

SÜLEYMAN SERDENGEÇTİ

ESSAYS IN EMPIRICAL FINANCE

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ESSAYS IN EMPIRICAL FINANCE

A Ph.D. Dissertation

by

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Ankara

December 2019



To Seyma, Kerem and Zeynep

ESSAYS IN EMPIRICAL FINANCE

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

by

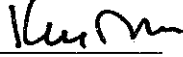
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In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN MANAGEMENT

THE DEPARTMENT OF MANAGEMENT
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
ANKARA

December 2019

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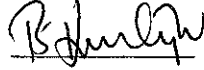
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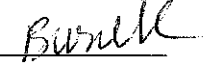
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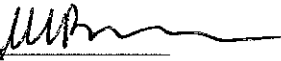
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ABSTRACT

ESSAYS IN EMPIRICAL FINANCE

Serdengeçti, Süleyman
Ph.D. in Department of Management
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December 2019

This thesis comprise three essays that investigate foreign exchange market volatility and its dynamics using high frequency exchange rate data. In the first essay, we decompose the jump component of USDTRY exchange rate volatility and investigate association of jump frequencies and sizes with portfolio flows, carry trade activity and proxies for heterogeneous expectations derived from foreign exchange rate forecasts, currency options and forecasts for key macro-economic variables. The findings of the essay show that portfolio flows, particularly bond flows significantly reduce size and frequency of jumps. Moreover, we observe significant increases in jump size and frequencies with increasing dispersion in beliefs in future exchange rate level and CPI. In the second essay, we study the dynamics of return and liquidity jumps for USDMXN, USDTRY and USDZAR exchange rates. The findings of the essay show that the duration between consecutive return jump arrivals are significantly reduced by average liquidity level in the same period. Furthermore, arrival rates of both liquidity and return jumps are significantly affected by market-wide risk and liquidity factors and key macroeconomic news releases. In the third essay, we investigate the trading volume and volatility nexus for USDTRY exchange rate by using local banks' foreign exchange transaction volume data. In this context, foreign currency denominated spot, forward and swap transactions in with local and foreign

customers and between each other for intraday realized volatility of different trading sessions. The findings of this study reveal that positive contemporaneous relationship between trading volume and volatility is evident for local customers and in local trading sessions. Moreover, dispersion in expectations for future foreign exchange rate strengthens this relationship.

Keywords: FX Jump Risk, FX Liquidity, Heterogeneous Expectations, High-frequency Analysis, Volume-Volatility Nexus



ÖZET

AMPIİRİK FİNANSTA MAKALELER

Serdengeçti, Süleyman
Doktora, İşletme
Tez Danışmanı: Prof. Dr. Kürşat Aydoğan

Aralık 2019

Bu tez, yüksek frekanslı veri kullanarak kur oynaklığı ve dinamiklerini inceleyen üç makaleden oluşmaktadır. İlk makalede, USDTRY paritesi oynaklığından sıçrama bileşeni ayrıştırılmış ve kur sıçramaları büyüklükleri ve frekansının sermaye akımları ile makroekonomik gösterge ve döviz kuru beklenti anketleri ile kur opsiyonlarından elde edilmiş heterojen beklenti göstergeleriyle olan ilişkisi incelenmiştir. Çalışmanın sonuçları sermaye akımlarının, özellikle de tahvil-bono akımlarının kur sıçramalarının hem büyüklüğünü hem de frekansını anlamlı şekilde düşürdüğünü göstermektedir. Bununla beraber, kur sıçramalarındaki büyüklük ve frekansın kur ve enflasyon beklentilerindeki farklılaşmanın artışıyla anlamlı şekilde arttığını gözlemlemekteyiz. İkinci makalede, USDMXN, USDTRY ve USDZAR pariteleri için kur ve likidite sıçramalarının dinamikleri ve birbirleri ile olan etkileşimleri incelenmiştir. Çalışmada, kur getirilerindeki sıçramaların aynı periyottaki ortalama likidite ile anlamlı şekilde arttığı görülmektedir. Bununla birlikte, piyasa risk ve likidite faktörleri ile makroekonomik veri açıklamalarının hem getiri hem de likidite sıçramalarını artırdığı gözlemlenmektedir. Üçüncü makalede bankaların günlük yabancı para karşılığı işlem hacimleri verisi kullanılarak işlem hacmi ve oynaklık ilişkisi incelenmektedir. Bu bağlamda, bankaların kendi aralarında veya yerli ve yabancı müşterileri ile gerçekleştirdiği spot,

vadeli ve swap işlem hacimlerinin farklı işlem saatleri için ayrı ayrı hesaplanan kur oynaklıkları ile olan ilişkisi ele alınmaktadır. Çalışmanın bulgularına göre işlem hacimleri ve oynaklık arasındaki pozitif eşanlı ilişki yerli müşterilerle olan spot işlemlerde ve yerel işlem saatleri ile yerel işlem saatlerinde gözlemlenmektedir. Ayrıca kur beklentilerindeki farklılaşmanın artmasıyla işlem hacmi ve oynaklık ilişkisinin güçlendiği gözlemlenmektedir.

Anahtar Kelimeler: Döviz Piyasası Likiditesi, Heterojen Beklentiler, İşlem Hacmi-Oynaklık İlişkisi, Kur Sıçrama Riski, Yüksek Frekanslı Analiz

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TABLE OF CONTENTS

ABSTRACT	iii
ÖZET	v
ACKNOWLEDGEMENTS	vii
TABLE OF CONTENTS	ix
LIST OF TABLES	xii
LIST OF FIGURES	xv
CHAPTER I: INTRODUCTION	1
1.1 Overview	1
CHAPTER II: IMPACT OF PORTFOLIO FLOWS AND HETEROGENEOUS EXPECTATIONS ON FX JUMPS: EVIDENCE FROM AN EMERGING MARKET	4
2.1 Introduction	4
2.2 Data and Summary Statistics	14
2.3 Jump Detection Methodology	15
2.4 Potential Sources of the Jumps I: Portfolio Flows	24
2.4.1 Equity and Bond Flows	24
2.4.2 Carry Trade Activity	27
2.4.3 Robustness Analysis: Generalized Method of Moments	32
2.5 Potential Sources of the Jumps II: Heterogeneous Expectations	35
2.5.1 Heterogeneity in FX Expectations	35
2.5.2 Deviations in Expectations for Key Macroeconomic Variables	39

2.5.3	Robustness Analysis: Granger Causality	45
2.6	Discussion and Conclusion	48
CHAPTER III: JUMPS AND COJUMPS IN EMERGING MARKET EX- CHANGE RATES AND LIQUIDITY		52
3.1	Introduction	52
3.2	Data and Summary Statistics	58
3.3	Jump Detection Methodology	61
3.4	Jump and Cojump Analysis for the Individual Exchange Rates	66
3.4.1	Preliminary Analysis	66
3.4.2	Modelling the Duration Between Consecutive Jumps and Co- jumps	73
3.4.3	Impact of Liquidity Jumps on Volatility	77
3.4.4	Impact of Return Jumps on Liquidity	81
3.4.5	Determinants of Jumps and Cojumps	84
3.5	Cojump Analysis Across Exchange Rates	89
3.5.1	Duration Analysis on Cojumps Across Exchange Rates	91
3.5.2	Cojumps and US Macro-News Announcements	95
3.6	Conclusion	95
CHAPTER IV: INTRADAY VOLUME-VOLATILITY NEXUS IN THE FX MARKETS: EVIDENCE FROM AN EMERGING MARKET		99
4.1	Introduction	99
4.2	Data and Summary Statistics	105
4.3	Methodology and Results	111
4.3.1	Contemporaneous Relations	113
4.3.2	Bivariate Dynamic Relations	114
4.3.3	Dispersion of Beliefs and Contemporaneous Dynamic Correla- tions	121

4.4 Conclusion	124
CHAPTER V: CONCLUSION	127
REFERENCES	129



LIST OF TABLES

2.1	Descriptive information of the sample variables	16
2.2	Descriptive statistics of the detected jumps	22
2.3	Impact of portfolio flows on jump size and frequency	26
2.4	Impact of carry trade activity on jump size and frequency	31
2.5	GMM estimation results for robustness	34
2.6	Impact of heterogeneous expectations for the foreign exchange rate levels on jump size and frequency	40
2.7	Impact of belief dispersion of the future value of key macro-economic variables on jump size and frequency	44
2.8	Causality test results between jumps and heterogeneous expectations	47
3.1	Summary table for US and domestic macroeconomic news and central bank announcements	60
3.2	Summary statistics for exchange rate returns and liquidity	61
3.3	Summary statistics for the detected return and liquidity jumps	67
3.4	Conditional probabilities of return jump occurrences around liquidity jumps	69
3.5	Intraday jump and cojump distribution of exchange rate returns and their liquidity	71
3.6	Summary statistics of the duration between consecutive return jumps, liquidity jumps, and return-liquidity cojumps	75

3.7	LACD(1,1) model fit results for the duration between consecutive return jumps	76
3.8	LACD(1,1) model fit results for the duration between consecutive liquidity jumps	77
3.9	LACD(1,1) model fit results for the duration between consecutive return-liquidity cojumps	78
3.10	Impact of liquidity jumps on volatility	82
3.11	Impact of return jumps on liquidity	85
3.12	Determinants of return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate	88
3.13	Impact of US based and local macroeconomic news announcements on return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate	90
3.14	Intraday cojump distribution across exchange rates	92
3.15	Summary statistics for the duration between consecutive return cojumps across exchange rates	93
3.16	LACD(1,1) model fit results for duration between consecutive return cojumps across exchange rates	94
3.17	Impact of US based macroeconomic news announcements on return cojumps across exchange rates	96
4.1	Summary statistics for FX transactions of banks against TRY	106
4.2	Summary statistics for USDTRY returns and volatility across trading sessions	108
4.3	GMM estimation results to analyse contemporaneous relation between volume and volatility	115
4.4	Results of VAR(p)-DCC(1,1)-EGARCH(1,1) model to analyse the bivariate dynamic relationship between volume and volatility	119

4.5	Results of VAR(p)-DCC(1,1)-EGARCH(1,1) model to analyse the bi- variate dynamic relationship between volume and volatility-cont. . .	120
4.6	Impacts of RND central moments on dynamic correlations between USDTRY volume and volatility	124



LIST OF FIGURES

2.1	High-frequency (5 min) levels and returns of USDTRY exchange rate between May 20, 2013 to August 1, 2019.	15
2.2	Estimated periodicity pattern and the intraday average absolute changes	18
2.3	Intradaily distributions of size and frequency of detected jumps . . .	20
2.4	Weekly time series of the average jump size and jump frequency for the local and off-shore trading hours	23
2.5	Carry trade profitability ratios (Carry-to-Risk Ratio) and net TRYJPY long positions	30
2.6	Mean absolute deviations in the expectations for 3 month ahead US- DTRY exchange rate derived from FX polls and risk neutral densities of currency options	38
2.7	Mean absolute deviations in the expectations for the 1 year ahead levels key macroeconomic variables	42
3.1	Intraday volatility and liquidity patterns	65
3.2	Monthly time series of return jumps, liquidity jumps, and return- liquidity cojumps for each exchange rate	72
3.3	Average absolute log-returns around liquidity jumps ($t = 0$)	78
3.4	Average proportional quoted spread around return jumps ($t = 0$) . . .	83
4.1	Hours of FX trading sessions in different locations	107

4.2	Intraday volatility patterns with respect to transaction volume by different trader and instrument types and intraday correlation patterns between volume and volatility	110
4.3	Average transaction volumes (in USD billions) by the day of the week with respect to different trader and instrument types	112
4.4	Dynamic conditional correlations between trading volumes and realized volatility with respect to different trader and transaction types .	118
4.5	Central moments derived from risk neutral distributions	123

CHAPTER I

INTRODUCTION

1.1. Overview

Using high frequency exchange rate data, this thesis contributes to the strand of literature that investigates the dynamics of FX jumps first, by focusing on the impact of heterogeneous expectations and portfolio flows on them for USDTRY exchange rate and second by examining the interaction between FX return and liquidity (co)jumps and their individual dynamics for USDMXN, USDTRY and USDZAR exchange rates. Furthermore, by examining the volume-volatility nexus in USDTRY market, the study aims to contribute to the small number of studies investigating volume-volatility relationship due to lack of transaction volume data in FX markets. The thesis is organized as follows:

In the next chapter of this thesis, motivated by the recent currency crisis in Turkey, we investigate the role of portfolio flows and heterogeneous expectations on the high frequency stochastic jump behavior of the US dollar value against the Turkish lira, one of the most traded emerging market currencies in the world. We group the detected jumps into different types with respect to their direction (up and down) and timing (local and off-shore trading hours). For each type of jumps, we examine their relation with portfolio flows (in the form of equity and bond flows, and carry trade activity), and dispersion in beliefs for the future exchange rate level and key

macroeconomic variables. We find that inflows to both equity and bond markets, and increasing carry trade activity significantly reduce the size of jumps and (partially) their intensity. On the other hand, heterogeneous expectations for the future exchange rate level, consumer price index and gross domestic product are found to increase the number of jumps and the average jump size.

In the third chapter, we study the dynamics of return and liquidity jumps, and their common occurrences (cojumps) for the value of Mexican Peso, Turkish Lira and South African rand against US dollar. In particular, we consider the return jumps, liquidity jumps, and return-liquidity cojumps for each exchange rate, then we analyze the return cojumps and liquidity cojumps across exchange rates. We find that the duration between consecutive return jumps are significantly reduced by average realized volatility in the same period for all currencies. Our empirical results also show that for Turkish lira, the average realized volatility between two consecutive liquidity jumps significantly reduce the duration between them.

Furthermore the findings of the paper show that the arrival rates of both return and liquidity rates are significantly positively affected by increasing market risk and liquidity factors like policy uncertainty, CDS and TED spread. Also, consistent with the earlier evidence, key local and US news releases like central bank decisions, CPI, GDP and Non-farm Payroll announcements significantly increase both return and liquidity jump occurrences.

In the last chapter, using a dataset on local banks' daily FX transaction volume segregated into counterparty and transaction types, this article investigates the relationship between trading volume and intraday realized volatility for the US dollar / Turkish lira parity (USDTRY), one of the most traded emerging market currencies against US dollar. We question whether type of counterparty and transaction affects intraday volume-volatility relationship across various trading sessions around the world. We reveal that only the spot transactions of domestic

customers have positive contemporaneous relation with realized volatility and this significance is valid only in global trading sessions that mostly overlap with the local trading hours. Furthermore, we utilize a metric for the belief dispersion on the level of future exchange rate via currency options and find that the dispersion significantly strengthens the volume-volatility nexus, confirming the Dispersion of Beliefs Hypothesis.



CHAPTER II

IMPACT OF PORTFOLIO FLOWS AND HETEROGENEOUS EXPECTATIONS ON FX JUMPS: EVIDENCE FROM AN EMERGING MARKET

2.1. Introduction

In the modern era of the financial markets, a common observation is the infrequent but large movements in asset prices so called jumps. Recent studies show that the presence of price discontinuities in asset prices in the form of sudden spikes or jumps not only deteriorate performance of modeling and forecasting asset returns and volatilities, but also are a priced risk factor with implications on the risk-return profile of the related assets. Jumps are commonly associated with a sudden flow of new information but there is no general consensus on which kind of market events (Bajgrowicz et al., 2016; Calcagnile et al., 2018; Loughran et al., 2019). In this paper, we pay our attention to the portfolio flows and expectation heterogeneity as the potential sources of jumps at the high frequency level. Motivated by the recent currency crisis in Turkey, we test our hypothesis on the USDTRY exchange rate; i.e., the value of the US dollar against the Turkish lira

which is one of the most traded emerging market currencies in the world.¹

Accordingly, we show that jump frequency and average jump size are negatively related to portfolio inflows. Moreover, we find that disagreement on the future level of the exchange rate and the inflation rate increase the average jump size, whereas dispersion of beliefs on the future gross domestic product (GDP) significantly increases the average jump size and partially the jump intensity.

A growing body of literature provides both theoretical and empirical evidence on the implications of jumps in asset prices and emphasizes the importance of their investigation. For instance, in the work of Caporin et al. (2017) and Barunik and Vacha (2018), jumps affect correlations between asset returns and thus have implications on asset allocation and risk management. Liu et al. (2003) state that jumps reduce investors' willingness to take short or leveraged positions and have implications on optimal portfolio allocation. This finding is supported by Lee and Hannig (2010) who argue that the degree of jump sizes has different implications on portfolio construction by investors with different risk aversion levels. For example, high levels of jump risk due to foreign exchange (FX) illiquidity might discourage foreign investors to invest in the stock market (Lee and Ryu, 2019). Moreover jumps, even if not related with fundamentals, may affect volatility and risk adjusted returns, and might lead to fat-tailed distributions of exchange rate expectations (Eraker et al., 2003). In fact, Bates (1996) argue that fear of substantial and infrequent jumps in exchange rates explains the excess kurtosis in currency option volatility smiles.

Jumps in asset prices not only disrupt the asset allocation decisions and investor sentiment, but also cause problems in modeling and forecasting key economic and financial variables (Zhang and Dufour, 2019). For instance, Andersen et al. (2007)

¹See the most recent Triennial Survey of foreign exchange and OTC derivatives trading by BIS (<https://www.bis.org/statistics/derstats3y.htm>).

state that jumps mitigate accuracy in both return and volatility forecasts as they have no predictive information. Accordingly, authors show that separating exchange rate jumps from smooth variation component significantly improves out of sample forecasts. In a similar fashion, Corsi and Renod (2010) show that separating continuous and discontinuous components of returns improves volatility forecasts. Likewise, Giot et al. (2010a) decompose realized variance into its continuous and jump components and find that the positive relationship between volume and volatility is valid only for the continuous component of volatility.

Among the price jumps in various asset classes, the case of exchange rate jumps takes a special place. Unlike the jumps in stock prices where the biggest hit is mostly taken by the company's investors, exchange rate jumps are agitating for both households and corporations in that country. These jumps are not only challenging to hedge but also problematic if not hedged since it can affect not only the financial markets but also the real sector through import & export channel (Li et al., 2018). Unforeseen large movements in exchange rates may increase institutional investors' fears of future jumps because they consider the occurrence of large fluctuations in the exchange rate to be more likely. Consequently, companies in the real sector might be unwilling to expand their investments within the country since they struggle to forecast their operational and financial performances. With a similar reasoning, banks become unwilling to provide loans in domestic currency which in turn dampens the economic growth of the country through reduced consumption channel. Similarly, jumps in exchange rates possess bigger challenges for policymakers. In particular, (i) central banks might have hard times in implementing inflation targeting or fixed currency regime in the presence of jumps since these jumps impact the level or stability of the exchange rates significantly; (ii) due to the instability of the local currency, households might prefer to use a safe currency to conduct their day-to-day transactions or keep their

savings which leads to an unofficial dollarization in the country, eventually making it much harder to implement an effective monetary policy; and (iii) states might experience troubles in deciding when to roll-over the foreign currency denominated debt because of the increased uncertainty in the FX market. In these scenarios, problems are not limited within the country itself since in case of an occurrence of simultaneous jumps in several countries for some reason, even a diversification at the international level would not compensate the total harm done.

In the strand of literature that investigates the determinants of jumps in exchange rate returns, most of the studies associate jumps with macroeconomic news announcements or central bank interventions. Lahaye (2016) shows that the jump and co-jump activity of exchange rates increase around scheduled macro-news announcements while Omrane and Savaser (2017) argue that this response is time-varying and depends on the economic conditions. Likewise, Chatrath et al. (2014); Füss et al. (2018) associate jumps with macroeconomic news arrival whereas Andersen et al. (2007) associate detected exchange rate jumps with both macroeconomic news announcements and central bank interventions. Beine et al. (2007) analyze the linkages between the jumps in the value of euro and Japanese yen against the US dollar and central bank interventions. Authors show that coordinated interventions lead to infrequent but large jumps. Dewachter et al. (2014) introduce the concepts of continuous volatility and discontinuous jumps for FX markets, and link them with communications of monetary authorities. Authors show that such communications have different effects on the continuous and discontinuous parts of the exchange rate volatility. Lahaye et al. (2011) show that important macroeconomic news announcements like federal funds target, non-farm payroll and GDP announcements are very likely to create jumps in exchange rates, in addition to stock index futures and bond futures. Lee and Wang (2019a) investigate the effects of country specific factors on exchange rate jumps and show

that announcements of macro-fundamentals like GDP differentials or trade balance can predict size and frequency of jumps.

Another candidate for the potential source of jumps in exchange rates is the excess volatility due to foreign portfolio flows and there is a substantial body of empirical evidence supporting this argument. For instance, Froot and Ramadorai (2005) decompose currency returns into intrinsic-value shocks (permanent) and expected-return shocks (transitory) and show that expected-return shocks are correlated with portfolio flows. Banti and Phylaktis (2015) consider capital flows as a proxy for the liquidity demand and associate exchange rate jumps with portfolio flows through the impact of such flows on liquidity. However, equity and bond flows may have different impact on the jumps in exchange rates, hence a separate analysis might be required. For example, Caporale et al. (2017) show that while equity inflows increase the exchange rate volatility for emerging Asian economies, bond inflows have the opposite impact. In their study, the difference is attributed to the higher hedging activity for bond investments compared to equity investments in emerging markets. Therefore, in the special case of jumps, an interesting aspect of such analysis would be whether equity and bond flows imply different impact on size and frequency of jumps since they have different investor bases and they are part of different trading strategies.

In addition to the equity and bond flows, carry trade activities might also constitute strong short term impact on exchange rate jumps for high yield emerging market currencies. In particular, jumps might occur with sudden and large amounts of unwinding of currency positions. According to Brunnermeier et al. (2008), carry currencies with higher interest rate differentials may experience more frequent positioning or position unwinding thus are subject to higher crash risk and might face more jumps in exchange rate returns, which is the case mostly for emerging market currencies (Suh, 2019). In parallel to this finding, Chernov et al. (2018)

recently show that the probability of a jump in an exchange rate corresponding to the appreciation of the US dollar is increasing in the foreign interest rate. In another study, Nirei and Sushko (2011) support these arguments above and discuss that asymmetries between negative and positive jumps may imply stochastic unwinding of carry trades. This, in turn, causes appreciation episodes in funding currencies like Japanese yen and depreciation pressures in investment currencies.

On top of the aforementioned potential sources, many papers emphasize the significant positive impact of heterogeneity in beliefs on the trading activity in the FX markets, thus increased volatility in exchange rates. Tauchen and Pitts (1983) and Harris and Raviv (1993) theoretically model this hypothesis for assets in general. Accordingly, the higher dispersion in beliefs is a proxy for higher uncertainty that the traders face by contaminating expectations for the fair value of the traded asset. Thus, this disagreement leads to more frequent quote updates, hence higher volatility. According to this argument, dispersion in beliefs increases only the volume related volatility, however heterogeneity of expectations can increase the volatility of the traded asset also through increased hedging demand (Buraschi and Jiltsov, 2006; Shalen, 1993). Indeed, Beber et al. (2010) empirically show that heterogeneity in expectations for future exchange rate levels affect the shape of implied volatility smile, volatility risk premiums and therefore, future currency returns. Subsequently, these findings imply that belief dispersion in future exchange rates might be a source of jump activity.

In the context of the heterogeneity argument, it is plausible to suppose that the implications of heterogeneous expectations theory for exchange rate forecasts might also be valid for the expectations of investors for the key macroeconomic variables. In fact, a limited strand of literature also associates heterogeneity in expectations for key macroeconomic variables with exchange rate volatility. For instance, Hogan and Melvin (1994) argue that heterogeneity in trade balance forecasts has strong

impact on the US dollar/Japanese yen fluctuations. In parallel to this scenario, heterogeneous beliefs on the future growth rate of the economy, inflation rate, current account balance or budget balance can be argued to have similar significant impact on the jump dynamics of an exchange rate.

In this study, our focus is on the jumps realized in the USDTRY exchange rate, and the reason is the following: It is widely known that emerging market currencies tend to have higher jump frequencies and larger jump sizes compared to those of the developed markets. Moreover, according to Lee and Wang (2019a), Turkish lira is the most frequently jumping currency with 1.1% jump probability and 17.06% day with at least one jumps probability between 2007 and 2015 among the sample group of most traded 16 emerging market currencies. This finding was supported by the recent events that took place in the foreign exchange market in 2018, in which the Turkish lira lost 42% of its value against the US dollar that makes it the second worst performing currency in the world after Argentine peso.

Indeed, the problem started in 2013 when the Fed decided to tighten its monetary policy that converts the loose conditions started with the quantitative easing operations to combat the 2008 financial crisis. During the period between 2008 and 2013, low US dollar interest rates let emerging markets to borrow more heavily in dollar-denominated debt, in an environment where many of these countries were already dealing with chronic current-account deficit problems. Beginning with the Fed's tightening policy, high dollar debt combined with high current account deficit diminished investors' confidence in the emerging markets' ability to repay their external debt. Turkey was no exception in this environment and the country suffered its share of challenges. Yet, the year 2018 was unlike the others for Turkey. Being the 13th largest economy in the world², the economy was already suffering

²According to the International Monetary Fund, the World Bank and the CIA World Factbook, Turkey has the 13th largest GDP in the world, adjusted for purchasing power parity.

from overheating concerns and spurred inflation due to government's prolonged stimulus package from 2017. Thing came to a point where the lira lost 16% of its value in a single day, following political tensions with the United States. Moreover, just in August, there were 11 days (out of 23 trading days) in which the USDTRY parity experienced at least $\mp 2\%$ change.³ After weeks of dragging its feet, the central bank eventually implemented an extensive hike in interest rates (from 17.75% to 24%) followed by the government's announcement of a fiscal austerity drive. Since then, the conditions seem to have been stabilized, however the lira still remains to be highly vulnerable to the changes in market sentiment. Considering all these developments that occurred in the last few years, it is clear that the USDTRY exchange rate is highly susceptible to all kinds of local and global political, economical and financial events, therefore an analysis on its jump dynamics is essential to various types of stakeholders in the market. We further believe that such an analysis would help and guide us in understanding the potential currency risks (with sources and consequences) that other emerging markets might experience in the cases of high foreign currency debt and high current account deficit.

In addition to the selection of the exchange rate, the choice of the time frequency to detect jumps is an essential factor in our analysis. Although earlier studies mostly prefer to focus on daily data, we perform our analysis using 5-minute interval high frequency data. The reason is that in today's modern financial markets, algorithmic (especially high frequency) trading constitutes the major part of all trading activities. In this framework, automated systems are designed to take actions in shortest possible times in response to real time floating data. Since the FX market is an OTC market, there is no possible way to estimate the share of

³This value represents the daily returns. In fact, in terms of intraday movements, there were only a few days in the rest of the year that USDTRY did not experience at least $\mp 1\%$ change within the day.

such computerized systems in the total trade volume, however, regarding the US equities, it is estimated that algorithmic traders execute 85% of the total trades (Glantz and Kissell, 2013). These technological advancements make it essential for us to perform our analysis at the high frequency level (Stenfors and Susai, 2019; Zhou et al., 2019).

In this paper, we proceed in the spirit of Lee and Wang (2019a) and study the determinants of jumps in USDTRY parity in an aggregate way. We first detect the jumps using 5-minute high frequency returns between the years 2013 and 2019 by the non-parametric jump detection methodology of Lee and Mykland (2008). In doing so, we decompose high frequency log-returns of USDTRY exchange rate into diffusion and jump components and classify the detected jumps by positive and negative jumps, and also jumps occurring in local trading hours and in off-shore trading hours. Then we construct weekly and monthly time series of the number of jumps and the corresponding average jump sizes based on the different jump classifications. Later, we synchronize the occurrence of these jumps with the selected variables and investigate their relationship. In particular, we study the linkages of these jump series with equity and bond portfolio flows, carry trade activity and heterogeneous expectations for the future exchange rate level and key macro-economic variables such as the GDP, consumer price index (CPI), current account balance and budget balance. Such an analysis allows us to describe the high frequency behavior of the USDTRY exchange rate and a comprehensive analysis of the jumps in this parity which have important implications for both investors and policymakers. In essence, our findings show that jump size and frequency are negatively related to portfolio (both equity and bond) inflows and carry trade activity. Furthermore, results provide empirical evidence for dispersion of beliefs hypothesis such that disagreement on the future levels of the exchange rate, GDP and CPI increase the average jump size. Among all the investigated key

macroeconomic variables, heterogeneity in the expected GDP, CPI and budget balance have limited positive significant impact on jump intensities as well, but only in local trading hours. As the final stage, we check for the robustness of these findings through generalized method of moments and Granger causality analyses, and confirm the validity of the main results.

Accordingly, our contribution to the literature is at least threefold. First, we investigate the determinants of jumps by addressing the relation between jump size and intensity in different trading sessions. Such a differentiation can help policymakers to focus on the right strategies to take action in battling against the excess volatility caused by jumps during the trading sessions. Moreover, even though it is an unorthodox way, policymakers would have the option to intervene to the FX market in off-shore trading hours when the market liquidity is low since they would know the potential determinants of the jumps during these periods. Second, we advance the literature by providing evidence for heterogeneous expectations hypothesis. To the best of our knowledge, this is the first paper that links exchange rate jumps with heterogeneous expectations. The heterogeneity in expectations for both foreign exchange rate and key macroeconomic variables are strongly related with monetary and fiscal policy uncertainty. Thus, the resulting positive relation between the two variables have implications on reducing fiscal and monetary uncertainty hence mitigating volatility risk premium. Third, revealing the relation between jump dynamics and the considered factors in this paper contributes to the modeling and forecasting of exchange rate returns and volatility, and thus facilitates the decision making in both future financial performance evaluation and fiscal & monetary policy operations.

The rest of the paper is organized as follows. Section 4.2 describes the source and content of the sample data. Section 2.3 explains the technical details of the jump detection methodology. Sections 2.4 and 2.5 include the main analysis, discuss the

empirical findings and check the results for robustness. Finally, Section 4.4 concludes.

2.2. Data and Summary Statistics

The intraday USDTRY spot exchange rate data is obtained from Bloomberg. This dataset is in 5-min frequency and covers slightly more than six years from May 20, 2013 to August 1, 2019. There are 1618 trading days over this period and thus 465,984 (1618×288) 5-min intervals. We have 464,596 observations after filtering for the missing values. As Turkish lira is traded in all global FX trading sessions, high frequency data is available during when the global FX market is open. Depending on whether it is summer time or the daylight saving time, the global FX market is open either from 00:00 Monday to 00:00 Friday or from 01:00 Monday to 01:00 Saturday with respect to Greenwich Mean Time (GMT). We omitted the very limited number of observations out of these global trading hours from the sample. All timestamps used in this study denote the local timezone in Turkey. The resultant exchange rate series and its corresponding returns are provided in Figure 2.1. The level series displays the trend in the depreciation of the Turkish lira against the US dollar since the 2013, whereas the return series exhibits the high intraday volatile periods during the summer of 2018.

The weekly unique portfolio flow data is obtained from the Central Bank of the Republic of Turkey (CBRT), and it contains the weekly net changes in equity and bond holdings of non-residents in USD millions.

