Three Essays on Current International Financial Markets

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ABSTRACT

Three Essays on Current International Financial Markets

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This dissertation consists of three essays that address recent developments in international financial markets that have been of concern for scholars, policymakers, and practitioners. The first essay examines how cultural factors can influence individual investors' trading behavior in response to risk in nine Eurozone countries. The markets studied were particularly affected by the global financial crisis, the subsequent European banking crisis, and the European sovereign debt crisis. Using mutual fund flows as proxy of investors' trading behavior, our evidence indicates that a country culture variable significantly affects investors' trading responsiveness to risk. Specifically, the impact of risk on fund flows is significantly positive and is larger in scale in countries with individualist cultures.

The second essay attempts to investigate the effects of negative interest rate policies (NIRP) on foreign exchange and equity markets of eight European countries and Japan. To see the impacts of these policies, event studies and regime-switching vector autoregressive regression analyses are conducted for the nine countries that implement NIRP. The results provide valid evidence that the announcement of NIRP has a transitory effect on currency depreciation; long term effects are less evident. On the day of NIRP implementation, both currency and equity market returns reacted in response to the event efficiently and negatively, especially in Switzerland's case. These outcomes suggest that simulative monetary policy by lowering interest rates below zero might have counter-effects from those observed when interest rates are lowered, but to rates that remain positive. Additionally, findings from the long term analyses explain that interest rate term structure and cointegration level of local and the U.S. equity index may be related to effectiveness of NIRP in currency and equity markets, respectively.

The last essay examines the determinants of the price of the leading cryptocurrency, Bitcoin. The analyses identify a number of factors that significantly affect the returns to investments in Bitcoin including: trading volume, high-low price spread, and extreme price change in the previous period. The latter result supports the assertion that recent severe price fluctuations in Bitcoin markets are primarily due to speculative investment activities. Furthermore, evidences suggested in this study explain possibility of market compromise and inefficiency of the cryptocurrency market, implying pivotal risks for Bitcoin market participants.

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Contribution of Authors

Part of this thesis is published work with Lorne N. Switzer and Jun Wang.

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Chapter 1: Introduction

My dissertation consists of three essays studying current issues on international financial markets, covering diverse topics that include: a) the influence of culture on risk taking, b) the impact of negative interest rate policies, and c) the behavior of cryptocurrency markets. These topics are relatively new in finance, and the literature is still in a nascent stage. However, given the increased recognition of the pertinence of these topics for global financial markets, we believe that they are worthy areas for investigation.

The first essay investigates how culture moderates the impact of risk on small investors' investment behavior in certain European countries. In this study, we look at investor responses to risk, using both traditional and extreme risk measures for countries particularly affected by the global financial crisis, the subsequent European banking crisis, and the European sovereign debt crisis. Specifically, we construct standard risk measures based on the logarithmic percentage changes of stock prices over different holding periods, with the assumptions of normality and symmetry of return distribution and risk averse investors. The standard deviation of returns is also an essential component of the traditional value-at-risk (VaR) measure. Such risk has been the focus of regulators in seeking to establish how much financial institutions should put aside to guard against the types of financial and operational risks banks (and the whole economy) face. However, because the standard deviation does not capture the risk to the investor when the distribution is non-symmetric, the traditional methods of calculating conventional value-at-risk (VaR) measures that are based on a normal distribution are problematic and need to be interpreted cautiously. Our second measure of risk that focuses on the distribution around the tail falls under the rubric of extreme value theory. Extreme risk observations are identified as the mild outliers in our samples, using the Tukey (1977) definition. They are computed using the percentage of extreme days, weeks, and months over a specific year. One advantage of this extreme measure is that we can decompose the total risk measure into a positive shock component and a negative shock component, so that we can observe accurately the behavior such investors whose utility responses to stock price change are asymmetric. Comparing the risks based on those two measures, our results show that the extreme measures do not always cohere with the classical standard deviation measure of risk for the countries considered.

Previous studies that examine these issues on large developed countries. In this study, we examine nine relatively small European countries that have been exposed to several external financial shocks over the past decade. More specifically, during the Global Financial crisis of 2007-08 and its aftermath, as G-7 countries generally recovered, relatively small economies such as Belgium, Greece, Ireland, and Portugal became the main epicenters of continued instability. For example, two of Belgium's largest banks: Fortis and Dexia, underwent reorganization and restructuring in order to survive. Fortis was spun off into two parts, while the Dutch group was nationalized and the Belgian component was sold to the French bank BNP Paribas. Ireland and Greece also went into a debt crisis in 2010. Allied Irish Bank and the Bank of Ireland received a €7 billion rescue package in 2009 and went into recapitalization. The four largest banks of Greece, National Bank of Greece SA, Piraeus Bank SA, Euro-bank Ergasias SA, and Alpha Bank AE, have been the regular recipients of emergency loans from the European Central Bank (ECB). Portugal applied for bail-out programs to cover its insolvent sovereign debt, drawing a €79 billion from the International Monetary Fund (IMF), the European Financial Stabilization Mechanism (EFSM), and the European Financial Stability Facility (EFSF). The debt crises of Ireland, Greece and Portugal marked the start of the European sovereign debt crisis. One might posit that the behavior of investors in such countries experiencing protracted financial instability may not be consistent with those in larger countries that have more or less recovered. Therefore, in this paper, we focus on individual investors' response to the two aforementioned risk measures in those nine relatively small Eurozone countries: Austria, Belgium, Denmark, Finland, Greece, Ireland, Norway, Portugal, and Sweden that were epicenters of continued instability. By using mutual fund flow as proxy of individual investor's trading behavior, our results show significantly different behavior of investors in those countries in terms of their sensitivity to risks.

We use the Hofstede (2001) culture dimension score on individualism vs. collectivism, as the culture factor. The detailed score for each country can be found in Table 1. Based on Hofstede's classification, a country with higher cultural dimension score is classified more as individualism culture. Individualism cultures describes societies that emphasize the moral worth of the individuals, the exercise of individuals' goals, desires, freedom, independence, and self-reliance, and advocate that interests of individuals should be priority. Considering these culture characteristics, we hypothesize that subjective assessments among individuals may explain the differential or contrasting behaviors to risk: individual investors are more likely to take the initiative in actively trading in response to market signals. In addition, investors may have high risk tolerance, or are even adventuresome so exhibit "flight to risk" preferences, in the sense that they invest more, rather than liquidating their investments when they sense risk. On the other hand, societies with collectivist traditions emphasize cohesiveness amongst members, and individuals in these societies are more likely to adjust their behavior with that of their cohorts, rather than maximizing their own private benefits. Therefore, we propose that more collectivist cultures constrain the initiative for investors to actively trading in response to market signals, and individual investors with these cultural attributes are more likely to exhibit herding behavior and are less sensitive to variations in the risk environment.

Our results support our hypothesis. We find that small investors' responses to risk (both traditional and extreme risks) in those small Eurozone countries are significantly influenced by country culture. In other words, the culture variable affects the impact of risk on investor's trading behavior. The impact of risk on fund flow is significantly positive and are larger from countries with more individualistic cultures. This implies that individual investors from these countries are more sensitive to variations in risk, in terms of engaging in active trading in response to risk changes. On the other hand, when controlling for the culture variable, small investors trading behavior is not directly affected by risk. Our results emphasize the importance of cultural factors in determining individual investor's behavior in response to risk in small Eurozone countries. To the best of our knowledge, our research is the first study that provides a detailed examination of individual investor's trading behavior and its key determinants in relatively small Eurozone countries that were particularly affected by the European banking and European sovereign debt crisis.

My second essay studies the impact of the negative-interest-rate-policies (NIRP) on foreign exchange and equity markets of eight European countries and Japan. Recently, several countries lowered their policy rates below zero percent as a means to emerge from severe recessionary conditions. One could argue that Japan provides the archetypical case of NIRP implementation. The country's long recession, the so-called "Lost 20 Years," has been one of the most troublesome episodes for the world economy in recent decades. In order to stimulate the Japanese economy, after unsuccessful attempts through public sector spending, quantitative easing, and deregulation, the Japanese government went beyond its long-standing zero-interest-rate policy as the Bank of Japan (BOJ) announced that the deposit rate for its accounts would be -0.1 percent from February 16, 2016.

The execution of NIRP was not unprecedented. Prior to the Japanese experiment, several European countries including Denmark, Norway, Sweden, and Switzerland implemented negative interest policies at various times. Bosnia and Herzegovina, Bulgaria, and Hungary joined the negative-interest-rate group in 2016. These three countries lowered their interest rates below the zero bound to maintain the interest rate differentials between themselves and the eurozone region, which were narrowing, as a result of the quantitative easing policy conducted by the ECB. Policymakers in other countries have also considered NIRP as one of their monetary policy options in order to overcome the possible recession or even stagflation.

Most studies on the economic effects of interest rate changes on financial markets have been conducted for regimes characterized by positive interest rate bounds. The empirical literature aimed at assessing how negative interest rates actually affect markets is still relatively limited. Moreover, numerous questions about the negative interest rate concept still remain to be clarified. This study aims to shed new light on the impact of NIRP on financial markets, and in turn enhance our understanding of the limitations of stimulative monetary policies through lower interest rates. I provide new evidence on the impact of negative interest rates on country exchange rates and equity markets over various time horizons. Specifically, I analyze cases of Europe and Japan using standard event studies as well as regime-switching vector autoregressive regression models. The results suggest that NIRP has transitory effects on local currency returns. Longer term effects are observed for only a few countries.

My last essay is an empirical analysis of the market for the world's leading cryptocurrency, Bitcoin. Bitcoin's unprecedented price appreciation in 2017 was deemed by many observers of international financial markets to represent a modern analogue to the Dutch tulip mania of the 17th century. It is difficult to infer an appropriate/efficient market price for virtual currencies such as

Bitcoin. Simple expectations models are confounded by the limited historical data series available since its inception, which hampers even rudimentary backtesting exercises.[1] Bitcoin and other cryptocurrencies that have emerged have achieved notoriety for several reasons including: a) allowing transactions among parties in a transparent manner; b) providing liquidity without arbitrary bounds set by centralized governmental authorities; and c) global compatibility. However, the acceptability of Bitcoin and other cryptocurrencies remains a matter of controversy due to factors that include: a) anonymity of wallet ownership permitting its use for money laundering and other criminal activities; b) security issue of the virtual exchange system; and c) market instability, reflected by extraordinary levels of volatility through time. These latter features are often used as a key deterrent to widespread adoption of cryptocurrencies such as Bitcoin in the real economy. Public pricing for Bitcoin commenced with the launch of the platform: BitcoinMarket.com in March 2010. The price of Bitcoin at the outset of trading was a mere $0.003. After16 months, it soared to $31. From that time forth, Bitcoin's price has experienced periods of extreme volatility characterised by episodes of explosive appreciations and depreciations, unhampered by regulated price limits or circuit breakers such as prevail in many organized exchanges. Bitcoin's appreciation from under $1,000 to over $18,000 in 2017-18 has been viewed by numerous market commentators as clear evidence of a classic irrational bubble.

As of December 31, 2017, the total market capitalization of Bitcoin was $237,466,518,547, and its 24 hours trading volume recorded $12,136,306,688 with circulating supply of 16,774,450 BTCs.[2] The sheer magnitude of this market has served as lightening rod for government regulators

[1] The origin of Bitcoin remains nebulous. In October 2008, an unknown developer, Satoshi Nakamoto presented a nine-page paper explaining the principal of a peer-to-peer electronic money system with blockchain technology. The program named Bitcoin Core was opened to the public in 2009 which inaugurated the world's biggest cryptocurrency to date. This virtual currency was expected to become an attractive medium of exchange to compete with and even supersede extant government-issued currencies.

[2] Bitcoin Transaction Volume Data from *coinmarketcap.com*: https://coinmarketcap.com/historical/20171231/

concerned with the integrity of international financial markets. Monetary authorities have begun to address several questions in this regard including: a) the potential for Bitcoin and other cryptocurrencies to substitute for and perhaps replace government-issued currencies; b) weakening the ability of central banks to conduct monetary policy; and c) exposure to excessive speculative behavior apart from that could creating instability in global financial markets.

Our contribution in this paper concerns c). Our focus is on whether Bitcoin prices are determined in an efficient market. We address this issue from several perspectives. First, we examine whether the pricing of Bitcoin can be explained by fundamental factors, as opposed to technical perturbations reflected by excess speculative behavior. Our focus here is on markets in which the cryptocurrency's trading volume is highest: the U.S. Dollar, Chinese Yuan, Japanese Yen, Euro, and South Korean Won, respectively. The study also examines the impact of several macroeconomic drivers in the pricing of Bitcoin. Overall, the results support the assertion that speculation can be considered the decisive factor underlying extreme volatility in the market. We also test for pricing efficiency based on deviations from no-arbitrage between spot and futures markets, using all CBOE and CME contracts traded from January 2018 contracts to March 2019. The findings are not consistent with market efficiency for the futures prices. Furthermore, we find that deviations from no-arbitrage prices widen during episodes of hackings, frauds issues and new alternative cryptocurrency releases.

Chapters 2 to 4 correspond to my three essays and I conclude in Chapter 5.

Chapter 2: Risk, Culture and Investor Behavior in Small (but notorious) Eurozone Countries

2.1 Literature Review:

How investors respond to risk has been a fundamental question in finance over the past several decades. Most studies that use the traditional volatility measure (standard deviation of stock returns) as it relates to investors' trading behavior find mixed results. For instance, Sirri and Tufano (1998), Barber, Odean, and Zheng (2005), Spiegel and Zhang (2013), and Kim (2017) assert that fund flows are negatively related to risk. On the other hand, O'Neal (2004) and Cashman et al. (2014) show a positive relation between fund inflows and risk. In a related vein, Clifford et al. (2013) show that fund inflows from small investors are positively related to unsystematic risk, while its relation to market risk is an open question. In a recent paper, Switzer et al. (2017) examine the responses of investors to both an extreme risk measure, and the traditional risk measure. They find that individual investors in G-7 countries have different reactions and sensitivities to these two types of risk.

Why investors from those countries exhibit different responses to the same risk measures? This is a critical important research question addressed in this study. Previous literature in this line of research show cross-country investor behavioral variations. For example, Statman (2008) investigates twenty-two countries and identifies significant differences in stated propensities for risk taking of investors. Grinblatt and Keloharju (2001) emphasis culture variables in explaining stockholder's behavior. Eun, Wang, and Xiao (2015) find that culture influences stock price synchronicity by affecting correlations in investors' trading activities and a country's information environment.

While these studies typically show that individualism plays a significant role, they do not explore the actual trading behavior of market participants across different countries. Several researchers endeavor to ascertain the influence of such cultural dimension's influence on performance of financial markets. For example, by using use Hofstede's culture dimension score of 26 developed countries' data, Chui et al. (2010) assert that country individualist score is positively related to trading volume, volatility, and the magnitude of momentum profits. Schmeling (2009) examines the impacts of investor sentiment on stock returns over 18 industrialized countries and finds that sentiment negatively forecasts aggregate stock returns. Chang and Lin (2015) provide comparable results. According to their findings, national cultures are associated with investor herding behavior. Such herding behavior is particularly observed in countries where Confucianism is dominant and in less sophisticated stock markets. Although these studies provide insights about how cultural factors influence overall investing activities in equity markets, they do not consider investors' attitudes against risk. Our paper provides new evidence on this issue, as we examine individual investor's trading behavior directly, as reflected in portfolio position changes in response to changing risk, and how culture factor plays a role in deterring investor's trading behavior based on different risk levels.

2.2. Sample Construction

The data of mutual fund net flows used in this study are obtained from Thomson Reuters DataStream and Thomson ONE. For each of the countries in this study, we choose the equity index with the longest history as the major stock index to use in this study. The historical prices for those indices are collected from *Bloomberg* and *Thomson Reuters DataStream*. Table 2 presents the details of the indices, including the time period and the number of observations for each country when we use daily, weekly, and monthly data to calculate risk variables.

[Insert Table 2 here]

The index for our sample countries start from as early as 1987, including Finland's OMS Helsinki Index, Ireland's Irish Overall Index, and Sweden's Stockholm All-Share Index, to as late as 1995, including Norway's OMX Oslo All Share Index. The index for each country covers more than 18 years, from as short as 225 months (19 years) to as long as 445 months (37 years). Therefore, our sample period covers major historical events and business cycles, allowing for a broad perspective for investigating investors' behavior across different market conditions.

2.2.1. Traditional Risk (bases on Standard Deviations) and Extreme Risk Estimation

2.2.1.1. Traditional risk measure

In order to calculate both the standard and extreme risk measure, we need to calculate returns from index prices first. Following previous literature, we use the logarithmic percentage change (L%) of the stock index closing price to estimate returns on a daily, weekly, and monthly basis, respectively. The summary statistics of logarithmic percentage changes for each country is shown in Table 3. Panels A, B, and C in Table 3 provide the statistics of returns based on daily, weekly, and monthly index prices, respectively. Panel D of Table 3 show the statistics during the crisis period of 2008-09, in addition to the whole sample period.

[Insert Table 3 here]

As shown in Table 3, Greece has the lowest average returns during over its sample period with -0.47% daily return, while Norway and Sweden have the highest returns during the sample period. For all countries, significant departures from normality are observed for all data frequencies, based on the Jarque-Bera statistics. At daily, weekly, and monthly frequencies, for all nine countries, the markets show negative skewness and leptokurtosis. Jarque-Bera test rejects the normality of the return distribution, implying that extreme measure of risk which does not assume normal distribution may be better than standard risk measure. However, in this study we compare and use both measures comprehensively to check investor's response.

We then annualize the returns to get annualized geometric returns before calculating traditional and extreme risks, assuming 252 effective trading days over a year. The traditional risk measure is calculated as the annualized geometric standard deviation of the annualized return of index for each country.

2.2.1.2. Extreme risk measure

The extreme measure of volatility is estimated as the percentage of extreme days, weeks or months over a given period. Most researchers define the extreme value as the lowest or the highest daily return of a stock market index observed over a given period (see e.g. Longin, 1996). Jones, Walker and Wilson (2004) use the statistical distribution of annualized geometric return to arbitrarily assign the distribution percentiles of 5% and 95% as cut-off points to distinguish extreme values. In our study, we define the extreme dates as the observations that are less than the difference between the lower quartile (Q1) and the value of 1.5 times of the interquartile range (IQR, aka. the lower inner fence), or greater than the sum of the upper quartile (Q3) and the value of 1.5 times of the interquartile range (IQR, aka. the upper inner fence), following the traditional outlier classification methodology suggested by Tukey (1977):

$$\textit{Extreme Observation} < Q1 - 1.5 \times IQR, \text{ or } \textit{Extreme Observation} > Q3 + 1.5 \times IQR$$

The range suggested by Tukey's fence is slightly narrower than $\pm 3\sigma$ in normally distributed dataset, which declares about 1% of outliers. The extreme risk for a given year is determined as the percentage of outliers during a given interval over that year, i.e. Percentage of Extremes = No. of Outliers / Annual Trading Days (Weeks or Months).

2.3. Comparison of Two Risk Measures

One weakness of the traditional risk measure is that it is treats positive and negative price changes symmetrically. However, the extreme volatility method provides both positive and negative measures, and can be used to more accurately predict the behavior of risk-averse investors who responses are more dramatic to negative changes than to the positive changes of equity prices.

Figure 1 portrays the time series of the extreme measure of risk for Belgium, Greece, Ireland, and Portugal from 1986-2016. As shown in these graphs, 35.8% of Ireland's trading days were characterized by extreme volatility in 2008; Belgian and Portuguese markets experienced extreme volatility on more than 25% of their trading days in the same year, reflecting the strong and persistent influence of the Global financial crisis in 2008-2009. Greece has 16% of extreme days in 2015, somewhat higher than its experience in 2008, when 13% of annual trading days are identified as extreme. In sum, the countries of this sample display some commonalities as well as differences in regards to the timing and magnitude of their exposure to extreme volatility over the sample period.

[Insert Figure 1 here]

In Table 4 to Table 6, we compare the traditional risk and extreme risk as measured by the percentage of extreme days, weeks, or months by each country, respectively. As Table 4 shows, estimated from daily data, volatility rankings of conventional risk measure are similar to those of extreme measures. In particular, the most volatile year and top ranked extreme years for each country are almost identical for all the nine countries.

[Insert Table 4 here]

Using weekly data to measure risk, as shown in Table 5, both methodologies almost cohere as well. In most countries, the most volatile 2 or 3 years are identical across risk measures. However, Greece and Sweden are exceptional cases. Traditional risk measure shows 1998, 2015, and 2014 as the most volatile years, while extreme measure suggests 2009, 1999, and 2011 in Greece. For Sweden, extreme measure approach indicates 2001, 2000, and 2002 are the most volatile years, whereas standard deviation catches 2008, 1998, and 2000 as the most unstable periods.

[Insert Table 5 here]

Using monthly data, we observe that in the majority of cases, the most volatile years based on extreme measure rankings also shown to be the most volatile based on traditional standard deviation analysis ranking.

[Insert Table 6 here]

According to Switzer et al (2017), for G-7 countries of their study, volatility as captured by the extreme measure shows similar patterns as the traditional volatility measure for most years. Many commonalities in the attribution of high risk by both measures are observed, consistent with Longin and Solnik (2001). However, differences are also observed, therefore, in our formal test, we use both risk measures in our analyses of investor behavior.

2.4. Results Based on Individual Countries

In this research, our objective is to explain investor's reaction to both risk variables by measuring net flows to equity mutual funds against changes in both extreme volatility and standard deviation changes. In our initial specifications, our dependent variables is the net flow to equity mutual funds, with the risk measures lagged by one period in separate specifications. Our control variables include returns (GeoMean), linear time trend (Time) to account for possible secular growth in such funds, as well as a financial market crisis dummy variable (Crisis) in our following models.

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma GeoStdDev(t\text{-}1) + \delta Time + \lambda Crisis + \varepsilon(t) \qquad \text{Model 1}$$

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma TotalExtr(t\text{-}1) + \delta\ Time + \lambda Crisis + \varepsilon(t) \qquad \text{Model 2}$$

$$NetFlows(t) = \alpha + \beta GeoMean(t\text{-}1) + \gamma NegExtr(t\text{-}1) + \zeta PosExtr(t\text{-}1) + \delta\ Time + \lambda Crisis + \varepsilon(t) \qquad \text{Model 3}$$

The variable *NetFlow* refers to the net flows to equity mutual funds, which are defined as new sales plus reinvestment of income less withdrawals and transfers; *TotalExtr* denotes the percentage of the number of extreme days over the measure horizon; *NegExtr* and *PosExtr* represent the percentages of number of negative and positive extreme days over the measure horizon, respectively; *Crisis* is a dummy variable to indicate the global financial crisis in 2008-9. We expect that regression coefficients for mean returns are positive, and for market volatility are negative, using the traditional or extreme day risk measures. In addition, when volatility is divided into negative and positive components, the coefficient for the negative extreme days should be negative since when stock market is negatively volatile, loss averse investors tend to hold less equity, and the coefficient for the positive extreme days probably positive.

In order to anticipate the effect of the crisis variable, we compare summary statistics during the financial crisis and the full sample period, based on Panel D of Table 3. In most countries, the average monthly logarithmic percentage changes are negative, ranging between -4.53 to -8.86 percent in 2008, and between -0.08 to 1.00 percent across the whole sample period. The standard deviations also increase, during the financial crisis years, while Kurtosis decreases in both 2008 and 2009. To prevent possible "overfitting" using the crisis dummy variable, we also estimate our above three models with crisis dummy variable excluded.

In Table 7, we provide the regression results for the nine countries. Panel A (B) shows the results for models 1-3 (4-6) that include (exclude) the crisis dummy variable.

[Insert Table 7 here]

There is no major difference in the results between Models 1-3 and Models 4-6, except for the case of Belgium. The regression data shows significant statistic values for the traditional measure of the risk in Austria's case. Austrian retail investors also respond to extreme risk measures, according to the result of Model 2. Furthermore, they move into markets subsequent to negative extreme event. It is interesting to observe Austria's case since the country is classified as a relatively less individualistic culture according to Hofstede (2001). The only other country in which investors respond to risk/extreme risk is Belgium, which is one of central figures of the European banking crisis, suffering from the default of its two largest banks. As shown in Model 3, small investors in Belgium exhibit "flight to risk" behavior with increased negative extreme measures, while there was fund outflow when there are positive extreme outliers. This gives us a scenario that Belgian investors are attracted to negative extreme events (buying the dips) and exit the markets on positive extreme events (sell at the high). However, when we run regression without financial crisis dummy variable, such behavior is no longer observable in Models 4, 5 and 6.

For both Portugal and Ireland, the crisis dummy variable plays significant role, though in different directions. With the crisis dummy included, funds flow out of the Portuguese market while the opposite happens in Ireland. Hofstede's individualism vs. collectivism score classifies Portugal as a highly collectivist and Ireland as a highly individualistic culture. Indeed, investors in highly individualistic cultures such as Ireland show high risk tolerance or even risk loving proclivities. Hence, during the crisis period, they are more inclined to exhibit "flight to risk" behavior. However, as we see from the separate country results, the impacts of risks on fund flow are not monotonic with respect to increases of Hofstede's individualism score. For example, at the same level of individualism score, countries such as Sweden and Norway do not show consistent result. Mutual fund flows of Greece, Norway, and Sweden are not significantly responsive to changes in with any of the variables in the models. Norway and Sweden show high levels of the individualism index. So far, the influence of culture on investor responsiveness to risk is not clear-cut.

[Insert Figure 2 here]

These results are also depicted in Figure 2, where the relationship between investors' behavior vs. extreme risk is shown for Belgium, Greece, Ireland, and Portugal. Figure 2.1 graphs the case of Belgium, which is classified as an individualistic. The investors' tendency of "flight to risk" is evident in the graph, as it is observed that the increased risk of the equity market has the negative relationship with the equity market's mutual fund inflow, especially in 2002, 2005, and 2008. In collectivist cultures, the relation between risk and fund flow is mixed. For example, Figure 2.2 shows that in Greece, the equity market volatility moves in the same trend with the equity market's mutual fund inflow. However, for another collectivist culture country, Portugal, the relation between risk and fund flow is negative, as shown in Figure 2.4. For Ireland, the mutual fund flow is not responsive to changes in equity market volatility. Therefore, we cannot conclude decisively that the cultural variable has monotonic impact on the relation between fund flow and extreme risk.

The drawback of the regression based on individual countries is that we cannot incorporate the culture variable directly in the regression, since it is a highly persistent/time-invariant. As a consequence, in order to clearly understand the impact of culture in the relation between extreme risk and fund flow, in the next section, we perform a serious of panel regressions including all the nine countries with culture dummy variable added.

2.5. Country Culture and Panel Regressions

One important research focus of this study is on the effects of cultural factors on small investors' behavior in response to both traditional and extreme risks. In order to examine the influence of individualism or collectivism in the market, we import Hofstede's cultural dimension score. As discussed in the previous section, according to the results of individual country analyses, investors' reaction against risks by country are non-monotonic, considering the cultural dimension score. This may due to the fact the impact of cultural factors on the relation between investors' response to risk factors are regime dependent, or there is a threshold level of culture score that affect such impact. Thus, in order to obtain distinct and intuitive outcomes, we separate the nine Eurozone countries into two groups: countries with individualistic cultures vs. countries with collectivist cultures, based on the median of Hofstede's cultural dimension score. Countries with Hofstede's score above the median are classified as individualistic, and we use a dummy variable, Individualism =1 to indicate this group. For our sample countries, Belgium, Denmark, Sweden, Ireland and Norway are members of this group. On the other hand, Finland, Austria, Greece, and Portugal are classified as collectivist societies (Individualism =0).

With this country classification, we perform panel regressions using the country specific, time invariant cultural variables, and consider the interaction between the culture variable and the risk variable to determine how culture moderates the impact of risk on investor's trading behavior. The maintained hypothesis of delayed responses of investors is carried forth from the previous regression models. In order to control for economic development for each country, we also add GDP per capita (*GDP*) to the analysis. The specific models follow:

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_2 GeoStdDev(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 1'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_2 GeoStdDev(t-1) + \beta_3 Individualism + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 2'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_2 GeoStdDev(t-1) + \beta_4 Individualism * GeoStdDev(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 3'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_5 TotalExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 4'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_3 Individualism + \beta_5 TotalExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 5'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_5 TotalExtr(t-1) + \beta_6 Individualism * TotalExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 6'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_7 NegExtr(t-1) + \beta_8 PosExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 7'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_3 Individualism + \beta_7 NegExtr(t-1) + \beta_8 PosExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 8'$$

$$NetFlows(t) = \alpha + \beta_1 GeoMean(t-1) + \beta_7 NegExtr(t-1) + \beta_8 PosExtr(t-1) + \beta_9 Individualism * NegExtr(t-1) + \beta_{10} Individualism * PosExtr(t-1) + \beta_{11} GDP(t-1) + \beta_{12} Crisis + \varepsilon(t) \quad 9'$$

In the regression models, Individualism is the cultural dummy variable. *GDP* represents for GDP per capita of each country at specific time point t. The definitions of the other variables are identical to the regression models in section 3. We also implement panel regressions that incorporate controls for year fixed effects. Table 8 below reports the results. Panel A provides results for models 1'to 9' without country fixed effects and Panel B reports results that include country fixed effects in the analyses.

[Insert Table 8 here]

We observe positive coefficients for the interaction variables *Individualism*Geo StdDev* and *Individualism*Total Extr.*, as shown in models 3' and 6' in both Panels A and panel B. However, it is interesting to note that neither the traditional risk nor the extreme risk measure affects fund flow directly, as shown by the insignificant coefficient of *Geo.Std.Deviation(t-1)* and coefficient of *Total Extreme Value (t-1)* in models 1', 2', 4' and 5' for both panels. We note that the culture-risk interaction variables show a significantly positive impact on fund flow (e.g., 0.163 in model 3' and 0.112 in model 6') at the 1% significant level. This finding can explain why our previous tests in section 3, based on risk variables only, does not systematically predict investors trading behavior. Further looking at the sign of the interaction terms in models 3' and 6' in both panels, in contrast to investors from collectivist cultures, investors based in individualistic cultures are more responsive to changes in both traditional and extreme risk. In addition, the positive sign of the interaction terms shows that investors from individualistic societies exhibit "flight to risk" behavior, performing like risk seekers with high risk tolerance. We use country size, as measured by GDP per capita as a control variable in the regressions. However, it is not found to be a significant determinant of investors' trading behavior.

Another noteworthy point is that when we further look at whether the positive extreme shock and negative extreme shock have different impact on investor's response to risk, we find out that investors are actually indifferent in this regard. For example, for each of the negative and positive extreme risk variables, the coefficients are not significant, shown in the results for models 7' and 8'. Similar results are also shown with the interaction terms (models 3', 6', and 9').

As a robustness check, we also separate sample countries into three groups based on Hofstede's culture score, with individualism in the top tercile group, neutral in the middle tercile group and collectivism in the bottom tercile group.[3] Our results based on this alternative classification are qualitatively and quantitatively consistent with the previous findings: the culture-risk interaction term has a significantly positive impact on fund flows. In addition, small investors with individualism (or neutral) cultural backgrounds exhibit flight to risk behavior.

[Insert Table 9 here]

We also conduct a further robustness check using simultaneous equations to account for the possibility that both risk and fund flows are determined simultaneously. Table 9 present the results of the simultaneous regression analyses using 2SLS. The results are consistent with our previous findings that there is a significant positive impact of the traditional risk-individualism interaction term on fund flow, as shown in model 3' that the coefficient of *Individualism*Geo StdDev* is 0.143 with 95% level. When we use extreme risk measure, the results are similar: the coefficient of *Individualism*Total Extr* in model 6' is 0.101 with 5% level. Therefore, our results are robust to alternative classification of the culture dummy variable as well as simultaneous model specification.

[3] Full sample results provide qualitatively and quantitatively similar findings, are available on request, and are omitted for brevity.

Chapter 3: The Effects of Negative Interest Rates on Equity and Currency Markets

3.1 Literature Review:

Since Gesell (1891) suggested an idea of taxing on cash in the late 19th century, the concept of negative interest rate had not been broadly discussed until Japan's long recession started in early 1990s. The global economy has been growing consistently for a century, except for several crisis periods. Therefore, it was deemed to be a natural phenomenon that money grows over time, and thus inflation and interest rates are positive in general. Is stimulative monetary policy through lower interest rates effective? This is a basic question that has been debated in the literature for decades. Most of the empirical work on this question has been conducted in an environment where nominal interest rates have a zero lower bound. Negative nominal interest rates as a policy instrument are a fairly new phenomenon, and might be viewed as a consequence of the persistence of recessionary conditions in several countries, despite attempts by central banks to stimulate the affected economies through stimulative monetary policies such as quantitative easing.[4]

In the aftermath of severe financial crises and recessions, several governments cut their interest rate to the "lower bound" of zero. After experiencing the Global Financial Crisis in 2007-08, the Federal Reserve introduced the zero-interest-rate policy (ZIRP) in 2008, and the BOJ cut its deposit rate to zero in 2010. Subsequently, the ECB also decided to lower their deposit rate and maintain them to be pinned at zero percent in 2012. However, due to unsatisfactory outcomes of ZIRP and other expansionary policies, monetary authorities in some countries decided to pursue negative-interest-rate strategy as a viable alternative to stimulate their economies.

[4] Federal Reserve of St. Louis, Economic Research:
https://fred.stlouisfed.org/categories/32242?t=nation&ob=pv&od=desc

The analysis of NIRP in the literature is not unprecedented. Flemming and Garbade (2004) analyze negative interest rates on certain U.S. Treasury security repurchase agreements. Redding (2000) observes that some U.S. Treasury bills generate a liquidity premium due to their heavy trading frequency. He shows that this liquidity premium is sufficient to lower the forward nominal interest rate below zero under certain conditions. Coenen (2003) asserts that the zero-interest-rate bound is economically insignificant under the Taylor's interest rate rule. Correspondingly, Jarrow (2013) shows that requirement of a zero-lower bound on interest rates in markets is not a valid constraint. He asserts that in a competitive and nearly frictionless market, a negative risk-free nominal interest rate can be consistent with an arbitrage free term structure evolution. Buiter (2009) analyzes three specific methodologies for lowering the nominal interest rates to negative realm and tests their feasibility. His study shows that the interest rates can be dropped below zero percent by abolishing currency, paying negative interest on currency by taxing money, and separating the numéraire from the currency. Among them, the methodology of taxing currency is the approach of monetary authorities in most countries examined in this study. Danthine (2017) moves the possibility beyond just below the zero bound, suggesting that the nominal interest rate can be significantly lower than zero.

Since employing and maintaining NIRP for a considerable period of time is a relatively recent practice adopted by a few central banks to date, extant evidence on its impact remains limited. On the other hand, the few empirical findings pertaining to this subject have shown that the effects of adopting a negative interest rate strategy can be significantly different in terms of direction, magnitude, and efficiency, not only across countries, sectors, and time horizons, but also across studies. The discrepancies in the results may be attributed to the differences in the objectives and motivations behind implementing NIRP, its launch date, as well as those in the countries' economic situations. These findings can also differ because of the various methodologies used in the literature to assess the impacts of the introduction of NIRP.

Tokic (2016) discusses the rationale for setting negative interest rates. Through the analysis based on the yield curve, the author explains that central banks are compelled to go below the zero bound for the policy interest rate in order to maintain the curve spread (the differential between long- and short-term yields) at a certain level allowing to increase bank profitability and stimulate the economy during a recession. The author also analyzes the repercussions of NIRP on investors in the stock, fixed-income, real estate, or commodity markets. Jurkšas (2017) examines the motives and the impacts of NIRP implementations on various markets and economic sectors in the Euro Area. The author conducts statistical analyses that show that NIRP's effects are significant and could be either positive or negative, depending on the sector and the time horizon over which these effects are assessed, while the local currency depreciates in short-term following NIRP. Siegel and Sexaue (2017) address the potential problems created by NIRP, as well as assess their impacts; they also put forward their recommendations on how to make and adjust investment decisions in such environments. Hameed and Rose (2017) investigate the effects of negative nominal interest rates on exchange rates (effective and bilateral). Their empirical findings imply that the behavior of exchange rates (e.g., volatility, deviations from uncovered interest parity) have not been substantially influenced by negative interest rates. Arteta, Kose, Stocker, and Taskin (2018) implements an event study to evaluate the effects of NIRP domestically in the five major economies that introduce the policy (the Euro Area, Japan, Switzerland, Sweden, and Denmark), as well as their potential global spillover impacts on several emerging and developing economies. These effects are examined over a 1-day event window around the implementation of

NIRP[5] on seven chosen variables, including interbank rates and bond yields with different maturities, swap rates, equity prices, and the nominal effective exchange rate. Their empirical results show that the effects of NIRP is in the expected direction of conventional monetary policy mechanisms. The authors argue, however, that financial stability could be threatened if these rates become more negative or should the governments need to continue applying the NIRP for longer periods of time.

3.2 Hypotheses

Manipulating the nominal interest rate has been a popular policy measure for central banks. The mechanism of the traditional monetary policy is based on the conventional economics theory: cutting the interest rate increases the aggregate amount of money in the market, and as the supply of money in the economy increases, more investment and consumption are expected as a primary following-up consequence. Unlike most historical cases, however, the nine central banks executed the policy by putting their steps into the negative interest territory. To identify the validity of the negative-interest-rate strategy as an expansionary monetary policy on the currency market returns, I set following hypothesis:

H1: The announcement (or implementation) of NIRP results in statistically significant changes in the value of the local currency in international markets. Whether a currency appreciates or depreciates depends on country specific factors.

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[5] The authors argue that the event study is restricted to a 1-day window in order to ensure that the data is not influenced by factors other than the introduction of a NIRP. When a 1-month window is considered instead, the authors obtain larger effects but qualitatively similar.

Lowering interest rates in general, with high capital mobility and flexible exchange rates can be viewed as a means to depreciate a currency, due to the short term violation of covered interest arbitrage conditions, which will create currency flows out of the country, as per the Mundell-Fleming Model.[6] Negative interest rates should be particularly undesirable for investors who expect positive returns as a norm. Currency flights therefore might be observed in less developed countries with weak economic fundamentals which will be reflected as significant depreciation of the local currency vis-à-vis foreign currency benchmark. For developed countries with stronger economic fundamentals, investors might perceive that negative interest rates will be particularly stimulative to GDP; higher GDP will be reflected in higher cash flows for investors, which would cause the domestic currency to appreciate in value.

The effects of NIRP on equity markets are another aspect that I attempt to verify. Corresponding to the currency exchange market analyses, I suggest the following hypothesis for the equity market analyses:

H2: The announcement (or implementation) of NIRP results in statistically significant change of the stock market returns. The direction of market reaction depends on country specific factors.

Analogous to the argument for currency responses, we might expect that for developed countries with stronger economic fundamentals, investors might perceive that negative interest rates will be particularly stimulative to GDP; higher GDP will be reflected in higher cash flows

[6] See e.g. Mundell(1963) and Fleming (1962). "Capital mobility and stabilization policy under fixed and flexible exchange rates." *Canadian Journal of Economic and Political Science*. 29 (4): 475–485. DOI:10.2307/139336. Reprinted in Mundell, Robert A. (1968). International Economics. New York: Macmillan.
Fleming, J. Marcus (1962). "Domestic financial policies under fixed and floating exchange rates." *IMF Staff Papers*. 9: 369–379. DOI:10.2307/3866091. Reprinted in Cooper, Richard N., ed. (1969). International Finance. New York: Penguin Books.

for investors, which would cause the domestic currency to appreciate in value. For emerging economies, for which investors are leerier, capital flight might occur, which would serve as a retardant to GDP and equity markets.

This study also investigates the influences of NIRP on the volatilities of both currency and equity returns. The question I address here is: Do the market participants accept this monetary policy as the same when it is executed in the negative territory? While most central banks introduce NIRP as a type of expansionary monetary policies, there exist some possible risks associated with the policy, according to previous literatures. For instance, Jobst and Lin (2016) point out that the negative interest rate may weigh on banks' profitability. Correspondingly, Taskin (2018) asserts that maintaining negative rate considerably lower than zero or extended time period may undermine financial stability of the economy. Under such environment, if NIRP strategies are deemed to be undesirable events in the financial markets, the volatilities of financial market returns may be amplified, and investors can face higher risks than the past. To verify whether or not this assertion is valid, I suggest the following two hypotheses:

H3: There is statistically significant change in the volatility of currency returns after NIRP.

H4: There is statistically significant change in the volatility of equity returns after NIRP.

3.3 Data Description

Breaking the long belief that zero percent is the lower bound of the nominal interest rates, the ECB announced a negative deposit rate in 2014 and Japan decided to eliminate the zero bound of the central bank's interest-rate policy in early 2016. Switzerland and Nordic countries such as Denmark, Norway, and Sweden introduced the policy a few years earlier than the Euro Area, while Bosnia and Herzegovina, Bulgaria, and Hungary announced the negative interest in 2016. Table 10 provides brief chronology of NIRP history for those nine countries.

[Please insert Table 10 about here]

In order to investigate NIRP's influences on both currency and stock markets of the nine countries, their historical daily equity index prices and spot exchange rates are collected. (See Table 11 for the list of reference indices and currencies.)

[Please insert Table 11 about here]

The U.S. Dollar is solely set as the reference currency throughout this analysis, as it is widely recognized as the largest key currency in the global economy. Kwok and Brooks (1990) show that the U.S. Dollar functions fair as a numeraire in general foreign exchange analysis. Alongside with the U.S. Dollar, the EURO was considered as another reference currency for the study. The majority of countries in this research, however, are located in Europe, and some of them such as Bosnia and Herzegovina, Bulgaria, and Denmark have pegged their currency to the EURO. In addition, most European currencies have relatively diminutive changes against the EURO over the time. Therefore, the EURO is not analyzed as a numeraire currency in this study. Table 12 presents the summary statistics of the data.

