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Trading Price Jump Clusters in Foreign Exchange Markets^{*}

Jan Novotný^{a,*}, Dmitri Petrov^{b,1}, Giovanni Urga^{c,2}

^a*Cass Business School, City University London, UK and CERGE-EI, CZ*

^b*Nomura International plc, London, UK*

^c*Cass Business School, City University London, UK and Bergamo University, Italy*

Abstract

We investigate trading opportunities of price jump clusters in the FX markets. We identify clusters for eight FX rates against the US dollar from 1-March-2013 to 6-June-2013 sampled at 5-minute frequency. We propose a high-frequency jump cluster-based trading strategy and show that price jumps carry a tradable signal for all currencies; however, when incorporating the bid-ask spread, the only profitable currencies are the Euro, yen and, in some cases, rand. From the portfolio perspective, a combination of the Euro and yen represents a strategy robust to the holding period, minimizes the transaction costs, and diversifies out the US-related risk.

Keywords: Price Jumps; Clusters; Foreign Exchange Markets; Trading; Profitable Strategy.

J.E.L. Classification Number: F31; C58; G11

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^{*}Centre for Econometric Analysis, Faculty of Finance, Cass Business School, City University London, 106 Bunhill Row, London, EC1Y 8TZ, UK and CERGE-EI, CZ. Jan.Novotny.1@city.ac.uk, Tel: +44 (0)20 7040 8089, Fax: +44 (0)20 7040 8881.

¹Nomura International plc, One Angel Lane, London, EC4R 3AB. dmitri.petrov@nomura.com, Tel: +44 20 7102 6732.

²Centre for Econometric Analysis, Faculty of Finance, Cass Business School, City University London, 106 Bunhill Row, London, EC1Y 8TZ, UK and Bergamo University, Italy. G.Urga@city.ac.uk, Tel: +44 (0)20 7040 8698, Fax: +44 (0)20 7040 8881.

1. Introduction

There is a huge body of evidence indicating that jumps play a crucial role in the dynamics of pricing of all types of financial assets, see *inter alia* Todorov (2010) and Lee (2012). In particular, Lahaye et al. (2011) show that jumps are linked to macro-announcements including real economy indicators and monetary policy decisions; Jiang et al. (2011) investigate the large price movements for T-bonds; Brunnermeier and Pedersen (2009) and Mancini et al. (2013) show that in the foreign exchange markets, price jumps are related to a lack of liquidity; Shleifer and Vishny (1997) focus on the liquidity around periods of significant financial markets news announcements.³ Finally, Broadie and Jain (2008), among others, show that price jumps are important for pricing derivatives and calculating risk profiles.

An important feature of price jumps which has attracted scarce attention in the literature is that jumps occur in clusters, a feature similar to volatility clustering. Osler (2005) explains the presence of clusters in the currency markets as a result of technical trading with stop-losses⁴ and the reaction of investors with different investment horizons ranging from algorithmic traders to central bankers and pension funds. Brand et al. (2010) report that clustering may be implied by processing of news announcements including the

³Price jumps can be also linked to market failure, as the alleged manipulation with 4pm WM/Reuters fix foreign exchange rates suggests. There is growing evidence suggesting that currency market were rigged in a similar way as the Libor rates. In particular, traders are suspected to have manipulated the 4pm WM/Reuters fix rate, an important rate used for pricing derivatives. This was provoked by the presence of regularly placed spikes in the Canadian dollar vs. US dollar and Euro vs. US dollar currency pairs positioned at the specific time when long-term contracts are fixed. This raises doubts about the efficiency of the Forex as the largest financial market with a turnover of \$5.3tn-a-day. In fact, the alleged manipulation can be thus revealed through technical analysis of the abnormal price movements. Revealing “suspicious” spikes, however, is tricky as foreign exchange markets serve very different purposes: They are used for speculative trading, they provide means for international trade and business, and they serve as a tool for conducting monetary policy. In particular, the latter two reasons are inherently long-term, with objectives other than instantaneous arbitrage opportunities and thus any comparison to equity markets or other asset classes should be done carefully.

⁴Linnainmaa (2010) confirms the role of stop-losses with rounded numbers on the price discovery process, temporal market inefficiencies and market drops.

“soft” communications after the announcements as in the case of the European Central Bank (ECB) communications, which are relevant for the money market.

The main contribution of this paper is threefold. First, we propose a formal procedure to identify clusters of price jumps and employ it for the foreign exchange spot prices of eight currencies (Euro, Japanese yen, Hungarian forint, Mexican peso, Polish zloty, Russian ruble, Turkish lira, and South African rand) against the US dollar observed at high-frequency over the period from March 1, 2013 to June 6, 2013. This unique and novel dataset, provided by Morningstar, covers the rise of “Abenomics” and periods when the US liquidity tapering expectation start to materialize.

Second, we explore whether the presence of clusters provides trading opportunities. We propose a high-frequency trading strategy based on the framework of Obizhaeva and Wang (2013), where a marginal trader goes one unit long/short for a fixed period of time based on the occurrence of price jumps. In fact, such a strategy can be interpreted as a form of delta trades, as it is volatility based. The results of the trading strategy suggest that the two most traded currency pairs in our sample, the Euro and the Japanese yen, bring a positive profit even after accounting for the bid-ask spread and slippage. In addition, the South African rand provides a positive outcome for some of the holding horizons. The Sharpe ratio is rather low for all the profitable trades with the profit and loss (P/L) ratio being well below two. Further, including the slippage into the trading strategy supports the claim that jumps carry a signal, as the slippage decreases the profitability of trades. Such seemingly inefficient behavior can be interpreted as the presence of over-hedging during the distressed period. It is a well-documented fact among practitioners that before scheduled news announcements and significant policy changes, the market makers mark-up the short term (overnight) implied volatility at the foreign exchange markets as the uncertainty increases and the impact of the announcements may

increase the realized volatility.⁵

Third, we evaluate the performance and risk profile for a portfolio of currencies. For the market-wide portfolio, the trader accumulates a loss due to the large bid-ask spreads. However, for a portfolio consisting of the developed market currencies, those with very low transaction costs, the portfolio is stable with respect to the holding period. Even for the portfolio, however, both the Sharpe and the P/L ratios suggest fragility of the trading strategy. Then, following Lustig et al. (2011), we construct the US dollar index, an equally weighted basket of all currencies, capturing the risk factors tracking the global (US-related) market. We estimate the beta for the jump trading strategies of individual currencies. The Euro and the Japanese yen have a very different risk profile with respect to the holding period, thus trading the Euro and the yen simultaneously also hedges US exposure. Finally, we discuss the hedging of all individual trends.

This paper is related to the existing literature in several directions. First, it contributes to the literature on *modeling the spot prices in foreign exchange markets*. Shleifer and Vishny (1997) point out that liquidity in the foreign exchange markets is crucial for arbitrage trading and market efficiency. Periods when markets expect ground-breaking news may suffer liquidity shocks as fund managers tend to rather over-hedge and thus are more reluctant to trade. Therefore, a period with heavily interventions by central banks may imply temporal market inefficiencies. Boudt and Petitjean (2014) show the link between price jumps and liquidity for the equity markets. Further, Lyons (2001) documents that foreign exchange markets are in particular of limited transparency, their market participants are very heterogeneous with different scope and volume of operations, and trading under the decentralized dealership structure.

⁵Investors hedge themselves against anticipated changes and buy volatility, driving the implied volatility further. Market evidence suggests that around scheduled news announcements, the short term implied volatility usually outperforms the realized volatility and thus markets are over-hedging the possible impact of the announcements. This is particularly amplified during turmoil periods of financial crises and significant regime changes.

Second, this paper extends the *momentum trading strategy* literature into the intraday scale. Menkhoff et al. (2012) empirically investigate momentum strategies in foreign exchange markets using daily data and show the presence of a persistent and profitable trend for some currency portfolios, mainly minor currencies with high transaction costs. This is in line with what is found for stocks with high-credit risk as identified by Avramov et al. (2007) and Eisdorfer (2008), or for non-investment grade corporate bonds by Jostova et al. (2013). In the case of equities, Chan et al. (1996) suggest that analysts tend to gradually incorporate information into the price and thus a trend can emerge. On the other hand, Hong et al. (2000) find the presence of strong momentum for stocks with weak coverage. Korajczyk and Sadka (2004) report that the momentum is very often present for assets with high transaction costs, which wipes out any profit. Baillie and Chang (2011) further relate the momentum strategy to uncovered interest rate parity.

Finally, this paper contributes to the existing literature on *profitable trading strategies*. Verdelhan (2010) shows that around the news announcement, the risk aversion of traders such as hedge funds, large investors, central banks and institutional investors rises. This implies that traders are less likely to exploit investment opportunities, i.e., the realized Sharpe ratio is higher than the subjective Sharpe ratio around announcements. Griffin et al. (2003) show that limit orders can make contrarian strategies profitable. The authors use NASDAQ 100 stocks sampled at a 5-minute frequency to explore the trading activity around the excess returns and show that individual and institutional activities after large returns are, on average, higher than prior to the announcements. The period of increased activity lasts between 15 and 30 minutes. Further, Hendershott et al. (2011) analyze the impact of automated trading at NYSE since its introduction in 2003 and find that it reduces trade-related price discovery. This strengthens the significance of limit-order book effects in foreign exchange markets which are liquid and involve many algorithm-based traders. Brandt et al. (2008) show that post-announcement trading produces significant

cumulative returns. Using stocks at quarterly frequency, the authors find a low-frequency arbitrage type of opportunity similar to our results and suggest that markets do not react efficiently to the earnings announcements. Finally, Brunnermeier et al. (2008) report that carry trades are subject to crash risk, while our trading strategy is de facto profiting on crash risk.

The remainder of the paper is organized as follows: in Section 2, we describe the high-frequency data set we use, the price jump estimation procedure and report some descriptive statistics. In Section 3, we propose a novel approach to identify clusters of price jumps. In Section 4, we introduce a trading strategy based on the price jump clusters, and discuss the dollar index and diversification of jumps in the portfolio of foreign currencies. Section 5 concludes.

2. Data Description and Price Jumps

In this section, we describe the high-frequency data set used in the paper, including the filtering procedure to clean the data and providing summary statistics of the log-returns. Next, we focus on the identification and properties of price jumps.

2.1. Data Description

We employ eight foreign exchange currency rates with respect to US dollar: the Euro (EUR), the Japanese yen (JPY), the Hungarian forint (HUF), the Mexican peso (MXN), the Polish zloty (PLN), the Russian ruble (RUB), the Turkish lira (TRY), and the South African rand (ZAR). The period covered spans from March 1, 2013, to June 6, 2013, and thus includes events such as “Abenomics” and US liquidity tapering expectations. Our unique data set comes from the Morningstar Direct high-frequency data service and includes the time stamp up to a millisecond, with both bid and ask quotes. The data represents a compilation of the binding quotes aggregated from an undisclosed number of participating banks.

The selected currencies are traded on the open markets. However, the eight currencies can be split in general into three categories based on the de facto exchange rate arrangements: The first category consisting of the Euro, the Japanese yen, the Mexican peso, and the Polish zloty are currencies with free float exchange rate arrangements with no interventions by central banks towards the manipulation of the exchange rate at all. The second category consists of the Hungarian forint, the Turkish lira, and the South African rand, which can be classified as currencies with floating exchange rate arrangements, where central banks intervene in the exchange rate on a limited scale. The last category is formed by the Russian ruble, which is targeted by the central banks against the dual currency anchor. However, during the economic turmoil, the anchoring was loosened as for many currencies with any form of peg. In addition, the Russian central bank pledged to direct the ruble to become a free floating currency. Lastly, the central banks of the currencies belonging to our sample are conducting monetary policy which strictly targets the inflation or the set of indicators, including inflation. The basis currency is the US dollar, as a global major currency with free float exchange rate arrangements.

The currency pairs covered in our sample have different trading patterns. The EUR and the JPY belongs to the major currency pairs and are traded globally. However, as the JPY is dominating the Asian markets, its activity pattern is spread more evenly across the trading hours of all three major financial centers. In comparison, the EUR has significantly lower activity during the Asian trading hours. The remaining six currencies belong to emerging market currencies and their market activity is more located towards their local trading hours. In particular, the Russian ruble was mostly traded in Moscow trading hours during the period under consideration. We address the issue of trading hours and the robustness of our results below in the paper.⁶

⁶In the Internet Appendix, we show that price jump clusters are features of the trading hours rather than a residual property stemming from the illiquid periods with reduced trading activity.

From a broad economic perspective, the Euro and the Japanese yen represent the dominant currencies of the two major developed markets. Further, the Japanese yen is a global funding currency for carry trades. The Mexican peso is an important trading partner of the US economy, member of NAFTA, and a representative currency of emerging country on the American continent. The Polish zloty and the Hungarian forint are members of two countries tightly (economically) integrated as a part of the European Union and members of the Visegrad economic region and CEFTA. In addition, the Hungarian forint serves as the local funding currency for carry trades, similar to the Japanese yen. It also suffers from continuous stress due to the threat of nationalization of the Hungarian financial sector during our sample period. The Russian ruble and the Turkish lira are tightly connected through the commodity link, as Russia is a net commodity exporter, while Turkey depends on the commodity imports. Finally, our sample contains the South African rand, which is a major African currency, which also embodies exposure to Chinese markets via metal prices.

