is 80 % of data set for the time period December 1st, until April 30th, 2022

Table 3.8: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Binary Classification Results Post Covid Era, Rolling Window Analysis

		Mean	Median
KNN	F1 Score (No Jump)	0.63	0.63
	F1 Score (Jump)	0.53	0.53
	Accuracy	0.59	0.59
ML Perceptron	F1 Score (No Jump)	0.62	0.62
	F1 Score (Jump)	0.56	0.56
	Accuracy	0.60	0.60
Decision Tree	F1 Score (No Jump)	0.58	0.58
	F1 Score (Jump)	0.56	0.56
	Accuracy	0.57	0.57
SVM	F1 Score (No Jump)	0.67	0.67
	F1 Score (Jump)	0.55	0.55
	Accuracy	0.63	0.63
Random Forest	F1 Score (No Jump)	0.63	0.63
	F1 Score (Jump)	0.57	0.57
	Accuracy	0.61	0.61
ARIMA	F1 Score (No Jump)	0.60	0.60
	F1 Score (Jump)	0.56	0.56
	Accuracy	0.59	0.59

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is bold-faced. Train sample is 80 % of data set for the time period December 1st, 2019 until April 30th, 2022. Window size is 150 and shift days is 50

Table 3.9: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Trinary Classification Results Post Covid Era, Rolling Window Analysis

		Mean	Median
KNN	F1 Score (No Jump)	0.53	0.53
	F1 Score (Positive Jump)	0.63	0.63
	F1 Score (Negative Jump)	0.59	0.59
	Accuracy	0.59	0.59
ML Perceptron	F1 Score (No Jump)	0.53	0.53
	F1 Score (Positive Jump)	0.66	0.66
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.60	0.60
Decision Tree	F1 Score (No Jump)	0.44	0.44
	F1 Score (Positive Jump)	0.55	0.55
	F1 Score (Negative Jump)	0.53	0.53
	Accuracy	0.50	0.50
SVM	F1 Score (No Jump)	0.56	0.56
	F1 Score (Positive Jump)	0.66	0.66
	F1 Score (Negative Jump)	0.65	0.65
	Accuracy	0.61	0.61
Random Forest	F1 Score (No Jump)	0.52	0.52
	F1 Score (Positive Jump)	0.65	0.65
	F1 Score (Negative Jump)	0.63	0.63
	Accuracy	0.59	0.59
ARIMA	F1 Score (No Jump)	0.49	0.49
	F1 Score (Positive Jump)	0.60	0.60
	F1 Score (Negative Jump)	0.57	0.58

The results are computed through averaging 14 currencies' average results over 50 replicate models. The best performance among the five algorithms is bold-faced. Train sample is 80 % of data set for the time period December 1st, 2019 until April 30th, 2022. Window size is 150 and shift days is 50

As discussed earlier, there are only a few studies on the prediction of jumps in financial time series using machine learning algorithms with high-frequency data. [Mäkinen et al. \(2019\)](#) work on predicting stock market jump occurrence as well as direction for 360 days, for 5 different liquid stocks traded in NASDAQ. They report an average of 0.53 to 0.72 F1 scores for binary classification problem for different machine learning algorithms that they utilize. For the prediction of jump direction, F1 scores for their best model of CNN is between 0.47 to 0.51 which does not significantly differ from a random selection model hence their results are inconclusive for jump direction prediction case. Another study on jump prediction is by [Kong et al. \(2021\)](#). The authors use Chinese stock market high frequency data for a sample period of 896 trading days. They report average accuracy ratios of 0.63 to 0.67 for the four machine algorithms regarding the binary classification, and 0.58 to 0.60 for the trinary classification problems. Their study reports random forest as the best performing model closely followed by SVM whereas KNN is the worst performing model. Compared to earlier studies, our results also follow a similar ranking in terms of model efficiency although we also find multi-layer perceptron model to be the most efficient in our set up. This may be because of the different utilization of information criteria used in the model set up or the characteristics and differences of the data sets as well as the underlying market characteristics. [Lee and Wang \(2020\)](#) also analyzed jumps for 18 exchange rates for a 15 minute frequency using a generalized jump regression approach. Authors find strong time-of-day effects within the jumps. In our analysis, by using the [Lee and Mykland \(2008\)](#) methodology and incorporating [Boudt et al. \(2011\)](#) we are able to account for the time-of-day effects and eliminate these short comings in our analysis. In general, statistical models are able to draw population inferences from a sample, however machine learning models are able to provide researchers with more generalised predictive patterns.

Machine learning algorithms are, by definition and construction, able to detect non-linear trends in time series analysis and also they are generalised enough to avoid over fitting on the training data set so that results are robust compared to traditional stochastic models. Furthermore, while most classical economic models tries to explain and look for a causal relationship between variables, here with machine learning methodologies, we are able to make out-of-sample predictions. Overall, we are able to predict both the occurrence as well as the direction of jumps more efficiently compared to the previous studies.

3.6. Concluding Remarks

Technological developments, such as algorithmic and high frequency trading, has changed the structure of foreign exchange markets. Similarly, the accumulation of huge amounts of data have lead way to the new opportunities for collecting, storing and analyzing various sources to forecast future trends and prices. On the other hand, with the new structure of high tech financial markets, jumps in prices have been observed much more frequently. Jumps have received attention in the literature over many years and determinants of jumps and jump detection methodologies have been extensively studied. Although jump detection methodologies have been developed over the years, jump forecasting concept is relatively new and researchers are looking for new methodologies to determine both the existence and direction of future jumps by using advanced quantitative models. A few recent studies that have used machine learning for analysis have focused on stock markets mostly and cover a relatively shorter period of time. Our study has a unique focus regarding the use of state of art machine learning methodologies in foreign exchange markets for jump detection. Although foreign exchange market jump prediction has been studied using other methodologies for

different frequencies of data, our study is unique in the sense that its focus is on high frequency analysis.

Our findings reveal that machine learning methodologies can be used for jump prediction in the foreign exchange market both for the arrival of the jump in the next 5-minute interval and also to determine the direction of the arriving jump in the same period. In our analysis, we reach average accuracy levels of 73% and we even reach up to 78% accuracy for specific exchange rates and methodologies. We also show that our results are robust to different sample sizes of test and training data where utilizing a larger data set for training leads to better accuracy results for predictions. Furthermore, in line with the current literature, high volatility of Covid pandemic effects our analysis as well and our prediction success for the occurrence of jumps decreases although machine learning methodologies are still able to detect the direction as well as the occurrence of jumps. Our findings have important implications for academics as well as practitioners. First, our findings imply that machine learning algorithms can successfully be used for jump prediction in the foreign exchange market using high frequency data. Because of their capabilities to process huge amounts of data in an efficient manner, machine learning algorithms can be used to analyze financial research problems where there have been limitations regarding processing capabilities related to other classical methodologies. Second, predicting the presence of jumps provides trading opportunities for practitioners (for example, by forecasting jumps, traders can go long/short for a period of time based on the occurrence of the price jump in the market) and hence more effectively manage their portfolio and increase their profits. Third, investors and corporations, having information regarding jump occurrence timings, may have an opportunity to hedge against foreign exchange risks more efficiently. Finally, central bankers or market makers can adjust liquidity injection timing with these jump prediction models where they

can try to minimize jump's strength if not completely eliminate its occurrence. We believe the integration of machine learning algorithms to finance will enhance the development of finance literature both in terms of explaining the relations between variables as well as for the forecasting methodologies.



CHAPTER IV

CONCLUSION

There is a growing amount of literature on the foreign exchange market, regarding both liquidity dynamics and jump occurrences. However, there are a limited number of studies investigating the commonality in liquidity in the foreign exchange market using high frequency level data with an extensive coverage. Furthermore, as for the jump prediction in foreign exchange market, there are a limited number of studies, especially using machine learning methodologies with high frequency data.

We first analyzed the foreign exchange market liquidity over a 4 year period with high frequency data where we used an extensive coverage of exchange rates for both emerging markets as well as developed economies, namely AUDUSD, EURUSD, GBPUSD, NZDUSD, USDCAD, USDCHF, USDHUF, USDJPY, USDMXN, USDNOK, USDPLN, USDSEK, USDTRY, USDZAR. More specifically, we address the following questions, (I) to what extent there is a commonality in liquidity in the foreign exchange market when analyzed with high frequency data? (II) does monetary policy meetings of Federal Reserve (FOMC) and European Central Bank (ECB) affect the market-wide liquidity?