[Please insert Table 12 about here]

To investigate NIRP's effects in longer term, I implement the regime-switching vector autoregressive regression analyses, defining regime 0 as pre-NIRP and 1 as ex-NIRP period. For the analyses, more than 2 years of historical daily index price data of the nine economies, the S&P 500, and the EUROSTOXX50 are collected from Bloomberg, same as the source of currency spot exchange rates. For the Euro Area, the German DAX Index is used as a proxy of the Euro Area Index. While the EUROSTOXX50 index serves as the representative equity market index of the Euro Area, it is not used as a proxy of the equity market. Since the EUROSTOXX50 is used as an explanatory variable, use of the index data causes collinearity problem in the regression models. Moreover, the index does not meet the comparability condition since this study is country by country analysis.

Add to the equity index prices, historical policy rates data of the nine governments are obtained from FactSet and Thomson Reuter DataStream. Table 13 provides the summary statistics.

[Please insert Table 13 about here]

In order to estimate an appropriate value of the U.S. Dollar against another international key currencies, 6 years of *Bloomberg Dollar Spot Index (BBDXY)* data is obtained from Bloomberg. From the same source, 2 years of the nine countries' overnight deposit rate, 5- year CDS spread, 2-year and 10-year national bond yields data are collected for the analysis. The yield curve of the sovereign bonds is defined as the differential between 2-year and 10-year bond yields. VIX currency index data is gathered from Chicago Board of Option Exchange (CBOE), in order to see the event's impact on currency volatility change. Due to its availability, only Euro VIX and Japanese Yen VIX data are obtained.

3.4 Research Methodology

3.4.1 Definition of Currency and Index Return

While the equity returns are computed with natural logarithm, it is not applicable for calculating the currency returns, recalling the Fisher effect. According to Fisher (1930), since each currency's value is relative to the numeraire currency, the interest rate differentials of local countries and numeraire country should be considered for appropriate calculation of currency returns. Kwok and Brooks (1990) suggest a relevant example of currency return estimation, considering the spot exchange rates and interest rates of the two countries compared. They define a currency return as currency exchange rate change less the interest rate differential between the numeraire economy and the objective economy:

$$\tilde{R}_{j,t} = \frac{E(\tilde{S}_{j,t} - S_{j,t-1})}{S_{j,t-1}} - (r_{n,t-1} - r_{j,t-1}) \quad (1)$$

Where $R_{j,t}$ is the expected daily returns of currency j on date t; $S_{j,t}$ is a spot exchange rates with respect to the numeraire currency n (U.S. Dollar). The daily interest rates of country j at time t is defined as $r_{j,t}$, while the rates of the numeraire economy (the United State) at time t is $r_{n,t}$. This model is using the arithmetic percentage in calculating returns of currency exchange rates from time t-1 to t. However, throughout this paper, we are using logarithmic returns for equity market returns. To be consistent with equity return computation, following equation is suggested to calculate currency returns.

$$R_{j,t} = ln\left(\frac{S_{j,t}}{S_{j,t-1}}\right) - (r_{n,t-1} - r_{j,t-1}) \quad (2)$$

Over the period covered in this study, the policy rate of the U.S. Federal Reserve had several changes since 2015, subsequent to a long stable period. It had been 0.25% since 2009, and raised to 0.5% on December 16, 2015, and again on December 14, 2016 to 0.75%.

3.4.2. Event Study

The fundamental research methodology of this paper is conventional short-term event study with constant mean model. The primary event date is defined as the day of NIRP announcement. For comparison, the day when the policy rates were turned from zero (or positive) to a negative number is also considered as the secondary event date. In this study, the primary event window for the analysis is defined as 21 days [-10, +10], uniformly. This gives two trading weeks before and after the event date, and it is a generally fair event window as suggested by Kwok and Brooks (1990). For accurate event study results, a year of estimation window is used.

The first model considered for measuring abnormal returns (AR) was the CAPM for equity market analyses. However, as I use the equity index returns as a proxy of stock market returns in this study, the equity indexes cannot represent the market. Thus, I lose the common proxy of the market variable for the analysis. The alternative model I suggest is the one factor model with constant mean return. According to Brown and Warner (1980 and 1985), despite its simplicity and restrictiveness, the results based on the constant mean model are as appropriate as those of other more complex models. Thus, it is used to find the significance of abnormal returns:

$$R_{j,t} = \hat{\alpha}_j + \beta_j \mu + \hat{\varepsilon}_{j,t} \tag{3}$$

$$\mu = \frac{1}{N} \sum_{T_0+1}^{T_1} R_{j,\tau} \tag{4}$$

$R_{j,t}$ represents the daily returns of currency and equity index of country j; μ is the constant average return of the estimation window.

3.4.3. Regime-Switching Vector Autoregressive Regression Model

In order to see more general and longer-term effects of NIRP of each government, 1 year before and after NIRP data are tested by regression models with regime-switching dummy variable. The day of NIRP implementation was set as the regime-switching moment, and the pre-event year is defined as regime 0, and post-event year is considered as regime 1. The length of each regime is 365 calendar days, 261 days after excluding Saturdays and Sundays. By using this methodology, it is feasible to verify whether there exists any evidence that the policy had a statistically valid change on each economy's stock and currency exchange market in the longer period. The models for currency exchange rates and equity market yields are formulated as follows:

$$cr_{j,t} = \alpha_j^{ex} + \beta_{1,j}^{ex} cr_{j,t-1} + \beta_{2,j}^{ex} smy_{j,t-1} + \beta_{3,j}^{ex} ONDR_{j,t-1} + \beta_{4,j}^{ex} 2yby_{j,t-1} + \beta_{5,j}^{ex} 10yby_{j,t-1} + \beta_{6,j}^{ex} Abs\_YCS + \beta_{7,j}^{ex} 5YCDS\_Spread_{t-1} + \beta_{8,j}^{ex} BBDXY_{t-1} + \beta_{9,j}^{ex} S\&P500_{t-1} + \beta_{10,j}^{ex} EUROSTOXX50_{t-1} + \beta_{11,j}^{ex} STATE + \varepsilon_j^{ex} \tag{5}$$

$$er_{j,t} = \alpha_j^{eq} + \beta_{1,j}^{eq} cr_{j,t-1} + \beta_{2,j}^{eq} er_{j,t-1} + \beta_{3,j}^{eq} ONDR_{j,t-1} + \beta_{4,j}^{eq} 2yby_{j,t-1} + \beta_{5,j}^{eq} 10yby_{j,t-1} + \beta_{6,j}^{eq} Abs\_YCS + \beta_{7,j}^{eq} 5YCDS\_Spread_{t-1} + \beta_{8,j}^{eq} BBDXY_{t-1} + \beta_{9,j}^{eq} S\&P500_{t-1} + \beta_{10,j}^{eq} EUROSTOXX50_{t-1} + \beta_{11,j}^{eq} STATE + \varepsilon_j^{eq} \tag{6}$$

In the models above, variables $er_{j,t}$ and $cr_{j,t}$refer currency and equity market return of country j at time t; $ONDR$, *2yby* and *10yby* are overnight deposit rate, 2-year and 10-year government bond's yield, respectively; *Abs_YCS* refers absolute value of yield curve slope, which is defined as the difference between 10-year and 2-year bond yields; *5YCDS_Spread* is 5-year CDS spread, and $STATE_{j,t}$ is regime dummy variable of country j at time t. Due to unavailability of the data, the two national bond yield variables are omitted for the analysis of Bosnia and Herzegovina. For Hungary as well, 3-year national government bond yields are used instead of the 2-year bond returns.

As previously mentioned, NIRP's impact on the currency and equity market volatilities is another topic to be investigated in this paper. While the models suggested above considers appropriate variables which can potentially influence the dependent variable, they do not capture volatilities of the currency and equity index returns. In order to see the effects on currency return volatilities, I run the regression with VIX index variable for European and Japanese currency markets.

$$EU(JY)VIX_{j,t} = \alpha_j^{vix} + \beta_{1,j}^{vix} EU(JY)VIX_{j,t-1} + \beta_{2,j}^{vix} cr_{j,t-1} + \beta_{3,j}^{vix} smy_{j,t-1} + \beta_{4,j}^{vix} 2yby_{j,t-1} + \beta_{5,j}^{vix} 10yby_{j,t-1} + \beta_{6,j}^{vix} 10yby_{j,t-1} + \beta_{7,j}^{vix} Abs\_YCS + \beta_{8,j}^{vix} 5YCDS\_Spread_{t-1} + \beta_{9,j}^{vix} BBDXY_{t-1} + \beta_{10,j}^{vix} S\&P500_{t-1} + \beta_{11,j}^{vix} EURSTX50_{t-1} + \beta_{12,j}^{vix} STATE_{11,t}^{vix} + \varepsilon_j^{ex} \quad (7)$$

$$EU(JY)VIX_{j,t} = \alpha_j^{vix} + \beta_{1,j}^{vix} cr_{j,t-1} + \beta_{2,j}^{vix} smy_{j,t-1} + \beta_{3,j}^{vix} 2yby_{j,t-1} + \beta_{4,j}^{vix} 10yby_{j,t-1} + \beta_{5,j}^{vix} 10yby_{j,t-1} + \beta_{6,j}^{vix} Abs\_YCS + \beta_{7,j}^{vix} 5YCDS\_Spread_{t-1} + \beta_{8,j}^{vix} BBDXY_{t-1} + \beta_{9,j}^{vix} S\&P500_{t-1} + \beta_{10,j}^{vix} EURSTX50_{t-1} + \beta_{11,j}^{vix} STATE_{11,t}^{vix} + \varepsilon_j^{ex} \quad (8)$$

However, these models cover volatilities of the EURO and Japanese Yen returns only. Therefore, in addition to the VIX regression analyses above, I conduct F-test and Bartlett's test to verify equality of variances between before and after NIRP, for both currency and equity market returns. Since these tests might not catch the homogeneity of the variance when the samples are not normally distributed, I also implement the Levene's test as an alternative test methodology.

3.5. Results

The outcomes of this study provide clues for the two main questions: a) are the effects of NIRP consistent with those of interest cut in positive territory, and b) how the volatilities of currency and equity returns are influenced by NIRP. As the first step, the short-term event studies are implemented for the currency and equity markets of the nine economies.

[Please insert Table 14 about here]

Panel A of Table 14 displays abnormal return analyses with primary event days (NIRP announcement day). It is observable that Danish Krone, Japanese Yen, and Norwegian Krone show significant depreciations of its own currency against the U.S. Dollar, while the others do not. If NIRP implementation date is considered as the event day (secondary event day), somewhat different results come out. Cumulative abnormal returns (CAR) analyses within the short-term event window (-10, 10) are presented in Panel B of the table. Over the primary event window, currencies of Bosnia and Herzegovina, Bulgaria, the Euro Area, Japan, Norway, and Sweden have negative returns and value appreciations. Panels C and D of the table show ARs and CARs of the currencies with the secondary event days (NIRP implementation day). Reviewing Panel C, on the days, Danish Krone, and Norwegian Krone experience currency depreciations, while Swiss Franc is appreciated. Swiss Franc shows following two days of bounce-ups after the secondary event day.

[Please insert Table 15 about here]

Table 15 shows the short-term effects of NIRP on the equity markets. The announcements of NIRP are significant events in the equity markets of Bosnia and Herzegovina, Sweden and Switzerland. Meanwhile the impacts are negative in Bosnia and Herzegovina, and positive in the other two countries, according to Panels A and B of the table. Panels C and D display the impacts of NIRP on the secondary event days. The case of Switzerland is notable, since it is observable that the significant fluctuation in its own currency exchange market may influence the equity market returns. The country's equity index also has significant two drops from the event day, with following bounce up on D+2. This consequence is understandable, recalling the economy structure of Switzerland. Since over 70% of the country's GDP rely on exports of goods and services, the significantly negative impacts on the equity market returns are possibly derived from the turmoil in its currency market. Moreover, the country has unique financial industry with its reputation of a safe heaven for money savings. Therefore, it is possible inference that the shock on the equity market is an inevitable consequence of 25% of its own currency appreciation against the U.S. Dollar on January 15, 2015.

[Please insert Table 16 about here]

If the event study is conducted with aggregated data by pooling all the countries as a portfolio, several more noteworthy outcomes are generated. From Panel A of Table 16, it is observable that the local currencies are depreciated on the event day, consistent with Jurkšas (2017). Besides, Panel B of the table shows more apparent evidence that supports the impact is valid in favor of the central banks' aim. On the days when actual policy rates go below the negative bound, the exchange rates are bounced up. According to Panels C and D of Table 16, average value of local currencies of the nine countries is significantly appreciated. However, one possible discussion about these results is that this appreciation may be led by Swiss Franc. The currency market of Swiss Franc had been compromised since the Swiss National Bank (SNB) had pegged exchange rate policy in September 2011 to depreciate its own currency. However, the SNB abolished the lower limit of its currency exchange rate, one euro per 1.2 Swiss Franc on

January 15, 2015, simultaneously with NIRP implementation. These actions of the SNB result in the unprecedented appreciation of the currency in short period of time, deriving pivotal impacts on its own economy.

The results explained above imply that the currency markets may react efficiently against NIRP execution, consistent with the efficient market hypothesis (EMH) of Fama (1998). However, those currency markets' efficiencies over the time is not statistically verified in the previous models. Therefore, investigating whether those currency markets are efficient may provide additional implication about the monetary policy. According to covered interest parity (CIP), currency arbitrage opportunities with nominal interest rate differentials can be diminished, if currency exchange markets are efficient. Holmes and Wu (1997) provide relevant example to test market efficiency with CIP using the panel unit root test methodologies. Following conventional CIP equation, the deviation from CIP vis-à-vis the U.S. Dollar is defined as follows:

$$u_t = r_{j,t} - r_{n,t} - (f_t - s_t)$$

Using this error term, u_t, a number of unit root tests are implemented to verify covered interest arbitrage in the financial markets of the nine countries. Presence of unit root process in the error term can be interpreted as violation of no-arbitrage condition. The descriptive statistics of currency market mispricing term is presented in Table 17.

[Please insert Table 17 about here]

Table 18 shows the results of the panel unit root tests with various relevant types of tests: Levin, Lin, and Chu test, Im, Pesaran, and Shin test, Fisher-Choi Augmented Dickey-Fuller (ADF) test, and Fisher-Choi Phillips-Perron (PP) test. Due to the data availability, six currencies are considered: Denmark Krone, the Euro, Japanese Yen, Norwegian Krone, Swedish Krona, and

Swiss Franc. Among these currencies, several have mixed backgrounds; Danish Krone and Swedish Krone are independent currencies, while those countries are members of the European Union (EU). Norway and Switzerland are classified as European countries due to their geographical location, whereas they are not members of the EU. Considering that the EU is representative economic and political union of European nations sharing monetary policies, investigating EU-specific factors may provide comprehensive insight about NIRP's effects. Therefore, the tests are conducted with two subgroups: EU (Denmark, the Euro Area, Sweden), and non-EU (Japan, Norway, and Switzerland). Reviewing the test results of all the six countries, I cannot reject unit roots for CIP based on the Levin, Lin and Chu (2002) tests, which assume homogeneous panels.

[Please insert Table 18 about here]

By assuming heterogeneity of panel countries, Im, Persaran and Shin (2003) W-statistic also provide evidences of unit root process for CIP in those countries. The statistics are different once the tests are executed in different subgroups. According to the outcomes, there is no apparent covered interest arbitrage opportunities in the currency markets of the EU countries during the period of NIRP, while that is not the case for non-EU group. It is notable to see that Switzerland is included in non-EU group. As previously introduced, the country experienced abnormal exchange rate impacts during the days surrounding NIRP execution.

[Please insert Table 19 about here]

Table 19 presents the unit root test results with structural period break, before and after NIRP by country. By setting NIRP implementation as the breakpoint, unit root processes of before and after NIRP are tested. The test statistics imply different effects of NIRP on each currency. At

5% level of p-value, ADF statistics show unit root process in both pre-year and post-year of NIRP for the Euro, Japanese Yen, and Norwegian Krone, implying covered interest arbitrage of those currencies. Denmark Krone and Swedish Krona have unit root processes after NIRP implementation, while Switzerland presents unit root process in pre-NIRP period. The PP test results show substantial similarity with minor differences.

[Please insert Table 20 about here]

The effects of NIRP on equity markets stand in contrast to those on currency exchange markets, showing relatively undistinguishable outcomes. Table 20 provides the portfolio event study analyses results of the equity returns. While it does not show significant ARs on the primary event days according to Panels A and B of the table, the equity returns on the secondary event days and D+2 have significant negative ARs. Despite presence of significant and positive ARs on D-2 and D+7, narrowing down the event window, the negative impacts of the policy implementations are observable in Panel D.

If the policies are sufficiently effective to increase aggregate amount of money in the economies, the local currencies are expected to be depreciated and equity indexes have positive returns with capital inflows. The outcomes from the event study show significant depreciations of local currencies on the days of NIRP announcement, while the currency appreciations and outflows from the equity markets are observed on NIRP implementation days.

[Please insert Table 21 about here]

Somewhat different outcomes are obtained if pre- and ex-year of NIRP are compared. Table 21 delivers the results of the currency return analyses using the suggested regression models. According to the table, significant differences of currency returns between before and after NIRP are captured with STATE variable in Bosnia and Herzegovina, Denmark, Hungary and Switzerland. Another noteworthy point is that bond yields and its absolute yield curve variables have significant coefficient in case of Bulgaria and Denmark. Moreover, 2-year bond yields are correlated with the currency returns in Bulgaria, Denmark, Hungary, Japan, Sweden and Switzerland. These indicate that bond yields and yield curve variables may also be decisive factors for local currency returns of those countries.

[Please insert Table 22 about here]

The regression results of the index return analyses are displayed in Table 22. For most countries' equity market returns, NIRP is not a considerable event, as Switzerland solely has a significant coefficient on its regime dummy variable. However, consistent with the currency market analyses, Switzerland may need to be considered as an exceptional case in the equity return analyses as well, due to the extraordinary exchange rate shock occurred in the event day. Instead of the state variable, it is observable that national bond yields and its interest term structure have significant influence on the equity returns in Denmark, Norway, the Euro Area and Switzerland. Furthermore, the S&P500 index return variable is also significant in most developed economies including Denmark, the Euro Area, Japan, Norway, Sweden and Switzerland. These outcomes imply that possible cointegrations with the U.S. equity markets have stronger impacts on the domestic equity returns than the stimulative monetary policy by the central banks.

The results of both currency and stock market return analyses generate additional issues to be addressed. For currency return regression analyses, I found evidence that currency return changes are possibly led by the interest term structures. However, the relation between the dependent variable and the interest rate curve is not clearly shown in the models. To investigate this issue, term structures of nominal interest rates of each country are compared. Table 23 provides the average bond yield curve slopes of the eight countries. Due to data unavailability, Bosnia and Herzegovina is excluded in this comparison. The term structure is defined as the differential of 10-year and 2-year government bond yields.

[Please insert Table 23 about here]

According to the table, Bulgaria, Hungary, and Denmark have relatively steeper slopes of the bond yield curves, while NIRP's effects are notable in Hungary and Denmark. These results imply that NIRP may be more effective in economies which have less flat yield curves of government bonds with exception of Bulgaria. Switzerland, where NIRP is significant event, has relatively flattened slope of the government bond yield curve. One might argue that Switzerland's case is a counterevidence of the relationship between the term structures and effectiveness of NIRP. However, as previously introduced, the country needs to be deemed as an exceptional case considering its currency market chaos on the event day (NIRP Implementation) caused by sudden exchange rate policy change announcement of the SNB on the same day.

The results from equity market analyses also generate additional inquiries to be clarified. If NIRP is not the decisive event for those stock market returns, which factors drive changes of equity returns? As the coefficients indicate, the U.S. equity market may explain changes of the local equity index returns of the nine countries. To observe the linkage between the local and the U.S. equity market, I test degrees of market cointegration of the nine individual indexes and the S&P500.

[Please insert Table 24 about here]

Table 24 shows how those local indexes are cointegrated with the U.S. stock market, using the S&P as the benchmark index. Column 2) provides test results of period, covered by the equity market return regression analyses. The Trace statistics of SOFIX, OSEAX, and SMI show cointegration of those indexes with the S&P500. If the period is narrowed down to the event window, somewhat different outcomes are shown. According to column 1), the Trace statistics of DAX, NIKKEI, OSEAX, and SMI are statistically significant, implying that those indexes are cointegrated with the U.S. equity market over the period. These outcomes are partially overlapped with the previous equity return analyses results, recalling those indexes have significant influences of the interest rate regime change in the longer-term regression analyses. On the other hand, with the extended period of time, the cointegrations of those indexes and the S&P500 are not captured. Japan's NIKKEI solely and significantly cointegrated with the U.S. equity market, consistent with Switzer and Tahaoglu (2015)'s analyses of equity market cointegration.

Although the analyses above provide comprehensive perspective about the effects of NIRP on currency and equity returns, its volatility factors are not captured by those models. I implement additional regressions with VIX currency volatility index data to examine the volatility changes by the negative policy rates. Although data of only the Euro Area and Japan are available for VIX currency index, it is noteworthy since they are only countries with no significant coefficient on its state variable in their currency markets returns. Meanwhile, EUVIX index has been influenced by 10-year bond yield and yield curve slope, and JYVIX analysis shows significant coefficients on the variable of BBDXY and S&P500.

[Please insert Table 25 about here]

Table 25 shows results of regression models on EUVIX and JYVIX. According to the table, no significant coefficient on variable STATE is observed for both EUVIX and JYVIX. This can be interpreted that no pivotal changes in volatility are captured in the models, questioning the effects of NIRP implementations in those two currency markets.

Subsequently, to have more comprehensive investigation for the other markets' volatility changes, several tests for equality of variance for all objective currencies and index returns. The F-test, Bartlett's test, and Levene's test are executed in order to see NIRP's effects on return volatility in currency and equity markets. Table 26 shows variances, standard deviations, and test results of the nine countries comparing before and after the policies.

[Please insert Table 26 about here]

At first glance, for both currency and index return, only Bulgaria displays a significant change in variance with the regime-switching according to F-test results. Bartlett's test results for currency returns show that none of these countries has significant statistics. The results are similar in stock market returns, showing that only Bulgaria and Switzerland are the two counties which have significant Bartlett's test statistics. However, Levene's test results suggest that there are statistical differences in variance between the two regimes. Considering currency return data, all the countries have significant Levene's test statistics at 5% standard error level. For index return data as well, except for Bosnia and Herzegovina, Bulgaria and Japan, all the others have critical value. These results provide firm evidence in favour of the negative interest rate policy's potentially influencing volatility of currency returns. Yet, its general direction is in ambiguity. Panel A of Table 26 shows Bosnia and Herzegovina, Bulgaria, Denmark, Hungary, Norway, and Switzerland have a decrease of volatility from regime 0 to regime 1, while variance of the eurozone, Japan, and Sweden move the opposite direction. Panel B exhibits mixed results as well, as the standard deviation and variance of four countries, Bosnia and Herzegovina, Denmark, Japan have decrease in volatility over the period, whereas the other six countries experience increases in the volatility.

In order to verify whether NIRP affects the structure of the volatility processes for currencies and equities, I implement GARCH models for all the currency and equity return data set. The GARCH (1,1) model is applied for currency returns consistent with the literature,[7] while the EGARCH model is used for the equity returns, considering asymmetric characteristic of stock market return data.

[Please insert Table 27 about here]

The volatility test results of GARCH (1,1) model for currency returns are presented in Panel A of Table 27. According to the table, for the 2-year of overall period, which covers before and after year of NIRP, all the sums of ARCH and GARCH terms of GARCH (1,1) model are less than 1, implying volatility persistence is not apparent after NIRP for the currency markets. In order to investigate the period-specific volatility of the currency returns, two GARCH (1,1) tests covering different periods are conducted for each by splitting the period with the breakpoint of NIRP. Consistent with the previous results, the impact on currency returns' volatility persistence is not indicated with an exception of Euro. Similar results are shown in the equity markets with the EGARCH model. Reviewing the corresponding EGARCH coefficient C(5) of Panel B, none of the equity indexes has a value more than 1 over the time. Overall, we can infer that the structure of the volatility process, is not affected by NIRP.

[7] See e.g. https://files.stlouisfed.org/files/htdocs/publications/review/02/05/43-54NeelyWeller.pdf and the references cited therein.

Chapter 4: Speculation, Overpricing, and Arbitrage in the Bitcoin Spot and Futures Markets

4.1 Literature Review:

The extraordinary appreciation of Bitcoin value over the year of 2017 is often considered as a result of speculative investment activities. However, it can be controversial to conclude the cryptocurrency as a speculative vehicle without relevant empirical evidence for the underlying determinants of the price of Bitcoin. In fact, several researchers argue that speculation is not a decisive factor of in the pricing of Bitcoin and regard the virtual currency as a type of commodity that is priced by interaction of supply and demand on the market. Bartos (2015) provides evidence that the pricing of Bitcoin is consistent with the efficient market hypothesis, and the speculations of investors do not significantly affect the price. Instead, he argues that positive and negative news for the cryptocurrency are key factors in Bitcoin pricing. Other papers examine a variety of external and internal factors that may influence the price of Bitcoin. Ciaian et al (2014) presents evidence that its price changes are affected by its attractiveness and vulnerability for investors, and the supply-demand fundamentals of the cryptocurrency. Bouoiyour and Seli (2016) show that geopolitical chaos such as China's deepening slowdown, Brexit, India's demonetization, anxiety over the U.S. President Donald Trump are significant determinants of Bitcoin price, using Bayesian quantile regression models. Jaroslav (2016) insists that emotional factors explain Bitcoin's price volatility better than rational factors.

Since mining of the cryptocurrency is quantitatively limited, its price behavior may be related to basic demand/supply factors. Its aggregate supply is constrained to be 21 million BTCs by its mining system, and no more Bitcoins will be mined beyond the amount. As of 29th December 2017, 16,770,512 BTCs have been mined, and its mining process is designed be slow down as time passes by. Tapscott (2016) anticipates that all the 21 million BTCs will be mined by the year of 2150. Because of this structural limitation of Bitcoin's supply in the market, as long as the speed of its demand upsurge is faster than its supply increase, the cryptocurrency's price must be escalated as a consequence.

On the other hand, Baek and Elbeck (2015) explain that the Bitcoin price movements are due to the behavior of pure speculators since they are significantly responsive to high-low price differentials. Yermack (2015) questions the function of Bitcoin as an appropriate currency in the real economy, showing that its returns are not correlated with any of key assets in the real world. Baur et al (2017) also provide similar results. They find the price of Bitcoin is not correlated with traditional asset classes, and thus conclude that Bitcoin trading is mainly executed as a speculative investment and do not function as a currency in current global economic system.

In a more recent study, Baur and Dimpfl (2018) look at the linkages between the spot and futures prices for Bitcoin. They show evidence that the futures price of Bitcoin is led by its spot price. This outcome is in contrast with most studies for financial and commodity futures whereby futures lead the spot, consistent with the informational advantages accorded to futures traders. They do not explore whether this result provides distinct arbitrage opportunities for traders, however. Such opportunities would be inconsistent with efficient markets. Our paper will provide new evidence on this score.

4.2 Data Description

This paper attempts to identify the determinants of the price of Bitcoin, and the pricing efficiency for the Bitcoin market from the onset of the market in March 2014. Throughout this study, the spot price of Bitcoin is defined as the spot exchange rate of Bitcoin against the U.S. Dollar. Using this benchmark, daily and monthly high, low, bid, ask and closings prices of Bitcoin are collected from Bloomberg. The trading volume data of the cryptocurrency is from *data.bitcoinity.org*, which covers data of 39 Bitcoin exchanges, including *Bit-x, Bitfinex, Bitflyer, Bitstamp, Btcchina, Coinbase, Gemini, Kraken*, and *Okcoin*. Considering the data availability, the daily data from April 2014 to January 2019 are obtained. Monthly data span the period from May 2010 to December 2018.

Since Bitcoin transactions occur globally with various currencies, we use the data of several major Bitcoin trading countries. More specifically, the analysis focuses on markets in which Bitcoin's trading volume is highest in the period of extreme volatility. Although the statistics have minor differences by the exchange venues, trading volumes in these five objective currencies in 2017 are reported the largest in the most statistic reports. Representatively, according to statistics by Bloomberg, as of January 10, 2018, 46.3% of Bitcoin transactions are by the U.S. Dollar, 38.4% are by Japanese Yen, 7.2% are by Euro, and 5.6% are by South Korean Won. Chinese Yuan had occupied the major part of overall Bitcoin transactions before the initial coin offering (ICO) ban was announced by the Chinese government at the end of January 2017. Based on these facts, four years of daily and monthly spot exchange rates data of Chinese Yuan, Japanese Yen, Euro, and South Korean Won against the U.S. Dollar are collected from the same source, to see the correlations of these currency rates on the price of Bitcoin.

This paper also tests correlations of Bitcoin and equity markets. Therefore, the abovementioned five economies' five-year historical equity index price data are obtained from Bloomberg. For the Euro Zone, the EUROSTOXX index is considered as the representative index of the economy. We also investigate the macro-economic indicators to capture their effects on the price of Bitcoin. For the five countries studied, economic statistics data including consumer price index, industrial production, and unemployment rate are gathered from the source of Thomson

Reuter One, the U.S. Bureau of Labor Statistics, the Bank of Japan, the European Central Bank, and the Bank of Korea. The descriptive statistics of the aforementioned variables are displayed in Table 28.

[Please insert Table 28 about here]

Lastly, we incorporated a governmental regulation factor of the five major bitcoin currency areas in the models as risk factor. The validity and acceptability of Bitcoin as a medium of exchange is still not a settled matter agreed among many government authorities. China provides the archetypical case. The People's Bank of China's ICO ban for its financial institutions had a notable influence in Bitcoin exchanges in terms of its price and transactions. This regulation was influential since Chinese Yuan had an overwhelming volume of transactions at that time. According to the Morgan Stanley's statistics, As of February 2016, 90% of the cryptocurrency was implemented in Chinese Yuan. However, this rate dropped to one-digit number immediately after the announcement. Along with such changes of transaction pattern, the price of Bitcoin dropped by $200 in major Bitcoin exchanges.[8] Please see Table 29 for the chronology of recent government retardants for the cryptocurrency markets. We capture the effects of these events in the analysis with dummy variables in the analyses.

[Please insert Table 29 about here]

Both the Chicago Mercantile Exchange (CME) and the CBOE introduced futures contracts on Bitcoin in December 2017. Our analyses of spot-futures pricing efficiency use all

[8] See Cermak, L., (2018). "Morgan Stanley report: The Bitcoin thesis is rapidly morphing, cryptos highly correlated" *J.P. Morgan Stanley.*
Graham, L., (2016). "Bitcoin price drops $200 after new ruling from Chinese regulators." *CNBC.*

contracts on these exchanges from January 2018 contracts to March 2019. The CBOE data are obtained from the exchange's website and the CME contracts are obtained from Bloomberg.

4.3 Research Methodology

As the first step to verify whether or not Bitcoin has been overpriced since 2017, an appropriate price of the cryptocurrency has to be defined and compared with the realized value. Abraham (1983) and Chatfield (2001, 2004) provide exponential smoothing methodology to estimate relevant price trends of the asset in the time series. In this paper, the single exponential trend values and the actual values are visually compared to see how much Bitcoin is overpriced over the period. The relation between actual value and trend value is defined as follows:

$$av_t = \alpha \cdot tv_{t-1}(1-\alpha) \cdot av_{t-1}, \qquad t = 1,2,\dots,T$$

and thus,

$$av_t = \alpha \sum_{k=0}^{T-1} (a-1)^k \cdot tv_{T-k} + (1-\alpha) \cdot av_0$$

av_t is the actual value of the asset at time t, and tv_t refers the exponential trend value; α defines the smoothing parameter, which minimize the in-sample sum-of-squared forecast errors. With the definitions of actual value and trend value explained above, the residual ε_t is defined as the differential of the two values:

$$av_t = tv_t - \varepsilon_t$$

As previously introduced, this study implements a number of regression analyses with macroeconomic indicators, index prices, and currency exchange rates to see the effects of related international factors. More specifically, variables reflecting inflation, production, and unemployment rate data of the five economies are analyzed with conventional regression models. Add to these variables, the equity market indexes and currency exchange rates are also examined.

The other important factors to be defined are variables reflecting speculative investment activities. One relevant example is a variable of high-low price spread of the Bitcoin. According to Baek and Elbeck (2015) the gap between monthly high and low price can represent an internal driver of the Bitcoin price changes. In this study, monthly and daily bid-ask spreads are brought as independent variables in order to observe the effects of liquidity of the asset. Add to these, trading volume of Bitcoin and notable price changes in the previous period are examined. Pooling all these explanatory variables, we suggest a model as follows:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{10} Soar_{t-1} + \beta_{11} Crash_{t-1} + \varepsilon_t \qquad \text{Model (1)}$$

Δr^{BTC} refers change of exchange rate for Bitcoin to the U.S. Dollar; $\Delta Spread$ is the monthly change in gap of monthly high and low price; $\Delta Volume$ measures monthly changes of trading volume; $\Delta BidAsk$ is the monthly bid-ask spread change, and $\Delta Regulation$ is governmental regulation dummy variable; $\Delta\, CPI_t^n$, $\Delta\, IP_t^n$, and $\Delta\, Unemp_t^n$ are monthly changes in the consumer price index, industrial production, and unemployment rate of country n in time t, respectively. In the model, $Soar_{t-1}$ and $Crash_{t-1}$ are dummies referring the price appreciation and depreciation larger than the upper fence and lower than the bottom fence. The definition of the upper and bottom fences follows Tukey (1977), who explains the positive and negative extreme values using interquartile range. Following the literature, the upper and bottom fences are described as follows:

The upper fence > Q3 + 1.5 × IQR, and the bottom fence < Q1 - 1.5 × IQR

While this idea of extreme outliers provides comprehensive and reasonable definitions of extraordinary price appreciation and depreciation, it is difficult to have an intuitive snapshot among models since the IQR values varies depends on the dataset. Thus, we also use a number of different dummy variables for price changes, including $Soar$_10%, $Soar$_20%, $Soar$_30%, $Crash$_10%, $Crash$_20%, and $Crash$_30%, each refers the cases of 10%, 20% and 30% of price appreciations and depreciations in the previous months, respectively. By taking these variables, we also suggest model (2) as follows:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{12} Soar\_10\%_{t-1} + \beta_{13} Soar\_20\%_{t-1} + \beta_{14} Soar\_30\%_{t-1} + \beta_{15} Crash\_10\%_{t-1} + \beta_{16} Crash\_20\%_{t-1} + \beta_{17} Crash\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (2)}$$

Additionally, to see the effects of price rises and drops independently, each of 10%, 20%, and 30% cases are separately regressed with the other explanatory variables. Therefore, we have six more subordinate models:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{12} Soar\_10\%_{t-1} + \varepsilon_t \qquad \text{Model (2-1)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{13} Soar\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (2-2)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{14} Soar\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (2-3)}$$

These models regress price soar dummies individually by the percentage of price increase. On the other hand, for crash dummy variables, we suggest following regressions:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{15} Crash\_10\%_{t-1} + \varepsilon_t \qquad \text{Model (2-4)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{16} Crash\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (2-5)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta\, Unemp_{t-1}^n + \beta_8^n \Delta\, Index_{t-1}^n + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{17} Crash\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (2-6)}$$

Models (1), (2) and their subordinate models are aggregate models which generate coefficients for all the key explanatory variables. However, we also put additional efforts to test for the robustness of the results considering the correlation structure of variables. According to correlation matrix for each variable presented in Table 30, it is observed that some index and exchange rate variables present significant correlations to each other.

[Please insert Table 30 about here]

In order to mitigate the effects of collinearity problems for the regressors, we designed models which concentrate only on macroeconomic indicators, indexes values, and exchange rates. Firstly, to see the influences of the macroeconomic factors separately, we suggest the following models:

$$\Delta r_t^{BTC} = \alpha + \beta_0 \Delta r_{t-1}^{BTC} + \beta_1 \Delta Spread_{t-1} + \beta_2 \Delta BidAsk_{t-1} + \beta_3 \Delta Volume_{t-1} + \beta_4 Regulation + \beta_5^n \Delta CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta Unemp_{t-1}^n + \beta_{10} Soar_{t-1} + \beta_{11} Crash_{t-1} + \varepsilon_t \qquad \text{Model (3)}$$

$$\Delta r_t^{BTC} = \alpha + \beta_0 \Delta r_{t-1}^{BTC} + \beta_1 \Delta Spread_{t-1} + \beta_2 \Delta BidAsk_{t-1} + \beta_3 \Delta Volume_{t-1} + \beta_4 Regulation + \beta_5^n \Delta CPI_{t-1}^n + \beta_6^n \Delta IP_{t-1}^n + \beta_7^n \Delta Unemp_{t-1}^n + \beta_{12} Soar\_10\%_{t-1} + \beta_{13} Soar\_20\%_{t-1} + \beta_{14} Soar\_30\%_{t-1} + \beta_{15} Crash\_10\%_{t-1} + \beta_{15} Crash\_20\%_{t-1} + \beta_{15} Crash\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (4)}$$

Considering the transactions of Bitcoin are implemented with various international currencies, it is pivotal to see how the cryptocurrency's price is correlated with the currency exchange rates distinctly:

$$\Delta r_t^{BTC} = \alpha + \beta_0 \Delta r_{t-1}^{BTC} + \beta_1 \Delta Spread_{t-1} + \beta_2 \Delta BidAsk_{t-1} + \beta_3 \Delta Volume_{t-1} + \beta_4 Regulation + \beta_8^n \Delta Index_{t-1}^n + \beta_{10} Soar_{t-1} + \beta_{11} Crash_{t-1} + \varepsilon_t \qquad \text{Model (5)}$$

$$\Delta r_t^{BTC} = \alpha + \beta_0 \Delta r_{t-1}^{BTC} + \beta_1 \Delta Spread_{t-1} + \beta_2 \Delta BidAsk_{t-1} + \beta_3 \Delta Volume_{t-1} + \beta_4 Regulation + \beta_8^n \Delta Index_{t-1}^n + \beta_{12} Soar\_10\%_{t-1} + \beta_{13} Soar\_20\%_{t-1} + \beta_{14} Soar\_30\%_{t-1} + \beta_{15} Crash\_10\%_{t-1} + \beta_{15} Crash\_20\%_{t-1} + \beta_{15} Crash\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (6)}$$

Likewise, the index prices of the five countries are regressed separately in the additional models as well. The impacts of currency and equity returns are investigated with the models (7) and (8) as follows:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{10} Soar_{t-1} + \beta_{11} Crash_{t-1} + \varepsilon_t \qquad \text{Model (7)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_9^n \Delta\, Xrate_{t-1}^n + \beta_{12} Soar\_10\%_{t-1} + \beta_{13} Soar\_20\%_{t-1} + \beta_{14} Soar\_30\%_{t-1} + \beta_{15} Crash\_10\%_{t-1} + \beta_{15} Crash\_20\%_{t-1} + \beta_{15} Crash\_30\%_{t-1} + \varepsilon_t \qquad \text{Model (8)}$$

For models (4), (6) and (8), we also implement additional six subordinate models with individual Soar_% and Crash_% dummies with the same methodologies used for subordinates of model (2). It was inevitable to use the monthly data for abovementioned models since the macro-economic statistics are announced monthly.

However, Bitcoin transactions are implemented continuously without any stoppage, and its price changes show higher level of daily volatility than any other financial instruments. Thus, it is meaningful to conduct the analyses with the daily data, which is relatively continuous. Excluding the macroeconomic variables, we regress the Bitcoin price changes on all the abovementioned independent variables with the daily data.

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_7 Soar_{t-1} + \beta_8 Crash_{t-1} + \varepsilon_t \qquad \text{Model (9)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_9 Soar\_10\%_{t-1} + \beta_{10} Soar\_20\%_{t-1} + \beta_{11} Crash\_10\%_{t-1} + \beta_{12} Crash\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (10)}$$

Unlike the models with monthly data, Soar and Crash of 30% dummies are excluded because there was no case of more than 30% of Bitcoin daily value rise or fall in the U.S. Dollar according to *Bloomberg* data. We also suggest subordinate models of model (10), which regress the price change dummy variables separately:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_9 Soar\_10\%_{t-1} + \varepsilon_t \qquad \text{Model (10-1)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_{10} Soar\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (10-2)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_{11} Crash\_10\%_{t-1} + \varepsilon_t \qquad \text{Model (10-3)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_{12} Crash\_10\%_{t-1} + \varepsilon_t \qquad \text{Model (10-4)}$$

In addition to these, models (11) - (14) are suggested in order to see the impacts of the equity market index returns and exchange rate changes, minimizing possible collinearity of variables:

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_7 Soar_{t-1} + \beta_8 Crash_{t-1} + \varepsilon_t \qquad \text{Model (11)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_5^n \Delta\, Index_{t-1}^n + \beta_9 Soar\_10\%_{t-1} + \beta_{10} Soar\_20\%_{t-1} + \beta_{11} Crash\_10\%_{t-1} + \beta_{12} Crash\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (12)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_7 Soar_{t-1} + \beta_8 Crash_{t-1} + \varepsilon_t \qquad \text{Model (13)}$$

$$\Delta\, r_t^{BTC} = \alpha + \beta_0 \Delta\, r_{t-1}^{BTC} + \beta_1 \Delta\, Spread_{t-1} + \beta_2 \Delta\, BidAsk_{t-1} + \beta_3 \Delta\, Volume_{t-1} + \beta_4\, Regulation + \beta_6^n \Delta\, Xrate_{t-1}^n + \beta_9 Soar\_10\%_{t-1} + \beta_{10} Soar\_20\%_{t-1} + \beta_{11} Crash\_10\%_{t-1} + \beta_{12} Crash\_20\%_{t-1} + \varepsilon_t \qquad \text{Model (14)}$$

Similar to the previous models, we regress the price soar and crash dummy variables separately for models (12) and (14), generating additional four subordinates for each model.