To obtain measures for heterogeneous expectations from the foreign exchange rate forecasts, we use two different datasets. The first one is the FX forecasts of Reuters FX polls. This dataset includes monthly forecasts of individual contributors where

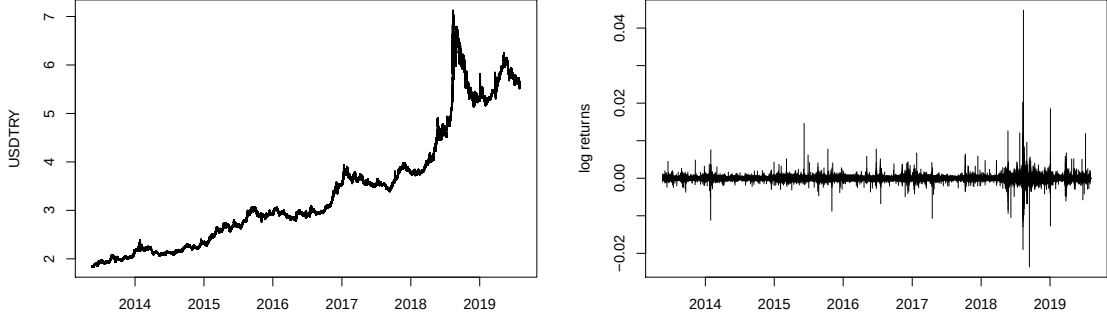


Figure 2.1: High-frequency (5 min) levels and returns of USDTRY exchange rate between May 20, 2013 to August 1, 2019.

the average number of forecasters is 30 through the sample period. The second dataset is the daily currency option prices and implied volatilities obtained from Bloomberg terminal by which we calculate the foreign exchange rate expectation moments via the derived risk neutral densities.

We obtain forecasts of the key macroeconomic variables from Consensus Economics. This dataset includes cross-section of individual forecasts for major macro-economic variables. The survey is monthly and covers the entire analysis period. The number of survey participants range from 11 to 25 with an average of 17 during the sample period. Table 2.1 summarizes the source and content of the variables under consideration.

2.3. Jump Detection Methodology

To extract the jump component of volatility, we employ the jump detection methodology developed by Lee and Mykland (2008). Compared to other jump detection methodologies, this method has the advantage of allowing determination of both size and direction of jumps by indicating their precise times (Neely, 2011).

Table 2.1: Descriptive information of the sample variables

Variable	Source	Frequency	Sample	Observations
USDTRY	Bloomberg	5-min	May 2013-July 2019	464,596
Currency Option Parameters	Bloomberg	Daily	May 2013-July 2019	1618
Equity/Bond Flows	CBRT	Weekly	May 2013-July 2019	323
USDTRY Forecasts	Thomson Reuters	Monthly	Jan 2014-July 2019	67
Macro Var. Forecasts	Consensus Economics	Monthly	May 2013-July 2019	74

This methodology basically involves calculating a test statistic for each return observation by comparing its absolute value with a rolling window local variation measure as the following:

$$J_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i}} \quad (2.1)$$

In this setup, each day t consists of M equally spaced intraday returns, where $r_{t,i}$ is the 5-min log-return of the spot exchange rate in the interval i of day t and $\eta_{t,i}$ is the local variation measure calculated by an integrated volatility measure. Since standard realized volatility measures (e.g., sum of squared log-returns) fail to estimate integrated volatility consistently in the presence of jumps, Lee and Mykland (2008) suggest estimating $\eta_{t,i}$ by a jump robust realized volatility measure called realized bi-power variation (RBPV) developed by Barndorff-Nielsen and Shephard (2004) as the following:

$$RBPV_t(M) = \mu^{-2} \frac{M}{M-2} \sum_{i=2}^M |r_{t,i}| |r_{t-1,i}| \quad (2.2)$$

where $\mu = \sqrt{2/\pi}$ and M is the number of observations in the local variation window. One important aspect of this local variation measure is the selection of appropriate window length. Lee and Mykland (2008) suggest that it is appropriate to use a window length of 270 data points for 5 minutes returns.

In calculating $J_{t,i}$, intraday periodicity has to be taken into account. In order to do this, Boudt et al. (2011) propose to re-scale returns by an intraday periodicity factor so that one can avoid over-detection (under-detection) of jumps in intraday intervals with high (low) volatility. Motivated by this, we follow the procedure suggested by Boudt and Petitjean (2014) and estimate the intraday periodicity factor $f_{t,i}$ by estimating a flexible Fourier specification as in Andersen and

Bollerslev (1998). In Figure 2.2, we show the estimated volatility periodicity factors and the realized intraday volatility pattern (average of absolute log-returns for each 5-min interval). The volatility is higher around local trading session and decreases through off-shore trading session. In the realized periodicity pattern, the spikes are observed around the opening and closing of the local trading sessions. Once we estimate the intraday periodicity factor $f_{t,i}$, we obtain the filtered jump statistic $FJ_{t,i}$ as the following:

$$FJ_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i} f_{t,i}} \quad (2.3)$$

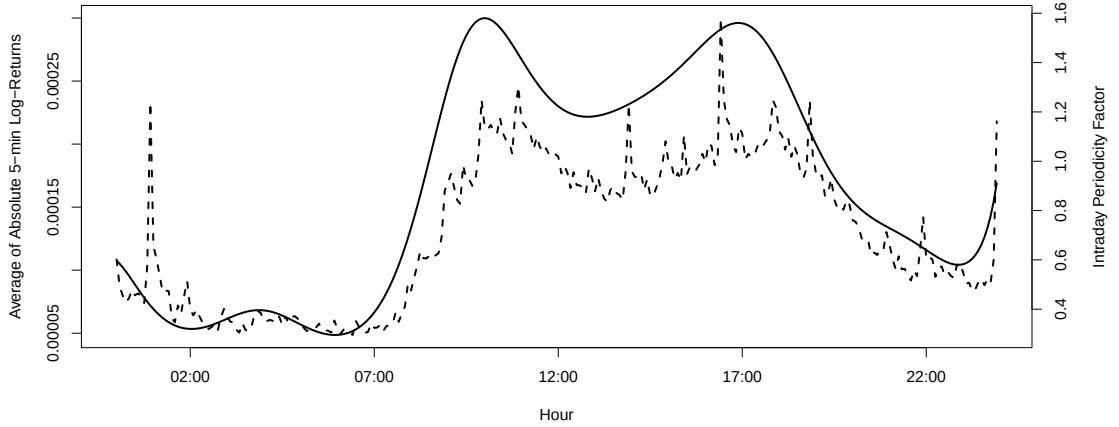


Figure 2.2: Estimated periodicity pattern and the intraday average absolute changes
Note: The dashed line is obtained by averaging absolute value logarithmic returns for each 5 minute interval. The solid line shows the periodicity pattern estimated from the sample of 5-min frequency observations from May 20, 2013 to August 1, 2019.

In order to overcome the problem of underestimation of $\eta_{t,i}$, and thus over-rejection of the null hypothesis of no jump in the local variation window in times of many repeating quotations or missing values, we eliminate the jump statistics for the returns whose local variation window contains 58 (that is more than 20% of 288, the number of 5-minute observations in a trading day) or more zero, or missing

values. This allows us to avoid false jump detection in public holidays when the market is open but there is too little trading activity.

Lee and Mykland (2008) show that the obtained jump statistic follows a standard Gumbell distribution. Thus we reject the null hypothesis of no jump if the filtered FJ statistics are greater than the value suggested by the Gumbell distribution; i.e.,

$$FJ_{t,i} > G_{-1}(1 - \alpha)S_n + C_n \quad (2.4)$$

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

$$C_n = (2 \log n)^{0.5} - \frac{\log(\pi) + \log(\log n)}{2(2 \log n)^{0.5}} \quad (2.5)$$

and

$$S_n = \frac{1}{(2 \log n)^{0.5}} \quad (2.6)$$

with n denoting the number of total observations. The α term in equation (3.5) is the significance of discontinuity in the local variation window and we use an α level of 5% in the rest of the paper.

Figure 2.3 illustrates the intra-daily size and frequency distribution of the detected jumps. The jumps in local trading sessions are lower in number but their magnitude are much larger compared to those realized during the off-shore trading hours. Similar to the daily volatility pattern, jump size and intensity both rise around the market opening and closing times and the intervals around local and US macro news release hours. Average jump size takes its highest value in the 5-minute interval covering 10:00 a.m., in which major local macro-news announcements are made. Similarly, both size and frequency of jumps are

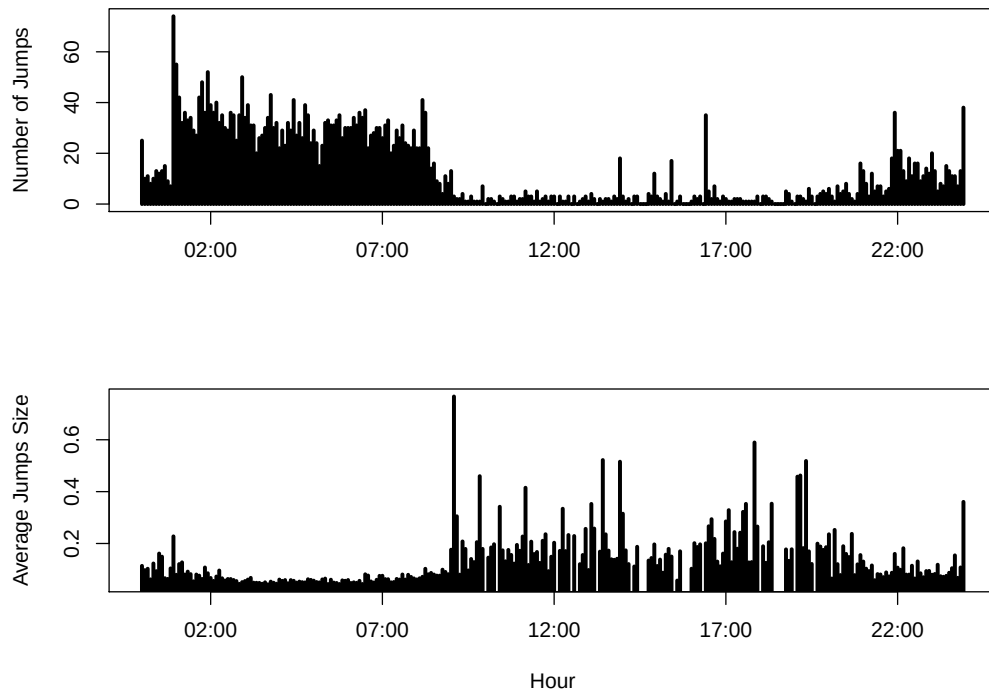


Figure 2.3: Intradaily distributions of size and frequency of detected jumps
 Note: This figure shows the intraday distribution of jump intensity and jump size. In the upper plot, we display the jump frequency within the corresponding 5-min intervals. In the lower plot, we calculate the average absolute percentage returns of jumps within the specified intervals.

relatively higher around US macro-news release hours, mostly around 15:30 (or 16:30 when daylight saving time is used).

As the size and frequency of jumps differ in local and off-shore trading sessions, we distinguish them for analysis purposes since characterization of jumps depending on their occurrence time may provide additional insight on their determinants. In particular, by separating jumps with respect to different trading sessions, we question whether their determinants vary across liquidity conditions. Due to its size and de-centralized structure of the FX market, various types of traders with different trading scopes and information sets are present in different trading sessions. Off-shore markets exhibit reduced participation of local retail, interbank and central bank activity thus with the reduced market depth, the likelihood of sudden return and jumps might increase due to illiquidity. In addition, since bid-ask spread widens around off-shore trading hours, another important consequence is the decrease in high frequency trading activity due to higher trading costs. To distinguish jumps occurring in local and off-shore trading sessions, we refer to jumps in local trading sessions as the jumps occurring between 08:00 to 18:00 in local time zone and otherwise off-shore trading hour jumps.

In Table 2.2, we present the summary statistics of the detected jumps with respect to trading hour classifications. We identify 3933 jumps over the whole sample period. The number of positive jumps exceeds negative ones by 16%. Average jump size is 0.09% and it is higher for positive jumps.⁴ A big portion of the jumps occur in off-shore trading sessions but their average size is less than half of those jumps occurring in local trading sessions. Extreme case analysis provides us fascinating results. Accordingly, at some point in the sample, Turkish lira lost 4.48% of its value against the US dollar in just 5 minutes. Although this observation is realized

⁴In our context, positive (negative) jump yields depreciation (appreciation) of the local currency against the US dollar.

Table 2.2: Descriptive statistics of the detected jumps

		$Jfrequency$	$Jsize$	$P(J)$	$Jdays$	$P(Jdays)$	$Jsize_{max}$	obs.
All Trading Sessions	J	3933	0.091	0.85%	1207	74.60%	4.48%	464,596
	J^-	1820	0.086	0.39%	921	56.92%	2.36%	464,596
	J^+	2113	0.094	0.45%	988	61.06%	4.48%	464,596
Local Trading Sessions	J	505	0.163	0.26%	374	23.11%	2.36%	193,698
	J^-	226	0.160	0.12%	201	12.42%	2.36%	193,698
	J^+	279	0.165	0.14%	231	14.28%	2.03%	193,698
Off-Shore Trading Sessions	J	3428	0.080	1.27%	1123	69.41%	4.48%	270,898
	J^-	1594	0.076	0.59%	833	51.48%	1.27%	270,898
	J^+	1834	0.084	0.68%	906	56.00%	4.48%	270,898

Note: In this table we report the descriptive statistics of the detected jumps at 5% significance level using the non-parametric approach suggested by Lee and Mykland (2008) after filtering the data for the intraday periodicity pattern suggested by Boudt et al. (2011). The sample includes 1618 business days covering the period from May 20, 2013 to August 1, 2019. $P(J)$ denotes the percentage of 5-min intervals with a jump in the sample whereas $P(Jdays)$ is the percentage of days with at least one jump in the sample. $Jsize_{max}$ is the maximum jump size observed in a single 5-min interval.

in an off-shore trading session, the case of the local trading session is not so different. Both positive and negative jumps larger than 2% occasionally occur in only 5 minutes when the FX market is at its most liquid state.

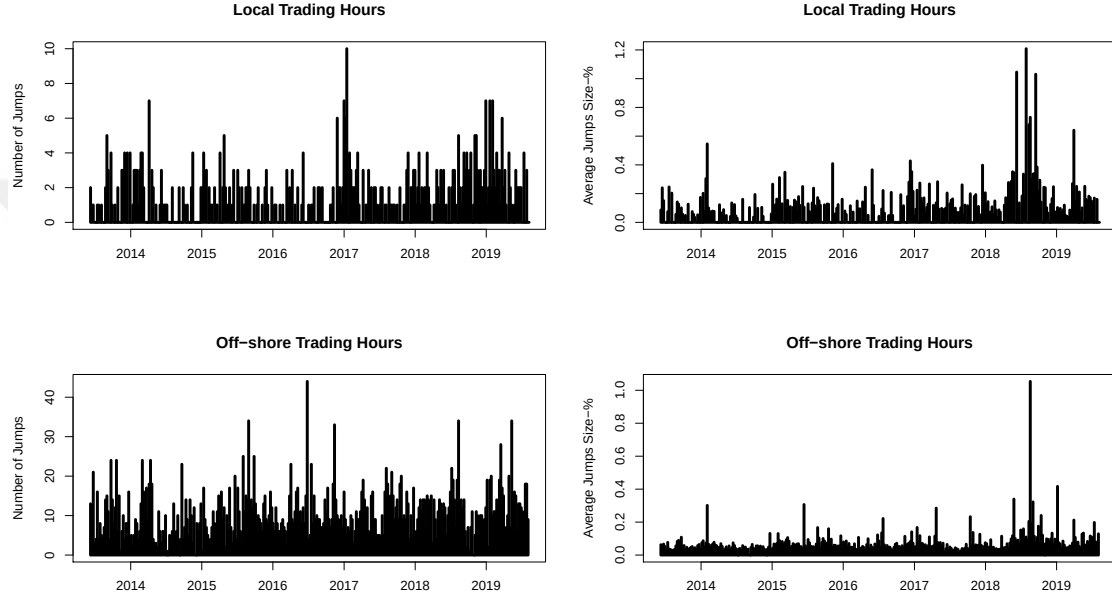


Figure 2.4: Weekly time series of the average jump size and jump frequency for the local and off-shore trading hours

Figure 2.4 displays the weekly time series of the number of jumps and the average jump size regarding the USDTRY exchange rate, segregated at the local and off-shore trading periods. During the off-shore trading hours, jump intensity exhibits more of a uniform distribution across time. On the other hand, there is a clear accumulation in the observed jumps in the years 2018 and 2019, reflecting the excess volatility and uncertainty in the economic and financial markets in Turkey during that time. The month with the highest average jump size is the August of 2018 when the country was experiencing one of the most turbulent financial periods in its history. In this month, average jump size is 0.36% with positive jumps having

an average of 0.40%, showing the serious depreciation of the local currency in short time periods. The maximum number of jumps, on the other hand, is observed in August 2017. In this month, there are 42 negative and 55 positive jumps, adding up to 97 in total. However, we need to emphasize that 61 out of 97 jumps that occurred in this month are realized in the off-shore trading hours.

2.4. Potential Sources of the Jumps I: Portfolio Flows

In this section, we try to find out the potential sources of the jumps in the USDTRY exchange rate series through a portfolio flow analysis. Specifically, we test for the effects of equity and bond flows, and carry trade activity.

2.4.1 Equity and Bond Flows

To investigate the linkage between the weekly foreign portfolio flows and the weekly average jump size and frequency, we aggregate high frequency jump observations into a weekly series denoted by J_t . To avoid synchronicity problems, we carefully match the jumps and the portfolio flow data (which is recorded from Monday to Friday) to cover exactly the same time period within a week. To analyze the impact of equity and bond portfolio flows, we follow a similar specification with Caporale et al. (2017) and estimate the following regression in equation (4.4).

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 F_t^{equity} + \varphi_3 F_{t-1}^{equity} + \varphi_4 F_t^{bond} + \varphi_5 F_{t-1}^{bond} + v_t \quad (2.7)$$

In this equation, F_t^{equity} and F_t^{bond} stand for net equity and bond inflows in million USD units in week t , respectively. When we estimate the model above, we consider several variants of the jump variable J_t . In particular, we analyze the number of

jumps and their average size; their direction (overall, positive, negative); and jump occurring times (overall, local trading hours, off-shore) that add up to $2 \times 3 \times 3 = 18$ versions of the J_t . Such an identification allows us to identify differential impacts of potential explanatory variables to different jump variants. The lagged jump term J_{t-1} is included to capture the potential jump clustering phenomena.^{5,6} In each estimation (and the following estimations within the rest of this paper), standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) procedure.

In addition to the segregate analysis of the impact of equity and bond flows, we want to see the effect of the overall portfolio flows on the exchange rate's jump dynamics. To do so, we sum up equity and bond flows and estimate the model in equation (4.5) for the total flows F_t^{total} :

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 F_t^{total} + \varphi_3 F_{t-1}^{total} + v_t \quad (2.8)$$

The estimation results of the models in equations (4.4) and (4.5) are displayed in Table 2.3. The regression results show that there is a contemporaneous and significantly negative impact of equity and bond inflows. The lagged equity and bond inflows on the other hand, has no significant impact on any variant of jump

⁵One of the stylized facts of the financial markets is volatility clustering, i.e., 'large asset price changes tend to be followed by large changes again, of either sign, and small changes tend to be followed by small changes' as stated by Mandelbrot (1963). Since jump is a special case of volatility, it is plausible to assume that similar effect might also be observed. For example, see Ait-Sahalia et al. (2015).

⁶Through the rest of the paper, when we search for the potential sources of jumps, the independent lagged jump term J_{t-1} is considered in the same category with the dependent concurrent jump term J_t with respect to the sign of the jump. In particular, when we try to explain the size or the frequency of the positive (negative) jumps, the lagged jump term J_{t-1} is also either the size or the frequency of the positive (negative) jumps. However, one might argue that lagged jumps can create concurrent jumps with the opposite sign as the markets tend to display bouncing effects from time to time. In this paper, for all the analyzed models in search for the sources of jumps, we also estimate their counterparts where the lagged jump term J_{t-1} is independent of the sign; i.e., it reflects the values related to the total jump characteristics. The corresponding results are qualitatively the same with the original findings (since jumps are usually found to occur symmetrically in a week in our analysis) and they are provided in the Internet Appendix.

Table 2.3: Impact of portfolio flows on jump size and frequency

	Equity & Bond Flows						Total Flows				
	J_{t-1}	F_t^{equity}	F_{t-1}^{equity}	F_t^{bond}	F_{t-1}^{bond}	R^2	J_{t-1}	$F_t^{totalflows}$	$F_{t-1}^{totalflows}$	R^2	
All	J^{freq}	173.11***	1.031	1.244	-1.85***	-0.371	4.7%	167.70587***	-1.23898**	0.080	4.0%
	$J^{freq,-}$	58.301	0.375	0.632	-0.95***	0.006	2.2%	56.475	-0.67525*	0.194	1.7%
	$J^{freq,+}$	166.79***	0.554	0.659	-0.85**	-0.473	4.1%	161.22558***	-0.542	-0.188	3.5%
	J^{size}	323.89***	-0.05***	0.03**	-0.01**	-0.006	13.9%	316.44882***	-0.01878***	-0.001	12.6%
	$J^{size,-}$	242.41***	-0.06***	0.03**	-0.02***	-0.008	10.5%	231.15213***	-0.02558***	-0.003	9.0%
	$J^{size,+}$	252.73***	-0.04**	0.028	-0.01**	-0.008	8.8%	250.62331***	-0.01811***	-0.003	8.1%
Local	J^{freq}	148.56*	0.677	0.240	-0.32445*	0.005	4.0%	159.03712**	-0.123	0.104	2.9%
	$J^{freq,-}$	-51.275	0.53201*	0.308	-0.121	0.049	2.3%	-34.379	0.014	0.132	0.8%
	$J^{freq,+}$	168.15**	0.228	0.035	-0.22648*	-0.067	4.1%	170.70948**	-0.136	-0.023	3.6%
	J^{size}	176.93*	-0.1**	-0.013	-0.017	0.000	6.2%	176.22044*	-0.03339***	-0.007	5.3%
	$J^{size,-}$	67.009	-0.07127*	0.000	-0.01887*	0.005	1.6%	63.706	-0.02911**	0.002	1.3%
	$J^{size,+}$	80.996	-0.08**	0.000	-0.02**	-0.014	3.6%	80.751	-0.03204**	-0.015	3.1%
Off-Shore	J^{freq}	161.63***	0.316	1.022	-1.53**	-0.399	3.9%	156.32729***	-1.11949**	-0.039	3.5%
	$J^{freq,-}$	69.942	-0.099	0.385	-0.85***	-0.051	2.1%	67.104	-0.6915**	0.069	1.9%
	$J^{freq,+}$	159.45***	0.305	0.624	-0.6257*	-0.408	3.4%	154.52529***	-0.409	-0.166	3.0%
	J^{size}	223.35***	-0.04***	0.022	-0.01***	-0.007	8.0%	219.60136***	-0.01816***	-0.003	7.2%
	$J^{size,-}$	244.32***	-0.05***	0.02543*	-0.02***	-0.006	10.7%	237.16511***	-0.02169***	-0.002	9.5%
	$J^{size,+}$	168.92***	-0.04**	0.021	-0.01**	-0.007	4.6%	168.41094***	-0.01606***	-0.003	4.1%

Note: This table presents the regression results of equations (4.4) and (4.5). The sample period is from May 2013 to July 2019. F_t^{equity} , F_t^{bond} and F_t^{total} stand for weekly equity, bond and total portfolio flows in million USD units respectively. The coefficient estimates are multiplied by 1000 for improving readability. J^{freq} and J^{size} denote the jump intensity and average jump size respectively. The "+" and "-" signs show direction of the jumps. Standard errors are adjusted using the Newey-West procedure. ***, **, and * refer to 1%, 5% and 10% significance levels.

size and frequency except the positive impact of lagged equity inflows on average size of negative jumps at 5% level. An increase in equity, bond or total foreign portfolio inflows significantly reduces the average jump size in general, and also the jump intensity in some occasions. In both local and off-shore trading sessions, equity and bond inflows significantly decrease the average size of positive jumps. In addition to that, the bond inflows significantly reduce the number of jumps in off-shore trading sessions. Overall, the coefficient estimates show that, increase in bond inflows decreases both the size and frequency of jumps significantly. One billion US dollar worth of equity inflow reduces overall jump sizes by 0.05% which is 55% of the average jump size. Likewise, the bond inflows that worth the same amount in US dollars reduce the average jump size by 0.01% which is 11% of the average jump size. Total of equity and bond inflows reduce the average size of upward and downward jumps in both local and off-shore trading sessions. We further observe that in the off-shore trading session, total inflows and the number of negative jumps are inversely related. As the jump component accounts for a significant portion of volatility, results confirm the hypothesis that foreign portfolio inflows have a stabilizing effect on the exchange rates.

2.4.2 Carry Trade Activity

In practice, while equity and bond flows mainly measure the flow in exchange traded funds, another important source of foreign funds are in the form of carry trade investments, and the Turkish lira is among the most heavily traded emerging market currencies in carry trade strategies. However, since such strategies involve over the counter transactions, their volume data is not readily available as in the case of equity and bond flows. Therefore, we use some proxies at this stage. Since carry trade investors seek for risk adjusted rate differentials, an ex-ante attractiveness measure such as carry-to-risk ratio can be a good proxy for carry

trade activity (or profitability) which is expected to have a significant impact on exchange rate jumps since this profitability performance can lead to unwinding or increasing carry trade positions and thus may lead to sudden upwards or downwards movements in the exchange rates (Curcucu et al., 2011; Galati et al., 2007).

Carry trade profitability can be calculated through a plain vanilla carry trade strategy by taking the differences in investing and the funding currency interest rates and adjusting it for risk via the implied volatility as in follows,

$$C_t = \frac{r_t^{TRY} - r_t^{USD}}{IV_t^{USDTRY}} \quad (2.9)$$

where r^{TRY} is the 3 month FX swap rate, r^{USD} is the 3 month LIBOR rate and IV^{USDTRY} denotes the 3 month at-the-money implied volatility derived from the USDTRY options. Changes in C_t enables us to decide whether a currency will be (hypothetically) subject to unwinding of carry trade positions or not; in other words, increasing C_t implies position formation in Turkish lira whereas decreasing C_t shows unwinding of long positions in Turkish lira. In order to analyze the impact of carry trade profitability on the exchange rate jump dynamics, we estimate the model in the following equation (4.6),

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 \Delta C_t + \varphi_3 \Delta C_{t-1} + v_t \quad (2.10)$$

and as in the previous analysis, we consider all 18 variants of the J_t to understand the impact of carry trade profitability in several dimensions.

Carry trade activity can also be measured by the net short positions in the funding currency and the net long positions in the target currency. For instance,

Brunnermeier et al. (2008) and Hutchison and Sushko (2013) use net futures positioning data from Commodity Futures Trading Commission for that purpose. In their setting, net long futures position in the target currency is used as a proxy for carry trade activity. Since a major funding currency in Turkish lira carry strategies is the Japanese yen (JPY), we also use the net long open interest in TRYJPY futures contracts traded in the Tokyo Financial Exchange as an alternative tractable measure of carry trade activity for robustness. Although trading volume in this market constitutes a small portion of the total trading volume of the Turkish lira derivatives, we still believe that the results might present new insights on the subject and provide consistency for the analysis of carry trade strategies involving US dollars. At this stage, the main model to be estimated is presented in the following equation (4.7) in which the NLP refers to the net long position in the Turkish lira.

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 \Delta NLP_t^{TRYJPY} + \varphi_3 \Delta NLP_{t-1}^{TRYJPY} + v_t \quad (2.11)$$

Figure 2.5 exhibits the carry trade profitability in time through investing in Turkish lira against the US dollar (on the right) and Japanese yen (on the left). Comparing these figures shows us that net long positions in TRYJPY futures contracts closely follow the carry-to-risk ratio of the Turkish lira against the US dollar, confirming the appropriateness of carry-to-risk ratio as a proxy for carry trade activity. Table 2.4 displays the estimation results of both equations (4.6) and (4.7). Increases in carry-to-risk ratio significantly reduce the number of positive jumps in local trading sessions and both negative and positive jump frequency in the off-shore trading sessions. Furthermore, we find that carry-to-risk ratio is negatively related to the average size of upward jumps in off-shore trading sessions. These findings are not surprising as the decreasing carry-to-risk ratio lowers the attractiveness of the Turkish lira, leading to unwinding of positions. Thus, negative

relationship between jump frequency and carry trade activity confirms the previous risk based explanations of Brunnermeier et al. (2008) on the subject. Furthermore, the significance of the negative impact is stronger in off-shore trading hours which implies a stronger carry trade activity in this period.

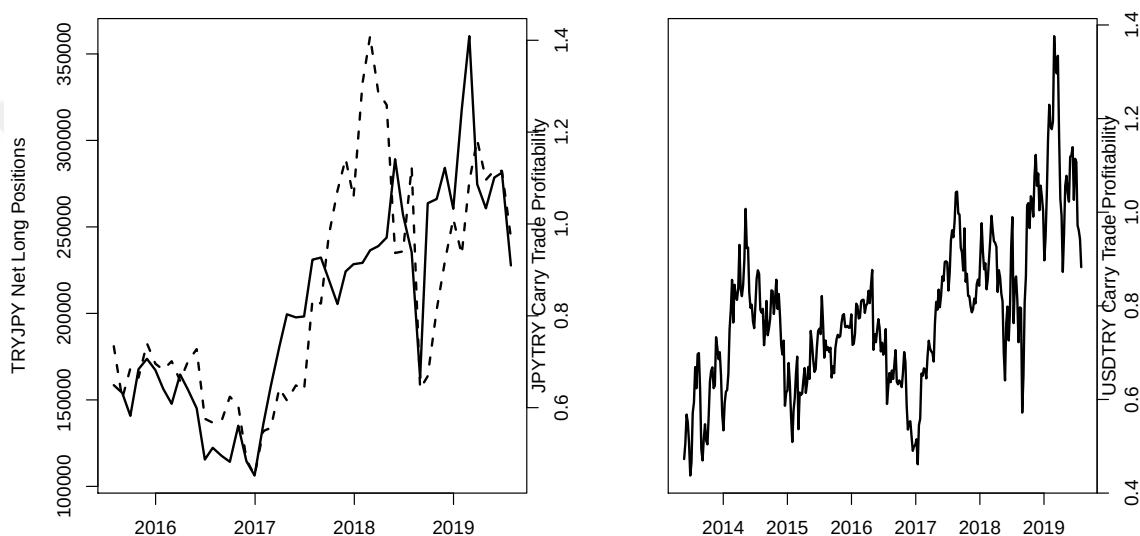


Figure 2.5: Carry trade profitability ratios (Carry-to-Risk Ratio) and net TRYJPY long positions

Note: Subfigure in the left shows the monthly net open interest in TRYJPY futures contracts and the risk adjusted profitability (carry-to-risk ratio) of JPYTRY carry trade. Net long open interest is plotted as the dashed line and is calculated by the difference between open long interests and the open short interest. Single futures contract size is 10,000 TRY. Subfigure in the right shows the weekly carry-to-risk ratio which measures ex-ante carry trade profitability of USDTRY exchange rate.