The findings of second section show that the commonality in liquidity in foreign exchange market is valid for an extended period of time and also it is permanent

even after the global financial crisis. In line with previous findings in the literature, we show that commonality in liquidity increases when data frequency is aggregated. Furthermore, we show that FOMC meetings have a significant effect on market wide liquidity in the foreign exchange market. From a central bank's perspective, this may indicate that increasing liquidity for a specific exchange rate may have positive spillovers to other currencies. Monetary policies aimed at relieving market constraints could also improve foreign exchange liquidity in the market as a whole.

In the third section, we investigate whether foreign exchange market jumps can be predicted with machine learning methodologies. We again use high frequency data, and investigate both developed and emerging market currencies (AUDUSD, USDCAD, USDCHF, USDCZK, EURUSD, GBPUSD, USDHUF, USDJPY, USDMXN, USDNOK, NZDUSD, USDPLN, USDSEK, USDZAR). We investigate to what extent can jumps in foreign exchange market be predicted with machine learning methodologies and to the effect of Covid pandemic on these predictions. Our analysis show that jump occurrences as well as jump prediction can be predicted using machine learning algorithms. Furthermore, although Covid pandemic has increased volatility in all the financial markets, including foreign exchange market, we can still predict the occurrence of jumps as well as their direction in the foreign exchange market. Also, we our findings show that machine learning methodologies have slightly superior performance to classical regression analysis tools when used for high frequency analysis in our data sample and selection. We think given their efficient performance when processing huge amounts of data, machine learning methodologies will be applied more in the future for financial analysis problems. Also, our findings imply that especially for traders, being able to predict jumps and their direction can provide more opportunities to manage exchange rate fluctuations effectively and market makers can also efficiently

inject liquidity to the market so that they can minimize a jump's strength if not completely eliminate its occurrence.



REFERENCES

- Abedin, M. Z., Moon, M. H., Hassan, M. K., & Hajek, P. (2021). Deep learning-based exchange rate prediction during the covid-19 pandemic. *Annals of Operations Research*, 1–52.
- Abid, A. (2020). Economic policy uncertainty and exchange rates in emerging markets: Short and long runs evidence. *Finance Research Letters*, 37, 101378.
- Aït-Sahalia, Y., & Jacod, J. (2009). Testing for jumps in a discretely observed process. *Annals of Statistics*, 184–222.
- Akyildirim, E., Goncu, A., & Sensoy, A. (2021). Prediction of cryptocurrency returns using machine learning. *Annals of Operations Research*, 297(1), 3–36.
- Akyildirim, E., Nguyen, D. K., & Sensoy, A. (2018). A tale of two risks in the emu sovereign debt markets. *Economics Letters*, 172, 102–106.
- Albu, L. L., & Lupu, R. (2020, November). Anomaly detection in stock market indices with neural networks. *Journal of Financial Studies*, 9(5), 10-23.
- Alessandretti, L., ElBahrawy, A., Aiello, L. M., & Baronchelli, A. (2018). Anticipating cryptocurrency prices using machine learning. *Complexity*, 2018, 8983590.
- Amihud, Y., & Mendelson, H. (1989). The effects of beta, bid-ask spread, residual risk, and size on stock returns. *The Journal of Finance*, 44(2), 479–486.
- Andersen, T., Bollerslev, T., & Dobrev, D. (2007, May). No-arbitrage

- semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics*, 138(1), 125–180.
- Andersen, T. G., & Bollerslev, T. (1998). Deutsche mark–dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance*, 53(1), 219–265.
- Bacchetta, P., & van Wincoop, E. (2013). On the unstable relationship between exchange rates and macroeconomic fundamentals. *Journal of International Economics*, 91(1), 18–26.
- Banti, C. (2016). Illiquidity in the stock and foreign exchange markets: an investigation of their cross-market dynamics. *Journal of Financial Research*, 39(4), 411–436.
- Banti, C., Phylaktis, K., & Sarno, L. (2012). Global liquidity risk in the foreign exchange market. *Journal of International Money and Finance*, 31(2), 267–291.
- Barndorff-Nielsen, O. E., & Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, 2(1), 1–37.
- Barndorff-Nielsen, O. E., & Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, 4(1), 1–30.
- Bartsch, Z. (2019). Economic policy uncertainty and dollar-pound exchange rate return volatility. *Journal of International Money and Finance*, 98, 102067.
- Beckmann, J., & Czudaj, R. (2017). The impact of uncertainty on professional exchange rate forecasts. *Journal of International Money and Finance*, 73, 296–316. (Global Economy: Future Financial and Macro Challenges)
- Bennani, H., Fanta, N., Gertler, P., & Horvath, R. (2020). Does central bank

- communication signal future monetary policy in a (post)-crisis era? the case of the ecb. *Journal of International Money and Finance*, 104, 102167.
- Benston, G. J., & Hagerman, R. L. (1974). Determinants of bid-ask spreads in the over-the-counter market. *Journal of Financial Economics*, 1(4), 353–364.
- Bishop, C. M., et al. (1995). *Neural networks for pattern recognition*. Oxford University Press.
- Boudt, K., Croux, C., & Laurent, S. (2011). Robust estimation of intraweek periodicity in volatility and jump detection. *Journal of Empirical Finance*, 18(2), 353–367.
- Boudt, K., & Petitjean, M. (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets*, 17, 121–149.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.
- Brockman, P., Chung, D. Y., & Pérignon, C. (2009). Commonality in Liquidity: A global perspective. *Journal of Financial and Quantitative Analysis*, 44(4), 851–882.
- Brunnermeier, M. K., & Pedersen, L. H. (2008). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6), 2201–2238.
- Bush, G., & Noria, G. L. (2021). Uncertainty and exchange rate volatility: Evidence from mexico. *International Review of Economics & Finance*, 75, 704–722.
- Byun, H. W., Baek, S., Ahn, J. J., Oh, K. J., & Kim, T. Y. (2015). Using a principal component analysis for multi-currencies-trading in the foreign exchange market. *Intelligent Data Analysis*, 19(3), 683–697.
- Cao, L., Chua, K., Chong, W., Lee, H., & Gu, Q. (2003). A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine. *Neurocomputing*, 55(1), 321–336.

- Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. *Computers & Electrical Engineering*, 40(1), 16–28.
- Chen, A., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the taiwan stock index. *Computers & Operations Research*, 30(6), 901-923.
- Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, 56(1), 3–28.
- Chowdhury, R., Rahman, M. A., Rahman, M. S., & Mahdy, M. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Physica A: Statistical Mechanics and its Applications*, 551, 124569.
- Das, S. R. (2002). The surprise element: jumps in interest rates. *Journal of Econometrics*, 106(1), 27-65.
- Deepak, R. S., Uday, S. I., & Malathi, D. (2017). Machine learning approach in stock market prediction. *International Journal of Pure and Applied Mathematics*, 115(8), 71–77.
- Demsetz, H. (1968). The cost of transacting. *The Quarterly Journal of Economics*, 82(1), 33–53.
- Dingli, A., & Fournier, K. S. (2017). Financial time series forecasting-a machine learning approach. *Machine Learning and Applications: An International Journal*, 4(1/2), 3.
- Dornbusch, R. (2019). The theory of flexible exchange rate regimes and macroeconomic policy. In *Flexible exchange rates and stabilization policy* (pp. 123–143). Routledge.
- Dumitru, A.-M., & Urga, G. (2012). Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Journal of Business & Economic Statistics*, 30(2), 242-255.

- Engel, C. (2014). Chapter 8 - exchange rates and interest parity. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics* (Vol. 4, p. 453-522). Elsevier.
- Fong, K. Y., Holden, C. W., & Trzcinka, C. A. (2017). What are the best liquidity proxies for global research? *Review of Finance*, 21(4), 1355–1401.
- Fratzscher, M. (2009). What explains global exchange rate movements during the financial crisis? *Journal of International Money and Finance*, 28(8), 1390–1407.
- Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55(1), 119–139.
- Freund, Y., Schapire, R. E., et al. (1996). Experiments with a new boosting algorithm. In *icml* (Vol. 96, pp. 148–156).
- Galeshchuk, S., & Mukherjee, S. (2017). Deep networks for predicting direction of change in foreign exchange rates. *Intelligent Systems in Accounting, Finance and Management*, 24(4), 100–110.
- Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of Business*, 67–78.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Goyenko, R. Y., Holden, C. W., & Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics*, 92(2), 153–181.
- Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *the Journal of Finance*, 43(3), 617–633.
- Grossmann, A., Love, I., & Orlov, A. G. (2014). The dynamics of exchange rate volatility: A panel var approach. *Journal of International Financial Markets, Institutions and Money*, 33, 1-27.
- Guyon, I., & Elisseeff, A. (2003, 01). An introduction of variable and feature