Another issue to be addressed in this study is efficiency of Bitcoin market.

4.4. Results

The results of this study are categorized by three parts. First, we generate graphs that show abnormality of Bitcoin price volatility. More specifically, the cryptocurrency's trend values and actual prices in the market are compared by using the detrended ratio and single exponential residuals. Similar comparisons are also made with the five countries' equity index prices. Secondly, we attempt to identify drivers of Bitcoin price changes by testing the relevant explanatory variables with both monthly and daily data. Lastly, several evidences of inefficiency of Bitcoin market are presented.

4.4.1. Bitcoin Overpricing

As the first step to find evidence of Bitcoin overpricing, its trend value and detrended ratio are computed and analyzed. For the trend value analyses, the results are shown in Figures 3 to 5.

[Please insert Figure 3 about here]

Figure 1 presents the notable increases and decreases of the price of Bitcoin over the time, in comparison to the five countries' equity index prices. As the figure shows, the recent fluctuations of the cryptocurrency are most remarkable among those of six different assets.

[Please insert Figures 4 and 5 about here]

Figures 4 and 5 provide another viewpoint of Bitcoin's price volatility. The y-axis of the graph is index returns, while its x-axis refers those of the cryptocurrency. By matching the two dataset, volatility level of the five analysed indexes and Bitcoin returns are compared in Figure 2. Figure 3 presents comparisons of Bitcoin and each individual equity market index returns. As the shape of scattered plots are horizontally wide, those outcomes can be deemed as an evidence of relatively high volatility level of Bitcoin returns.

[Please insert Figures 4-1 and 5-1 about here]

Figures 4-1 and 5-1 compare volatility levels of Bitcoin during 2017-18 period with that of the period before the year of 2017. As observed in these figures, scattered plots form more flattened shapes before 2017 than the subsequent period.

[Please insert Figures 6 and 7 about here]

Figures 6 and 7 show single exponential residuals of Bitcoin and the five indexes from March 2010 to June 2018. Referring Figure 6, although the trend values of Bitcoin are similar to those of the indexes until the end of 2016, its residuals fluctuate thereafter. Figure 7 presents the by-country comparisons. The single exponent residuals in the graphs support that Bitcoin's price changes over the year of 2017 are beyond the relevant or traditional volatility level.

Such excessive volatility of recent Bitcoin prices can be shown also by degree of detrend. Following Baek and Elback (2015), we define the detrended ratio as follows, in order to quantitate abnormality of the cryptocurrency and index prices.

$$\textit{Detrended Ratio} = \textit{Actual Value} \,/\, \textit{Trend Value}$$

By calculating the detrended ratio, Bitcoin's distinguished detrend ratio can be displayed quantitatively, by comparing its standard deviation with those of the suggested index price changes.

[Please insert Table 31 about here]

Table 31 compares summary statistics of the Bitcoin's detrended ratios and the five indexes. As the table presents, the standard deviation of Bitcoin's detrended ratio is about seven times of S&P500 over the period. The detrended ratios of other indexes shows about one fifth of the cryptocurrency's detrended ratio. Therefore, it is fair to consider that recent price appreciation of the electronic coin is an abnormal phenomenon compare to the equity markets.

4.4.2. Bitcoin Price Determinants

The other issue of this paper addresses is the determinants of Bitcoin price changes. As previously explained, we suggest number of models which contain the possible explanatory variables. In order to see the effects of the relevant variables, number of regression models are implemented with both monthly and daily data. The models (1) to (8) are the analyses with monthly data and their results are shown in Table 32.

[Please insert Table 32 about here]

The outcomes above provide clues to infer factors affecting on the price of Bitcoin. Model (1) shows no significant coefficient for any variables. However, for model (2), *Bitcoin(USD) (t-1), IP (China), SHSZ300 (t-1), NIKKEI (t-1), XRate CNY-USD (t-1)*, and *XRate JPY-USD (t-1)* have significant effect on Bitcoin price change. Additionally, *10% Crash (t-1), 20% Crash (t-1)*, and *30% Crash (t-1)* are also significant in the model. If the soar and crash dummy variables are regressed separately, it generates somewhat different results. Except for *Bitcoin(USD) (t-1)* and *XRate CNY-USD (t-1)* in model (2-4), all the other external explanatory variables are not significant.

If the analyses are focused on macro-economic factors corresponding models (3) and (4), China's CPI shows significant effects on the cryptocurrency's price change, except model (4-1). All the other explanatory variables do not explain the dependent variable. This result is consistent with Yermack (2015), showing that most real economy variables, especially macroeconomic factors are not correlated with Bitcoin price.

Models (5) and (6) provide analyses focusing on index prices of suggested equity markets. Interestingly, the European stock price and trading volume index have significant coefficients in common, while *NIKKEI (t-1)* is significant in models (6), (6-1), (6-4), (6-5), and (6-6). Bitcoin's price change and 10% Crash at t-1 are significant in model (6), while *S&P500 (t-1)* is shown as a decisive variable in model (6-6).

Models (7) and (8) contain exchange rate variables while macroeconomic factors and index prices are excluded. According to the results, trading volume at t-1 is significant in all the models except for model (8). It is noteworthy to observe that trading volume is commonly significant in most of models (5)-(8) and its subordinate models.

Additional analyses are implemented with the daily data excluding the macro economic variables as previously introduced in models (9) to (14). The results are tabulated in Table 33.

[Please insert Table 33 about here]

The regression analyses with daily data show that daily high-low price spread plays a significant role in Bitcoin price change. Also, Chinese and Japanese stock market indexes are also significant explanatory variables, according to models (9) to (12). Additionally, models (9), (11), and (13) show crashes in the previous period have negative impact on the dependent variable. These results of daily data analyses are consistent of Baek and Elback (2015) showing that the high-low price spread may be the pivotal driver of Bitcoin price change.

In summary, the regression analyses of Bitcoin volatility levels and its detrended ratio provide evidence that its price volatility is out of appropriate and traditional range. More importantly, according to the regression analyses results, the variables related to speculative investment behavior such as trading volume, high-low price spread and price crash in the previous period are significantly related to the price of Bitcoin. Furthermore, most of the suggested macroeconomic factor variables are insignificant in the regression models. These results imply that Bitcoin has limited linkage to the real economy.

4.4.3. Market Efficiency of Bitcoin Market

One of the key discussions in this chapter is whether or not Bitcoin is overpriced. One of the reasons for this perception is the unprecedented speed of its value appreciation. However, if Bitcoin market is efficient, even with such fast value changes, the market price of the cryptocurrency reflects its essential fair value and therefore no remarkable mispricing exists. The issue, then is whether or not market participants regard the cryptocurrency market as an efficient market. Our results so far are not supportive of the efficient market hypothesis, however. Reviewing the regression results, several past price change variables are correlated with the price of Bitcoin. These coefficients imply that the Bitcoin traders may take signals from the historical data as information which influences on the market price of Bitcoin. In other words, Bitcoin market may not be deemed as an efficient market in a weak-form sense, since traders can take advantage from the historical price data of the cryptocurrency.

Other arguments can be used to support the view that the price of Bitcoin does not fairly reflect its intrinsic value. Under the assumption that cryptocurrency markets are examples of the perfect competition market, analyzing the marginal mining cost of Bitcoin may provide the outline to find its appropriate intrinsic value. According to Loery and Chang (2018), the lowest mining cost of 1 BTC is measured as about $3,200. Also, J.P. Morgan analyzes that the worldwide weighted averaged cash cost to mine 1 BTC is about $4,060, and this can be dropped to $1,260 or less in near future.[9] Supposing that the price determination mechanism is same as that of the perfect competition market, the marginal cost of mining 1 BTC can be a rational price of the cryptocurrency. However, significant gap between the marginal mining cost and the actual price is observed in late 2017 to early 2018, as 1 BTC is about $18,000 in December 2017.

Reviewing the considerable gap between the market price and mining cost of Bitcoin, one can argue that there are some other factors which constitute intrinsic value of the cryptocurrency, and the gap can be explained by the factor. However, the results of the study raise serious questions regarding the appropriateness or viability of Bitcoin as a medium of exchange. Bitcoin's extreme volatility shown in the previous sections renders it as problematic in this regard, to say

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[9] Eric Lam, Bitcoin is worth less than the cost to mine it, JPMorgan Says, Bloomberg, Jan 25, 2019, https://www.bloomberg.com/news/articles/2019-01-25/bitcoin-is-worth-less-than-the-cost-to-mine-it-jpmorgan-says, Accessed on Feb 4, 2019

the least. As the value of Bitcoin changes continuously and dramatically in the market without any discrete time segmentation, it is difficult to relate it to a basket of real goods or services in a certain period of time. Pricing of goods and services in Bitcoin may at some point be viable, to the extent that exchange rates between Bitcoin and fiat currencies become stable. Since its issuance and trading is largely outside the jurisdiction of monetary authorities, this is most unlikely. Fundamentally, one cannot expect Bitcoin to serve as a liquid store of value and have extra intrinsic value other than its marginal mining cost. Of course, the mining cost vary over the world, and the time-series data of marginal cost of Bitcoin mining is not available. However, considering the estimated worldwide weighted average marginal mining cost and absence of factors which give intrinsic value for Bitcoin, it is possible to infer that the rational value of the cryptocurrency was not fairly and efficiently reflected in the market price.

Evidence of inefficiency of Bitcoin market can be inferred from derivatives markets. A number of recent studies provide explanations about Bitcoin's mispricing by explaining the lack of synchronization between spot markets and futures markets. For example, Baur and Dimpfl (2018) show evidence that the futures price of Bitcoin is led by its spot price. This outcome is in contrast with most studies for financial and commodity futures whereby futures lead the spot. Problems in identifying the trading activity reflected in the spot markets are severe, however; this does not undercut the potential importance of futures in pricing or in arbitrage.[10] The futures markets for Bitcoin have shown some resilience, since its introduction, especially the CME

[10] As Young (2010) notes: "According to Bitwise, more than 95 percent of the reported bitcoin volume is inflated or faked, which leaves the futures market responsible for around 35 percent of global bitcoin volume." See https://www.ccn.com/cme-sees-meteroic-bitcoin-demand-546m-in-1-day, accessed on April 13, 2019

contract. One of the leading cryptocurrency exchanges, Bakkt plans to launch the world's first physically delivered Bitcoin futures contracts.[11]

Can futures prices serve as valid predictors of spot prices? To address this question, we implement Fama's (1984) regression approach. The two equations to be estimated are following:

$$P_{t+1} - P_t = \alpha_1 + \beta_1(F_t - P_t) + \varepsilon_{1,t+1} \tag{1}$$

and

$$F_t - P_{t+1} = \alpha_2 + \beta_2(F_t - P_t) + \varepsilon_{2,t+1} \tag{2}$$

where P_t and F_t are the spot and future price of Bitcoin at time t, respectively. $F_t - P_{t+1}$ defines the risk premium and $(F_t - P_t)$ refers the basis at time t. Estimations of these two equations may provide evidence that the differentials between spot ands future prices contain information about future spot prices or risk premium at the expiration of the future contract. The prerequisite condition of relevant estimation of these two equations is stationarity of the data series. In order to test for stationarity of the dataset, we conducted three different unit root tests including: Dickey and Fuller (1979, 1981), augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests.

[Please insert Table 34 about here]

The results reported in the table show the basis, the risk premium, and the change in the future spot prices data series are stationary, rejecting existence of unit root process. Therefore, we can infer that the regression models are not subject to the spurious inference issues associated with time series.

[Please insert Table 35 about here]

[11] Jeremy Wall, Bakkt raises $182.5 million and its launch may be delayed again, January 1, 2019, https://www.investinblockchain.com/bakkt-raises-182-5-million-launch-delayed-again, accessed on April 13, 2019

Table 35 presents the results of the estimation of the equations. Given the significance of the coefficients β_1 for both CBOE and CME contracts in the equation (1), we can infer that the basis, $(F_t - P_t)$ contains some information about the spot price change of Bitcoin in the future. The results of estimation of the equation (2) are consistent with those of the equation (1). From the estimated coefficients β_2, we can also conclude that the basis at time t can be a predictor of the risk premium. However, the Wald tests do not support unbiasedness of the predictors, since the joint tests for α_1=0, β_1=1 and α_2=0, β_2=1 are significant for all the contracts examined, as shown in Table 36.

[Please insert Table 36 about here]

Do the futures markets facilitate efficient pricing through arbitrage? We address this issue using the cost-of-carry model as in MacKinlay and Ramaswamy (1988), Bhatt and Cakici (1990), and Switzer, Varson, and Zghidi (2000). Mispricing is based on the deviation of the futures price prevailing in the market at time t for a contract with a maturity of T: $F_{(t,T)}$ and the arbitrage free expected Futures price $F^e_{(t,T)}$:

$$x_t = \left(F_{(t,T)} - F^e_{(t,T)}\right)/P_t$$

where $F_{(t,T)}$ is Bitcoin future price at time t with the maturity date of T, and $F^e_{(t,T)} = P_t e^{rf*(t-T)}$, where rf is risk free rate. Deviations from no-arbitrage are identified using panel unit root tests on x_t. Since both Chicago Mercantile Exchange (CME) and CBOE introduced the futures in December 2017, data consisting of all contracts from January 2018 contracts to March 2019 contracts are used in the tests. The CBOE data are obtained from the exchange's website and the CME contracts are obtained from Bloomberg. Descriptive statistics of the mispricing term and absolute value of the mispricing term are presented in Table 37.

[Please insert Table 37 about here]

In order to investigate existence of arbitrage opportunity in the Bitcoin market, we conducted two different unit root tests for the mispricing term data series. Evidence of unit root processes in the mispricing term data can support chance persistence of arbitrage opportunities through time, which would be indicative of inefficiency.

[Please insert Table 38 about here]

As shown in Panel A of Table 38, using the CBOE's futures contracts data of both monthly nearby-contracts and rolled over 7 days before expiration, the test statistics indicate the presence of unit root processes of the mispricing term. The test results with CME's futures contracts data are similar. According to Panel B of Table 38, we cannot reject the unit roots hypothesis at the 5% level, which indicates that the hypothesis of no-arbitrage is not supported. Furthermore, the signs of the t-statistics provide clues for direction of price change of Bitcoin. As we see the signs are negative for all the cases, we can see the mispricing terms are significantly negative, which indicates that futures prices exceed efficient prices based on the cost of carry. Why do these arbitrage opportunities persist?

4.4.4. Further Discussion on Bitcoin Market Efficiency

Several factors might serve as sources of inefficiency in the markets. Such factors would include trading frictions due to the extreme volatility of the markets, and failures of significant spot exchanges would adversely affect both long and short trading of spot Bitcoins. Regarding the latter, given the lack of physical delivery of the physical product at expiration combined with an illiquid spot market may inhibit short selling.[12] Although Bitcoin has been touted for the

[12] A number of exchanges do market contracts for short selling. See: https://99bitcoins.com/short-sell-bitcoin/

integrity of its security system, a number of cases highlight its actual vulnerabilities: indeed, a number of hacking and fraud events have taken place since its initial release to the latest case of Quadriga.[13] The chronology of major Bitcoin exchange security issues is shown in Table 39 and Figure 8.

[Please insert Table 39 and Figure 8 about here]

Theoretically and practically, Bitcoin itself is secure from hacking attacks due to the blockchain technology. However, exchanges and wallet service providers are not. Especially, centralized cryptocurrency exchanges are vulnerable to such hacks and frauds, and the security of the coin owners are not guaranteed by the service provider. As long as the concerns about hacks and frauds remain, the virtual currency's stability and function as a store of value is remained to be jeopardized.

While Bitcoin is the leading cryptocurrency market, it does not have a monopoly on the market, as numerous virtual currencies have been released in the last several years. Table 40 shows the list of major alternative cryptocurrencies and their release dates.

[Please insert Table 40 about here]

As those cryptocurrencies may serve as alternatives or substitutes of Bitcoin, releases of competitive virtual monies are reviewed to capture the possible impacts on the price of Bitcoin. Figure 9 provides a snapshot of such alternative coin releases and corresponding changes of the price of Bitcoin since April 2010.

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[13] Doug Alexander, Quadriga Crypto Mystery Deepens With 'Cold Wallets' Found Empty, Bloomberg, March 1, 2019, https://www.bloomberg.com/news/articles/2019-03-01/quadriga-has-6-cold-wallets-but-they-don-t-hold-any-crypto, accessed on April 13, 2019

[Please insert Figure 9 about here]

While the alternative coins have been released over the time, their impacts on Bitcoin prices is not clear-cut. For example, Litecoin, Stellar, Ripple, Tether, and Ethereum were launched before 2017: a casual glance at notable Bitcoin price appreciation or depreciation during the time. Subsequently, EOS, Bitcoin Cash, and TRON were launched during bullish period of Bitcoin market, and Bitcoin SV was introduced in the bearish period. However, those releases do not show any uniformed impact on Bitcoin's price. One explanation is that Bitcoin is still the dominant player among the cryptocurrencies. In fact, the market capitalization of Bitcoin is five times larger than Ripple, which is the second biggest cryptocurrency market as of January 30, 2019. This distinguishable market capitalization of Bitcoin imply that the alternatives may not have sufficient market shares to influence Bitcoin's price.

A casual glance at Figures 9 and 10 and Tables 39 and 40 in the period up to 2017 suggests that the impacts of Bitcoin security concerns and new coin releases on the price of Bitcoin were muted. One could argue that up until 2017, the legitimacy of the market was still in question. This changed with the launching of futures contracts on Bitcoin in December 2017, on both the CBOE and the CME. Figures 9 and 10 provide graphs of the mispricing term and absolute value of mispricing term since the inception of futures trading on these major exchanges.

[Please insert Figures 9 and 10 about here]

As can be seen, mispricing and absolute mispricing the price crash exhibit a significant spike in the first week of November 2018. This month was particularly bearish, with bitcoin exhibiting a monthly decline of about 37%. Was the jump in Bitcoin mispricing attributable to security concerns related to hacking and other forms of fraud? Notable events, for example were the thefts of Bithumb and Zaif which resulted in losses of There might be several reasons for such bearish market, and one possible cause is concern about Bitcoin security, which might be triggered by a number of Bitcoin hacks and frauds continuously occurred in 2018. Especially, amount of Bitcoin stolen in the cases of Bithumb and Zaif are several thousands BTCs, reflecting losses of 31 million and 60 million U.S. dollar, respectively.

To formally capture impacts of these issues on Bitcoin price, we regress the mispricing term, x_t on dummy variables that represent events of identified Bitcoin hacks/frauds issue as well as alternative coin releases. The model as follows:

$$x_t = \alpha + \beta_1 * Hack\_Cum_{\mathrm{t}} + \beta_2 * NewCoin_{\mathrm{t}} + \varepsilon_t$$

where $Hack\_Cum_{\mathrm{t}}$ is cumulative amount of stolen Bitcoin by the time t, and $NewCoin_{\mathrm{t}}$ is dummy variable indicating on D-1 to D+5 of new cryptocurrency releases. For $NewCoin_{\mathrm{t}}$, only top 50 cryptocurrencies in market capitalization are considered, as of April 11, 2019.[14] The results are shown in Table 41.

[Please insert Table 41 about here]

Reviewing the results, we can conclude that hacks and frauds of Bitcoin are pivotal issues which may amplify the mispricing term. Alternative coin release variable also shows significant coefficients except for CBOE's futures contract with nearby rollover data series. Overall, both Bitcoin security concerns and new cryptocurrency releases may lead considerable gap between the futures price and spot price in the future.

[14] Data Source: https://coinmarketcap.com/

Additionally, in order to verify persistency of effects captured above, we conducted GARCH test for the model. Considering asymmetric characteristic of the data series, EGARCH model is implemented. Table 42 shows the results of EGARCH estimation.

[Please insert Table 42 about here]

According to the table, all the EGARCH coefficient C(7) are less than one, implying that the effect of the independent dummy variables are not persistent. Thus, we can infer that the volatility structure of Bitcoin mispricing term is not affected by the two dummy variables: Bitcoin hacks and alternative cryptocurrency releases.

Chapter 5: Conclusions

In this thesis, I study three aspects of recent international financial markets and explore their implications for policy making and investment decisions. These three aspects include a) cultural factor's impact on investment behavior; b) effects of negative interest rate policies on financial markets; and c) pricing of the leading cryptocurrency, Bitcoin. The first essay addresses the issue of culture and risk behavior focuses on nine small European countries over a long-time frame and show that two different risk measures, i.e. the traditional risk measure and the extreme risk measure, capture different responses from investors in those countries. More importantly, we find that a country culture factor plays a critical role in explaining small stockholders' behavior, and in particular the trading responses of such investors to changes in the risk environment. In country specific regressions, with the exception of Austria, small investors domiciled in collectivist countries do not show much responsiveness to changes in the risk environment, which implies that collectivism constrains the initiative for investors to actively trade in response to market signals. In a pooled panel regression where we can control for the highly persistent and time invariant country variable, we find that the culture-risk interaction variable has a significantly positive impact on fund flows. In addition, small investors from individualistic societies exhibit "flight to risk" behavior, consistent with high risk tolerance.

I investigate the effects of negative interest rate policies (NIRP) on the financial markets of the eight European countries and Japan in my second essay. The results from Chapter 3 explain that the consequences of NIRP might not correspond to its policy objective. By implementing the event study analyses, I find the evidences of transitory effects of the policy announcements on the currency returns, while insufficient impacts are found in the equity markets. In extended term analyses with regression models, the effects on currency market returns are not in the direction of the traditional expansionary monetary policy mechanism. The analyses provide evidences for NIRP's limited reverse-effects on the currency returns, and the effects are more observable in the countries with steeper yield curves of sovereign bonds. Furthermore, for the equity markets, the S&P500 index variable plays significant role in most cases of developed economies, rather than interest regime switching variable. More specifically, the Euro Area, Japan, Norway, and Switzerland show notable cointegrations between the U.S. and those equity markets during the event window. Throughout the analyses, Switzerland presents notable differences from the other economies due to the SNB's pegged exchange rate abolishment along with NIRP execution. Overall, findings of this study suggest that lowering policy rate under the zero bound as a stimulative monetary policy may cause unfavorable consequences, unlike conventional interest rate cuts during periods in which interest rates remain bounded from above by zero. I believe this research contributes to the literature of interest rate risk by delivering significant new evidence on the impact of NIRP.

The last essay attempts to show the abnormality of recent severe Bitcoin price instability and to investigate possible drivers of recent price changes of the cryptocurrency by analyzing its historical price data and relevant explanatory variables. We visualize that the cryptocurrency's recent price ascents and descents are anomalous and not consistent with efficient markets. The outcomes of the analyses portray that the realized prices of Bitcoin have notable gaps with its exponential trend values, having unprecedented volatility level and abnormal detrended ratios. One could support the assertion that Bitcoin is overpriced. Its instability certainly renders it as unviable as a medium of exchange. The analyses show that the price of Bitcoin is significantly related to its daily trading volume, monthly high-low price spread, and value crash in the previous trading day, while most of the other explanatory variables are significant. These results of regression analyses are in favor of the argument that the price of Bitcoin has mainly moved with internal speculative investing activities. This study also provides evidence of inefficiency of Bitcoin market and presence of external risks which may influence the cryptocurrency's essential value. Finally, the results also show significant and persistent mispricing of the Bitcoin spot prices in relation to futures prices, that represent deviations from no-arbitrage bounds. Moreover, we show that such mispricing may be amplified by hackings and alternative cryptocurrency releases. Identifying the precise causes of these apparent arbitrage opportunities remains a topic for future research.

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Figures

Figure 1. Extreme Risk Measure (in %) for Belgium, Greece, Ireland, and Portugal during 1983-2016

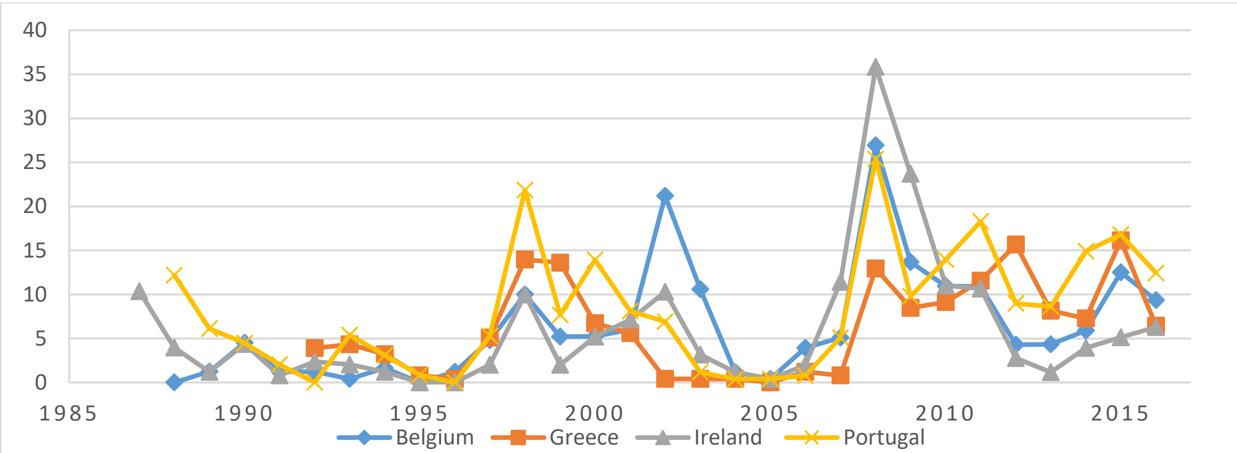


Figure 1.1. Extreme Risk Measure (in %) for Belgium, 1988-2016

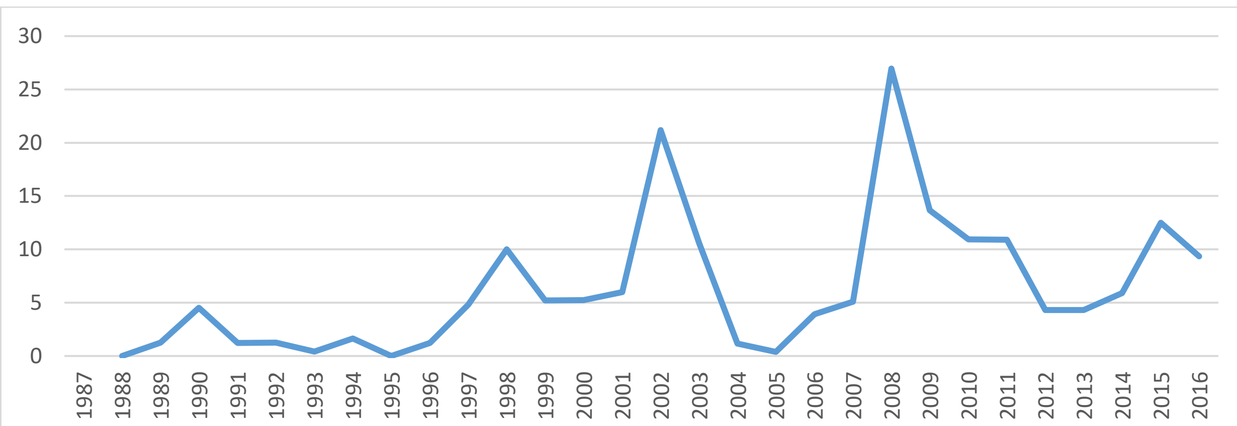


Figure 1.2. Extreme Risk Measure (in %) for Greece, 1992-2016

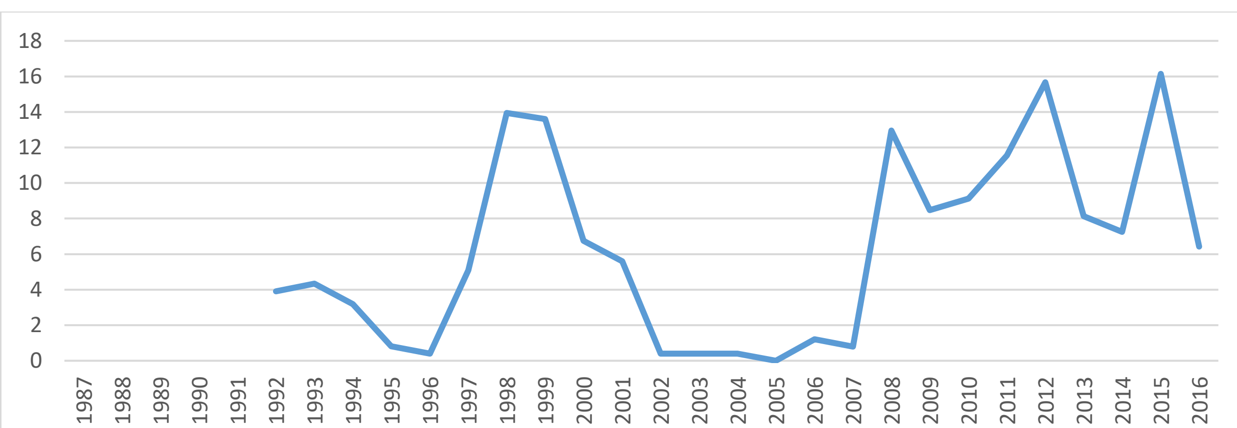


Figure 1.3. Extreme Risk Measure (in %) for Ireland, 1987-2016

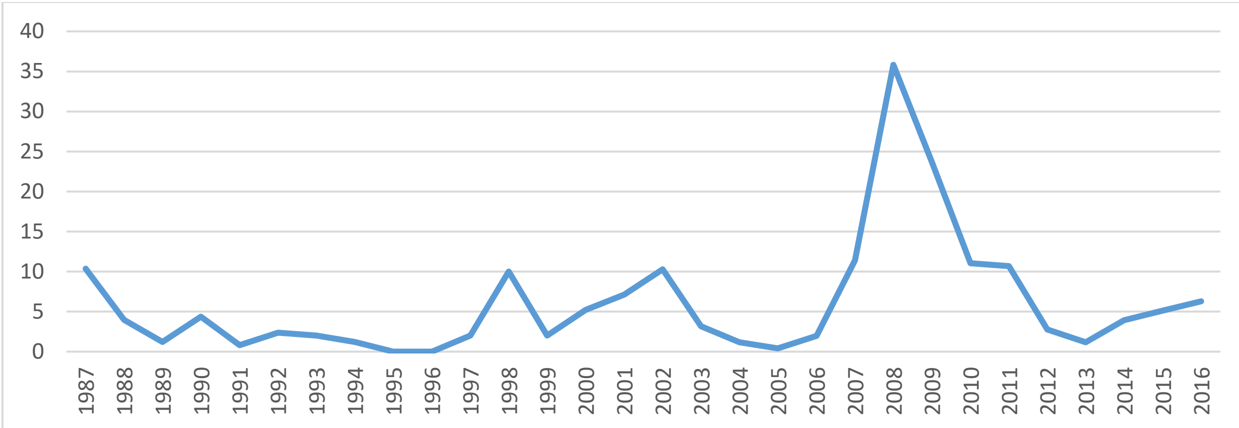


Figure 1.4. Extreme Risk Measure (in %) for Portugal, 1988-2016

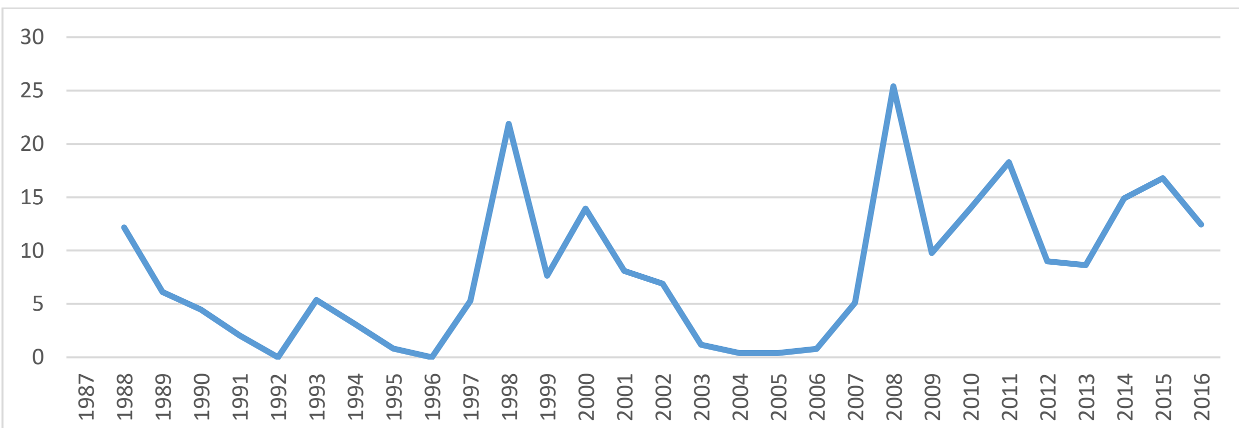
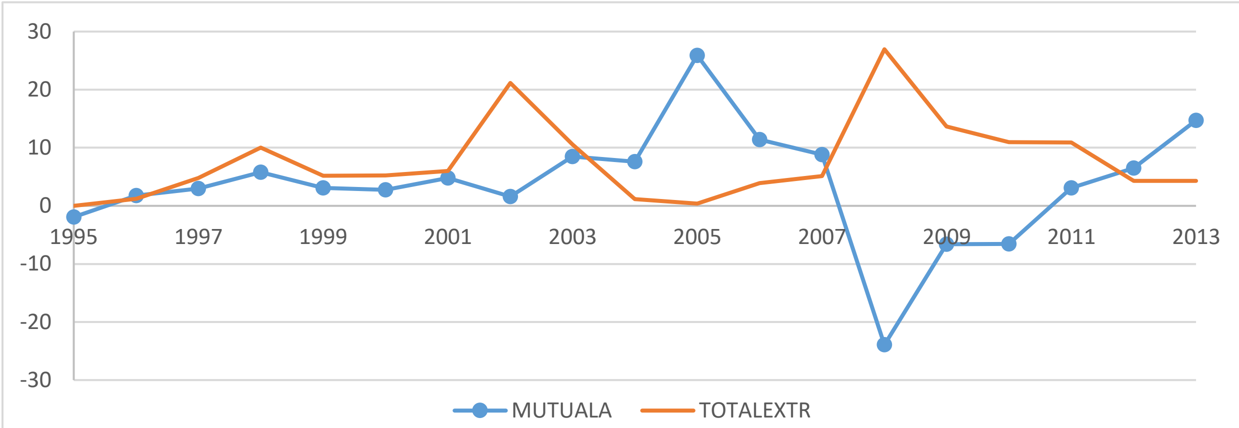


Figure 2.1. Net Flows (annual) into Equity Mutual Funds for Belgium (in USD $100 Million) vs. Extreme Risk Measure (in %) in Belgium, 1995-2013



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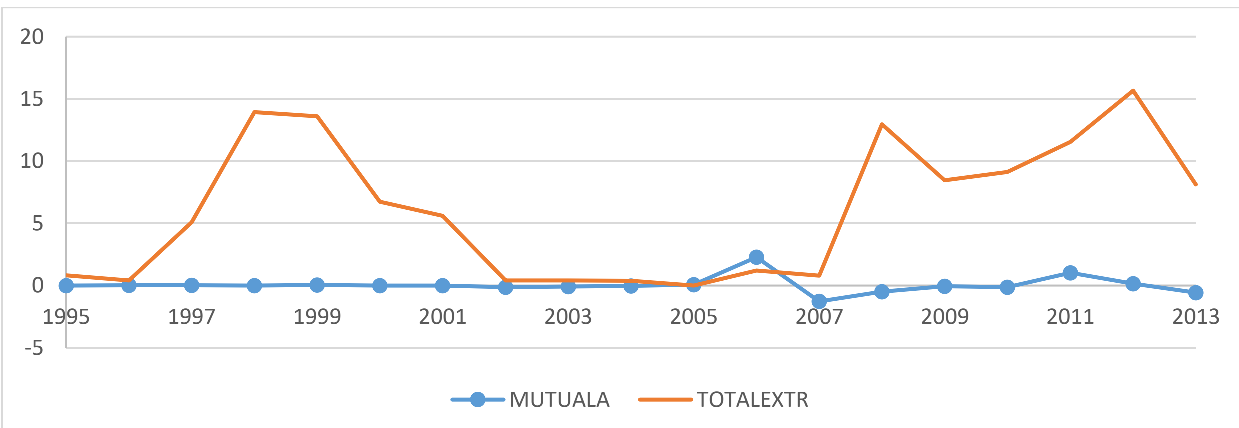


Figure 2.3. Net Flows (annual) into Equity Mutual Funds for Belgium (in USD $100 Million) vs. Extreme Risk Measure (in %) in Ireland, 2002-2012

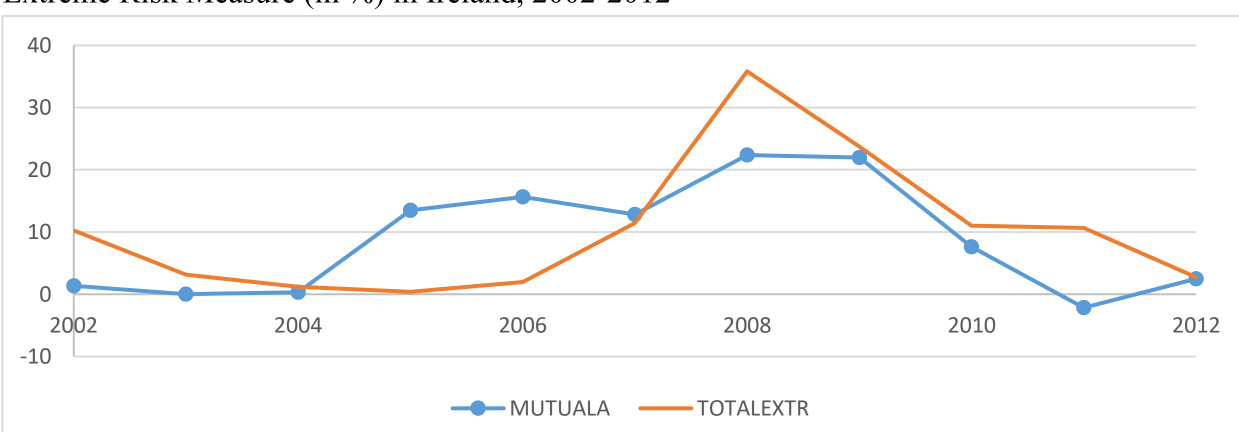


Figure 2.4.