We apply the filtering method originally proposed by Brownlees and Gallo (2006) and further extended by Barndorff-Nielsen et al. (2011), and remove the outliers in the data. The filter works as follows: at every instant, we estimate moving window properties of the data process and filter out observations which are likely to be present in the data feed due to technical error. Details of the filtering procedure are reported in the Internet Appendix. We work with spot prices, as our analysis is based on the intraday features.⁷

The filtered tick-by-tick data are then re-sampled at a 30-second frequency. Let $Y_t^{(j)}$ denote the price of asset j at every time point of the 30-second grid defined as the last realized filtered mid-quote recorded. We employ the pre-averaging approach by Podolskij

⁷In this paper, we do not make use of excess returns, a common measure in the financial literature dealing with foreign exchange markets (for instance, see Lustig et al., 2010, 2011), as the intraday trading is not affected by the interest rates. On the other hand, the rates play a crucial role for the low-frequency trading and in particular for carry trade strategies.

and Vetter (2009) and Jacod et al. (2009) to control for market micro-structure noise. Pre-averaged log-returns are defined as

$$r_t^{(j)} = \frac{1}{K} \sum_{i=1}^K \log Y_{t-K+i}^{(j)} - \frac{1}{K} \sum_{i=1}^K \log Y_{t-2K+i}^{(j)}, \quad (1)$$

where $2K$ is the size of the window over which the pre-averaging is calculated. Log-returns are based on non-overlapping prices sampled at 5-minute frequency with $K = 10$. The combination of 30-second and 5-minute frequencies is optimal in order to employ as many data points as possible while dealing with market micro-structure noise and controlling for the role of stale quotes. We consider a trading day starting at 0:00:00 and ending at 22:00:00 London time, as to avoid the global overnight period with all major trading centers closed.⁸

Table 1 provides some summary statistics of log-returns. Currencies with the largest volatility in terms of the standard deviation are not necessarily those with largest share of price jumps as measured by the kurtosis. The most volatile currencies are the South African rand and the Hungarian forint, while the Turkish lira is the least volatile. For each currency, we also present the excess kurtosis, which ranges from 10.06 for the Russian ruble to 39.88 for the Japanese yen. This evidence supports the deviation from normality and likely the presence of fat tails. The significantly large values of excess kurtosis for all currencies motivates us to focus on the price jump arrival process explicitly. In addition, the Japanese yen jointly with the Euro and the Polish zloty show the highest deviation from normality and are the candidates for the currencies with highest share of price jumps in their volatility process, while the Russian ruble seems to be the one suffering the least by price jumps. Further, there is no clear correlation between overall volatility

⁸The trading period for emerging markets can be too wide and include periods with very low trading. In particular, in 2013 the Russian ruble was traded mainly during Moscow trading hours, with very low liquidity outside those trading hours. However, as we report in the Internet Appendix, the main jump activity falls into the trading hours of particular exchanges.

Table 1: Descriptive statistics of log-returns.

	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
N (#)	18,222	18,222	18,222	18,222	18,222	18,222	18,222	18,222
Mean (10^{-6})	1.49	0.64	-1.21	-0.44	0.19	1.43	2.05	3.98
SD (10^{-4})	2.67	3.97	4.31	3.16	3.67	2.60	2.27	4.50
Skewness	-0.06	0.06	-0.16	-0.26	0.43	-0.06	-0.02	0.39
Kurtosis	20.68	39.88	12.81	15.20	20.56	10.06	23.70	14.91
Min (10^{-2})	-0.40	-0.85	-0.40	-0.47	-0.33	-0.22	-0.42	-0.50
Max (10^{-2})	0.36	0.86	0.36	0.33	0.73	0.21	0.29	0.59

Note: The table presents the descriptive statistics of 5-minute log-returns calculated based on the pre-averaging by Podolskij and Vetter (2009) and Jacod et al. (2009) with $K = 10$ and data sampled at 30-second frequency. SD stands for the standard deviation, and Min and Max represents the minimum and maximum realized returns, respectively.

and kurtosis as the most volatile currency, the South African rand, has the second lowest kurtosis, while the least volatile currency, the Turkish lira, has the second largest kurtosis.

The results suggest that the data generating process for currencies is to be affected by the price jumps, which may be in correspondence with specific market announcements such as macro-news, central bank disclosures and other exogenous shocks. Moreover, it is a question whether currencies show clusters of jumps in response to the above mentioned shocks rather than a large one-off jump incorporating all the new information at once. In the Internet Appendix, we illustrate a case study of four trading days with significant news announcement, which reveals the likely presence of clusters of price jumps rather than to observe price jumps randomly distributed across a trading day.

In the next section, we use a non-parametric test to identify price jumps and report a full description of the price jumps for each currency.

2.2. Price Jumps

To test for the presence of the price jumps, we employ Lee and Mykland (2008) procedure

$$\frac{\max_{t \in A_m} \left| \frac{|r_t^{(j)}|}{\widehat{IV}_t^{(j)}} \right| - C_m}{S_m} \rightarrow \xi, \quad (2)$$

where A_m is the tested region with m observations, $r_t^{(j)}$ are pre-averaged log-returns in (1), $C_m = (2 \ln m)^{1/2} - \frac{\ln \pi + \ln(\ln m)}{2(2 \ln m)^{1/2}}$, $S_m = \frac{1}{(2 \ln m)^{1/2}}$, and with $\widehat{IV}_t$ being an estimator of the Integrated Variance at time t defined as

$$\widehat{IV}^{(j)}_t = \frac{\pi}{2} \left(\frac{n}{n-1} \right) \frac{1}{n-1} \sum_{i=0}^{n-2} |r_{t-i}| |r_{t-(i+1)}|, \quad (3)$$

where n is the length of the moving window. The ξ statistic follows the standard Gumbel distribution with probability distribution function $P(\xi \leq x) = \exp(e^{-x})$. The convergence is based on the fact that under the null of no jumps, $\left| \frac{|r_t^{(j)}|}{\widehat{IV}_t^{(j)}} \right|$ converges stable in law to $N(0, 1)$.

In the estimation procedure, we consider $n = 258$, and employ the test statistics for every t being an integer-multiple of the 5 minutes. We consider the 99% confidence level and test for the presence of the price jumps for every trading day. The Lee and Mykland (2008) test with pre-averaging thus allows us to map the returns sampled at 30-second frequency into a 5-minute indicator time series of price jump arrivals. We estimate price jumps for every time series independently and then construct the panel of indicator time series.

Table 2 presents summary statistics of price jumps for each of eight currencies considered in this paper. The upper panel of the table describes the features of the price jump arrival process for each currency independently. Our sample contains 70 trading days. The percentage of trading days with at least one price jump ranges from 65.71% for the Japanese yen to 82.85% for the Euro. This is significantly higher than what was reported by Lahaye et al. (2011), who found, though using a different sample and identification techniques, that the percentage of days with at least one price jump for foreign exchange

markets is around 25%. The total number of jumps detected ranges from 111 for the Turkish lira to 155 for the Euro. It is worth noting that the Japanese yen, which had the least number of trading days with at least one price jump is not the one with least number of price jumps detected, showing the fourth largest number of jumps. This evidence suggests that price jumps for the Japanese yen are clustered at intraday level more densely relative to other currencies. The frequency of price jumps varies between 0.61% to 0.85%. In Table 2, we also report the arrivals of positive and negative price jumps. We calculate a measure of asymmetry, $A = \frac{|N_{pos} - N_{neg}|}{N_{pos} + N_{neg}}$, with N_{pos} and N_{neg} standing for the number of positive and negative jump arrivals, respectively. The table suggests the presence of three different groups of currencies. In the first group, the Euro and the Japanese yen have a medium asymmetry of 12.26% and 14.28%, respectively. The second group, containing the Hungarian forint, the Mexican peso, the Polish zloty and the Russian ruble, shows nearly symmetric arrivals of positive and negative price jumps. The third group, composed of the Turkish lira and the South African rand, has very asymmetric distribution of price jump arrivals of 24.32% and 23.08%, respectively, skewed towards positive price jumps. Note that positive price jump corresponds to depreciation of the emerging market currency and, therefore, relative to the emerging market, this means a negative drop in the value of the currency. Coincidentally, the two currencies were reportedly also among those the most affected ones by the FED's talk on tapering in mid- and late-May: the Turkish lira depreciated 5.5% and the South African rand depreciated 12% in the period under consideration.

The lower panel of Table 2 reports summary statistics of the magnitude of jumps. First, we present the average magnitude of price jumps, which clearly exceeds the magnitude implied by the average mean together with the standard deviation of returns as presented in Table 1. The highest average magnitude of price jumps is observed for the Hungarian forint and the South African rand, while the smallest price jumps are shown

for the Turkish lira and the Russian ruble. In light of the fact that the latter two currencies are the least liquid, it is surprising that the liquidity-caused price jumps, which are the most likely for these two currencies, are much lower in magnitude compared to the news-driven price jumps, which are more likely to be the dominant source of price jumps for more liquid currencies. In addition, we do not observe any significant difference in the magnitude of positive and negative jumps. Finally, we report the contribution of price jumps to the overall realized quadratic variance of the price process: the highest one is observed for the Euro, where price jumps explain 28.2% of its overall volatility. The lowest contribution of price jumps comes from the South African rand and the Mexican peso, explaining only 16.7% and 17.0%, respectively, of the overall volatility. The high contribution of price jumps to the total volatility stresses the importance of handling the price jumps properly and taking them into account for a liquid asset such as the EUR currency pair.⁹

In this paper, we identify price jumps assuming that the intraday periodicity is neutral for performance of the Lee and Mykland test. Consequently, this implies that during periods of the day with low overall volatility, we weaken the detection of price jumps, while during periods with high volatility, we tend to detect not only price jumps but also significantly large price movements. As the intraday level of volatility corresponds to the market activity and overall liquidity (as for instance in Chordia et al., 2001), the test procedure (2) tends to ignore the price jumps emerging from low trading activity. Thus the detection procedure used in this paper best reflects the way in which market

⁹In the Internet Appendix, we report that for some of the currency pairs, the size and frequency of the jumps is higher at the beginning and towards the end of the sample. These two sub-periods coincide with Mr. Kuroda's appointment as the head of the Bank of Japan and Chairman Bernanke as initial announcement of a possible start of the QE tapering. The latter factor can be particularly noticed for the Polish zloty, the Turkish lira and the South African rand, for which the distribution of returns towards the end of the sample tends to show significant increase in volatility and in both the arrival activity and magnitude of price jumps. This suggests that the period following the FED comment caused a turmoil on these markets and increased market activity involving these currencies.

Table 2: Descriptive statistics of arrivals and magnitudes of price jumps.

	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
Price jumps: Arrivals								
Trading Days (#)	70	70	70	70	70	70	70	70
Days with Jumps (#)	58	46	57	56	53	57	51	51
Days with Jumps (%)	82.85%	65.71%	81.42%	80.00%	75.71%	81.42%	72.85%	72.9%
Jumps (#)	155	126	148	116	135	148	111	117
Jumps (%)	0.85%	0.69%	0.81%	0.64%	0.74%	0.81%	0.61%	0.64%
Positive Jumps (#)	87	54	61	55	64	70	69	72
Negative Jumps (#)	68	72	87	61	71	78	42	45
Positive Jumps (%)	56.13%	42.86%	41.22%	47.41%	47.41%	47.30%	62.16%	61.54%
Negative Jumps (%)	43.87%	57.14%	52.78%	52.59%	52.59%	52.70%	37.84%	38.46%
Asymmetry A (%)	12.26%	14.28%	5.56%	5.18%	5.18%	5.40%	24.32	23.08%
Price jumps: Magnitudes								
Avg. (10^{-2})	0.14	0.20	0.21	0.15	0.19	0.12	0.11	0.21
Avg. Positive (10^{-2})	0.14	0.21	0.21	0.14	0.19	0.12	0.11	0.22
Avg. Negative (10^{-2})	0.15	0.20	0.21	0.15	0.18	0.11	0.11	0.20
Standard Deviation (10^{-2})	0.06	0.12	0.07	0.07	0.08	0.03	0.06	0.09
Skewness	-0.33	0.36	0.31	-0.12	0.43	0.10	-0.59	-0.24
Kurtosis	-0.99	1.56	-1.45	-0.81	-0.44	-1.65	0.57	-0.80
Realized QV (10^{-2})	0.13	0.29	0.34	0.18	0.25	0.12	0.09	0.36
Realized JV (10^{-2})	0.04	0.07	0.07	0.03	0.06	0.02	0.02	0.06
Realized JV (%)	28.2%	24.1%	21.9%	17.0%	22.5%	17.2%	18.0%	16.7%

Note: The upper part of the table reports the descriptive statistics for the price jump arrivals of returns identified as price jumps for the eight currency pairs. (#) indicates for the number of particular quantity, while (%) denotes the percentage. The asymmetry is defined as $A = |N_{pos} - N_{neg}| \cdot (N_{pos} + N_{neg})^{-1}$. The lower part of the table provides descriptive statistics of the magnitude of returns, which are identified as price jumps. Avg. denotes the average magnitude, Avg. positive and Avg. negative denotes the average magnitude of positive and negative price jumps, respectively. QV stands for the Quadratic Variance of all log-returns, while JV stands for the Jump Variance—the Quadratic Variance of returns identified as price jumps. The Realized JV (%) denotes the percentage of the Quadratic Variance composed of jump returns.

practitioners perceive price jumps, i.e. large price movements relative to the average daily volatility levels.