As mentioned earlier, carry-to-risk ratio measures carry trade activity implicitly whereas the net changes in long TRYJPY futures positions provide a more direct measure. Since, the Japanese yen denominated instruments have long been providing low yield, the high interest rates provided by the Turkish lira makes TRYJPY as a popular carry trade pair. Accordingly, an increase in net long

Table 2.4: Impact of carry trade activity on jump size and frequency

Carry Trade Profitability				TRY/JPY Net Long Positions					
	J_{t-1}	C_t	C_{t-1}	R^2	J_{t-1}	NLP_t^{TRYJPY}	NLP_{t-1}^{TRYJPY}	R^2	
All	J^{freq}	0.148***	-16.736***	-3.651	4.3%	-36.8733	-0.1341*	0.0544	8.8%
	$J^{freq,-}$	0.062	-4.881	-2.149	1.2%	-183.4973	-0.0637**	0.018	11.7%
	$J^{freq,+}$	0.138**	-11.742***	-1.999	4.8%	52.3938	-0.0715*	0.0343	7.5%
	J^{size}	0.396***	-0.092	-0.094	16.3%	596.1289***	-0.0009***	0.0002	56.2%
	$J^{size,-}$	0.326***	0.02	-0.05	10.8%	562.3427***	-0.001***	0	57.0%
	$J^{size,+}$	0.274***	-0.156**	-0.165	10.0%	479.5376***	-0.0008***	0.0004	43.8%
Local	J^{freq}	0.177**	-1.73	1.833	3.7%	686.3612***	-0.0185	0.0042	45.9%
	$J^{freq,-}$	0.004	1.186	1.332	1.2%	595.3123***	-0.0142**	0.0061	34.7%
	$J^{freq,+}$	0.205***	-2.902***	0.766	5.9%	457.8866***	-0.0015	-0.0019	21.3%
	J^{size}	0.275***	-0.125	0.011	7.7%	608.6433***	-0.0011**	-0.0004	57.6%
	$J^{size,-}$	0.088**	0.099	0.29	1.9%	351.803**	-0.0018***	-0.0009	40.1%
	$J^{size,+}$	0.15**	-0.192	-0.132	3.1%	617.6753***	-0.0009***	0	48.9%
Off-Shore	J^{freq}	0.12**	-15.075***	-5.851	3.6%	-36.4452	-0.1312**	0.0517	8.9%
	$J^{freq,-}$	0.037	-6.024**	-3.558	1.7%	-189.5123	-0.062**	0.0138	10.4%
	$J^{freq,+}$	0.12**	-8.991**	-2.776	3.6%	72.9318	-0.0719**	0.0376	9.4%
	J^{size}	0.262***	-0.08	-0.175**	9.8%	374.1526***	-0.0008***	0.0003	43.0%
	$J^{size,-}$	0.32***	-0.026	-0.152*	12.1%	424.7652***	-0.0008***	0.0002	43.7%
	$J^{size,+}$	0.205***	-0.147**	-0.184*	7.7%	257.9756**	-0.0009***	0.0003	37.8%

Note: This table presents the regression results of equations (4.6) and (4.7). The sample period is from May 2013 to July 2019 for carry trade profitability and January 2015 to July 2019 for TRY/JPY net long positions. C_t^i and NLP_t^{TRYJPY} denote alternative carry trade activity (profitability) measures using US dollar and Japanese yen respectively. The coefficient estimates of NLP_t^{TRYJPY} are multiplied by 1000 for improving readability. J^{freq} and J^{size} denote the number of jumps and the average jump size. The "+" and "-" signs show direction of jumps. Newey-West standard errors are used. ***, **, and * refers to 1%, 5% and 10% significance levels.

positions significantly reduces the average jump size in local trading sessions, and both the jump size and intensity in the off-shore trading sessions. In numbers, 100,000 increase in the number of monthly net long futures contracts (that is 1 billion Turkish lira in size) reduces the number of jumps by 13.4 and jump magnitude by 0.09% on average. Similar to the carry-to-risk ratio, significance of the coefficients in off-shore trading sessions are higher suggesting a higher carry trade activity in this period of the day. Furthermore, the magnitude of the coefficients are relatively larger in the case of both size and frequency of positive jumps compared to the negative jumps confirming the previously addressed asymmetry between positive and negative jumps in the literature by Piccotti (2018) and Kapadia and Zekhnini (2019). Overall, we find that an increase in carry trade positions (proxied by either carry-to-risk ratio or net long positions in TRYJPY futures contracts) is negatively related to the average jump size and intensity.

2.4.3 Robustness Analysis: Generalized Method of Moments

The investigation of the relation between portfolio flows and exchange rate jumps can suffer from simultaneity bias when portfolio outflows (inflows) coincide with exchange rate appreciation (depreciation) episodes. Furthermore, both variables are subject to omitted variable bias as they can be affected by variables like changes in liquidity or risk premium. Likewise, both carry-to-risk ratio and jumps can be strongly related with the changes in volatility risk premium (Cho et al., 2019). For example, Busch et al. (2011) find that implied volatility has a good out-of sample predictive power for the jump components of equity, bond and foreign exchange rate realized volatilities.

To mitigate such potential endogeneity issues, we use Generalized Method of Moments (GMM) estimation procedure in this sub-section. Within this framework, we use the lagged values of the endogenous variables as instrumental variables, and

for each X_t and J_t pair we estimate the following system of structural equations,

$$\Delta X_t = \phi_0 + \phi_1 J_t + \phi_2 \Delta X_{t-1} + \phi_3 J_{t-1} + u_t \quad (2.12)$$

$$J_t = \gamma_0 + \gamma_1 \Delta X_t + \gamma_2 \Delta X_{t-1} + \gamma_3 J_{t-1} + v_t \quad (2.13)$$

where J_t is the 18 different jump variants described earlier and the ΔX_t is the first differences of weekly (i) equity flows, (ii) bond flows, (iii) total flows, and (iv) carry-to-risk ratio variables. In total, we have $18 \times 4 = 72$ pairs to be analyzed. Table 2.5 documents the coefficient estimates of the contemporaneous terms of equations (2.12) and (2.13).

Although a broad view of GMM estimation results capture the previously shown negative relationship, some specific cases exhibit slight differences for the individual jump variants. For the equity and bond flows, the differential impact is particularly evident for positive jump frequency in local trading hours. That is, while the weekly net equity inflows significantly increase average jump size, bond flows have the reverse impact. Similarly, equity and bond flows have opposite impacts on the average jump size in off-shore trading session. The total portfolio flows reduce both the average size and frequency of the negative and positive jumps in the local trading sessions.

Similarly, an increase in the carry-to-risk ratio significantly reduces the frequency of both positive and negative jumps, but such an increase has a significantly positive impact on the average jump size. This finding actually is in line with the previous papers by Brunnermeier et al. (2008) and Jurek (2014) who state that carry trade activity leads to infrequent, however larger jumps in exchange rates.

Table 2.5: GMM estimation results for robustness

	F_t^{equity}				F_t^{bond}				F_t^{total}				C_t	
	ϕ_1	γ_1	ϕ_1	γ_1	ϕ_1	γ_1	ϕ_1	γ_1	ϕ_1	γ_1	ϕ_1	γ_1		
All	J^{freq}	-27.6514***	-0.0279***	-18.0416	-0.0020	-0.0032	-35.1395	-0.0075***	-117.8113***					
	$J^{freq,-}$	-71.6622***	-0.0140***	182.6494	0.0034	-0.0017	-109.5180	-0.0110**	-43.0979**					
	$J^{freq,+}$	4.0420	0.0020	-13.1206	-0.0007	0.0018	39.1350	-0.0152***	-61.4308***					
	J^{size}	-3967.5533**	-0.0002***	-2421.1616	0.0000	-0.0001***	-19167.8947**	0.7929***	1.2344***					
	$J^{size,-}$	-1696.7101***	-0.0006***	1439.7802	0.0000	0.0000	-366.7980	0.7420***	1.1585***					
	$J^{size,+}$	1128.4767*	0.0003**	-917.7155	0.0000	0.0000	-1918.2996	0.4408***	1.0062***					
Local	J^{freq}	-227.7318***	-0.0044***	-542.5942***	-0.0018***	-0.0012***	-809.3676***	0.0149	11.6374					
	$J^{freq,-}$	-217.9807***	-0.0040***	-636.7906***	-0.0014***	-0.0013***	-691.1394***	0.0238	4.0400					
	$J^{freq,+}$	292.3455***	0.0034***	-584.4258***	-0.0015***	-0.0014***	-577.6702***	0.0175	6.7419					
	J^{size}	377.6992	0.0003	-2752.0508***	-0.0002***	-0.0002***	-3078.903***	0.4507***	2.1985***					
	$J^{size,-}$	-845.3483***	-0.0009***	-618.0777	-0.0001	-0.0002***	-2071.4621***	-0.1587	-2.7367**					
	$J^{size,+}$	-378.8308	-0.0004	-2866.6588***	-0.0003***	-0.0003***	-3185.8469***	0.2093**	1.8254**					
Off-Shore	J^{freq}	-31.0965***	-0.0269***	8.5480	0.0013	-0.0018	-23.1068	-0.0082***	-117.1573***					
	$J^{freq,-}$	-75.0348***	-0.0133***	67.8389	0.0012	-0.0019	-131.7449	-0.0116**	-46.2379**					
	$J^{freq,+}$	-23.7021*	-0.0093*	20.6708	0.0011	0.0024	53.9872	-0.0174***	-55.8372***					
	J^{size}	-3879.5125***	-0.0003***	7910.3142*	0.0001***	0.0000	-4076.3453	0.8499***	0.9879***					
	$J^{size,-}$	-4132.2362***	-0.0002***	8503.7981**	0.0001***	0.0000	1834.5194	1.0747***	0.9148***					
	$J^{size,+}$	-1813.4159*	-0.0003**	3820.1335	0.0001*	0.0000	-2339.7645	0.5718***	0.9694***					

Note: In this table, we report the estimates of the contemporaneous coefficients of equations (2.12) and (2.13). F_t^{equity} , F_t^{bond} and F_t^{total} stand for weekly equity, bond and total portfolio flows in million USD units respectively. C_t is the weekly carry-to-risk ratio of the USDTRY exchange rate.

2.5. Potential Sources of the Jumps II: Heterogeneous Expectations

In this section, we investigate the relation between the jump activity in the USDTRY parity and the heterogeneity in the expectations for future exchange rate levels and macroeconomic variables.

2.5.1 Heterogeneity in FX Expectations

Theoretical as well as late empirical studies suggest that an increase in future expectation heterogeneity might yield excess volatility through either volume or hedge related trading channel, thus can potentially increase the number and size of the jumps in exchange rates (Buraschi and Jiltsov, 2006; Tauchen and Pitts, 1983). To test this argument, we first use the Reuters' historical FX polls data for three month horizons in order to construct a heterogeneity measure of expectations for FX forecasts. Following Beber et al. (2010), we use the mean absolute deviation (MAD) of expectations as an empirical proxy for the differences in beliefs. That is, we calculate the average of absolute deviations from the mean expectations. In addition, we calculate the cross-sectional skewness (SKW) and kurtosis (KUR) of forecasts to capture the time-varying leptokurtosis and asymmetry in the expectations. With this respect, skewness provides insight on the tendency of the expectations (Lin et al., 2019) and kurtosis shows analysts' view on the probability of extreme returns.

To analyze the impact of heterogeneity in expectations on the exchange rate jump dynamics, we estimate the model presented in equation (2.14) which has a similar specification to the one used by Beber et al. (2010). Since the independent variable series related to heterogeneity are not stationary in levels, we take their log

differences in the estimations.

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 \Delta MAD_t + \varphi_3 \Delta SKW_t + \varphi_4 \Delta KUR_t + v_t \quad (2.14)$$

While FX polls give an opportunity to extract foreign exchange rate expectations' moments directly, the currency options can provide an alternative metric to obtain central moments of expectations. In this part, we link jumps with central moments of foreign exchange rate expectations derived from central moments of risk neutral densities (RND) of currency options with 3 month maturities. The use of RND as a proxy for market expectations is common in the literature (Abarca et al., 2010; Castrén, 2005; Csávás, 2010). One advantage of this measure is its ability to provide expectation moments at a higher frequency. In addition, it gives real time market expectations for the future exchange rate level.

In order to extract a measure of dispersion of beliefs on a daily basis, we use the methodology proposed by Malz (1997) to derive risk neutral densities from currency options. According to this methodology, we can derive risk neutral densities by solving the equations (4.16) and (4.17). In this framework, equation (4.16) is derived by Breeden and Litzenberger (1978) and relates the option-delta with the option's strike price,⁷

$$\delta = e^{-r\tau} \Phi\left(-\frac{\ln(\frac{S_t}{X_{i,t}}) - (r - \sigma^2/2)\tau}{\sigma\sqrt{\tau}}\right) \quad (2.15)$$

whereas equation (4.17) shows the parametric functional form of the RND,

$$\sigma(\delta) = b_0 atm_t + b_1 rr_t(\delta - 0.5) + b_2 str_t(\delta - 0.5)^2 \quad (2.16)$$

⁷In equation (4.16), τ is the option's time to maturity in annual terms, r is the continuously compounded annual yield to maturity, S_t is the underlying asset's price on day t , $X_{i,t}$ denotes the alternative strike prices on day t , σ is the underlying asset's volatility and Φ is the cumulative normal distribution.

where atm_t , rr_t and str_t represent at-the-money, 25-delta risk reversal and 25-delta strangle of 3-month currency options on trading day t respectively. Solving equations (4.16) and (4.17) simultaneously provides RNDs for each trading day. That is, we obtain risk neutral probabilities $\omega_{i,t}$ for each potential strike price $X_{i,t}$ on day t .⁸ When we obtain RNDs for each possible strike price, we can calculate the probability distributions for each possible return $r_{i,t}^e$, which allows us to obtain a consistent central moment series across time:

$$r_{i,t}^e = \ln(X_{i,t}) - \ln(S_t) \quad (2.17)$$

where S_t is the spot USDTRY exchange rate on day t . As a belief dispersion measure of exchange rate, we obtain the MAD of expectations using the possible returns and the associated risk neutral probability ω_i as in the following equation (2.18),

$$MAD_t^{rnd} = \sum_{n=1}^N \omega_i [r_{i,t}^e - \bar{r}_{i,t}^e] \quad (2.18)$$

with $\bar{r}_{i,t}^e$ denoting the weighted mean of expectations. Once we obtain the new dispersion measure MAD_t^{rnd} from risk neutrals densities, we can estimate the impact of the heterogeneity in future exchange rate expectations on the jump size and frequency by estimating the model in equation (4.23).

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 \Delta MAD_t^{rnd} + \varphi_3 \Delta SKW_t^{rnd} + \varphi_4 \Delta KUR_t^{rnd} + v_t \quad (2.19)$$

⁸On each day t , i runs from 1 to 700; i.e., there are 700 different strike price on each day for the USDTRY parity where the consecutive strike prices differ by 0.01 Turkish lira. However, quotations are mostly accumulated around at-the-money strike levels.

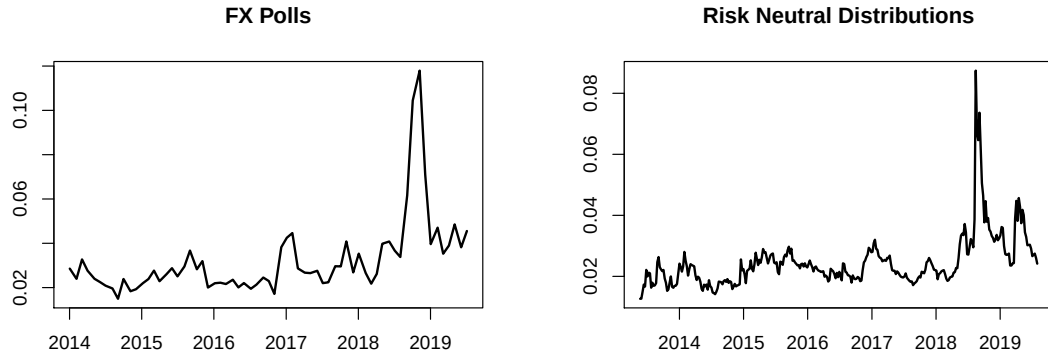


Figure 2.6: Mean absolute deviations in the expectations for 3 month ahead USDTRY exchange rate derived from FX polls and risk neutral densities of currency options

Figure 2.6 displays the mean absolute deviations derived from both the Reuters FX polls and currency options. While FX polls are monthly forecasts, risk neutral densities are taken at weekly frequency. Accordingly, even though they are sampled at different frequencies, both dispersion measures show similar patterns in time, providing consistency and robustness to the findings.

For all 18 variants of J_t , the estimation results for equations (2.14) and (4.23) are provided in Table 2.6. In the left panel, the coefficient estimates for the changes in monthly dispersion in 3 month ahead USDTRY exchange rate expectations are tabulated. The results show that higher dispersion in exchange rate expectations significantly increase the frequency of positive jumps in the local trading sessions. In numbers, 10% increase in the mean absolute deviation in 3-month ahead USDTRY forecasts increase monthly jump intensity in local trading sessions by 5.9 on average. Likewise, dispersion in FX expectations have significantly positive impact on average jump size of positive jumps in local trading sessions. An increase by the same amount increases average jump size by 0.17%. These results are consistent with the literature that proposes a positive relation between heterogeneous expectations and the exchange rate volatility (Beber et al., 2010).

In the right panel of Table 2.6, we present the coefficient estimates for the dispersion in beliefs obtained from risk neutral densities of currency options. Similar to the dispersion measure derived from Reuters FX polls, the results indicate a significantly positive impact of the weekly market based dispersion measure MAD^{rnd} on the average size of positive jumps but we observe this significance in both in local and off-shore trading sessions. A possible explanation for this result is the stronger linkage between FX spot market and the currency option market compared to FX polls. With a similar reasoning, the positive relationship between belief dispersion and the positive jumps are stronger with more significant coefficient estimates for both local and off-shore trading sessions. Since an increase in MAD^{rnd} indicates an increase in heterogeneity among the optimistic and pessimistic option traders' view about the future exchange rate level, the resulting equilibrium between these two groups leads to volatility. Accordingly, an increase in the differences of option traders' beliefs (who are considered among the most professional and informed investors) leads to an increase in the average positive jump size in all trading sessions. Since the positive jumps significantly contribute to the exchange rate volatility, we can say that an increase in the dispersion in future exchange rate expectations is associated with higher foreign exchange rate volatility.

2.5.2 Deviations in Expectations for Key Macroeconomic Variables

In parallel to the argument that the heterogeneity in future expectations for exchange rates has a positive impact on the jump size and intensity, one might argue that an analogous belief dispersion in key macro-economic variables has the potential to create a similar effect. According to Lahiri and Sheng (2010), the belief dispersion in GDP and inflation forecast stems from differences in prior

Table 2.6: Impact of heterogeneous expectations for the foreign exchange rate levels on jump size and frequency

		Reuters FX Polls					Risk Neutral Densities				
		J_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2	J_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2
All	J^{freq}	0.0976	78.4546	4.0911	-2.1069*	7.3%	0.1293**	157.5468	-5.8952**	-0.9371	5.7%
	$J^{freq,-}$	0.0217	-10.929	1.3458	-0.9697*	4.1%	5.8%	27.187	-2.2953	-0.4731	1.9%
	$J^{freq,+}$	0.1104	98.1236	2.7834*	-1.1595	9.5%	0.1108**	140.6243	-3.6385**	-0.3757	6.7%
	J^{size}	0.457***	1.3555*	0.0101	-0.003	38.5%	0.4689***	10.6093***	-0.0012	0.0371	35.4%
	$J^{size,-}$	0.424***	1.4739*	0.0098	-0.0012	37.9%	0.3508***	7.3028**	-0.0339	0.0429	17.9%
	$J^{size,+}$	0.3722***	1.3958*	0.0095	-0.0037	29.2%	0.3501***	12.2849***	0.0084	0.0362	32.4%
Local	J^{freq}	0.5833***	62.8456*	-0.1384	0.4121*	36.8%	0.1572**	10.2353	-1.6274*	-0.2025	5.2%
	$J^{freq,-}$	0.3254**	-4.9863	-0.0151	0.2766*	15.9%	1.0%	-15.7521	-0.3763	-0.1447	0.3%
	$J^{freq,+}$	0.4399***	55.8467**	-0.0665	0.1417	23.3%	0.1628**	25.0299	-1.2736*	-0.0552	7.6%
	J^{size}	0.5686***	2.2962***	0.0014	-0.0132***	53.0%	0.3177**	13.9015**	-0.0821	0.0429	18.8%
	$J^{size,-}$	0.277**	4.2781*	-0.0021	-0.0054	33.7%	7.1%	3.8686	-0.2261*	0.0892	5.5%
	$J^{size,+}$	0.5604***	1.7249**	0.0161	-0.0137**	45.7%	0.2305***	18.8655***	0.0225	0.01	26.9%
Off-Shore	J^{freq}	0.0763	51.1011	4.1798	-2.5622**	9.0%	0.1119**	152.5496	-4.2676*	-0.6829	4.2%
	$J^{freq,-}$	-0.0225	12.2809	1.2984	-1.2577**	6.4%	3.6%	45.3544	-1.92	-0.3046	1.7%
	$J^{freq,+}$	0.1206	47.6436	2.8656*	-1.3184*	11.3%	0.1075**	117.1136	-2.3295	-0.2932	4.7%
	J^{size}	0.2356*	0.8771	0.0092	-0.0019	15.3%	0.3577***	11.0303***	0.0324	0.0332	34.5%
	$J^{size,-}$	0.2827**	0.7958	0.0109*	-0.0015	18.4%	0.4118***	8.5897***	0.0133	0.0124	33.5%
	$J^{size,+}$	0.1432	1.0631	0.0077	-0.0017	11.5%	0.2784**	12.3783***	0.0344	0.0456	29.5%

Note: This table presents the regression results of equations (2.14) and (4.23). The sample period is from January 2014 to July 2019 for the FX polls and May 2013 to July 2019 for risk neutral densities. MAD_t , SKW_t and KUR_t refer to the mean absolute deviation, skewness and kurtosis of the future expectations for exchange rates, respectively. J^{freq} and J^{size} denote the number of jumps and the average jump size. The "+" and "-" signs show direction of jumps. Newey-West standard errors are used. ***, **, * and * refers to 1%, 5% and 10% significance levels.

beliefs and the interpretation of new public information. Such an information asymmetry across traders leads to different valuations of exchange rate and make them react with higher magnitudes to relevant information arrivals. In fact, Hogan and Melvin (1994) find such evidence in the case of heterogeneity in trade balance forecasts and the USDJPY exchange rate. However, to the best of our knowledge, this strand of literature is mostly uncharted. To investigate further, we proceed as in the case of heterogeneity in FX expectations and use mean absolute deviations as a measure belief dispersion for the selected four key macroeconomics variables; namely GDP, CPI, current account balance and budget balance.

In this setup, we use the Consensus Economics forecasts of survey respondents as our main variable for the future expectations. This dataset includes the monthly forecast series of individual contributors for the current and the next calendar year and previously used by several academic studies (e.g., Ehrmann et al. (2019); Ehrmann and Talmi (2019); Tanaka et al. (2019)). However, since these dates are fixed throughout the year, the forecast horizon changes in every month which creates an inconsistency for the calculation of central moments. To avoid this consistency problem in calculating the time series of central moments of expectations, we obtain the one year ahead forecasts of each contributor by following the interpolation method suggested by Doornik et al. (2012). The methodology basically weighs the current year forecasts with the next calendar year forecasts as the following:

$$F_{i,t}^{1year-ahead} = \frac{12 - (m - 1)}{12} F_{i,t}^{current} + \frac{m - 1}{12} F_{i,t}^{next} \quad (2.20)$$

where m is the number of forecast month and $F_{i,t}^{current}$ and $F_{i,t}^{next}$ are the current and next calendar year forecast values of the macroeconomic variable i on forecast date t .

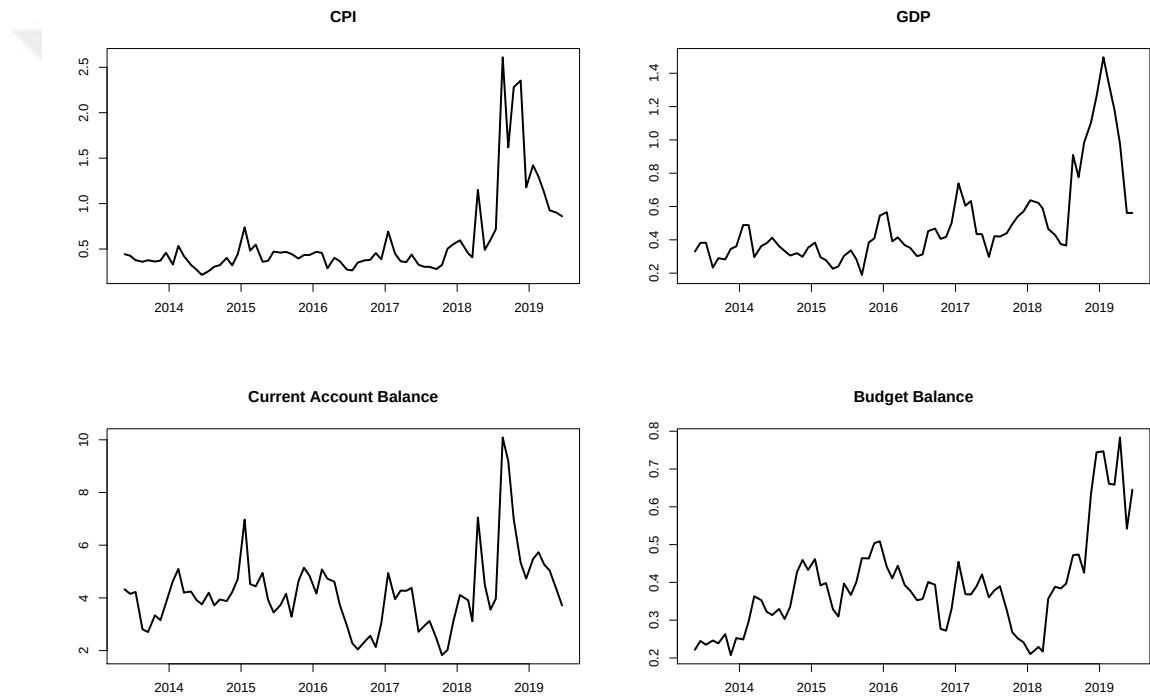


Figure 2.7: Mean absolute deviations in the expectations for the 1 year ahead levels key macroeconomic variables

After we obtain monthly cross-section of one year-ahead forecast series, we can calculate the time series of central moments using them. Figure 2.7 displays the calculated mean absolute deviations of this one year-ahead forecasts of the key macroeconomic variables. Accordingly, without an exception, mean absolute deviation for each sample macroeconomic variable exhibits similarities with that of the FX expectations, which is not surprising since foreign exchange rate is an important driver for them all. For all the variables, the disagreement on the future level is highest around the financial turbulence experience in the summer of 2018 in Turkey. While the three macroeconomic variables recovered from high levels of uncertainty in expectations, the belief dispersion on the budget balance is still relatively high due to the increasing government expenditures to recover from this turbulence.

To investigate the impact of heterogeneity in expectations for macroeconomic variables, we proceed in a similar fashion to the previous analyses and estimate the model presented in the following equation (2.21).

$$J_t = \mu + \varphi_1 J_{t-1} + \varphi_2 \Delta MAD_t^{macro} + \varphi_3 \Delta SKW_t^{macro} + \varphi_4 \Delta KUR_t^{macro} + v_t \quad (2.21)$$

In Table 2.7, we present the coefficient estimates for the mean absolute deviations of the four macroeconomic variables. The results show that higher dispersion in GDP and budget balance expectations significantly increase the number of jumps in the upward direction. Furthermore, the results indicate that the dispersion in GDP expectations increases the average jump size, particularly in off-shore trading sessions whereas the dispersion in beliefs for future current account levels is not significant for none of the jump size or frequency variant. Higher dispersion in CPI

Table 2.7: Impact of belief dispersion of the future value of key macro-economic variables on jump size and frequency

	GDP					CPI					
	J^i_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2	J^i_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2	
All	J^{freq}_t	0.0911	-0.4826	-1.2591	-0.4382	0.9%	0.102	9.0609	-0.5567	0.4482	3.5%
	$J^{freq}_t, -$	0.0069	-3.2303	-0.2855	-0.0573	0.2%	-0.0017	3.8066	-1.289	-0.0115	2.4%
	$J^{freq}_t, +$	0.1046	2.7093	-1.0569	-0.3842	1.4%	0.1512	5.2492	0.74	0.5137	5.7%
	J^{size}_t	0.5621***	0.1256**	0.0062	0.0025	42.8%	0.601***	0.0455**	-0.0065	0.004	43.6%
	$J^{size}_t, -$	0.5296***	0.0983	0.0117	0.0051	34.2%	0.5336***	0.0197	-0.0049	0.0027	29.7%
Local	$J^{size}_t, +$	0.5118***	0.1496**	0.0046	0.0009	40.4%	0.572***	0.066***	-0.0074	0.0045	47.4%
	J^{freq}_t	0.4624***	14.7519**	1.864	0.4552	29.3%	0.4261***	1.5718	0.0724	0.174	18.5%
	$J^{freq}_t, -$	0.1756*	5.0647	0.3809	0.1393	8.7%	0.112	-0.3663	0.1444	0.0178	2.0%
	$J^{freq}_t, +$	0.4144***	8.7082**	1.5354	0.3132	24.0%	0.4055***	1.5532*	0.0287	0.157	18.0%
	J^{size}_t	0.4416***	0.0498	-0.0251	0.004	24.9%	0.4446***	0.0659	-0.0207	0.0105	24.1%
Off-Shore	$J^{size}_t, -$	0.2547*	-0.0394	-0.0075	0.0044	6.7%	0.2548***	-0.034	-0.0351	0.0069	9.6%
	$J^{size}_t, +$	0.3573***	0.2441	0.0063	0.0052	23.6%	0.4134***	0.1151**	-0.0118	0.0117*	30.4%
	J^{freq}_t	0.0794	-12.8044	-3.2528	-0.9797	1.5%	0.0827	8.2922	-0.7703	0.2959	3.0%
	$J^{freq}_t, -$	0.01	-7.8344	-0.6925	-0.1873	1.1%	-0.0148	4.318	-1.512	-0.019	3.3%
	$J^{freq}_t, +$	0.0861	-4.8909	-2.6625	-0.7901	1.8%	0.1331	4.021	0.7187	0.3637	4.3%
	J^{size}_t	0.4899***	0.1232**	0.0067	0.0017	37.3%	0.5389***	0.0473***	-0.0039	0.0029	40.5%
	$J^{size}_t, -$	0.4969***	0.1179**	0.0116	0.0033	36.0%	0.5331***	0.041***	-0.0045	0.0014	35.9%
	$J^{size}_t, +$	0.4427***	0.1251*	0.0024	0.0003	32.6%	0.4969***	0.054***	-0.004	0.0036	38.7%
	Budget Balance					Current Account Balance					
	J^i_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2	J^i_{t-1}	ΔMAD_t	ΔSKW_t	ΔKUR_t	R^2	
All	J^{freq}_t	0.0914	-15.9914	-1.0691	-0.7911	1.2%	0.1057	3.135	3.5859	-0.3191	6.3%
	$J^{freq}_t, -$	0.0032	-17.352	-0.6149	-0.1878	1.4%	0.0167	1.2933	2.4203	-0.2135	6.4%
	$J^{freq}_t, +$	0.1111	1.1645	-0.347	-0.6002	1.4%	0.1189	1.8585	1.1715	-0.181	5.6%
	J^{size}_t	0.5702***	0.1119	-0.0018	-0.0013	35.2%	0.6437***	0.0099	-0.0079	-0.0016	41.6%
	$J^{size}_t, -$	0.5191***	0.146*	0.0113	0.003	31.2%	0.5925***	0.0075	-0.006	-0.0028	34.2%
Local	$J^{size}_t, +$	0.5386***	0.0859	-0.0112	-0.0042	30.4%	0.5869***	0.011	-0.0086	-0.0004	36.9%
	J^{freq}_t	0.4374***	17.958**	-0.2605	-0.364	23.8%	0.4183***	0.4904	0.3585	-0.0298	18.3%
	$J^{freq}_t, -$	0.1081	5.9469	0.9923	0.3238	5.6%	0.123	-0.0199	0.0811	-0.0177	1.6%
	$J^{freq}_t, +$	0.4108***	11.5207**	-0.7877	-0.4506	22.5%	0.3947***	0.4702	0.2874	-0.0175	17.7%
	J^{size}_t	0.4328***	0.3129*	0.0055	0.0013	21.9%	0.473***	0.0185	-0.0072	-0.0052	24.7%
Off-Shore	$J^{size}_t, -$	0.2446**	0.2425	0.0665	0.0136	9.2%	0.236**	-0.0012	0.0289*	-0.0174	11.1%
	$J^{size}_t, +$	0.3883***	0.2848	-0.02	-0.0022	18.6%	0.4313***	0.0248	-0.0254	0.0049	25.7%
	J^{freq}_t	0.0785	-33.9946	-1.9808	-0.9416	2.1%	0.0915	2.7793	3.1969	-0.2724	5.6%
	$J^{freq}_t, -$	0.0043	-23.1297	-1.7366	-0.5795	2.8%	0.0128	1.3259	2.3359	-0.1984	6.8%
	$J^{freq}_t, +$	0.0922	-10.9273	-0.19	-0.3875	1.5%	0.1036	1.4734	0.8645	-0.141	4.3%
	J^{size}_t	0.5056***	0.082	-0.0054	-0.0011	27.1%	0.554***	0.0086	-0.005	-0.0011	33.0%
	$J^{size}_t, -$	0.4947***	0.0976	-0.0015	0.0003	27.3%	0.5589***	0.0078	-0.0066	-0.0008	32.5%
	$J^{size}_t, +$	0.4698***	0.071	-0.0078	-0.002	22.8%	0.5021***	0.0091	-0.0034	-0.0012	28.1%

Note: This table presents the regression results of equation (2.21). The sample period is from May 2013 to July 2019. MAD_t , SKW_t and KUR_t respectively refer to the mean absolute deviation, skewness and kurtosis of the future expectations for (i) gross domestic product (GDP), (ii) consumer price index (CPI), (iii) budget balance, and (iv) current account balance. J^{freq}_t and J^{size}_t denote the number of jumps and the average jump size. The "+" and "-" signs show direction of jumps. Newey-West standard errors are used. ***, **, and * refers to 1%, 5% and 10% significance levels.

expectations, on the other hand, has significant positive impact on the average size of positive jumps in both local and off-shore trading sessions. In numbers, 1% change in mean absolute deviation of inflation expectations increases the average positive jump size by 0.115% and 0.054% in local and off-shore trading sessions respectively. Since the average number of jumps in a given month is around 30, these numbers translate into significant contribution to foreign exchange rate volatility. As Giordani and Söderlind (2003) argue, disagreement on inflation forecasts is a good proxy of inflation uncertainty and thus a good proxy for monetary policy uncertainty. In this regard, this finding is not surprising given the importance of CPI expectations for monetary policy decisions as the central bank of Turkey follows an inflation targeting framework in conducting its monetary policy. These results are also consistent with those of Xiong and Yan (2010) who theoretically show that increasing dispersion in beliefs about future economic conditions between agents makes them take on speculative positions against each other and the resulting relative fluctuations in their wealth increases the volatility of the traded assets.