Net Flows (annual) into Equity Mutual Funds for Belgium (in USD $100 Million) vs. Extreme Risk Measure (in %) in Portugal, 1995-2013

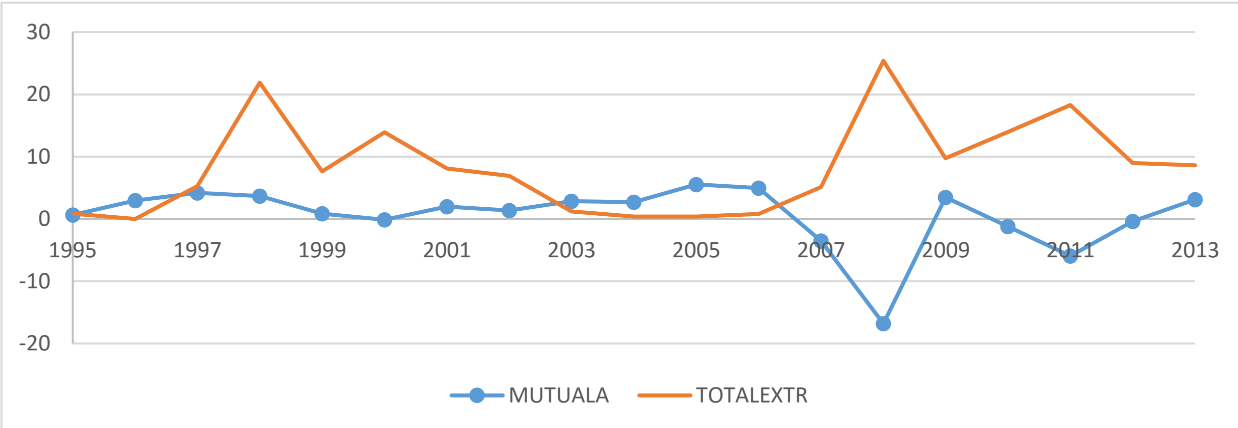


Figure 3. Comparison of Bitcoin and Index Prices (Mar 2010 – Jun 2018)

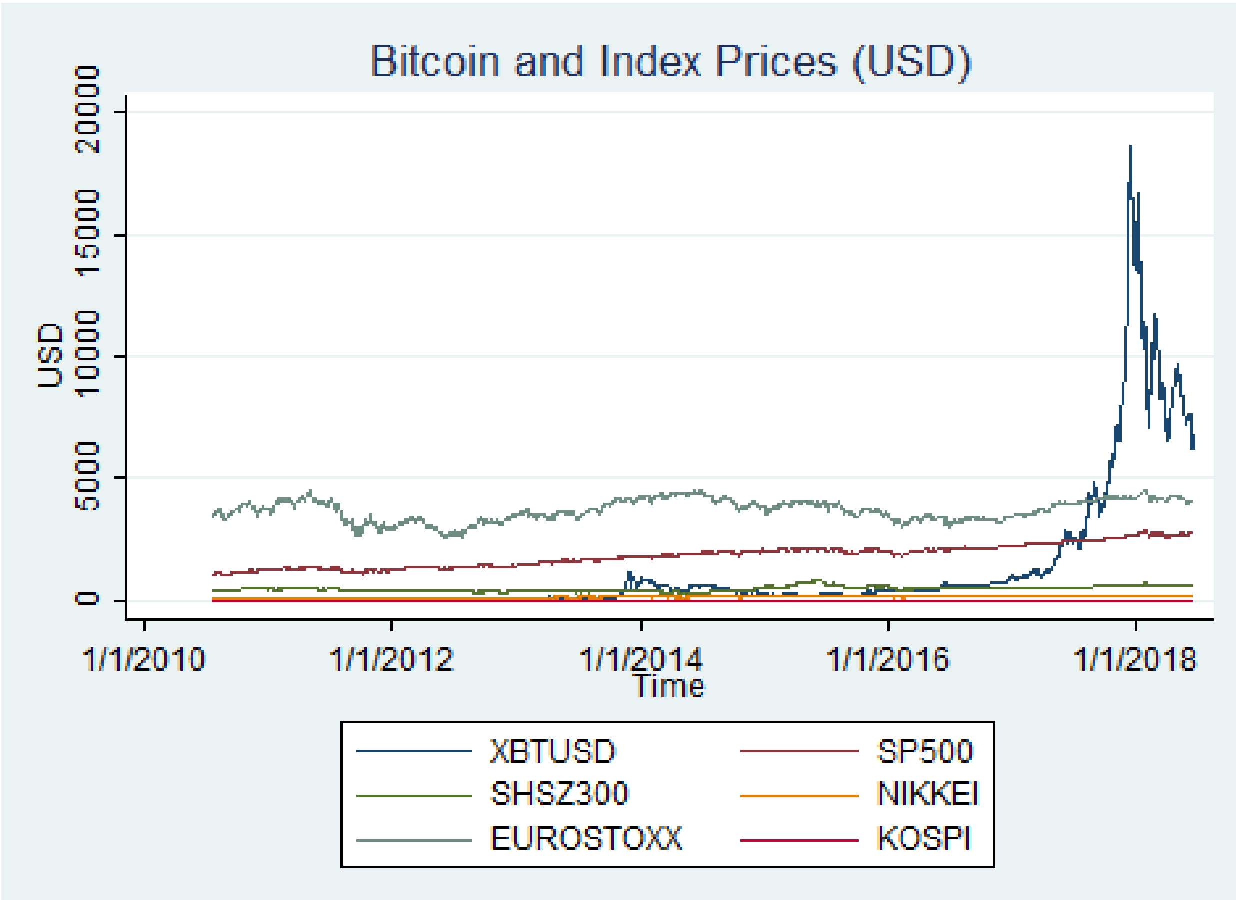


Figure 4. Scatter Plot Chart of Bitcoin and Indexes Returns

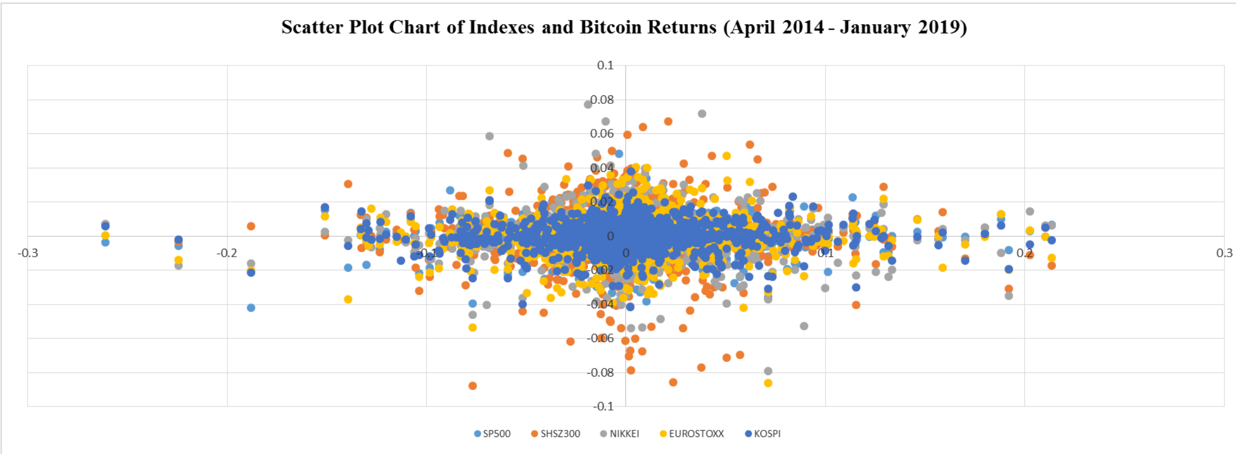
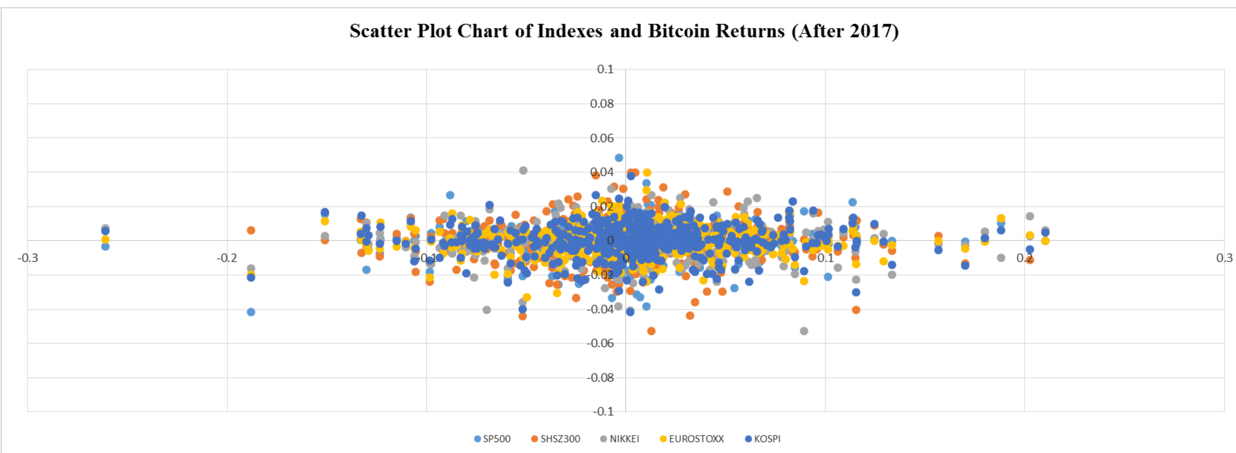


Figure 4-1. Scatter Plot Chart of Bitcoin and Indexes Returns Before and After 2017



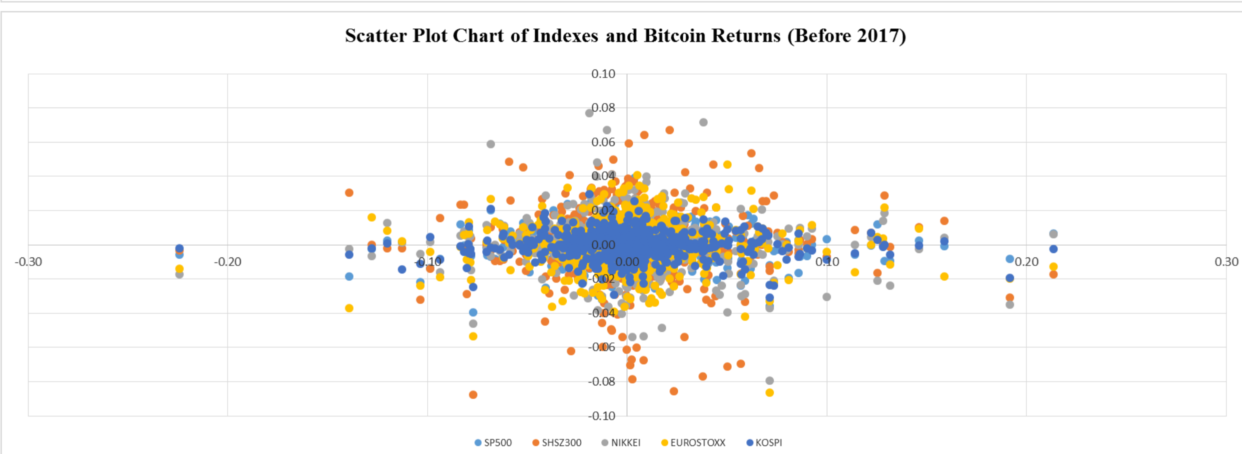
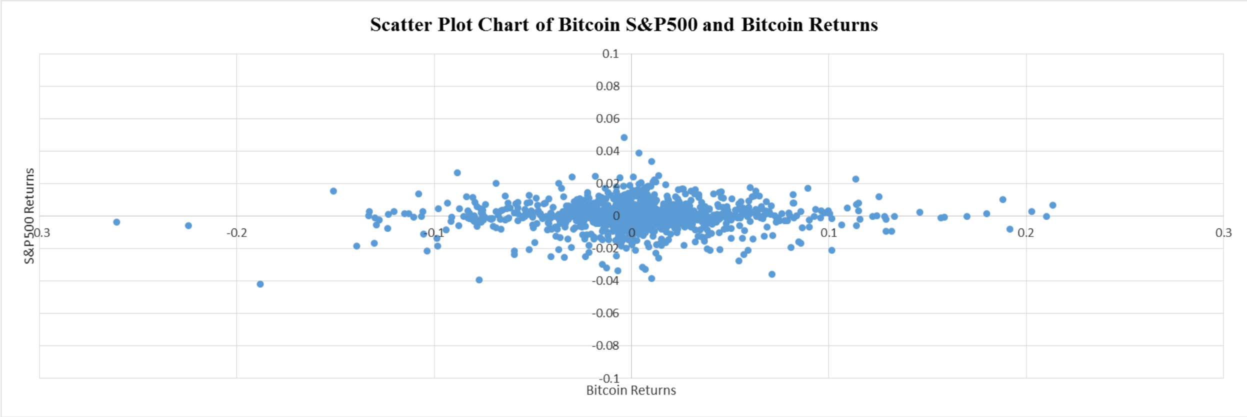
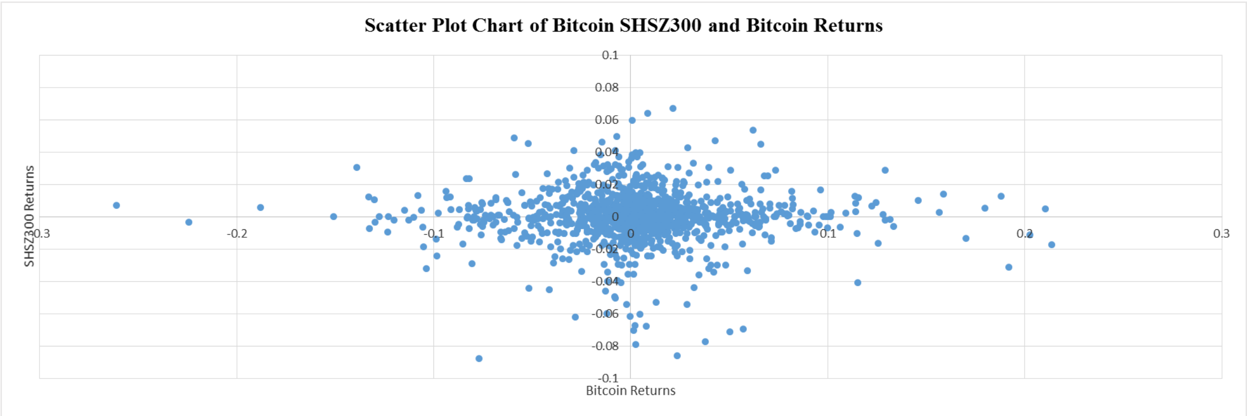
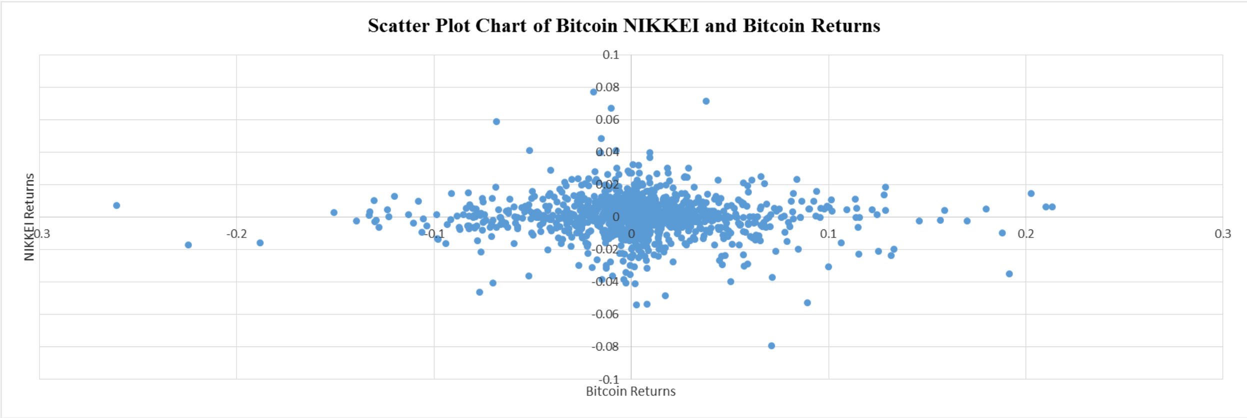
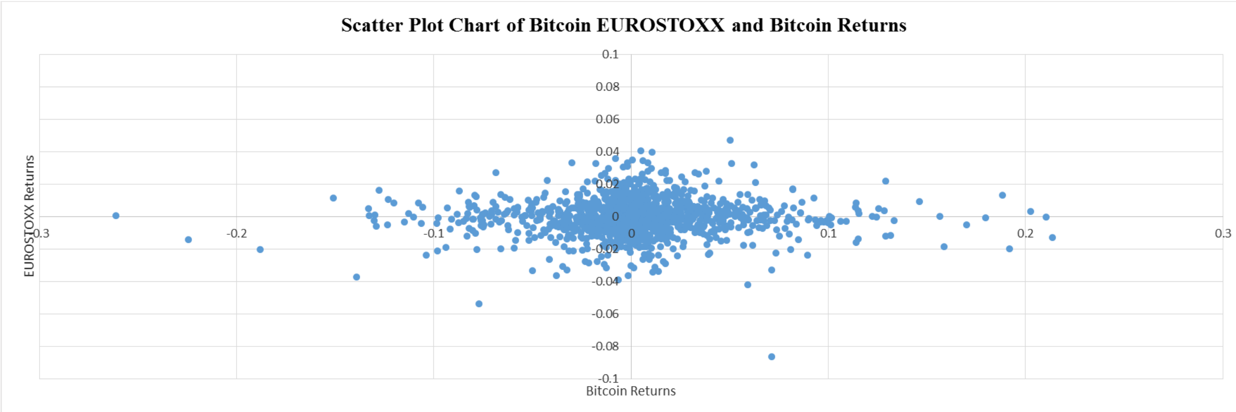


Figure 5. Scatter Plot Chart of Bitcoin and Index Returns by Country








Scatter Plot Chart of Bitcoin EUROSTOXX and Bitcoin Returns
EUROSTOXX Returns
Bitcoin Returns
0.1
0.08
0.06
0.04
0.02
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-0.02
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-0.08
-0.1
-0.3
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-0.1
0.1
0.2
0.3

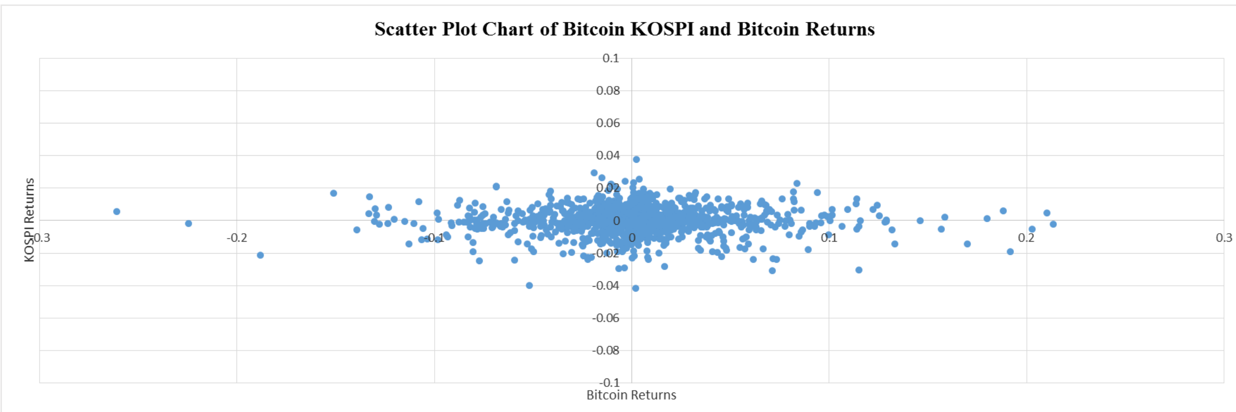
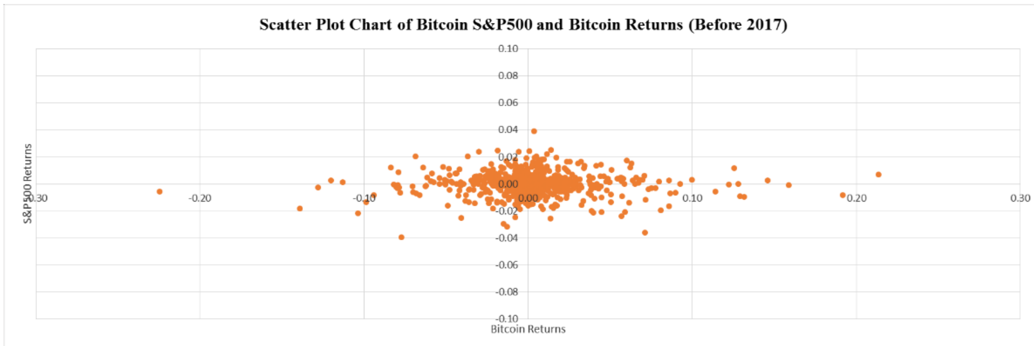
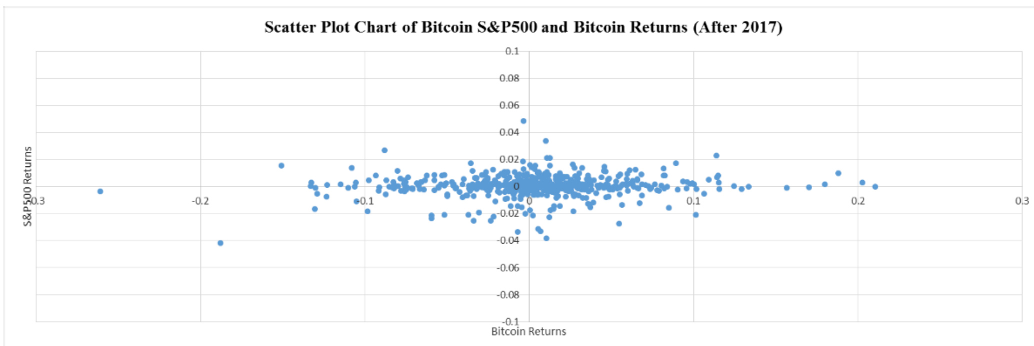

Scatter Plot Chart of Bitcoin KOSPI and Bitcoin Returns
KOSPI Returns
Bitcoin Returns
0.1
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.3
-0.2
-0.1
0.1
0.2
0.3

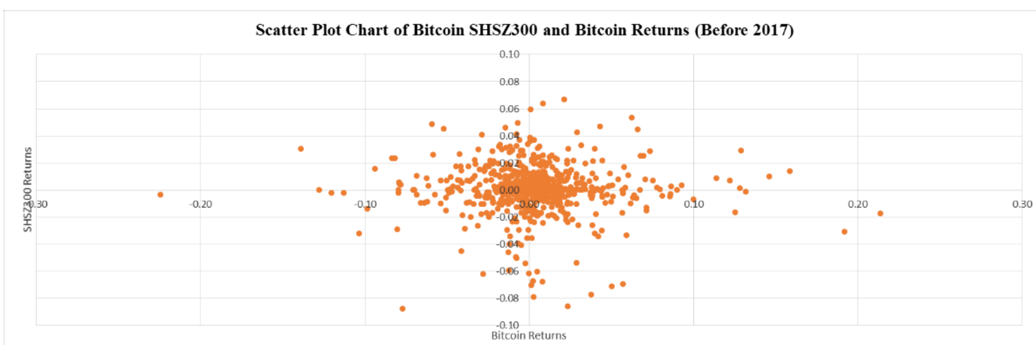
Figure 5-1. Scatter Plot Chart of Bitcoin and Indexes Returns Before and After 2017

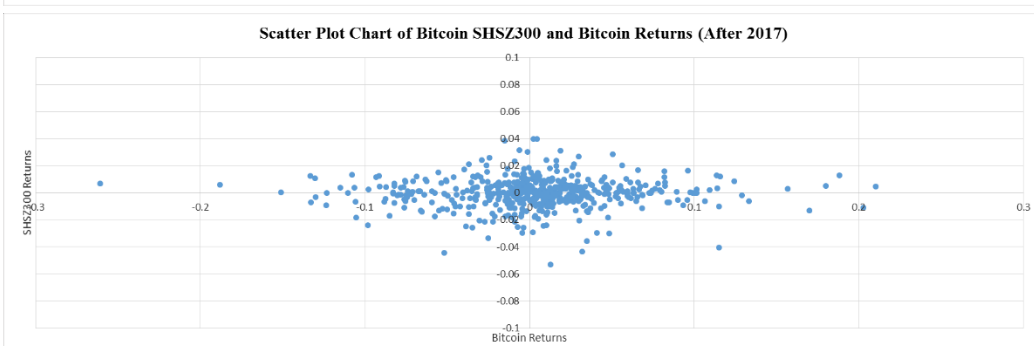
US – S&P 500



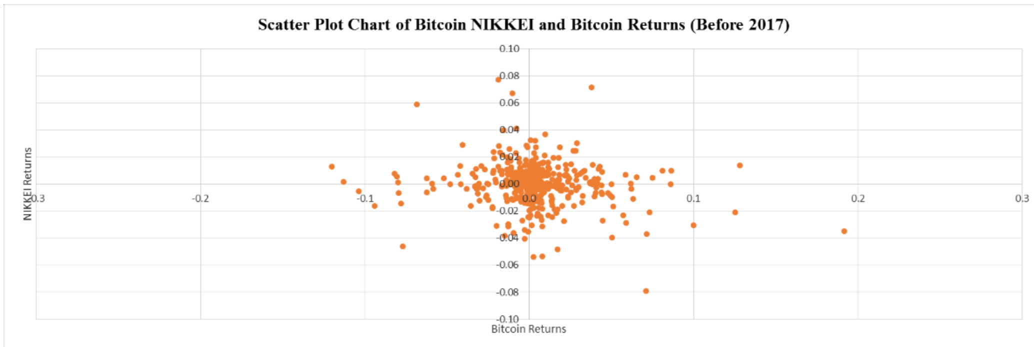


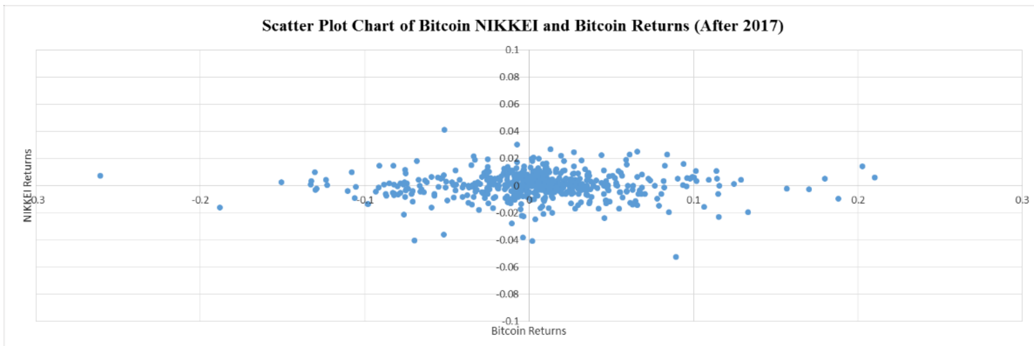
China – SHSZ CSI 300



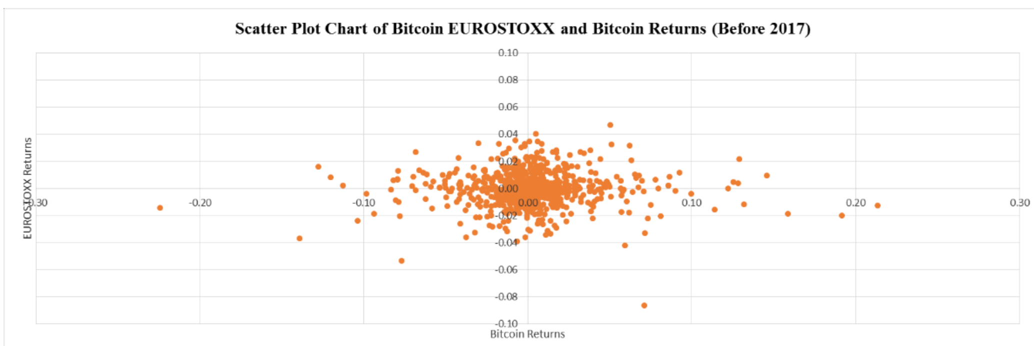


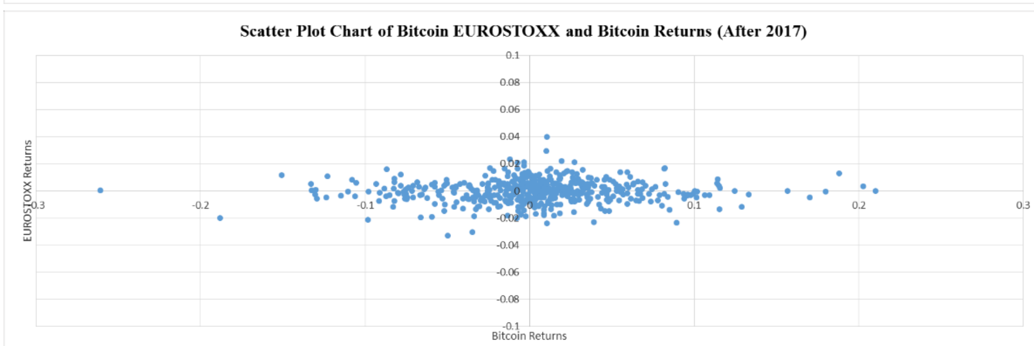
Japan – Nikkei 225



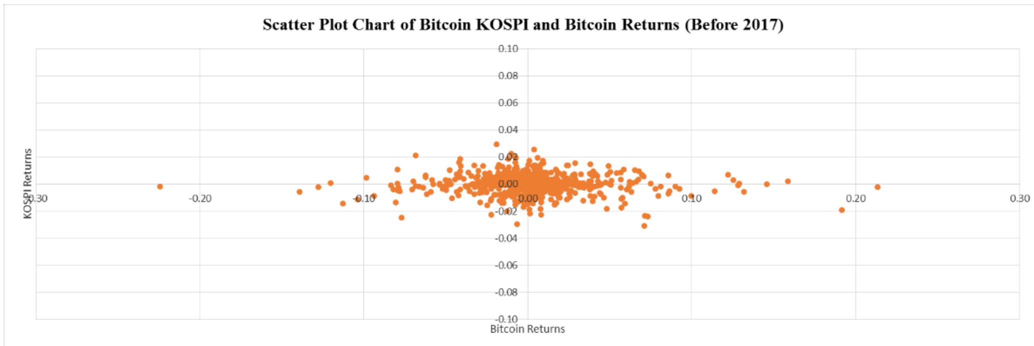


Euro Zone – EUROSTOXX50





Korea – KOSPI 200



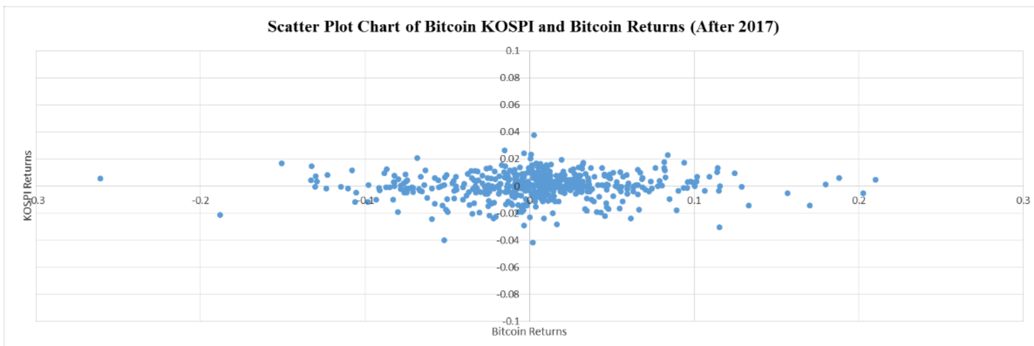


Figure 6. Comparison of Single Exponential Residuals of Bitcoin and Index Price (March 2010 – January 2019)

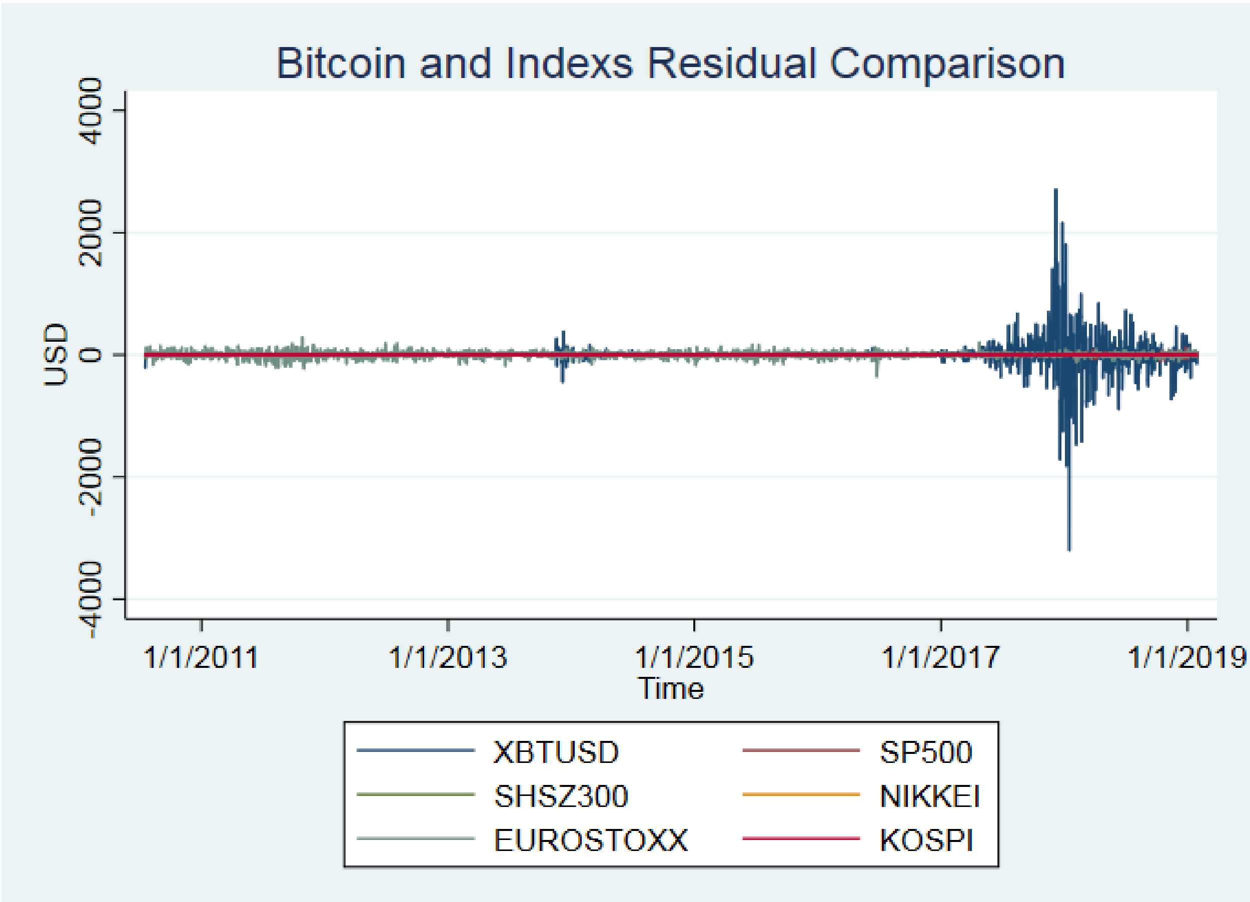


Figure 7. Comparison of Single Exponential Residuals of Bitcoin and Index Price by Country (March 2010 – January 2019)

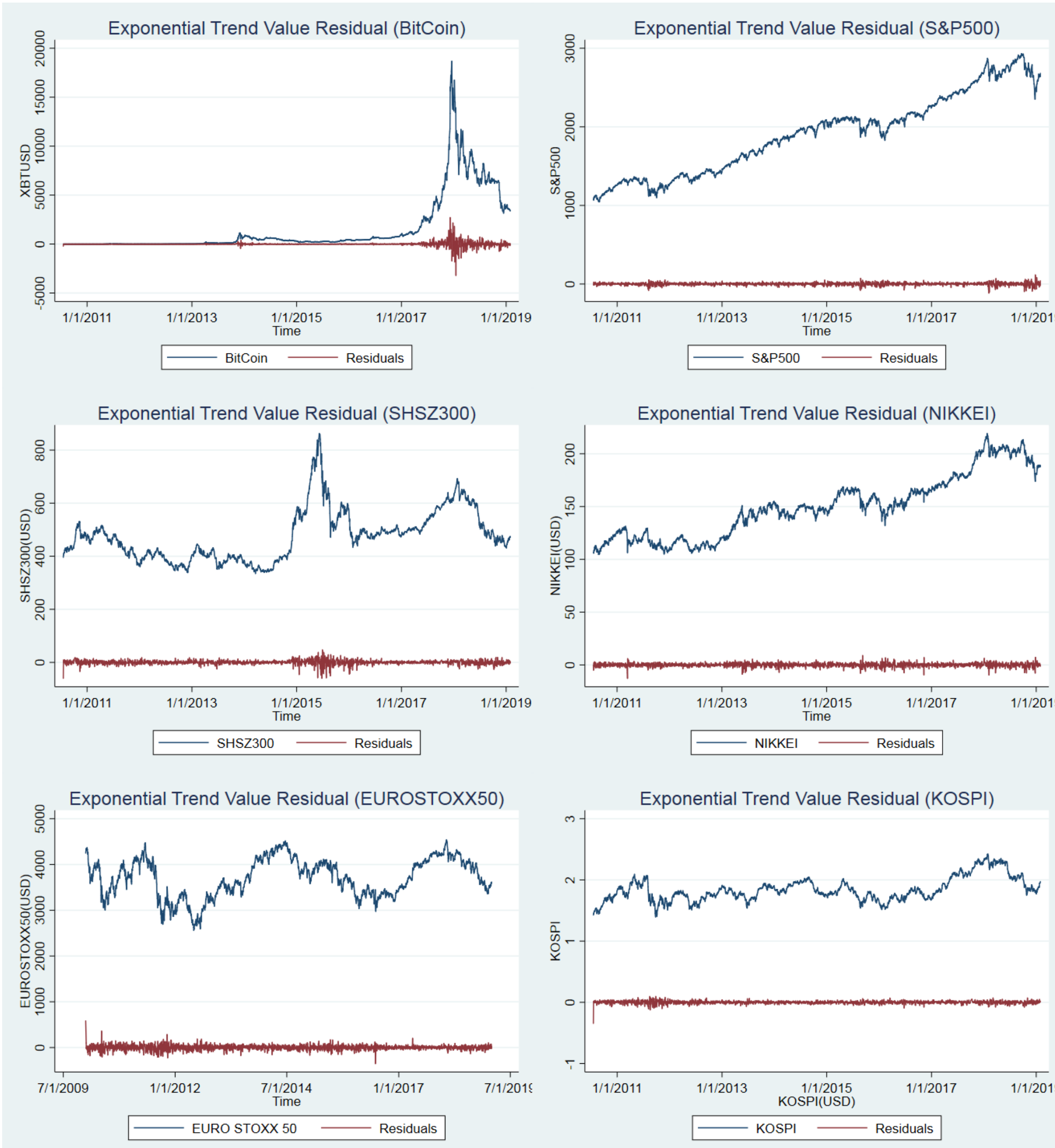


Figure 8. BitCoin Price Changes and Major Exchange Hacks (March 2010 – January 2019)

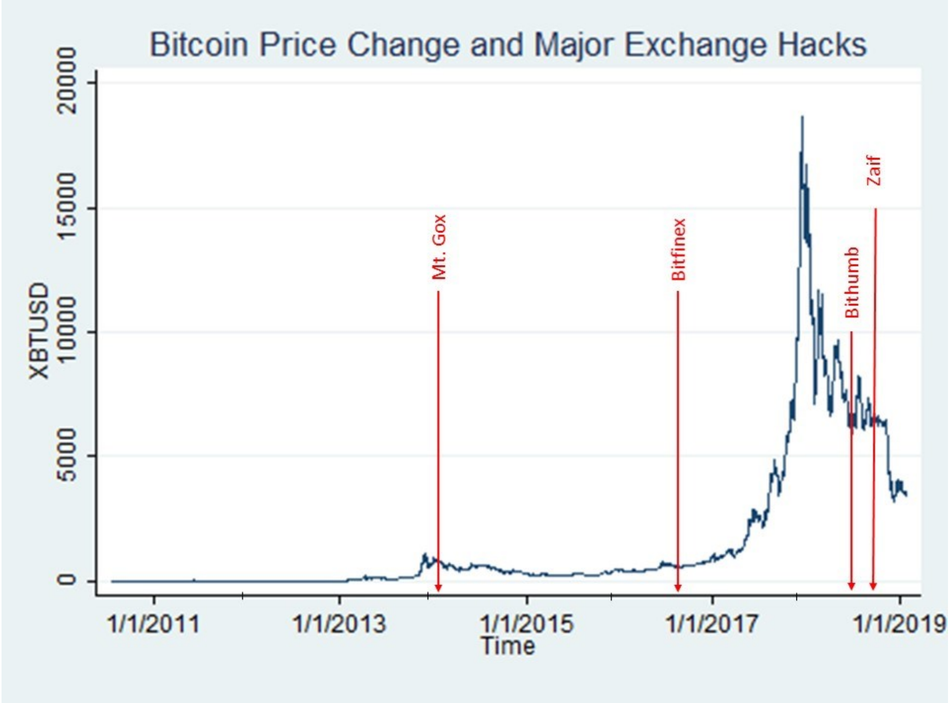


Figure 9. BitCoin Price Changes and Release of Alternative Coins (March 2010 – January 2019)

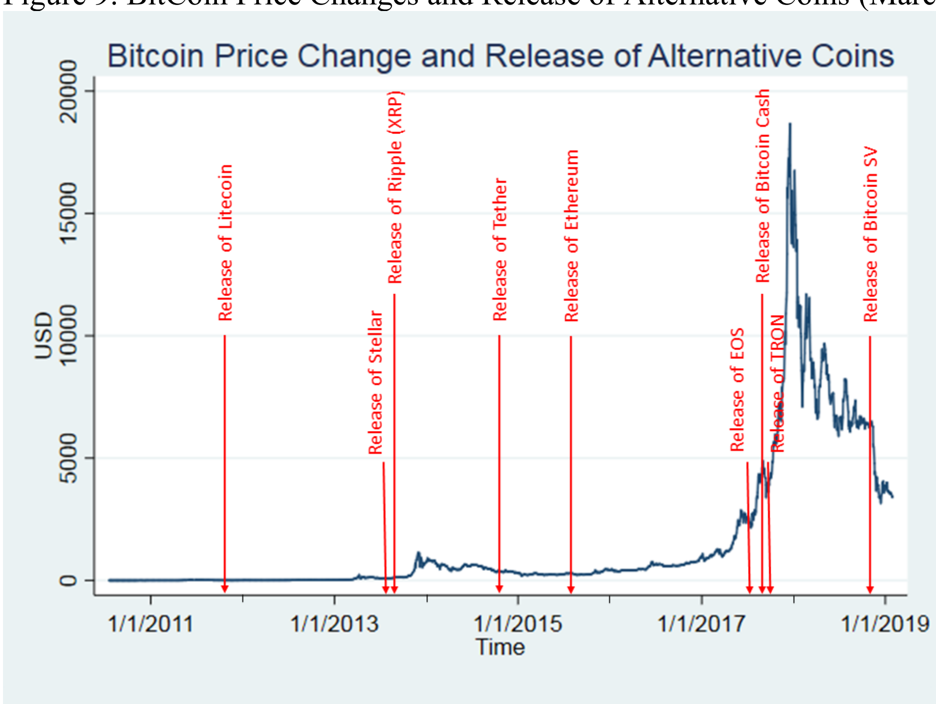
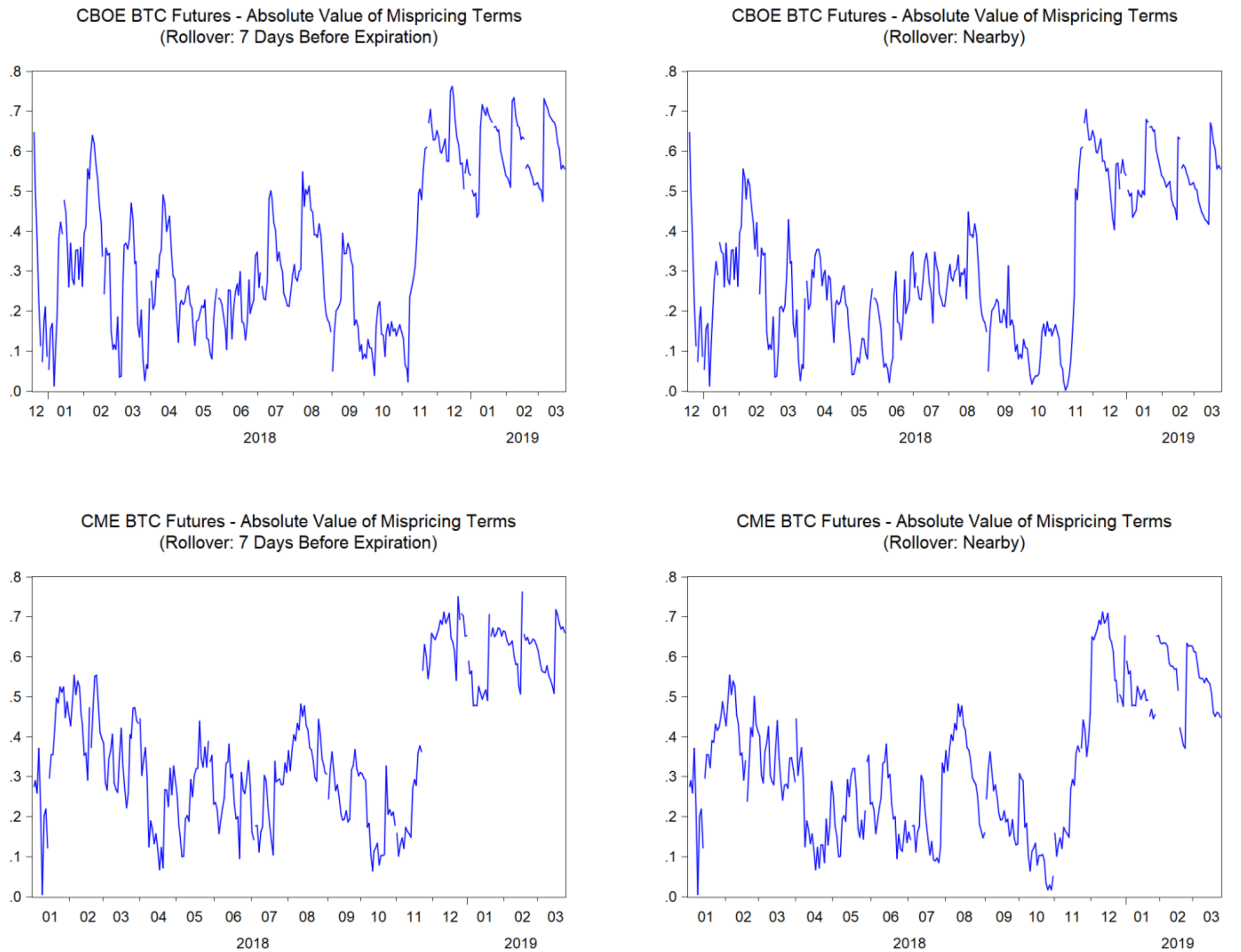


Figure 9. Bitcoin Futures Mispricing Terms (CBOE: December 2017 – March 2019, CME: January 2018 – March 2019)

Figure 10. Absolute Value of Bitcoin Futures Mispricing Terms (CBOE: December 2017 – March 2019, CME: January 2018 – March 2019)



Tables

Table 1: Hofstede's Cultural Dimension Score (Individualism vs Collectivism)

Rank	Country	Score (Individualism)	For our study Dummy = individualism (1) vs. Collectivism (0)
1	United States	91	N/A
2	United Kingdom	89	N/A
3	Canada	80	N/A
3	Netherland	80	N/A
5	Italy	76	N/A
6	Belgium	75	Individualism
7	Denmark	74	Individualism
8	France	71	N/A
8	Sweden	71	Individualism
10	Ireland	70	Individualism
11	Norway	69	Individualism
12	Switzerland	68	N/A
13	Germany	67	N/A
14	Finland	63	Collectivism
15	Austria	55	Collectivism
16	Spain	51	N/A
17	Japan	46	N/A
18	Greece	35	Collectivism
19	Portugal	27	Collectivism

[dataset] Hofstede, G., 2001. The 6-D model of national culture: country comparison. https://www.hofstede-insights.com/country-comparison/

Table 2. Statistics of Indices

We focus on nine relatively small Eurozone countries in this study: Austria, Belgium, Denmark, Finland, Greece, Ireland, Norway, Portugal, and Sweden that were epicenters of European banking crisis, and the European sovereign debt crisis. For each country, we choose the equity index with the longest history as the major stock index to use in this study. The historical prices for those indices are collected from Bloomberg and Thomson Reuters DataStream. This table presents the details of _the nine indices, including time period and the number of observations for each country when we use daily, weekly, and monthly data to calculate risk variables.