In order to illustrate the role of the intraday market activity, we also estimate price jumps using the Lee and Mykland (2008) test corrected for the intraday volatility based on the non-parametric Weighted Standard Deviation factor, $\hat{f}^{WSD}$, proposed by Boudt et al. (2011). The details of the estimation with the intraday volatility correction are in the Internet Appendix.¹⁰

The upper panel of contingency Table 3 reports the marginal and the total numbers of price jumps estimated using the intraday volatility correction for each currency together with the number of price jumps detected with and without the intraday volatility correction. The inclusion of the intraday volatility factor affects the number of estimated price jumps. In particular, for the Mexican peso, the Russian ruble, the Turkish lira and the South African rand, the procedure with intraday volatility factor estimates a higher number of price jumps. This suggests that the low-activity periods of the trading day may contain a larger amount of price jumps. The lower panel of Table 3 reports the marginal and the total numbers of price jumps, when we restrict the window on the London trading hours only, defined as the time from 9:00 to 17:00 GMT.¹¹ The intraday volatility correction suppresses the identification of large normal price movements as price jumps and, on the other hand, tends to reveal the price jumps outside the main trading hours ignored by the test without intraday volatility factor.

It is worth noticing that most of the price jumps identified with the intraday volatility factor coincide with those identified without the factor. Thus, the uncorrected price jump

¹⁰The use of the full sample therefore affects the forward looking nature of the trading strategy, which is further affected by the correction proposed by Boudt et al. (2011) requiring the knowledge of the overall volatility for a given day. See also the Internet Appendix.

¹¹We have chosen the London trading hours as London is considered the main currency trading center, the data used for this study comes from the London-based data provider and the six out of the eight currency pairs are geographically located in the same time zone, i.e., except the Japanese yen and the Mexican peso.

Table 3: Contingency table.

	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
ID=0	155	126	148	116	135	147	111	117
ID=1	106	93	149	372	138	221	474	340
Overlapping	56	58	43	20	43	54	36	32
London trading: 9:00 – 17:00								
	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
ID=0	124	73	110	83	100	72	75	72
ID=1	36	30	28	24	24	14	17	10
Overlapping	34	25	28	7	24	14	17	8

Note: Table reports the contingency tables of detected price jumps for each currency using the method without intraday correction ($ID = 0$), the one with the intraday volatility correction based on the Boudt et al. (2011) and the $\hat{f}^{WSD}$ correction factor ($ID = 1$), and the number of overlapping price jumps identified by both approaches. The upper panel considers the trading period 0:00 – 22:00, while the lower panel restricts the trading day to 9:00 – 17:00 corresponding to the London trading hours.

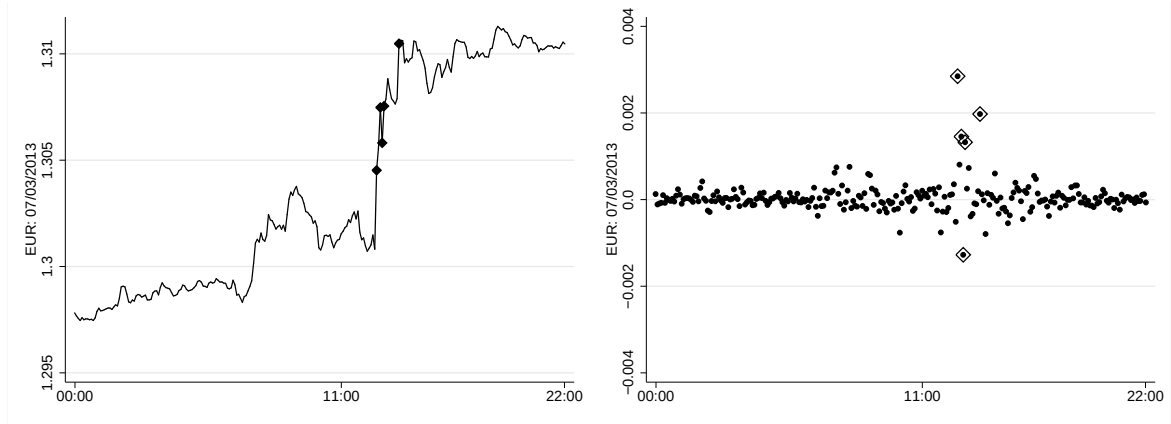
identification following the Lee and Mykland (2008) procedure truly identifies the large price jumps during the main activity period, together with large volatility movements.

To summarize, there is evidence that price jumps are an important feature of high-frequency time series accounting for a significant portion of market volatility. In the next section, we formalize the clustering of price jumps in the high-frequency foreign exchange markets and identify the properties of such clusters for each currency.

3. Clusters of Price Jumps in Foreign Exchange Markets

The clustering of price jumps implies that if we observe a jump, the probability of observing another jump in close proximity is higher relative to the case of no jumps. Figure 1 further illustrates this point reporting the EUR in March 7, 2013, a representative day with a cluster of price jumps. The left hand side panel of the figure shows that there is both volatility clustering during the trading day and the clustering of price jumps. We observe 5 jumps in total occurring around London midday. On that particular day, markets opened higher during London trading hours, reaching exchange rate levels around 1.3 EUR/USD. Soon after the ECB President Mario Draghi held a speech announcing

Figure 1: March 7, 2013: levels and log-returns of the EUR.



Note: The left panel depicts the levels of the EUR currency pair for March 7, 2013. During this day, the ECB President Mario Draghi held a speech in which he announced that rates were left unchanged and highlighted that the Euro area economy was improving. The right panel depicts the log-returns of the EUR with five highlighted instances which were identified as price jumps.

that rates were left unchanged and highlighting the fact that the Euro area was improving, the currency broke the level of 1.305 and as, reportedly, the shorts were squeezed out, the Euro jumped further to 1.31, which was another strong support level where the price was stabilized. For convenience, in the right panel of Figure 1, we report the log-returns to show the observations identified as a cluster of price jumps. The figure provides evidence in support of the interpretation our identification method: The price jumps corresponds to the largest price movements for that particular day and thus likely to be interpreted by market participants as significant price movements worth to notice, especially, if those largest price movements occur close to each other and following the significant news release.

In the next section, we propose a framework to formally identify clusters of price jumps and obtain their statistical properties.

3.1. Modeling Clusters

We adopt the k -means clustering algorithm proposed in the seminal paper by MacQueen (1967) to formally assess the presence and the statistical properties of clusters. To

this purpose, we start with the following assumptions:

Assumption A.1. Every cluster contains price jumps from the same trading day.

Assumption A.2. Every cluster contains only a sequence of price jumps which do not have a time gap between them longer than ΔT_k . In particular, we set $\Delta T_k = 2$ hours.¹²

Assumption A.3. Every cluster must contain at least two price jump arrivals.

Assumption A.1 reflects the presence of the over-night trading period, which is discarded from the data. Assumption A.2 sets a threshold distance ΔT_k between price jumps to be considered as a member of the same cluster. Such a distance reflects the peculiarity of the foreign exchange markets, in particular the high-liquidity and fast information processing due to the vast amount of trading algorithms seeking arbitrage opportunities. Assumption A.3 reflects the requirement that a cluster can be formed by at least two price jumps.

The k -means clusters are given by the following proposition:

Proposition 1. (*Clusters*) Given a set of n price jump arrivals $X = \{x_1, \dots, x_n\}$ and Assumptions A.1-A.3, the k -means non-overlapping clusters K_i , $i = 1, \dots, k$, spanning the set of jumps X , are given as a solution to the following optimization problem:

$$\{K_1, \dots, K_k\} = \min_{\tilde{k}} \arg \min_{\tilde{K}_1, \dots, \tilde{K}_{\tilde{k}}} \sum_{i=1}^{\tilde{k}} \sum_{x_j \in \tilde{K}_i} |x_j - \mu_i|, \quad (4)$$

where μ_i is a centroid of the i -th cluster K_i .

As we work at a 5-minute sampling frequency, we allow the position of the centroid μ_j for each currency to be at the 5-minute grid points only. The centroids are thus considered on the same time scale as price jumps and we can directly match them together.¹³ This

¹²Therefore, whenever two consecutive jumps are separated by a period longer than 2 hours, they are treated as belonging to distinct clusters. Varying the threshold ΔT_k around 2 hours affects the results quantitatively; however, the qualitative features retain the same meaning. Results for other threshold values are available upon request.

¹³We define the centroid of a cluster as the first occurring solution out of all possible solutions. Restricting ourselves to a 5-minute grid simplifies the optimization procedure to search for centroids significantly, as we can directly evaluate (4) at all possible candidate points.

approach allows us to partition the price jump arrivals for every currency into k currency-specific clusters. Note that we assess the clusters of rare events, sampled at a 5-minute frequency in the intraday framework. Thus, we estimate clusters with a small number of price jumps.

The intuition behind the k -means cluster is such that we consider all price jumps occurring close to each other (clusters) as an unique entity representing a response of markets to change in the economic fundamentals, to geopolitical shocks and to monetary policy adjustments. Thus, the clusters of price jumps measure how rapidly each market (currency) reacts to shocks. In our case, the clusters contain a small number of price jumps; however, if we allow for price jumps in a cluster to be separated by more than hours, i.e., $\Delta T_k > 2$ hours, we increase the span of the clusters at the cost of having clusters overlapping.

Based on the proposed clustering framework, for a given sample and a given currency, we assess the clusters of price jumps. In addition, we define for every cluster j an average size s_j as

$$s_j = \frac{1}{N_j} \sum_{x_i \in K_j} |x_i - \mu_j| , \quad (5)$$

which measures how large is on average the given cluster with its mass positioned at μ_j .

To assess the clustering properties for each currency, we adopt the following three average cluster indicators:

Number of clusters, $NC^{(x)}$. The overall number of clusters allows us to compare the propensity of a given currency to form price jump clusters relative to other currencies given that they have the same number of price jumps. The number of clusters provides a mixed message for currencies with different numbers of price jumps.

Average number of price jumps per cluster, $J/C^{(x)}$. As the number of price jumps for each currency may differ over a given sample, the $J/C^{(x)}$ indicator measures the cardinality of clusters and it is useful to directly compare the different currencies.

Average size of cluster, $S^{(x)}$. In addition to the cardinality of the price jump clusters, $S^{(x)}$ measures the average time span over which the clusters occur. For instance, for currencies with a similar average number of price jumps per cluster, the average size measures the density of clusters, where currencies of smaller size will have jumps occurring closer to each other.

3.2. Empirical Results

Table 4 reports the properties of clusters of price jumps estimated for each currency independently.¹⁴ Namely, we report in Panel (A) the overall information about the number of price jumps, in Panel (B) the number of clusters, $NC^{(x)}$, in Panel (C) the average number of price jumps per cluster, $J/C^{(x)}$, in Panel (D) the average size of clusters, $S^{(x)}$, measured in minutes based on the size, s_j , and in Panel (E) the number of clusters, $NC^{(x)} | N_j \geq 5$, which have at least five price jumps. In addition, the values <1-st/99-th> in Panels (B)-(E) represent the interval based on the 1-st/99-th percentiles of the bootstrapped values to test the null hypothesis that the cluster characteristics deviate from those implied by the process with independently arriving price jumps using 10,000 realizations of the Monte Carlo analysis by employing the fully non-parametric bootstrap without replacement by reshuffling the time series with realized price jump arrivals (see Davidson and MacKinnon, 2004).

The results suggest interesting features: First, the number of clusters significantly vary, ranging from 32 for the Euro to 14 for Turkish lira. Second, the number of price jump is not tightly correlated to the number of price jumps as the Russian ruble and

¹⁴The Internet Appendix provides also dates and times for each identified cluster.

the Hungarian forint have the same number of price jumps, while the number of clusters differs by 20%, suggesting diversity across currencies. Third, the clusters involved in this study work with rare events, as the clusters tend to be rather small. Fourth, the number of price jumps per cluster varies between 3.6 jumps per each cluster for the Japanese yen to 2.6 jumps per cluster for the South African rand. Surprisingly, the Japanese yen, which is more liquid and actually belongs to the set of major global currencies shows larger clustering than the South African rand or the Mexican peso. However, the Japanese yen does not form the largest spanning clusters; it forms the third smallest clusters with an average size span over 36.9 minutes. Therefore, the Japanese yen has rather dense clusters with large number of price jumps occurring close to each other. Finally, the Japanese yen has the largest number of large clusters, while the South African rand tends to have rather small clusters.