2.5.3 Robustness Analysis: Granger Causality

Here we provide an analysis to check the validity of our results on the heterogeneous expectations in the search for potential sources of jumps in the USDTRY exchange rate. The reason is that the evidence is mixed on the direction of causality between the heterogeneous expectations and the volatility. For instance, in the work of Atmaz and Basak (2018), the belief dispersion increases volatility, on the other hand Jongen et al. (2008) find a significantly positive causal relationship from heterogeneous expectations to volatility but also provide evidence on the reverse causality with changing volatility measures. Both findings have implicit implications on an asset price's jump dynamics.

In this part, we perform a causality analysis between the jump variants and heterogeneous expectations. Since our empirical results propose the heterogeneous expectations as determinants of jump characteristics, a potential reverse relationship must also be addressed due to dynamic interaction between these variables. Such a reverse relation might exist given the high dependence of unhedged foreign portfolio investment performance to exchange rates, and high exchange rate pass through characteristic of the CPI in Turkey.

To formally test the direction of this causality, we estimate the following reduced form vector auto-regression (VAR) equations.

$$\Delta X_t = \phi_0 + \sum_{k=1}^p \phi_{1k} \Delta X_{t-k} + \sum_{k=1}^p \phi_{2k} J_{t-k} + u_t \quad (2.22)$$

$$J_t = \gamma_0 + \sum_{k=1}^p \gamma_{1k} J_{t-k} + \sum_{k=1}^p \gamma_{2k} \Delta X_{t-k} + v_t \quad (2.23)$$

By estimating these system of equations, we test two null hypothesis and obtain so called Granger causality test results. The first null hypothesis is that

$H_0 = \gamma_{21} = \gamma_{22} = \dots \gamma_{2p} = 0$, in other words, its rejection would imply that jumps (size or intensity) Granger cause the heterogeneous expectations. And the second null hypothesis is that $H_0 = \phi_{21} = \phi_{22} = \dots = \phi_{2p} = 0$ and its rejection would imply that heterogeneous expectations Granger cause jumps (size or intensity). In this system of equations, optimal number of lag orders p are selected according to the Akaike Information Criteria (AIC).

In Table 2.8, we report the estimated t-statistics from Granger causality tests and their corresponding significance levels. According to these estimation results, although there are few instances of bivariate causality or causality in the reverse direction, we generally observe a univariate causality from belief dispersion

Table 2.8: Causality test results between jumps and heterogeneous expectations

		MAD Granger cause jumps					
		$\Delta MAD_t^{FX_{polls}}$	ΔMAD_t^{RND}	ΔMAD_t^{GDP}	ΔMAD_t^{CPI}	ΔMAD_t^{BB}	ΔMAD_t^{CA}
All	J^{freq}	0.130	17.487***	1.327	0.704	0.678	0.955
	$J^{freq,-}$	1.591	1.124	1.358	0.707	1.215	0.815
	$J^{freq,+}$	1.356	1.038	1.103	0.864	0.428	0.975
	J^{size}	1.805	1.263	2.345**	2.824**	2.736*	0.630
	$J^{size,-}$	3.985***	2.133**	3.085***	4.401***	3.538**	1.000
Local	$J^{size,+}$	3.365***	1.914*	1.803*	2.662**	2.687**	0.274
	J^{freq}	4.024***	1.289	2.067	1.651	1.217	0.141
	$J^{freq,-}$	1.005	1.785*	0.467	1.878	0.748	0.142
	$J^{freq,+}$	2.217*	0.925	1.374	1.100	0.003	0.441
	J^{size}	0.717	2.475**	6.972***	3.981***	1.616	0.552
Off-Shore	$J^{size,-}$	5.391***	7.202***	5.297***	8.078***	4.102***	2.159**
	$J^{size,+}$	5.522***	3.672***	0.541	2.894**	0.766	2.186*
	J^{freq}	3.639**	5.141***	1.175	0.730	0.577	0.884
	$J^{freq,-}$	2.559*	1.305	1.525	0.925	1.002	0.797
	$J^{freq,+}$	2.766*	1.225	1.007	0.804	0.526	0.478
	J^{size}	2.357*	1.325	2.274**	2.390**	1.997	0.779
	$J^{size,-}$	4.051***	1.958*	2.134**	3.112**	1.726	1.373
	$J^{size,+}$	3.221***	1.993*	2.326**	2.845**	3.146***	0.633

		Jumps Granger cause MAD					
		$\Delta MAD_t^{FX_{polls}}$	ΔMAD_t^{RND}	ΔMAD_t^{GDP}	ΔMAD_t^{CPI}	ΔMAD_t^{BB}	ΔMAD_t^{CA}
All	J^{freq}	0.400	11.474***	0.748	0.790	0.248	0.839
	$J^{freq,-}$	1.280	1.101	0.665	0.617	0.230	0.681
	$J^{freq,+}$	0.945	1.255	0.805	0.905	0.245	1.024
	J^{size}	1.444	0.899	0.818	1.884*	0.542	2.635*
	$J^{size,-}$	1.157	6.285***	0.744	2.775**	1.041	2.982**
Local	$J^{size,+}$	1.636	17.026***	1.140	3.003**	1.559	1.913
	J^{freq}	1.032	1.722	0.688	0.027	0.805	1.014
	$J^{freq,-}$	0.480	1.258	2.168**	0.041	3.797**	0.446
	$J^{freq,+}$	2.910**	1.329	0.921	0.161	0.008	0.979
	J^{size}	0.424	1.800*	3.220**	1.614	0.032	2.357*
Off-Shore	$J^{size,-}$	1.654	6.234***	0.470	3.124***	0.600	3.087***
	$J^{size,+}$	1.537	20.019***	1.956	0.184	0.406	1.888
	J^{freq}	0.246	1.247	0.879	1.261	0.231	1.095
	$J^{freq,-}$	1.185	0.951	0.890	1.030	0.170	1.027
	$J^{freq,+}$	0.989	0.882	0.888	1.402	0.290	1.888*
	J^{size}	1.277	0.978	2.633**	2.633**	1.231	1.610
	$J^{size,-}$	0.912	2.563**	1.417	1.613	1.446	3.203***
	$J^{size,+}$	1.280	3.666***	1.430	2.852**	1.091	1.454

Note: In this table we report the t-statistics and corresponding significance levels of Granger causality tests between heterogeneity in 1 year ahead forecasts of key macroeconomic variables measured by mean absolute deviation (MAD), and monthly average jump size and frequency.

measures to jumps which confirms the appropriateness of the direction of causality in our analysis. In particular, for the dispersion of belief measures obtained from Reuters FX polls and risk neutral densities, we find significant Granger causality towards jumps, particularly for the average size of the upward and downward jumps in both local and off-shore trading sessions. Likewise, both types of dispersion in belief measures Granger cause total jump intensities. The causality is significant from mean absolute deviations to the average jump size, and it is relatively stronger compared to the causality from mean absolute deviations to the jump intensity. In the case of heterogeneity in expectations for macroeconomic variables, particularly for GDP and CPI expectations, there is a significant causality from belief dispersion to the average jump size in both local and off-shore trading sessions. Similarly, changes in dispersion in beliefs for budget balance Granger cause average jump size in overall trading sessions. For the causality in the reverse direction, significant cases are very few. Namely, average jump size has limited impact on the heterogeneity in the expectations for CPI and current account deficit. The case of current account balance in particular is no surprise since its future level almost entirely depends on the exchange rate dynamics as Turkey's industrial sector is highly dependent on raw material imports.

2.6. Discussion and Conclusion

Compared to continuous asset prices, jumps produce infrequent, yet extensive price changes and extreme volatility, which represent a significant source of non-diversifiable risk. In recent years, world has witnessed several cases of sudden and large deviations in asset prices, in particular for the currencies of the emerging markets. Just in August of 2018, Argentine peso and Turkish lira lost 29% and 25% of their value against the US dollar. Similarly, South Africa's rand

experienced a depreciation of an almost 10% around the same times, followed by the depreciation of the Indonesian rupiah to its weakest level since the 1997 Asian financial crisis. Motivated by these drastic developments in the emerging markets' currency fluctuations, we focus on the jumps in the US dollar/Turkish lira parity and their potential sources. In particular, we try to reveal the determinants of the size, direction, intensity and timing of the jumps occurring in the USDTRY exchange rate series. This multidimensional analysis is especially important since identification of different jump size and intensity variants and determining their sensitivity to flows and expectations may help increase the precision of foreign exchange rate and volatility forecasts. Moreover, since the adverse effects of jumps can be diffusive on both foreign exchange liquidity and volatility levels in the periods following jumps, policy makers can incorporate monitoring of these jumps to their actions that are related to foreign exchange liquidity provision and risk management.

Accordingly, we find that (i) there is a contemporaneous and significantly negative impact of portfolio inflows. An increase in the equity or bond portfolio inflow reduces the average jump size in both local and off-shore trading sessions. In addition to that, bond inflows reduce the number of jumps with a stronger impact in the off-shore trading sessions relative to the local trading hours; (ii) an increase in the winding of the carry trade positions reduces the average jump size in local trading sessions, and both the jump size and intensity in the off-shore trading sessions. Moreover, the impact of such reduction is relatively stronger in the case of positive jumps compared to the negative ones, presenting an asymmetric effect of carry trade activity; (iii) an increase in the heterogeneity in the expectations for the future exchange rate level also increases the positive and negative jump size in both local and off-shore trading sessions, and the intensity of the positive jumps in local trading hours within a limited effect; (iv) higher dispersion in GDP and

budget balance expectations increases the number of positive jumps in local trading sessions. Furthermore, an increase in the dispersion in GDP and CPI expectations increases the jump size, particularly in off-shore trading sessions, with relatively bigger impact on the average size of positive jumps than negative ones. The results of this paper provides critical policy suggestions. First, an important implication of our findings is that aligning expectations for foreign exchange rate levels and key macroeconomic variables would help not only to mitigate size and frequency of jumps and reduce overall foreign exchange rate volatility but also to increase policy effectiveness. For instance, as suggested in Reitz and Taylor (2008), for the coordination channel of intervention to work, the misalignment in exchange rate expectations should be reduced. In this regard, increased effectiveness of both monetary and fiscal policies can be achieved by improving their communication which will in turn anchor expectations and the resulting reduction in dispersion in beliefs.

Second, another important consequence of jumps in the exchange rate is the resulting dollarization whose deteriorating impact on monetary policy transmission is well documented in the literature. Due to the past experiences of sudden devaluations, sudden spikes in exchange rate may trigger excess demand from both households and the firms with external debt creating a vicious cycle of increasing volatility and increasing FX demand which further increases the depreciation and dollarization. Particularly, when the number and the size of spikes in low liquidity environment during the off-shore trading hours increase, the households become more risk averse as they are not able to trade in those hours and their savings are at risk. This can partially explain the non-resolving record level foreign currency deposit accounts (more than 180bn. USD as of July 2019) in the aftermath of 2018 currency crisis in Turkey, despite the increase in deposit rates in local currency and appreciating Turkish lira against the US dollar. Accordingly, it would be wise for

policymakers to focus on the sources of the positive jumps in off-shore trading hours to create a positive household sentiment against dollarization. Our findings show that bond inflows and synchronicity in the expectations for GDP and CPI would have such effect in particular, therefore policymakers should focus on this aspect as a priority.

Third, excess jump activity in both directions in local trading hours create arbitrage opportunities within very short time periods, even a few minutes. For example, HSBC announced that they made 120mn. US dollar profit in 1 day during the Turkish lira crisis in August 2018.⁹ In such turbulent periods, it becomes tempting to catch similar arbitrage profits, even at the household level. Accordingly, market participants trade excessively in the foreign exchange market, which eventually increases the volume related volatility. This in turn leads to a destabilizing cycle of volume-volatility.¹⁰ Although it is a minor effect, a social byproduct of this process is the productivity inefficiency since many employees prefer to follow the development in the exchange rate at the workplaces instead of executing their jobs. To prevent such negative outcomes, policymakers should pay attention to the sources of jumps in both directions during the local trading hours. According to our analysis, equity and bond flows, and heterogeneity in expectations for the future exchange rate have such particular impact. Consequently, the economic and financial environment to attract foreign portfolio flows should be restored and future exchange rate expectations should be guided more effectively.

⁹<https://www.bloomberg.com/news/articles/2019-02-19/hsbc-made-120-million-in-one-day-during-turkish-currency-rout>

¹⁰In fact, a recent study by Sensoy and Serdengeçti (2019) shows that the spot FX transactions of Turkish lira against the US dollar by domestic investors in Turkey have significant positive relation with the intraday realized volatility of the USDTRY rate during the local trading hours. Therefore, this aspect is particularly important.

CHAPTER III

JUMPS AND COJUMPS IN EMERGING MARKET EXCHANGE RATES AND LIQUIDITY

3.1. Introduction

Decomposition of returns into jumps and time-varying diffusion components is increasingly being studied in the recent empirical finance literature. This identification has undisputed implications on modeling and forecasting asset prices and their volatilities for the scope of investment, policy making and risk management. Characterizing different types of price and liquidity discontinuities is particularly important for foreign exchange rates. FX market is the world's largest market in terms of trading volume and it is relatively more volatile compared to stock and bond markets. Furthermore, foreign portfolio investments in equities and bonds, or carry trade strategies require well elaboration of risk factors related to FX market. Therefore, the need for studying and gaining insight into the jump and co-jump dynamics of exchange rates is of utmost significance for investors, regulators and policy-makers. In this paper, we focus on the dynamics of discontinuities in both the level and liquidity of exchange rates for three highly popular emerging market currencies, namely Mexican peso, Turkish lira and South

African rand which are among the most traded emerging market currencies in the world.

Exploring both foreign exchange rate and liquidity jumps is important for several reasons. First, sudden changes in liquidity levels may serve as a signal for upcoming exchange rate jumps. For instance, Boudt and Petitjean (2014) show that for the stocks that constitute Dow Jones Industrial Average Index, liquidity shocks in the effective bid-ask spread significantly increases the probability of a jump occurrence in stock prices. Likewise, in the case of scheduled macroeconomic news announcements, liquidity conditions surrounding the announcements can predict the reaction of asset prices to the surprises in these announcements as demonstrated by Jiang et al. (2011). In their study, authors show that liquidity shocks preceding macroeconomic news announcements (in the form of changes in bid-ask spread or market depth) have significant predictive performance for jumps in Treasury bond prices. With regard to same bond market, Dungey et al. (2009) show that two-thirds of co-jumps across the maturity structure coincide with liquidity shocks around scheduled US news releases. Second, jumps may carry information on informed trader activity or changes in liquidity provision of monetary authorities (Piccotti, 2018). For instance, Gnabo et al. (2012) show that jumps trigger false rumours on central bank interventions. Third, both return and liquidity jumps have risk and return implications for investors. Jumps create risks for traders which can not be hedged away and enforce investors to demand larger risk premiums. They increase crash risk of exchange rates and thus increase volatility skew and cost of hedging. For example, Barunik and Vacha (2018) show that exchange rate co-jumps significantly influence correlation in currency markets that deteriorates the portfolio construction process. Mancini et al. (2013) show that liquidity risk is a priced risk factor affecting carry trade returns. In a similar manner, Li et al. (2017) argue that asset price discontinuity is a non-diversifiable

risk and also a priced risk factor affecting expensiveness of the corresponding options. On the other hand, Novotny et al. (2015) find that jumps in currency returns provide profitable trade opportunities. Similarly, Lee and Wang (2019b) suggest jump-robust carry trade strategies which show higher returns and lower standard deviations than the regular carry trade. Fourth, currency traders can take highly leveraged positions with little to no margin requirements on FX spot transactions. However, this feature induces currency liquidity deterioration in crisis periods or in times of unexpected high volatility (Karnaukh et al., 2015). In particular, jumps may trigger stop loss or take profit strategies with sudden spikes for high frequency leveraged traders. Eventually, increasing bid-ask spread may lead to a decrease in high speed trading activity due to higher trading costs. The above-mentioned implications created a growing interest for empirical studies that investigate the determinants of jumps. Consequently, this strand of literature successfully linked jumps and cojumps with scheduled macroeconomic news announcements as in Chatrath et al. (2014); Dungey and Hvozdyk (2012); Lahaye (2016); Lahaye et al. (2011); Lee and Wang (2019b), and central bank actions or communications as in Andersen et al. (2007); Beine et al. (2007); Dewachter et al. (2014). In these studies, jumps occur as a response to liquidity or information shocks. As shown by Füss et al. (2018), the higher the information arrival before the announcements, the higher the jump reaction is. On the other hand, literature that specifically focuses on FX liquidity mostly links jumps with the liquidity conditions of the market and the traded asset (Mancini et al., 2013). In these studies, the feedback from jumps to liquidity and liquidity to jumps are two-sided. In fact, asymmetric information models suggest that increasing informed trading activity around jumps may lead to increase in bid-ask spreads in the period following jumps. Likewise increasing volatility persistence following jumps may lead to widening bid-ask spreads. Accordingly, it is essential to study the jumps in

both the level and the liquidity of the exchange rates within the same framework. As stated earlier, the aim of this study is to advance the above-mentioned literature by examining the dynamics of discontinuities in foreign exchange rates and their liquidity for three major emerging market currencies. According to BIS 2019 Triennial Survey of foreign exchange and OTC derivatives trading, our sample currencies of Mexican peso, South African rand and Turkish lira rank 2nd, 5th and 6th in the category of most traded emerging market currencies in the world respectively, with 113.7, 72.1, 71.2 billion USD average daily turnovers of both spot and derivative transactions.¹ Moreover, according to Oxford Economics, they belong to the group of top five risky currencies in the world together with Argentine peso and Ukrainian hryvnia as of early 2019.² This picture is not surprising since our sample countries suffered both systematic and idiosyncratic shocks in recent years. While Fed's signal in 2013 to end the quantitative easing operations and late global trade wars fuelled growing fear of renewed volatility in all these markets, Mexico had to face several tariffs on its imports to the US and political tensions with its government. In the mean time, Turkey experienced its biggest financial crisis since 2001 after concerns about its overheating economy and spurred inflation, followed by political tensions with the US. South Africa, on the other hand, has unexpectedly entered into an economic recession in 2018 for the first time in nearly a decade and its currency has consistently been seen as a prime candidate for contagion for a brief period of time in recent years. All these evidence led us believe that an analysis on the jump and co-jump dynamics of these currencies is essential for international investors, risk managers and in particular, central banks to understand the reasons for such phenomena and their potential

¹In the same ranking, Chinese yuan, Indian rupee and Russian ruble take the 1st, 3rd and 4th place. However, due to their controlled (or dirty floating) nature and lack of high-frequency data availability, they are not included in our analysis.

²<https://www.lemoci.com/wp-content/uploads/2019/05/navigating-the-next-em-currency-crisis-130519.pdf>

consequences, which would be beneficial not only for the sample markets but also for a wider range of emerging markets as well.

In our empirical setup, we first detect exchange rate jumps by employing the high frequency non-parametric jump test of Lee and Mykland (2008) and apply the same framework to examine the liquidity jump activity. After determining the jumps in exchange rates and their liquidity, our analysis is split into two stages. At the first stage, we focus on jump and cojump activity for individual individual exchange rates. In particular, we start with identifying the intraday timing of both return and liquidity jumps, and return-liquidity cojumps for each exchange rate and examine the determinants of the duration between such consecutive actions. Using logarithmic autoregressive conditional duration model, we find that an increase in the average bid-ask spread (realized volatility) between two consecutive return (liquidity) jumps significantly reduce the duration between return (liquidity) jumps in general. On the other hand, liquidity and volatility between two consecutive return-liquidity cojumps play only a partial role on the duration between such consecutive cojumps. Then we study the impact of liquidity and return jumps on volatility and liquidity respectively at the high frequency level for each exchange rate. Accordingly, we find that contemporaneous impact of both positive and negative liquidity jumps on volatility is significantly positive, suggesting that positive (negative) spread jumps are observed simultaneously with increased (decreased) volatility. Similarly, contemporaneous impact of both positive and negative return jumps is found to be significantly positive on the bid-ask spread. Results emphasize the vicious return-liquidity spirals discussed by Brunnermeier and Pedersen (2009), even at the high-frequency level. We further investigate the determinants of such return and liquidity jumps and their cojumps using several global risk factors. We find that even though different risk factors might play significant roles on return or liquidity jumps, economic policy

uncertainty is the only one that has significant positive impact on both return and liquidity jumps. On the other hand, no common source is found in the case of return-liquidity cojumps. Analysis on the impact of local and global scheduled macroeconomic news and central bank announcements reveals that US CPI, FOMC and non-farm payroll announcements mostly coincide with return and liquidity jumps and their co-jumps. However, impact of domestic news and announcements is very little to none in general. Such a situation shows us the increased importance of the US economy and Fed's decisions on investor sentiment after the global financial crisis, and stresses on the potential challenges faced with other central banks (and policy makers in general) when one clearly dominates the others. At the second stage of our analysis, we focus on the cojumps across exchange rates. Since the number of liquidity cojumps is not high enough to make statistical inference, we focus only on return cojumps and start by analyzing the duration between such consecutive cojumps. We find that global factors, as well as idiosyncratic ones, play a significant role on this duration. In particular, an increase in the US economic policy uncertainty or VIX significantly decreases the duration between cojumps. Regarding the impact of macroeconomic news and announcements, we observe a similar effect to the previous analysis and find that CPI and non-farm payroll announcements lead to cojumps across exchange rate returns, whereas FOMC announcements have limited impact this time. Our paper's contribution to the literature is manifold. First, we extend the literature that studies jumps in exchange rates by investigating their impact on liquidity levels and vice versa, which is essential for various types of market participants. Second, in addition to the jumps in exchange rate levels, we also investigate the jumps in liquidity which allows us to characterize their high frequency behavior and their impact on foreign exchange rate returns. Such an analysis provides a comprehensive examination as it covers all types of information

arrivals that lead return and liquidity jumps. To the best of our knowledge, no study has been carried out on the dynamics of both return and liquidity jumps. Furthermore, there is no quantitative analysis that examines the duration between consecutive jump occurrences. Third, our sample period coincides with the tranquil times for emerging markets after 2013 when the Fed signaled to tighten its monetary policy. Such a time period is especially important to analyse since it helps us to understand the jump and co-jump characteristics of emerging market currencies in a diminished investor confidence environment.³ Fourth, in parallel to the latest trend in research, we utilize high-frequency intraday data. This is particularly important since algorithmic (especially high frequency) trading constitutes the major part of all trading activities in today's modern FX markets where computers react to information instantaneously. In such an environment, high frequency analysis is the only way to uncover the true dynamics of jump and cojump processes.

The rest of the paper is organized as follows. Section 4.2 explains the data and its sources. Section 3.3 describes the jump detection methodology employed throughout the paper. Section 3.4 analyzes return and liquidity jumps, and return-liquidity cojumps for each exchange rate individually. Section 3.5 discusses the dynamics of cojumps across exchange rates. Finally, Section 4.4 concludes.

3.2. Data and Summary Statistics

The high-frequency foreign exchange rate series for US dollar to Mexican peso (USDMXN), Turkish lira (USDTRY) and South African rand (USDZAR) are obtained from Gain Capital, a New-York based dealer. The company was founded

³Between 2008 and 2013, emerging markets borrowed heavily in dollar-denominated debt with almost zero rates, while many of them were still struggling with chronic current-account deficit problems. After Fed's tightening policy, high dollar debt combined with high current account deficit diminished investors' confidence in these markets' ability to repay their external debt.

in 1999 and now provides service to 140,000+ retail and institutional investors with access to trade in over 12,500+ FX, shares, commodities markets and contracts-for-differences indices. The data set is comprised sub-second level tick-by-tick bid and ask quotations with time stamps. The observations are available in global forex trading hours which is from Sunday 22:00 to Friday 22:00 in Greenwich Mean Time (GMT).⁴ The sample covers an almost four year period from January 5, 2015 to December 14, 2018, adding up to 1029 trading days in total. We aggregated the ultra-high frequency bid and ask rate data into 5-min intervals and obtain 296,352 (288x1029) intraday observations. We use the mid-quote, i.e., simple average of bid and ask quotes, as the exchange rate level. Our main liquidity measure is the proportional quoted spread which is defined as the ratio of bid-ask spread to the mid-quote.

We obtain the actual times of scheduled macroeconomic news announcements and central bank actions from Bloomberg terminal. Table 3.1 shows the summary information for both local and US macroeconomic news releases. The daily local and global risk and liquidity proxies (TED spread, VIX, rate differential (RD) between US and local rates implied by 3 month forward rates, and risk reversal (RR)) are obtained from Bloomberg terminal with a daily frequency and the daily US economic policy uncertainty index (EPU) is obtained from EPU website.⁵ The descriptive statistics for 5-min foreign exchange rate returns and the corresponding liquidity measures are tabulated in Table 3.2.

⁴Throughout the paper, all timestamps in figures and tables are stated in GMT.

⁵<https://www.policyuncertainty.com/>

Table 3.1: Summary table for US and domestic macroeconomic news and central bank announcements

Event	Mexico			Turkey			South Africa		
	Frequency	Hour	Obs	Frequency	Hour	Obs	Frequency	Hour	Obs
Consumer Price Index (CPI)	Monthly	13:00	48	Monthly	07:00	48	Monthly	08:00	48
Gross Domestic Product (GDP)	Quarterly	13:00	16	Quarterly	07:00	16	Quarterly	09:30	16
Central Bank Rate Decision	Six-week	18:00	32	Monthly	11:00	41	8-weeks	13:25	24
Industrial Production ^a	Monthly	13:00	48	Monthly	07:00	47	Monthly	11:00	48
Current Account Balance	Quarterly	14:00	16	Monthly	07:00	48	Quarterly	08:00	16
Budget Balance	Monthly	19:30	47	Monthly	08:00	40	Monthly	12:00	47
Unemployment Rate	Monthly	13:00	47	Monthly	07:00	47	Quarterly	09:30	16
US									
Event	Frequency	Hour	Obs						
Budget Statement	Monthly	18:00	48						
Business Inventories	Monthly	14:00	48						
Consumer Confidence	Monthly	14:00	47						
Consumer Credit	Monthly	19:00	48						
CPI	Monthly	12:30	48						
Durable Goods Orders	Monthly	12:30	47						
Factory Orders	Monthly	14:00	48						
FOMC Announcement	Six-week	18:00	31						
FOMC Meeting Minutes	Six-week	18:00	32						
GDP-Advance	Quarterly	12:30	16						
GDP-Second	Quarterly	12:30	15						
GDP-Final	Quarterly	12:30	16						
Housing Starts	Monthly	12:30	47						
Industrial Production	Monthly	13:15	48						
Initial Jobless Claims	Bi-weekly	12:30	206						
ISM Manufacturing	Monthly	14:00	47						
Leading Index	Monthly	14:00	47						
New Home Sales	Monthly	14:00	47						
Non-farm Payrolls	Monthly	12:30	48						
Personal Income	Monthly	12:30	47						
Producer Price Index (PPI)	Monthly	12:30	48						
Retail Sales	Monthly	12:30	48						
Trade Balance	Monthly	12:30	48						

This table presents the list of scheduled macroeconomic news and central bank announcements for Mexico, Turkey, South Africa and US. For each macroeconomic news announcement we provide the number of observations between January 5, 2014 and December 14, 2018. The presented time stamps are in GMT and 1 hour forward for the daylight saving time. The timing of some of the announcements may change due to delays in releases or unscheduled monetary policy meetings but we present their standard times in the table.

^aFor South Africa, we use manufacturing production announcements due to data unavailability.