No.	Country	Index	Daily Data		Weekly Data		Monthly Data	
			Time Period	Obs.	Time Period	Obs.	Time Period	Obs.
1	Austria	Austrian Traded Index (ATX)	June 5, 1992 - March 24, 2017	6150	June 5, 1992 - March 24, 2017	1295	June 30, 1992 - February 28, 2017	297
2	Belgium	Belgium All Share Index (BELAS)	October 3, 1988 - March 24, 2017	7162	October 7, 1988 - March 24, 2017	1486	October 7, 1988 - February 28, 2017	341
3	Denmark	OMX Copenhagen 20 Index (KFX)	December 4, 1989 - March 24, 2017	6837	December 8, 1989 - March 24, 2017	1425	December 29, 1989 - February 28, 2017	327
4	Finland	OMS Helsinki Index (HEX)	January 30, 1987 - February 28, 2017	7549	January 30, 1987 - February 24, 2017	1570	January 30, 1987 - January 31, 2017	361
5	Greece	Athens Stock Exchange (ASE) Index	Jun 30, 1992 - February 28, 2017	6140	July 3, 1992 - February 24, 2017	1282	July 31, 1992 - January 31, 2017	294
6	Ireland	Irish Overall Index (ISEQ)	January 2, 1987 - March 24, 2017	7609	February 4, 1983 - February 24, 2017	1786	January 31, 1983 - February 28, 2017	410
7	Norway	OMX Oslo All Share Index (OSEAX)	December 29, 1995 - March 24, 2017	5331	December 29, 1995 - March 24, 2017	1109	December 29, 1995 - February 28, 2017	255
8	Portugal	Portugal All Share Index (PSI)	January 5, 1988 - March 24, 2017	7154	January 9, 1988 - March 24, 2017	1520	January 29, 1988 - February 28, 2017	350
9	Sweden	Stockholm All-Share Index (SAX)	January 2, 1987 - February 28, 2017	7573	January 2, 1987 - February 28, 2017	1574	January 31, 1980 - January 31, 2017	445

Table 3. Summary Statistics of Daily/Weekly/Monthly Logarithmatic Percent Changes (i.e. returns) of Indices

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Daily Data												
Austria	0.0168	0.0600	1.3605	-0.3699	7.0939	13033.5632	-4.1698	-2.1652	-1.4002	1.4208	1.9056	3.4388
Belgium	0.0296	0.0599	1.0437	-0.1100	7.6207	17342.4548	-2.9831	-1.6847	-1.0868	1.0716	1.5673	2.7324
Denmark	0.0312	0.0596	1.1896	-0.2878	5.4294	8490.7097	-3.3404	-1.8812	-1.2997	1.3315	1.8244	3.0799
Finland	0.0283	0.0560	1.6216	-0.2981	7.6116	18332.9331	-4.6496	-2.5136	-1.6873	1.6915	2.4616	4.5382
Greece	-0.0047	0.0115	1.8742	-0.2601	5.6020	8096.5801	-5.4298	-2.9842	-2.0064	2.0397	2.8572	5.1334
Ireland	0.0238	0.0495	1.2607	-0.8218	10.5498	36138.0111	-3.8700	-1.8522	-1.2400	1.3019	1.7842	3.3301
Norway	0.0381	0.1043	1.3554	-0.5958	6.0898	8551.5429	-4.1378	-2.1205	-1.4159	1.4479	2.0026	3.3202
Portugal	0.0131	0.0140	1.0759	-0.3667	9.7827	28683.4787	-3.1829	-1.6620	-1.0920	1.1272	1.6241	2.8246
Sweden	0.0342	0.0801	1.3225	-0.1239	5.3008	8884.3645	-3.8125	-2.0677	-1.4092	1.4066	1.9700	3.5672
Panel B. Weekly Data												
Austria	0.0801	0.2580	3.0910	-1.4792	14.4433	11719.3723	-8.2113	-4.5514	-3.4394	3.2815	4.3767	6.7723
Belgium	0.1420	0.3113	2.3731	-1.4583	14.9052	14272.7576	-6.7343	-3.9823	-2.4188	2.6087	3.4002	5.7797
Denmark	0.1512	0.3175	2.6330	-0.9537	6.6591	2846.9231	-7.0802	-4.1158	-2.8720	3.0625	3.8407	5.8779
Finland	0.1362	0.2652	3.5620	-0.5548	3.6421	947.6775	-10.1309	-5.5977	-4.0108	4.0295	5.6184	8.7303
Greece	-0.0185	0.0574	4.2358	-0.1996	3.3167	595.6637	-12.0981	-6.9053	-4.8627	4.6592	6.1885	10.9949
Ireland	0.1702	0.3937	2.8646	-1.5298	12.7169	12724.0204	-8.5059	-4.1356	-2.8895	3.2471	4.2346	6.6763
Norway	0.1834	0.5046	2.9096	-1.1327	7.3826	2753.1451	-8.3526	-4.8245	-2.9110	3.0252	3.8062	6.8770
Portugal	0.0528	0.1028	2.5132	-0.7780	6.2558	2630.1025	-8.2099	-3.7179	-2.7498	2.7429	3.9139	6.5868
Sweden	0.1646	0.4128	2.8486	-0.6693	5.4360	2054.1876	-7.6722	-4.5096	-3.1517	3.1939	4.2327	7.1231

Panel C. Monthly Data

Austria	0.3615	1.0892	6.1555	-1.1407	3.7602	238.5806	-18.5845	-10.1973	-6.9855	7.5428	8.8351	12.4084
Belgium	0.6137	1.0386	4.6288	-1.0080	2.4974	145.9397	-14.5691	-8.1971	-4.6983	5.3307	6.7679	9.5863
Denmark	0.6637	0.9758	5.3089	-0.5545	1.3498	41.4537	-14.8811	-8.1400	-6.0569	6.9451	8.2421	11.6878
Finland	0.5861	0.6732	7.4341	-0.2154	1.6876	45.5041	-19.1259	-11.3699	-8.3427	8.8410	11.4745	20.3757
Greece	-0.0887	0.4265	9.0829	-0.2345	1.3781	25.8701	-25.3191	-15.4895	-11.8359	10.4745	14.0990	20.0462
Ireland	0.7458	1.3983	6.0320	-1.0131	3.2589	250.9545	-17.6699	-9.1039	-6.3349	7.1754	9.5612	12.6107
Norway	0.8019	1.3902	5.9166	-1.3484	4.4471	286.2679	-22.8869	-8.3305	-5.5780	7.3036	8.8279	11.1287
Portugal	0.2573	0.3602	5.4960	-0.4136	2.3449	89.9131	-16.1342	-8.3648	-5.9919	6.6518	8.8381	14.5988
Sweden	1.0082	1.2433	5.9358	-0.4064	2.0092	86.9052	-15.3517	-9.3336	-6.1547	7.7278	10.2612	14.0407

Panel D. Whole sample period vs. crisis period.

Period	Observation	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
								1%	5%	10%	90%	95%	99%
Austria													
Jun 1992 - Feb 2017	296	0.3615	1.0892	6.1555	-1.1407	3.7602	238.5806	-18.5845	-10.1973	-6.9855	7.5428	8.8351	12.4084
2009	12	2.9535	3.3022	8.5102	-0.8379	0.7025	1.6508	-14.7698	-10.4303	-5.4879	12.0763	12.8230	13.4021
2008	12	-7.8906	-5.1448	12.6039	-0.6202	0.3061	0.8161	-31.9413	-29.3298	-25.6027	2.7774	7.2486	11.4020
Belgium													
Oct 1988 - Feb 2017	340	0.6137	1.0386	4.6288	-1.0080	2.4974	145.9397	-14.5691	-8.1971	-4.6983	5.3307	6.7679	9.5863
2009	12	2.0548	3.2581	6.0660	-0.4587	-0.3349	0.4768	-9.1809	-6.9306	-4.5274	9.2403	10.0677	10.5426
2008	12	-5.3790	-3.6539	9.0788	-0.2209	-1.2006	0.8183	-20.1941	-17.5311	-14.7823	5.2510	6.3431	7.1137
Denmark													
Dec 1989 - Feb 2017	326	0.6637	0.9758	5.3089	-0.5545	1.3498	41.4537	-14.8811	-8.1400	-6.0569	6.9451	8.2421	11.6878
2009	12	2.5572	1.8970	7.0328	0.7288	1.3946	2.0348	-7.8010	-6.7073	-5.3600	7.3126	12.3817	17.2850
2008	12	-5.2324	-3.8184	8.9896	-0.4373	-0.6429	0.5892	-20.5937	-19.7455	-18.2835	5.1821	6.4481	7.2954

Finland													
Jan 1987 - Jan 2017	360	0.5861	0.6732	7.4341	-0.2154	1.6876	45.5041	-19.1259	-11.3699	-8.3427	8.8410	11.4745	20.3757
2009	12	1.4832	2.5201	8.6403	0.1700	1.4814	1.1552	-14.0734	-10.4541	-6.6444	7.7624	13.2955	18.4713
2008	12	-6.3652	-6.1905	6.8957	-0.6141	-0.4420	0.8520	-19.5638	-16.3998	-13.0412	0.5285	0.8950	1.2246
Greece													
Jul 1992 - Jan 2017	293	-0.0887	0.4265	9.0829	-0.2345	1.3781	25.8701	-25.3191	-15.4895	-11.8359	10.4745	14.0990	20.0462
2009	12	1.7204	2.6189	10.7347	-0.3204	-0.1370	0.2147	-16.8673	-15.8082	-13.7705	12.1840	15.8038	19.0224
2008	12	-8.8693	-6.1391	10.3716	-1.0793	1.3006	3.1757	-31.2140	-25.3777	-19.1827	-0.9396	2.0115	4.8559
Ireland													
Jan 1983 - Feb 2017	409	0.7458	1.3983	6.0320	-1.0131	3.2589	250.9545	-17.6699	-9.1039	-6.3349	7.1754	9.5612	12.6107
2009	12	1.9889	3.4268	9.0016	-0.4051	0.5340	0.4708	-14.9858	-12.9271	-9.9477	10.1154	13.7264	17.0055
2008	12	-9.0412	-5.9859	8.7199	-0.1941	-1.2916	0.9095	-22.9332	-20.3369	-17.6670	1.9485	2.6709	2.7593
Norway													
Dec 1995 - Feb 2017	254	0.8019	1.3902	5.9166	-1.3484	4.4471	286.2679	-22.8869	-8.3305	-5.5780	7.3036	8.8279	11.1287
2009	12	3.6776	4.0228	5.2600	0.1802	0.6893	0.3025	-5.3866	-4.1903	-2.5998	9.6991	11.8826	13.5900
2008	12	-6.2202	-5.2617	12.8421	-0.4010	-0.9388	0.7624	-27.0131	-25.6363	-23.9752	7.6412	9.4098	11.0751
Portugal													
Jan 1988 - Feb 2017	349	0.2573	0.3602	5.4960	-0.4136	2.3449	89.9131	-16.1342	-8.3648	-5.9919	6.6518	8.8381	14.5988
2009	12	2.8017	2.6839	4.9600	-0.0534	-0.6464	0.2146	-5.5719	-3.9126	-2.1452	8.1656	9.3783	10.5464
2008	12	-5.7293	-2.5220	8.6310	-0.8762	0.0096	1.5356	-22.6329	-19.3963	-16.0307	2.2100	3.8644	5.2217
Sweden													
Jan 1980 - Jan 2017	444	1.0082	1.2433	5.9358	-0.4064	2.0092	86.9052	-15.3517	-9.3336	-6.1547	7.7278	10.2612	14.0407
2009	12	3.1910	1.9663	5.6680	1.2865	3.1955	8.4160	-5.3646	-2.7040	0.0672	9.1543	13.0364	16.3422
2008	12	-4.5332	-1.3914	8.3117	-0.7971	-1.0682	1.8412	-19.2165	-17.2613	-15.0661	3.0916	3.3752	3.5383

Table 4. The Top 15-year Rankings of Volatility as Measured by Standard Deviation and by the Percentage of Extreme Days for Each of the Nine European Countries

	Austria				Belgium				
	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	47.9863	2008	28.4000	2008	35.7265	2008	35.7265	1
2	2009	35.7144	2009	24.1935	2002	25.6784	2002	25.6784	2
3	2011	29.1925	2011	13.3065	2009	22.5379	2009	22.5379	3
4	1998	24.3126	1992	8.4507	2011	21.2453	2011	21.2453	4
5	2010	23.8813	2012	7.6923	2015	20.5910	2015	20.5910	5
6	2016	21.8380	1998	7.6613	2003	19.8203	2003	19.8203	6
7	2012	21.7115	2010	7.6305	2010	19.5069	2010	19.5069	7
8	2006	20.5959	2016	5.622	2016	18.9441	2016	18.9441	8
9	2007	20.2668	1997	5.2632	1998	18.6076	1998	18.6076	9
10	1997	20.1104	2007	4.4534	1999	16.0590	1999	16.0590	10
11	2015	20.0032	2015	4.0323	2014	15.8120	2014	15.8120	11
12	1992	18.5516	2006	3.6585	2000	15.6013	2000	15.6013	12
13	2014	16.8607	2000	3.2520	2007	15.2289	2007	15.2289	13
14	1993	16.6748	1993	3.2129	2001	14.7436	2001	14.7436	14
15	1999	16.2005	2014	2.8340	2013	14.5637	2013	14.5637	15

	Denmark				Finland				
	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	38.4943	2008	23.2000	2000	54.7089	2000	35.4582	1
2	2009	26.6886	2009	12.4498	2001	51.0954	2001	33.3333	2
3	2002	24.4199	2002	10.0402	2002	39.1523	2002	24.8996	3
4	1998	23.3034	1998	9.6000	2008	37.5657	2008	15.4150	4
5	2016	22.0259	2001	8.8353	1998	33.0828	1999	13.5458	5
6	2000	21.8666	2011	8.3333	1999	31.0529	1998	12.8000	6
7	2011	21.2402	2016	7.5397	2009	29.9125	2011	12.6482	7
8	2015	20.4903	2000	7.1713	2011	28.2242	2009	12.3506	8
9	2001	19.9714	2015	6.0241	2003	27.8146	2003	9.2000	9
10	2010	19.8851	1992	5.6000	1997	23.4500	1992	4.3825	10
11	2003	17.9649	2010	5.5777	1995	22.5236	1997	4.0161	11
12	2007	17.6929	2007	4.8193	1992	22.0537	2007	3.2000	12
13	1992	17.4694	2003	4.0161	2012	20.8853	2006	3.1873	13
14	2012	16.0330	2006	3.9683	1993	20.3695	2012	2.8000	14
15	2006	15.8967	2012	3.6145	2004	20.1625	2010	2.7778	15

Table 4. Cont'd

	Greece				Ireland				
	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2015	46.4653	2015	16.1435	2008	47.8976	2008	35.8268	1
2	2012	39.9886	2012	15.6627	2009	32.6774	2009	23.7154	2
3	2008	38.8718	1998	13.9442	1987	30.7513	2007	11.4173	3
4	1998	38.4077	1999	13.6000	2010	25.2077	2010	11.0236	4
5	1999	37.6695	2008	12.9555	2007	23.2181	2011	10.6719	5
6	2011	37.0962	2011	11.5538	2011	22.8458	1987	10.3586	6
7	2014	34.6443	2010	9.1270	2016	22.7368	2002	10.2767	7
8	2010	34.1359	2009	8.4677	1998	22.5521	1998	10.0000	8
9	2009	33.2648	2013	8.1301	2002	22.0552	2001	7.1146	9
10	2000	32.4245	2014	7.2581	2001	19.4826	2016	6.2992	10
11	2016	32.0999	2000	6.7460	2015	18.8086	2000	5.2209	11
12	1997	31.0177	2016	6.4257	2000	17.6076	2015	5.1181	12
13	2013	30.4778	2001	5.6000	1990	16.7002	1990	4.3825	13
14	2001	28.6758	1997	5.0980	1999	16.4688	1988	3.9841	14
15	1993	26.0297	1993	4.3307	2014	16.2031	2014	3.9370	15

	Norway				Portugal				
	Geometric Standard Deviation		Percentage of Extreme Days		Geometric Standard Deviation		Percentage of Extreme Days		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	46.8717	2008	24.2063%	2008	32.8977	2008	25.3906%	1
2	2009	31.7568	2009	17.5299%	1998	26.4106	1998	21.8623%	2
3	1998	25.2844	2011	9.0909%	2010	22.3970	2011	18.2879%	3
4	2011	24.6472	1998	8.3665%	2011	22.0392	2015	16.7969%	4
5	2006	24.0700	2006	6.7729%	2015	22.0009	2014	14.9020%	5
6	2010	21.1818	2002	6.0241%	2014	20.0170	2010	13.9535%	6
7	2002	20.7336	2016	5.5336%	2000	19.3877	2000	13.9344%	7
8	2016	20.3397	2010	5.1587%	2016	19.3550	2016	12.4514%	8
9	2007	19.7297	2000	4.7809%	1989	18.0892	1988	12.1827%	9
10	2000	19.3475	2001	3.6290%	1988	17.9535	2009	9.7656%	10
11	2001	19.1654	2005	3.5573%	2009	17.5111	2012	8.9844%	11
12	2015	17.6858	2014	3.2000%	2012	17.2451	2013	8.6275%	12
13	2005	17.5407	2007	3.2000%	2001	16.9526	2001	8.0972%	13
14	2012	16.5922	2012	3.1873%	2013	16.8674	1999	7.6613%	14
15	1999	16.0560	1999	1.9841%	1997	16.3335	2002	6.9106%	15

Table 4. Cont'd

	Sweden			
	Geometric Standard Deviation		Percentage of Extreme Days	
Rank	Year	GeoStdDev(%)	Year	L(%)
1	2008	37.9923	2008	21.0317%
2	2001	29.9827	2000	15.9363%
3	2002	29.2078	2002	14.0000%
4	2000	28.5168	2001	12.8000%
5	1987	28.2888	2009	11.5538%
6	2009	27.2778	2011	10.6719%
7	2011	26.9015	1998	10.0000%
8	1998	26.7977	1987	8.0000%
9	1992	23.7326	1992	7.1713%
10	2007	19.4590	2007	5.2000%
11	1990	19.3971	1990	4.8000%
12	2003	19.2338	2003	4.4177%
13	2016	19.2001	2006	4.3825%
14	1997	19.1660	1997	4.0161%
15	2015	18.6994	2016	3.9526%

Table 5. The Top 15-year Rankings of Volatility as Measured by Standard Deviation and by the Percentage of Extreme Weeks for Each of the Nine European Countries

	Austria				Belgium				
	Geometric Standard Deviation		Percentage of Extreme Weeks		Geometric Standard Deviation		Percentage of Extreme Weeks		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	51.7178	2008	59.6154	2008	37.2575	2008	63.4615	1
2	2009	36.6474	2009	57.6923	2009	24.4423	2011	53.8462	2
3	2011	29.6846	1992	48.2759	2011	22.1039	2009	51.9231	3
4	2010	25.6182	2010	45.2830	2001	21.4142	1997	50.0000	4
5	1998	23.8982	1998	44.2308	1998	21.3581	2002	46.1538	5
6	1992	23.2436	2011	38.4615	2002	20.7649	1999	45.2830	6
7	2006	21.5954	2014	36.5385	2003	19.4470	1998	44.2308	7
8	2012	19.5731	2012	34.6154	2015	17.9414	2015	42.3077	8
9	2016	19.5607	1997	34.6154	2010	17.8058	2010	41.5094	9
10	2007	19.4641	2015	32.6923	1990	17.6666	2014	36.5385	10
11	1999	19.4486	1999	32.0755	1999	17.5854	2013	36.5385	11
12	1997	19.1372	1993	32.0755	2016	17.4139	2003	36.5385	12
13	2014	19.0307	2016	30.1887	2007	16.4739	1990	36.5385	13
14	2015	18.4312	2007	28.8462	1997	16.3341	2016	35.8491	14
15	1993	18.1802	2006	28.8462	2000	16.1972	2007	34.6154	15

	Denmark				Finland				
	Geometric Standard Deviation		Percentage of Extreme Weeks		Geometric Standard Deviation		Percentage of Extreme Weeks		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	40.6063	2009	51.9231	2000	52.3659	2000	67.3077	1
2	2009	28.7925	2008	46.1538	2001	48.5823	2002	61.5385	2
3	2001	23.9041	1998	42.3077	2008	35.3267	2001	61.5385	3
4	2016	21.4325	2000	40.3846	2002	34.4546	2008	50.0000	4
5	2011	21.2590	1997	40.3846	1998	32.4487	1999	49.0566	5
6	2010	21.1865	2015	36.5385	2011	29.8203	2009	48.0769	6
7	2002	20.6397	2001	36.5385	2009	29.0908	1998	44.2308	7
8	2000	19.3637	2002	34.6154	2003	28.0922	2011	42.3077	8
9	1998	19.2449	2016	33.9623	1999	27.9954	2003	42.3077	9
10	1992	19.2035	2003	32.6923	1992	27.5150	1992	40.3846	10
11	1997	18.3778	1992	32.6923	1995	25.5737	1993	37.7358	11
12	2015	17.5312	1999	32.0755	1993	24.5855	1995	36.5385	12
13	1999	16.9973	2011	30.7692	2004	23.4496	1991	34.6154	13
14	1990	16.6178	2010	30.1887	1997	21.7572	1997	32.6923	14
15	2007	16.6049	1993	30.1887	2012	20.6029	1994	28.8462	15

Table 5. Cont'd

	Greece				Ireland				
	Geometric Standard Deviation		Percentage of Extreme Weeks		Geometric Standard Deviation		Percentage of Extreme Weeks		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	1998	45.5930	2009	57.6923	2008	50.4654	2008	69.2308	1
2	2015	42.9724	1999	56.6038	1987	37.6552	2009	67.3077	2
3	2014	41.8967	2011	51.9231	2009	34.7781	2007	51.9231	3
4	2008	40.9340	2014	50.0000	1998	26.0643	1987	50.0000	4
5	1999	40.8248	2015	48.9362	2001	24.6354	1998	42.3077	5
6	2012	39.8754	2013	48.0769	2007	23.9698	2001	40.3846	6
7	2011	33.6441	1998	48.0769	2010	23.3425	2010	39.6226	7
8	2013	33.4140	2012	46.1538	2011	22.0351	1986	38.4615	8
9	2000	33.3201	2010	45.2830	2002	21.6112	2014	36.5385	9
10	2009	33.2355	2008	44.2308	1986	20.3187	2011	36.5385	10
11	2010	31.3972	1997	42.3077	2014	18.8292	1994	36.5385	11
12	2001	31.1299	2000	34.6154	1990	18.6988	2015	34.6154	12
13	1997	30.6134	2001	32.6923	2016	17.3470	2002	34.6154	13
14	2016	28.9728	2016	32.0755	2000	17.2497	1990	32.6923	14
15	1992	23.2622	1992	32.0000	1988	16.8934	2000	30.7692	15

	Norway				Portugal				
	Geometric Standard Deviation		Percentage of Extreme Weeks		Geometric Standard Deviation		Percentage of Extreme Weeks		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	45.8560	2008	55.7692	2008	33.2408	1998	76.9231	1
2	2009	29.1440	2009	50.0000	1998	31.7820	2014	59.6154	2
3	1998	28.1193	1998	40.3846	2014	24.7682	2008	55.7692	3
4	2001	23.5154	2010	33.9623	1988	23.6870	2010	52.8302	4
5	2011	22.9092	2007	30.7692	2010	22.1164	2016	50.9434	5
6	2006	21.1417	2006	30.7692	2011	21.2006	2015	50.0000	6
7	2010	20.6750	2002	30.7692	2015	20.5779	1997	50.0000	7
8	1999	18.6570	2011	28.8462	2016	19.3491	2009	48.0769	8
9	2002	18.5096	1999	26.4151	1997	19.1329	2011	46.1538	9
10	2016	18.1036	2001	25.0000	2001	18.8394	1988	43.1373	10
11	2007	17.8288	2016	24.5283	2000	18.7302	2007	42.3077	11
12	2005	17.3425	2005	23.0769	1989	18.6647	2000	42.3077	12
13	2014	17.0615	2003	23.0769	1999	18.0941	1999	41.5094	13
14	2000	16.7580	2014	21.1538	2009	17.9053	2002	40.3846	14
15	2003	15.8350	1997	21.1538	1990	17.8543	2001	40.3846	15

Table 5. Cont'd

	Sweden			
	Geometric Standard Deviation		Percentage of Extreme Weeks	
Rank	Year	GeoStdDev(%)	Year	L(%)
1	2008	38.0421	2001	57.6923
2	1998	28.6410	2000	55.7692
3	2000	27.3161	2002	53.8462
4	2001	27.0393	2008	48.0769
5	2002	26.8213	2009	44.2308
6	2011	26.7513	1998	44.2308
7	1990	26.5180	2011	36.5385
8	1987	25.8891	1990	34.6154
9	1992	25.7377	1992	32.6923
10	2009	25.5469	1991	32.6923
11	1991	18.6649	1987	31.3725
12	2010	18.6029	1999	30.1887
13	2007	18.5062	2003	26.9231
14	1994	18.0107	1994	26.9231
15	1997	17.9156	1993	24.5283

Table 6. The Top 15-year Rankings of Volatility as Measured by Standard Deviation and by the Percentage of Extreme Months for Each of the Nine European Countries

	Austria				Belgium				
	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	43.6612	1993	91.6667	2008	31.4498	1998	91.6667	1
2	2009	29.4802	2008	83.3333	1998	23.5242	1997	91.6667	2
3	1998	29.1508	2005	83.3333	2002	21.6430	2009	83.3333	3
4	1997	23.1339	2016	75.0000	1990	21.2586	2005	83.3333	4
5	1993	21.8066	2015	75.0000	2009	21.0132	2004	83.3333	5
6	2010	21.5577	1997	75.0000	2003	20.1805	2015	75.0000	6
7	1992	21.3587	2012	66.6667	2015	19.1744	2008	75.0000	7
8	1999	20.8975	2010	66.6667	2000	17.0880	1989	75.0000	8
9	2015	20.4569	2009	66.6667	1997	16.5425	2014	66.6667	9
10	2011	20.3502	2004	66.6667	1991	15.0907	2012	66.6667	10
11	2012	18.0167	2002	66.6667	1989	13.9651	2010	66.6667	11
12	2016	17.9077	1999	66.6667	2010	13.5704	1993	66.6667	12
13	2001	17.7594	1998	66.6667	2001	13.3557	1990	66.6667	13
14	2006	17.4930	1994	66.6667	1992	12.2344	2011	58.3333	14
15	1996	16.8506	1992	66.6667	1999	12.0797	2007	58.3333	15

	Denmark				Finland				
	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	31.1409	2016	83.3333	2001	58.8500	2001	100.0000	1
2	2009	24.3624	2002	83.3333	1992	39.5677	2004	91.6667	2
3	1998	23.1493	1997	83.3333	2002	35.0402	2002	91.6667	3
4	2001	22.9897	1992	83.3333	1999	34.1264	1998	91.6667	4
5	2002	22.8876	2009	75.0000	1998	33.2609	1997	83.3333	5
6	2003	21.2062	1990	75.0000	2009	29.9307	1994	83.3333	6
7	1990	21.1136	2015	66.6667	1991	28.2831	1993	83.3333	7
8	1992	20.2355	2010	66.6667	1995	26.0440	1987	81.8182	8
9	2011	19.0249	2008	66.6667	2004	25.1911	2015	75.0000	9
10	1997	18.5076	2005	66.6667	1994	24.9458	2011	75.0000	10
11	2015	18.3247	2003	66.6667	2003	24.3057	2009	75.0000	11
12	1994	17.1399	2001	66.6667	1997	24.2671	2000	75.0000	12
13	2000	17.0473	1999	66.6667	2008	23.8874	1999	75.0000	13
14	1993	16.0979	1993	66.6667	2000	21.2439	1992	75.0000	14
15	2012	15.3780	2011	58.3333	1990	20.9775	1991	75.0000	15

Table 6. Cont'd

	Greece				Ireland				
	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	1998	56.6405	2010	91.6667	1987	45.1398	2008	100.0000	1
2	2012	43.5045	2000	83.3333	2009	31.1825	2001	91.6667	2
3	2015	40.4667	1997	83.3333	2008	30.2065	1992	91.6667	3
4	1997	37.4118	2012	75.0000	1998	27.0171	2005	83.3333	4
5	2009	37.1860	2009	75.0000	2002	26.6785	2002	83.3333	5
6	2008	35.9283	2008	75.0000	1990	25.1560	1997	83.3333	6
7	2013	35.1912	2003	75.0000	2010	23.3673	1990	83.3333	7
8	2011	34.6977	2001	75.0000	1986	22.2488	1987	83.3333	8
9	2000	33.8414	1999	75.0000	1991	22.1082	1985	83.3333	9
10	2010	32.2309	2015	72.7273	2001	22.0702	1983	81.8182	10
11	2001	31.0690	2016	66.6667	1988	21.2369	2009	75.0000	11
12	2016	30.6310	2013	66.6667	2016	20.1764	1994	75.0000	12
13	2003	27.3089	1998	66.6667	1984	19.1826	1986	75.0000	13
14	2014	26.9293	2014	58.3333	2000	19.0909	1984	75.0000	14
15	1993	23.9730	2011	58.3333	1985	18.7222	2016	66.6667	15

	Norway				Portugal				
	Geometric Standard Deviation		Percentage of Extreme Months		Geometric Standard Deviation		Percentage of Extreme Months		
Rank	Year	GeoStdDev(%)	Year	L(%)	Year	GeoStdDev(%)	Year	L(%)	Rank
1	2008	44.4863	2005	91.6667	1998	38.1811	1988	100.0000	1
2	1998	32.4518	2008	83.3333	2008	29.8985	1998	91.6667	2
3	2002	22.4656	2007	83.3333	1989	25.1228	1997	91.6667	3
4	2001	21.7071	2003	83.3333	1988	24.5670	1994	91.6667	4
5	2010	20.4839	2002	83.3333	2002	23.0465	2002	83.3333	5
6	2003	20.1908	2001	83.3333	2000	21.9241	1999	83.3333	6
7	2005	19.1972	2010	75.0000	1997	19.6740	1993	83.3333	7
8	2009	18.2212	2009	75.0000	2015	19.2287	2015	75.0000	8
9	1999	17.9293	2004	66.6667	2010	19.1633	2014	75.0000	9
10	2011	16.7016	2000	66.6667	2014	18.4535	2012	75.0000	10
11	2006	16.6438	1998	66.6667	2001	17.8566	2010	75.0000	11
12	2000	16.5380	2006	58.3333	1994	17.1879	2009	75.0000	12
13	2004	15.6969	1999	58.3333	2009	17.1818	2003	75.0000	13
14	2012	13.8440	2015	50.0000	2007	16.3367	1989	75.0000	14
15	1997	13.8072	1997	50.0000	1999	16.2677	2016	66.6667	15

Table 6. Cont'd

	Sweden			
	Geometric Standard Deviation		Percentage of Extreme Months	
Rank	Year	GeoStdDev(%)	Year	L(%)
1	1987	37.0711	1997	91.6667
2	1992	32.3222	2002	83.3333
3	2002	31.7092	1987	83.3333
4	2001	30.5038	2015	75.0000
5	1990	29.5851	2001	75.0000
6	1983	28.8175	1989	75.0000
7	2008	28.7925	1988	75.0000
8	1998	25.9940	1983	75.0000
9	1994	21.7047	1981	75.0000
10	1993	21.0375	2005	66.6667
11	2000	20.9825	2003	66.6667
12	1981	20.2546	1998	66.6667
13	1997	19.9931	1994	66.6667
14	1991	19.8585	1993	66.6667
15	2009	19.6344	1992	66.6667

Table 7. Regression Results of Equity Mutual Fund Net Flows on Risk Measures for Small Eurozone Countries

	Austria (1996-2012)			Belgium (1995-2013)		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable (Austria: n=17; Belgium: n=19)						
Constant	2.4426	7.7979	6.9923	2.4233	2.8781	0.3985
	0.77	3.98	3.88	0.63	0.65	0.10
GeoMean(t-1)	9.5968	8.1307	26.7668	0.0000	-6.0533	-1.5173
	0.81	0.82	2.08	-	-0.20	-0.06
GeoStdDev(t-1)	0.4081			-1.7749		
	2.20			-0.08		
TotalExtr(t-1)		0.1976			-0.0345	
		2.85			-0.23	
NegExtr(t-1)			0.7464			1.1290
			2.65			2.22
PosExtr(t-1)			-0.4502			-1.7044
			-1.36			-2.38
Time	-0.5968	-0.6136	-0.7059	0.3782	0.4107	0.5843
	-2.15	-2.52	-3.17	1.13	1.09	1.75
Dummy Variable	-9.7441	-9.3226	-10.7261	-23.4073	-23.4763	-28.1261
	-2.43	-2.55	0.00	-3.24	-3.14	-4.16
Adjusted R Square	0.3863	0.4860	0.0596	0.3307	0.3567	0.5162
	Austria (1996-2012)			Belgium (1995-2013)		
	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
Panel B: Annual Observation without Financial Crisis Variable (Austria: n=17; Belgium: n=19)						
Constant	3.1549	7.9911	7.4769	1.2937	1.4899	0.1372
	0.85	3.42	3.13	0.27	0.27	0.02
GeoMean(t-1)	20.5567	19.7462	33.2442	0.0000	38.4154	44.9684
	1.60	1.87	1.96	-	1.13	1.27
GeoStdDev(t-1)	0.3679			40.2214		
	1.69			1.65		
TotalExtr(t-1)		0.1914			-0.0150	
		2.31			-0.08	
NegExtr(t-1)			0.5542			0.5583
			1.51			0.78
PosExtr(t-1)			-0.2382			-0.8332
			-0.55			-0.83
Time	-0.7288	-0.7640	-0.8402	0.1343	0.1481	0.2078
	-2.28	-2.71	-2.89	0.32	0.32	0.44
Adjusted R^2	0.1541	0.2681	0.2698	-0.0235	-0.0246	-0.0467

Table 7. Cont'd	Denmark (2003-2013)			Finland (1995-2012)		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable (Denmark: n=11; Finland: n=19)						
Constant	-1.9165	-1.3322	-1.9737	3.8327	2.4267	3.5382
	-1.03	-1.32	-1.58	0.75	0.69	0.90
GeoMean(t-1)	-2.0470	-0.7117	5.0563	-9.5690	-9.3994	-17.6914
	-0.34	-0.12	0.56	-0.89	-0.88	-1.09
GeoStdDev(t-1)	0.0597			-1.2308		
	0.64			-0.61		
TotalExtr(t-1)		0.0407			-0.0322	
		0.91			-0.58	
NegExtr(t-1)			0.2428			-0.3713
			1.05			-0.75
PosExtr(t-1)			-0.1350			0.2691
			-0.67			0.61
Time	0.5586	0.5399	0.5130	0.4734	0.4853	0.4990
	3.98	3.88	3.54	1.69	1.74	1.75
Dummy Variable	-1.0069	-1.0615	-0.9845	-7.3596	-7.5456	-8.2332
	-0.77	-0.84	-0.76	-1.61	-1.63	-1.70
Adjusted R Square	0.6288	0.6509	0.6385	0.0880	0.0857	0.0474

	Denmark (2003-2013)			Finland (1995-2012)		
	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
Panel B: Annual Observation without Financial Crisis Variable (Denmark: n=11, Finland: n=18)						
Constant	-1.8887	-1.4059	-2.0784	3.3158	2.0470	2.5779
	-1.04	-1.43	-1.73	0.62	0.55	0.62
GeoMean(t-1)	-0.5161	0.8002	6.7826	-5.1050	-4.3124	-8.1711
	-0.09	0.14	0.81	-0.47	-0.40	-0.50
GeoStdDev(t-1)	0.0510			-0.8899		
	0.57			-0.42		
TotalExtr(t-1)		0.0355			-0.0161	
		0.82			-0.28	
NegExtr(t-1)			0.2496			-0.1825
			1.12			-0.35
PosExtr(t-1)			-0.1499			0.1332
			-0.77			0.29
Time	0.5475	0.5297	0.5020	0.3662	0.3778	0.3797
	4.04	3.91	3.61	1.27	1.32	1.28
Adjusted R^2	0.6502	0.6658	0.6638	-0.0149	-0.0220	-0.0917