When we compare the results to those implied by the homogeneously arriving price jumps, the results suggest that for each currency, the size of clusters is significantly smaller than that implied by the homogeneously arriving price jumps and for all currencies except the South African rand, we reject the null hypothesis of independently and homogeneously distributed price jumps, as there is a very large number of large clusters. In the Internet Appendix, we report the full analysis of clusters of all different sizes.

The observed clustering may have a number of interesting intuitive explanations; each would require a separate study with detailed empirical analysis. We provide two likely explanations why the price jump clusters occurs. First, the clustering is in line with a heterogeneous market model in which agents with different information sets and trading horizons would move the price in line with their expectations. If one assumes that each of the heterogeneous traders would have a threshold price-deviation value, which is defined by transactions cost, then moves exceeding this threshold could be strong enough motivation for an agent to correct the position. This would require a more frequent

Table 4: Descriptive statistics of clustering formation.

	Cluster	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
(A)	$n^{(x)}$	155	126	148	116	135	148	111	117
(B)	$NC^{(x)}$	32	21	31	18	27	25	14	24
	$\langle 1 - \text{st}/99 - \text{th} \rangle$	$\langle 22/49 \rangle$	$\langle 13/36 \rangle$	$\langle 20/46 \rangle$	$\langle 10/31 \rangle$	$\langle 16/40 \rangle$	$\langle 20/46 \rangle$	$\langle 20/29 \rangle$	$\langle 10/32 \rangle$
(C)	$J/C^{(x)}$	3.1	3.6	3.0	2.7	2.9	3.2	3.1	2.6
	$\langle 1 - \text{st}/99 - \text{th} \rangle$	$\langle 2.1/2.7 \rangle$	$\langle 2.1/2.6 \rangle$	$\langle 2.1/2.7 \rangle$	$\langle 2.0/2.6 \rangle$	$\langle 2.1/2.6 \rangle$	$\langle 2.1/, 2.7 \rangle$	$\langle 2.1/2.6 \rangle$	$\langle 2.0/2.6 \rangle$
(D)	$S^{(x)}$ [mins]	32.2	36.9	40.1	29.0	49.2	34.5	51.1	49.1
	$\langle 1 - \text{st}/99 - \text{th} \rangle$	$\langle 72.6/125.4 \rangle$	$\langle 64.0/130.1 \rangle$	$\langle 70.4/127.3 \rangle$	$\langle 59.7/132.0 \rangle$	$\langle 66.7/128.9 \rangle$	$\langle 70.8/126.5 \rangle$	$\langle 57.9/126.5 \rangle$	$\langle 59.5/131.4 \rangle$
(E)	$NC^{(x)} N_j \geq 5$	4	6	3	2	2	3	2	0
	$\langle 1 - \text{st}/99 - \text{th} \rangle$	$\langle 0/1 \rangle$	$\langle 0/1 \rangle$	$\langle 0/1 \rangle$	$\langle 0/0 \rangle$	$\langle 0/1 \rangle$	$\langle 0/1 \rangle$	$\langle 0/1 \rangle$	$\langle 0/1 \rangle$

Note: The table reports some descriptive statistics of the clusters based on Proposition 1 for each currency independently. Panel (A) reports the number of price jumps $n^{(x)}$, Panel (B) the number of clusters $NC^{(x)}$, Panel (C) the average number of price jumps per cluster $J/C^{(x)}$, Panel (D) the average size of clusters $S^{(x)}$ measured in minutes, and, finally, Panel (E) the number of clusters $NC^{(x)} | N_j \geq 5$ which have at least five price jumps. In Panels (B)-(E), we present the $<1\text{-st}/99\text{-th}>$ percentile interval of a given quantity based on the bootstrapped empirical distribution. The bootstrapped distribution is calculated on the basis of 10,000 realizations of the underlying theoretical price jump arrival processes given for each currency by the independent homogenous Poisson process, such that the number of arrivals coincide with the observed number, respectively.

occurrence of jumps in the opposite directions. Jump clustering could be a result of different accessibility to information and different time required by sub-groups of agents with various investment horizons to come up with a market view. The decision time for a high-frequency trader would be shorter than for a group of large macro hedge funds that decide to re-specify their asset re-allocation as a result of the new piece of information. In such case, further jumps could occur in both directions.

Second, the occurrence of price jump clusters could also be a result of stop-losses that are breached as a result of sharp price movements. Breach of such stop-losses would trigger forced sales at the current levels and could result in further price jumps if the positioning of the traders has been large enough. This hypothesis might be further analysed by closer investigation of the exact jump subsequence, as well as jump occurrence levels. Round number would serve as support to the hypothesis that market participants tend to set their limit orders to relatively round levels. We can see this from Figure 1, where the rounded numbers suggest a likely presence of several resistance levels, which were broken down and thus stop-losses defending them were triggered.

In general, each currency tends to form less small clusters than implied by the hypothesis of the independently arriving price jumps, while forming more big clusters. This can result in the average number of clusters being indistinguishable from that implied by the independently arriving jumps case. The results thus show that currencies are clustered in groups with density of price jumps. Therefore, the arrival of a jump signal the arrival of a few more price jumps rather than one more jump. This is a general feature across currencies. We leave the investigation of the original source of price jump clusters for further analysis. In what follows, we exploit the information content in the presence of price jump clusters through a trading exercise.

The clusters in the FX markets suggests a profitable opportunity, where if the trader observes an increase in volatility, (s)he would go long gamma as (s)he anticipates the

period of higher volatility. At the intraday level, however, such a strategy is not feasible as the necessary options would not be traded. In this paper, however, we focus on the directional implications of the price jump clusters as the detection of a price jump implies the increased likelihood for further large price movements. In particular, if the initial price jump is clustered with price jumps of the same sign, the detection of the initial price jump can be turned into the trading signal to enter into a position. To have a successful trading strategy, the cumulative change in the price due to the subsequent price jumps, cannot be compensated by the non-jump returns.

Table 5 reports the distribution of 5-minute returns occurring up to one hour after the price jump was detected, where we explicitly distinguish between the positive and negative jumps. The distribution of the post jump returns suggest that the price jump implies a shift in the mean and skewness of returns in the direction of the price jump. In particular, for all currencies except the Turkish lira, the average mean after the positive price jump is larger than the average mean of returns following negative jumps. For five currencies, even the sign of the average returns coincides with the sign of the price jump. For all currencies except the Mexican peso, the distribution is more skewed towards the direction of the price jump. Both mean and skewness therefore imply the directionality in the post jump period, which is also supported by the minimum and maximum of the post jump returns.

4. Trading the Clusters

For the purpose of the trading exercise, we assume that the trader enters the position by buying the currency at spot, holds it for a certain time horizon, and then unwinds the position. We also assume that the trader is marginal, and (s)he does not have the power to significantly affect the prices. Such traders are genuine to the foreign exchange markets with their large daily turnover and presence of large institutional investors and central banks. In fact, the absolute amount of currency traded depends on the depth of

Table 5: Descriptive statistics of log-returns following the price jump.

Sign	EUR		JPY		HUF		MXN	
	+	-	+	-	+	-	+	-
mean (10^{-6})	14.30	-47.03	38.27	-5.30	6.66	-4.95	2.57	-4.73
SD (10^{-4})	3.37	4.92	4.68	8.29	4.86	7.46	3.50	5.33
skew	0.41	-1.32	1.68	-1.41	0.02	-0.41	-1.17	0.23
kurtosis	14.74	12.54	13.18	26.89	12.51	7.29	31.59	6.46
min (10^{-4})	-30.22	-39.68	-21.03	-85.21	-33.80	-33.49	-47.01	-25.69
max (10^{-4})	21.51	19.94	37.04	61.72	35.89	38.68	22.21	26.40
Sign	PLN		RUB		TRY		ZAR	
	+	-	+	-	+	-	+	-
mean	19.22	2.04	9.23	2.97	11.48	14.78	26.62	-87.60
SD (10^{-4})	4.08	6.42	3.38	4.36	2.81	3.48	5.60	7.24
skewness	0.65	-0.06	0.13	-0.08	1.22	0.22	1.34	-1.06
kurtosis	10.69	7.12	9.53	6.47	15.60	7.62	14.39	9.27
min (10^{-4})	-26.99	-27.91	-22.24	-22.24	-12.51	-14.24	-30.96	-49.88
max (10^{-4})	27.43	39.33	18.65	18.65	27.89	19.66	43.16	24.32

Note: Table reports the distribution of 5-minute log-returns occurring up to one hour after the positive (+) and the negative (−) price jump was detected, respectively.

the market.

4.1. Trading Strategies

We assume that a speculative FX trader is endowed with an unlimited initial budget, denominated in the basis currency. For a given trading period $[0, T]$, the trader can enter the directional trade in any of the N currencies available on the market. At any time, (s)he may go long or short of any foreign currency with an amount corresponding to one unit of the basis currency. N currencies represent an opportunity set for the trader, over which (s)he can exercise her strategies.

We make the following assumptions:

Assumption T.1. The trader can enter the position at any time, (s)he can go either long or short $c^{(i)}(t)$ amount of foreign currency corresponding to one unit of basis currency. We also assume that the trader can have at any time any number of open trades in each of N currencies, where positions are netted.

Assumption T.2. The trader perceives time in discrete equidistant steps δt , i.e., (s)he evaluates the trading horizon $[0, T]$ at the discrete times t_j , $j = 1, \dots, \lfloor T/\Delta \rfloor$. At any moment t_j , the trader can first decide to enter the position or not based on the information available up to time t_{j-1} . This decision is made independently for each currency. The information set available to the trader also contains the information from the previous trading days.

Assumption T.3. The trader cannot hold a position over night and thus cannot enter a position which cannot be closed during the same trading day.

Assumption T.1 implies that the trader does not impact the price process and (s)he is thus a genuine price taker. In addition, it prevents operational risk and excessive risk taking by the trader. Not allowing netting the positions means that if the trader is long in a currency and receives a signal to short the currency (s)he is not closing the current position but rather entering into a new short position. Assumption T.2 assures that the proposed strategy is feasible with the real perception of time. It also sets the maximum amount of risk the trader can undertake. Finally, Assumption T.3 allows us to calculate the risk exposure day-by-day and thus limits the risk profile and helps to avoid accruing an overnight interests.

The trader operates over a certain investment horizon $[0, T]$ where (s)he executes the set of strategies by entering into $\sum_{x=1}^N n^{(x)}$ trades, where $n^{(x)}$ denotes the number of trades in currency x . Each such trade is either a long (+) or short (−) position undertaken at time $t_j^{(x)}$; and it lasts for $\Delta t_j^{(x)}$ periods. For a given investment horizon $[0, T]$, let $\Theta_{[0, T]}$ denote the set of trading strategies

$$\Theta_{[0, T]} = \left\{ \left(t_j^{(x)}, \Delta t_j^{(x)}, \pm \right) : \text{T.1 to T.3 holds} \right\},$$

where at time $t_j^{(x)}$, the trader decides about the entire realization of the trade $\left(t_j^{(x)}, \Delta t_j^{(x)}, \pm \right)$,

i.e., (s)he fixes the holding period when the trade is open without possibility to close the position before the expiry. The impact of each trade—the return to a unit investment—corresponds to a relative change of the currency over the trading horizon with respect to the direction of the trade.

We introduce two explicit trading strategies. The first is based on the price jump clustering, denoted as “jump trader”: the trader enters the position immediately after (s)he spots a jump. This strategy is intended to mimic real trader behavior. The second strategy is a “random trader”: the trader enters the positions randomly mimicking the same amount of positions of the “jump trader”. The purpose of the random trader is rather to serve as a bootstrap threshold to evaluate the jump-based strategy than to mimic the real noise trader.

Jump Trader. The trading strategy can be described as follows: For every time t_j , the trader tests for the presence of the price jump arrival in period t_{j-1} . If a price jump arrival for the currency x at time t_{j-1} is detected, the trader takes a position at time $t_j^{(x)}$ by buying/selling the foreign currency corresponding to one unit of basis currency and holds it for period $\Delta t^{(x)}$, which is held constant. The direction of the trade corresponds to the sign of the price jump, where the trader buys if the jump is up and sells otherwise. The trader does this for every currency x independently.

Random Trader. In this case, the trading strategy works as follows: For every currency x , the trader fixes the holding period $\Delta t^{(x)}$ and keeps it constant. Then, for every asset (s)he randomly draws $n^{(x)}$ time moments $t_n^{(x)}$ in which (s)he enters into the trade, where $n_+^{(x)}$ of them are long (+) trades and $n_-^{(x)} = n^{(x)} - n_+^{(x)}$ are short (−) trades. The strategy contains information on how many trades will be initiated prior to trading.