Table 3.2: Summary statistics for exchange rate returns and liquidity

	Returns			Liquidity		
	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR
Mean	1.05×10^{-6}	2.80×10^{-6}	0.70×10^{-6}	0.0003	0.0006	0.0007
Min	-0.0178	-0.0551	-0.0459	5.32×10^{-7}	20.83×10^{-7}	6.37×10^{-7}
Max	0.0313	0.1036	0.0395	0.0040	0.0093	0.0041
Std.	0.0005	0.0007	0.0007	0.0002	0.0007	0.0006
Skew.	0.6393	9.1241	0.4282	2.2078	4.0276	1.6610
Kurt.	106.41	1,784.10	161.80	6.05	28.17	2.42
Obs	296,352	296,352	296,352	296,352	296,352	296,352

This table shows the summary statistics for high frequency returns and liquidity measures for the sample foreign exchange rates. The sample covers the period from January 5, 2015 to December 14, 2018. The data is sampled at 5-min frequency. Returns are calculated with logarithmic foreign exchange rate changes and the liquidity measure is the proportional quoted spread; i.e., the ratio of bid-ask spread to the mid-quote.

3.3. Jump Detection Methodology

We employ the intraday jump detection procedure developed by Lee and Mykland (2008) to identify both return and liquidity jumps. Among the variety of jump detection methodologies, this procedure is particularly useful since it determines the size, direction and exact time stamp of each jump (Boudt and Petitjean, 2014; Neely, 2011). This identification further allows calculation of average and total jump sizes or jump intensities within lower frequencies to make daily or monthly analysis.

Since standard continuous diffusion models fail to account for sudden price changes in forms of spikes or jumps in asset prices, Lee and Mykland (2008) assume a model class called Brownian semi-martingale with finite activity jumps as the underlying stochastic process. This allows for decomposing exchange rate volatility into jumps and time-varying diffusion components as follows:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \quad (3.1)$$

where p_t is the log of mid-quote exchange rate in our setup, $\mu(t)$ 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, $\kappa(t)$ is the jump size. Consequently, authors introduce a test statistic for each return observation by comparing its absolute value with a rolling window local variation measure as follows:

$$J_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i}} \quad (3.2)$$

In this framework, each trading day t consists of M equally spaced intraday returns, where $r_{t,i}$ is the 5-min log-return of the mid-quote spot exchange rate in the interval i of day t and $\eta_{t,i}$ is the local variation measure calculated by an integrated volatility measure. Standard realized volatility measures (e.g., sum of squared log-returns) fail to estimate integrated volatility consistently in the presence of jumps. Barndorff-Nielsen and Shephard (2004,0) show that under the price generation process defined in equation (3.1), realized bi-power variation (RBPV) defined in equation (3.3) converges to integrated volatility and thus consistently estimates the integrated variance,

$$RBPV_t(M) = \mu^{-2} \frac{M}{M-2} \sum_{i=2}^M |r_{t,i}| |r_{t-1,i}| \quad (3.3)$$

where $\mu = \sqrt{2/\pi}$ and M is the number of observations in the local variation window. One free parameter to choose in this setup is the window length of the local variation measure. Accordingly, we follow Lee and Mykland (2008) and use a window length of 270 data points for 5 minutes returns.

Another situation that needs to be taken into account is the intraday periodicity which might have a deteriorating effect on $J_{t,i}$. In order to correct this, Boudt et al. (2011) propose to re-scale the returns by an intraday periodicity adjustment factor.

We perform this adjustment following the procedure suggested by Boudt and Petitjean (2014) and estimate the modified filtered jump statistic $\tilde{J}_{t,i}$ provided in equation (3.4),

$$\tilde{J}_{t,i} = \frac{|r_{t,i}|}{\eta_{t,i} f_{t,i}} \quad (3.4)$$

where $f_{t,i}$ is the intraday periodicity factor obtained by a flexible Fourier specification as in Andersen and Bollerslev (1998).

Final step of the jump detection procedure involves filtration of the unhealthy data. In times of many repeating quotations or missing values, we might face with the problem of underestimating $\eta_{t,i}$, and thus over-rejecting the null hypothesis of no jump in the local variation window. To avoid this situation, we eliminate the jump statistics for the returns whose local variation window contains 58 or more zero observations (that is more than 20% of 288, the number of 5-minute observations in a trading day), or missing values.

Lee and Mykland (2008) show that the obtained jump statistic follows a standard Gumbell distribution. Thus we reject the null hypothesis of no jump if the filtered $\tilde{J}_{t,i}$ statistics are greater than the value suggested by the Gumbell distribution; i.e.,

$$\tilde{J}_{t,i} > G_{-1}(1 - \alpha)S_n + C_n \quad (3.5)$$

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

$$C_n = (2 \log n)^{0.5} - \frac{\log(\pi) + \log(\log n)}{2(2 \log n)^{0.5}} \quad (3.6)$$

and

$$S_n = \frac{1}{(2 \log n)^{0.5}} \quad (3.7)$$

with n denoting the number of total observations. The α term in equation (3.5) is

the significance of discontinuity in the local variation window and we use an α level of 5% in the rest of the paper.

Regarding liquidity jumps, we apply the non-parametric setup above to our liquidity measure motivated by Adrian et al. (2015). In particular, as a proxy for high-frequency liquidity measure, we employ the widely used proportional bid-ask spread which is calculated as follows,

$$L_t = \frac{Q_t^{ask} - Q_t^{bid}}{(Q_t^{ask} + Q_t^{bid})/2} \quad (3.8)$$

where Q_t^{ask} and Q_t^{bid} refer to ask and bid quotations at time t respectively.

Consequently, $p(t)$ is replaced by L_t in equation (3.1) and the whole procedure is repeated. In this way, we are able to identify sudden changes in liquidity such that the positive jumps indicate deteriorating liquidity conditions and the negative ones denote improving liquidity of the exchange rate.

Figure 3.1 emphasizes the importance of appropriate handling of diurnal cycles in intraday volatility and liquidity respectively since both variables exhibits strong intraday periodicities. The upper subfigure displays the intraday volatility pattern that is obtained by averaging absolute value of logarithmic returns in the cross-section of sample days. Likewise, lower subfigure presents intraday liquidity pattern obtained by averaging proportional quoted bid-ask spread for each 5-min interval across sample days. The liquidity patterns shows spikes around opening and closing sessions as well as around macro-economic news announcements, and it is highest during local trading hours.⁶ In an earlier work, Bollerslev and Melvin (1994) state that magnitude of the bid-ask spread of an exchange rate increases with higher volatility, which is validated by our findings at the high-frequency level

⁶Since the liquidity measure in the figure is the bid-ask spread, an increase (decrease) in this variable refers to a decrease (increase) in liquidity.

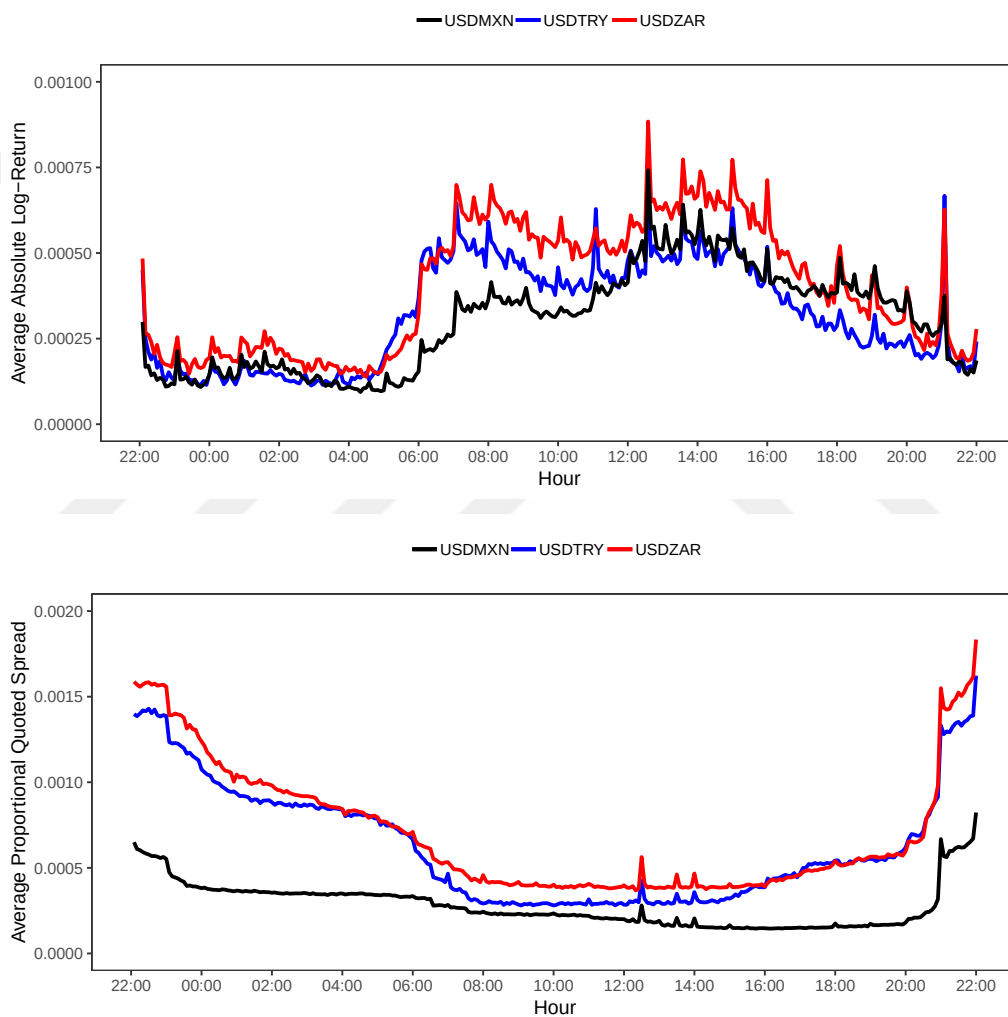


Figure 3.1: Intraday volatility and liquidity patterns

as well. According to Figure 3.1, intraday periodicity of liquidity is almost like the mirror image of the daily volatility pattern.

3.4. Jump and Cojump Analysis for the Individual Exchange Rates

In this section, we try to (i) model the duration between both return and liquidity jumps, and also liquidity-return cojumps, (ii) analyze the impact of liquidity jumps on volatility, (iii) investigate the effect of return jumps on liquidity, and finally (iv) examine the determinants of return jumps, liquidity jumps, and return-liquidity cojumps for the separate cases of USDMXN, USDTRY and USDZAR.

3.4.1 Preliminary Analysis

Before describing the econometric framework, we start with providing the summary statistics for all (and also only news-related) exchange rate and liquidity jumps in Table 3.3.⁷ This table provides information on the number of return jumps (RJ) and liquidity jumps (LJ), their probability of occurrence, and the maximum and average jump size for all (RJ, LJ), positive (RJ^+, LJ^+) and negative (RJ^-, LJ^-) jumps. According to Table 3.3, the highest numbers of both return and liquidity jumps are observed for USDTRY with 4393 and 1937 jumps respectively, supporting the recent work by Lee and Wang (2019a). On the other hand, highest average jump size for return (liquidity) belongs to USDZAR (USDMXN) with a magnitude of 0.2% (2.68). For all currencies, both the size and number of return jumps are larger for positive jumps compared to negative ones indicating the relatively higher downside risk in the value of the local currency in these emerging

⁷In the rest of the paper, when we talk about jumps in general, we use the notation J , whereas if we want to specify whether it is a return or liquidity jump, we use RJ and LJ respectively.

countries. In addition, comparison of the number of return and liquidity jumps for all cases shows that experiencing a liquidity jump is almost as half likely as experiencing a return jump.

Table 3.3: Summary statistics for the detected return and liquidity jumps

		All Jumps				News related Jumps			
		$\#J$	$P(J)$	$max(J)$	$mean(J)$	$\#J$	$P(J)$	$max(J)$	$mean(J)$
USDMXN	RJ	1827	0.62%	0.0313	0.0017	81	0.03%	0.0171	0.0042
	RJ^-	912	0.31%	0.0178	0.0017	53	0.02%	0.0171	0.0044
	RJ^+	915	0.31%	0.0313	0.0017	28	0.01%	0.0074	0.0039
	LJ	707	0.24%	6.8349	2.6794	22	0.01%	6.2660	2.6740
	LJ^-	399	0.13%	6.3951	2.6475	9	0.00%	6.2660	3.5016
	LJ^+	308	0.10%	6.8349	2.7208	13	0.00%	3.6554	2.1009
	RJ	4393	1.48%	0.1036	0.0017	124	0.04%	0.0551	0.0046
	RJ^-	2040	0.69%	0.0551	0.0016	68	0.02%	0.0551	0.0047
	RJ^+	2353	0.79%	0.1036	0.0017	56	0.02%	0.0277	0.0045
USDTRY	LJ	1937	0.65%	5.9194	1.4584	53	0.02%	4.8429	1.9540
	LJ^-	1020	0.34%	5.9194	1.4193	14	0.00%	4.8429	2.2143
	LJ^+	917	0.31%	5.5216	1.5018	39	0.01%	3.1201	1.8606
	RJ	3205	1.08%	0.0459	0.0020	94	0.03%	0.0147	0.0050
	RJ^-	1596	0.54%	0.0459	0.0020	61	0.02%	0.0147	0.0047
	RJ^+	1609	0.54%	0.0395	0.0021	33	0.01%	0.0112	0.0056
	LJ	1422	0.48%	7.4223	1.9826	32	0.01%	6.5923	3.8024
	LJ^-	774	0.26%	6.9953	1.9137	14	0.00%	6.4730	4.1498
	LJ^+	648	0.22%	7.4223	2.0648	18	0.01%	6.5923	3.5322

This table provides descriptive statistics for detected jumps. The sample covers the period from January 5, 2015 to December 14, 2018. The jumps are detected by using the non-parametric jump test procedure of Lee and Mykland (2008). In this table, $\#J$, $P(J)$, $max(J)$ and $mean(J)$ denote the number of jumps, probability of jump occurrence, maximum jump size and the average jump size respectively. RJ and LJ refer to return and liquidity jumps respectively whereas $-$ and $+$ superscripts symbolize negative and positive jumps respectively,

The basic properties of jumps that are associated with scheduled-news announcements may differ in nature. For instance, Evans (2011) shows that news related jumps have higher average size compared to non-news related jumps. To empirically differentiate between these two types, we define news-jumps as the jumps surrounding the scheduled macro-news announcements (Boudt and Petitjean, 2014; Piccotti, 2018). To do this, we identify the key domestic and US

scheduled macroeconomic news announcements and if a jump occurs within three 5-min intervals that precede or follow the news announcement interval (that is 15 minutes before or after, denoted by $[-3,+3]$), we define those jumps as the jumps that occur in the interval surrounding the scheduled macro-news announcements that are described in Table 3.1. In the right hand side panel of Table 3.3, we provide the same statistics for only news-related jumps. The number of such jumps indicate that only a small portion of total jumps are occurring around scheduled news announcements. This is in line with the findings of Boudt and Petitjean (2014); Lahaye et al. (2011) who argue that a large number of both exchange rate and liquidity jumps have no association with scheduled news announcements. Furthermore, it supports Li et al. (2017) who find that jumps can coincide with other announcements on political or financial events as well. For all currencies and different jump variants, news related average jump size is significantly larger compared to full sample of jumps. In addition, contrary to full sample jump statistics, the negative return jumps are more frequent than positive ones suggesting that on average, the realizations of news releases are better than expectations for the selected emerging markets, thus have an appreciating impact on local currencies in the sample period. The higher number of positive liquidity jumps indicates the associated uncertainty surrounding news releases. While the jumps following news are related with surprises, the preceding jumps can be associated with private information or position closing.

We follow the analysis of individual jumps in exchange rate returns and liquidity by identifying cojumps in return and liquidity levels for each currency. First of all, to provide a preliminary analysis on the cojump relation between return and liquidity jumps, we present the conditional probabilities of return jumps in various lags around liquidity jumps for each currency in Table 3.4. Conditioned upon a liquidity jump, the probability of a return jump in the same interval is 3.5%, 21.1%

Table 3.4: Conditional probabilities of return jump occurrences around liquidity jumps

	-5	-4	-3	-2	-1	0	1	2	3	4	5	before	after	no-cojump
USDMXN	2.12%	2.12%	2.12%	2.26%	3.11%	3.54%	1.84%	1.70%	2.55%	2.12%	1.27%	11.74%	9.48%	75.25%
USDTRY	4.80%	4.90%	5.01%	5.89%	8.05%	21.12%	7.95%	6.35%	5.83%	5.11%	5.06%	28.65%	30.30%	19.93%
USDZAR	2.88%	2.81%	2.74%	2.32%	4.64%	9.99%	5.06%	3.52%	3.94%	3.31%	3.87%	15.40%	19.69%	54.92%

This table presents the probability of observing a return jump within a specific period around a liquidity jump. In the columns, numbers ranging from -5 to 5 denote the number of 5-minute lagged and lead intervals respectively around a liquidity jump, while value under these columns are the empirical probabilities of return jumps within the defined time intervals. Values under the columns titled 'before' and 'after' report the aggregate probability of observing a return jump before and after 25 minutes of a liquidity jump respectively. Finally, the values under the column 'no-cojump' indicates the probability of observing zero return jump before or after 25 minutes of a liquidity jump.

and 10% for USDMXN, USDTRY and USDZAR respectively. For all currencies, the highest probability of a return jump occurrence is in the same interval in which the liquidity jump occurs. For USDTRY and USDZAR, it is slightly more likely that a return jump will follow a liquidity jump within 5 intervals (i.e., 25 minutes), whereas the reverse case is valid only for USDMXN. An interpretation for this finding is the probability of informed trading. In the case of return jumps, traders might extend bid-ask spreads in the period following these jumps to avoid costs from informed trading. We observe that return jump occurrence around $[-5,+5]$ neighborhood is most prevalent for USDTRY with 80% probability. On the other hand, this probability is 25% and 55% for USMXN and USDZAR respectively. Overall, this table supports the view that while liquidity jumps may lead to return jumps, the reverse scenario is also very likely and can not be disregarded.

In Table 3.5, we provide intraday frequencies of return and liquidity jumps and also return-liquidity cojumps for each exchange rate. A cojump CJ technically refers to a simultaneous jump in both return and liquidity levels. However, to extend our analysis further, we introduce two variants of the cojump definition that are (i) return jumps followed by liquidity jumps ($LJ \rightarrow RJ$) and (ii) liquidity jumps followed by return jumps ($RJ \rightarrow LJ$) within three 5-min intervals.⁸ Accordingly, for all currencies, return-liquidity cojump activity is most intense around the off-shore trading hours when liquidity is lower. In addition, cojump activity slightly intensifies during the period between 12:00 and 14:00 where a huge portion of US macroeconomic news announcements are made. Thus macroeconomic news announcements appear to have significant positive impact on jump counts which will be further investigated in this paper later.

⁸Throughout the paper, when we mention about cojumps, we denote them by CJ and refer to simultaneous jumps in the same 5 minute interval. However, results regarding the other two definitions are always presented in the relevant tables under the corresponding notations (i.e., $LJ \rightarrow RJ$ or $RJ \rightarrow LJ$) whenever we perform an analysis on the actual cojumps.

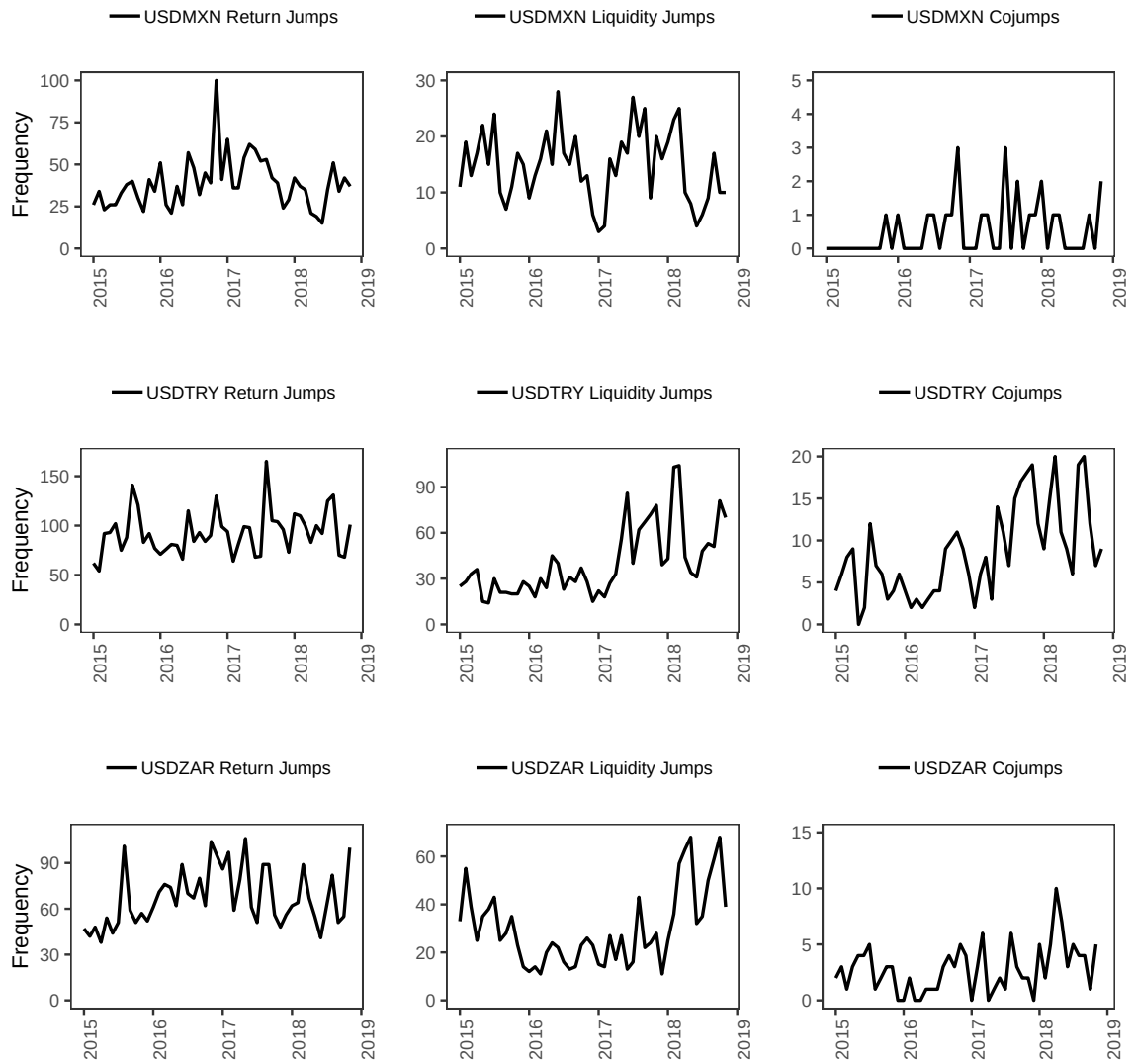


Figure 3.2: Monthly time series of return jumps, liquidity jumps, and return-liquidity cojumps for each exchange rate

While Tables 3.4 and 3.5 tabulate microdetails about the jump and cojump actions, Figure 3.2 provides a wider picture and displays the number of return jump, liquidity jump and return-liquidity cojump activity per month for the whole sample. Accordingly, regarding return jumps, USDTRY and USDZAR display relatively more uniform patterns compared to USDMXN. The significant increase in the number of return jumps in USDMXN by the end of 2016 is most probably due to the US presidential election and the following escalated political tension between the US and Mexico. Regarding liquidity jumps, USDTRY and USDZAR exhibit similar patterns through time, with a significant increase in 2017 and afterwards. A similar pattern is also observed in the number of return-liquidity cojumps for these two exchange rates, probably due to the similar characteristics in Turkey's and South Africa's economic and financial fundamentals.

3.4.2 Modelling the Duration Between Consecutive Jumps and Cojumps

In this part, we model the duration between consecutive return and liquidity jumps, and also return-liquidity cojumps for each exchange rate using logarithmic autoregressive conditional duration (LACD) model of Bauwens and Giot (2000) which is an extension of the autoregressive conditional duration model presented in the seminal paper by Engle and Russell (1998). In calculation of consecutive jump and cojump durations, we exclude the non-trading weekend periods (i.e., from Friday 22:00 GMT to Sunday 22:00 GMT). In Table 3.6, we present the summary statistics for the estimated durations. The units of presented numbers are in days. The average duration between two consecutive return (liquidity) jumps is 0.56 (1.56), 0.23 (0.53) and 0.32 (0.72) days for USDMXN, USDTRY and USDZAR respectively, which indicates that on the average, a liquidity jump is less likely to occur than a return jump for each exchange rate, supporting the earlier evidence.

Moreover, standard deviations of the average durations between both consecutive return and liquidity jumps are much higher for USDMXN than the other two exchange rates, showing the relatively irregular jump occurrence patterns for the USDMXN compared to USDTRY and USDZAR. Interestingly, USDTRY experiences return-liquidity cojumps in every two and a half days on the average, which is almost three times more often than USDZAR and 13 times more often than USDMXN, indicating the emphasized liquidity-return spirals for this specific exchange rate.

Following the conventional notation, we define x_i as the adjusted duration Δt_i ⁹ between two consecutive return jumps which is modelled as the following,

$$x_i = \mu_i \epsilon_i \quad (3.9)$$

where ϵ_i is a sequence of independent and identically distributed non-negative random variables following an exponential distribution such that $E(\epsilon_i) = 1$ and μ_i has the following LACD(1,1) form:

$$\mu_i = \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \varphi \overline{LIQ}_i + \epsilon_t \quad (3.10)$$

While modeling the duration between consecutive return jumps, we incorporate average liquidity $\overline{LIQ}_i = \sum_{j=1}^N L_j / N$ between these consecutive jump occurrences to the model as an exogenous variable to determine its impact on duration. The estimated parameters are tabulated in Table 3.7. Accordingly, the LACD model parameters are statistically significant at the 1% level, and an increase in the average bid-ask spread between two jumps significantly reduce the duration between two consecutive return jumps.

⁹The detected jumps are already adjusted for intraday seasonality in our setup.

Table 3.6: Summary statistics of the duration between consecutive return jumps, liquidity jumps, and return-liquidity cojumps

	Return Jumps			Liquidity Jumps			Return-Liquidity Cojumps		
	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR
Min	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Max	6.292	4.045	4.156	16.976	11.545	14.024	120.122	41.757	65.007
Mean	0.563	0.234	0.321	1.456	0.530	0.723	31.292	2.490	7.079
Std.	0.788	0.402	0.514	2.085	0.916	1.127	33.936	3.981	9.985
Obs.	1826	4392	3204	706	1936	1421	24	408	141

Note: The values in the table (except the number of observations) are in days.

Table 3.7: LACD(1,1) model fit results for the duration between consecutive return jumps

	USDMXN	USDTRY	USDZAR
ω	-0.468***	-1.581***	-1.680***
α	0.093***	0.138***	0.120***
β	0.230***	-0.102***	-0.100***
φ	-0.477***	-0.481***	-1.240***

This table presents the estimation results of the following LACD(1,1) model for x_i , the duration between consecutive return jumps,

$$x_i = \mu_i \epsilon_i$$

$$\mu_i = \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \varphi \overline{LIQ} + \epsilon_t$$

with $\overline{LIQ}_i$ is the average proportional spread of the exchange rate between consecutive return jump occurrences. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

In a similar fashion above, we model the adjusted duration $\tilde{x}_i$ between consecutive liquidity jumps as follows:

$$\tilde{x}_i = \mu_i \epsilon_i \tag{3.11}$$

$$\mu_i = \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \psi \overline{RV}_i + \epsilon_t \tag{3.12}$$

where $\overline{RV}_i = \sum_{j=1}^N r_j^2 / N$ denotes the average realized volatility of the exchange rate between the consecutive liquidity jump occurrences. We present the estimated coefficients in Table 3.8. The model parameters are statistically significant in all cases. However, while an increase in the realized volatility between two consecutive liquidity jumps significantly reduce the duration between them for USDTRY, it has the opposite effect in the case of USDMXN and USDZAR.

We finally model the duration $\hat{x}_i$ between consecutive return-liquidity cojumps for each exchange rate. Like the earlier models, we have the following approach,

$$\hat{x}_i = \mu_i \epsilon_i \tag{3.13}$$

$$\mu_i = \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \epsilon_t \tag{3.14}$$

Table 3.8: LACD(1,1) model fit results for the duration between consecutive liquidity jumps

	USDMXN	USDTRY	USDZAR
ω	-0.0006	0.0296***	0.0208***
α	-0.008151**	0.0175***	0.0137***
β	0.957512***	0.998***	0.9859***
ψ	0.030082***	-0.0013***	0.0222***

This table presents the estimation results of the following LACD(1,1) model for $\tilde{x}_i$, the duration between consecutive liquidity jumps,

$$\begin{aligned}\tilde{x}_i &= \mu_i \epsilon_i \\ \mu_i &= \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \psi \overline{RV}_i + \epsilon_t\end{aligned}$$

with $\overline{RV}_i$ is the average realized volatility of the exchange rate between consecutive liquidity jump occurrences. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

however, this time, we use both the average liquidity and average realized volatility of the exchange rate between consecutive cojumps as exogenous variables to determine their impact on duration, and the results are reported in Table 3.9. Accordingly, individual components of liquidity and volatility does not play a significant role in the duration between liquidity-return cojumps for the USDMXN, suggesting that other systematic components might be responsible for this phenomena. On the other hand, volatility plays a partial and both volatility and liquidity play a strong role on the return-liquidity cojumps in the cases of USDTRY and USDZAR respectively, indicating more of a idiosyncratic structure of cojumps for these exchange rates relative to the USDMXN.

3.4.3 Impact of Liquidity Jumps on Volatility

In this part, we examine the high frequency impact of liquidity jumps on exchange rate volatility for each currency. Figure 3.3 shows how absolute value of the exchange rate returns, a proxy for volatility, behave around liquidity jumps. There is an undeniable positive impact of liquidity jumps on the magnitudes of realized returns, and motivated by this observation, we further investigate this relationship.