Table 7. Cont'd	Greece (2003-2013)			Ireland (1995-2012)		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable (Greece: n=19, Ireland: n=11)						
Constant	0.2781	0.0801	0.0839	7.1932	5.6588	10.3754
	0.51	0.21	0.21	0.97	1.24	0.84
GeoMean(t-1)	-0.4488	-0.3883	-0.3515	22.5714	27.4193	-11.3329
	-0.42	-0.37	-0.29	0.69	0.93	-0.12
GeoStdDev(t-1)	-0.0110			-1.8291		
	-0.59			-0.27		
TotalExtr(t-1)		-0.0057			-0.0120	
		-0.42			-0.08	
NegExtr(t-1)			-0.0006			-0.7822
			-0.01			-0.42
PosExtr(t-1)			-0.0113			0.6076
			-0.14			0.41
Time	0.0110	0.0097	0.0096	0.0117	-0.0972	-0.0750
	0.31	0.27	0.26	0.01	-0.12	-0.09
Dummy Variable	-0.4872	-0.4651	-0.4999	25.1384	25.4558	24.9086
	-0.79	-0.75	-0.61	2.82	2.87	2.58
Adjusted R Square	-0.2057	-0.2200	-0.3134	0.4184	0.4120	0.3181

	Greece (2003-2013)			Ireland (1995-2012)		
	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
Panel B: Annual Observation without Financial Crisis Variable (Greece: n=19, Ireland: n=11)						
Constant	0.2541	0.0804	0.0633	10.8503	6.9073	15.5529
	0.47	0.21	0.16	1.05	1.07	0.92
GeoMean(t-1)	-0.2048	-0.1601	-0.4038	-36.2552	-26.9905	-96.2743
	-0.20	-0.16	-0.34	-1.03	-0.84	-0.75
GeoStdDev(t-1)	-0.0098			-4.8519		
	-0.53			-0.51		
TotalExtr(t-1)		-0.0054			-0.0479	
		-0.40			-0.23	
NegExtr(t-1)			-0.0289			-1.4663
			-0.49			-0.57
PosExtr(t-1)			0.0195			1.0958
			0.31			0.53
Time	0.0050	0.0044	0.0068	0.6344	0.4075	0.4284
	0.15	0.12	0.19	0.54	0.36	0.36
Adjusted R^2	-0.1757	-0.1849	-0.2548	-0.1613	-0.1959	-0.3268

Table 7. Cont'd	Norway (1997-2013)			Portugal (1995-2013)		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation with Financial Crisis Dummy Variable (Norway: n=17; Portugal: n=19)						
Constant	0.6241	0.2738	0.4143	4.2220	4.3452	4.1639
	0.76	0.59	0.63	1.28	1.79	1.64
GeoMean(t-1)	-0.5150	-0.1188	-0.9350	-19.0232	-19.4260	-13.6505
	-0.22	-0.05	-0.27	-1.58	-1.58	-0.74
GeoStdDev(t-1)	-0.3677			0.0066		
	-0.57			0.04		
TotalExtr(t-1)		-0.0065			-0.0025	
		-0.33			-0.04	
NegExtr(t-1)			-0.0335			0.1693
			-0.37			0.42
PosExtr(t-1)			0.0274			-0.1721
			0.25			-0.43
Time	0.0244	0.0190	0.0173	-0.2368	-0.2334	-0.2657
	0.49	0.38	0.33	-1.18	-1.16	-1.21
Dummy Variable	-1.3454	-1.4294	-1.4458	-9.5473	-9.5090	-10.5338
	-1.70	-1.84	-1.78	-2.56	-2.57	-2.35
Adjusted R Square	0.0908	0.0751	-0.0002	0.2496	0.2496	0.2033
	Norway (1997-2013)			Portugal (1995-2013)		
	Model (4)	Model (5)	Model (6)	Model (4)	Model (5)	Model (6)
Panel B: Annual Observation without Financial Crisis Variable (Norway: n=17, Portugal: n=19)						
Constant	0.9339	0.2795	0.3672	5.1340	4.3824	4.7160
	1.09	0.55	0.51	1.33	1.54	1.63
GeoMean(t-1)	0.2369	1.1121	0.6116	-11.6650	-11.0451	-23.6160
	0.10	0.49	0.17	-0.85	-0.79	-1.14
GeoStdDev(t-1)	-0.6878			-0.0786		
	-1.03			-0.37		
TotalExtr(t-1)		-0.0128			-0.0207	
		-0.62			-0.26	
NegExtr(t-1)			-0.0297			-0.3403
			-0.31			-0.87
PosExtr(t-1)			0.0083			0.3022
			0.07			0.76
Time	0.0167	0.0051	0.0040	-0.3115	-0.3185	-0.2403
	0.32	0.10	0.07	-1.34	-1.37	-0.95
Adjusted R^2	-0.0409	-0.0943	-0.1824	-0.0273	-0.0320	-0.0535

Table 7. Cont'd	Sweden (1995-2013)		
	Model (1)	Model (2)	Model (3)
Panel A: Annual Observation (Sweden: n=19)			
Constant	-5.6016	-1.3133	0.2287
	-0.60	-0.25	0.04
GeoMean(t-1)	-17.1531	-16.9401	-25.2051
	-0.62	-0.59	-0.83
GeoStdDev(t-1)	0.3240		
	0.81		
TotalExtr(t-1)		0.1506	
		0.76	
NegExtr(t-1)			-0.5469
			-0.71
PosExtr(t-1)			0.8997
			1.10
Time	0.6340	0.6420	0.6337
	1.70	1.72	1.69
Dummy Variable	-11.8822	-11.9234	-9.4073
	-1.63	-1.63	-1.20
Adjusted R^2	0.1623	0.1586	0.1518
	Model (4)	Model (5)	Model (6)
Panel B: Annual Observation without Financial Crisis Variable (Sweden: n=19)			
Constant	-6.4102	-1.8243	0.5465
	-0.65	-0.33	0.10
GeoMean(t-1)	-1.0663	-0.9150	-17.6518
	-0.04	-0.03	-0.59
GeoStdDev(t-1)	0.3450		
	0.81		
TotalExtr(t-1)		0.1591	
		0.77	
NegExtr(t-1)			-0.8457
			-1.15
PosExtr(t-1)			1.2330
			1.57
Time	0.4964	0.5049	0.5346
	1.30	1.32	1.44
Adjusted R^2	0.0700	0.0655	0.1245

Table 8. Pooled regression results of equity mutual fund net flows on risk measures

Panel A: Pooled regression results of equity mutual fund net flows on risk measures, with no country fixed effect controlled.
The countries examined are separated into two groups, individualism and collectivism, based on Hofstede's culture dimension score of individualism vs. collectivism.

VARIABLES	(1) Model 1'	(2) Model 2'	(3) Model 3'	(4) Model 4'	(5) Model 5'	(6) Model 6'	(7) Model 7'	(8) Model 8'	(9) Model 9'
Geometric Mean (t-1)	-9.045**	-9.740**	-9.053**	-8.035	-8.224*	-1.432	-6.569	-7.738	-5.112
	(4.157)	(4.025)	(3.909)	(5.072)	(4.859)	(4.079)	(5.242)	(4.963)	(4.874)
Geo. Std. Deviation (t-1)	0.00983	0.00239	-0.0907						
	(0.0561)	(0.0573)	(0.0697)						
Individualism		4.196***			4.647***			4.082***	
		(1.456)			(1.414)			(1.503)	
Individualism*Geo StdDev (t-1)			0.163***						
			(0.0553)						
Total Extreme Value (t-1)				-0.0632	-0.0780*	-0.112**			
				(0.0435)	(0.0418)	(0.0511)			
Individualism*Total Extr (t-1)						0.112***			
						(0.0399)			
Negative Extreme Value (t-1)							0.0608	0.0580	0.105
							(0.127)	(0.123)	(0.163)
Positive Extreme Value (t-1)							0.00169	-0.0250	-0.220
							(0.134)	(0.133)	(0.205)
Individualism*Neg Extr (t-1)									0.0157
									(0.217)
Individualism*Pos Extr (t-1)									0.221
									(0.255)
GDP (t-1)	2.60e-05	-4.34e-05	-3.10e-05	1.99e-05	-5.86e-05**	-1.60e-05	2.52e-05	-4.33e-05	-7.64e-06
	(2.18e-05)	(2.85e-05)	(2.61e-05)	(2.20e-05)	(2.87e-05)	(2.40e-05)	(2.31e-05)	(3.09e-05)	(2.69e-05)
Crisis	-5.446*	-5.240	-5.334*	-3.034	-2.269	-1.459	-5.691*	-5.460*	-5.765*
	(3.145)	(3.186)	(3.146)	(2.726)	(2.797)	(2.689)	(3.119)	(3.180)	(3.182)
Constant	2.888*	3.486**	5.336***	4.296***	5.065***	5.078***	2.417**	3.142***	3.860***
	(1.608)	(1.600)	(1.850)	(1.274)	(1.193)	(1.344)	(1.139)	(1.112)	(1.296)
Fixed Effect	No	No	No	No	No	No	No	No	No
Observations	141	141	141	141	141	141	141	141	141
R-squared	0.058	0.111	0.108	0.080	0.143	0.144	0.065	0.113	0.095

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Pooled regression results of equity mutual fund net flows on risk measures, with country fixed effect controlled.

VARIABLES	(1) Model 1'	(2) Model 2'	(3) Model 3'	(4) Model 4'	(5) Model 5'	(6) Model 6'	(7) Model 7'	(8) Model 8'	(9) Model 9'
Geometric Mean (t-1)	-8.278	-9.594	-10.10*	-8.839	-9.429	-7.362	-9.733	-10.79	-8.674
	(6.087)	(5.644)	(5.793)	(6.681)	(6.512)	(6.883)	(7.284)	(7.062)	(6.795)
Geo. Std. Deviation (t-1)	0.0165	-0.00314	-0.105						
	(0.0581)	(0.0604)	(0.0782)						
Individualism		4.396***			4.446***			4.258***	
		(1.278)			(1.333)			(1.385)	
Individualism*Geo StdDev (t-1)			0.182***						
			(0.0450)						
Total Extreme Value (t-1)				0.0197	-0.00766	-0.0411			
				(0.0366)	(0.0395)	(0.0432)			
Individualism*Extreme Measure (t-1)						0.103***			
						(0.0207)			
Negative Extreme Value (t-1)							-0.0477	-0.0631	-0.0514
							(0.151)	(0.114)	(0.0873)
Positive Extreme Value (t-1)							0.142	0.0952	-0.0620
							(0.174)	(0.136)	(0.191)
Individualism*Neg Extr (t-1)									0.106
									(0.129)
Individualism*Pos Extr (t-1)									0.134
									(0.218)
GDP (t-1)	1.66e-05	-5.95e-05*	-5.02e-05*	1.86e-05	-6.11e-05	-1.41e-05	2.45e-05	-5.22e-05	-1.77e-05
	(1.93e-05)	(3.20e-05)	(2.61e-05)	(2.11e-05)	(3.67e-05)	(2.40e-05)	(2.18e-05)	(3.66e-05)	(2.49e-05)
Crisis = o,	-	-	-	-	-	-	-	-	-
Constant	2.455	3.524*	5.595**	2.342	3.646**	3.630**	1.858	3.177**	3.902**
	(1.763)	(1.962)	(2.204)	(1.369)	(1.617)	(1.618)	(1.159)	(1.416)	(1.539)
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141	141	141	141	141	141	141	141	141
R-squared	0.011	0.084	0.088	0.012	0.085	0.065	0.021	0.087	0.066
Number of year	18	18	18	18	18	18	18	18	18

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Simultaneous Regression Results (2 Groups: Individualism vs Collectivism), 2SLS Estimates

	Model (2')		Model (3')		Model (4')		Model (5')		Model (6')	
VARIABLES	Net Flow	Geo.StDev	Net Flow	Geo.StDev	Net Flow	Total Extr.	Net Flow	Total Extr.	Net Flow	Total Extr.
Geometric Mean (t-1)	-2.872	8.552	-2.405	8.599	-2.158	15.76	-3.657	16.06	-2.196	16.05
	(5.514)	(5.950)	(5.513)	(5.946)	(5.419)	(11.63)	(5.299)	(11.52)	(5.335)	(11.60)
Geo. StdDev (t-1)	0.212**		0.125							
	(0.0851)		(0.0951)							
Individualism	4.012***	-0.571					3.555**	4.321		
	(1.505)	(1.881)					(1.497)	(3.642)		
Net Flow(t-1)		0.230**		0.219*		0.539**		0.461**		0.509**
		(0.115)		(0.114)		(0.224)		(0.223)		(0.219)
Individualism*Geo StdDev (t-1)			0.143**							
			(0.0559)							
Total Extr. (t-1)					0.106***		0.0896**		0.0313	
					(0.0372)		(0.0365)		(0.0495)	
Individualism*Total Extr. (t-1)									0.101**	
									(0.0451)	
GDP (t-1)	-4.46e-05	-1.97e-05	-2.82e-05	-2.89e-05	2.78e-05	-0.000109	-3.13e-05	-0.000180*	-1.48e-06	-0.000109
	(3.96e-05)	(4.87e-05)	(3.63e-05)	(3.78e-05)	(3.10e-05)	(7.39e-05)	(3.91e-05)	(9.44e-05)	(3.32e-05)	(7.37e-05)
Crisis	-5.773***	17.60***	-5.857***	17.59***	-6.036***	39.42***	-5.782***	39.37***	-5.849***	39.33***
	(1.949)	(2.404)	(1.948)	(2.403)	(1.962)	(4.699)	(1.913)	(4.655)	(1.936)	(4.689)
Constant	-0.944	19.88***	0.758	0.219*	0.887	17.71***	1.603	18.35***	0.0313	17.79***
	(2.331)	(1.854)	(2.529)	(0.114)	(1.679)	(3.590)	(1.657)	(3.589)	(0.0495)	(3.582)
Var(e.netflow)	44.53***		44.51***		45.20***		42.82***		43.92***	
	(5.851)		(5.836)		(5.607)		(5.304)		(5.450)	
Var(e.risk)	67.22***		67.11***		256.6***		252.0***		255.8***	
	(8.188)		(8.162)		(31.250)		(30.590)		(31.02)	
Covariance	-21.94***		-21.35***		-39.22***		-37.81***		-38.99***	
	(6.760)		(6.778)		(11.910)		(11.340)		(11.53)	
Observations	141	141	141	141	141	141	141	141	141	141

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Overview of Central Banks with Negative Policy Rates

Year	Country	Date	Rate	Announcement	Measures
2012	Denmark	July 5, 2012	-0.20%	July 5, 2012	Certificates of deposit (CD)
		January 2013	-0.10%		
		April 2014	+0.05%		
		September 2014	-0.05%		
		January 19, 2015	-0.20%		
		January 22, 2015	-0.35%		
		January 29, 2015	-0.50%		
		February 5, 2015	-0.75 %		
		January 8, 2016	-0.65 %		
2014	Euro Area	June 11, 2014	-0.10%	June 5, 2014	Deposit rate
		September 10, 2014	-0.20%		
		December 9, 2015	-0.30%		
		March 16, 2016	-0.40%		
2015	Switzerland	January 15, 2015	-0.75%	December 18, 2014	Sight deposits at SNB (with an exemption threshold)
	Sweden	February 12, 2015	-0.10%	February 12, 2015	Reverse repo rate
		March 18, 2015	-0.25%		
		July 2, 2015	-0.35%		
		February 11, 2016	-0.50%		
	Norway	September 24, 2015	-0.25%	September 24, 2015	Reserve rate
		March 17, 2016	-0.50%		
2016	Bulgaria	January 4, 2016	-0.30%	November 26, 2015	Deposit rate
		March 16, 2016	-0.40%		
	Japan	February 16, 2016	-0.10%	January 29, 2016	Deposit rate
	Hungary	March 23, 2016	-0.05%	March 22, 2016	Deposit rate
	Bosnia and Herzegovina	July 1, 2016	-0.20%	April 18, 2016	Deposit rate

Table 11. Reference Index and Currency for Countries that Implement NIRP

Country	Currency	Currency Symbol	Index	Index Symbol
Bosnia and Herzegovina	Bosnia and Herzegovina Convertible Mark	BAM	MSCI Bosnia and Herzegovina	MXBAH
Bulgaria	Bulgarian Lev	BGN	SOFIX Index	SOFIX
Denmark	Danish Krone	DKK	OMX Copenhagen Index	KAX
Euro Area	EURO	EUR	Deutsche Boerse AG German Stock Index	DAX
Hungary	Hungarian Forint	HUF	Budapest Stock Exchange Budapest Stock Index	BUX
Japan	Japanese Yen	JPY	Nikkei 225	NKY
Norway	Norwegian Krone	NOK	Oslo Stock Exchange All Share Index	OSEAX
Switzerland	Swiss Franc	CHF	Swiss Market Index	SMI
Sweden	Swedish Krona	SEK	OMX Stockholm 30 Index	OMX

Table 12. Summary Statistics of Daily Currency Return Logarithmatic Percent Changes

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Overall Period												
Bosnia & Herzegovina	-0.0001	0.0000	0.0055	-0.3255	3.0781	215.71	-0.0153	-0.0089	-0.0067	0.0065	0.0084	0.0130
Bulgaria	0.0003	0.0002	0.0064	-0.1889	1.9942	89.77	-0.0167	-0.0101	-0.0073	0.0078	0.0105	0.0167
Denmark	0.0002	0.0000	0.0059	0.0481	0.9560	20.12	-0.0147	-0.0093	-0.0064	0.0074	0.0102	0.0159
Euro Area	0.0003	0.0000	0.0053	-0.0515	2.6968	158.72	-0.0143	-0.0083	-0.0048	0.0064	0.0084	0.0144
Hungary	0.0000	0.0000	0.0067	0.1515	1.9815	87.56	-0.0182	-0.0106	-0.0080	0.0081	0.0110	0.0165
Japan	-0.0001	0.0002	0.0067	-0.7692	4.3611	466.03	-0.0173	-0.0108	-0.0076	0.0070	0.0101	0.0176
Norway	0.0004	0.0006	0.0081	0.1310	0.2790	3.19	-0.0181	-0.0132	-0.0098	0.0103	0.0144	0.0212
Sweden	0.0005	0.0005	0.0063	-0.2999	1.0602	32.33	-0.0164	-0.0112	-0.0064	0.0082	0.0113	0.0148
Switzerland	0.0002	0.0008	0.0105	-12.2975	227.9075	1145080.63	-0.0173	-0.0091	-0.0063	0.0070	0.0107	0.0162
Panel B. Regime 0 – Ex-Event												
Bosnia & Herzegovina	0.0000	0.0000	0.0063	-0.3526	3.1160	111.00	-0.0179	-0.0094	-0.0073	0.0073	0.0091	0.0136
Bulgaria	0.0004	0.0003	0.0076	-0.2615	1.2049	18.76	-0.0202	-0.0121	-0.0085	0.0094	0.0133	0.0183
Denmark	0.0005	0.0001	0.0068	0.0735	0.5891	4.01	-0.0158	-0.0098	-0.0081	0.0085	0.0115	0.0165
Euro Area	-0.0001	-0.0001	0.0037	-0.2337	1.3714	22.83	-0.0107	-0.0057	-0.0040	0.0047	0.0066	0.0074
Hungary	-0.0001	0.0004	0.0074	-0.1510	0.8669	9.16	-0.0196	-0.0118	-0.0091	0.0085	0.0126	0.0170
Japan	-0.0001	0.0002	0.0053	-0.9397	4.8040	289.40	-0.0154	-0.0092	-0.0061	0.0054	0.0065	0.0118
Norway	0.0010	0.0010	0.0086	0.0515	-0.0895	0.20	-0.0179	-0.0136	-0.0104	0.0124	0.0150	0.0212
Sweden	0.0010	0.0008	0.0054	0.0001	1.8121	35.71	-0.0150	-0.0066	-0.0046	0.0080	0.0097	0.0168
Switzerland	0.0005	0.0004	0.0042	0.0134	1.9020	39.35	-0.0096	-0.0062	-0.0042	0.0051	0.0070	0.0125
Panel C. Regime 1 – Post-Event												
Bosnia & Herzegovina	-0.0001	0.0000	0.0046	-0.2511	0.6219	6.95	-0.0105	-0.0083	-0.0062	0.0052	0.0070	0.0104
Bulgaria	0.0001	0.0000	0.0051	0.0111	2.3926	62.26	-0.0149	-0.0081	-0.0053	0.0067	0.0078	0.0112
Denmark	-0.0001	-0.0002	0.0048	-0.2513	0.5164	5.65	-0.0127	-0.0075	-0.0056	0.0062	0.0079	0.0102
Euro Area	0.0007	0.0004	0.0065	-0.1327	1.5924	28.34	-0.0154	-0.0110	-0.0062	0.0083	0.0125	0.0162
Hungary	0.0001	-0.0003	0.0060	0.7214	3.9048	188.45	-0.0123	-0.0084	-0.0068	0.0075	0.0095	0.0143
Japan	0.0000	-0.0001	0.0079	-0.6871	3.2291	133.93	-0.0253	-0.0116	-0.0082	0.0088	0.0121	0.0183
Norway	-0.0002	0.0001	0.0074	0.1290	0.7860	7.44	-0.0182	-0.0121	-0.0094	0.0080	0.0134	0.0170
Sweden	0.0000	-0.0001	0.0070	-0.3416	0.4060	6.87	-0.0177	-0.0129	-0.0089	0.0084	0.0118	0.0145
Switzerland	-0.0001	0.0012	0.0142	-9.8289	133.7825	198840.42	-0.0207	-0.0126	-0.0085	0.0097	0.0123	0.0215

Table 13. Summary Statistics of Daily Index Return Logarithmatic Percent Changes

Country	Mean	Median	StdDev	Skewness	Kurtosis	Jarque-Bera	Percentile					
							1%	5%	10%	90%	95%	99%
Panel A. Overall Period												
Bosnia & Herzegovina	-0.0004	0.0000	0.0077	-0.4662	7.5782	1270.43	-0.0246	-0.0120	-0.0073	0.0064	0.0106	0.0248
Bulgaria	0.0002	0.0000	0.0067	-0.1501	8.2602	1488.84	-0.0147	-0.0087	-0.0066	0.0073	0.0103	0.0168
Denmark	0.0003	0.0007	0.0109	-0.4441	2.3843	141.07	-0.0300	-0.0182	-0.0129	0.0120	0.0168	0.0275
Euro Area	0.0006	0.0006	0.0104	-0.2281	0.9295	23.37	-0.0275	-0.0177	-0.0122	0.0136	0.0182	0.0255
Hungary	0.0010	0.0004	0.0105	-0.3667	3.9674	354.73	-0.0260	-0.0159	-0.0110	0.0140	0.0167	0.0265
Japan	0.0001	0.0002	0.0148	-0.1713	5.4977	661.20	-0.0411	-0.0246	-0.0155	0.0142	0.0208	0.0384
Norway	0.0000	0.0000	0.0124	-0.0432	1.7438	66.43	-0.0302	-0.0181	-0.0146	0.0141	0.0208	0.0328
Sweden	0.0001	0.0002	0.0108	-0.3022	1.5954	63.43	-0.0277	-0.0198	-0.0124	0.0128	0.0180	0.0262
Switzerland	-0.0001	0.0001	0.0106	-1.5978	12.7995	3792.63	-0.0256	-0.0154	-0.0112	0.0108	0.0148	0.0264
Panel B. Regime 0 – Ex-Event												
Bosnia & Herzegovina	-0.0001	0.0000	0.0076	0.0817	10.4053	1177.73	-0.0216	-0.0106	-0.0057	0.0064	0.0093	0.0271
Bulgaria	0.0010	0.0007	0.0069	-0.0900	12.4257	1679.44	-0.0115	-0.0075	-0.0060	0.0085	0.0111	0.0173
Denmark	0.0005	0.0009	0.0081	-1.1168	6.2101	473.66	-0.0209	-0.0138	-0.0082	0.0094	0.0124	0.0192
Euro Area	0.0005	0.0009	0.0116	-0.0846	0.3168	1.40	-0.0282	-0.0194	-0.0151	0.0155	0.0192	0.0268
Hungary	0.0008	0.0002	0.0096	-0.1421	2.9906	98.14	-0.0235	-0.0129	-0.0098	0.0122	0.0164	0.0239
Japan	0.0008	0.0002	0.0139	-0.6829	7.2384	590.08	-0.0364	-0.0174	-0.0132	0.0142	0.0228	0.0373
Norway	0.0004	0.0000	0.0132	-0.0054	1.1255	13.78	-0.0308	-0.0177	-0.0150	0.0160	0.0241	0.0313
Sweden	-0.0006	0.0000	0.0127	-0.2842	0.9645	13.63	-0.0312	-0.0232	-0.0176	0.0142	0.0197	0.0285
Switzerland	-0.0001	0.0000	0.0118	-0.5503	3.0551	114.68	-0.0347	-0.0184	-0.0141	0.0142	0.0172	0.0285
Panel C. Regime 1 – Post-Event												
Bosnia & Herzegovina	-0.0008	0.0000	0.0078	-0.9906	5.2735	345.11	-0.0271	-0.0164	-0.0085	0.0060	0.0106	0.0169
Bulgaria	-0.0005	0.0000	0.0065	-0.2859	3.0858	107.11	-0.0188	-0.0121	-0.0076	0.0064	0.0091	0.0146
Denmark	0.0000	0.0005	0.0131	-0.2083	0.8247	9.28	-0.0306	-0.0247	-0.0168	0.0152	0.0210	0.0340
Euro Area	0.0007	0.0004	0.0089	-0.4992	1.7962	45.93	-0.0244	-0.0155	-0.0092	0.0111	0.0162	0.0205
Hungary	0.0011	0.0005	0.0115	-0.5044	4.1965	202.58	-0.0279	-0.0170	-0.0121	0.0152	0.0170	0.0275
Japan	-0.0004	0.0002	0.0156	0.2114	4.4776	219.98	-0.0437	-0.0274	-0.0198	0.0139	0.0190	0.0418
Norway	-0.0004	0.0000	0.0115	-0.1411	2.6746	78.66	-0.0282	-0.0181	-0.0139	0.0120	0.0161	0.0335
Sweden	0.0007	0.0003	0.0085	-0.0271	1.2934	18.23	-0.0218	-0.0128	-0.0093	0.0105	0.0150	0.0239
Switzerland	0.0003	0.0003	0.0072	-0.1022	2.3620	61.13	-0.0217	-0.0116	-0.0076	0.0085	0.0114	0.0212

Table 14. Abnormal Return Analysis for Currency Exchange Markets

Panel A: Abnormal Returns (AR) (Event Date: NIRP Announcement Day)

Day	USD / BAM	USD / BGN	USD / DKK	USD / EUR	USD / HUF	USD / JPY	USD / NOK	USD / SEK	USD / CHF
D-10	-0.050%	-0.568%	1.311% **	0.187%	1.282%	-0.921%	-0.490%	-0.293%	-0.655%
	-0.085	-0.879	2.232	0.349	1.204	-1.389	-0.605	-0.470	-0.617
D-9	0.060%	0.225%	-0.275%	0.173%	0.267%	0.288%	-0.421%	0.062%	0.751%
	0.102	0.349	-0.469	0.323	0.251	0.435	-0.520	0.099	0.707
D-8	-0.114%	0.783%	0.519%	-0.181%	-0.450%	0.271%	0.290%	0.329%	-0.295%
	-0.193	1.212	0.884	-0.338	-0.423	0.408	0.358	0.527	-0.278
D-7	0.247%	0.370%	0.074%	0.091%	1.302%	-0.599%	0.134%	-1.260% **	-0.501%
	0.417	0.572	0.126	0.170	1.223	-0.903	0.166	-2.021	-0.472
D-6	-0.260%	-0.192%	0.181%	0.268%	-0.090%	0.646%	-0.694%	0.775%	-0.535%
	-0.439	-0.297	0.308	0.500	-0.085	0.974	-0.857	1.243	-0.504
D-5	-0.045%	-0.734%	0.159%	-0.099%	-0.090%	0.912%	-0.959%	-0.514%	0.137%
	-0.075	-1.136	0.271	-0.185	-0.085	1.375	-1.184	-0.824	0.129
D-4	0.119%	0.791%	-1.767% ***	-0.277%	-0.070%	-0.407%	1.111%	1.747% ***	-0.443%
	0.201	1.225	-3.008	-0.516	-0.066	-0.614	1.371	2.802	-0.417
D-3	0.982% *	0.059%	0.708%	0.241%	0.520%	0.100%	0.692%	-0.489%	0.168%
	1.660	0.091	1.205	0.449	0.489	0.150	0.854	-0.784	0.158
D-2	0.192%	-0.105%	-0.268%	-0.263%	0.559%	0.217%	0.722%	-0.447%	-0.611%
	0.325	-0.162	-0.456	-0.490	0.526	0.328	0.890	-0.717	-0.575
D-1	-0.228%	0.146%	0.644%	0.187%	-0.501%	0.116%	-0.253%	0.516%	1.347%
	-0.386	0.225	1.096	0.348	-0.471	0.175	-0.312	0.827	1.269
D-0	-0.229%	0.096%	1.140% *	-0.481%	0.089%	1.932% ***	2.112% ***	0.763%	0.678%
	-0.387	0.149	1.940	-0.897	0.083	2.914	2.606	1.223	0.639
D+1	-0.491%	0.129%	0.775%	0.064%	-0.792%	-0.126%	0.799%	-0.279%	0.430%
	-0.830	0.199	1.320	0.120	-0.744	-0.190	0.986	-0.447	0.405
D+2	0.622%	0.231%	-0.211%	0.350%	-1.074%	-0.849%	0.071%	-0.113%	-0.069%
	1.052	0.358	-0.360	0.653	-1.009	-1.280	0.088	-0.181	-0.065
D+3	0.025%	-0.668%	0.476%	0.322%	-0.090%	-1.742% ***	-0.729%	-1.170% *	0.387%
	0.043	-1.034	0.811	0.600	-0.085	-2.629	-0.900	-1.877	0.365
D+4	0.589%	0.156%	0.075%	0.091%	-0.090%	-0.956%	0.411%	0.415%	-0.201%
	0.996	0.242	0.127	0.169	-0.085	-1.443	0.507	0.666	-0.189
D+5	-0.331%	-3.080% ***	0.277%	-0.207%	1.048%	0.075%	-1.096%	0.664%	-0.242%
	-0.560	-4.767	0.471	-0.387	0.985	0.113	-1.352	1.065	-0.228
D+6	-0.252%	0.580%	-0.371%	0.064%	2.127% **	-0.879%	-0.698%	-0.511%	0.357%
	-0.425	0.897	-0.632	0.118	1.998	-1.325	-0.862	-0.820	0.336
D+7	-0.229%	0.305%	-0.192%	-0.275%	0.428%	-0.643%	0.337%	0.300%	0.214%
	-0.387	0.471	-0.328	-0.514	0.402	-0.970	0.415	0.482	0.202
D+8	-0.398%	-0.545%	-0.188%	0.172%	-0.622%	-1.543% **	-1.611% **	-0.045%	-0.110%
	-0.673	-0.843	-0.320	0.321	-0.584	-2.327	-1.988	-0.072	-0.103
D+9	-0.814%	-1.244% *	0.045%	-0.398%	0.294%	-0.826%	-0.803%	-1.408% **	0.526%
	-1.377	-1.925	0.077	-0.742	0.276	-1.246	-0.991	-2.257	0.496
D+10	-0.614%	0.730%	-0.003%	-0.113%	-0.857%	0.734%	-0.892%	1.187% *	-0.059%
	-1.039	1.129	-0.005	-0.211	-0.805	1.107	-1.101	1.904	-0.055

Panel B: Cumulative Abnormal Returns (CAR) (Event Date: NIRP Announcement Day)

(-10,10)	-1.220%	-2.536%	3.108%	-0.085%	3.188%	-4.200%	-1.969%	0.230%	1.274%
(-10,0)	0.902%	0.775%	1.286%	0.328%	2.728%	0.623%	0.131%	0.426%	-0.637%
(0,10)	-2.122%	-3.311%	1.822%	-0.413%	0.460%	-4.822%	-2.100%	-0.195%	1.911%

*** p<0.01, ** p<0.05, * p<0.1

Table 14. Cont'd

Panel C: Abnormal Returns (AR) (Event Date: NIRP Implementation Day)

Day	USD / BAM	USD / BGN	USD / DKK	USD / EUR	USD / HUF	USD / JPY	USD / NOK	USD / SEK	USD / CHF
D-10	-0.347%	-0.460%	1.312% **	0.267%	-0.185%	-0.851%	-0.490%	-0.293%	-0.075%
	-0.637	-0.703	2.238	0.495	-0.275	-1.289	-0.605	-0.470	-0.130
D-9	-0.221%	-0.411%	-0.275%	-0.101%	-0.948%	-1.745% ***	-0.421%	0.062%	0.747%
	-0.406	-0.629	-0.468	-0.186	-1.407	-2.644	-0.520	0.099	1.303
D-8	0.494%	0.377%	0.520%	-0.278%	-0.137%	-0.959%	0.290%	0.329%	0.484%
	0.905	0.577	0.887	-0.515	-0.203	-1.453	0.358	0.527	0.843
D-7	-0.434%	-0.490%	0.075%	0.240%	0.351%	0.073%	0.134%	-1.260% **	0.293%
	-0.796	-0.749	0.127	0.445	0.521	0.111	0.166	-2.021	0.511
D-6	-0.698%	-0.171%	0.182%	-0.264%	0.207%	-0.881%	-0.694%	0.775%	0.371%
	-1.279	-0.262	0.311	-0.490	0.307	-1.335	-0.857	1.243	0.646
D-5	2.566% ***	0.087%	0.160%	0.185%	-0.883%	-0.645%	-0.959%	-0.514%	0.369%
	4.704	0.133	0.273	0.344	-1.311	-0.977	-1.184	-0.824	0.644
D-4	0.722%	0.321%	-1.766% ***	-0.482%	-1.171% *	-1.545% **	1.111%	1.747% ***	-0.438%
	1.323	0.492	-3.012	-0.895	-1.739	-2.341	1.371	2.802	-0.763
D-3	-0.567%	0.030%	0.709%	0.063%	0.320%	-0.828%	0.692%	-0.489%	0.015%
	-1.039	0.046	1.209	0.117	0.475	-1.255	0.854	-0.784	0.026
D-2	-0.206%	0.476%	-0.267%	0.349%	0.438%	0.732%	0.722%	-0.447%	0.487%
	-0.378	0.727	-0.455	0.647	0.651	1.109	0.890	-0.717	0.848
D-1	0.061%	-0.076%	0.645%	0.320%	0.519%	1.181% *	-0.253%	0.516%	-0.172%
	0.111	-0.116	1.100	0.594	0.771	1.790	-0.312	0.827	-0.299
D-0	-0.332%	0.312%	1.141% *	0.089%	0.773%	-0.468%	2.112% ***	0.763%	-19.418% ***
	-0.609	0.477	1.946	0.166	1.148	-0.709	2.606	1.223	-33.856
D+1	-0.185%	0.746%	0.776%	-0.209%	0.277%	0.022%	0.799%	-0.279%	2.263% ***
	-0.339	1.141	1.324	-0.387	0.411	0.033	0.986	-0.447	3.945
D+2	0.804%	-0.335%	-0.210%	0.062%	0.070%	-0.761%	0.071%	-0.113%	2.371% ***
	1.475	-0.512	-0.359	0.116	0.104	-1.153	0.088	-0.181	4.133
D+3	-0.286%	-1.431% **	0.477%	-0.277%	-0.443%	-0.545%	-0.729%	-1.170% *	-0.479%
	-0.524	-2.188	0.814	-0.513	-0.658	-0.825	-0.900	-1.877	-0.835
D+4	0.355%	0.030%	0.075%	0.171%	-0.775%	0.253%	0.411%	0.415%	-1.820% ***
	0.650	0.045	0.129	0.317	-1.151	0.383	0.507	0.666	-3.174
D+5	0.105%	0.570%	0.277%	-0.399%	-0.062%	-0.733%	-1.096%	0.664%	1.248% **
	0.193	0.871	0.473	-0.740	-0.092	-1.111	-1.352	1.065	2.176
D+6	-0.036%	-0.004%	-0.370%	-0.114%	-0.658%	0.067%	-0.698%	-0.511%	0.971% *
	-0.066	-0.006	-0.631	-0.212	-0.977	0.102	-0.862	-0.820	1.692
D+7	-0.042%	-0.210%	-0.192%	0.036%	-0.229%	0.724%	0.337%	0.300%	2.523% ***
	-0.077	-0.321	-0.327	0.066	-0.340	1.097	0.415	0.482	4.400
D+8	-0.263%	0.063%	-0.187%	-0.073%	-0.459%	0.877%	-1.611% **	-0.045%	-0.034%
	-0.482	0.096	-0.319	-0.136	-0.682	1.329	-1.988	-0.072	-0.060
D+9	-0.190%	-0.500%	0.046%	-0.060%	0.367%	-1.160% *	-0.803%	-1.408% **	0.198%
	-0.348	-0.764	0.078	-0.111	0.545	-1.758	-0.991	-2.257	0.345
D+10	0.429%	0.197%	-0.002%	-0.182%	-0.449%	1.160% *	-0.892%	1.187% *	2.022% ***
	0.786	0.301	-0.003	-0.338	-0.666	1.758	-1.101	1.904	3.525

Panel D: Cumulative Abnormal Returns (CAR) (Event Date: NIRP Implementation Day)

(-10,10)	1.728%	-0.880%	3.127%	-0.656%	-3.078%	-6.031%	-1.969%	0.230%	-8.075%
(-10,0)	1.369%	-0.317%	1.295%	0.300%	-1.489%	-5.467%	0.131%	0.426%	2.081%
(0,10)	0.360%	-0.563%	1.832%	-0.956%	-1.589%	-0.564%	-2.100%	-0.195%	-10.156%

*** p<0.01, ** p<0.05, * p<0.1

Table 15. Abnormal Return Analysis for Equity Markets

Panel A: Abnormal Returns (AR) (Event Date: NIRP Announcement Day)

Day	MXBAH	SOFIX	KAX	DAX	BUX	NKY	OSEAX	OMX	SMI
D-10	-1.715% **	-0.139%	-0.336%	0.184%	0.034%	0.325%	-1.968%	0.505%	-0.023%
	-2.248	-0.195	-0.308	0.173	0.050	0.016	-1.603	0.462	-0.022
D-9	0.203%	-0.567%	-0.289%	0.430%	-0.179%	-0.253%	-1.099%	0.327%	-0.023%
	0.267	-0.793	-0.264	0.405	-0.264	-0.012	-0.895	0.299	-0.022
D-8	-0.365%	-0.490%	-1.462%	1.216%	-0.941%	1.417%	-0.692%	0.240%	-0.591%
	-0.479	-0.686	-1.337	1.145	-1.388	0.069	-0.564	0.220	-0.569
D-7	0.347%	0.922%	-0.862%	0.431%	-0.131%	-2.908%	0.625%	0.964%	0.120%
	0.455	1.291	-0.788	0.405	-0.193	-0.141	0.509	0.882	0.115
D-6	0.547%	-0.296%	1.017%	-0.070%	0.358%	-1.589%	1.594%	-0.603%	-0.023%
	0.717	-0.414	0.930	-0.066	0.527	-0.077	1.298	-0.552	-0.022
D-5	-0.810%	0.025%	0.037%	-0.056%	0.213%	6.581%	0.694%	0.656%	-0.023%
	-1.061	0.035	0.034	-0.053	0.315	0.320	0.565	0.600	-0.022
D-4	0.204%	-0.587%	2.506% **	-0.010%	-0.877%	1.765%	-1.306%	0.833%	-0.023%
	0.267	-0.821	2.291	-0.009	-1.294	0.086	-1.064	0.762	-0.022
D-3	-0.145%	0.788%	1.114%	0.015%	-1.165% *	-1.507%	0.386%	-0.416%	-0.153%
	-0.190	1.103	1.019	0.014	-1.719	-0.073	0.314	-0.380	-0.148
D-2	-2.331% ***	-0.808%	1.427%	-0.359%	0.326%	3.558%	-1.201%	0.828%	0.612%
	-3.056	-1.130	1.305	-0.338	0.482	0.173	-0.978	0.757	0.590
D-1	-0.086%	-1.328% *	0.219%	0.016%	0.445%	0.155%	-0.615%	-0.433%	-0.433%
	-0.113	-1.859	0.201	0.015	0.656	0.008	-0.501	-0.396	-0.417
D-0	-1.273% *	0.194%	0.459%	0.159%	0.526%	3.631%	-1.407%	2.067% *	2.644% **
	-1.669	0.271	0.419	0.150	0.775	0.177	-1.146	1.891	2.548
D+1	-0.781%	0.553%	-0.663%	0.341%	0.780%	2.832%	2.314% *	0.945%	-0.242%
	-1.024	0.773	-0.606	0.321	1.151	0.138	1.885	0.865	-0.233
D+2	0.394%	-0.529%	-0.453%	0.161%	0.284%	0.228%	-1.634%	0.176%	0.917%
	0.517	-0.740	-0.414	0.152	0.419	0.011	-1.330	0.161	0.884
D+3	0.413%	0.283%	1.187%	0.148%	0.077%	-2.332%	0.161%	-0.883%	-2.096% **
	0.542	0.395	1.085	0.139	0.113	-0.113	0.131	-0.807	-2.020
D+4	-0.333%	-0.164%	-0.671%	-0.844%	-0.436%	0.016%	1.804%	1.370%	-1.844% *
	-0.436	-0.230	-0.614	-0.795	-0.644	0.001	1.469	1.254	-1.777
D+5	0.019%	-0.204%	-0.379%	-0.165%	-0.769%	-0.460%	0.875%	0.498%	0.397%
	0.025	-0.285	-0.346	-0.156	-1.134	-0.022	0.713	0.456	0.383
D+6	-0.063%	-0.032%	0.536%	-0.314%	-0.055%	1.963%	-0.630%	0.019%	-0.361%
	-0.082	-0.044	0.490	-0.295	-0.082	0.095	-0.513	0.017	-0.348
D+7	0.029%	-0.041%	1.052%	-0.345%	-0.652%	-4.684%	3.319% ***	0.874%	-1.447%
	0.038	-0.057	0.962	-0.325	-0.961	-0.228	2.703	0.800	-1.395
D+8	1.573% **	-0.153%	0.284%	0.313%	-0.223%	-1.469%	2.063% *	0.276%	-0.367%
	2.063	-0.215	0.259	0.295	-0.328	-0.071	1.680	0.252	-0.353
D+9	0.029%	-0.294%	0.626%	0.047%	-0.453%	0.871%	1.851%	-0.179%	1.010%
	0.038	-0.412	0.573	0.045	-0.668	0.042	1.508	-0.164	0.973
D+10	0.029%	-0.212%	1.410%	0.686%	0.374%	-4.092%	-1.471%	0.356%	-0.572%
	0.038	-0.296	1.289	0.646	0.552	-0.199	-1.198	0.325	-0.551