- selection. *Journal of Machine Learning Research*, 3, 1157 - 1182.
- Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The model confidence set. *Econometrica*, 79(2), 453–497.
- Hegazy, O., Soliman, O. S., & Salam, M. A. (2014). A machine learning model for stock market prediction. *arXiv preprint:1402.7351*.
- Heller, H. R. (1978). Determinants of exchange rate practices. *Journal of Money, Credit and Banking*, 10(3), 308–321.
- Hodrick, R. J., & Prescott, E. C. (1997). Postwar us business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 1–16.
- Huang, W., Lai, K. K., Nakamori, Y., & Wang, S. (2004, 03). Forecasting foreign exchange rates with artificial neural networks: A review. *International Journal of Information Technology and Decision Making*, 3, 145-165.
- Huang, Y., Bai, M., & Li, Z. (2007). Principal component analysis and bp neural network modeling for futures forecasting. *Mathematics in Practice and Theory*, 37(13), 23–27.
- Ince, H., & Trafalis, T. B. (2007). Kernel principal component analysis and support vector machines for stock price prediction. *IIE Transactions*, 39(6), 629–637.
- Jang, H., & Lee, J. (2019). Machine learning versus econometric jump models in predictability and domain adaptability of index options. *Physica A: Statistical Mechanics and its Applications*, 513, 74–86.
- Jaquart, P., Dann, D., & Weinhardt, C. (2021). Short-term bitcoin market prediction via machine learning. *Journal of Finance and Data Science*, 7, 45–66.
- Jiang, G. J., Lo, I., & Verdelhan, A. (2011). Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the us treasury market. *Journal of Financial and Quantitative Analysis*, 46(2), 527–551.

- Jiang, G. J., & Oomen, R. C. (2008). Testing for jumps when asset prices are observed with noise—a “swap variance” approach. *Journal of Econometrics*, 144(2), 352-370.
- Jorion, P. (1988). On jump processes in the foreign exchange and stock markets. *Review of Financial Studies*, 1, 427-445.
- Joulin, A., Lefevre, A., Grunberg, D., & Bouchaud, J.-P. (2008). Stock price jumps: News and volume play a minor role. *arXiv preprint:0803.1769*.
- Jung, G., & Choi, S.-Y. (2021). Forecasting foreign exchange volatility using deep learning autoencoder-LSTM techniques. *Complexity*, 2021, 6647534.
- Kaczmarczyk, K., & Hernes, M. (2020). Financial decisions support using the supervised learning method based on random forests. *Procedia Computer Science*, 176, 2802–2811.
- Kamara, A., Lou, X., & Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics*, 89(3), 444–466.
- Karnaukh, N., Ranaldo, A., & Söderlind, P. (2015). Understanding fx liquidity. *The Review of Financial Studies*, 28(11), 3073–3108.
- Kercheval, A., & Zhang, Y. (2015, 06). Modelling high-frequency limit order book dynamics with support vector machines. *Quantitative Finance*, 15, 1-15.
- King, M. R., Osler, C. L., & Rime, D. (2013). The market microstructure approach to foreign exchange: Looking back and looking forward. *Journal of International Money and Finance*, 38, 95–119.
- Kong, A., Zhu, H., & Azencott, R. (2021). Predicting intraday jumps in stock prices using liquidity measures and technical indicators. *Journal of Forecasting*, 40(3), 416–438.
- Krol, R. (2014). Economic policy uncertainty and exchange rate volatility. *International Finance*, 17(2), 241–256.

- Ladha, L., & Deepa, T. (2011). Feature selection methods and algorithms. *International Journal on Computer Science and Engineering*, 3(5), 1787–1797.
- Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, 26(6), 893–921.
- Lee, S. S. (2012). Jumps and information flow in financial markets. *Review of Financial Studies*, 25(2), 439–479.
- Lee, S. S., & Mykland, P. A. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies*, 21(6), 2535–2563.
- Lee, S. S., & Wang, M. (2020). Tales of tails: Jumps in currency markets. *Journal of Financial Markets*, 48, 100497.
- Lek, S., & Guégan, J.-F. (2012). *Artificial neuronal networks: application to ecology and evolution*. Springer Science & Business Media.
- Li, L. (2021). Financial trading with feature preprocessing and recurrent reinforcement learning. *arXiv preprint:2109.05283*.
- Liu, L. Y., Patton, A. J., & Sheppard, K. (2015). Does anything beat 5-minute RV? a comparison of realized measures across multiple asset classes. *Journal of Econometrics*, 187(1), 293–311.
- Majhi, R., Panda, G., & Sahoo, G. (2009). Efficient prediction of exchange rates with low complexity artificial neural network models. *Expert Systems with Applications*, 36(1), 181–189.
- Mäkinen, Y., Kannianen, J., Gabbouj, M., & Iosifidis, A. (2019). Forecasting jump arrivals in stock prices: New attention-based network architecture using limit order book data. *Quantitative Finance*, 19(12), 2033–2050.
- Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The*

- Journal of Finance*, 68(5), 1805–1841.
- Maté, C., & Jiménez, L. (2021). Forecasting exchange rates with the iMLP: New empirical insight on one multi-layer perceptron for interval time series (its). *Engineering Applications of Artificial Intelligence*, 104, 104358.
- Moghaddam, A. H., Moghaddam, M. H., & Esfandyari, M. (2016). Stock market index prediction using artificial neural network. *Journal of Economics, Finance and Administrative Science*, 21(41), 89–93.
- Morana, C. (2009). On the macroeconomic causes of exchange rate volatility. *International Journal of Forecasting*, 25(2), 328–350.
- Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of financial economics*, 58(1-2), 215–260.
- Murad, S. (2022). The role of domestic and foreign economic uncertainties in determining the foreign exchange rates: an extended monetary approach. *Journal of Economics and Finance*, 1–12.
- Narayan, P. K. (2022). Understanding exchange rate shocks during covid-19. *Finance Research Letters*, 45, 102181.
- Nasir, M. A. (2020). Forecasting inflation under uncertainty: The forgotten dog and the frisbee. *Technological Forecasting and Social Change*, 158, 120172.
- Nasir, M. A., & Morgan, J. (2018). Pre-brexite: the eu referendum as an illustration of the effects of uncertainty on the sterling exchange rate. *Journal of economic studies*.
- Nobre, J., & Neves, R. F. (2019). Combining principal component analysis, discrete wavelet transform and xgboost to trade in the financial markets. *Expert Systems with Applications*, 125, 181-194.
- Ntakaris, A., Magris, M., Kannianen, J., Gabbouj, M., & Iosifidis, A. (2018). Benchmark dataset for mid-price forecasting of limit order book data with

- machine learning methods. *Journal of Forecasting*, 37(8), 852-866.
- Oja, E., Kiviluoto, K., & Malaroiu, S. (2000). Independent component analysis for financial time series. In *Proceedings of the IEEE 2000 adaptive systems for signal processing, communications, and control symposium (cat. no.00ex373)* (p. 111-116).
- Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3), 642–685.
- Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock market index using fusion of machine learning techniques. *Expert Systems with Applications*, 42(4), 2162–2172.
- Pericoli, M., & Taboga, M. (2012). Bond risk premia, macroeconomic fundamentals and the exchange rate. *International Review of Economics Finance*, 22(1), 42-65.
- Piccotti, L. R. (2018). Jumps, cojumps, and efficiency in the spot foreign exchange market. *Journal of Banking & Finance*, 87, 49-67.
- Qian, B., & Rasheed, K. (2010). Foreign exchange market prediction with multiple classifiers. *Journal of Forecasting*, 29(3), 271–284.
- Ryll, L., & Seidens, S. (2019). Evaluating the performance of machine learning algorithms in financial market forecasting: A comprehensive survey. *arXiv preprint:1906.07786*.
- Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, 80(2), 309–349.
- Satterthwaite, F. E. (1941). Synthesis of variance. *Psychometrika*, 6(5), 309–316.
- Sensoy, A. (2016). Commonality in liquidity: Effects of monetary policy and macroeconomic announcements. *Finance Research Letters*, 16, 125–131.
- Serdengecti, S., Sensoy, A., & Nguyen, D. K. (2021). Dynamics of return and liquidity (co)jumps in emerging foreign exchange markets. *Journal of*