Moreover, traders face some market imperfections when implementing the trading strategies. In particular, it is important to take into account *i) transaction costs*, and *ii)*

Table 6: Average bid-ask spread.

	EUR	JPY	HUF	MXN	PLN	RUB	TRY	ZAR
$ba^{(x)}$	1 bp	2 bp	12 bp	4 bp	11 bp	13 bp	4 bp	6 bp

Note: The table reports the average bid-ask spread calculated from the filtered bid and ask quotes. The spread is expressed in basis points (bp).

information loss which a trader suffers when evaluating trading strategies in real time.¹⁵

In what follows, we describe the way in which the two market imperfections are accounted for in our trading exercise.

Transaction Costs. Since every trade carries additional transaction fees, we subtract every closed trade for the bid-ask spread. As the bid-ask spreads are stable over time,¹⁶ we calculate for each currency the average bid-ask spread, $ba^{(x)}$, and discount that value from each realized return. Table 6 reports the average bid-ask spread calculated from the filtered bid and ask quotes expressed in basis points (bp). The Euro and the Japanese yen, the most liquid currencies, have an average bid-ask spread at 1 bp and 2 bp, respectively. On the other hand, the Russian ruble, one of the least liquid currencies in our sample, has an average bid-ask spread at 13 bp.

The cumulative return corrected for the bid-ask spread is calculated as

$$\kappa_{ba}^{(x)} = \kappa^{(x)} - n^{(x)}ba^{(x)}. \quad (6)$$

Information Loss. The real-time processing of the trading information is sensitive to the presence of outliers and false information. The detection of the price jumps is based solely on the lagged returns, or past information, and thus does not cause any major problem, except a possible computational time. On the other hand, the filtering algorithm

¹⁵A possible trading constraint is the price impact, as discussed, for example, in Obizhaeva and Wang (2013). It is assumed to be negligible in our case.

¹⁶See the Internet Appendix for details, where we also show that the bid-ask spread does not increase significantly after the price jump is detected.

introduced in Section 2 utilizes both the lagged and lead prices. To decide whether a current price is an outlier due to the market micro-structure noise, we employ the information about both past and future returns. Such information is not available to traders and this constitutes an information loss.

To account for the information loss and decrease in detection efficiency, we assume that we misdetect price jumps at a rate of slippage, η , which works as follows: For every trade, we draw a random number $\xi \sim U[0, 1]$. If the ξ exceeds $1 - \eta$, the slippage occurs. In such a case, the trade is not initiated; however, another trade occurs at a different random time. The random trade can even occur in the preceding period, as slippage is a technical way to introduce noise and uncertainty into the trading strategy. The expected number of trades for any slippage rate is the same. Finally, for strategies with the slippage, we perform 100 repetitions and measure the average of variables of interest.

In the next section, we report the outcome of the implementation of the trading strategies for our currencies.

4.2. Currency-by-Currency Trading Outcomes

First, we assume that the trader operates on one currency pair at a time. Thus, for each currency we employ the jump trader strategy with a holding period varying from 10 to 125 minutes with a 5 minutes time step and evaluate the performance independently. The holding period is fixed at the beginning and does not change. In order to prevent an overnight position, the trade cannot take place after 20:00. We mainly focus on three representative investment strategies: short-term with a 15-minute holding period, medium-term with a 60-minute holding period, and long-term with a 120-minute holding period. In Table 7, we report the outcome of the trading strategies for the eight currencies over the three periods. Details for all the trading horizons from 10 to 125 minutes are reported in the Internet Appendix.

First, we present the gross cumulative returns for each combination of the trading

horizon and currency. The strategies tend to be profitable overall with only four cases out of 24 presented being negative, which were the Mexican peso and the Russian ruble for the medium- and the long-term horizons. The most profitable short-term trading strategy is realized for the Euro with 8.23%. For the medium- and long-term trading strategies, the Japanese yen dominates the gross cumulative profits with 10.67% and 17.29%, respectively. Based on the trading exercise, the currencies form three groups: The first group, consisting of the Euro, the Mexican peso, the Polish zloty, and the Russian ruble, shows a reduction in cumulative returns with increasing holding period. The second group, comprising the Japanese yen and the South African rand, has the opposite behavior as the gross cumulative returns are increasing as the trader holds the position longer. Finally, the third group, including the Hungarian forint and the Turkish lira, does not show any sensitivity to the length of the holding period.

Therefore, the jump trader strategy is at first glance positive. However, when we take into account the bid-ask spread as defined in (6), most of the profit disappears. The Euro and the Japanese yen remain profitable, while the South African rand is profitable for the medium- and the long-term horizons. The incorporation of the bid-ask spreads turns the trading profit in the remaining currencies into loss.

The effect of slippage in addition to the bid-ask spread works as expected; it introduces the noise into the signal provided by the detection of price jumps and spoils the net profit further. The slippage, however, is rather mild as the Euro, the Japanese yen and the South African rand still remain profitable, for both $\eta = 0.05$ and $\eta = 0.10$, respectively. In addition, as the net cumulative return decreases with the increasing rate of slippage, we get indirect confirmation that the presence of price jumps tends to carry a tradeable signal.

The percentage of profitable net trades is systematically higher than 50% for the three profitable currencies (the Euro, the Japanese yen, and the South African rand)

with 63.64% for the short-term trading of the Euro. It is worth pointing out that for the short-term trading and the Russian ruble, the number of profitable net trades is 9.42% while the strategy itself delivers positive gross cumulative returns.

Further, we present three additional risk measures. The first, the Sharpe ratio, is rather low for profitable trades and thus suggests that risk adjusted excessive returns are not too strong. In particular, the highest Sharpe ratio is for the Euro and short-term trading with a value of 0.40. This value is well below the subjective thresholds perceived by market professionals for strong profitable strategies. This message is further supported by the P/L ratio based on the returns with bid-ask spreads, which reaches its highest value of 1.90 for the Euro at the short-term horizon; however, in more than half of the cases, it is below one. Finally, the full drawdown and the drawdown scaled to 5-minute frequency shows that the Japanese yen, an otherwise profitable currency, bears large downside risk as it systematically belongs to the currencies with the largest drawdown.

Finally, we present the cumulative returns for the “random trader,” which realizes the same amount of trades as the “jump trader”, though at random times. In particular, at the short-term horizon, the jump trader of all currencies except the Russian ruble clearly outperforms the random trader. However, as the trading horizon increases, the picture becomes less distinct. At medium-term horizon, the jump trader outperforms the noise signal only for the Euro, the Japanese yen, the South African rand, and the Polish zloty, while at the long-term horizon, only the former three currencies continue to beat the noise. The trading outcome of this strategy further stresses the role of the low bid-ask spreads, as for the Euro and the Japanese yen, the random trader tends to achieve the best profit (least loss) when (s)he faces low spreads.

4.2.1. The Cumulative Returns

A graphical representation of the trading outcomes for all the trading horizons considered in our analysis appears in Figure 2, where we report the gross cumulative returns

Table 7: Outcome from trading strategies.

Holding period	Cumulative return		$\kappa_{ba}^{(x)}$ with slippage		Profitable trades	Sharpe ratio	P/L ratio	Drawdown $DD^{(x)}$		$\kappa_{ba}^{(x)}$ of “random trader”		
	$\kappa^{(x)}$	$\kappa_{ba}^{(x)}$	$\eta = 0.05$	$\eta = 0.10$				full	5-minute	99%	50%	1%
Short-term 15 minutes	EUR	8.23%	6.32%	5.75%	63.64%	0.40	1.90	-0.27%	-0.13%	0.08%	-1.54%	-3.08%
	JPY	5.44%	2.66%	2.38%	55.28%	0.13	1.20	-0.74%	-0.35%	-0.43%	-2.46%	-4.56%
	HUF	8.51%	-9.13%	-10.02%	31.29%	-0.35	0.89	-0.52%	-0.25%	-15.16%	-17.65%	-20.23%
	MXN	2.20%	-2.12%	-2.33%	38.89%	-0.18	0.93	-0.48%	-0.23%	-2.80%	-4.32%	-5.87%
	PLN	5.62%	-9.23%	-9.73%	29.63%	-0.51	0.64	-0.43%	-0.20%	-12.86%	-14.87%	-16.85%
	RUB	1.47%	-16.47%	-17.26%	9.42%	-1.30	0.37	-0.49%	-0.23%	-16.55%	-17.93%	-19.27%
	TRY	1.88%	-2.40%	-2.58%	33.64%	-0.27	0.97	-0.24%	-0.11%	-3.16%	-4.28%	-5.36%
	ZAR	6.04%	-0.80%	-1.11%	49.12%	-0.05	0.92	-0.48%	-0.23%	-4.55%	-6.84%	-9.10%
Medium-term 60 minutes	EUR	6.94%	5.40%	4.72%	57.79%	0.17	1.16	-0.72%	-0.20%	1.83%	-1.54%	-4.98%
	JPY	10.67%	8.21%	7.14%	55.28%	0.20	1.46	-0.97%	-0.27%	1.95%	-2.48%	-6.84%
	HUF	3.85%	-13.79%	-14.22%	32.65%	-0.29	0.99	-1.18%	-0.33%	-12.42%	-17.60%	-22.99%
	MXN	-0.59%	-4.91%	-4.89%	36.11%	-0.26	0.85	-0.69%	-0.19%	-1.21%	-4.34%	-7.54%
	PLN	4.74%	-10.11%	-10.51%	34.07%	-0.27	0.96	-1.01%	-0.28%	-10.92%	-14.83%	-18.79%
	RUB	-0.27%	-18.21%	-17.94%	14.49%	-0.86	0.61	-0.75%	-0.21%	-15.18%	-17.93%	-20.61%
	TRY	1.04%	-3.24%	-3.40%	33.64%	-0.19	1.17	-0.68%	-0.19%	-2.05%	-4.26%	-6.45%
	ZAR	9.35%	2.51%	1.75%	51.75%	0.07	1.14	-0.72%	-0.20%	-2.00%	-6.86%	-11.57%
Long-term 120 minutes	EUR	5.96%	4.42%	3.68%	61.04%	0.10	0.85	-0.94%	-0.19%	3.19%	-1.56%	-6.17%
	JPY	17.29%	14.83%	12.97%	53.66%	0.23	1.88	-1.25%	-0.25%	4.07%	-2.47%	-8.76%
	HUF	5.74%	-11.90%	-12.20%	38.10%	-0.19	0.98	-1.39%	-0.28%	-10.15%	-17.60%	-25.21%
	MXN	-0.66%	-4.98%	-5.84%	45.37%	-0.17	0.76	-0.79%	-0.16%	0.13%	-4.30%	-8.82%
	PLN	1.16%	-13.69%	-13.75%	35.56%	-0.29	0.83	-1.19%	-0.24%	-9.48%	-14.89%	-20.56%
	RUB	-1.99%	-19.93%	-20.47%	18.84%	-0.78	0.52	-0.79%	-0.16%	-14.09%	-17.95%	-21.81%
	TRY	1.96%	-2.32%	-2.55%	41.12%	-0.11	1.05	-0.69%	-0.14%	-1.18%	-4.28%	-7.37%
	ZAR	12.33%	5.49%	3.92%	54.39%	0.13	1.21	-0.78%	-0.16%	-0.10%	-6.75%	-13.32%

Note: The table reports the results of the trading strategies for the “jump trader” for three trading horizons: the short-term holding period of 15 minutes, the medium-term period of 60 minutes, and the long-term period of 120 minutes. The table presents the the gross cumulative returns, $\kappa^{(x)}$, the net cumulative returns adjusted for the bid-ask spread, $\kappa_{ba}^{(x)}$, the net cumulative returns with 5% and 10% slippage, respectively, based on 100 repetitions, $\kappa_{ba}^{(x)}$ with $\eta = 0.05$ and $\eta = 0.10$, the percentage of profitable trades and three risk measures: the Sharpe ratio, the P/L ratio, and the drawdown (the full one and the one adjusted to 5-minute time scale), the net cumulative return of the random trader, in particular the 1st, 50th and 99th percentiles of the empirical distribution based on the 10,000 bootstraps. The average bid-ask spread and the number of initiated trades are as follows: EUR (1 bp and 154 trades), JPY (2 bp and 123 trades), HUF (12 bp and 147 trades), MXN (4 bp and 108 trades), PLN (11 bp and 135 trades), RUB (13 bp and 138 trades), TRY (4 bp and 107 trades), and ZAR (6 bp and 114).

$\kappa^{(x)}$ ($\bullet$), the cumulative return corrected for the bid-ask spread $\kappa_{ba}^{(x)}$ ($\blacklozenge$), and a pair of net cumulative returns with slippage $\eta = 0.05$ ($\times$) and $\eta = 0.1$ ($+$), respectively. In addition, we depict 1-st, 50-th and 99-th centiles, respectively, of the distribution of $\kappa_{ba}^{(x)}$ for “random trader” based on 10,000 replications.