Table 3.9: LACD(1,1) model fit results for the duration between consecutive return-liquidity jumps

	USDMXN	USDTRY	USDZAR
ω	-0.8714	0.0143***	-0.0914***
α	-0.0845**	0.0104***	-0.0069***
β	1.2474***	1.001***	1.0423***
φ	0.0021	-0.0037	-0.0022***
ψ	0.0063	0.0287*	-0.0007***

This table presents the estimation results of the following LACD(1,1) model for $\hat{x}_i$, the duration between consecutive return-liquidity jumps,

$$\hat{x}_i = \mu_i \epsilon_i$$

$$\mu_i = \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \epsilon_t$$

with $\overline{LIQ}_i$ and $\overline{RV}_i$ are the average proportional spread and the average realized volatility of the exchange rate between consecutive return-liquidity jump occurrences respectively. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

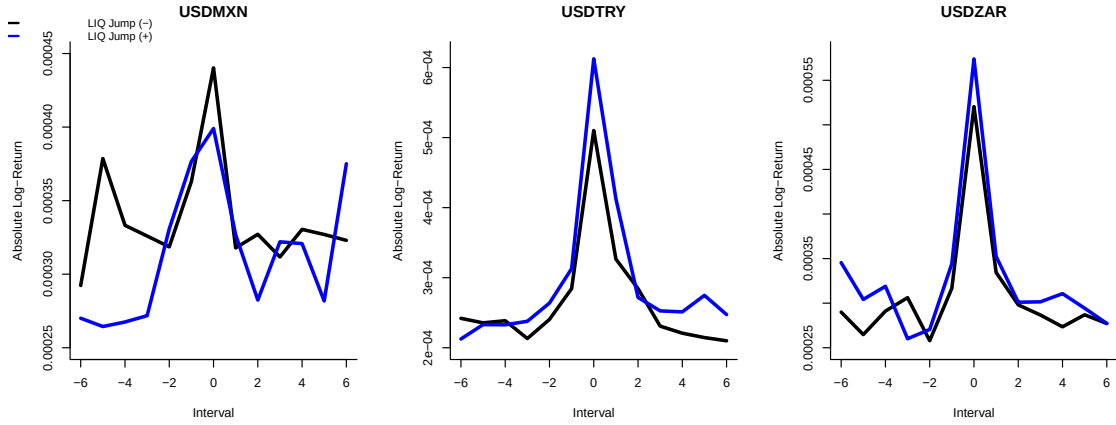


Figure 3.3: Average absolute log-returns around liquidity jumps ($t = 0$)

For this analysis, we employ a two-stage weighted least squares (WLS) estimation procedure with a similar setting by Andersen et al. (2003). Since we focus on the impact of liquidity jumps affecting conditional volatility, this model suits well for our analysis. In the first stage, for each exchange rate, we fit the following linear model:

$$r_t = \beta_0 + \sum_{k=1}^K \beta_k r_{t-k} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \delta_{d,l} \times LJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \epsilon_t \quad (3.15)$$

where the left hand side variable r_t denotes the 5-minute logarithmic returns.¹⁰ To capture the persistence in return series, we add its lagged values up to 5 unit lags, thus $K = 5$ with each unit lag refers to 5 minutes. LJ_t^d denotes the size of the liquidity jump with direction d at time t . L equals 3, thus we get coefficient estimates of jumps with -3 to +3 unit lags that is, 15 minutes before and after the liquidity jump arrival. We include both lead and lag jump variables since the volatility may rise ahead of the liquidity jumps, or it might as well increase as a response to a liquidity shock. To discriminate the effects of negative and positive liquidity jumps, we use different variables for each type of jumps, thus d runs over $\{+, -\}$ separately where $+$ and $-$ denote positive and negative jumps respectively. D_t^d is a dummy variable which equals 1 if the liquidity jump with direction d within $[t - 3, t + 3]$ is associated with a scheduled macroeconomic news announcement, that is if there is a US or local news announcement in 15 minutes that precede or follow the liquidity jump. These dummies are added to the model to assess whether scheduled news-related jumps have differential impact on volatility.

In the second stage, we fit the absolute value of estimated residuals from

¹⁰Readers should be aware that the notation used in this part is independent of the notation in Section 3.3.

equation (4.4) to the following specification,

$$\begin{aligned}
|\epsilon_t| = c + \varphi \frac{\hat{\sigma}_{d,t}}{\sqrt{288}} + \sum_{d \in \{+,-\}} \sum_{l=-3}^L \delta_{d,l} \times L J_{t+l}^d + \sum_{d \in \{+,-\}} \eta_d \times D_t^d \\
+ \sum_{q=1}^Q (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^P \mu_p n^p + \vartheta_t
\end{aligned} \tag{3.16}$$

where $\hat{\sigma}_{d,t}$ is the one day ahead volatility forecast estimated with a MA(1)-GARCH(1,1) model which captures expected volatility in day t . The sine and cosine terms capture the intraday circadian nature of volatility. The polynomial terms $\mu_p n^p$ capture the persistence in volatility with $P = 3$. We also include the period before the announcements because the pre-announcement activity is documented in the literature (Lucca and Moench, 2015) and the lead coefficients capture such effects (Neely and Dey, 2010).

The regression results are tabulated in Table 3.10. For all the exchange rates, contemporaneous impact of liquidity jumps on volatility is significantly positive for both positive and negative jumps. Significant positive lead coefficients for negative liquidity jumps suggest that volatility is considerably higher before negative liquidity jumps. However, lagged effects have no significant impact for USDMXN and USDTRY, but it is significantly negative for USDZAR. Literature on the volume-volatility nexus proposes a positive relationship between trading activity and liquidity. From this perspective, the sudden improvements in liquidity, which is likely to be observed around opening of local or global trading hours, may lead to increased volatility as well. For all currencies, we see such an impact contemporaneously and ahead of the liquidity jumps, but not with lags. Another explanation for these liquidity jumps following significantly higher volatility episodes can be found in the literature on asymmetric information which is often proxied by the bid-ask spread (Aldridge, 2010). As argued by Venkatesh and Chiang (1986), increasing bid-ask spread reflects the suspicion of traders for the

certain underlying information causing the jump. Likewise, as pointed out by Chordia et al. (2001), trading activity may slow down in the period following high volatility episodes and bid-ask spreads may widen as a response to risk of engaging in short-term speculative activity. For the positive liquidity jumps, lead coefficients is significantly positive and negative for USDTRY and USDZAR respectively, whereas lagged coefficients are significantly positive for both exchange rates. The Wald statistic that tests the significance of cumulative impact of lead and lag effects indicates that the impact is significantly positive only for USDTRY, and the cumulative impact is not significant for USDMXN.

The news dummy for negative jumps is significantly positive USDMXN and USDTRY indicating that news-related negative liquidity jumps have significant impact on volatility. On the other hand, dummy for news-related positive liquidity jumps is significant only for USDTRY with a negative sign and it has weaker significance compared to the positive jump case. This indicates that conditional impact of news associated with negative liquidity jumps on volatility is limited relative to that of news associated with positive liquidity jumps.

3.4.4 Impact of Return Jumps on Liquidity

In this part, we change the dependent and the explanatory variables of the previous model in equations (4.4) and (3.16) and focus on the high frequency impact of return jumps on the liquidity levels. The motivation behind this exploration is provided in Figure 3.4. According to this figure, liquidity responds dramatically to the return jumps and we observe abnormal liquidity levels right before and after these jumps as well.

For further examination, we revise our previous WLS setting with the following

Table 3.10: Impact of liquidity jumps on volatility

	USDMXN		USDTRY		USDZAR	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
LJ_{t+3}^-	0.0112*	0.0708	0.0154	0.1648	0.0177**	0.0275
LJ_{t+2}^-	0.0196**	0.0205	0.0262**	0.0300	-0.0029	0.7942
LJ_{t+1}^-	0.0373***	0.0000	0.0481***	0.0001	0.0251**	0.0223
LJ_t^-	0.0482***	0.0000	0.149***	0.0000	0.1035***	0.0000
LJ_{t-1}^-	0.0145*	0.0876	-0.008	0.5076	-0.0044	0.6881
LJ_{t-2}^-	0.0149*	0.0783	-0.0084	0.4864	0.0052	0.6346
LJ_{t-3}^-	-0.0038	0.6550	-0.0089	0.4634	-0.0558***	0.0000
LJ_{t+3}^+	-0.0135	0.1528	0.0194	0.1160	-0.0089	0.4261
LJ_{t+2}^+	-0.0101	0.2837	0.0323***	0.0090	-0.0211*	0.0585
LJ_{t+1}^+	-0.0088	0.3517	0.038***	0.0021	-0.0471***	0.0000
LJ_t^+	0.0312***	0.0011	0.2235***	0.0000	0.1201***	0.0000
LJ_{t-1}^+	0.0193***	0.0052	0.0314***	0.0056	0.0167**	0.0408
LJ_{t-2}^+	-0.007	0.4602	0.0439***	0.0004	0.0097	0.3842
LJ_{t-3}^+	0.0057	0.5477	0.1276***	0.0000	0.0142	0.2041
D_t^-	0.4108***	0.0015	0.5545***	0.0008	0.2156	0.1359
D_t^+	-0.0253	0.8127	-0.2292**	0.0226	0.0249	0.8450
ΣLJ_{lead}^-	0.0682***	0.0000	0.0897***	0.0000	0.0399**	0.0239
ΣLJ_{lag}^-	0.0256*	0.0863	-0.0253	0.2387	-0.055***	0.0048
ΣLJ_{lead}^+	-0.0324*	0.0504	0.0896***	0.0000	-0.0772***	0.0001
ΣLJ_{lag}^+	0.018	0.2322	0.2029***	0.0000	0.0406**	0.0236

This table presents the estimation results for the two-stage weighted least squares model defined by the following equations

$$r_t = \beta_0 + \sum_{k=1}^K \beta_k r_{t-k} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \delta_{d,l} \times LJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \epsilon_t$$

and

$$|\epsilon_t| = c + \varphi \frac{\hat{\sigma}_{d,t}}{\sqrt{288}} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \delta_{d,l} \times LJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \sum_{q=1}^Q (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^P \mu_p n^p + \vartheta_t$$

where r_t denotes the 5-minute logarithmic returns with $K = 5$ units, LJ_t^d is the size of the liquidity jump with direction d at time t with $L = 3$, D_t^d is a dummy variable which equals 1 if the liquidity jump with direction d within $[t-3, t+3]$ is associated with a scheduled macroeconomic news announcement. ΣLJ_{lead}^d and ΣLJ_{lag}^d denote the cumulative impact of lead and lagged liquidity jumps in direction d . In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

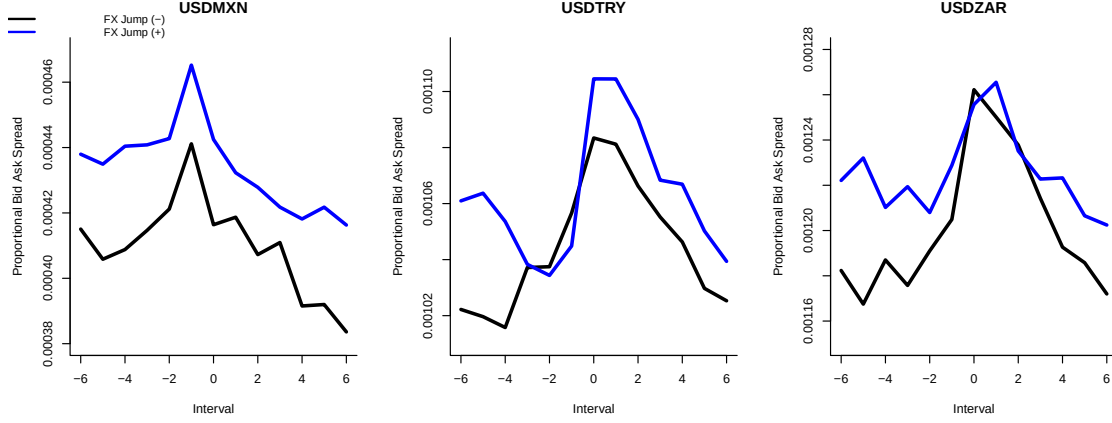


Figure 3.4: Average proportional quoted spread around return jumps ($t = 0$)

equations,

$$L_t = \beta_0 + \sum_{k=1}^K \beta_k L_{t-k} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \gamma_{d,l} \times RJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \epsilon_t \quad (3.17)$$

where L_t is the 5-minute proportional bid-ask spread described in equation (3.8), and RJ and D are the return counterparts of the liquidity related variables defined for the estimation of equation (4.4). In the second stage, we fit the absolute value of estimated residuals in equation (4.5) to the following specification in equation (3.18) where we find the expected daily liquidity $\hat{liq}_{d,t}$ by estimating a MA(1)-GARCH(1,1) model in a similar spirit with the previous analysis.

$$|\epsilon_t| = c + \varphi \hat{liq}_{d,t} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \gamma_{d,l} \times RJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \sum_{q=1}^Q \left(\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288} \right) + \sum_{p=1}^P \mu_p n^p + \vartheta_t \quad (3.18)$$

We present the regression results in Table 3.11. The contemporaneous impact of both positive and negative return jumps is significantly positive on the liquidity of USDTRY and USDZAR, but not that of USDMXN. According to the the Wald

test results, lead coefficients of both negative and positive return jumps significantly increase the proportional bid-ask spread which indicates that liquidity conditions become significantly worse for both positive and negative jumps for all currencies. Furthermore, significantly higher or lower bid-ask spread before the jumps may lead to asymmetries in buyer and seller initiated order flows and create those jumps. This finding is in line with that of Piccotti (2018) who shows that illiquidity increases before jumps. On the other hand, worsening liquidity conditions in the period following return jumps is valid for only the negative return jumps in USDZAR. All the news dummies that identifies return jumps that are related to US and local news releases are found to have significant negative impact on liquidity which is not surprising as the majority of the news announcements are done in local trading hours for all currencies. In this period, liquidity conditions are far better compared to jumps that occur in off-shore trading hours.

3.4.5 Determinants of Jumps and Cojumps

In this part, we investigate the determinants of return jumps, liquidity jumps and also return-liquidity cojumps for each exchange rate. We proceed as follows: We first count daily jump and cojump arrivals and for each count series, we run the following generalized linear model with Poisson model family,

$$J_t \text{ (or } CJ_t) = \beta_0 + \beta_1 \Delta TED_t + \beta_2 \Delta VIX_t + \beta_3 EPU + \beta_4 \Delta RD_t + \beta_5 \Delta CDS_t + \beta_6 \Delta RR_t + \epsilon_t \quad (3.19)$$

where TED denotes a popular market-wide funding liquidity measure (e.g., Brunnermeier et al. (2008), Mancini et al. (2013)) which is calculated as the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 contracts and captures market stress level. EPU denotes the daily US

Table 3.11: Impact of return jumps on liquidity

	USDMXN		USDTRY		USDZAR	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
RJ_{t+3}^-	3.4282***	0.0091	6.9956**	0.0399	6.1209**	0.0111
RJ_{t+2}^-	2.526*	0.0500	10.3494***	0.0047	12.8544***	0.0000
RJ_{t+1}^-	24.9407***	0.0000	28.9326***	0.0000	29.7468***	0.0000
RJ_t^-	3.705*	0.0737	41.0154***	0.0000	45.5505***	0.0000
RJ_{t-1}^-	2.3818	0.1166	-11.6889***	0.0012	-3.4852	0.2097
RJ_{t-2}^-	-1.4891	0.3179	3.2032	0.4359	9.3527***	0.0022
RJ_{t-3}^-	0.476	0.7593	7.3047*	0.0955	14.6245***	0.0000
RJ_{t+3}^+	-0.1698	0.9160	-2.905	0.2784	8.0561***	0.0007
RJ_{t+2}^+	3.8372**	0.0151	-0.5047	0.8498	-0.7944	0.7198
RJ_{t+1}^+	23.3074***	0.0000	17.5283***	0.0000	22.8608***	0.0000
RJ_t^+	3.8289	0.1008	44.6823***	0.0000	27.1048***	0.0000
RJ_{t-1}^+	-1.4251	0.4294	-9.5513***	0.0024	-2.2549	0.3685
RJ_{t-2}^+	0.1083	0.9472	2.3077	0.4224	-1.2735	0.5772
RJ_{t-3}^+	-5.1358***	0.0095	11.6259***	0.0007	7.0076**	0.0170
D_t^-	-0.1781***	0.0000	-0.3337***	0.0000	-0.4609***	0.0000
D_t^+	-0.1962***	0.0000	-0.3288***	0.0000	-0.3675***	0.0000
ΣRJ_{lead}^-	30.8949***	0.0000	46.2776***	0.0000	48.7221***	0.0000
ΣRJ_{lag}^-	1.3687	0.5914	-1.181	0.8624	20.492***	0.0001
ΣRJ_{lead}^+	26.9748***	0.0000	14.1186***	0.0033	30.1224***	0.0000
ΣRJ_{lag}^+	-6.4526**	0.0283	4.3823	0.4005	3.4792	0.4142

This table presents the estimation results for the two-stage weighted least squares model defined by the following equations

$$L_t = \beta_0 + \sum_{k=1}^K \beta_k L_{t-k} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \gamma_{d,l} \times RJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d + \epsilon_t$$

and

$$|\epsilon_t| = c + \varphi \hat{l} q_{d,t} + \sum_{d \in \{+, -\}} \sum_{l=-3}^L \gamma_{d,l} \times RJ_{t+l}^d + \sum_{d \in \{+, -\}} \eta_d \times D_t^d \\ + \sum_{q=1}^Q (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^P \mu_p n^p + \vartheta_t$$

where L_t denotes the proportional bid-ask spread at time t with $K = 5$ units, RJ_t^d is the size of the return jump with direction d at time t with $L = 3$, D_t^d is a dummy variable which equals 1 if the return jump with direction d within $[t-3, t+3]$ is associated with a scheduled macroeconomic news announcement. ΣRJ_{lead}^d and ΣRJ_{lag}^d denote the cumulative impact of lead and lagged return jumps in direction d . In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

policy uncertainty index and added to the model to capture both monetary and fiscal policy related uncertainties. These variables are included to control for both the market stress and uncertainty. Abrupt increases (decreases) in these variables can cause dramatic decreases (increases) in foreign investment positions and might lead to capital flight to (from) safer currencies. Among the independent variables that control idiosyncratic factors for each currency, RD denotes the rate differential between US and the local rate. RR is the risk reversal which is a proxy for downside risk and provides a measure for downside risk pricing (Hutchison and Sushko, 2013).¹¹ Since series are not stationary in levels except for the EPU, we use the first differences as the regressors.

The regression results of the equation (3.19) are tabulated in Table 3.12. The results show that different risk and liquidity factors have significant impact on jump counts of different exchange rates. For USDMXN, changes in CDS significantly affects both return and liquidity jumps. The results also show that, while return jumps followed by liquidity jumps (i.e., $LJ \rightarrow RJ$) are not significantly related to any of the regressors, number of liquidity jumps followed by return jumps ($RJ \rightarrow LJ$) significantly increase by the raise in both EPU and CDS. This asymmetry is not surprising as the reaction of liquidity to return jumps is more severe with increasing probability of private information in higher uncertainty conditions. On the other hand, for USDTRY, both return and liquidity jump frequencies show significant positive reaction to an increase in TED, EPU and rate differential RD. This finding supports the earlier evidence on positive relation between jump arrivals and interest rate differentials as shown by Li et al. (2017). The number of cojumps significantly increase with higher TED spread and risk reversal. TED spread being significant for both individual return and liquidity jumps and also their cojumps confirms the findings by Karnaukh et al. (2015) who

¹¹Wong (2019) shows that risk reversal and the currency volatility skew predicts jumps during the European financial crises of 2007-2015.

show a significantly negative relationship between the TED spread and the foreign exchange liquidity. Findings are also parallel to those by Banti and Phylaktis (2015) who show that the individual liquidity conditions of relatively less liquid currencies like TRY is very sensitive to market-wide liquidity. For USDZAR, while return jumps increase with higher EPU, rate differential and CDS, the liquidity jumps are positively related with EPU and risk reversal only. Overall, among different risk and liquidity factors, EPU is the only one that has significantly positive impact on both return and liquidity jumps. This finding is not so surprising since a higher EPU implies higher uncertainty and as suggested by Beckmann and Czudaj (2017), uncertainty in the future stance of economic policy have significant deteriorating impact on foreign exchange expectations that causes forecast errors. This would in turn lead to speculative trading activity and thus increase both return and liquidity jump occurrences. Also, the risk reversal significantly increases liquidity jumps for all three exchange rates under consideration. While the literature that provides empirical examination between VIX and FX liquidity finds significantly negative relationship between the two variables (Mancini et al., 2013), we do not observe such an occurrence in the case of liquidity jump arrivals for any of the sample exchange rates.

Relation to Local and Global Macro-News Announcements

In this part, we further investigate the determinants of jumps and cojumps by examining their linkages with the US and local macroeconomic news announcements. In order to do so, we run the following probit regression model for each exchange rate:

$$P(J_t \text{ (or } CJ_t) = 1|X) = \Phi(\alpha + \sum_{m=1}^M \phi_m News_t^{US} + \sum_{n=1}^N \theta_n News_t^{Local}) \quad (3.20)$$

Table 3.12: Determinants of return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate

USDMXN					
	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>	<i>LJ</i> → <i>RJ</i>	<i>RJ</i> → <i>LJ</i>
ΔTED	1.0033	0.5988	2.4686	7.6576	5.5565
ΔVIX	3.4122	-0.609	-0.6713	-1.9529	-4.5912
<i>EPU</i>	0.0032*	0.0038***	0.0004	0.0019	0.0096***
ΔRD	-0.6673	0.6028**	-1.0868**	-1.1382	0.3902
ΔCDS	16.5556**	10.6222***	6.9134*	17.7987	27.3372**
ΔRR	-7.9201*	2.718***	2.2994	-17.2989*	5.6485

USDTRY					
	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>	<i>LJ</i> → <i>RJ</i>	<i>RJ</i> → <i>LJ</i>
ΔTED	0.0012***	2.3151***	2.8723***	2.4087	-0.623
ΔVIX	0.013***	0.7495*	0.0827	0.9497	0.7872
<i>EPU</i>	0.0001***	0.0017***	0.0002	0.0003	0.0019
ΔRD	0.0028***	0.1086**	0.0278	-0.1649	0.0899
ΔCDS	-0.0056***	2.8817*	-0.4951	6.0736	10.5918*
ΔRR	-0.0214***	2.3933**	3.1865**	6.1647*	2.9211

USDZAR					
	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>	<i>LJ</i> → <i>RJ</i>	<i>RJ</i> → <i>LJ</i>
ΔTED	0.9366	1.2049	1.9485*	-1.377	4.3053
ΔVIX	-1.9829	0.7491	0.0112	3.0096	3.7374*
<i>EPU</i>	0.0032***	0.0026***	0	0.0022	0.0028*
ΔRD	2.9417**	-0.1164	-0.2291	-1.2332	-2.2772
ΔCDS	16.1051***	0.5198	0.9645	9.2576	14.9434*
ΔRR	-7.9153**	5.1241***	-1.9345	-8.0127	0.6287

This table present the estimation results of the Poisson regression $X_t = \beta_0 + \beta_1 \Delta TED_t + \beta_2 \Delta VIX_t + \beta_3 EPU + \beta_4 \Delta RD_t + \beta_5 \Delta CDS_t + \beta_6 \Delta RR_t + \epsilon_t$ where X can be *RJ*, *LJ*, *CJ^{RJ,LJ}*, *LJ* → *J* or *J* → *LJ*. *RJ* and *LJ* refer to return and liquidity jumps respectively. *CJ^{RJ,LJ}* denotes return-liquidity cojump. As extended definitions of cojumps, *LJ* → *RJ* and *RJ* → *LJ* refer to (i) return jumps followed by liquidity jumps and (ii) liquidity jumps followed by return jumps within 15-minutes respectively. TED is the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 contracts and captures market stress level. EPU denotes the daily US policy uncertainty index. RD denotes the rate differential between US and the local rate for the selected currency. RR is the risk reversal. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

In this setup, $News^{US}$ and $News^{Local}$ are dummy variables for US based and local macro-news announcements respectively, where the full list of announcement can be found in Table 3.1.¹² The estimated coefficients are in Table 3.13. Occurrence of return jumps are found to coincide with key macroeconomic variables like CPI, non-farm payroll and FOMC announcements which is consistent with the earlier works by Lahaye et al. (2011) and Lee (2012). In both studies, authors show that among all US macroeconomic news announcements, non-farm payroll and FOMC announcements are the most important ones for jumps in bond and equity prices and also exchange rates. For the local news announcements, central bank rate decisions are found to have significantly positive impact on return jump probabilities. For the liquidity jumps, CPI announcement is effective for Turkey, whereas central bank rate decision in Mexico has significant impact on both return and liquidity jumps for USDMXN. However, monetary policy rate decision announcements by these central banks have no effect on the probability of return-liquidity cojump occurrence for any of the exchange rates.

3.5. Cojump Analysis Across Exchange Rates

After our analysis on jumps and cojumps at the individual foreign exchange rate level, we pass to the cojump analysis across exchange rates. To examine the behavior of return or liquidity cojumps across our sample exchange rates, we provide Table 3.14 where daily distribution of such cojumps are presented. The number of return cojumps is highest for the USDTRY-USDZAR pair. This is not surprising as these two currencies have higher similarities compared to others,

¹²As argued by Andersen et al. (2003), quantifying surprises in central bank decisions requires more advanced techniques since FOMC rate announcements, meeting minutes or local rate decisions are non-standard as they may contain information on unconventional policies like quantitative easing or forward guidance that may surpass the rate decision. Therefore, we use dummy variables instead of surprises for monetary policy decision announcements.

Table 3.13: Impact of US based and local macroeconomic news announcements on return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate

	USDMXN			USDTRY			USDZAR		
	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>	<i>RJ</i>	<i>LJ</i>	<i>CJ^{RJ,LJ}</i>
US News Announcements									
Budget Statement	-3.617	-2.995	-2.313	-3.589	-2.909	-2.751	-3.474	-2.801	-2.609
Business Inventories	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
Consumer Confidence	-2.64	-2.7	-2.276	-2.986	-2.873	-2.718	-2.864	-2.765	-2.577
Consumer Credit	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
CPI	1.392***	-2.633	-2.137	1.18***	0.854**	1.349***	0.911***	0.43	1.66***
Durable Goods Orders	0.426	-3.455	-2.168	0.18	0.592	-2.564	-3.488	-2.936	-2.411
Factory Orders	0.478	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	0.553	-2.614
FOMC Announcement	2.474***	-2.753	-2.323	2.222***	-2.914	-2.756	2.425***	0.742*	1.457***
FOMC Meeting Minutes	1.762***	-2.745	-2.316	1.428***	-2.906	-2.748	1.439***	-2.798	-2.606
GDP-Advance	0.962*	-2.715	-2.242	1.087***	-3.124	-2.665	1.313***	-2.847	-2.526
GDP-Final	-2.648	1.409**	-2.156	-2.87	-2.941	-2.566	-2.742	-2.908	-2.429
GDP-Second	-2.757	-2.735	-2.294	-3.032	-3.049	-2.723	-2.875	-2.816	-2.582
Housing Starts	0.15	-2.704	-2.24	-3.692	-3.326	-3.602	0.124	-2.989	-3.768
Industrial Production	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
Initial Jobless Claims	-0.298	-0.022	-2.208	-0.649*	-0.279	-3.479	-0.512	0.235	-3.612
ISM Manufacturing	0.793**	0.795*	-2.323	0.459	0.454	-2.756	-2.907	0.562	-2.614
Leading Index	-2.72	-2.731	-2.303	-3.021	-2.891	-2.735	-2.911	-2.783	-2.593
New Home Sales	-2.61	-2.673	-2.251	-2.966	-2.853	-2.699	-2.844	-2.745	-2.559
Non-farm Payrolls	2.489***	0.512	-2.222	2.196***	1.189***	1.493***	2.368***	-3.267	-2.506
Personal Income	0.51	-2.726	-2.252	0.23	-3.004	-2.676	0.378	-2.857	-2.536
PPI	0.589*	-2.649	-2.148	0.003	0.515	-2.551	0.515	-3.113	-2.414
Retail Sales	0.955***	-2.572	-2.092	0.981***	0.003	-3.758	0.946***	0.483	-3.932
Trade Balance	-0.526	0.518	-2.157	-0.147	-3.846	-3.997	-0.62	0.676	-2.437
Local News Announcements									
Budget Balance	0.486	-2.753	-2.323	-3.03	-2.914	-2.756	-2.903	-2.815	-2.608
CPI	-2.696	-2.753	-2.323	0.81***	0.761**	-2.756	0.284	-2.795	-2.604
Current Account Balance	-2.619	-2.681	-2.258	-2.968	-2.855	-2.701	-2.97	-2.772	-2.583
GDP NSA YoY	-2.696	-2.753	-2.323	-2.848	-2.741	-2.595	1.629***	-2.806	-2.614
Industrial Production	-2.696	-2.753	-2.323	-3.012	-2.897	-2.74	0.572*	-2.806	-2.614
Central Bank Decision	1.525***	0.974**	-2.316	2.089***	0.512	-2.756	0.979***	-2.823	-2.603
Unemployment Rate	-2.685	-2.742	-2.313	-3.012	-2.897	-2.74	-2.907	-2.806	-2.614

This table presents the estimation results of the following probit regression: $P(J_t \text{ (or } CJ_t) = 1|X) = \Phi(\alpha + \sum_{m=1}^M \phi_m News_t^{US} + \sum_{n=1}^N \theta_n News_t^{Local})$. In the model, $News_t^{US}$ and $News_t^{Local}$ are dummy variables for US based and local macro-news announcements respectively. J and LJ refer to return and liquidity jumps respectively. $CJ^{RJ,LJ}$ denotes return-liquidity cojump. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

leading them to show more common reaction in general. While return cojumps are mostly accumulated in off-shore trading hours, they also intensify between 12:00 and 14:00 suggesting that US macro news releases can be a major driver behind these cojumps. For the liquidity cojumps, the number of occurrences is very low. While the maximum number of liquidity cojumps is found for USDTRY-USDZAR pair with 46 occurrences, the number of such cojumps that occur at the same time for all three exchange rates is only 2. Since the number of liquidity cojumps is very low, we limit ourselves to the analysis of return cojumps in this section. We proceed in a similar manner to the previous section, and focus on the analysis of modelling the duration between consecutive return cojumps, and also examine the determinants of these cojumps through macroeconomic news announcement analysis.

3.5.1 Duration Analysis on Cojumps Across Exchange Rates

In this part, we analyze the duration between consecutive return cojumps across exchange rates. Tables 3.15 reports the summary statistics related to such cojumps. Accordingly, we see that shortest average duration between return cojumps is observed for the USDTRY-USDZAR pair, with such cojumps occurring on every 2.4 days which is 50% more frequent than cojumps occurring between USDTRY-USDMXN pair. Return cojumps among all three sample exchange rates occur on the average around every 10 days. Among all bilateral return cojumps, the one between USDMXN-USDZAR pair has the most irregular pattern with a standard deviation of 5 days, whereas the most regular pattern arises in the case of USDTRY-USDZAR pair with the lowest standard deviation for duration.

Next, we model the duration x_i between consecutive return cojumps across exchange rates using a similar LACD(1,1) model that we have implemented earlier.

Table 3.14: Intraday cojump distribution across exchange rates

	$RCJ^{MXN,TRY}$	$RCJ^{MXN,ZAR}$	$RCJ^{TRY,ZAR}$	$RCJ^{MXN,TRY,ZAR}$	$LCJ^{MXN,TRY}$	$LCJ^{MXN,ZAR}$	$LCJ^{TRY,ZAR}$	$LCJ^{MXN,TRY,ZAR}$
00:00-02:00	51	62	85	20	1	1	1	0
02:00-04:00	55	67	82	24	3	1	4	0
04:00-06:00	40	29	44	9	0	0	0	0
06:00-08:00	2	4	5	1	0	0	0	0
08:00-10:00	2	1	1	1	0	0	0	0
10:00-12:00	2	2	2	1	1	0	0	0
12:00-14:00	28	28	31	23	3	1	4	1
14:00-16:00	3	1	3	1	0	0	0	0
16:00-18:00	6	6	7	3	0	2	0	0
18:00-20:00	32	38	53	25	0	0	1	0
20:00-22:00	14	14	29	7	0	2	1	0
22:00-00:00	40	35	74	13	7	6	35	1
Total	275	287	416	128	15	13	46	2

This table provides the intraday distribution of cojumps in FX return and liquidity. $RCJ^{i,j}$ and $LCJ^{i,j}$ refer to return cojump and liquidity cojump between exchange rates i and j respectively. $RCJ^{i,j,k}$ and $LCJ^{i,j,k}$ refer to cojump occurrences at the same time for all three exchange rates.

Table 3.15: Summary statistics for the duration between consecutive return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
Min	0.003	0.003	0.003	0.003
Max	27.358	46.656	16.750	55.840
Average	3.633	3.510	2.400	7.806
Std.	4.400	5.096	3.136	9.499
Obs.	274	286	415	1271

Note: The values in the table (except the number of observations) are in days.