- International Financial Markets, Institutions and Money*, 73, 101377.
- Sermpinis, G., Dunis, C., Laws, J., & Stasinakis, C. (2012). Forecasting and trading the EUR/USD exchange rate with stochastic neural network combination and time-varying leverage. *Decision Support Systems*, 54(1), 316-329.
- Shen, S., Jiang, H., & Zhang, T. (2012). Stock market forecasting using machine learning algorithms. *Department of Electrical Engineering, Stanford University, Stanford, CA*, 1-5.
- Sirignano, J., & Cont, R. (2019). Universal features of price formation in financial markets: perspectives from deep learning. *Quantitative Finance*, 19(9), 1449-1459.
- Smales, L. A. (2021). The influence of policy uncertainty on exchange rate forecasting. *Journal of Forecasting*.
- Tsai, C.-F., & Hsiao, Y.-C. (2010). Combining multiple feature selection methods for stock prediction: Union, intersection, and multi-intersection approaches. *Decision Support Systems*, 50(1), 258-269.
- Tsantekidis, A., Passalis, N., Tefas, A., Kannianen, J., Gabbouj, M., & Iosifidis, A. (2020). Using deep learning for price prediction by exploiting stationary limit order book features. *Applied Soft Computing*, 93, 106401.
- Vayanos, D. (2004). *Flight to quality, flight to liquidity, and the pricing of risk* (Tech. Rep.). National Bureau of Economic Research.
- Wu, D., Wang, X., Su, J., Tang, B., & Wu, S. (2020). A labeling method for financial time series prediction based on trends. *Entropy*, 22(10), 1162.
- Yao, J., & Tan, C. L. (2000). A case study on using neural networks to perform technical forecasting of forex. *Neurocomputing*, 34(1-4), 79-98.
- Yeung, J. F. A., Wei, Z.-k., Chan, K. Y., Lau, H. Y., & Yiu, K.-F. C. (2020). Jump detection in financial time series using machine learning algorithms. *Soft*

Computing, 24(3), 1789–1801.

- Yu, H., Chen, R., & Zhang, G. (2014). A svm stock selection model within pca. *Procedia Computer Science*, 31, 406-412. (2nd International Conference on Information Technology and Quantitative Management, ITQM 2014)
- Zhang, H., Chen, J., & Shao, L. (2021). Dynamic spillovers between energy and stock markets and their implications in the context of covid-19. *International Review of Financial Analysis*, 77, 101828.
- Zheng, H., & Shen, Y. (2008). Jump liquidity risk and its impact on CVaR. *Journal of Risk Finance*, 9, 477–492.
- Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation*, 5(1), 1–20.

APPENDICES

Table 4.1: K Nearest Neighbourhood (KNN) Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.70	0.87	0.77	0.83	0.62	0.71	0.76	0.74	0.74	0.74
CAD	0.68	0.85	0.76	0.80	0.60	0.69	0.74	0.73	0.72	0.73
CHF	0.66	0.80	0.72	0.75	0.58	0.65	0.70	0.69	0.69	0.69
CZK	0.65	0.82	0.73	0.76	0.57	0.65	0.71	0.69	0.69	0.69
EUR	0.68	0.83	0.75	0.79	0.61	0.69	0.74	0.72	0.72	0.72
GBP	0.67	0.84	0.75	0.79	0.59	0.67	0.73	0.71	0.71	0.71
HUF	0.69	0.81	0.75	0.77	0.64	0.70	0.73	0.72	0.72	0.72
JPY	0.71	0.86	0.78	0.82	0.64	0.72	0.76	0.75	0.75	0.75
MXN	0.68	0.79	0.73	0.75	0.62	0.68	0.71	0.71	0.70	0.71
NOK	0.63	0.77	0.69	0.71	0.55	0.62	0.67	0.66	0.66	0.66
NZD	0.65	0.87	0.74	0.80	0.53	0.64	0.73	0.70	0.69	0.70
PLN	0.66	0.82	0.73	0.76	0.58	0.66	0.71	0.70	0.70	0.70
SEK	0.62	0.81	0.70	0.73	0.51	0.60	0.68	0.66	0.65	0.66
ZAR	0.60	0.74	0.66	0.66	0.51	0.58	0.63	0.63	0.62	0.63
Mean	0.66	0.82	0.73	0.77	0.58	0.66	0.71	0.70	0.70	0.70
Median	0.66	0.82	0.73	0.77	0.58	0.66	0.71	0.70	0.70	0.70

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.2: Multi Layer Perceptron Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.72	0.87	0.79	0.84	0.67	0.74	0.78	0.77	0.77	0.77
CAD	0.70	0.84	0.76	0.80	0.64	0.71	0.75	0.74	0.74	0.74
CHF	0.70	0.81	0.75	0.77	0.65	0.71	0.74	0.73	0.73	0.73
CZK	0.68	0.82	0.74	0.78	0.62	0.69	0.73	0.72	0.72	0.72
EUR	0.71	0.84	0.76	0.80	0.65	0.72	0.75	0.74	0.74	0.74
GBP	0.70	0.84	0.76	0.80	0.64	0.71	0.75	0.74	0.74	0.74
HUF	0.73	0.81	0.77	0.79	0.70	0.74	0.76	0.75	0.75	0.75
JPY	0.75	0.85	0.80	0.83	0.72	0.77	0.79	0.78	0.78	0.78
MXN	0.71	0.81	0.75	0.78	0.67	0.72	0.74	0.74	0.74	0.74
NOK	0.65	0.80	0.72	0.74	0.57	0.64	0.69	0.68	0.68	0.68
NZD	0.68	0.86	0.76	0.81	0.60	0.69	0.75	0.73	0.72	0.73
PLN	0.69	0.82	0.75	0.78	0.63	0.70	0.74	0.73	0.73	0.73
SEK	0.66	0.82	0.73	0.76	0.57	0.65	0.71	0.70	0.69	0.70
ZAR	0.63	0.80	0.70	0.72	0.53	0.61	0.67	0.66	0.66	0.66
Mean	0.69	0.83	0.75	0.79	0.63	0.70	0.74	0.73	0.73	0.73
Median	0.69	0.83	0.75	0.79	0.63	0.70	0.74	0.73	0.73	0.73

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.3: Decision Tree Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.67	0.73	0.70	0.70	0.64	0.67	0.69	0.68	0.68	0.68
CAD	0.68	0.70	0.69	0.69	0.67	0.68	0.69	0.69	0.69	0.69
CHF	0.64	0.67	0.65	0.65	0.62	0.64	0.65	0.65	0.64	0.65
CZK	0.64	0.68	0.66	0.66	0.61	0.63	0.65	0.65	0.64	0.65
EUR	0.67	0.69	0.68	0.68	0.65	0.67	0.67	0.67	0.67	0.67
GBP	0.65	0.69	0.67	0.67	0.63	0.65	0.66	0.66	0.66	0.66
HUF	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68
JPY	0.70	0.73	0.71	0.71	0.68	0.70	0.70	0.70	0.70	0.70
MXN	0.65	0.65	0.65	0.65	0.66	0.65	0.65	0.65	0.65	0.65
NOK	0.61	0.64	0.63	0.62	0.59	0.61	0.62	0.62	0.62	0.62
NZD	0.65	0.71	0.68	0.68	0.62	0.65	0.66	0.66	0.66	0.66
PLN	0.64	0.66	0.65	0.65	0.62	0.64	0.64	0.64	0.64	0.64
SEK	0.61	0.65	0.63	0.63	0.59	0.61	0.62	0.62	0.62	0.62
ZAR	0.59	0.61	0.60	0.60	0.57	0.58	0.59	0.59	0.59	0.59
Mean	0.65	0.68	0.66	0.66	0.63	0.65	0.66	0.65	0.65	0.65
Median	0.65	0.68	0.66	0.66	0.63	0.65	0.66	0.65	0.65	0.65

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.4: Support Vector Machine (SVM) Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.73	0.88	0.79	0.85	0.67	0.75	0.79	0.77	0.77	0.77
CAD	0.68	0.88	0.77	0.84	0.58	0.68	0.76	0.73	0.73	0.73
CHF	0.69	0.85	0.76	0.81	0.63	0.70	0.75	0.74	0.73	0.74
CZK	0.67	0.85	0.75	0.80	0.58	0.67	0.74	0.72	0.71	0.72
EUR	0.70	0.87	0.78	0.83	0.63	0.72	0.77	0.75	0.75	0.75
GBP	0.69	0.86	0.77	0.82	0.62	0.70	0.76	0.74	0.74	0.74
HUF	0.71	0.85	0.77	0.81	0.65	0.72	0.76	0.75	0.75	0.75
JPY	0.73	0.88	0.80	0.85	0.67	0.75	0.79	0.78	0.77	0.78
MXN	0.70	0.84	0.77	0.81	0.64	0.71	0.75	0.74	0.74	0.74
NOK	0.64	0.84	0.73	0.77	0.52	0.62	0.70	0.68	0.67	0.68
NZD	0.68	0.89	0.77	0.84	0.58	0.69	0.76	0.74	0.73	0.74
PLN	0.68	0.85	0.76	0.80	0.60	0.69	0.74	0.73	0.72	0.73
SEK	0.65	0.85	0.74	0.78	0.54	0.64	0.72	0.70	0.69	0.70
ZAR	0.62	0.82	0.71	0.74	0.50	0.60	0.68	0.66	0.65	0.66
Mean	0.68	0.86	0.76	0.81	0.60	0.69	0.75	0.73	0.73	0.73
Median	0.68	0.86	0.76	0.81	0.60	0.69	0.75	0.73	0.73	0.73