The Japanese yen and the South African rand show increasing returns as the trader holds the position for a longer period. The trend suggests that a period of 125 minutes, the longest considered in this study, is not the limit and profits most likely peak at a much longer horizon. For other currencies, we see the convergence of the net profits towards the band defined by the noise trader, suggesting that the signal from detecting the jump deteriorates with time. In other words, the jump reveals a temporary signal, which can be potentially exploited over moments very near the price jump.

We now define the *lifetime of a price jump* effect on the markets as the longest trading horizon of the jump trader, for which the net cumulative returns outperforms the random trader, given by the 99-th percentile. Using that metric, the Japanese yen and the South African rand reveal a permanent effect of the price jump, while for the other currencies, the effect is rather temporary, ranging from 20 minutes for the Russian ruble and the Turkish lira to around 125 minutes for the Euro. Any trader who aims to exploit the directional signal generated by the price jump has to be faster than these lifetimes.

The cumulative returns also stress the role of the bid-ask spreads, which destroy most of the gross profits for the emerging markets currencies. Further, the effect of slippage decreases the profitability of the jump trader strategy; however, as the net cumulative return of the jump trader moves closer to the median of the random trader, the effect of slippage changes and becomes random. This suggests that in these instances, the detection of a jump does not generate a signal but is rather a noise.

Finally, the skewness of the distribution of the net cumulative returns of the random trader fluctuates with the holding period without any obvious trend. Further, the longer

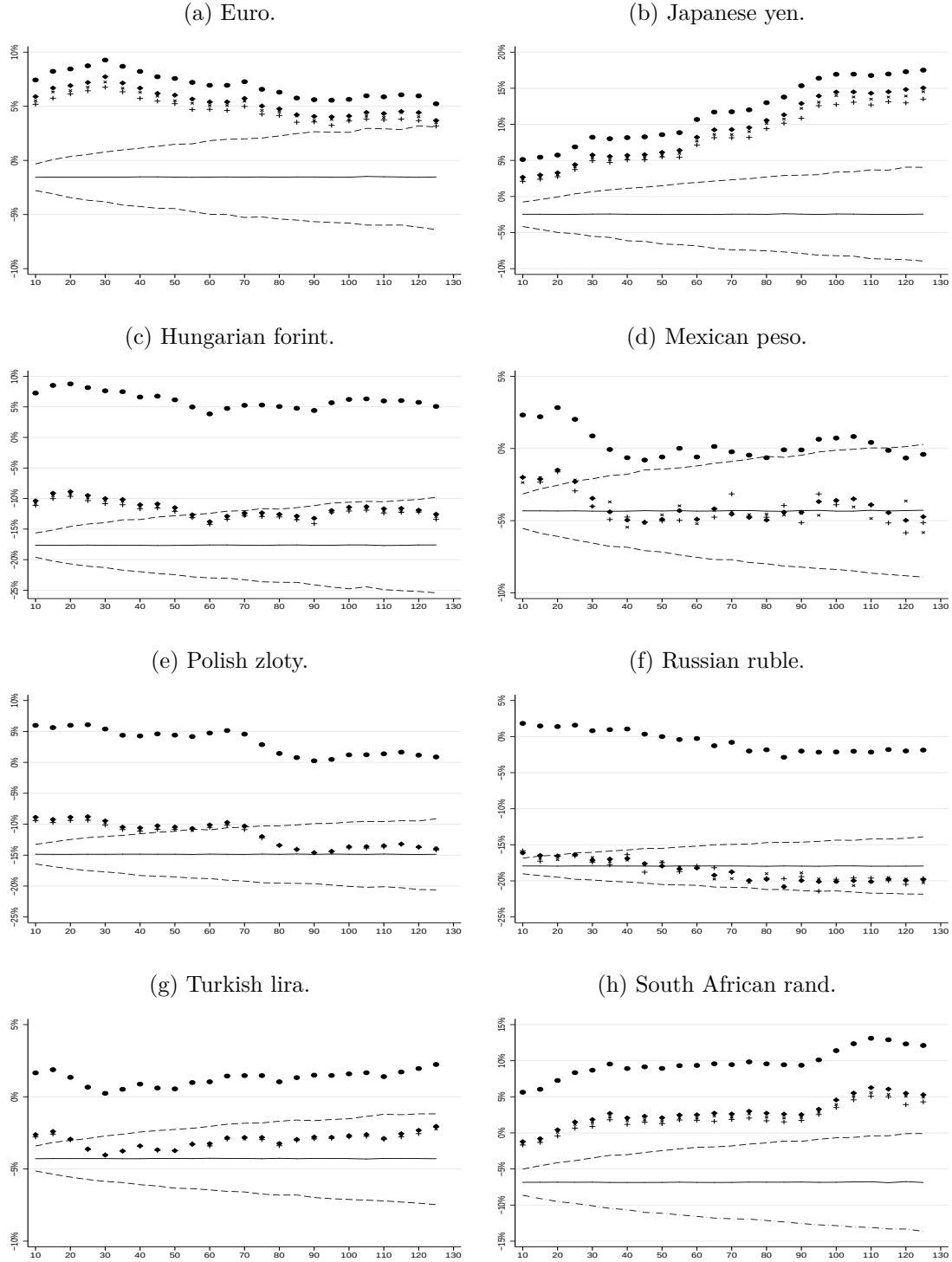
the holding period is, the higher the chance to find profitable random traders becomes. For instance, in the case of the Euro, for holding periods of 10 minutes, the top 1% the most successful “noise traders” lose -0.33% net cumulative return, while for holding period of 125 minutes, the same traders can realize a 3.09% cumulative return. This corresponds to the fact that the variance of returns scales as $\propto \sqrt{\Delta t}$. As Table 7 suggests, the difference between 99% and 1% percentiles of the distribution of cumulative returns of the noise trader satisfies this property.

4.2.2. The Risk Measures and The Profitability

Figure 3 captures the three risk measures and the profitability of the jump trader performance for all holding periods ranging from 10 minutes to 125 minutes. Firstly, judging the performance solely by the Sharpe ratio captured in Panel (a), the best strategy is clearly for the Euro and the shortest trading horizon. With an increasing holding period, the Euro’s Sharpe ratio decreases and for positions lasting 55 and more minutes, the Japanese yen beats it. When the jump trader decides to hold the position even longer, the Euro’s Sharpe ratio is outperformed by the South African rand as well. In addition, around the 60-minute holding period, the Sharpe ratio stabilizes for most of the currencies in a plateau-like manner. In the long-term perspective, the Japanese yen beats the market. On the contrary, the worst performing currency is the Russian ruble, under-performing comparing to the other currencies.

Panel (b) depicts the P/L ratio for all eight currency pairs. The Euro and the Japanese yen have a P/L ratio consistent with the Sharpe ratio: The short-term positions are dominated by the Euro, later replaced by the Japanese yen. The Euro, however, significantly under-performs a large share of currencies with longer holding horizons. At the longer horizons, the Japanese yen and the South African rand tend to systematically beat the other currencies. From the overall perspective, the jump trader strategies fluctuates around one, providing a very weak trading signal in terms of the P/L ratio. Finally, the

Figure 2: Cumulative returns.



Note: The figure depicts the gross cumulative returns $\kappa^{(x)}$ (●), those corrected for bid-ask spread $\kappa_{ba}^{(x)}$ (◆), and a pair of net cumulative returns with slippage $\eta = 0.05$ (×) and $\eta = 0.1$ (+), respectively. In addition, the picture depicts the 50-th (solid line), and 1-st and 99-th centiles (dash lines) of the distribution of $\kappa_{ba}^{(x)}$ for "random trader" based on 10,000 replications.

Russian ruble confirms its role as the worst-performing investment vehicle in the sample.

Panel (c) depicts the downside risk in terms of the drawdown normalized to 5 minutes. Clearly, the Euro is stable, showing a difference relative to the remaining seven currencies, which have significantly large downside risks at short-term horizons. This fact supports the profitability of the Euro as the best short-term investment instrument for the jump trader. Surprisingly, the Russian ruble has quite a low downside risk, suggesting that the detected jump is not providing any useful signals for a trader and, (s)he systematically loses money on the bid-ask spreads as (s)he follows a strategy with a high noise-to-signal ratio.

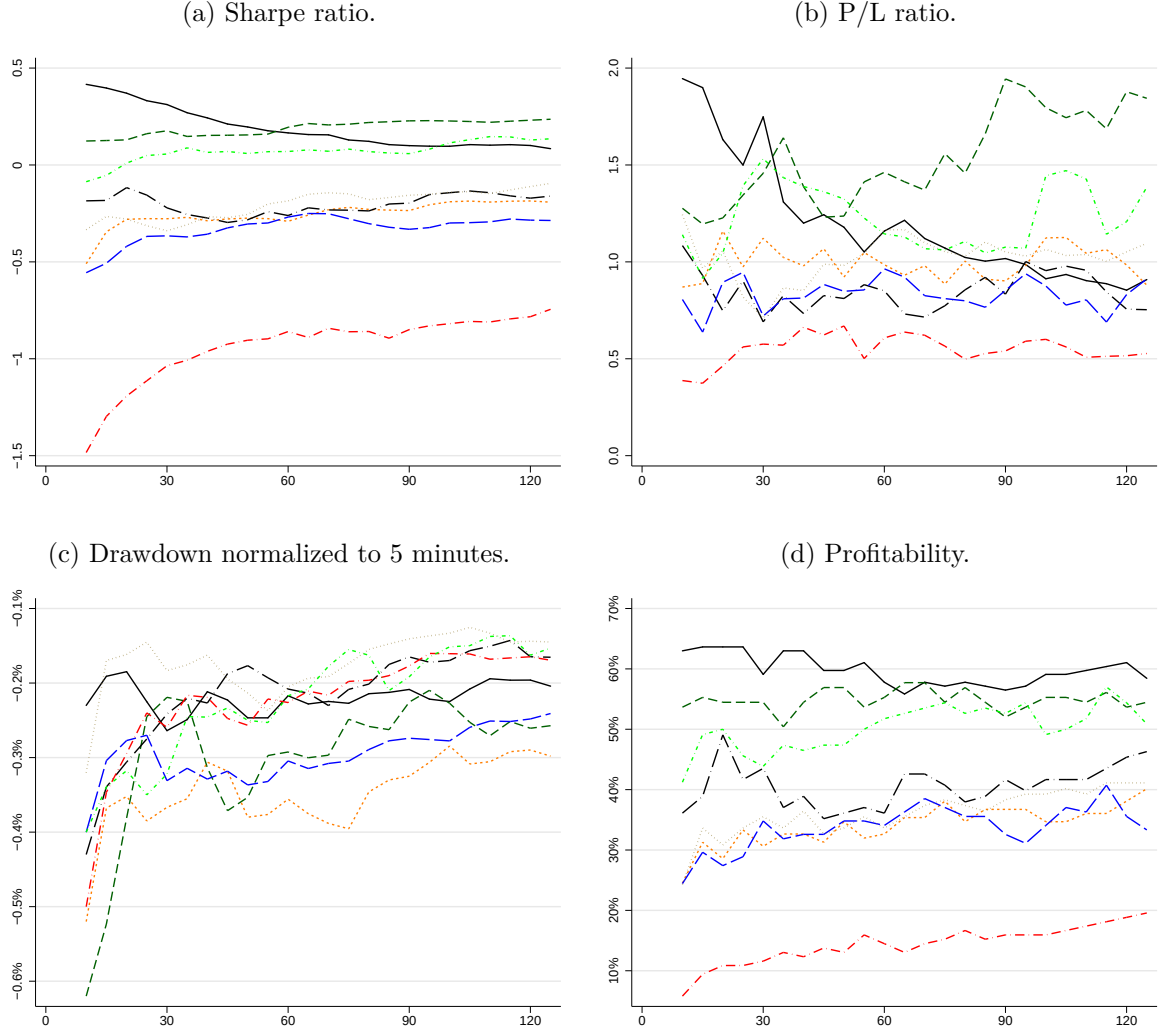
Panel (d) provides the overview of the profitable net trades. Profitability coincides with the overall performance of trading strategies, where whenever the profitability is higher than 50%, the jump trader is making money in net terms. This agrees with the small Sharpe and P/L ratios, which implies that for a profitable currency, the jump trader has to be correct in majority of his/her trades. Consequently, the loss accrued on trading the Russian ruble is truly due to following the noise signal, where the trader consistently loses on transaction fees. On the other hand, the price jump signal is consistently the most accurate for the Euro, which is surprising as this is ought to be one of the most liquid currencies with the highest degree of market efficiency in terms of predictability.

4.2.3. The Time Perspective

Figure 4 reports the cumulative returns $\kappa_{ba}^{(x)}$, corrected for the bid-ask spread, for the short-, medium-, and long-term horizons for each currency. Let us focus in particular on three currencies with profitable trading strategies. First, the trading strategy for the Euro shows steadily increasing cumulative returns. It reveals some periods of higher profitability, especially the period at the end of April, when traders realized significant improvements in profits.

On the other hand, in the case of the Japanese yen, the entire profit is realized mainly

Figure 3: Risk measures and profitability.