Panel B: Cumulative Abnormal Returns (CAR) (Event Date: NIRP Announcement Day)

	MXBAH	SOFIX	KAX	DAX	BUX	NKY	OSEAX	OMX	SMI
(-10,10)	-4.111%	-3.079%	6.758%	1.983%	-2.463%	4.046%	3.662%	8.420%	-2.520%
(-10,0)	-4.150%	-2.479%	3.370%	1.796%	-1.917%	7.544%	-3.583%	2.901%	-0.560%
(0,10)	0.039%	-0.600%	3.387%	0.187%	-0.547%	-3.498%	7.245%	5.520%	-1.960%

*** p<0.01, ** p<0.05, * p<0.1

Table 15. Cont'd

Panel C: Abnormal Returns (AR) (Event Date: NIRP Implementation Day)

Day	MXBAH	SOFIX	KAX	DAX	BUX	NKY	OSEAX	OMX	SMI
D-10	-0.152%	0.163%	-0.336%	0.184%	1.282%	-3.228% **	-1.968%	0.505%	-0.004%
	-0.206	0.243	-0.308	0.174	1.204	-2.298	-1.603	0.462	-0.004
D-9	-0.385%	1.107% *	-0.289%	0.431%	0.267%	-0.880%	-1.099%	0.327%	-0.004%
	-0.522	1.650	-0.264	0.406	0.251	-0.627	-0.895	0.299	-0.004
D-8	-0.363%	-0.022%	-1.462%	1.217%	-0.450%	-1.357%	-0.692%	0.240%	-0.501%
	-0.492	-0.033	-1.337	1.147	-0.423	-0.966	-0.564	0.220	-0.543
D-7	0.113%	-0.022%	-0.862%	0.431%	1.302%	1.066%	0.625%	0.964%	-0.727%
	0.153	-0.033	-0.788	0.407	1.223	0.759	0.509	0.882	-0.788
D-6	-0.883%	0.503%	1.017%	-0.070%	-0.090%	-5.581% ***	1.594%	-0.603%	0.293%
	-1.197	0.750	0.930	-0.066	-0.085	-3.974	1.298	-0.552	0.318
D-5	-2.094% ***	2.249% ***	0.037%	-0.056%	-0.090%	-2.366% *	0.694%	0.656%	2.644% ***
	-2.839	3.354	0.034	-0.052	-0.085	-1.685	0.565	0.600	2.868
D-4	-0.170%	0.002%	2.506% **	-0.009%	-0.070%	-0.026%	-1.306%	0.833%	-0.376%
	-0.230	0.002	2.291	-0.008	-0.066	-0.018	-1.064	0.762	-0.408
D-3	0.026%	-0.022%	1.114%	0.016%	0.520%	-4.989% ***	0.386%	-0.416%	0.514%
	0.035	-0.033	1.019	0.015	0.489	-3.552	0.314	-0.380	0.558
D-2	0.221%	-0.022%	1.427%	-0.359%	0.559%	6.885% ***	-1.200%	0.828%	1.435%
	0.300	-0.033	1.305	-0.338	0.526	4.902	-0.978	0.757	1.557
D-1	1.765% **	-0.826%	0.219%	0.017%	-0.501%	0.173%	-0.615%	-0.433%	-0.950%
	2.392	-1.232	0.201	0.016	-0.471	0.123	-0.501	-0.396	-1.030
D-0	1.597% **	0.010%	0.459%	0.160%	0.089%	-1.394%	-1.407%	2.067% *	-9.074% ***
	2.165	0.015	0.419	0.151	0.083	-0.992	-1.146	1.891	-9.843
D+1	-0.068%	0.052%	-0.663%	0.342%	-0.792%	2.225%	2.315% *	0.945%	-6.153% ***
	-0.092	0.077	-0.606	0.322	-0.744	1.584	1.885	0.865	-6.674
D+2	-4.636% ***	-1.187% *	-0.453%	0.162%	-1.074%	-1.454%	-1.633%	0.176%	3.151% ***
	-6.285	-1.770	-0.414	0.152	-1.009	-1.035	-1.330	0.161	3.418
D+3	0.026%	0.989%	1.187%	0.148%	-0.090%	0.871%	0.161%	-0.883%	0.316%
	0.035	1.475	1.085	0.140	-0.085	0.620	0.131	-0.807	0.343
D+4	-1.568% **	-0.622%	-0.671%	-0.844%	-0.090%	-0.393%	1.804%	1.370%	-2.109% **
	-2.126	-0.927	-0.614	-0.795	-0.085	-0.280	1.469	1.254	-2.287
D+5	0.026%	-0.009%	-0.379%	-0.165%	1.048%	-0.878%	0.875%	0.498%	-0.117%
	0.035	-0.014	-0.346	-0.155	0.985	-0.625	0.713	0.456	-0.127
D+6	0.826%	-0.727%	0.536%	-0.313%	2.127% **	1.375%	-0.630%	0.019%	1.997% **
	1.120	-1.084	0.490	-0.295	1.998	0.979	-0.513	0.017	2.166
D+7	-0.069%	0.044%	1.052%	-0.345%	0.428%	0.272%	3.319% ***	0.874%	1.640% *
	-0.094	0.066	0.962	-0.325	0.402	0.193	2.703	0.800	1.779
D+8	0.026%	-0.284%	0.284%	0.314%	-0.622%	-1.030%	2.063% *	0.276%	1.270%
	0.035	-0.424	0.259	0.296	-0.584	-0.733	1.680	0.252	1.378
D+9	-0.951%	-0.948%	0.626%	0.048%	0.294%	0.340%	1.852%	-0.179%	-1.096%
	-1.289	-1.414	0.573	0.045	0.276	0.242	1.508	-0.164	-1.189
D+10	-1.033%	-0.092%	1.410%	0.686%	-0.857%	4.001% ***	-1.471%	0.356%	1.475%
	-1.400	-0.137	1.289	0.647	-0.805	2.849	-1.198	0.325	1.600

Panel D: Cumulative Abnormal Returns (CAR) (Event Date: NIRP Implementation Day)

(-10,10)	-7.744%	0.334%	6.758%	1.997%	3.188%	-6.368%	3.667%	8.420%	-6.374%
(-10,0)	-1.921%	3.107%	3.370%	1.803%	2.728%	-10.303%	-3.580%	2.901%	2.325%
(0,10)	-5.824%	-2.774%	3.387%	0.194%	0.460%	3.936%	7.247%	5.520%	-8.699%

*** p<0.01, ** p<0.05, * p<0.1

Table 16. Portfolio Average Abnormal Return Analysis for Currency Exchange Markets

Panel A: Average Abnormal Returns (AAR) (Event Date: NIRP Announcement Day)

Day	AAR	z		Std Error	Minimum	Maximum	CAAR
D-10	-0.022%	-0.8067		0.0082	-0.921%	1.311%	-0.0220%
D-9	0.126%	0.4257		0.0034	-0.421%	0.751%	0.1036%
D-8	0.128%	0.7193		0.0041	-0.450%	0.783%	0.2315%
D-7	-0.016%	-0.2407		0.0072	-1.260%	1.302%	0.2157%
D-6	0.011%	0.2813		0.0050	-0.694%	0.775%	0.2267%
D-5	-0.137%	-0.5717		0.0055	-0.959%	0.912%	0.0896%
D-4	0.089%	0.3257		0.0103	-1.767%	1.747%	0.1789%
D-3	0.331%	1.4244		0.0044	-0.489%	0.982%	0.5101%
D-2	0.000%	-0.1104		0.0045	-0.611%	0.722%	0.5098%
D-1	0.219%	0.9238		0.0056	-0.501%	1.347%	0.7290%
D-Day	0.678%	2.7568	***	0.0092	-0.481%	2.112%	1.4066%
D+1	0.057%	0.2729		0.0055	-0.792%	0.799%	1.4632%
D+2	-0.116%	-0.2482		0.0055	-1.074%	0.622%	1.3475%
D+3	-0.354%	-1.5687		0.0077	-1.742%	0.476%	0.9930%
D+4	0.054%	0.3299		0.0046	-0.956%	0.589%	1.0473%
D+5	-0.321%	-1.5535		0.0120	-3.080%	1.048%	0.7259%
D+6	0.046%	-0.2383		0.0091	-0.879%	2.127%	0.7721%
D+7	0.027%	-0.0752		0.0037	-0.643%	0.428%	0.7992%
D+8	-0.543%	-2.1965	**	0.0064	-1.611%	0.172%	0.2561%
D+9	-0.514%	-2.5634	**	0.0068	-1.408%	0.526%	-0.2581%
D+10	0.013%	0.3079		0.0074	-0.892%	1.187%	-0.2456%

Panel B: Cumulative Average Abnormal Returns (CAAR) (Event Date: NIRP Announcement Day)

Window	CAAR	z	
[-10,10]	-0.246%	0.367814	
[-10,0]	0.014066	1.763108	*
[0,10]	-0.009746	-1.440100	
[-5,5]	0.004992	0.597290	
[-5,0]	0.011799	1.938641	*
[0,5]	-0.000031	-0.004433	
[-3,3]	0.008141	1.304215	
[-3,0]	0.012277	2.497336	**
[0,3]	0.00264	0.606396	
[-2,2]	0.008374	1.607700	
[-2,0]	0.008966	2.061282	**
[0,2]	0.006185	1.605909	
[-1,1]	0.009534	2.825540	***
[-1,0]	0.008968	2.602609	***
[0,1]	0.007342	2.142314	**

*** p<0.01, ** p<0.05, * p<0.1

Table 16. Cont'd

Panel C: Average Abnormal Returns (AAR) (Event Date: NIRP Implementation Day)

Day	AAR	z		Std Error	Minimum	Maximum	CAAR
D-10	-0.125%	-0.4590		0.0062	-0.851%	1.312%	-0.1247%
D-9	-0.368%	-1.6192		0.0069	-1.745%	0.747%	-0.4927%
D-8	0.125%	0.6424		0.0049	-0.959%	0.520%	-0.3682%
D-7	-0.113%	-0.5619		0.0052	-1.260%	0.351%	-0.4813%
D-6	-0.130%	-0.5718		0.0056	-0.881%	0.775%	-0.6117%
D-5	0.041%	0.5999		0.0107	-0.959%	2.566%	-0.5711%
D-4	-0.167%	-0.9209		0.0122	-1.766%	1.747%	-0.7379%
D-3	-0.006%	-0.1164		0.0054	-0.828%	0.709%	-0.7439%
D-2	0.254%	1.1076		0.0044	-0.447%	0.732%	-0.4903%
D-1	0.305%	1.4885		0.0046	-0.253%	1.181%	-0.1857%
D-Day	-1.670%	-9.2027	***	0.0670	-19.418%	2.112%	-1.8555%
D+1	0.468%	2.2227	**	0.0080	-0.279%	2.263%	-1.3877%
D+2	0.218%	1.2370		0.0091	-0.761%	2.371%	-1.1699%
D+3	-0.542%	-2.5018	**	0.0055	-1.431%	0.477%	-1.7123%
D+4	-0.098%	-0.5426		0.0074	-1.820%	0.415%	-1.8108%
D+5	0.064%	0.4940		0.0073	-1.096%	1.248%	-1.7470%
D+6	-0.151%	-0.5938		0.0051	-0.698%	0.971%	-1.8976%
D+7	0.361%	1.7983	*	0.0087	-0.229%	2.523%	-1.5368%
D+8	-0.193%	-0.7714		0.0065	-1.611%	0.877%	-1.7293%
D+9	-0.390%	-1.7536	*	0.0062	-1.408%	0.367%	-2.1192%
D+10	0.386%	2.0550	**	0.0092	-0.892%	2.022%	-1.7337%

Panel D: Cumulative Average Abnormal Returns (CAAR) (Event Date: NIRP Implementation Day)

Window	CAAR	z	
[-10,10]	-1.734%	-1.739111	*
[-10,0]	-1.856%	-2.898560	***
[0,10]	-1.548%	-2.279071	**
[-5,5]	-1.135%	-1.849640	*
[-5,0]	-1.244%	-2.875653	***
[0,5]	-1.561%	-3.385738	***
[-3,3]	-0.974%	-2.178954	**
[-3,0]	-1.118%	-3.361446	***
[0,3]	-1.527%	-4.122365	***
[-2,2]	-0.426%	-1.407307	
[-2,0]	-1.112%	-3.814271	***
[0,2]	-0.984%	-3.315709	***
[-1,1]	-0.897%	-3.170491	***
[-1,0]	-1.365%	-5.454711	***
[0,1]	-1.202%	-4.935589	***

*** p<0.01, ** p<0.05, * p<0.1

Table 17. Descriptive Statistics of Currency Mispricing Terms

	Denmark	Euro	Japan	Norway	Sweden	Switzerland
Mean	1.60E-05	-1.82E-05	1.45E-06	-2.64E-05	7.02E-06	2.48E-05
Median	0.00015	9.91E-06	-0.000135	-0.000112	3.59E-05	5.96E-05
Maximum	0.00146	0.00162	0.00157	0.00120	0.00098	0.00101
Minimum	-0.00110	-0.00120	-0.00178	-0.00046	-0.00060	-0.00053
Std. Dev.	0.00066	0.00075	0.00095	0.00036	0.00035	0.00033
Skewness	0.00857	0.37056	-0.13364	1.76422	0.64728	0.62192
Kurtosis	2.42268	2.64539	1.92494	6.49143	3.78373	4.67819
Jarque-Bera	0.34749	0.70313	1.27832	25.66657	2.38554	4.54529
Observations	25	25	25	25	25	25

Table 18. Panel Error Term Unit Root Test Results (July 2011 – July 2017)

Considering the data availability, currencies of six economies are considered: Denmark, the Euro Area, Japan, Norway, Sweden, and Switzerland. Here, the sample of countries are divided into two groups: EU (Denmark, the Euro Area, Sweden), and non-EU (Japan, Norway, and Switzerland).

Method		Levin, Lin, and Chu		Im, Pesaran, and Shin		Fisher-Choi ADF				Fisher-Choi PP			
						Fisher Chi-sq		Choi Z-stat		Fisher Chi-sq		Choi Z-stat	
		Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Overall	Level	0.74430	0.7717	-1.3735	0.0848*	27.3460	0.0069***	-1.5500	0.0606*	44.4956	0.0000***	-2.7164	0.0033***
	1st Diff.	-7.2319	0.0000***	-	-	-	-	-	-	-	-	-	-
EU Countries	Level	-2.2430	0.0124**	-3.0292	0.0012***	15.0670	0.0198**	-2.2067	0.0137**	35.8004	0.0000***	-4.6902	0.0000***
	1st Diff.	-	-	-	-	-	-	-	-	-	-	-	-
non-EU Countries	Level	1.3884	0.9175	1.0868	0.8614	7.0898	0.3126	0.8775	0.8099	8.6952	0.1915	0.8487	0.8020
	1st Diff.	-2.9725	0.0015***	-6.3024	0.0000***	45.9695	0.0000***	-5.5717	0.0000***	45.9695	0.0000***	-5.5717	0.0000***

*** p<0.01, ** p<0.05, * p<0.1

Table 19. By-country Error Term Unit Root Test Results (Before and After NIRP)

Considering the data availability, six economies are considered: Denmark, the Euro Area, Japan, Norway, Sweden, and Switzerland. The unit root tests are implemented by country, with periodic breakpoint of NIRP. For each country, pre- and post-year of NIRP implementation are compared.

Method		Denmark (DKK)				Euro Area (EUR)				Japan (JPY)			
		ADF		PP		ADF		PP		ADF		PP	
		Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Overall	Level	-2.3897	0.3750	-2.3277	0.4046	-5.9491	0.0003***	-5.9450	0.0003***	-2.0571	0.5422	-2.1166	0.5113
	1st Diff.	-5.4625	0.0011***	-5.4625	0.0011***	-	-	-	-	-4.8311	0.0042***	-4.8314	0.0041***
Pre-NIRP	Level	-3.7964	0.0562*	-3.8528	0.0517*	-3.4927	0.0865*	-3.4936	0.0864*	-1.7926	0.6454	-1.8234	0.6312
	1st Diff.	-	-	-	-	-	-	-	-	-2.7467	0.2450	-5.0712	0.0107**
Post-NIRP	Level	-2.9801	0.1850	-2.6389	0.2742	-3.8637	0.0552*	-6.0330	0.0033***	-1.1749	0.8622	-0.6970	0.9432
	1st Diff.	-3.9609	0.0600**	-5.0982	0.0128**	-	-	-	-	-3.1109	0.1639	-4.7663	0.0191**

Method		Norway (NOK)				Sweden (SEK)				Switzerland (CHF)			
		ADF		PP		ADF		PP		ADF		PP	
		Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Overall	Level	-3.3270	0.0859*	-3.3129	0.0881*	-2.7962	0.2118	-2.7962	0.2118	-2.6513	0.2636	-2.6449	0.2656
	1st Diff.	-	-	-	-	-6.5860	0.0001***	-6.8250	0.0001***	-3.2842	0.0974*	-6.7760	0.0001***
Pre-NIRP	Level	-1.7926	0.6454	-1.8234	0.6312	-3.7805	0.0575*	-5.5847	0.0045***	-1.2350	0.8529	-0.9333	0.9148
	1st Diff.	-2.7467	0.2450	-5.0712	0.0107**	-	-	-	-	-2.6885	0.2609	-2.6937	0.2571
Post-NIRP	Level	-2.7214	0.2516	-3.6560	0.0732*	-3.4580	0.0950*	-3.4587	0.0949*	-4.0240	0.0444**	-4.4943	0.0233**
	1st Diff.	-4.7781	0.0232**	-	-	-	-	-	-	-	-	-	-

*** p<0.01, ** p<0.05, * p<0.1

Table 20. Portfolio Average Abnormal Return Analysis for Equity Markets

Panel A: Average Abnormal Returns (AAR) (Event Date: NIRP Announcement Day)

Day	AAR	z	Std Error	Minimum	Maximum	CAAR
D-10	-0.3482%	-1.2248	0.0088	-1.9682%	0.5049%	-0.3482%
D-9	-0.1610%	-0.4267	0.0048	-1.0988%	0.4298%	-0.5092%
D-8	-0.1854%	-1.1963	0.0097	-1.4622%	1.4166%	-0.6946%
D-7	-0.0547%	0.8449	0.0121	-2.9079%	0.9639%	-0.7493%
D-6	0.1038%	0.7806	0.0093	-1.5893%	1.5938%	-0.6455%
D-5	0.8131%	0.2442	0.0221	-0.8095%	6.5812%	0.1676%
D-4	0.2784%	0.0656	0.0124	-1.3060%	2.5058%	0.4460%
D-3	-0.1203%	-0.0201	0.0085	-1.5067%	1.1142%	0.3258%
D-2	0.2281%	-0.7321	0.0170	-2.3311%	3.5576%	0.5538%
D-1	-0.2290%	-0.8023	0.0054	-1.3283%	0.4448%	0.3249%
D-Day	0.7777%	1.1390	0.0170	-1.4073%	3.6305%	1.1026%
D+1	0.6755%	1.0900	0.0124	-0.7809%	2.8318%	1.7781%
D+2	-0.0505%	-0.1135	0.0073	-1.6335%	0.9173%	1.7276%
D+3	-0.3380%	-0.1782	0.0119	-2.3315%	1.1867%	1.3896%
D+4	-0.1225%	-0.5906	0.0111	-1.8439%	1.8038%	1.2671%
D+5	-0.0208%	-0.1224	0.0052	-0.7686%	0.8751%	1.2462%
D+6	0.1181%	-0.2539	0.0076	-0.6303%	1.9630%	1.3644%
D+7	-0.2105%	0.5125	0.0215	-4.6844%	3.3191%	1.1539%
D+8	0.2552%	1.1938	0.0105	-1.4693%	2.0625%	1.4090%
D+9	0.3899%	0.6452	0.0075	-0.4526%	1.8513%	1.7989%
D+10	-0.3881%	0.2018	0.0161	-4.0920%	1.4096%	1.4109%

Panel B: Cumulative Average Abnormal Returns (CAAR) (Event Date: NIRP Announcement Day)

Window	CAAR	z
[-10,10]	1.4109%	0.2306
[-10,0]	1.1026%	-0.4004
[0,10]	1.0860%	1.0624
[-5,5]	1.8917%	-0.0062
[-5,0]	1.7481%	-0.0431
[0,5]	0.9214%	0.4998
[-3,3]	0.9435%	0.1447
[-3,0]	0.6565%	-0.2077
[0,3]	1.0647%	0.9686
[-2,2]	1.4018%	0.2599
[-2,0]	0.7768%	-0.2283
[0,2]	1.4027%	1.2214
[-1,1]	1.2243%	0.8237
[-1,0]	0.5488%	0.2381
[0,1]	1.4533%	1.5761

*** p<0.01, ** p<0.05, * p<0.1

Table 20. Cont'd

Panel C: Average Abnormal Returns (AAR) (Event Date: NIRP Implementation Day)							
Day	AAR	z		Std Error	Minimum	Maximum	CAAR
D-10	-0.3950%	-0.7786		0.0137	-3.2283%	1.2815%	-0.3950%
D-9	-0.0584%	0.0981		0.0069	-1.0986%	1.1065%	-0.4534%
D-8	-0.3767%	-0.9971		0.0081	-1.4622%	1.2167%	-0.8301%
D-7	0.3211%	0.7744		0.0077	-0.8624%	1.3019%	-0.5090%
D-6	-0.4244%	-0.8589		0.0208	-5.5811%	1.5940%	-0.9334%
D-5	0.1861%	0.9205		0.0168	-2.3661%	2.6444%	-0.7473%
D-4	0.1537%	0.4203		0.0104	-1.3058%	2.5058%	-0.5936%
D-3	-0.3167%	-0.5118		0.0181	-4.9887%	1.1142%	-0.9103%
D-2	1.0861%	2.6658	***	0.0233	-1.2002%	6.8854%	0.1758%
D-1	-0.1280%	-0.2995		0.0083	-0.9498%	1.7647%	0.0478%
D-Day	-0.8325%	-2.4185	**	0.0330	-9.0741%	2.0671%	-0.7847%
D+1	-0.1997%	-1.1277		0.0250	-6.1531%	2.3145%	-0.9844%
D+2	-0.7721%	-2.7042	***	0.0205	-4.6362%	3.1510%	-1.7565%
D+3	0.3029%	0.9791		0.0064	-0.8825%	1.1867%	-1.4536%
D+4	-0.3469%	-1.4636		0.0126	-2.1086%	1.8040%	-1.8005%
D+5	0.0999%	0.3069		0.0061	-0.8784%	1.0481%	-1.7006%
D+6	0.5789%	1.6261		0.0108	-0.7270%	2.1265%	-1.1217%
D+7	0.8017%	2.1622	**	0.0113	-0.3448%	3.3193%	-0.3201%
D+8	0.2552%	0.7199		0.0094	-1.0295%	2.0627%	-0.0648%
D+9	-0.0017%	-0.4709		0.0094	-1.0959%	1.8515%	-0.0665%
D+10	0.4973%	1.0566		0.0168	-1.4706%	4.0014%	0.4308%

Panel D: Cumulative Average Abnormal Returns (CAAR) (Event Date: NIRP Implementation Day)			
Window	CAAR	z	
[-10,10]	0.4308%	0.0217	
[-10,0]	-0.7847%	-0.2971	
[0,10]	0.3830%	-0.4022	
[-5,5]	-0.7672%	-0.9747	
[-5,0]	0.1487%	0.3171	
[0,5]	-1.7484%	-2.6242	***
[-3,3]	-0.8600%	-1.2915	
[-3,0]	-0.1911%	-0.2820	
[0,3]	-1.5015%	-2.6357	***
[-2,2]	-0.8462%	-1.7370	*
[-2,0]	0.1256%	-0.0302	
[0,2]	-1.8043%	-3.6087	***
[-1,1]	-1.1602%	-2.2203	**
[-1,0]	-0.9605%	-1.9220	*
[0,1]	-1.0323%	-2.5076	**

*** p<0.01, ** p<0.05, * p<0.1

Table 21. Regression Results of Currency Return Analysis

VARIABLES	Bosina (USD/BAM)	Bulgaria (USD/BGN)	Denmark (USD/DKK)	Euro Area (USD/EUR)	Hungary (USD/HUF)	Japan (USD/JPY)	Norway (USD/NOK)	Sweden (USD/SEK)	Switzerland (USD/CHF)
Index Return (t-1)	-0.055	-0.019	0.071 **	0.244 ***	-0.032	0.010	-0.082	-0.032	-0.169 **
	0.15	0.68	0.03	0.00	0.37	0.69	0.16	0.51	0.02
Currency Return (t-1)	0.272 **	0.052	-0.055	-0.239 **	0.146 **	-0.077	-0.093	-0.134 **	-0.108 *
	0.01	0.59	0.56	0.01	0.03	0.28	0.30	0.03	0.07
O/N Deposit Rate (t-1)		0.014 *	-0.016 ***	0.004	0.000	-0.001	-0.008	-0.001	-0.002
		0.09	0.00	0.38	0.57	0.30	0.30	0.54	0.49
2-Yr Bond Yield (t-1)		0.008 ***	0.006 **	0.007	0.004 **	0.020 *	0.004	0.007 **	-0.028 ***
		0.00	0.02	0.30	0.01	0.07	0.77	0.02	0.00
10-Yr Bond Yield (t-1)		-0.014 **	0.020 ***	-0.001	0.000	0.000	0.024 **	0.004	-0.003
		0.02	0.00	0.86	0.86	0.97	0.03	0.12	0.41
Abs Yield Curve Slope		0.012 *	-0.025 ***	0.000	0.000	-0.001	-0.011	-0.003	0.002
		0.06	0.00	1.00	0.87	0.30	0.15	0.20	0.48
5-Yr CDS Spread (t-1)		0.001	0.016 **	0.005	0.007	-0.005	-0.005	-0.001	0.001
		0.95	0.04	0.57	0.64	0.66	0.63	0.91	0.84
BBDXY (t-1)	-0.286 *	-0.104	0.017	-0.042	-0.053	0.113	0.313 *	0.136	0.278 **
	0.06	0.45	0.90	0.73	0.64	0.25	0.06	0.19	0.05
S&P500 Return (t-1)	-0.030	0.060	0.103 ***	0.022	-0.005	0.057	0.001	0.023	0.047
	0.53	0.18	0.00	0.59	0.91	0.22	0.99	0.55	0.46
EURSTX 50 Return (t-1)	0.038	0.004	-0.041 *	-0.233 ***	0.066 *	0.031	0.070	0.021	0.147 **
	0.21	0.88	0.09	0.00	0.06	0.35	0.21	0.63	0.01
STATE	-0.004 ***	-0.002	-0.003 ***	0.000	-0.002 **	0.001	-0.002	-0.002	-0.035 ***
	0.00	0.22	0.00	0.65	0.04	0.76	0.33	0.13	0.00
Constant	-0.002 ***	-0.001	0.005	-0.003 **	-0.008	-0.003	-0.028 ***	-0.002	-0.005 ***
	0.00	0.74	0.23	0.05	0.10	0.15	0.01	0.20	0.01
Observations	324	459	485	489	486	472	225	488	487
R-squared	0.192	0.207	0.505	0.058	0.182	0.073	0.133	0.321	0.195

Robust pval in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 22. Regression Results of Index Return Analysis

VARIABLES	Bos&Herz (MXBAH)	Bulgaria (SOFIX)	Denmark (KAX)	Euro Area (DAX)	Hungary (BUX)	Japan (NIKKEI)	Norway (OSEAX)	Sweden (SAX)	Switzerland (SMI)
Index Return (t-1)	-0.052	-0.048	-0.076	0.127	-0.100 *	-0.279 ***	-0.200 **	-0.247 ***	-0.246 ***
	0.42	0.32	0.24	0.29	0.06	0.00	0.02	0.00	0.00
Currency Return (t-1)	-0.034	0.067	0.221	0.283	0.041	0.038	0.149	0.295 ***	0.366 ***
	0.86	0.51	0.23	0.14	0.69	0.79	0.26	0.01	0.00
O/N Deposit Rate (t-1)		-0.001	0.032 ***	0.010	0.000	-0.003	0.052 ***	0.006	-0.003
		0.91	0.00	0.29	0.82	0.30	0.00	0.23	0.29
2-Yr Bond Yield (t-1)		-0.002	-0.009 *	0.010	-0.001	0.013	0.003	0.005	-0.020 ***
		0.56	0.09	0.44	0.57	0.54	0.86	0.24	0.00
10-Yr Bond Yield (t-1)		-0.007	-0.030 ***	-0.018 **	-0.004	0.005	-0.054 ***	-0.016 ***	-0.003
		0.31	0.00	0.04	0.16	0.61	0.00	0.00	0.33
Abs Yield Curve Slope		0.004	0.037 ***	0.015 *	0.000	-0.005	0.052 ***	0.011 **	0.003
		0.53	0.00	0.07	1.00	0.13	0.00	0.01	0.20
5-Yr CDS Spread (t-1)		-0.005	0.034 **	-0.002	0.022	0.011	-0.012	0.009	0.008
		0.77	0.02	0.89	0.30	0.64	0.41	0.29	0.24
BBDXY (t-1)	0.061	-0.111	-0.092	-0.500 **	-0.092	0.725 ***	-0.249	-0.326 *	-0.237 *
	0.83	0.45	0.73	0.04	0.58	0.00	0.32	0.06	0.08
S&P500 Return (t-1)	0.010	0.052	0.177 ***	0.358 ***	0.066	0.657 ***	0.549 ***	0.418 ***	0.400 ***
	0.90	0.26	0.01	0.00	0.34	0.00	0.00	0.00	0.00
EURSTX 50 Return (t-1)	0.030	-0.014	0.108 **	-0.318 ***	0.075	0.222 ***	-0.010	-0.033	0.022
	0.57	0.65	0.02	0.01	0.15	0.00	0.90	0.65	0.69
STATE	0.000	-0.001	0.000	0.000	-0.003	0.003	0.001	-0.003	-0.018 ***
	0.91	0.66	0.90	0.90	0.13	0.34	0.71	0.14	0.00
Constant	-0.002	0.008 **	-0.008	0.005	0.017 **	0.000	0.001	0.008 ***	-0.001
	0.14	0.03	0.27	0.12	0.03	0.91	0.95	0.01	0.51
Observations	267	457	473	479	476	448	219	473	476
R-squared	0.005	0.042	0.142	0.064	0.024	0.281	0.234	0.140	0.211

Robust pval in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 23. Comparison of Average Term Structure of Interests

The yield curve slopes are calculated by differentials of 10-year government bond yields and 2-year government bond yields. For Hungary, due to availability issue, 3-year government bond yields are used instead of 2-year yields. Each value is average of the differentials over the period from 1 year before to 1 year after the NIRP.

	Bulgaria	Hungary	Denmark	Euro Area	Sweden	Norway	Switzerland	Japan
Avg. Term Structure	2.0276%	1.6212%	1.4116%	1.3212%	1.1629%	0.9263%	0.7865%	0.2606%
Rank	1	2	3	4	5	6	7	8

Table 24. Indexes Cointegration with the U.S. Equity Market

For those nine countries' indexes, Johansen cointegration tests are implemented, using the S&P500 as the benchmark index. Daily data of each equity index returns are used for the test, and Linear deterministic trends are assumed. The data covers three different period of time. 1) the primary event window is D-10 to D+10 of the event day. 2) Regime 0+1 is two years of data, before and after NIRP. 3) to see the longer-term cointegration, 6 years of longer-term period, which covers all the analyses data in this study is considered.

		1) Primary Event Window			2) Regime 0+1 (2 years)			3) July 5, 2011 - July 1, 2017		
Country	Index	Trace Stat.	Prob.		Trace Stat.	Prob.		Trace Stat.	Prob.	
Bos & Herz	MXBAH	13.33255	0.1032		8.666291	0.3972		6.615036	0.6228	
Bulgaria	SOFIX	12.87747	0.1194		18.86822	0.0149	**	3.606961	0.9326	
Denmark	KAX	12.87747	0.1194		12.2596	0.1449		8.059453	0.4591	
Euro Area	DAX	25.02436	0.0014	***	3.29829	0.9517		9.189588	0.3482	
Hungary	BUX	7.152566	0.5600		7.378296	0.5341		11.49918	0.1826	
Japan	NIKKEI	13.99046	0.0832	*	11.52513	0.1812		20.00238	0.0098	***
Norway	OSEAX	22.58429	0.0036	***	18.72791	0.0157	**	7.091516	0.5670	
Sweden	OMX	5.380235	0.7672		12.30256	0.1430		6.171222	0.6753	
Switzerland	SMI	17.79775	0.0221	**	22.99693	0.0031	***	2.881643	0.9720	

Table 25. Results of VIX Volatility Index Regression Models

	Euro		Japanese Yen	
VARIABLES	Model (E2)	Model (E4)	Model (J2)	Model (J4)
EUVIX (t-1)	-0.084			
	[0.25]			
JYVIX (t-1)			-0.055	
			[0.38]	
Index Return (t-1)	-0.085	-0.203	-0.228	-0.202
	[0.87]	[0.70]	[0.22]	[0.28]
Currency Return (t-1)	-0.561	-0.636	0.415	0.381
	[0.46]	[0.40]	[0.55]	[0.58]
Overnight Deposit rate (t-1)	-0.012	-0.011	-0.003	-0.002
	[0.71]	[0.74]	[0.67]	[0.68]
2-Yr Bond Yield (t-1)	0.113	0.11	-0.129	-0.126
	[0.14]	[0.15]	[0.50]	[0.51]
10-Yr Bond Yield (t-1)	-0.113**	-0.110**	0.071	0.069
	[0.04]	[0.05]	[0.67]	[0.68]
Abs Yield Curve Slope	0.108**	0.105*	-0.115	-0.113
	[0.04]	[0.05]	[0.49]	[0.50]
5-Yr CDS Spread (t-1)	-0.068	-0.073	-0.013	-0.009
	[0.26]	[0.23]	[0.89]	[0.93]
BBDXY (t-1)	0.985	0.947	1.785**	1.825**
	[0.34]	[0.35]	[0.04]	[0.04]
S&P500 Return (t-1)	-0.41	-0.308	-1.045**	-0.958*
	[0.22]	[0.33]	[0.03]	[0.05]
EURSTX 50 Return (t-1)	-0.288	-0.193	0.006	0.082
	[0.60]	[0.72]	[0.98]	[0.79]
STATE	0.001	0.001	-0.022	-0.021
	[0.86]	[0.88]	[0.28]	[0.30]
Constant	0.007	0.007	0.014	0.014
	[0.68]	[0.68]	[0.33]	[0.33]
Observations	475	475	457	457
R-squared	0.036	0.031	0.057	0.055

Robust pval in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 26. Test Results for Equality of Variance and Mean

Panel A: Equality of Variance and Mean of Currency Returns

Variance	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Regime 0 (Est. Window)	4.24E-05	5.79E-05	6.30E-05	1.49E-05	6.54E-05	3.00E-05	7.93E-05	1.65E-04	3.63E-05
Event Window	1.80E-05	7.45E-05	4.12E-05	6.10E-06	2.91E-05	7.61E-05	7.84E-05	2.67E-05	6.40E-05
Regime 1	2.50E-05	2.64E-05	2.41E-05	4.00E-05	3.95E-05	6.31E-05	5.86E-05	7.26E-05	5.04E-05

Standard Deviation	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Regime 0 (Est. Window)	0.0065	0.0076	0.0079	0.0039	0.0081	0.0055	0.0089	0.0128	0.0060
Event Window	0.0042	0.0086	0.0064	0.0025	0.0054	0.0087	0.0089	0.0052	0.0080
Regime 1	0.0050	0.0051	0.0049	0.0063	0.0063	0.0079	0.0077	0.0085	0.0071

F-Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	0.0340	0.1350	1.7110	2.9710	0.0580	0.0470	2.6560	0.1220	3.4780
df	511	516	519	505	512	520	521	509	521
p-value	0.4554	0.0062	0.6209	0.9684	0.5490	0.7299	0.5060	0.5473	0.1666
		***							

Bartlett's Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	0.584	1.665	0.840	0.425	0.005	0.165	0.089	0.145	0.766
df	1	1	1	1	1	1	1	1	1
p-value	0.445	0.197	0.359	0.514	0.943	0.684	0.765	0.703	0.381

Levene's Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	10.864	14.211	20.428	26.131	8.497	25.024	6.033	51.374	15.179
df1	1	1	1	1	1	1	1	1	1
df2	510	515	518	504	511	519	520	508	520
p-value	0.001	0.000	0.000	0.000	0.004	0.000	0.014	0.000	0.000
	***	***	***	***	***	***	**	***	***

Panel B: Equality of Variance and Mean of Equity Returns

Variance	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Regime 0 (Est. Window)	0.00007664	0.00004335	0.00017783	0.00008612	0.00012216	0.00024400	0.00013348	0.00005473	0.00007402
Event Window	0.00026284	0.00002830	0.00009371	0.00001865	0.00006669	0.00105758	0.00022367	0.00005050	0.00014793
Regime 1	0.00007514	0.00005372	0.00006878	0.00013450	0.00020720	0.00009357	0.00017450	0.00014415	0.00016148

Standard Deviation	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Regime 0 (Est. Window)	0.0088	0.0066	0.0133	0.0093	0.0111	0.0156	0.0116	0.0074	0.0086
Event Window	0.0162	0.0053	0.0097	0.0043	0.0082	0.0325	0.0150	0.0071	0.0122
Regime 1	0.0087	0.0073	0.0083	0.0116	0.0144	0.0097	0.0132	0.0120	0.0127

F-Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	0.5584	7.5508	0.2450	0.0016	0.3596	0.1194	0.4430	0.3626	1.9193
df	340	476	486	493	489	466	521	491	484
p-value	0.4554	0.0062	0.6209	0.9684	0.5490	0.7299	0.5060	0.5473	0.1666
		***							

Bartlett's Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	0.023	8.248	1.278	0.636	0.005	2.218	2.157	2.830	0.968
df	1	1	1	1	1	1	1	1	1
p-value	0.880	0.004	0.258	0.425	0.943	0.136	0.142	0.093	0.325
		***						**	

Levene's Test	Bos&Herz	Bulgaria	Denmark	Euro Area	Hungary	Japan	Norway	Switzerland	Sweden
Test Statistic	0.479	0.358	35.438	9.409	5.717	0.712	3.645	32.342	24.426
df1	1	1	1	1	1	1	1	1	1
df2	339	475	485	492	488	465	520	490	483
p-value	0.489	0.550	0.000	0.002	0.017	0.399	0.057	0.000	0.000
			***	***	**		*	***	***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 27. GARCH Results for the Currency and Equity Returns

Panel A: Results for Currency Returns – GARCH (1,1)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

1. Overall Period

VARIABLES	BAM / USD	BGN / USD	DKK / USD	EUR / USD	HUF / USD	JPY / USD	NOK / USD	SEK / USD	CHF / USD
C	1.71E-07	1.44E-07	2.76E-07	1.79E-07	6.77E-07	7.63E-07	1.05E-05	2.00E-06	1.60E-06
α: RESID(-1)^2	-0.013725	0.0156641	-0.012954	0.0571653	0.024806	0.0448262	0.051859	0.048223	-0.001119
β: GARCH(-1)	1.0073425	0.9791945	1.00157	0.9387652	0.961045	0.9434469	0.821851	0.918212	0.988795
α + β	0.9936179	0.9948585	0.9886158	0.9959305	0.985851	0.9882731	0.87371	0.966435	0.987676
R-squared	-0.008742	-0.035196	-0.077495	-0.001992	-0.021797	-0.017556	-0.00208	-0.003266	-0.004532

2. Pre-NIRP Year

VARIABLES	BAM / USD	BGN / USD	DKK / USD	EUR / USD	HUF / USD	JPY / USD	NOK / USD	SEK / USD	CHF / USD
C	4.28E-05	2.27E-05	6.27E-07	2.18E-07	6.55E-07	4.61E-06	1.71E-05	6.54E-06	3.77E-07
α: RESID(-1)^2	0.103486	0.090867	0.040644	-0.034892	-0.027967	0.154794	0.059911	0.10649	0.048103
β: GARCH(-1)	-0.125225	0.513729	0.943554	1.011889	1.021612	0.698613	0.726931	0.717688	0.926772
α + β	-0.021739	0.604596	0.984198	0.976997	0.993645	0.853407	0.786842	0.824178	0.974875
R-squared	-0.00011	-0.000001	-0.046789	-0.000223	-0.006985	-0.005906	-0.000122	-0.000355	-0.000024