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.5: Random Forest Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.72	0.86	0.78	0.82	0.66	0.74	0.77	0.76	0.76	0.76
CAD	0.71	0.84	0.77	0.81	0.65	0.72	0.76	0.75	0.74	0.75
CHF	0.69	0.79	0.74	0.76	0.65	0.70	0.72	0.72	0.72	0.72
CZK	0.68	0.80	0.73	0.76	0.62	0.68	0.72	0.71	0.71	0.71
EUR	0.70	0.83	0.76	0.79	0.65	0.71	0.75	0.74	0.74	0.74
GBP	0.69	0.80	0.74	0.76	0.63	0.69	0.72	0.72	0.72	0.72
HUF	0.73	0.79	0.76	0.77	0.70	0.74	0.75	0.75	0.75	0.75
JPY	0.75	0.84	0.79	0.82	0.72	0.76	0.78	0.78	0.78	0.78
MXN	0.71	0.78	0.74	0.76	0.68	0.71	0.73	0.73	0.73	0.73
NOK	0.65	0.77	0.71	0.72	0.58	0.64	0.68	0.68	0.67	0.68
NZD	0.67	0.85	0.75	0.80	0.59	0.68	0.73	0.72	0.71	0.72
PLN	0.69	0.80	0.74	0.76	0.65	0.70	0.73	0.72	0.72	0.72
SEK	0.66	0.79	0.72	0.74	0.59	0.65	0.70	0.69	0.69	0.69
ZAR	0.62	0.76	0.69	0.69	0.54	0.61	0.66	0.65	0.65	0.65
Mean	0.69	0.81	0.74	0.77	0.64	0.69	0.73	0.72	0.72	0.72
Median	0.69	0.81	0.74	0.77	0.64	0.69	0.73	0.72	0.72	0.72

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.6: ARIMA Binary Classification Results

Currency	No Jump			Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.63	0.67	0.65	0.66	0.61	0.63	0.65	0.64	0.64	0.64
CAD	0.65	0.66	0.64	0.66	0.63	0.64	0.66	0.65	0.64	0.65
CHF	0.58	0.62	0.60	0.60	0.55	0.56	0.59	0.58	0.58	0.58
CZK	0.60	0.66	0.63	0.62	0.55	0.58	0.61	0.61	0.60	0.61
EUR	0.65	0.70	0.67	0.67	0.61	0.63	0.66	0.65	0.65	0.65
GBP	0.61	0.66	0.63	0.63	0.56	0.59	0.62	0.61	0.61	0.61
HUF	0.58	0.64	0.61	0.61	0.54	0.57	0.60	0.59	0.59	0.59
JPY	0.60	0.67	0.63	0.64	0.55	0.58	0.62	0.61	0.61	0.61
MXN	0.60	0.64	0.61	0.61	0.56	0.58	0.60	0.60	0.59	0.60
NOK	0.62	0.62	0.62	0.62	0.61	0.61	0.62	0.62	0.62	0.62
NZD	0.62	0.66	0.63	0.64	0.59	0.61	0.63	0.62	0.62	0.62
PLN	0.64	0.67	0.65	0.65	0.62	0.63	0.65	0.64	0.64	0.64
SEK	0.63	0.64	0.63	0.64	0.62	0.63	0.63	0.63	0.63	0.63
ZAR	0.55	0.64	0.59	0.58	0.48	0.52	0.57	0.56	0.56	0.56
Mean	0.61	0.65	0.63	0.63	0.58	0.60	0.62	0.62	0.61	0.62
Median	0.62	0.66	0.63	0.63	0.58	0.60	0.62	0.62	0.61	0.62

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.7: Summary of Binary Classification Results

Currency	KNN			ML Perceptron			Decision Tree			SVM			Random Forest			ARIMA		
	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)	F1 (No Jump)	Score (No Jump)	Accuracy (Jump)
AUD	0.77	0.74	0.74	0.79	0.79	0.77	0.71	0.69	0.70	0.80	0.74	0.77	0.79	0.74	0.77	0.65	0.63	0.64
CAD	0.74	0.67	0.70	0.75	0.67	0.71	0.68	0.65	0.66	0.76	0.65	0.72	0.75	0.68	0.72	0.64	0.64	0.65
CHF	0.73	0.72	0.71	0.75	0.72	0.74	0.66	0.66	0.66	0.77	0.72	0.75	0.74	0.71	0.73	0.60	0.56	0.58
CZK	0.74	0.70	0.70	0.75	0.70	0.73	0.66	0.65	0.66	0.77	0.70	0.74	0.74	0.70	0.72	0.63	0.58	0.61
EUR	0.76	0.72	0.74	0.77	0.72	0.75	0.68	0.67	0.68	0.78	0.73	0.76	0.77	0.72	0.75	0.67	0.63	0.65
GBP	0.75	0.71	0.72	0.76	0.71	0.74	0.68	0.66	0.67	0.77	0.71	0.74	0.74	0.75	0.73	0.63	0.59	0.61
HUF	0.74	0.72	0.72	0.76	0.72	0.74	0.67	0.66	0.66	0.77	0.71	0.74	0.75	0.72	0.74	0.61	0.57	0.59
JPY	0.78	0.77	0.76	0.79	0.77	0.78	0.71	0.70	0.70	0.80	0.76	0.78	0.79	0.76	0.78	0.63	0.58	0.61
MXN	0.72	0.68	0.69	0.74	0.68	0.71	0.64	0.62	0.63	0.75	0.66	0.71	0.73	0.67	0.70	0.61	0.58	0.60
NOK	0.70	0.64	0.66	0.72	0.64	0.68	0.62	0.60	0.61	0.73	0.62	0.68	0.71	0.64	0.68	0.62	0.61	0.62
NZD	0.75	0.70	0.71	0.77	0.70	0.74	0.69	0.66	0.68	0.77	0.69	0.74	0.76	0.70	0.73	0.63	0.61	0.62
PLN	0.74	0.73	0.71	0.76	0.73	0.74	0.65	0.65	0.65	0.77	0.72	0.75	0.75	0.72	0.73	0.65	0.63	0.64
SEK	0.72	0.67	0.68	0.73	0.67	0.70	0.64	0.62	0.63	0.74	0.66	0.70	0.72	0.67	0.70	0.63	0.63	0.63
ZAR	0.67	0.63	0.64	0.70	0.63	0.67	0.60	0.59	0.59	0.71	0.61	0.67	0.69	0.63	0.66	0.59	0.52	0.56
Mean	0.74	0.70	0.71	0.75	0.70	0.73	0.66	0.65	0.66	0.76	0.69	0.73	0.75	0.70	0.72	0.63	0.60	0.62
Median	0.74	0.70	0.71	0.75	0.70	0.73	0.66	0.65	0.66	0.76	0.69	0.73	0.75	0.70	0.72	0.63	0.60	0.62
Median	0.74	0.70	0.71	0.75	0.70	0.73	0.66	0.65	0.66	0.76	0.69	0.73	0.75	0.70	0.72	0.63	0.60	0.62

The results are computed through averaging over 50 replicate models for each of the currencies. The best performance among the six algorithms is boldfaced.