Note: The figure depicts the risk measures and profitability based on the net cumulative returns for the “jump trader”. Panel (a) plots the Sharpe ratio, Panel (b) plots the Profit and Loss (P/L) ratio, Panel (c) depicts the full drawdown and the drawdown scaled to 5-minute time scale, finally, Panel (d) captures the profitability of the jump initiated trades. The currency pairs are: EUR (solid black line), JPY (dash dark green line), HUF (short dash orange line), MXN (long-dash dot black line), PLN (long-dash blue line), RUB (dash dot red line), TRY (dot brown line), and ZAR (short-dash dot lime line).

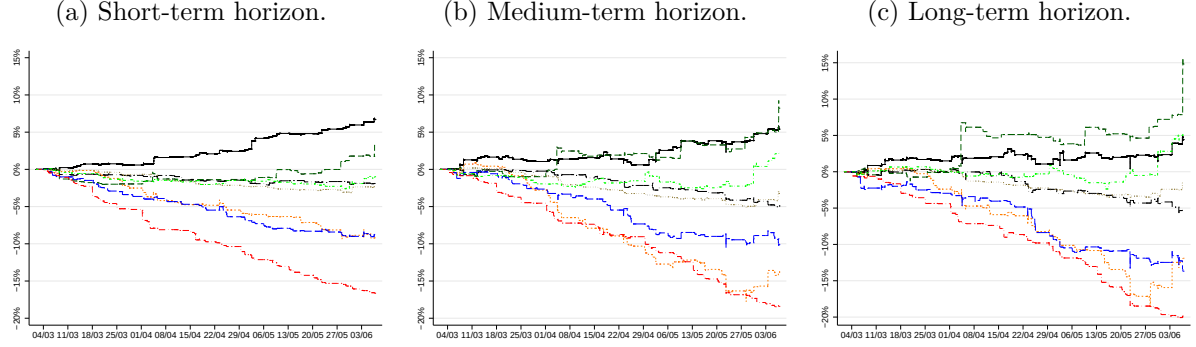
in two trades; otherwise the strategy is mildly profitable. This is stressed more at longer holding horizons. In particular, the first jump in cumulative returns occurred on March 4. This coincides with the announcement by the Bank of Japan that it would increase bond purchases from 5.2 to 7 trillion yen and would buy longer-term bonds with maturity up to 40 years. Further, the Bank of Japan announced targeting of monetary base. The second jump in cumulative returns took place on June 6, when the Japanese yen reportedly suffered one of the most massive unwinding of positions in history. Traders were short in yen and long in dollars for quite a while. At the same time, the ECB's announcement of the recovery perspective and the FED's announcements were perceived by the market as rather weaker than expected. Consequently, the dollar weakened, which prompted unwinding the positions in short yen and long dollar. Such market movements could be described as traders selling dollars, and the JPYUSD likely seemed reasonable as the yen was trading at its weakest level in 5 years.

For the South African rand, the profit is realized by the end of the period, though the jump trader was losing money over most of the period. This trend reversal in profits corresponds to the period when volatility, as captured by the three-months ATM volatility, soared together with the forward based three-months interest rates.¹⁷ A similar trend reversal towards the end of the sample is observed for the Hungarian forint and the Turkish lira as well; however, the bid-ask spreads are responsible for all the losses.

Finally, as can be seen from the detailed results in the Internet Appendix for each currency, we cannot reject the hypothesis that the bid-ask spread varies with the distance from the price jump. The jump trader does not enter into the trade at the 5-minute time step containing the price jump, but in the next period. Such a delay provides a safety buffer for the proposed trading strategy to avoid periods of no market liquidity. The

¹⁷See the Internet Appendix for the detailed figures of the 3-month ATM volatility and 3-month carry trade interest rates for each of the eight currency pairs.

Figure 4: The cumulative net returns.



Note: The figure depicts the cumulative net returns for the “jump trader”. Panel (a) the short-term holding period of 15 minutes, Panel (b) the medium-term holding period of 60 minutes, and Panel (c) the long-term holding period of 120 minutes. The currency pairs are: EUR (solid black line), JPY (dash dark green line), HUF (short dash orange line), MXN (long-dash dot black line), PLN (long-dash blue line), RUB (dash dot red line), TRY (dot brown line), and ZAR (short-dash dot lime line).

jump trader is in fact the post-jump trader, as there is a sufficient delay between the jump and the trading activity. Lastly, in the case of all currencies but the Russian ruble, the variation is on the order of tens of percents on average. In the case of the Russian ruble, the variance of the bid-ask spread shows much higher variation, in many cases reaching hundreds of percents above the average.

The results suggest the presence of a profitable trading strategy on one of the most liquid global currency markets and therefore seem to question the efficient market hypothesis as proposed by Malkiel and Fama (1970). Firstly, the profits are not so strong as they may appear. The jump trading strategy has a low Sharpe ratio and the P/L ratio is well below two. Still, the results suggest that price jumps carry information, which can be exploited to a small degree.

Secondly, the profit realized by the proposed marginal trader is not in contradiction with the basic principle of financial markets as it reflects several different phenomena. In addition to investment in the currencies, the foreign exchange markets serve to hedge the economic operations in foreign currencies and to conduct monetary policy. In particular,

monetary policy may be behind the positive profitability, as global markets experienced turmoil in terms of the monetary policy announcements throughout our sample. The announcement of the tapering by the FED and beginning of Abenomics may suggest the presence of trends in foreign exchange markets, for which the price jumps could serve as indicators.

Further, the dates with important announcements tend to be overhedged, as investors are risk averse and usually tend to over protect themselves (Verdelhan, 2010 supports the claim that around announcements, the risk aversion of traders rises).¹⁸ In addition, the excessive usage of technical trading may create trading opportunities. For instance, Griffin et al. (2003) illustrates such a feature for the NASDAQ 100 stocks and usage of limit orders. Finally, Brandt et al. (2008) show that post-announcement trading can produce a significant cumulative return in low-frequency equity markets. Our findings may be interpreted as an extension of a recognized post-earning announcement anomalous drift in the literature into the high-frequency domain.

Thus far, we have evaluated the trading outcome on a currency-by-currency basis to understand how the jump trader strategy works. However, the trader operates over an entire portfolio of currencies. Thus, in the next section, we focus on a portfolio perspective and discuss the optimal choices of the portfolio and evaluate the risk profile from the portfolio perspective. Then, we introduce the US dollar index and calculate beta of each currency. Finally, we discuss the hedging implications for trading each currency.

4.3. Portfolio Trading Outcomes

In this section, we identify a portfolio profile of the jump trader and discuss possible hedging strategies.

¹⁸There is a general consensus among practitioners that implied volatility on days with important announcements exceeds the realized volatility. This means that investors are rather overprotected. In fact, fund managers tend to be punished for not protecting themselves against consequences of the important news announcements rather than for incurring an extra cost for insuring their positions.

4.3.1. Portfolio Profile

We consider a trader operating his/her portfolio in the following way: The trader operates the single-currency jump strategy over each currency in the portfolio and evaluates the profit and risk profile for the entire portfolio. There is no cross-currency trading or signal processing, and the trader hedges his/her positions implicitly. We consider two portfolios: The first, the *market-wide* portfolio consists of all eight currency pairs, which the trader trades at every moment (s)he spots the signal. The second, the *developed markets* portfolio consists of the Euro and the Japanese yen, as the previous section robustly shows the negative role of the large bid-ask spreads. The trader thus trades whenever (s)he spots the signal at currencies which are liquid and inexpensive to trade.

Table 8 captures the details of the two portfolios performance. The number of trades for both portfolios suggest that there is a significant number of cases in which the trader initiates trades at the same time at multiple currencies and thus the portfolio properties are not simply additive compositions of the performance when trading the individual currencies. Specifically, there are 684 trades over the market-wide portfolio and 247 trades for the developed markets only.¹⁹ The performance of the two portfolios is as one may expect from the role of the bid-ask spreads: The market-wide portfolio is losing money, while trading the developed market currencies provide a positive cumulative return composed of two profitable assets.

Let us further focus on the developed market currencies. First, the profitability of the price jump trading strategies is higher than the weighted average of the individual currencies. In the medium-term, the percentage of profitable trades for the portfolio is higher than either of the two individual currencies. This suggests that overlapping jumps play a role and loss at one currency is hedged by profit at another. However, the

¹⁹Table 7 shows that there are overlapping jumps as the sum of the number of price jumps for individual currencies is different from the number of trades realized at the portfolio level.

Table 8: Portfolio perspective of the trading outcomes.

Portfolio	Holding period	Net return $\kappa_{ba}^{(x)}$	Profitable trades	Sharpe ratio	P/L ratio	Drawdown $DD^{(x)}$ full	5-minute
Market-wide	short	-34.40%	36.88%	-0.21	0.89	-1.77%	-1.02%
	medium	-39.00%	37.76%	-0.12	1.09	-4.84%	-1.40%
	long	-31.50%	43.44%	-0.07	1.00	-5.43%	-1.11%
Developed markets	short	9.68%	60.32%	0.23	1.39	-0.74%	-0.43%
	medium	13.62%	59.11%	0.18	1.20	-1.37%	-0.39%
	long	19.25%	58.30%	0.17	1.28	-1.42%	-0.29%

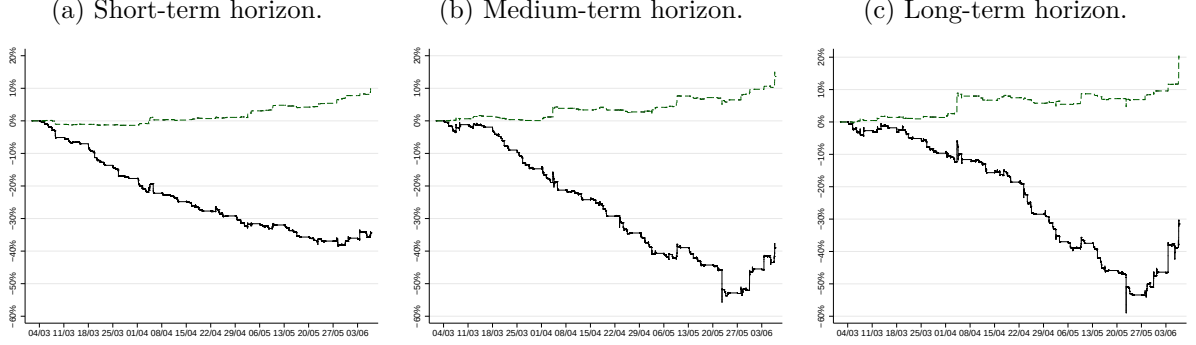
Note: The table presents the outcomes of the trading strategies for the “jump trader” for: *i*) the market-wide portfolio, and *ii*) and the developed markets portfolio. The results are for three trading horizons: the short-term holding period of 15 minutes, the medium-term holding period of 60 minutes, and the long-term holding period of 120 minutes. We report the net cumulative returns adjusted for the bid-ask spread, the percentage of the profitable trades and three risk measures: the Sharpe ratio, the P/L ratio, the full drawdown and the 5-minute drawdown. There are 684 trades for the market-wide portfolio and 247 trades for the developed markets portfolio.

cumulative returns are rather a sum of individual profits. Consequently, both the Sharpe and the P/L ratios are a weighted average of the two currencies. The drawdown then suggests that there may be a wrong-way risk in terms of joint nonprofitable trades in both currencies.

When we compare Table 8 with Table 7, the combined portfolio is more stable with respect to the holding period. In particular, the portfolio robustly combines the short-term profitability of the Euro and the long-term profitability of the Japanese yen.

Figure 5 depicts the cumulative returns for the market-wide and the developed currencies portfolios. The short-term portfolio for the developed market currencies is in a loss during March, while it becomes profitable later. The medium- and long-term portfolios are profitable from the very beginning for the same portfolio and this tends to be robust. The two major profit-building events we have witnessed for the Japanese yen, are pronounced in the portfolio perspective as well. Finally, the market-wide portfolio shows a trend reversal in the cumulative profit during the last two weeks of our sample. It is worth noting that this is not only due to the profit in the Japanese yen, but rather

Figure 5: The cumulative net returns for portfolio.



Note: The figure depicts the cumulative net returns for the “jump trader” over the entire market-wide portfolio (solid line) and the portfolio consisting of the developed market currencies (dash line). Panel (a) refers to the short-term holding period of 15 minutes, Panel (b) to the medium-term holding period of 60 minutes, and Panel (c) to the long-term holding period of 120 minutes.

the trend reversal in individual currencies connected to the previously reported period of increased market volatility and interest rates.

Our sample contains currency pairs involving the US dollar and both portfolios are exposed in the same way to the US dollar-related risk. In particular, if the detected signal for price jumps linked to the US economy is mixed, the trader is exposed to this in all his/her trades, which would affect the jump strategy. To properly explore the link between individual currency performance and the US dollar performance, we define the market risk factor and estimate the beta for each currency.