This time, the main difference is, in addition to the exchange rate specific factors, we also include the global factors of TED spread, VIX and EPU index as explanatory variables since cojumps across borders are most likely driven by such widely influential drivers. The model is presented in equation (3.21) and the estimation results are provided in Table 3.16.

$$\begin{aligned}
 x_i &= \mu_i \epsilon_i \\
 \mu_i &= \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \theta_1 TED + \theta_2 VIX + \theta_3 EPU \\
 &+ \varphi_{FX1} \overline{LIQ}_{i1} + \psi_{FX1} \overline{RV}_{i1} + \varphi_{FX2} \overline{LIQ}_{i2} + \psi_{FX2} \overline{RV}_{i2} + \epsilon_t
 \end{aligned} \tag{3.21}$$

According to Table 3.16, global factors, as well as idiosyncratic ones, play a significant role on the duration between consecutive cojumps. For all three combinations of bilateral cojumps, an increase in the EPU index has a strong negative impact on the duration; i.e., rising uncertainty in US economic policy increases the intensity of return cojumps across exchanges. Similar effect is found for VIX on the cojumps between USDMXN-USDZAR and USDTRY-USDZAR pairs. Idiosyncratic factors of liquidity and volatility mostly preserve their original impacts that they had on return and liquidity jumps respectively.

Table 3.16: LACD(1,1) model fit results for duration between consecutive return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
ω	0.6985***	0.4034***	0.2314***	-0.1029
α	0.0695**	0.0116	0.1117***	-0.0551
β	-0.0539	0.0641	0.0582**	1.016
TED	-0.0969	-0.0479	0.1309**	-0.0152
VIX	-0.0591	-0.1884***	-0.2906***	-0.0015
EPU	-0.4165***	-0.0985*	-0.2148***	-0.0108
φ_{MXN}	-0.6241***	-0.149**		-0.0029
ψ_{MXN}	0.0078	-0.2271***		-0.0021
φ_{TRY}	-1.0633***		-0.1901***	-0.0168
ψ_{TRY}	-1.9046***		-0.147***	0.0007
φ_{ZAR}		-1.0466***	-1.3625***	-0.0169
ψ_{ZAR}		-1.0533***	-1.4053***	-0.0098

This table presents the estimated parameters of the following LACD(1,1) model that investigates the determinants of the duration x_i between consecutive return cojumps.

$$\begin{aligned}
 x_i &= \mu_i \epsilon_i \\
 \mu_i &= \omega + \alpha \ln \epsilon_i + \beta \ln \mu_i + \theta_1 TED + \theta_2 VIX + \theta_3 EPU \\
 &+ \varphi_{FX1} \overline{LIQ}_{i1} + \psi_{FX1} \overline{RV}_{i1} + \varphi_{FX2} \overline{LIQ}_{i2} + \psi_{FX2} \overline{RV}_{i2} + \epsilon_t
 \end{aligned}$$

TED is the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 contracts and captures market stress level. EPU denotes the daily US policy uncertainty index. $\overline{LIQ}$ and $\overline{RV}$ denote the average liquidity and realized volatility variables of the corresponding exchange rate between consecutive return cojumps. In case that three exchange rates are considered simultaneously, model is extended to cover $\overline{LIQ}_{i3}$ and $\overline{RV}_{i3}$ as well. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

3.5.2 Cojumps and US Macro-News Announcements

We examine the impact of scheduled US macroeconomic news releases on the cojumps across exchange rates via equation (3.22). Different from equation (3.20), we include only the US announcements this time since the cojumps across currencies are not idiosyncratic. Moreover, due to the very limited number of observations for liquidity cojumps, analysis is performed only for return cojumps across exchange rates.

$$P(CJ_t = 1|X) = \Phi(\alpha + \sum_{m=1}^M \phi_m News_t^{US}) \quad (3.22)$$

We provide the regression results in Table 3.17. Announcements of CPI and non-farm payrolls have significant positive impact on all pairwise exchange rate cojump combinations. For the triple exchange rate cojump probabilities, none of the announcements has a significant impact. On the other hand, FOMC announcements, FOMC meeting minutes and GDP-Advance announcements have significant positive impact only for return cojumps across USDMXN and USDTRY. Overall, results that are found in this part and also those found in Section 3.4.4 show us that investor sentiment in emerging markets are now dependent on the US economy and the actions by the Fed more than ever which points out to the potential challenges faced with policy makers around the world when one clearly dominates the others.

3.6. Conclusion

Although there is a growing attention on the dynamics of foreign exchange return jumps in the literature, there are very limited number of studies that investigate the linkages between return jumps and liquidity. Moreover, to the best of our

Table 3.17: Impact of US based macroeconomic news announcements on return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
US News Announcements				
Budget Statement	-3.589	-2.7231	-2.5762	-2.6671
Business Inventories	-3.0315	-2.7287	-2.5814	-2.6721
Consumer Confidence	-2.9882	-2.686	-2.5421	-2.6341
Consumer Credit	-3.0315	-2.7287	-2.5814	-2.6721
CPI	1.1784***	0.8537**	1.3496***	-2.4725
Durable Goods Orders	0.1791	0.5917	-2.3832	-2.5057
Factory Orders	-3.0315	-2.7287	-2.5814	-2.6721
FOMC Announcement	2.2198***	-2.7287	-2.5814	-2.6721
FOMC Meeting Minutes	1.4267***	-2.7202	-2.5736	-2.6646
GDP-Advance	1.0858***	-2.9292	-2.4878	-2.5855
GDP-Final	-2.8719	-2.7518	-2.3854	-2.4937
GDP-Second	-3.034	-2.8558	-2.548	-2.641
Housing Starts	-3.6929	-3.1278	-3.4113	-2.5831
Industrial Production	-3.0315	-2.7287	-2.5814	-2.6721
Initial Jobless Claims	-0.6503*	-0.2792	-3.2832	-2.5492
ISM Manufacturing	0.4576	0.4541	-2.5814	-2.6721
Leading Index	-3.0225	-2.705	-2.5596	-2.6511
New Home Sales	-2.9673	-2.6654	-2.5231	-2.6158
Non-farm Payrolls	2.1941***	1.1886***	1.4934***	-2.5642
Personal Income	0.2283	-2.811	-2.4988	-2.5964
PPI	0.0017	0.5147	-2.3699	-2.4845
Retail Sales	0.9801***	0.0033	-3.5731	-2.4244
Trade Balance	-0.1473	-3.6516	-3.8149	-2.494

This tables present the estimation results of the following probit regression: $P(CJ_t = 1|X) = \Phi(\alpha + \sum_{m=1}^M \phi_m News_t^{US})$. $News_t^{US}$ is a dummy variable for US based macro-news announcements. $CJ^{i,j}$ refers to return cojump between exchange rates i and j . $CJ^{i,j,k}$ refers to return cojump occurrences at the same time for all three exchange rates i, j, k . In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

knowledge determinants of liquidity jumps has not been examined along with their interaction and co-occurrence with return jumps. To take a first step in this subject, in this paper, we investigate the dynamics of both return and liquidity (co)jumps and their high frequency interaction for three major emerging market exchange rates, namely USDMXN, USDTRY and USDZAR. More specifically, we address the following questions: (I) What is the impact of liquidity and volatility conditions in-between periods on the durations of consecutive return and liquidity (co)jump arrivals? (II) What is the high frequency transmission of liquidity jumps on volatility and return jumps on liquidity? Do the impacts of positive and negative jumps differ? (III) How various risk and liquidity factors affect daily (co)jump arrivals (IV) Which local and US macroeconomic news announcements have impact on the likelihood of return and liquidity (co)jump occurrences? The findings of the paper reveal that the duration between consecutive jump arrivals is significantly reduced by the average liquidity in the period between the jumps. Likewise, the duration between consecutive liquidity jumps are significantly reduced by average realized volatility but for only USDTRY exchange rate. The high-frequency investigation of the impact of return and liquidity jumps on the levels of liquidity and volatility by employing an event type analysis reveal that contemporaneous effects of return and liquidity jumps for both negative and positive jumps are significant for all currencies. We also show that daily arrivals of jump variants significantly increase with increases in US economic policy uncertainty. With a further analysis on high frequency impacts of local and US macroeconomic news announcements, we observe that announcements on US CPI, GDP, non-farm payroll and FOMC decisions and minutes significantly increase the likelihood of both return and liquidity (co)jumps.

The findings of the paper also suggest several policy implications. First, insights from characterization of different jumps and cojumps can be incorporated in

decision making process. It can be used for establishing efficient operational framework in managing foreign exchange liquidity because, as demonstrated by Ait-Sahalia et al. (2015), jump intensity can serve as a proxy for market stress with significant out-of sample forecasting performance. They may eventually help build up leading indicators to provide early warning signals. Second, for a country that demands big amounts of foreign financing, jumps in exchange rate increase volatility risk premium and thus affects cost of funding. In a lower frequency horizon when combined with high pass-through effects, jumps also lead to deteriorated inflation forecasts and thus distorts central bank decisions in inflation targeting regimes as in the analyzed currencies.

CHAPTER IV

INTRADAY VOLUME-VOLATILITY NEXUS IN THE FX MARKETS: EVIDENCE FROM AN EMERGING MARKET

4.1. Introduction

The volume-volatility relationship has long been an interest for microstructure research as it has implications for trading, risk management and policy making objectives. Long before the availability of financial market data, there were several papers trying to set up a theoretical background for the relationship between these two variables. In the competitive models such as the ones by Easley and O'Hara (1987) and Holthausen and Verrecchia (1990), the expected outcome would be a positive relationship between volume and volatility due to the price impact by informed traders who submit large orders. However, in the strategic models by Foster and Viswanathan (1996); Kyle (1985) and Chordia and Subrahmanyam (2004), informed traders submit splitted orders in order to hide their private information, yielding to small executed trades hence a weak or even a negative relationship between volume and volatility.

The competitive theoretical models in the abovementioned papers indeed depend on two famous hypothesis, namely mixture of distribution hypothesis (MDH) of

Clark (1973) and sequential information arrival hypothesis (SIAH) of Copeland (1976). While stochastic arrival of information and positive relationship between volume and volatility are proposed by both hypotheses, their approach on how the equilibrium is restored differs. MDH implies a contemporaneous relationship between volume and volatility as both variables are driven by the same mixing variable, the flow of information.¹ In SIAH, agents receive information sequentially and the equilibrium is established only when the information is disseminated to all agents and they have identical set of information. Numerous studies empirically tested these two hypotheses and found that the validity of these hypotheses are market and state dependent. For instance, Foster (1995) investigates oil futures market and finds supporting evidence for MDH as volume and volatility is contemporaneously determined in this market. Likewise, Luu and Martens (2003) and Ciner (2002) confirm the MDH for S&P500 Index futures contracts and commodity futures markets respectively. In the case of currency futures, Bauwens et al. (2005) find a positive relationship between volume and volatility for the intraday Euro/USD parity from May 2001 to November 2001, again supporting the MDH. On the other hand, Mougoué and Aggarwal (2011) reject the validity of MDH but accepts SIAH for GBP, JPY and CAD currency futures. Being among a few studies focusing on spot foreign exchange markets, Galati (2001) investigates volume-volatility relation for seven emerging market currencies including the Indonesian rupiah, the Indian rupee, the Mexican peso, the Brazilian real, the Colombian peso, the South African rand and the Israeli shekel. Except for the Mexican peso and the Brazilian real, author finds positive and contemporaneous relationship between trading volume and volatility supporting the MDH. In addition to that, results by Bjørnnes et al. (2005) for the daily Swedish Krona/Euro

¹Li and Wu (2006) examine the volume-volatility relationship with the control for information flow. Accordingly, authors are able to provide a theoretical support for a negative relationship between volume and volatility based on the MDH framework.

exchange rate between 1995–2002, and Bauwens et al. (2006) for the weekly Norwegian Krone/Euro exchange rate over January 1993 to December 2003 also support the MDH.

A recent hypothesis regarding the volume-volatility nexus belongs to Harris and Raviv (1993) and Shalen (1993). According to their dispersion of beliefs hypothesis (DBH) that builds upon MDH, an asymmetric relationship between volume and volatility is possible due to the heterogeneous interpretation of the same publicly available information by market participants. This hypothesis is empirically supported by the works of Balduzzi et al. (1996); Chen (2012); Giot et al. (2010b); Wagner and Marsh (2005) and Koubaa and Slim (2019), in which volume-volatility relationship is found to have various asymmetric structures through the evolution of financial markets across different periods of the business cycles.

Although there is a vast amount of studies in the literature on the volume-volatility relationship in the stock markets, the same literature for the FX market remains limited due to its fragmented structure, hence lack of reliable trade volume data. In addition to that, the size and structure of FX market and the variety of traders in the market necessitate elaboration of volume-volatility relation in consideration of trader types, transaction types and trading sessions for several reasons. First of all, although they acquire the same information, interpretation and acting on this information may differ among traders as suggested by the DBH. Daigler and Wiley (1999) argue that the type of trader matters for volume-volatility relationship and show that the positive relationship between the two variables is determined by general public. They propose that the uninformed traders, who are mostly the general public, can not differentiate between the volume arising from liquidity demand and the volume due to a change in fundamental value and thus their trading activity increases volatility. Second, unlike the case of stock markets, timing of traders' presence in the market may differ due to different trading

sessions. Many studies show that the intraday volatility and volume patterns mostly overlap. In the model of Admati and Pfleiderer (1988), the reason why trading volume and volatility is concentrated in certain periods is explained by strategic behaviour of liquidity traders and informed traders. Daigler and Wiley (1999) suggest that intraday volatilities can be more related with daily volume as majority of the transactions are made in normal trading hours. However, critical news arrival may create volatility out of local trading hours as well. For instance, as stated by Fischer and Rinaldo (2008), global FX trading volume increases around FOMC announcements but the volume and volatility relationship is expected to be stronger for transactions of foreign investors compared to local investors since local trading session is closed around announcements. Third, there is significant variation in liquidity in different trading sessions which may affect volume-volatility relation across different trading sessions. Osler (2008) states that except from USD, EUR and JPY, the liquidity in most of the currencies are concentrated around local trading hours. For example, a lower volume may trigger higher volatility in a low liquidity environment. Thus, the volatility and volume relation in non-trading hours may be weaker. Fourth, as size of the market participants increase, their trade size and information quality increases as well. Chan and Fong (2000) find that trade size is more important than number of trades for volume-volatility relationship. Large currency orders are more likely to be placed by informed traders (Easley and O'Hara, 1987) and larger trades are associated with higher volatility (Gradojevic et al., 2017). Chang et al. (1997) find that volume-volatility relationship is much stronger for trades of large speculators in commodity and bond market futures. Supporting these views, Bjørnnes (2005) provide evidence for differentiation of volume-volatility relationship across participants such that trading volume by large banks increases volatility the most and they also document that large players have relation with the determinants of timing of speculative

attacks (Bjønnes et al., 2014). Fifth, it is crucial to discriminate across contract types as their cash flows and intention of use may differ. For example, at the initial agreement of forward contracts there is no initial cash flows.² On the other hand, there is simultaneous buying and selling of local currency and foreign currency for FX swaps. The impact on the liquidity is determined by the sides and currency legs of these contracts. In addition, the use of FX swaps and forwards for either speculative or hedging purposes may have different impact on the relationship between trading volume and realized volatility. For instance, while forwards are used for speculative positioning, use of FX swaps are more common for hedging the currency exposure. This argument is supported by Antonio Garganoy (2008) who show that information content of volume depends on the traded instrument.

As stated above, the literature on volume-volatility relationship in FX markets is scarce and to the best of our knowledge, the only studies among those that focus on the impact of participant and contract type belong to Bjønnes (2005); Bjønnes et al. (2005). The reason is the fact that unlike financial assets that are traded in organized exchanges, foreign exchange transactions occur mostly in the over-the-counter markets in which information on trades are not kept under a central database. In this study, we contribute to this sparse literature in at least two main ways by utilizing a dataset of the Central Bank of the Republic of Turkey that covers all daily foreign currency transactions traded against Turkish Lira (TRY) by local banks segregated at the trader type and instrument type level. First, we investigate the volume-volatility relationship in the FX market controlling for time of the day, participant type and instrument type concurrently for the first time in the literature. This analysis adds insights on how banks' trading activity with a particular type of counterparty and contract affects intra-daily volatility in

²Forwards does not incur initial cash flow but they can be part of a multiple transaction strategy. For instance a foreign investor might simultaneously buy TRY spot and write a put option or sell it forward.

each trading session. Second, our results provide intuition on the source and timing of exchange rate volatility that yields to implications for a more precise policy making and investment strategies.

Accordingly, we find significant positive contemporaneous relationship between volume and volatility only for spot and forward transactions of domestic customers. This finding partially supports the MDH in the FX markets and is consistent with the literature proposing that it is the uninformed and retail traders that create volatility. Further, the regression results for realized volatilities of different trading sessions suggest that the positive or negative relationship between volume and volatility is stronger in times when the majority of transactions occur such as the local and London trading sessions (which overlaps the most with the local trading session). Our dynamic model, on the other hand, shows that there is no bivariate Granger causality between any of the realized volatility and transaction volume combination, rejecting the SIAH. Furthermore, we document that the correlation between spot trading volume of both foreign and domestic customers and realized volatility is time varying, and higher contemporaneous correlation between volume and volatility is associated with the higher dispersion of beliefs on the future USDTRY exchange rate level. Our results not only re-iterate previous findings that the relationship depends on the counterparty and transaction type but also provide new evidence on the impact of the investigated trading session. In addition, consistent with the late studies, we show that level and dispersion of beliefs on the future level of exchange rate reinforces contemporaneous correlation between the two variables.

The rest of the paper is organized as the following: In Section 4.2, we begin by describing the data and provide summary statistics. Section 4.3 first proposes the hypotheses and defines the econometric setting, then discusses empirical results. Finally, Section 4.4 concludes.

4.2. Data and Summary Statistics

Our data comes from the Central Bank of the Republic of Turkey (CBRT) and the sample covers the period from May 20th, 2013 to November 2nd, 2018, consisting of 1355 daily observations after excluding public holidays in Turkey and December 25th where most of the major financial markets are closed. Volume of foreign exchange transactions are reported to CBRT by local banks on a daily basis. The data includes all foreign currency transactions traded against TRY by local banks and compromised of 2 dimensions. In the first dimension, the total transaction volume is disaggregated into 4 type of counterparties: (i) Domestic interbank transactions represent transaction volume among domestic banks including the CBRT. For this category, since two sides of the transaction are banks, transaction amounts are divided by two to avoid double reporting in the analysis; (ii) transactions with domestic customers include domestic retail and institutional customers; (iii) the transactions of banks with their branches and headquarters located outside of Turkey (which are omitted in the analysis since they are more likely to be accounting purposes rather than actual trade); and (iv) transactions with foreign institutional and retail customers are aggregated under foreign customers category. The second dimension disaggregates each type of counterparty transaction volume into 3 types: (i) Spot transactions include purchase or sale of TRY against a foreign currency with value date up to 2 days; (ii) forward transactions include all derivative contracts (except FX swap transactions) such as options, forwards, interest swaps etc.; and (iii) swap transactions consist of FX swap contracts as of value date.

Table 4.1 gives the summary statistics of transaction volumes data.³ Majority of

³To give an idea for the coverage of our data, we can compare it with Triennial Central Bank Survey of Foreign Exchange and OTC Derivatives Markets of Bank for International Settlements

Table 4.1: Summary statistics for FX transactions of banks against TRY

Counterparty	Transaction	Min	Max	Mean	Std.	Obs.	ADF Test	PP-Test
Domestic Interbank	Spot	36	3270	537	290	1355	-5.8***	-973.9***
	Forward	0	359	57	68	1355	-3.2*	-247.4***
	Swap	0	922	272	160	1355	-5.9***	-932.4***
Domestic Customers	Spot	2105	14870	4304	1019	1355	-7.9***	-927.7***
	Forward	94	3094	631	338	1355	-3.7**	-499.8***
	Swap	56	1671	471	230	1355	-4.6***	-721.8***
Foreign Customers	Spot	465	7225	3229	895	1355	-7.6***	-875.1***
	Forward	11	2939	502	359	1355	-5.7***	-1092.3***
	Swap	187	16899	7428	2669	1355	-5.8***	-742.2***
Total	Spot	3504	18769	8070	1628	1355	-6.9***	-936.5***
	Forward	181	5051	1190	637	1355	-4.2***	-582.8***
	Swap	249	18100	8171	2750	1355	-6.2***	-792.2***

Notes: This table documents the summary statistics for FX volume data. The data covers the period from May 20th, 2013 to November 2nd, 2018. The trading volume values are in million USD. ADF and PP tests refer to Augmented Dickey Fuller test and Phillips-Perron test for stationarity respectively. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

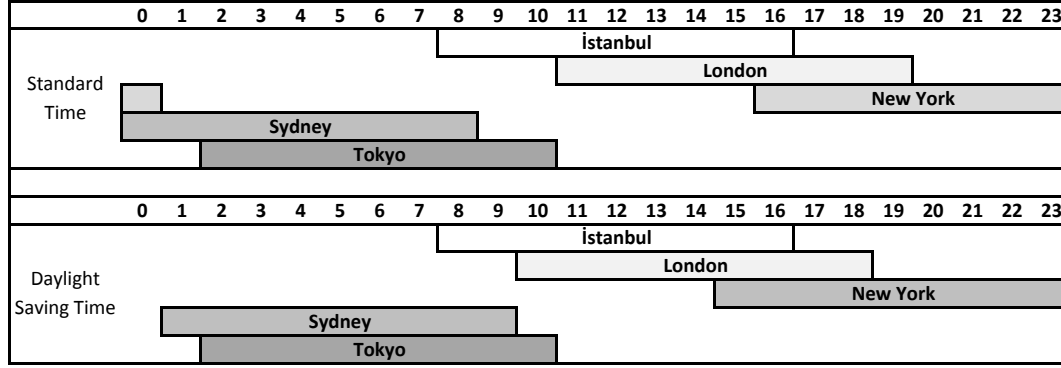


Figure 4.1: Hours of FX trading sessions in different locations

total transactions are made with foreign customers and their total transaction volume is twice the domestic customers. In terms of transaction types, swap and spot transactions constitute big part the total transactions. While domestic customers are more active in spot transactions, 70% of the transactions with foreign customers are carried out via FX swap contracts. The last two columns provide Augmented Dickey Fuller test and Phillips-Perron test statistics which reveal that the trade volume series under consideration are trend stationary.

We obtain high-frequency USDTRY exchange rate data from Bloomberg. TRY⁴ is continuously traded over all trading sessions under consideration. For each trading session, the daily intraday realized volatility proxies are calculated by summing up squares of logarithmic returns for 5-min intervals. Figure 4.1 displays the trading hours of major forex markets with respect to local time in Turkey. For each market, trading sessions span between 08:00 and 17:00 in their own local time.⁵

(BIS, 2016) which gives average daily transaction volumes for April, 2016. For spot, forward and swap transactions, daily averages of the same month of our data corresponds 107%, 27% and 61% of this BIS transaction volume data. Overall, our data represents a big portion of total FX trading volume for USDTRY exchange rate.

⁴Turkish lira is freely convertible and has one of the most liquid and liberal FX markets among emerging market currencies. According to BIS (2016), it has the 16th highest FX turnover currency. In the special case of emerging market currencies, TRY ranks 3rd after Chinese yuan and Mexican peso.

⁵In different sources the trading hours are shown differently but for consistency we assume 08:00 to 17:00 for all.

Table 4.2: Summary statistics for USDTRY returns and volatility across trading sessions

	Panel A: Log returns				Panel B: Realized volatility				Obs.
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	
IST	-2.7479	5.3760	0.0103	0.3325	0.0052	25.7441	0.1292	0.8306	1355
LDN	-1.5944	4.6955	0.0048	0.3324	0.0056	21.4501	0.1208	0.6731	1355
NYC	-2.9172	6.4646	-0.0117	0.3145	0.0025	41.0983	0.1054	1.1307	1355
TKY	-3.1550	3.3748	0.0213	0.2289	0.0012	11.2594	0.0604	0.4404	1355
SYD	-2.5130	2.0598	0.0167	0.1894	0.0006	11.8344	0.0513	0.4336	1355

Notes: The data covers the period from May 20th, 2013 to November 2nd, 2018. IST, LDN, NYC, TKY, and SYD stand for Istanbul, London, New York, Tokyo and Sydney trading hours respectively. The log returns are obtained by summing up 5-min log returns and realized volatilities are obtained by summing up squares of 5-min log returns between 08:00 to 17:00 for each trading session.

Local trading hours in Turkey have overlapping periods with all other trading sessions and the biggest overlap is with London trading hours. The overlapping periods change with the switches between standard time (ST) and daylight saving time (DST).

In Table 4.2, summary statistics of 5-min USDTRY log-returns and the corresponding realized volatilities across main forex trading sessions are documented. On average, while highest depreciation occurs in Tokyo session, volatility is higher in the local trading session. This is consistent with theoretical models in which volatility and volume is highest when the arrival of information is more intense. In terms of returns, one can observe that TRY appreciates on the average only in New York session. This is also consistent with the previous literature on intraday patterns that find home currencies are inclined to depreciate during domestic trading sessions and appreciate during off-shore trading sessions (Breedon and Ranaldo, 2013; Zhang, 2018). Moreover, although mean realized volatility is highest in local trading session, the variation in realized volatility is highest in the NY session.

The hourly patterns in Figure 4.2 display the differential impact of counterparty types and transaction types on both USDTRY realized volatility and its unconditional correlations between trading volume. In the top sub-figure of the Figure 4.2, we show the impact of differential counterparty transactions. The realized volatility is stronger for local trading hours as majority of the information arrival and thus the transactions occur during these hours. Furthermore, when we condition upon the days of high domestic activity and low foreign customer activity, we observe that on the average the volatility is lower. Differential between the two patterns in top of Figure 4.2 also supports the hypothesis that the daily volatility pattern depends on the relative intensity of the counterparty type. For

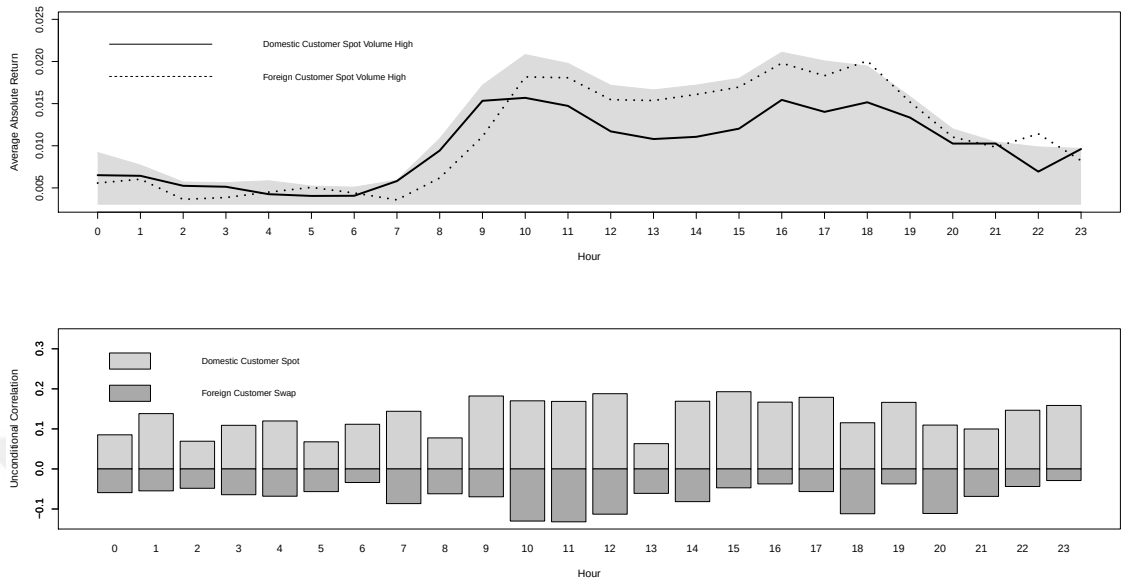


Figure 4.2: Intraday volatility patterns with respect to transaction volume by different trader and instrument types and intraday correlation patterns between volume and volatility

instance, although volatility is consistent with a U-shaped pattern as frequently observed in the literature, a careful reader can identify that the lunch break impact for domestic customers is higher compared to foreign customers, and the time zone differential is evident for the foreign customers as well.

Bottom sub-figure of Figure 4.2 provides contemporaneous correlations between the volume of two most traded instrument types (spot and swap) and hourly USDTRY realized volatilities. While the spot transactions of domestic customers are positively correlated with the volatility, the correlation between realized volatility and foreign customer swap transactions is negative for all hourly intervals. The correlations of domestic spot transactions and realized volatility show a similar pattern with the intraday volatility as they are higher in local trading sessions and reach the local minimum around lunch hours. On the other hand, negative correlation between swap transactions and realized volatility is stronger around opening and closing hours of the London trading session.

4.3. Methodology and Results

As a proxy of volatility we use realized volatility obtained from 5-min USDTRY exchange rate data since realized volatility estimates are less noisy than widely used other volatility measures such as absolute returns (Chan and Fong, 2006), and it allows us to estimate volatility precisely for each trading session. To obtain an intraday volatility measure for each trading session, we first calculate log returns for each 5-minute interval as follows:

$$r_t = \log(p_t) - \log(p_{t-1}) \quad (4.1)$$

where p_t is the USDTRY exchange rate in interval t . Realized volatility for trading session i on day t is then obtained with the following equation:

$$RV_t^i = \sum_{j=1}^T r_j^2 \quad (4.2)$$

where T is the number of 5-min observations (i.e. 108) in each trading session.

Previous studies emphasize the importance of decomposition of volume data into expected and unexpected components. Bessembinder and Seguin (1993) argue that it is the unexpected component of volume that has strongly positive relationship with volatility. Expected component of the volume has a negative relation with volatility as it enhances liquidity and market depth. As an important component of expected volume, many studies document the day of the week effects for retail and institutional investors (Lakonishok and Maberly, 1990). The weekly patterns in Figure 4.3 indicate that this argument is valid in our dataset as well. The patterns suggest that the day of the week effect differs for domestic and foreign customers in the sense that while domestic customer transactions are higher on Monday and

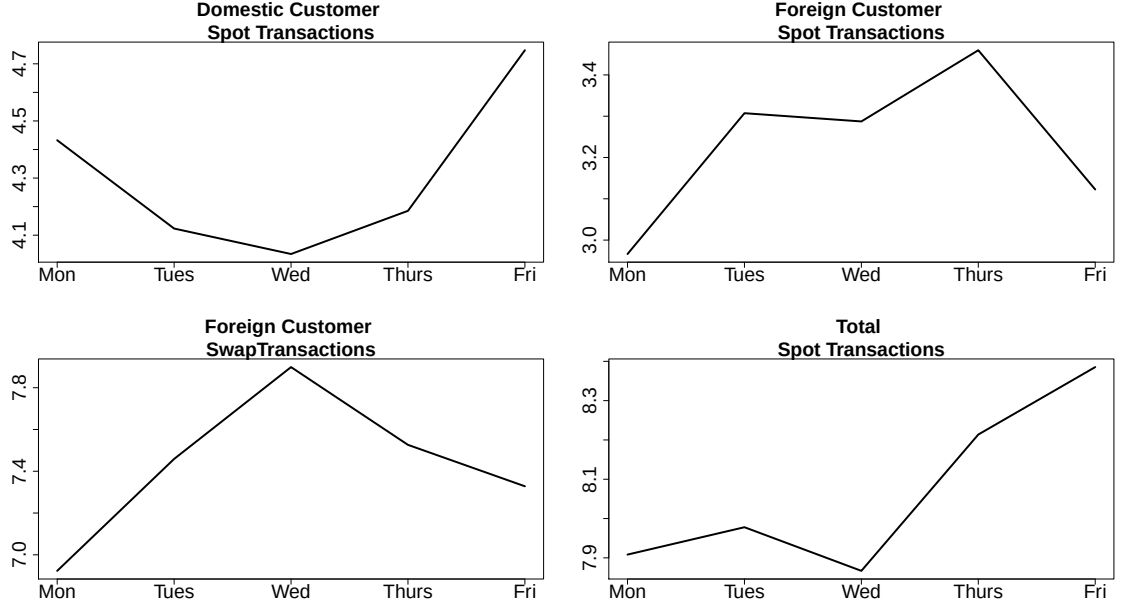


Figure 4.3: Average transaction volumes (in USD billions) by the day of the week with respect to different trader and instrument types

Friday, both spot and swap transactions by foreigners are more concentrated in the middle of a business week.