Table 4.8: K Nearest Neighbourhood Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.58	0.74	0.65	0.81	0.62	0.70	0.79	0.73	0.76	0.72	0.70	0.70	0.70
CAD	0.58	0.68	0.62	0.76	0.73	0.74	0.80	0.69	0.74	0.71	0.70	0.70	0.70
CHF	0.52	0.61	0.56	0.73	0.71	0.72	0.75	0.64	0.69	0.66	0.65	0.65	0.65
CZK	0.53	0.65	0.59	0.73	0.65	0.69	0.73	0.65	0.69	0.67	0.65	0.65	0.65
EUR	0.60	0.68	0.64	0.75	0.64	0.69	0.76	0.74	0.75	0.70	0.69	0.69	0.69
GBP	0.58	0.68	0.63	0.83	0.66	0.73	0.74	0.76	0.75	0.71	0.70	0.70	0.70
HUF	0.59	0.63	0.61	0.75	0.72	0.73	0.75	0.73	0.74	0.70	0.69	0.69	0.69
JPY	0.63	0.71	0.66	0.79	0.71	0.75	0.78	0.75	0.76	0.73	0.72	0.72	0.72
MXN	0.62	0.59	0.61	0.65	0.68	0.67	0.78	0.79	0.78	0.69	0.69	0.69	0.69
NOK	0.50	0.54	0.52	0.65	0.62	0.63	0.66	0.64	0.65	0.60	0.60	0.60	0.60
NZD	0.55	0.71	0.61	0.78	0.58	0.66	0.70	0.66	0.68	0.67	0.65	0.65	0.65
PLN	0.54	0.64	0.58	0.74	0.62	0.68	0.71	0.68	0.70	0.66	0.65	0.65	0.65
SEK	0.49	0.60	0.54	0.71	0.60	0.65	0.70	0.66	0.68	0.63	0.62	0.62	0.62
ZAR	0.46	0.51	0.48	0.65	0.59	0.62	0.64	0.63	0.63	0.58	0.58	0.58	0.58
Mean	0.55	0.64	0.59	0.74	0.65	0.69	0.74	0.70	0.71	0.68	0.66	0.67	0.66
Median	0.55	0.64	0.59	0.74	0.65	0.69	0.74	0.70	0.71	0.68	0.66	0.67	0.66

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.9: Multi Layer Perceptron Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.59	0.76	0.66	0.82	0.67	0.73	0.83	0.73	0.78	0.74	0.72	0.72	0.72
CAD	0.60	0.72	0.65	0.81	0.75	0.78	0.82	0.71	0.76	0.74	0.73	0.73	0.73
CHF	0.56	0.66	0.60	0.76	0.73	0.74	0.76	0.64	0.69	0.69	0.68	0.68	0.68
CZK	0.57	0.71	0.63	0.78	0.66	0.71	0.76	0.68	0.72	0.70	0.68	0.69	0.68
EUR	0.60	0.72	0.66	0.78	0.67	0.72	0.80	0.73	0.76	0.72	0.71	0.71	0.71
GBP	0.60	0.73	0.66	0.85	0.68	0.75	0.78	0.77	0.78	0.74	0.72	0.73	0.72
HUF	0.65	0.69	0.67	0.78	0.77	0.77	0.81	0.77	0.79	0.75	0.74	0.74	0.74
JPY	0.66	0.74	0.70	0.81	0.72	0.76	0.79	0.78	0.78	0.75	0.74	0.74	0.74
MXN	0.67	0.65	0.66	0.69	0.70	0.69	0.83	0.84	0.84	0.74	0.74	0.73	0.74
NOK	0.54	0.63	0.58	0.69	0.64	0.66	0.73	0.66	0.69	0.65	0.64	0.65	0.64
NZD	0.56	0.75	0.64	0.82	0.59	0.69	0.75	0.68	0.71	0.70	0.67	0.67	0.67
PLN	0.59	0.69	0.63	0.78	0.67	0.72	0.76	0.72	0.73	0.70	0.69	0.70	0.69
SEK	0.53	0.68	0.59	0.76	0.63	0.69	0.75	0.67	0.71	0.68	0.66	0.66	0.66
ZAR	0.49	0.63	0.55	0.70	0.60	0.65	0.72	0.63	0.67	0.64	0.62	0.62	0.62
Mean	0.59	0.70	0.63	0.77	0.68	0.72	0.78	0.71	0.74	0.71	0.70	0.70	0.70
Median	0.59	0.70	0.63	0.77	0.68	0.72	0.78	0.71	0.74	0.71	0.70	0.70	0.70

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.10: Decision Tree Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.54	0.58	0.55	0.68	0.63	0.65	0.70	0.69	0.70	0.64	0.63	0.63	0.63
CAD	0.53	0.55	0.54	0.71	0.73	0.72	0.72	0.66	0.68	0.65	0.65	0.65	0.65
CHF	0.49	0.52	0.51	0.65	0.68	0.67	0.67	0.59	0.63	0.60	0.60	0.60	0.60
CZK	0.48	0.54	0.51	0.65	0.61	0.63	0.66	0.61	0.63	0.59	0.59	0.59	0.59
EUR	0.56	0.58	0.57	0.65	0.62	0.63	0.69	0.70	0.69	0.63	0.63	0.63	0.63
GBP	0.53	0.54	0.54	0.72	0.66	0.68	0.65	0.70	0.67	0.63	0.63	0.63	0.63
HUF	0.54	0.52	0.53	0.67	0.68	0.68	0.68	0.70	0.69	0.63	0.63	0.63	0.63
JPY	0.59	0.59	0.59	0.72	0.68	0.70	0.68	0.71	0.70	0.66	0.66	0.66	0.66
MXN	0.55	0.50	0.53	0.57	0.61	0.59	0.70	0.74	0.72	0.62	0.62	0.61	0.62
NOK	0.46	0.48	0.47	0.57	0.57	0.57	0.62	0.59	0.60	0.55	0.54	0.55	0.54
NZD	0.53	0.58	0.55	0.69	0.58	0.63	0.59	0.65	0.62	0.61	0.60	0.60	0.60
PLN	0.49	0.51	0.50	0.64	0.60	0.62	0.64	0.66	0.65	0.59	0.59	0.59	0.59
SEK	0.46	0.50	0.48	0.62	0.57	0.59	0.63	0.62	0.62	0.57	0.56	0.56	0.56
ZAR	0.42	0.45	0.44	0.58	0.54	0.56	0.57	0.56	0.56	0.52	0.52	0.52	0.52
Mean	0.51	0.53	0.52	0.65	0.62	0.64	0.66	0.65	0.65	0.61	0.60	0.60	0.60
Median	0.51	0.53	0.52	0.65	0.62	0.64	0.66	0.65	0.65	0.61	0.60	0.60	0.60

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.11: Support Vector Machine (SVM) Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.59	0.81	0.68	0.85	0.66	0.74	0.85	0.71	0.77	0.76	0.73	0.73	0.73
CAD	0.60	0.78	0.68	0.81	0.74	0.77	0.86	0.68	0.76	0.76	0.73	0.74	0.73
CHF	0.55	0.71	0.62	0.75	0.70	0.72	0.80	0.62	0.70	0.70	0.68	0.68	0.68
CZK	0.55	0.76	0.64	0.78	0.66	0.72	0.80	0.62	0.70	0.71	0.68	0.68	0.68
EUR	0.60	0.76	0.67	0.80	0.65	0.72	0.81	0.72	0.76	0.73	0.71	0.72	0.71
GBP	0.58	0.75	0.65	0.85	0.65	0.74	0.79	0.74	0.77	0.74	0.71	0.71	0.71
HUF	0.62	0.71	0.66	0.76	0.72	0.74	0.80	0.73	0.76	0.73	0.72	0.72	0.72
JPY	0.67	0.77	0.72	0.82	0.73	0.77	0.81	0.76	0.78	0.76	0.76	0.76	0.76
MXN	0.64	0.71	0.67	0.71	0.68	0.69	0.86	0.80	0.83	0.74	0.74	0.74	0.74
NOK	0.53	0.67	0.59	0.71	0.63	0.67	0.76	0.63	0.69	0.66	0.64	0.65	0.64
NZD	0.56	0.79	0.65	0.86	0.59	0.70	0.77	0.65	0.70	0.72	0.68	0.68	0.68
PLN	0.57	0.72	0.64	0.79	0.65	0.71	0.77	0.69	0.72	0.71	0.69	0.69	0.69
SEK	0.52	0.70	0.59	0.77	0.61	0.68	0.77	0.66	0.71	0.68	0.65	0.66	0.65
ZAR	0.49	0.65	0.55	0.70	0.58	0.63	0.72	0.62	0.67	0.64	0.61	0.62	0.61
Mean	0.58	0.73	0.64	0.78	0.66	0.71	0.80	0.69	0.74	0.72	0.69	0.70	0.69
Median	0.58	0.73	0.64	0.78	0.66	0.71	0.80	0.69	0.74	0.72	0.69	0.70	0.69