4.3.2. The US Dollar Index as a Measure of the Market Risk

We define the US dollar index as follows: We denominate all currencies with respect to the US dollar, and normalize them to 100 on March 1, 21:35 as this is the first observed price for which we have the full moving window needed to estimate price jumps. The index is given as an equally weighted basket of currencies

$$p_t^{(USDI)} = \sum_{i=1}^8 \frac{1}{8} p_t^{(curr_i)}, \quad (7)$$

with $curr_i$, $i = 1, \dots, 8$, representing for all currencies denominated to the US dollar and properly normalized. As reported in Section 2, each currency is pre-averaged and sampled at a 5-minute frequency. The log-returns are then constructed based on the normalized US dollar index. The US dollar index is constructed in such a way that idiosyncratic jumps are diversified out in the portfolio, while the common jumps, related either to the global or the US economy are pronounced.

We execute the jump trading strategy for the US dollar index.²⁰ We calculate the gross cumulative return for each currency pair and the dollar index on a weekly basis. We work with the gross return as we want to understand the link between the signals generated by the detection of price jumps, while the contribution of the bid-ask spreads is deterministic. The US dollar index serves as a market risk factor capturing events impacting both the US economy and the global economy.²¹ We calculate the beta for each currency as

$$cr_t^{(i)} = \alpha^{(i)} + \beta^{(i)} cr_t^{(USDI)} + \varepsilon_t^{(i)}, \quad (8)$$

where $cr_t^{(i)}$ is the weekly cumulative gross return for each currency, $cr_t^{(USDI)}$ is the weekly cumulative gross return for the US dollar index, and $\varepsilon_t^{(i)}$ is idiosyncratic and heteroskedastic error term.

Table 9 presents the estimated values for equation (8) using three trading horizons: the short-term holding period of 15 minutes, the medium-term holding period of 60 minutes, and the long-term holding period of 120 minutes. At the short-term holding period, the Japanese yen shows beta of 2.55, suggesting an overexposure to the jump

²⁰The detailed summary statistics and measures of performance of the US dollar index is reported in the Internet Appendix.

²¹The market β for the FX markets is not as straightforward to define as for equities, see James et al. (2012) for further discussion. Therefore, we take the profitability of the US Index as a relevant market benchmark and measure the respective currencies relatively to the US Index.

trading related to the global and the US economy. For that case, the regression shows the highest estimation accuracy, as captured by the R^2 coefficient. As the holding period increases, the beta disappears, while for the remaining currency, the beta turns out to be significant. As the Euro and the Japanese yen behave differently with respect to the US dollar index, the combination of the two developed market currencies diversifies out the market risk. The Euro has a beta close to one, suggesting a tight economic link between the Eurozone and the US economy. Similarly to the Japanese yen, the Turkish lira has an analogous risk profile with significant correlation to the market at the short-term holding period, which decreases as the holding period increases.

The Hungarian forint and the Polish zloty, the currencies of two economically linked economies, have different risk profiles, as the beta of the forint has its beta of one, while the zloty is overexposed to market risk. Consequently, based on the fact that the Polish trade links are more confined to the Eurozone than those of Hungary, which is more globally diversified, one would expect the beta of the USDPLN to be smaller compared to the USDHUF. In fact, at long-term horizon, the beta of the Polish zloty is highest in our sample, suggesting that it is an overleveraged investment vehicle with respect to the jump trading strategy on the US market.

5. Conclusions

In this paper, we investigate the trading opportunities of price jump clusters in the foreign exchange markets. We propose a formal procedure to identify clusters of price jumps and validate it empirically using the tick-by-tick foreign exchange spot prices for the Euro, the Japanese yen, the Hungarian forint, the Mexican peso, the Polish zloty, the Russian ruble, the Turkish lira, and the South African rand denominated in US dollars over the period ranging from March 1, 2013 to June 6, 2013, sampled at 5-minute frequency and pre-averaged to control for market microstructure noise. We find clusters of price jumps to be robustly present across all currencies, with the Euro showing the

Table 9: The US dollar risk factor.

	Short-term			Medium-term			Long-term		
	$\alpha \cdot 10^{-3}$	β	R^2	$\alpha \cdot 10^{-3}$	β	R^2	$\alpha \cdot 10^{-3}$	β	R^2
EUR*	-0.090	0.646	0.113	-0.122	0.729**	0.296	-2.923	1.113***	0.397
JPY	2.042	2.554***	0.582	3.529	0.908	0.116	5.268	0.503	0.016
HUF	-1.659	1.264	0.149	-2.885	0.733	0.107	-7.845	1.064*	0.124
MXN	-0.805	0.028	0.000	-0.773	0.465**	0.220	-3.127	0.724***	0.373
PLN	0.079	0.725	0.171	0.629	1.224***	0.372	-0.338	1.530***	0.500
RUB	0.350	-0.218	0.082	0.500	0.378	0.194	0.313	0.660***	0.443
TRY	0.955	0.935**	0.449	1.749	0.216	0.081	1.125	0.466***	0.541
ZAR	-0.874	1.207	0.330	-1.949	1.045	0.250	-2.661	1.103**	0.311

Note: Table reports α and β for the weekly gross cumulative returns of each currency and the US dollar index given by the following regression equation:

$$cr_t^{(i)} = \alpha^{(i)} + \beta^{(i)} cr_t^{(USDI)} + \varepsilon_t^{(i)}, \quad (9)$$

where $cr_t^{(i)}$ is the weekly cumulative gross return for each currency, $cr_t^{(USDI)}$ is the weekly cumulative gross return for the US dollar index, and $\varepsilon_t^{(i)}$ is an idiosyncratic heteroskedastic error term. The error terms are estimated using the robust White estimator of variance. The results are for three trading horizons: the short-term holding period of 15 minutes, the medium-term holding period of 60 minutes, and the long-term holding period of 120 minutes.

highest number of clusters and the Japanese yen having the most dense clusters.

We exploit tradeable information due to the presence of clusters, and we propose a strategy where traders open a position soon after identifying a price jump in the spot market. Such a strategy is to be profitable, though not fully exploitable in the case of emerging market currencies with high bid-ask spreads. For all currencies, however, the price jumps carry significant information about the directionality of each asset. The results further suggest the presence of two types of currencies. The first group, which includes the Euro, the Japanese yen and the South African rand, reveal net profitable trading strategies of the jump trader. In particular, the Euro showed positive cumulative returns, which diminish with an increasing holding period. On the other hand, the Japanese yen and the South African rand experienced positive cumulative returns, which actually grow with an increasing holding period. The second group of five remaining currencies reveal unprofitable trading strategies. In particular, the Hungarian forint and

the Polish zloty show a negative cumulative return, decreasing with the holding period, where the bid-ask spread takes all the profitability in the jump signal. The Mexican peso is unprofitable and, except for the very shortest holding periods, indistinguishable from the random trader. The Turkish lira reveals convex cumulative returns, which due to the bid-ask spread, are not profitable either. Finally, the least profitable currency, the Russian ruble, is characterized by large bid-ask spreads, with decreasing cumulative returns and the lowest ratio of profitable trades. In addition, there is also evidence that the jump trader at the Russian ruble underperforms the random trader. In terms of the Sharpe ratio, the price jump trading strategy is rather weak, which is also confirmed by the P/L ratios.

Finally, the portfolio consisting of the Euro and the Japanese yen provides a stable profitable strategy with respect to the holding period and thus constitutes an optimal currency set to be explored by the price jump trader. Analyzing the risk profile of the individual currencies with respect to the market risk captured by the US dollar index, we further show that the portfolio of the Euro and the Japanese yen diversifies such a risk across all the holding periods.

References

- Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and credit rating. *The Journal of Finance* 62 (5), 2503–2520.
- Baillie, R. T., Chang, S. S., 2011. Carry trades, momentum trading and the forward premium anomaly. *Journal of Financial Markets* 14 (3), 441–464.
- Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., Shephard, N., 2011. Multivariate realised kernels: consistent positive semi-definite estimators of the covariation of equity prices with noise and non-synchronous trading. *Journal of Econometrics* 162 (2), 149–169.
- Boudt, K., Croux, C., Laurent, S., 2011. Robust estimation of intraweek periodicity in volatility and jump detection. *Journal of Empirical Finance* 18 (2), 353–367.
- Boudt, K., Petitjean, M., 2014. Intraday liquidity dynamics and news releases around price jumps: Evidence from the djia stocks. *Journal of Financial Markets* 17 (C), 121–149.
- Brand, C., Buncic, D., Turunen, J., 2010. The impact of ecb monetary policy decisions and communication on the yield curve. *Journal of the European Economic Association* 8 (6), 1266–1298.
- Brandt, M. W., Kishore, R., Santa-Clara, P., Venkatachalam, M., 2008. Earnings announcements are full of surprises. *Duke University Working Paper*.
- Broadie, M., Jain, A., 2008. Pricing and hedging volatility derivatives. *The Journal of Derivatives* 15 (3), 7–24.

- Brownlees, C. T., Gallo, G. M., 2006. Financial econometric analysis at ultra-high frequency: Data handling concerns. *Computational Statistics & Data Analysis* 51 (4), 2232–2245.
- Brunnermeier, M. K., Nagel, S., Pedersen, L. H., 2008. Carry trades and currency crashes. Tech. rep., National Bureau of Economic Research.
- Brunnermeier, M. K., Pedersen, L. H., 2009. Market liquidity and funding liquidity. *Review of Financial Studies* 22 (6), 2201–2238.
- Chan, L. K., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. *The Journal of Finance* 51 (5), 1681–1713.
- Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. *The Journal of Finance* 56 (2), 501–530.
- Davidson, R., MacKinnon, J. G., 2004. *Econometric theory and methods*. Oxford University Press New York.
- Eisdorfer, A., 2008. Delisted firms and momentum profits. *Journal of Financial Markets* 11 (2), 160–179.
- Griffin, J. M., Harris, J. H., Topaloglu, S., 2003. The dynamics of institutional and individual trading. *The Journal of Finance* 58 (6), 2285–2320.
- Hendershott, T., Jones, C. M., Menkveld, A. J., 2011. Does algorithmic trading improve liquidity? *The Journal of Finance* 66 (1), 1–33.
- Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance* 55 (1), 265–295.

- Jacod, J., Li, Y., Mykland, P. A., Podolskij, M., Vetter, M., 2009. Microstructure noise in the continuous case: the pre-averaging approach. *Stochastic Processes and their Applications* 119 (7), 2249–2276.
- James, J., Marsh, I., Sarno, L., 2012. *Handbook of Exchange Rates*. Vol. 2. John Wiley & Sons.
- Jiang, G. J., Lo, I., Verdelhan, A., 2011. Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the us treasury market. *Journal of Financial and Quantitative Analysis* 46 (02), 527–551.
- Jostova, G., Nikolova, S., Philipov, A., Stahel, C. W., 2013. Momentum in corporate bond returns. *Review of Financial Studies* 26 (7), 1649–1693.
- Korajczyk, R. A., Sadka, R., 2004. Are momentum profits robust to trading costs? *The Journal of Finance* 59 (3), 1039–1082.
- Lahaye, J., Laurent, S., Neely, C., 2011. Jumps, cojumps and macro announcements. *Journal of Applied Econometrics* 26 (6), 893–921.
- Lee, S., 2012. Jumps and information flow in financial markets. *Review of Financial Studies* 25 (2), 439–479.
- Lee, S., Mykland, P., 2008. Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies* 21 (6), 2535–2563.
- Linnainmaa, J. T., 2010. Do limit orders alter inferences about investor performance and behavior? *The Journal of Finance* 65 (4), 1473–1506.
- Lustig, H., Roussanov, N., Verdelhan, A., 2010. Countercyclical currency risk premia. Tech. rep., National Bureau of Economic Research.

- Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. *Review of Financial Studies* 24 (11), 3731–3777.
- Lyons, R. K., 2001. The microstructure approach to exchange rates. The MIT Press, Cambridge, MA.
- MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. In: *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*. Vol. 1. California, USA, pp. 281–297.
- Malkiel, B. G., Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* 25 (2), 383–417.
- Mancini, L., Ranaldo, A., Wrampelmeyer, J., 2013. Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance* 68 (5), 1805–1841.
- Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Currency momentum strategies. *Journal of financial economics* 106 (3), 660–684.
- Obizhaeva, A. A., Wang, J., 2013. Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets* 16 (1), 1–32.
- Osler, C. L., 2005. Stop-loss orders and price cascades in currency markets. *Journal of international Money and Finance* 24 (2), 219–241.
- Podolskij, M., Vetter, M., 2009. Estimation of volatility functionals in the simultaneous presence of microstructure noise and jumps. *Bernoulli* 15 (3), 634–658.
- Shleifer, A., Vishny, R. W., 1997. The limits of arbitrage. *The Journal of Finance* 52 (1), 35–55.

Todorov, V., 2010. Variance risk-premium dynamics: The role of jumps. *Review of Financial Studies* 23 (1), 345–383.

Verdelhan, A., 2010. A habit-based explanation of the exchange rate risk premium. *The Journal of Finance* 65 (1), 123–146.