These observations lead us to apply a decomposition procedure which involves fitting an ARMA model with the day of the week dummies as external regressors, as suggested by Bjørnnes (2005). We estimate an ARMA(p, q) model where the optimal p and q are determined according to Bayesian Information Criteria (BIC). The resulting residuals from the estimation are used as unexpected volumes.

$$Vol_t = \sum_{i=1}^p Vol_{t-p} + \epsilon_t + \sum_{j=1}^q \epsilon_{t-q} + \sum_{k=1}^4 DayDummy_k \quad (4.3)$$

Once we obtain daily series for unexpected transaction volumes and realized volatility for each trading session, we carry out contemporaneous and dynamic analysis for volume-volatility relationship in the rest of this paper.

4.3.1 Contemporaneous Relations

Examining the existence of a simultaneous relationship between volume and volatility requires a correct treatment of simultaneity bias as both variables are endogenously determined. Thus, following previous empirical studies in analysing contemporaneous relations, we employ the generalized method of moments (GMM) technique which not only fixes simultaneity bias but also gives heteroskedasticity consistent standard errors in our estimations (Foster, 1995; Mougoué and Aggarwal, 2011). Using lagged values of endogenous variables as instruments, we estimate the following system of equations:

$$Vol_t^j = \zeta_0 + \zeta_{1i}RV_t^i + \zeta_{2i}RV_{t-1}^i + \zeta_{3i}Vol_{t-1}^j + \nu_{2t} \quad (4.4)$$

$$RV_t^i = \varphi_0 + \varphi_{1i}Vol_t^j + \varphi_{2i}Vol_{t-1}^j + \varphi_{3i}RV_{t-1}^i + \nu_{1t} \quad (4.5)$$

In Table 4.3, the coefficient estimates of contemporaneous terms of our GMM model is documented. The positive contemporaneous relationship between volume and volatility is evident only for domestic customers' spot and forward transactions. As expected, these significant positive relations are observed for local trading session and London and Tokyo trading sessions which overlap the most with the local trading session. For the OTC foreign exchange markets, it is harder to distinguish informed traders from uninformed traders. However, as the literature suggests, institutional investors compared to individuals (Chen and Daigler, 2008) and foreign investors compared to local investors (Froot and Ramadorai, 2008; Grinblatt and Keloharju, 2000) have informational advantage as they have more sophisticated tools to collect private information and act on fundamentals. Thus, the positive contemporaneous relation between volatility and domestic customer spot trade volume confirms the findings of Daigler and Wiley (1999) who argue

that volatility is created by uninformed traders. The spot transactions of foreign customers on the other hand, have significant negative contemporaneous relationship with realized volatility, in particular during London and New York trading sessions. The negative relation is because of the fact that the foreigners' trading volume is significantly correlated with their foreign portfolio holdings in Turkish equity and bond markets. Thus, their high trading activity mostly overlaps with resilient periods as flow of funds contribute to foreign exchange liquidity. Therefore, on average we observe a negative relationship between volume and volatility in the special case of foreign customers. Interestingly, in the case of domestic interbank transactions, almost all contemporaneous coefficients are significantly negative. This finding can be attributed to the strategic trading behaviour of domestic banks in the interbank market when the volatility is lower. They also have the informational advantage by knowing both domestic and foreign order flows and having the local market expertise compared to other market participants.

Overall, we can accept MDH only for spot and forward transactions of domestic customers and only for local trading session and the global sessions that have big overlaps with the local trading session.

4.3.2 Bivariate Dynamic Relations

In this section, to assess the dynamic relationship between volume and volatility, we start with a $\text{VAR}(p)\text{-DCC}(1,1)\text{-EGARCH}(1,1)$ specification in which the outcome will tell us whether there is bivariate causality and time varying contemporaneous correlation between the two variables. The estimation procedure of these system of equations has two stages. First, for each transaction volume and realized volatility pair, we select an optimal lag according to Bayesian Information Criteria (BIC) and then estimate a $\text{VAR}(p)$ model as the following:

Table 4.3: GMM estimation results to analyse contemporaneous relation between volume and volatility

		Domestic Interbank			Domestic Customers			Foreign Customers			Total	
		Spot	Forward	Swap	Spot	Forward	Swap	Spot	Forward	Swap	Forward	Swap
IST	ζ_{11}	-0.098 (-4.154)***	-0.019 (-3.137)***	-0.062 (-3.028)***	0.661 (7.743)***	0.113 (3.371)***	-0.104 (-4.752)***	-0.192 (-1.516)	-0.264 (-7.501)***	-1.238 (-10.184)***	0.133 -0.547	-0.368 (-6.804)***
	φ_{11}	-3.821 (-3.162)***	-8.867 (-3)***	-6.624 (-2.084)**	1.357 (4.371)***	4.484 (1.847)**	-3.963 (-3.657)***	-0.598 (-1.246)	-3.23 (-4.081)***	-0.798 (-8.048)***	0.047 -0.229	-2.143 (-4.141)***
LDN	ζ_{12}	-0.097 (-4.504)***	-0.017 (-3.171)***	-0.091 (-5.841)***	0.637 (10.476)***	0.126 (4.516)***	-0.101 (-4.817)***	-0.36 (-3.254)***	-0.278 (-9.344)***	-1.21 (-12.925)***	0.404 (1.814)*	-0.4 (-8.445)***
	φ_{12}	-3.17 (-2.993)***	-7.696 (-2.917)***	-8.065 (-3.034)***	1.522 (5.462)***	4.805 (2.078)**	-3.782 (-3.543)***	-0.755 (-1.9)**	-3.225 (-4.582)***	-0.821 (-9.837)***	0.148 (0.843)*	-2.067 (-4.498)***
NYC	ζ_{13}	-0.106 (-2.412)**	-0.027 (-3.588)***	-0.004 (-0.082)	0.048 -0.302	0.032 -0.462	0.074 (2.25)**	-0.374 (-2.74)***	-0.027 (-0.386)	-1.476 (-3.091)***	-0.84 (-4.213)***	-0.301 (-3.819)***
	φ_{13}	-5.099 (-2.626)***	-17.076 (-4.034)***	-0.426 (-0.092)	0.249 -0.464	1.308 -0.423	4.125 (2.379)**	-1.502 (-2.355)**	-0.444 (-0.305)	-0.609 (-3.093)***	-0.91 (-3.416)***	-2.717 (-3.591)***
TKY	ζ_{14}	-0.267 (-7.593)***	-0.038 (-3.414)***	-0.104 (-2.455)**	0.913 (3.662)***	-0.11 (-1.62)	-0.04 (-0.818)	-0.31 (-1.232)	0.211 (2.018)**	-2.554 (-7.774)***	-0.606 (-1.289)	0.08 (-0.548)
	φ_{14}	-2.961 (-5.429)***	-4.134 (-3.002)***	-2.256 (-1.624)**	0.317 (1.721)**	-0.898 (-1.154)	-0.302 (-0.579)	-0.314 (-1.155)	0.35 (0.901)**	-0.365 (-5.235)***	-0.135 (-1.184)	-0.018 (-0.067)
SYD	ζ_{15}	-0.274 (-5.835)***	-0.042 (-3.026)***	-0.218 (-6.754)***	-1.281 (-4.997)***	-0.285 (-8.282)***	-0.021 (-0.35)	0.068 -0.204	-0.106 (-0.809)	-3.174 (-7.509)***	-1.942 (-4.115)***	-0.76 (-5.321)***
	φ_{15}	-2.559 (-4.625)***	-3.96 (-2.921)***	-4.064 (-4.094)***	-0.441 (-2.585)***	-3.474 (-5.651)***	-0.123 (-0.23)	-0.028 (-0.098)	-0.187 (-0.463)	-0.294 (-5.923)***	-0.304 (-3.07)***	-0.92 (-3.642)***

Notes: This table presents the parameter estimates of contemporaneous terms in Equations 4.4 and 4.5. The exogenous terms are not documented to save space. The regression sample covers daily observations from May 20th, 2013 to November 20th, 2018. The values in the parentheses are *t*-stats. *, **, and *** denote statistical significance at 10%, 5% and 1% respectively.

$$Vol_t^j = \phi_0 + \sum_{k=1}^p \phi_{1k} Vol_{T-k}^j + \sum_{k=1}^p \phi_{2k} RV_{T-k}^i + u_t \quad (4.6)$$

$$RV_t^i = \gamma_0 + \sum_{k=1}^p \gamma_{1k} RV_{T-k}^i + \sum_{k=1}^p \gamma_{2k} Vol_{T-k}^j + v_t \quad (4.7)$$

This first stage of estimation not only serves as the mean equation for the conditional variance and dynamic correlation estimations, but also provides a test for bivariate Granger causality. Specifically, as an outcome of these system of equations, two null hypothesis are tested. Rejection of the first null hypothesis of $H_0 = \gamma_{21} = \gamma_{22} = \dots \gamma_{2p} = 0$ indicates that trading volume Granger causes realized volatility and the rejection of second hypothesis of $H_0 = \phi_{21} = \phi_{22} = \dots = \phi_{2p} = 0$ indicates intraday realized volatility Granger causes trading volume.

In the second stage, we estimate a DCC-EGARCH(1,1) specification. In this model, the error terms in the Equations 4.6 and 4.7 follow an EGARCH(1,1) process:

$$u_t = \sqrt{\sigma_{1t}^2} \epsilon_{1t} \quad (4.8)$$

$$\ln \sigma_{1t}^2 = \omega_1 + \beta_1 \ln \sigma_{1t-1}^2 + \gamma_1 \frac{\epsilon_{1t-1}}{\sqrt{\sigma_{1t-1}^2}} + \alpha_1 \left[\frac{\epsilon_{1t-1}}{\sqrt{\sigma_{1t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (4.9)$$

$$v_t = \sqrt{\sigma_{2t}^2} \epsilon_{2t} \quad (4.10)$$

$$\ln \sigma_{2t}^2 = \omega_2 + \beta_2 \ln \sigma_{2t-1}^2 + \gamma_2 \frac{\epsilon_{2t-1}}{\sqrt{\sigma_{2t-1}^2}} + \alpha_2 \left[\frac{\epsilon_{2t-1}}{\sqrt{\sigma_{2t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (4.11)$$

and to allow for variation in correlation matrix, we use DCC(1,1) specification developed by Engle (2002) which defines time varying variance-covariance matrix as the following:

$$\Sigma_t = D_t^{1/2} R D_t^{1/2} \quad (4.12)$$

where the time varying correlation matrix is obtained by

$$\mathbf{R} = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix} \quad (4.13)$$

$$R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t^{-1/2}) \quad (4.14)$$

and

$$Q_t = (1 - \delta_1 - \delta_2) \bar{Q} + \delta_1 (u_{t-1} u_{t-1}^*) + \delta_2 Q_{t-1} \quad (4.15)$$

in which δ_1 and δ_2 are DCC(1,1) parameters.

In Panel A and B of Table 4.4, we document F-statistics and their corresponding significance levels from Granger causality tests obtained by the estimation of Equations 4.6 and 4.7. The results show that the only Granger causality from realized volatility to volume is observed for total spot transactions. In other words, only with the information of total spot transactions we can improve our forecasts on realized volatility in all trading sessions. Regarding the reverse direction, we observe that forward transactions in the interbank market Granger cause realized volatility in all trading sessions. Moreover, spot transactions of domestic customers Granger cause realized volatility in New York and Sydney trading sessions, possibly because of their trade volume concentration around the early and late hours of the local trading session. Overall, the results are largely insignificant and for the significant cases, the causality between volatility and volume is unidirectional which invalidates SIAH.

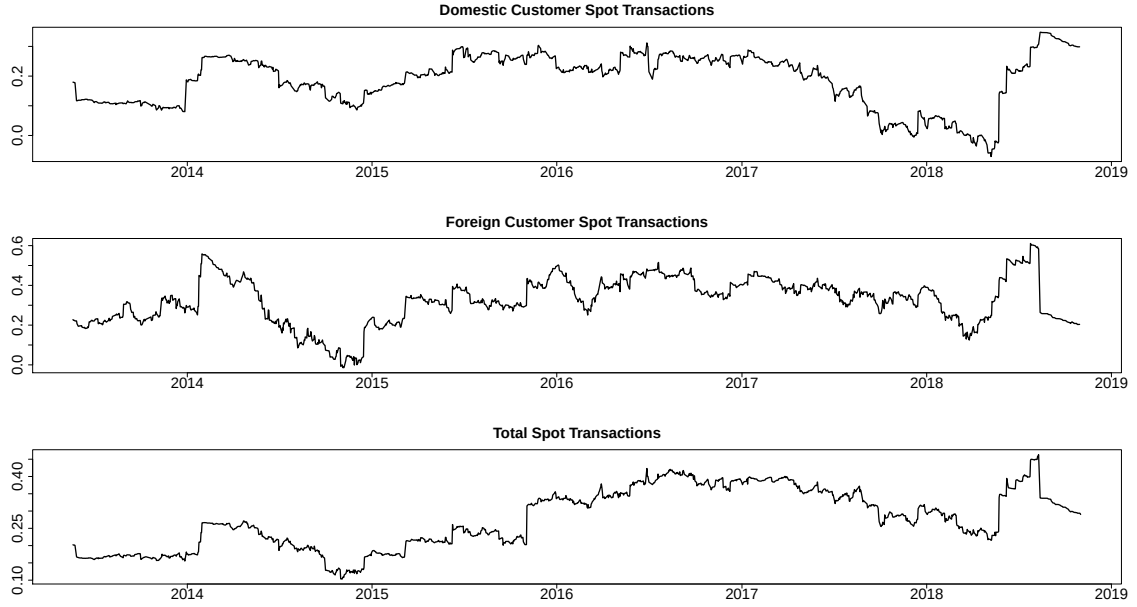


Figure 4.4: Dynamic conditional correlations between trading volumes and realized volatility with respect to different trader and transaction types

We document DCC(1,1) parameters in Panel C of Table 4.4. The joint significance of the estimated DCC parameters rejects the null hypothesis of a constant correlation. About half of the transaction volume-realized volatility pairs, we reject the null hypothesis of constant correlation which implies that the contemporaneous correlation between the two variables is significantly time-varying.

Among significantly time-varying correlation series, we selectively display major volume-volatility pairs in Figure 4.4. One can observe that the correlations increase during severe currency depreciation episodes like first quarter of 2014, and third quarters of 2016 and 2018. In the subsequent section, we relate this variation with the central moments of expectations on the future level of the USDTRY exchange rate.

Table 4.4: Results of VAR(p)-DCC(1,1)-EGARCH(1,1) model to analyse the bivariate dynamic relationship between volume and volatility

Panel A: H_0 =Realized volatility does not Granger cause volume

	Domestic Interbank			Domestic Customers			Foreign Customers			Total	
	Spot	Forward	Swap	Spot	Forward	Swap	Spot	Forward	Swap	Spot	Swap
IST	2.202*	0.500	0.010	0.334	2.642	1.867	1.481	0.624	0.136	1.208	3.379*
LDN	2.091*	0.543	0.496	0.490	1.224	0.900	1.891	0.741	2.213*	0.920	2.194*
NYC	2.569	1.064	0.204	0.014	1.014	2.337	0.061	0.279	0.034	0.070	0.001
TYO	1.308	0.379	0.170	0.450	0.822	0.879	1.006	0.616	1.303	0.715	1.169
SYD	1.317	0.696	0.154	0.305	1.417	0.317	1.239	0.327	2.227*	0.340	2.049

Panel B: H_0 =Volume does not Granger cause realized volatility

	Domestic Interbank			Domestic Customers			Foreign Customers			Total	
	Spot	Forward	Swap	Spot	Forward	Swap	Spot	Forward	Swap	Spot	Swap
IST	0.322	3.684***	0.010	1.179	0.379	0.076	0.805	1.404	0.006	0.004	1.211
LDN	0.419	3.478***	0.323	1.461	0.152	0.794	0.744	1.266	0.218	0.864	0.906
NYC	0.085	20.449***	0.057	3.473*	0.024	0.117	0.056	0.056	0.000	1.514	0.638
TYO	0.158	3.842***	0.538	2.424**	0.118	0.261	1.733	1.107	0.058	1.930*	0.948
SYD	1.469	3.704***	0.576	4.170***	0.256	0.341	1.494	1.047	0.191	1.865	0.935

Notes: The resulting four central moment series are displayed in Figure 4.5. Panel A and B document F-statistics and their corresponding significance levels from Granger causality tests obtained by the estimation of Equations 4.6 and 4.7. *, **, and *** denote statistical significance at 10%, 5% and 1% respectively.

Table 4.5: Results of $\text{VAR}(p)\text{-DCC}(1,1)\text{-EGARCH}(1,1)$ model to analyse the bivariate dynamic relationship between volume and volatility-cont.

Panel C: DCC Parameters

		Domestic Interbank			Domestic Customers			Foreign Customers			Total	
		Spot	Forward	Swap	Spot	Forward	Swap	Spot	Forward	Swap	Forward	Swap
IST	δ_1	0.00	0.02	0.01***	0.00	0.01**	0.00	0.01**	0.02	0.13	0.01**	0.15
	δ_2	0.95	0.98***	0.99***	0.95***	0.99***	0.92	0.99***	0.98***	0.3***	0.99***	0.24
LDN	δ_1	0.00	0.01	0.01	0.01**	0.01*	0.00	0.02**	0.01*	0.00	0.01	0.07
	δ_2	0.96***	0.99***	0.99***	0.99***	0.99***	0.88***	0.98***	0.99***	0.93***	0.99***	0.22
NYC	δ_1	0.00	0.02***	0.01	0.35***	0.01*	0.26**	0.00	0.15***	0.38	0.03*	0.45***
	δ_2	0.86***	0.98***	0.99***	0.28**	0.99***	0.34	0.91***	0.76***	0.33	0.87***	0.32
TYO	δ_1	0.00	0.04***	0.00	0.03	0.02**	0.01	0*	0.00	0.04	0*	0.05
	δ_2	0.89***	0.96***	0.93***	0.78***	0.98***	0.97***	1***	1***	0.85***	1***	0.83***
SYD	δ_1	0.01	0.07*	0.06*	0.00	0.03*	0.02	0.09***	0.01**	0.00	0.01	0.00
	δ_2	0.82***	0.9***	0.8***	0.9***	0.97***	0.56	0.82***	0.98***	0.93	0.89***	0.9***

Notes: Panel C reports only the estimates and significance levels of the DCC parameters δ_1 and δ_2 to save space. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

4.3.3 Dispersion of Beliefs and Contemporaneous Dynamic Correlations

A complementary hypothesis for MDH and SIAH that extends our understanding in volume-volatility relationship is the dispersion of belief hypothesis (DBH). The literature contributing to this hypothesis asserts that heterogeneity of expectations on the future value of the investigated asset contributes to positive volume-volatility relationship. For instance, in the work of Shalen (1993), a model of a futures market is derived in which heterogeneity of expectations increases hedging demand and thus contributes to the positive volume and volatility relationship. Similarly, in the models of Tauchen and Pitts (1983) and Harris and Raviv (1993), differences of beliefs on the value of asset being traded increases trading volume and thus price volatility of this asset. Using open interest as a proxy for dispersion of beliefs, Mougoué and Aggarwal (2011) empirically test the impact of dispersion of beliefs on volume and volatility relationship and find that increasing dispersion of beliefs reinforces volume-volatility relationship.

In this section, we extend this literature by testing how belief heterogeneity on future values of USDTRY exchange rate impacts the corresponding volume-volatility relationship. At this stage, we use currency option volatility smiles in order to extract a measure of dispersion of beliefs on a daily basis. Specifically, we derive risk neutral distributions (RNDs) using currency option volatility parameters and then extract their central moments as proxies for expectations.⁶ Use of RNDs' as a proxy for market expectations is common in the literature (Abarca et al., 2010; Csávas, 2010).

There are several methods to derive risk neutral densities from volatility smiles. We

⁶For calculating a proxy for heterogeneity of expectations on USDTRY exchange rate, we use volatility smile data of USDTRY options obtained from Bloomberg. For each day in our sample, options with 1 month to maturity are used because of their liquidity.

use the methodology proposed by Malz (1997) to derive risk neutral densities from currency options. In his setting, author uses the expression for the option-delta and the strike price derived in the work by Breeden and Litzenberger (1978):

$$\delta = e^{-r\tau} \Phi\left(-\frac{\ln(\frac{S_t}{X_{i,t}}) - (r - \sigma^2/2)\tau}{\sigma\sqrt{\tau}}\right) \quad (4.16)$$

and a parametric functional form of the RND is given by:

$$\sigma(\delta) = b_0 atm_t + b_1 rr_t(\delta - 0.5) + b_2 str_t(\delta - 0.5)^2 \quad (4.17)$$

where atm_t , rr_t and str_t represent at the money, 25-delta risk reversal and 25-delta strangle of 1-month currency options respectively. Simultaneous solving of Equations 4.16 and 4.17 provides RNDs for each trading day. Thus, we obtain risk neutral probabilities $\omega_{i,t}$ for each potential strike price $X_{i,t}$, then we calculate the expected returns as the following:

$$r_{i,t}^e = \log(X_{i,t}) - \log(S_t) \quad (4.18)$$

where S_t is the spot USDTRY exchange rate on day t . Within this framework, central moments are obtained as the following:

The first central moment, weighted mean gives the location for expectations:

$$rnd_{\mu} = \sum_{n=1}^N \omega_i r_{i,t}^e \quad (4.19)$$

As a belief dispersion measure of exchange rate, we obtain the standard deviation of RNDs:

$$rnd_{\sigma} = \sqrt{\sum_{n=1}^N \omega_i [r_{i,t}^e - \bar{r}_{i,t}^e]^2} \quad (4.20)$$

Skewness of RND's give the tendency of the distribution:

$$rnd_\gamma = \frac{\sum_{n=1}^N \omega_i [r_{i,t}^e - \bar{r}_{i,t}^e]}{rnd_\sigma^3} \quad (4.21)$$

Kurtosis gives probability of extreme returns:

$$rnd_\kappa = \frac{\sum_{n=1}^N \omega_i [r_{i,t}^e - \bar{r}_{i,t}^e]^2]}{rnd_\sigma^4} - 3 \quad (4.22)$$

The resulting four central moment series are displayed in Figure 4.5.

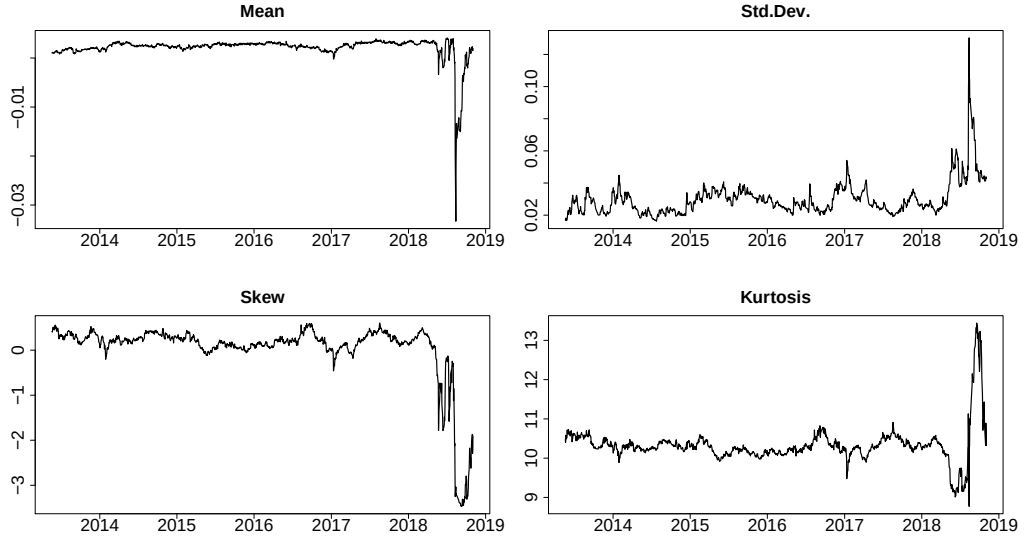


Figure 4.5: Central moments derived from risk neutral distributions

The model presented in Equation 4.23 helps us to estimate the impact of central moments derived from risk neutral distributions on the dynamic conditional correlations obtained in the previous subsection:

$$\rho_t = \eta + \rho_{t-1} + rnd_\mu + rnd_\sigma + rnd_\gamma + rnd_\kappa + v_t \quad (4.23)$$

Table 4.6: Impacts of RND central moments on dynamic correlations between USDTRY volume and volatility

	Domestic Spot(LDN)	Foreign Spot(LDN)	Total Spot(IST)
ρ_{t-1}	0.989 (0.000***)	0.976 (0.000***)	0.991 (0.000***)
rnd_{μ}	-0.049 (0.818)	3.874 (0.000***)	1.386 (0.000***)
rnd_{σ}	0.149 (0.023**)	0.586 (0.000 ***)	0.153 (0.0036 ***)
rnd_{γ}	-0.000 (0.740)	-0.001 (0.718)	-0.001 (0.037**)
rnd_{κ}	-0.002 (0.010 **)	0.004 (0.016 **)	0.000 (0.473)

The regression sample covers daily observations from May 20, 2013 to November 2, 2018. The values in the parantheses are p -values. *,** and *** denote statistical significance at 10%, 5% and 1% respectively.

Table 4.6 documents the estimation results of the model in Equation 4.23.

Accordingly, the dynamic contemporaneous correlation between volume and volatility is significantly and positively affected by the dispersion of beliefs on the future value of the USDTRY exchange rate. Moreover, the level of future exchange rate expectations also has significant positive impact for foreign and total spot transactions.

4.4. Conclusion

The relationship between traded volume and volatility in the FX markets carries a substantial importance for dealers, risk managers, policy makers and regulators. However, the literature on the subject remains shallow due to lack of enriched FX market data. The purpose of this paper is to provide evidence on this relationship for the USDTRY exchange rate from an uncharted perspective; that is taking the

trader type, transaction type and trading sessions into account at the same time. In order to do that, we create realized volatility series from high-frequency USDTRY exchange rate returns for five major FX trading sessions, namely Istanbul, London, New York, Sydney and Tokyo, and investigate volume-volatility relationship for each session by using a dataset on disaggregated FX transactions volume at both counterparty level (domestic banks, domestic retail and institutional investors, foreign retail and institutional investors) and instrument level (spot, options, forwards, futures, interest rate swaps, currency swaps) collected from all the banks operating in Turkey by the Central Bank of the Republic of Turkey.

Accordingly, through a system Generalized Method of Moments framework, we document a significant positive contemporaneous volume-volatility relationship only for spot transactions of domestic customers and only around local trading hours, a result partially supporting the Mixed Distribution Hypothesis of Clark (1973). With the help of Vector Auto Regression analysis, we further show that there is no evidence for bivariate Granger causality between volume and volatility except for a limited number of cases in Istanbul, New York and Sydney trading hours which rejects the Sequential Information Arrival Hypothesis of Copeland (1976). The dynamic contemporaneous analysis via the DCC methodology shows that the correlation between spot FX volume and realized volatility is positive and significantly time varying. To understand the potential sources that might impact the dynamics of this time varying correlation between volume and volatility, we derive a measure of dispersion of beliefs by using the moments of risk neutral distributions derived from the USDTRY options. The analysis shows that dispersion of beliefs on the level of future USDTRY exchange rate significantly increases correlations between realized volatility and both local and foreign customer spot transaction volumes, eventually supporting the Dispersion of Beliefs Hypothesis of Harris and Raviv (1993) and Shalen (1993).

Overall, our results support the view that the volume-volatility relationship depends on the type of counterparty, traded instrument and the trading session in the FX markets; moreover, it is time varying. The findings of the paper have some important implications for trading and policy objectives. In particular, differential volume-volatility nexus in different counterparties, instruments and trading sessions might help traders enhance their intraday volatility forecasts. Likewise, for regulatory purposes, policy makers need to track market activity for each counterparty and instrument closely, and take into account their differential implications on intraday volatility. For instance, a policy maker should consider the fact that uninformed traders are more likely to increase volatility and in the cases when these investors become active in the market, the policies that aim to mitigate information asymmetries and lower the resulting speculative demand might help currency stabilization and successful liquidity provision. Furthermore, since currency options have been found to provide various components of expectations of the future exchange rate and have implications on volume-volatility nexus, a policy maker might better assess the impact of a restriction or deregulation for a particular instrument on volatility by using the metrics derived from these options.

CHAPTER V

CONCLUSION

This thesis employs high-frequency analysis to investigate dynamics of foreign exchange volatility for major emerging market currencies by focusing on behavior of stochastic return and liquidity jumps and the trading volume and volatility relationship. In the second chapter of the thesis, we investigate the determinants of size and frequency of high-frequency stochastic jumps in USDTRY exchange rate. This chapter aims to contribute to the growing literature on dynamics of FX jumps whose investigation is important for investing, hedging and policy making objectives as these jumps have important implications on modelling and forecasting of foreign exchanges. The results document that, portfolio flows in forms of equity and bond flows and carry trade activity significantly reduce both size and frequency of the jumps. Furthermore, heterogeneity in expectations for the future exchange rate level and key macroeconomic variables like CPI and GDP have significantly positive impact in jump size and frequencies.

In the third chapter, we examine the dynamics and interaction of return and liquidity jumps for USDMXN, USDTRY and USDZAR exchange rates. The findings of the study reveal that, for all currencies, the duration between consecutive return jumps are significantly negatively related with average liquidity in between period of the consecutive jumps. Similarly, the duration between consecutive liquidity jumps are significantly lower with higher realized volatility in

the period between jumps of USDTRY only. The high-frequency analysis further shows that key macroeconomic variables like US CPI, US Non-farm payroll and FOMC announcements and local CPI, GDP and central bank decisions significantly increase probability of both return and liquidity jump occurrences.

The fourth chapter examines the trading volume and volatility relationship for USDTRY exchange rate. Specifically, we measure contemporaneous and lagged relationship between banks' foreign exchange trading volumes segregated into customer and contract types and the realized volatility series obtained for major trading sessions. We observe significantly positive contemporaneous volume-volatility relationship for the banks' spot transactions with local customers. Furthermore, increasing dispersion of beliefs which we proxy with standard deviation of risk neutral densities derived from currency options.

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