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.12: Random Forest Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.60	0.76	0.67	0.82	0.67	0.73	0.83	0.74	0.78	0.75	0.72	0.73	0.72
CAD	0.60	0.69	0.64	0.79	0.77	0.78	0.82	0.72	0.77	0.74	0.73	0.73	0.73
CHF	0.56	0.66	0.61	0.75	0.73	0.74	0.78	0.65	0.71	0.70	0.68	0.68	0.68
CZK	0.55	0.68	0.61	0.76	0.69	0.72	0.77	0.66	0.71	0.69	0.67	0.68	0.67
EUR	0.61	0.70	0.65	0.78	0.69	0.73	0.79	0.75	0.77	0.72	0.71	0.71	0.71
GBP	0.60	0.67	0.63	0.82	0.69	0.75	0.75	0.79	0.77	0.72	0.71	0.72	0.71
HUF	0.64	0.66	0.65	0.77	0.76	0.76	0.79	0.76	0.77	0.73	0.73	0.73	0.73
JPY	0.66	0.71	0.68	0.80	0.74	0.77	0.78	0.76	0.77	0.74	0.74	0.74	0.74
MXN	0.67	0.63	0.65	0.69	0.69	0.69	0.81	0.84	0.83	0.73	0.73	0.73	0.73
NOK	0.53	0.62	0.57	0.68	0.63	0.66	0.72	0.65	0.68	0.65	0.64	0.64	0.64
NZD	0.57	0.70	0.63	0.80	0.61	0.69	0.71	0.70	0.70	0.69	0.67	0.67	0.67
PLN	0.58	0.65	0.61	0.76	0.66	0.71	0.74	0.73	0.74	0.69	0.68	0.69	0.68
SEK	0.54	0.64	0.59	0.74	0.63	0.68	0.74	0.70	0.72	0.67	0.66	0.66	0.66
ZAR	0.49	0.59	0.54	0.69	0.60	0.64	0.70	0.63	0.66	0.63	0.61	0.61	0.61
Mean	0.59	0.67	0.62	0.76	0.68	0.72	0.77	0.72	0.74	0.70	0.69	0.69	0.69
Median	0.59	0.67	0.62	0.76	0.68	0.72	0.77	0.72	0.74	0.70	0.69	0.69	0.69

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.13: ARIMA Trinary Classification Results

Currency	No Jump			Positive Jump			Negative Jump			Average			Accuracy
	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	
AUD	0.51	0.56	0.53	0.67	0.60	0.63	0.63	0.61	0.62	0.60	0.59	0.59	0.59
CAD	0.48	0.61	0.53	0.61	0.53	0.56	0.58	0.48	0.52	0.55	0.55	0.54	0.55
CHF	0.51	0.45	0.47	0.67	0.66	0.66	0.56	0.63	0.59	0.58	0.58	0.57	0.58
CZK	0.53	0.58	0.55	0.70	0.65	0.67	0.63	0.59	0.61	0.62	0.61	0.61	0.61
EUR	0.56	0.59	0.57	0.71	0.74	0.72	0.73	0.66	0.68	0.66	0.65	0.65	0.65
GBP	0.41	0.59	0.48	0.57	0.40	0.46	0.60	0.49	0.54	0.52	0.50	0.49	0.50
HUF	0.47	0.56	0.51	0.61	0.44	0.50	0.59	0.64	0.61	0.55	0.54	0.53	0.54
JPY	0.49	0.57	0.52	0.68	0.59	0.63	0.63	0.60	0.61	0.60	0.59	0.59	0.59
MXN	0.54	0.53	0.53	0.51	0.65	0.56	0.67	0.57	0.61	0.59	0.57	0.57	0.57
NOK	0.50	0.50	0.50	0.64	0.75	0.68	0.59	0.51	0.54	0.58	0.58	0.57	0.58
NZD	0.46	0.57	0.51	0.65	0.63	0.63	0.53	0.38	0.43	0.55	0.55	0.54	0.55
PLN	0.45	0.53	0.49	0.63	0.61	0.61	0.67	0.57	0.61	0.58	0.57	0.57	0.57
SEK	0.48	0.55	0.51	0.67	0.70	0.68	0.61	0.50	0.54	0.59	0.58	0.58	0.58
ZAR	0.43	0.44	0.43	0.62	0.56	0.58	0.58	0.62	0.59	0.54	0.54	0.54	0.54
Mean	0.49	0.54	0.51	0.64	0.61	0.61	0.61	0.56	0.58	0.58	0.57	0.57	0.57
Median	0.49	0.54	0.51	0.64	0.61	0.61	0.61	0.56	0.58	0.58	0.57	0.57	0.57

The results are computed through averaging over 50 replicate models for each of the currencies for the full sample period, from January 2018 until April 2022.

Table 4.14: Summary of Trinary Classification Results

Currency	KNN			ML Perceptron			Decision Tree			SVM			Random Forest			ARIMA		
	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)	F1 (No Jump)	Score (Postive Jump)	F1 Score Accu racy (Nega Jump)
AUD	0.65	0.70	0.76	0.66	0.73	0.78	0.55	0.65	0.70	0.63	0.68	0.74	0.77	0.73	0.67	0.53	0.62	0.59
CAD	0.62	0.74	0.74	0.65	0.78	0.76	0.54	0.68	0.72	0.65	0.68	0.77	0.76	0.78	0.64	0.53	0.56	0.55
CHF	0.56	0.72	0.69	0.65	0.74	0.69	0.51	0.67	0.63	0.60	0.62	0.72	0.70	0.71	0.61	0.47	0.66	0.58
CZK	0.59	0.69	0.69	0.65	0.71	0.72	0.51	0.63	0.63	0.59	0.64	0.72	0.70	0.71	0.61	0.67	0.61	0.61
EUR	0.64	0.69	0.75	0.66	0.72	0.76	0.57	0.63	0.69	0.63	0.67	0.72	0.76	0.77	0.65	0.57	0.72	0.65
GBP	0.63	0.73	0.75	0.66	0.75	0.78	0.54	0.68	0.67	0.63	0.65	0.74	0.77	0.75	0.63	0.48	0.54	0.50
HUF	0.61	0.73	0.74	0.67	0.77	0.79	0.53	0.68	0.69	0.63	0.66	0.74	0.76	0.77	0.65	0.51	0.50	0.61
JPY	0.66	0.75	0.76	0.70	0.76	0.78	0.59	0.70	0.70	0.66	0.72	0.77	0.77	0.77	0.68	0.52	0.63	0.59
MXN	0.61	0.67	0.78	0.66	0.69	0.84	0.53	0.59	0.72	0.62	0.67	0.69	0.83	0.74	0.65	0.53	0.56	0.61
NOK	0.52	0.63	0.65	0.58	0.66	0.69	0.47	0.57	0.60	0.54	0.59	0.67	0.69	0.64	0.57	0.50	0.68	0.58
NZD	0.61	0.66	0.68	0.65	0.69	0.71	0.55	0.63	0.62	0.60	0.65	0.70	0.70	0.68	0.63	0.51	0.63	0.55
PLN	0.58	0.68	0.70	0.65	0.72	0.73	0.50	0.62	0.65	0.59	0.64	0.71	0.72	0.69	0.61	0.49	0.61	0.57
SEK	0.54	0.65	0.68	0.62	0.69	0.71	0.48	0.59	0.62	0.56	0.59	0.68	0.71	0.65	0.59	0.51	0.68	0.58
ZAR	0.48	0.62	0.63	0.55	0.65	0.67	0.44	0.56	0.56	0.52	0.55	0.63	0.67	0.61	0.54	0.43	0.58	0.54
Mean	0.59	0.69	0.71	0.63	0.72	0.74	0.52	0.64	0.65	0.60	0.64	0.71	0.74	0.69	0.62	0.51	0.58	0.57
Median	0.59	0.69	0.71	0.63	0.72	0.74	0.52	0.64	0.65	0.60	0.64	0.71	0.74	0.69	0.62	0.51	0.58	0.57

The results are computed through averaging over 50 replicate models for each of the currencies. The best performance among the six algorithms is boldfaced.

Table 4.15: Model Confidence Set Analysis for Binary Classification Results

	AUD	CAD	CHF	CZK	EUR	GBP	HUF	JPY	MXN	NOK	NZD	PLN	SEK	ZAR
KNN	0.31	0.35	0.35	0.35	0.33	0.34	0.34	0.31	0.38	0.39	0.34	0.36	0.38	0.42
ML Perceptron	0.28	0.33	0.32	0.31	0.28	0.30	0.30	0.26	0.34	0.35	0.31	0.30	0.34	0.38
Decision Tree	0.26	0.31	0.28	0.29	0.27	0.29	0.27	0.24	0.31	0.33	0.29	0.27	0.32	0.35
SVM	0.25	0.31	0.29	0.29	0.27	0.29	0.28	0.24	0.32	0.33	0.29	0.28	0.32	0.36
Random Forest	0.26	0.32	0.28	0.28	0.26	0.28	0.28	0.24	0.32	0.33	0.28	0.27	0.32	0.35
ARIMA	0.38	0.42	0.47	0.48	0.40	0.37	0.44	0.42	0.43	0.44	0.43	0.44	0.40	0.49

RMSE scores are reported. The results are computed through averaging over 50 replicate models for each of the currencies. The alpha=0.05 and 1000 bootstrap replications are executed.

Table 4.16: Model Confidence Set Analysis for Trinary Classification Results

	AUD	CAD	CHF	CZK	EUR	GBP	HUF	JPY	MXN	NOK	NZD	PLN	SEK	ZAR
KNN	0.52	0.56	0.57	0.58	0.54	0.57	0.54	0.48	0.61	0.63	0.57	0.57	0.61	0.67
ML Perceptron	0.46	0.54	0.51	0.50	0.47	0.48	0.47	0.41	0.54	0.58	0.50	0.49	0.54	0.60
Decision Tree	0.45	0.49	0.44	0.46	0.45	0.44	0.40	0.39	0.48	0.53	0.46	0.43	0.51	0.55
SVM	0.44	0.50	0.46	0.47	0.45	0.45	0.41	0.38	0.50	0.53	0.46	0.44	0.51	0.56
Random Forest	0.46	0.50	0.45	0.45	0.45	0.46	0.42	0.36	0.49	0.53	0.48	0.43	0.51	0.56
ARIMA	0.60	0.67	0.65	0.59	0.59	0.74	0.63	0.63	0.66	0.66	0.68	0.68	0.67	0.68

RMSE scores are reported. The results are computed through averaging over 50 replicate models for each of the currencies. The alpha=0.05 and 1000 bootstrap replications are executed.

Table 4.17: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Binary Classification Results Post Covid Era

Currency	KNN			ML Perceptron			Decision Tree			SVM			Random Forest			ARIMA		
	F1 Score (No Jump)	F1 Score (Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Jump)	Accuracy
AUD	0.66	0.57	0.62	0.69	0.66	0.68	0.64	0.63	0.63	0.75	0.71	0.73	0.69	0.65	0.68	0.64	0.54	0.60
CAD	0.71	0.68	0.70	0.73	0.70	0.72	0.62	0.64	0.63	0.76	0.73	0.75	0.72	0.71	0.71	0.69	0.65	0.68
CHF	0.67	0.66	0.67	0.71	0.69	0.70	0.61	0.64	0.63	0.75	0.71	0.74	0.70	0.70	0.70	0.68	0.65	0.67
CZK	0.65	0.57	0.62	0.69	0.62	0.66	0.59	0.58	0.59	0.70	0.59	0.66	0.66	0.59	0.63	0.67	0.57	0.63
EUR	0.62	0.50	0.57	0.66	0.55	0.61	0.56	0.54	0.55	0.66	0.53	0.61	0.63	0.53	0.59	0.64	0.55	0.60
GBP	0.67	0.61	0.64	0.66	0.58	0.62	0.59	0.57	0.58	0.68	0.58	0.64	0.65	0.61	0.63	0.65	0.56	0.61
HUF	0.62	0.53	0.58	0.65	0.56	0.61	0.56	0.54	0.55	0.67	0.52	0.61	0.63	0.55	0.60	0.65	0.56	0.61
JPY	0.73	0.68	0.71	0.70	0.69	0.70	0.64	0.66	0.65	0.76	0.73	0.75	0.74	0.74	0.71	0.66	0.69	0.69
MXN	0.64	0.63	0.63	0.71	0.69	0.70	0.57	0.59	0.58	0.73	0.68	0.71	0.67	0.67	0.67	0.66	0.62	0.64
NOK	0.58	0.49	0.54	0.65	0.55	0.61	0.54	0.54	0.54	0.67	0.53	0.62	0.62	0.55	0.59	0.64	0.55	0.60
NZD	0.69	0.61	0.66	0.70	0.64	0.67	0.58	0.57	0.57	0.73	0.63	0.69	0.68	0.62	0.65	0.65	0.59	0.62
PLN	0.63	0.56	0.60	0.67	0.59	0.63	0.56	0.54	0.55	0.69	0.56	0.63	0.64	0.58	0.61	0.65	0.56	0.61
SEK	0.60	0.53	0.56	0.64	0.54	0.60	0.55	0.53	0.55	0.66	0.51	0.60	0.63	0.55	0.59	0.62	0.53	0.58
ZAR	0.60	0.53	0.57	0.65	0.54	0.60	0.56	0.54	0.55	0.67	0.52	0.61	0.62	0.54	0.59	0.65	0.52	0.60
Mean	0.65	0.58	0.62	0.68	0.62	0.65	0.58	0.58	0.58	0.71	0.61	0.67	0.66	0.61	0.64	0.66	0.58	0.62
Median	0.65	0.58	0.62	0.68	0.62	0.65	0.58	0.58	0.58	0.71	0.61	0.67	0.66	0.61	0.64	0.66	0.58	0.62

The results are computed through averaging over 50 replicate models for each of the currencies. Train sample is 80 % of data set for the time period December 1st, until April 30th, 2022.

Table 4.18: Prediction Performance of Machine Learning Algorithms on the Testing Sets for Trinary Classification Results Post Covid Era

KNN			ML Perceptron			Decision Tree			SVM			Random Forest			ARIMA		
Currency	F1 Score (No Jump)	F1 Score (Pos-itive Jump)	F1 Score (Neg-ative Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Positive Jump)	F1 Score (Neg-ative Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Positive Jump)	F1 Score (Neg-ative Jump)	Accuracy	F1 Score (No Jump)	F1 Score (Positive Jump)	F1 Score (Neg-ative Jump)	F1 Score	Accuracy
AUD	0.51	0.70	0.50	0.57	0.55	0.75	0.63	0.56	0.56	0.60	0.76	0.61	0.66	0.54	0.75	0.57	0.52
CAD	0.62	0.78	0.71	0.70	0.52	0.73	0.71	0.66	0.66	0.63	0.80	0.75	0.73	0.57	0.76	0.61	0.58
CHF	0.59	0.73	0.81	0.70	0.58	0.78	0.78	0.69	0.69	0.62	0.78	0.81	0.74	0.52	0.75	0.64	0.61
CZK	0.52	0.61	0.61	0.57	0.54	0.70	0.65	0.55	0.55	0.55	0.70	0.60	0.61	0.53	0.69	0.61	0.58
EUR	0.48	0.54	0.61	0.54	0.49	0.62	0.65	0.55	0.49	0.51	0.60	0.63	0.58	0.46	0.60	0.62	0.49
GBP	0.56	0.64	0.62	0.60	0.52	0.69	0.67	0.56	0.52	0.56	0.67	0.67	0.63	0.52	0.67	0.61	0.58
HUF	0.49	0.58	0.56	0.54	0.51	0.64	0.61	0.53	0.51	0.48	0.63	0.59	0.57	0.49	0.62	0.58	0.56
JPY	0.65	0.75	0.58	0.68	0.64	0.79	0.57	0.69	0.69	0.68	0.78	0.58	0.70	0.63	0.78	0.60	0.64
MXN	0.54	0.67	0.71	0.64	0.57	0.71	0.80	0.64	0.54	0.56	0.69	0.79	0.68	0.51	0.67	0.67	0.61
NOK	0.43	0.51	0.58	0.50	0.46	0.66	0.67	0.50	0.55	0.46	0.65	0.65	0.58	0.43	0.60	0.66	0.57
NZD	0.56	0.58	0.45	0.54	0.57	0.64	0.52	0.54	0.46	0.60	0.62	0.51	0.59	0.55	0.60	0.54	0.53
PLN	0.49	0.59	0.62	0.56	0.49	0.60	0.65	0.53	0.53	0.51	0.62	0.63	0.58	0.47	0.61	0.63	0.53
SEK	0.46	0.59	0.59	0.54	0.45	0.65	0.61	0.52	0.48	0.47	0.64	0.60	0.57	0.46	0.65	0.61	0.49
ZAR	0.46	0.52	0.56	0.51	0.49	0.58	0.60	0.50	0.45	0.51	0.56	0.60	0.55	0.54	0.64	0.66	0.55
Mean	0.53	0.63	0.61	0.59	0.53	0.68	0.65	0.55	0.52	0.56	0.68	0.65	0.63	0.52	0.67	0.65	0.56
Median	0.53	0.63	0.61	0.59	0.53	0.68	0.65	0.55	0.52	0.56	0.68	0.65	0.63	0.52	0.67	0.65	0.56

The results are computed through averaging over 50 replicate models for each of the currencies. Train sample is 80 % of data set for the time period December 1st, until April 30th, 2022.