3. Post-NIRP Year

VARIABLES	BAM / USD	BGN / USD	DKK / USD	EUR / USD	HUF / USD	JPY / USD	NOK / USD	SEK / USD	CHF / USD
C	4.19E-07	7.24E-06	4.98E-06	3.58E-08	4.00E-05	6.33E-05	3.37E-05	3.37E-05	7.03E-06
α: RESID(-1)^2	0.033959	0.013898	-0.037763	-0.014563	0.132307	0.067455	0.152735	0.152735	0.024824
β: GARCH(-1)	0.964802	0.702362	0.825747	1.02472	-0.165633	-0.06925	0.239623	0.239623	0.831818
α + β	0.998761	0.71626	0.787984	1.010157	-0.033326	-0.001795	0.392358	0.392358	0.856642
R-squared	-3.015418	-0.000024	-0.000022	-0.003489	-0.000062	-0.000012	-0.000271	-0.000271	-0.007088

Panel B: Results for Equity Returns - EGARCH

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

1. Overall Period

VARIABLES	Bos&Herz (MXBAH)	Bulgaria (SOFIX)	Denmark (KAX)	Euro Area (DAX)	Hungary (BUX)	Japan (NIKKEI)	Norway (OSEAX)	Sweden (SAX)	Switzerland (SMI)
C(2)	-0.39815	-1.67294	-0.61323	-0.80373	-0.41791	-0.667310	-0.21709	-0.83335	-2.06753
C(3)	0.113871	0.166386	0.147225	0.15294	0.11682	0.072953	0.01367	0.15067	0.458703
C(4)	0.055591	0.105444	-0.042980	-0.14810	-0.11044	-0.282890	-0.15698	-0.19254	-0.30395
C(5)	0.965552	0.846417	0.944802	0.925073	0.963868	0.930218	0.97638	0.921458	0.815726
R-squared	-0.00153	-1.60E-05	-0.00017	-0.0004	-0.00144	-2.20E-05	-0.00214	-0.00071	-0.00154

2. Pre-NIRP Year

VARIABLES	Bos&Herz (MXBAH)	Bulgaria (SOFIX)	Denmark (KAX)	Euro Area (DAX)	Hungary (BUX)	Japan (NIKKEI)	Norway (OSEAX)	Sweden (SAX)	Switzerland (SMI)
C(2)	-6.570981	-13.7528	-1.15E+01	-0.520557	-13.13213	-0.751651	-1.090929	-1.240111	-1.240111
C(3)	0.587399	0.138494	-0.132133	-0.155938	0.130958	0.085573	0.002378	0.17849	0.17849
C(4)	0.224617	0.089592	-0.086002	-0.292603	0.044777	-0.28552	-0.238962	-0.172011	-0.172011
C(5)	0.368005	-0.351723	-0.341272	0.932073	-0.457563	0.922213	0.879515	0.884593	0.884593
R-squared	-0.000207	-0.000341	-0.000152	-0.005839	-0.000183	-0.001382	-0.000158	-0.002724	-0.002724

3. Post-NIRP Year

VARIABLES	Bos&Herz (MXBAH)	Bulgaria (SOFIX)	Denmark (KAX)	Euro Area (DAX)	Hungary (BUX)	Japan (NIKKEI)	Norway (OSEAX)	Sweden (SAX)	Switzerland (SMI)
C(2)	-18.50785	-1.30E+00	-7.93699	-0.217151	-0.546783	-0.452892	-0.353236	-0.658590	-1.170406
C(3)	0.062831	0.291976	-0.04483	-0.055505	0.107688	-0.014376	0.095905	-0.042432	0.010951
C(4)	0.536980	0.196786	0.027519	-0.055804	-0.211022	-0.312554	-0.192732	-0.244562	-0.273735
C(5)	-0.822353	0.896221	0.172379	0.970096	0.950489	0.946172	0.968321	0.922189	0.874033
R-squared	-0.001269	-0.000836	-0.000022	-0.001157	-0.000936	-0.004528	-0.006824	-0.000017	0.000000

Table 28. Descriptive Statistics (May 2014 – December 2018, Monthly Data)

Panel A: Monthly Data (March 2014 – December 2018)

Variables	BTC-USD	Spread	Bid-Ask	CPI (US)	CPI (CHN)	CPI (JPN)	CPI (EUR)	CPI (KOR)	IP (US)
Mean	0.0376	0.0194	2.0831	0.1196	0.1518	0.0333	0.0696	0.0875	0.0804
St. Dev.	0.2245	0.7691	2.8489	0.2075	0.4585	0.2612	0.5059	0.3237	0.5050
Skewness	0.0497	0.6952	2.7017	-0.6900	0.6683	0.3433	-0.7861	0.2298	0.4506
Kurtosis	-0.0436	3.0267	9.6547	1.9963	1.8263	-0.0624	2.0908	0.6764	-0.0392

Variables	IP (CHN)	IP (JPN)	IP (EUR)	IP (KOR)	Unemp. Rate (US)	Unemp. Rate (CHN)	Unemp. Rate (JPN)	Unemp. Rate (EUR)	Unemp. Rate (KOR)
Mean	0.5075	0.1271	0.1143	0.0196	-0.0429	-0.0027	-0.0179	-0.0661	0.0018
St. Dev.	0.1349	1.4442	1.0289	1.7955	0.1248	0.0258	0.1081	0.0668	0.1940
Skewness	0.3356	-0.5822	0.5360	-0.0423	-0.1104	1.1869	-1.0654	-0.1378	0.6403
Kurtosis	1.9003	1.7863	0.9608	-0.7242	-0.4312	8.9882	2.2254	-0.2958	0.2095

Variables	CNY-USD	JPY-USD	EUR-USD	KRW-USD	S&P500	SHSZ300	NIKKEI	EUROSTOX	KOSPI
Mean	-0.0016	-0.0009	0.0010	-0.0011	0.0051	0.0043	0.0046	-0.0046	-0.0007
St. Dev.	0.0114	0.0290	0.0233	0.0251	0.0319	0.0771	0.0385	0.0418	0.0481
Skewness	-0.3988	0.3357	0.3989	0.6343	-0.7234	-0.3141	-0.5273	0.0395	-0.4698
Kurtosis	0.6597	1.6848	0.5090	0.7860	1.6489	2.2481	0.7849	-0.6738	2.0174

Panel B: Daily Data (April 2014 – January 2019)

Variables	BTC-USD	Spread	Bid-Ask	CNY-USD	JPY-USD	EUR-USD
Mean	0.0024	0.0004	2.0075	-0.0001	-0.0001	0.0000
St. Dev.	0.0432	0.6287	6.8885	0.0022	0.0056	0.0054
Skewness	0.0900	0.5467	19.5408	-0.2907	0.5601	-0.1178
Kurtosis	4.8345	1.3685	480.5404	6.7355	5.2741	2.3406

Variables	KRW-USD	SP500	SHSZ300	NIKKEI	EUROSTOXX	KOSPI
Mean	0.0000	0.0003	-0.0012	-0.0034	0.0002	0.0001
St. Dev.	0.0053	0.0083	0.0560	0.1345	0.0127	0.0082
Skewness	-0.0893	-0.4191	-31.3190	-34.6839	3.0356	-0.4403
Kurtosis	1.3451	4.0344	1058.5476	1213.2091	55.5101	2.3779

Table 29. The Chronology of Government Regulations about Bitcoin Transaction

Date	Country	Description
June 4, 2018	The United States	The Securities and Exchange Commission announced that Valerie A. Szczepanik has been named Associate Director of the Division of Corporation Finance and Senior Advisor for Digital Assets and Innovation for Division Director Bill Hinman, the newly created branch to manage cryptocurrency.
January 22, 2018	South Korea	South Korea brought in a regulation that requires all the bitcoin traders to reveal their identity, thus putting a ban on anonymous trading of bitcoins
January 19, 2018	The United States	The Commodities Futures Trading Commission (CFTC) filed charges against two cryptocurrency fraud cases.
December 27, 2017	South Korea	Korea's government announced that it will impose additional measures to regulate speculation in cryptocurrency trading within the country.
December 6, 2017	South Korea	Korea's Financial Services Commission issued a ban on the trading of bitcoin futures, prompting several securities firms to cancel seminars scheduled in December for bitcoin future investors
November 11, 2017	The United States	Treasury Secretary Steven Mnuchin mentioned he had established working-groups at treasury looking at bitcoin and that it is something they will be watching "very carefully."
September 29, 2017	The United States	The U.S. Securities and Exchange Commission (the SEC) filed a civil complaint in the U.S. District Court for the Eastern District of New York against the sponsors of two "initial coin offerings" (ICOs) for alleged violations of U.S. securities laws
September 4, 2017	China	China banned all companies and individuals from raising funds through ICO activities, reiterating that ICOs are considered illegal activity in the country
July 25, 2017	The United States	The SEC issued an investor bulletin about initial coin offerings, saying they can be "fair and lawful investment opportunities" but can be used improperly. The SEC has issued three enforcement actions against ICO sponsors- one halt and exposure of two alleged frauds. SEC Chairman Clayton has also expressed concern about market participants who extend to customers credit in U.S.
July 1, 2017	The United States	The National Conference of Commissioners on Uniform State Laws voted to approve a model act providing for the regulation of digital currency business at state level

[Source 1: www.marketwatch.com / Here's how the U.S. and the world regulate bitcoin and other cryptocurrencies by Francine McKenna, accessed on February 9, 2018]
[Source 2: https://www.sec.gov/news/press-release/2018-102 / [Press Release] SEC Names Valerie A. Szczepanik Senior Advisor for Digital Assets and Innovation, accessed on Jan 31, 2019]

Table 30. Correlation Matrix of Relevant Variables

Panel A: Variables with Monthly Data

	BTC-USD	BTC-USD (t-1)	Spread (t-1)	Bid-Ask (t-1)	Vol	CPI US	CPI CHN	CPI JPN	CPI EUR	CPI KOR	IP US	IP CHN	IP JPN	IP EUR	IP KOR	Unem US	Unem CHN	Unem JPN	Unem EUR	Unem KOR	S&P5 (t-1)	SS3 (t-1)	NKY (t-1)	EUS (t-1)	KSP (t-1)	CNY USD (t-1)	JPY USD (t-1)	EUR USD (t-1)	KRW USD (t-1)
BTC-USD	1.00																												
BTC-USD (t-1)	0.06	1.00																											
Spread (t-1)	0.08	0.02	1.00																										
Bid-Ask (t-1)	0.04	0.00	-0.02	1.00																									
Volume	-0.21	0.09	0.20	-0.05	1.00																								
CPI (US)	0.24	0.13	0.07	0.18	-0.15	1.00																							
CPI (CHN)	-0.18	-0.01	-0.07	-0.03	-0.03	0.03	1.00																						
CPI (JPN)	0.11	0.05	0.11	0.26	0.14	0.27	0.12	1.00																					
CPI (EUR)	0.13	-0.01	0.07	-0.06	-0.19	0.10	-0.12	0.10	1.00																				
CPI (KOR)	0.06	-0.20	-0.09	-0.01	0.10	0.16	0.41*	0.09	-0.21	1.00																			
IP (US)	0.16	0.07	-0.05	0.42*	-0.10	0.04	-0.10	0.09	-0.02	-0.18	1.00																		
IP (CHN)	0.01	-0.02	0.24	0.05	-0.02	-0.02	-0.01	-0.19	0.03	0.03	-0.02	1.00																	
IP (JPN)	0.12	-0.02	0.18	-0.13	0.00	-0.17	-0.02	-0.12	0.05	0.02	0.21	0.05	1.00																
IP (EUR)	0.10	0.18	-0.01	-0.12	0.15	0.17	0.06	0.16	-0.11	-0.10	0.03	0.07	0.13	1.00															
IP (KOR)	0.07	-0.08	0.19	0.12	-0.07	0.15	0.07	0.03	0.01	0.00	-0.02	0.36*	-0.35*	0.00	1.00														
Unemp (US)	0.04	-0.08	0.11	0.03	-0.08	0.05	0.06	0.13	-0.12	0.15	-0.06	-0.26	0.14	-0.08	-0.32	1.00													
Unemp (CHN)	0.07	-0.01	-0.02	-0.19	-0.02	-0.05	0.12	-0.33	0.09	0.01	0.12	-0.07	0.26	0.07	0.02	-0.23	1.00												
Unemp (JPN)	0.06	0.05	0.18	-0.07	-0.11	-0.19	-0.02	-0.21	0.03	-0.21	0.19	0.07	0.30	-0.18	0.04	-0.04	-0.01	1.00											
Unemp (EUR)	-0.01	-0.04	0.10	-0.03	0.08	-0.01	0.02	-0.12	-0.05	0.11	-0.09	0.00	0.07	0.00	-0.18	0.41*	-0.11	0.06	1.00										
Unemp (KOR)	-0.02	-0.06	-0.17	-0.13	-0.15	0.07	0.51*	0.10	0.18	0.19	-0.18	0.04	0.13	0.11	-0.06	-0.01	0.25	-0.20	-0.23	1.00									
S&P500 (t-1)	0.25	0.21	0.39*	-0.07	-0.06	-0.05	-0.03	-0.04	0.02	-0.04	0.01	0.26	0.35*	0.10	0.10	0.19	-0.06	0.25	0.20	0.04	1.00								
SHSZ300 (t-1)	0.14	0.05	0.19	-0.11	-0.06	-0.14	-0.01	0.19	0.11	-0.20	0.11	-0.06	0.03	-0.03	0.01	0.11	-0.09	0.06	0.08	0.04	0.45*	1.00							
NIKKEI (t-1)	0.26	0.21	0.28	-0.12	-0.13	-0.08	0.02	0.06	0.23	-0.11	0.03	0.11	0.38*	0.08	0.00	0.14	0.04	0.15	0.00	0.17	0.72*	0.50*	1.00						
ESTX (t-1)	0.04	0.22	0.20	-0.13	-0.18	-0.20	0.10	-0.02	0.13	-0.06	-0.15	0.14	0.43*	0.12	-0.11	0.23	-0.13	0.19	0.14	0.23	0.66*	0.29	0.70*	1.00					
KOSPI (t-1)	0.14	0.16	0.25	-0.12	-0.35*	-0.05	0.13	0.05	0.14	-0.17	0.09	0.12	0.25	-0.05	0.13	0.18	-0.05	0.25	-0.09	0.26	0.55*	0.49*	0.63*	0.58*	1.00				
CNY-USD (t-1)	0.16	0.08	0.10	0.05	-0.19	-0.07	0.16	0.10	-0.04	-0.13	0.12	0.18	0.12	-0.05	-0.03	0.07	-0.16	0.20	0.04	0.14	0.27	0.41*	0.34*	0.31	0.55*	1.00			
JPY-USD (t-1)	0.10	-0.01	-0.24	-0.03	-0.17	0.01	-0.12	0.02	-0.01	-0.06	0.13	0.00	0.05	-0.10	-0.02	0.02	-0.07	0.09	-0.22	-0.03	-0.15	-0.11	0.03	-0.06	0.24	0.29	1.00		
EUR-USD (t-1)	-0.19	-0.15	0.09	-0.20	0.25	-0.06	0.07	-0.09	-0.19	-0.01	-0.22	-0.03	-0.11	0.21	0.17	-0.11	0.05	-0.09	-0.03	-0.02	-0.10	0.04	-0.03	-0.14	-0.20	-0.18	-0.39*	1.00	
KRW-USD (t-1)	0.12	0.13	0.08	0.08	-0.41*	0.05	0.14	0.09	0.10	-0.08	0.16	0.12	0.13	-0.24	0.13	0.25	-0.03	0.05	-0.06	0.17	0.32	0.36*	0.32	0.30	0.75*	0.40*	0.39*	-0.36*	1.00

Panel B: Variables with Daily Data

	BTC-USD	BTC-USD (t-1)	Spread (t-1)	Bid-Ask (t-1)	Volume	S&P500 (t-1)	SHSZ300 (t-1)	NIKKEI (t-1)	EURSTX (t-1)	KOSPI (t-1)	CNY-USD (t-1)	JPY-USD (t-1)	EUR-USD (t-1)	KRW-USD (t-1)
BTC-USD	1.00													
BTC-USD (t-1)	0.03	1.00												
Spread (t-1)	-0.04	-0.07	1.00											
Bid-Ask (t-1)	0.04	0.00	0.29*	1.00										
Volume	-0.01	-0.09*	0.12*	0.01	1.00									
S&P500 (t-1)	0.05	0.04	0.00	-0.01	-0.07	1.00								
SHSZ300 (t-1)	0.05	-0.01	-0.01	0.01	0.04	0.10*	1.00							
NIKKEI (t-1)	-0.01	0.07	-0.08*	-0.03	-0.05	0.05	0.02	1.00						
ESTX (t-1)	0.04	-0.01	0.01	0.00	0.01	0.46*	0.07*	-0.43*	1.00					
KOSPI (t-1)	0.03	0.00	-0.02	-0.04	0.01	0.24*	0.10*	0.51*	0.32*	1.00				
CNY-USD (t-1)	0.01	-0.04	0.01	0.00	0.07*	0.08*	0.11*	0.04	0.08*	0.18*	1.00			
JPY-USD (t-1)	-0.03	0.02	-0.01	-0.02	0.00	-0.37*	-0.03*	-0.02	-0.34*	-0.16*	0.17*	1.00		
EUR-USD (t-1)	0.05	0.01	-0.05	0.02	0.04	0.12*	0.01	0.02	0.23*	0.11*	-0.07	-0.32*	1.00	
KRW-USD (t-1)	0.00	0.02	0.03	-0.02	0.02	0.27*	0.07	-0.03	0.18*	0.28*	0.37*	0.25*	-0.29*	1.00

Table 31. Statistic Measures of Detrend Ratios of Bitcoin and Indexes

Statistic Measure	Bitcoin	S&P500	SHSZ	NIKKEI	EUSTOXX	KOSPI
Standard Deviation	0.067925	0.009203	0.014968	0.013133	0.013951	0.01235
Skewness	1.090718	-0.42525	-0.60099	-2.66675	-0.15835	-0.27621
Kurtosis	14.87181	4.657465	4.638201	39.4934	4.442844	3.034228

Table 32. Regression Results with Monthly Data (April 2014 – December 2018)

VARIABLES	Model 1	Model 2	Model 2-1	Model 2-2	Model 2-3	Model 2-4	Model 2-5	Model 2-6
Bitcoin (USD) (t-1)	0.038	1.641*	0.066	0.011	-0.081	0.443*	0.028	0.144
	[0.848]	[0.093]	[0.830]	[0.977]	[0.828]	[0.086]	[0.921]	[0.601]
Spread (t-1)	-0.008	-0.051	-0.011	-0.010	-0.004	-0.002	-0.012	-0.011
	[0.928]	[0.479]	[0.895]	[0.906]	[0.962]	[0.983]	[0.881]	[0.893]
Bid-Ask Spread (t-1)	-0.002	0.002	-0.002	-0.003	-0.006	-0.001	-0.001	-0.007
	[0.929]	[0.910]	[0.933]	[0.900]	[0.784]	[0.925]	[0.942]	[0.789]
Trading Volume (t-1)	-0.059	-0.013	-0.057	-0.059	-0.067	-0.069	-0.056	-0.057
	[0.471]	[0.880]	[0.474]	[0.490]	[0.450]	[0.402]	[0.476]	[0.474]
Regulation	-0.099	-0.167	-0.099	-0.116	-0.164	-0.216	-0.093	-0.158
	[0.496]	[0.445]	[0.491]	[0.541]	[0.451]	[0.219]	[0.594]	[0.441]
CPI (US)	0.095	0.258	0.096	0.093	0.127	0.140	0.097	0.113
	[0.707]	[0.245]	[0.706]	[0.719]	[0.616]	[0.508]	[0.699]	[0.648]
CPI (China)	-0.169	-0.095	-0.169	-0.174	-0.187	-0.157	-0.169	-0.181
	[0.189]	[0.523]	[0.190]	[0.197]	[0.164]	[0.192]	[0.191]	[0.161]
CPI (Japan)	0.015	0.120	0.007	0.013	-0.003	0.026	0.006	0.026
	[0.953]	[0.596]	[0.976]	[0.961]	[0.992]	[0.926]	[0.980]	[0.913]
CPI (Euro Zone)	0.040	0.107	0.041	0.038	0.021	0.033	0.043	0.027
	[0.713]	[0.406]	[0.697]	[0.734]	[0.850]	[0.724]	[0.688]	[0.804]
CPI (Korea)	0.167	0.057	0.167	0.168	0.188	0.187	0.167	0.152
	[0.360]	[0.747]	[0.371]	[0.355]	[0.338]	[0.270]	[0.361]	[0.421]
IP (US)	0.017	-0.019	0.021	0.020	0.030	-0.003	0.021	0.030
	[0.877]	[0.865]	[0.848]	[0.850]	[0.783]	[0.973]	[0.847]	[0.787]
IP (China)	-0.264	-1.264**	-0.262	-0.238	-0.220	-0.301	-0.272	-0.294
	[0.436]	[0.047]	[0.444]	[0.592]	[0.544]	[0.386]	[0.443]	[0.398]
IP (Japan)	-0.004	-0.058	-0.001	-0.005	-0.015	-0.030	-0.001	-0.016
	[0.931]	[0.425]	[0.981]	[0.930]	[0.795]	[0.541]	[0.990]	[0.800]
IP (Euro Zone)	0.051	0.056	0.050	0.051	0.044	0.052	0.050	0.049
	[0.287]	[0.350]	[0.302]	[0.322]	[0.384]	[0.264]	[0.309]	[0.318]
IP (Korea)	0.019	0.002	0.020	0.017	0.018	0.007	0.020	0.016
	[0.570]	[0.962]	[0.552]	[0.676]	[0.571]	[0.806]	[0.551]	[0.640]
Unemp Rate (US)	0.189	-0.211	0.209	0.217	0.204	0.160	0.206	0.182
	[0.679]	[0.564]	[0.637]	[0.613]	[0.642]	[0.693]	[0.643]	[0.688]
Unemp Rate (China)	-0.235	3.921	-0.347	-0.429	-1.103	-0.831	-0.287	-0.374
	[0.933]	[0.243]	[0.900]	[0.872]	[0.717]	[0.758]	[0.921]	[0.890]
Unemp Rate (Japan)	0.262	0.387	0.245	0.254	0.302	0.519	0.238	0.234
	[0.618]	[0.440]	[0.630]	[0.630]	[0.575]	[0.328]	[0.651]	[0.645]
Unemp Rate (Euro)	-0.058	-1.942	-0.084	-0.080	0.078	-0.038	-0.129	-0.069
	[0.925]	[0.133]	[0.894]	[0.896]	[0.914]	[0.950]	[0.842]	[0.909]
Unemp Rate (Korea)	0.083	-0.312	0.092	0.096	0.139	0.070	0.082	0.119
	[0.804]	[0.413]	[0.781]	[0.769]	[0.693]	[0.815]	[0.791]	[0.707]
S&P500 (t-1)	1.840	3.431	1.844	1.776	1.902	1.385	1.875	2.121
	[0.364]	[0.120]	[0.380]	[0.420]	[0.353]	[0.511]	[0.351]	[0.296]
SHSZ300 (t-1)	-0.220	-1.379*	-0.215	-0.216	-0.127	-0.222	-0.228	-0.285
	[0.761]	[0.092]	[0.777]	[0.765]	[0.861]	[0.693]	[0.751]	[0.717]
NIKKEI (t-1)	2.042	4.563**	1.995	2.106	1.938	3.102	1.994	2.025
	[0.277]	[0.047]	[0.279]	[0.280]	[0.304]	[0.109]	[0.280]	[0.280]
EURO STOXX50 (t-1)	-1.889	-2.231	-1.949	-1.994	-1.704	-2.167	-1.929	-1.889
	[0.410]	[0.386]	[0.385]	[0.374]	[0.478]	[0.292]	[0.403]	[0.395]
KOSPI (t-1)	-1.127	-4.119	-0.964	-1.027	-1.136	-1.521	-0.970	-1.424
	[0.647]	[0.103]	[0.675]	[0.656]	[0.625]	[0.485]	[0.671]	[0.567]
XRate CNY-USD (t-1)	6.767	15.189**	6.773	7.007	5.866	8.158*	6.855	6.927
	[0.140]	[0.028]	[0.175]	[0.126]	[0.283]	[0.060]	[0.136]	[0.121]

XRate JPY-USD (t-1)	-0.554	-5.345*	-0.572	-0.662	-0.088	-0.695	-0.600	-0.991
	[0.786]	[0.093]	[0.792]	[0.745]	[0.972]	[0.694]	[0.768]	[0.662]
XRate EUR-USD (t-1)	-1.449	-4.023	-1.492	-1.638	-1.513	-1.800	-1.508	-1.921
	[0.545]	[0.152]	[0.531]	[0.573]	[0.530]	[0.423]	[0.526]	[0.492]
XRate KRW-USD (t-1)	0.521	8.053	0.262	0.251	-0.184	0.987	0.261	0.935
	[0.899]	[0.108]	[0.950]	[0.951]	[0.964]	[0.783]	[0.949]	[0.833]
10% Soar (t-1)		0.141	-0.008					
		[0.557]	[0.958]					
20% Soar (t-1)		-0.298		0.034				
		[0.246]		[0.899]				
30% Soar (t-1)		-0.720			0.170			
		[0.153]			[0.648]			
10% Crash (t-1)		0.730**				0.258		
		[0.013]				[0.126]		
20% Crash (t-1)		-0.605*					-0.019	
		[0.097]					[0.923]	
30% Crash (t-1)		0.894**						0.146
		[0.035]						[0.670]
Soar (t-1)	0.061							
	[0.824]							
Crash (t-1) = o,	-							
Constant	0.169	0.393	0.169	0.155	0.153	0.116	0.171	0.187
	[0.390]	[0.118]	[0.400]	[0.524]	[0.450]	[0.571]	[0.406]	[0.367]
Observations	55	55	55	55	55	55	55	55
R-squared	0.384	0.593	0.383	0.384	0.389	0.453	0.383	0.389

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 32. Cont'd

VARIABLES	Model 3	Model 4	Model 4-1	Model 4-2	Model 4-3	Model 4-4	Model 4-5	Model 4-6
Bitcoin (USD) (t-1)	0.092	0.930	0.247	0.233	-0.056	0.297	0.062	0.132
	[0.632]	[0.251]	[0.349]	[0.376]	[0.819]	[0.268]	[0.796]	[0.546]
Spread (t-1)	0.023	0.018	0.022	0.019	0.021	0.026	0.021	0.022
	[0.655]	[0.745]	[0.658]	[0.704]	[0.684]	[0.604]	[0.667]	[0.664]
Bid-Ask Spread (t-1)	-0.003	0.000	-0.003	-0.001	-0.007	-0.003	-0.002	-0.004
	[0.879]	[0.998]	[0.871]	[0.959]	[0.673]	[0.859]	[0.893]	[0.840]
Trading Volume (t-1)	-0.090	-0.083	-0.077	-0.085	-0.088	-0.098	-0.087	-0.089
	[0.141]	[0.158]	[0.174]	[0.154]	[0.140]	[0.113]	[0.151]	[0.134]
Regulation	-0.030	-0.060	-0.021	0.017	-0.106	-0.078	-0.016	-0.046
	[0.853]	[0.803]	[0.897]	[0.924]	[0.617]	[0.671]	[0.925]	[0.791]
CPI (US)	0.123	0.198	0.114	0.137	0.151	0.142	0.125	0.131
	[0.578]	[0.377]	[0.590]	[0.534]	[0.490]	[0.502]	[0.565]	[0.550]
CPI (China)	-0.172*	-0.158	-0.180**	-0.159*	-0.209**	-0.164*	-0.175*	-0.176*
	[0.051]	[0.176]	[0.044]	[0.082]	[0.045]	[0.067]	[0.052]	[0.053]
CPI (Japan)	0.155	0.112	0.132	0.124	0.123	0.175	0.145	0.155
	[0.487]	[0.655]	[0.545]	[0.573]	[0.574]	[0.468]	[0.511]	[0.475]
CPI (Euro Zone)	0.022	0.026	0.019	0.031	0.005	0.023	0.026	0.020
	[0.802]	[0.793]	[0.822]	[0.721]	[0.952]	[0.788]	[0.765]	[0.818]
CPI (Korea)	0.190	0.199	0.200	0.180	0.228	0.196	0.195	0.188
	[0.255]	[0.265]	[0.242]	[0.284]	[0.195]	[0.225]	[0.239]	[0.261]
IP (US)	0.045	0.038	0.052	0.050	0.055	0.042	0.050	0.051
	[0.594]	[0.615]	[0.495]	[0.520]	[0.438]	[0.565]	[0.513]	[0.499]
IP (China)	-0.029	-0.289	-0.049	-0.115	-0.010	-0.028	-0.049	-0.032
	[0.917]	[0.498]	[0.865]	[0.714]	[0.974]	[0.924]	[0.871]	[0.908]
IP (Japan)	0.004	0.004	0.012	0.017	-0.010	-0.006	0.008	0.002
	[0.921]	[0.938]	[0.713]	[0.692]	[0.804]	[0.877]	[0.839]	[0.960]
IP (Euro Zone)	0.027	0.011	0.027	0.024	0.027	0.024	0.027	0.026
	[0.521]	[0.810]	[0.505]	[0.582]	[0.520]	[0.559]	[0.523]	[0.547]
IP (Korea)	0.010	0.023	0.015	0.020	0.009	0.004	0.011	0.009
	[0.636]	[0.426]	[0.512]	[0.489]	[0.691]	[0.861]	[0.623]	[0.697]
Unemp Rate (US)	0.049	0.025	0.093	0.042	0.055	0.036	0.050	0.049
	[0.869]	[0.941]	[0.745]	[0.883]	[0.849]	[0.910]	[0.865]	[0.869]
Unemp Rate (China)	1.203	1.094	1.017	1.239	0.097	0.995	1.218	1.134
	[0.628]	[0.704]	[0.675]	[0.597]	[0.971]	[0.687]	[0.621]	[0.643]
Unemp Rate (Japan)	0.236	0.315	0.223	0.214	0.324	0.332	0.219	0.222
	[0.597]	[0.528]	[0.629]	[0.631]	[0.484]	[0.495]	[0.624]	[0.622]
Unemp Rate (Euro)	0.138	0.043	0.110	0.073	0.280	0.125	0.036	0.131
	[0.798]	[0.956]	[0.826]	[0.879]	[0.621]	[0.804]	[0.947]	[0.806]
Unemp Rate (Korea)	0.047	0.045	0.076	0.053	0.106	0.042	0.047	0.062
	[0.863]	[0.865]	[0.758]	[0.835]	[0.650]	[0.866]	[0.844]	[0.797]
10% Soar (t-1)		-0.076	-0.083					
		[0.665]	[0.475]					
20% Soar (t-1)		-0.255		-0.108				
		[0.220]		[0.506]				
30% Soar (t-1)		0.050			0.195			
		[0.841]			[0.361]			
10% Crash (t-1)		0.233				0.122		
		[0.155]				[0.347]		
20% Crash (t-1)		-0.091					-0.037	
		[0.662]					[0.810]	
30% Crash (t-1)		0.224						0.035
		[0.388]						[0.865]
Soar (t-1)	0.062							
	[0.802]							
Crash (t-1) = o,	-							
Constant	0.052	0.146	0.089	0.096	0.054	0.015	0.060	0.053
	[0.735]	[0.476]	[0.588]	[0.586]	[0.730]	[0.930]	[0.715]	[0.729]
Observations	55	55	55	55	55	55	55	55
R-squared	0.245	0.314	0.254	0.251	0.258	0.263	0.245	0.245

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 32. Cont'd

VARIABLES	Model 5	Model 6	Model 6-1	Model 6-2	Model 6-3	Model 6-4	Model 6-5	Model 6-6
Bitcoin (USD) (t-1)	0.019	1.165*	0.112	0.121	0.038	0.296	0.072	0.112
	[0.913]	[0.084]	[0.624]	[0.542]	[0.844]	[0.178]	[0.752]	[0.586]
Spread (t-1)	0.001	-0.011	-0.004	-0.008	-0.004	0.002	-0.004	-0.007
	[0.987]	[0.775]	[0.903]	[0.803]	[0.899]	[0.961]	[0.899]	[0.850]
Bid-Ask Spread (t-1)	0.003	0.007	0.003	0.005	0.003	0.003	0.003	0.002
	[0.796]	[0.540]	[0.773]	[0.716]	[0.818]	[0.714]	[0.791]	[0.837]
Trading Volume (t-1)	-0.086**	-0.084**	-0.077**	-0.079*	-0.084**	-0.096**	-0.083**	-0.086**
	[0.023]	[0.038]	[0.033]	[0.051]	[0.038]	[0.013]	[0.027]	[0.019]
Regulation	-0.018	-0.065	-0.029	-0.013	-0.033	-0.058	-0.032	-0.046
	[0.900]	[0.680]	[0.839]	[0.930]	[0.824]	[0.676]	[0.823]	[0.745]
S&P500 (t-1)	2.316	2.185	2.232	2.372	2.267	1.891	2.249	2.391*
	[0.102]	[0.182]	[0.117]	[0.102]	[0.110]	[0.182]	[0.110]	[0.098]
SHSZ300 (t-1)	-0.065	-0.036	-0.106	-0.130	-0.075	0.018	-0.066	-0.043
	[0.868]	[0.927]	[0.780]	[0.730]	[0.843]	[0.962]	[0.869]	[0.915]
NIKKEI (t-1)	1.982	2.388*	2.024*	1.941	1.937	2.245*	1.933*	1.834*
	[0.100]	[0.098]	[0.100]	[0.110]	[0.118]	[0.068]	[0.092]	[0.098]
EURO STOXX50 (t-1)	-2.083*	-2.596**	-2.072*	-2.130*	-2.073*	-2.196**	-2.082*	-2.128*
	[0.075]	[0.032]	[0.076]	[0.072]	[0.081]	[0.042]	[0.073]	[0.081]
KOSPI (t-1)	-0.476	-0.104	-0.290	-0.141	-0.346	-0.425	-0.308	-0.414
	[0.516]	[0.907]	[0.676]	[0.841]	[0.611]	[0.537]	[0.652]	[0.551]
10% Soar (t-1)		-0.108	-0.037					
		[0.425]	[0.700]					
20% Soar (t-1)		-0.169		-0.061				
		[0.179]		[0.634]				
30% Soar (t-1)		-0.139			0.020			
		[0.517]			[0.912]			
10% Crash (t-1)		0.287*				0.148		
		[0.086]				[0.159]		
20% Crash (t-1)		-0.013					0.015	
		[0.938]					[0.901]	
30% Crash (t-1)		0.230						0.071
		[0.329]						[0.683]
Soar (t-1)	0.173							
	[0.179]							
Crash (t-1) = o,	-							
Constant	0.000	-0.043	0.016	0.009	0.003	-0.042	0.002	0.000
	[0.992]	[0.351]	[0.746]	[0.811]	[0.930]	[0.302]	[0.961]	[1.000]
Observations	55	55	55	55	55	55	55	55
R-squared	0.203	0.289	0.196	0.198	0.195	0.230	0.194	0.197

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 32. Cont'd

VARIABLES	Model 7	Model 8	Model 8-1	Model 8-2	Model 8-3	Model 8-4	Model 8-5	Model 8-6
Bitcoin (USD) (t-1)	0.056	0.912	0.103	0.048	0.018	0.318	0.140	0.094
	[0.737]	[0.252]	[0.649]	[0.843]	[0.923]	[0.130]	[0.503]	[0.653]
Spread (t-1)	0.040	0.037	0.040	0.038	0.041	0.040	0.038	0.036
	[0.387]	[0.419]	[0.402]	[0.392]	[0.376]	[0.353]	[0.397]	[0.418]
Bid-Ask Spread (t-1)	0.002	0.004	0.002	0.002	0.001	0.003	0.001	0.002
	[0.884]	[0.801]	[0.888]	[0.914]	[0.938]	[0.844]	[0.938]	[0.919]
Trading Volume (t-1)	-0.077*	-0.076	-0.075*	-0.077*	-0.080*	-0.087**	-0.077*	-0.076*
	[0.056]	[0.106]	[0.067]	[0.059]	[0.065]	[0.027]	[0.055]	[0.063]
Regulation	-0.040	-0.085	-0.045	-0.051	-0.057	-0.083	-0.062	-0.053
	[0.771]	[0.577]	[0.736]	[0.725]	[0.679]	[0.507]	[0.644]	[0.701]
XRate CNY-USD (t-1)	2.723	3.247	2.721	2.959	2.562	3.634	3.102	2.750
	[0.412]	[0.383]	[0.399]	[0.363]	[0.458]	[0.248]	[0.314]	[0.412]
XRate JPY-USD (t-1)	0.431	0.289	0.472	0.393	0.528	0.473	0.295	0.315
	[0.735]	[0.845]	[0.735]	[0.760]	[0.667]	[0.704]	[0.819]	[0.830]
XRate EUR-USD (t-1)	-1.275	-1.185	-1.299	-1.397	-1.357	-1.393	-1.343	-1.432
	[0.432]	[0.573]	[0.423]	[0.476]	[0.417]	[0.389]	[0.406]	[0.451]
XRate KRW-USD (t-1)	-1.022	-0.513	-1.017	-1.109	-1.215	-1.272	-0.961	-1.023
	[0.442]	[0.787]	[0.440]	[0.480]	[0.396]	[0.344]	[0.477]	[0.441]
10% Soar (t-1)		-0.085	-0.020					
		[0.555]	[0.866]					
20% Soar (t-1)		-0.098		0.019				
		[0.556]		[0.912]				
30% Soar (t-1)		-0.103			0.061			
		[0.666]			[0.759]			
10% Crash (t-1)		0.227				0.158		
		[0.156]				[0.142]		
20% Crash (t-1)		0.060					0.064	
		[0.724]					[0.603]	
30% Crash (t-1)		0.102						0.035
		[0.622]						[0.852]
Soar (t-1)	0.071							
	[0.578]							
Crash (t-1) = o,	-							
Constant	0.038	-0.001	0.046	0.039	0.037	-0.007	0.033	0.038
	[0.365]	[0.992]	[0.333]	[0.340]	[0.357]	[0.890]	[0.439]	[0.331]
Observations	55	55	55	55	55	55	55	55
R-squared	0.106	0.166	0.105	0.105	0.108	0.146	0.109	0.105

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33. Regression Result with Daily Data (11 April 2014 – 30 January 2019)

VARIABLES	Model 9	Model 10	Model 10-1	Model 10-2	Model 10-3	Model 10-4
Bitcoin (USD) (t-1)	-0.024	0.051	0.086*	0.035	0.025	0.030
	[0.747]	[0.367]	[0.071]	[0.457]	[0.632]	[0.518]
Spread (t-1)	0.005**	0.005**	0.004**	0.004**	0.004**	0.004**
	[0.013]	[0.019]	[0.027]	[0.046]	[0.032]	[0.045]
Bid-Ask Spread (t-1)	0.000	-0.000	0.000	-0.000	0.000	-0.000
	[0.804]	[0.948]	[0.976]	[0.983]	[0.956]	[0.980]
Trading Volume (t-1)	0.001	0.000	-0.001	-0.002	-0.001	-0.001
	[0.775]	[0.982]	[0.880]	[0.689]	[0.825]	[0.853]
Regulation	-0.011	-0.023	-0.015	-0.022	-0.017	-0.017
	[0.724]	[0.390]	[0.652]	[0.409]	[0.580]	[0.576]
S&P500 (t-1)	0.379	0.339	0.347	0.340	0.334	0.348
	[0.101]	[0.143]	[0.134]	[0.146]	[0.150]	[0.136]
SHSZ300 (t-1)	0.033***	0.035***	0.035***	0.035***	0.034***	0.035***
	[0.004]	[0.002]	[0.003]	[0.002]	[0.004]	[0.003]
NIKKEI (t-1)	0.350**	0.381**	0.400***	0.372**	0.376**	0.373**
	[0.022]	[0.011]	[0.008]	[0.016]	[0.015]	[0.016]
EURO STOXX50(t-1)	-0.180	-0.188	-0.197	-0.171	-0.169	-0.180
	[0.265]	[0.257]	[0.237]	[0.298]	[0.300]	[0.273]
KOSPI (t-1)	-0.095	-0.127	-0.140	-0.110	-0.115	-0.105
	[0.667]	[0.559]	[0.520]	[0.620]	[0.603]	[0.635]
XRate CNY-USD (t-1)	0.026	-0.062	-0.031	0.022	0.038	0.034
	[0.972]	[0.935]	[0.967]	[0.977]	[0.960]	[0.964]
XRate JPY-USD (t-1)	0.142	0.117	0.076	0.078	0.081	0.078
	[0.673]	[0.718]	[0.817]	[0.815]	[0.807]	[0.813]
XRate EUR-USD (t-1)	0.436	0.532*	0.504	0.469	0.460	0.458
	[0.192]	[0.098]	[0.121]	[0.163]	[0.170]	[0.173]
XRate KRW-USD (t-1)	-0.082	-0.020	-0.024	-0.064	-0.059	-0.077
	[0.811]	[0.954]	[0.943]	[0.851]	[0.862]	[0.823]
10% Soar (t-1)		-0.036*	-0.030			
		[0.060]	[0.103]			
20% Soar (t-1)		0.059		0.027		
		[0.218]		[0.561]		
10% Crash (t-1)		-0.008			-0.015	
		[0.537]			[0.256]	
20% Crash (t-1)		-0.042				-0.052
		[0.387]				[0.279]
Soar (t-1)	-0.007					
	[0.579]					
Crash (t-1)	-0.024***					
	[0.007]					
Constant	0.004***	0.003*	0.002	0.002	0.002	0.002
	[0.009]	[0.073]	[0.101]	[0.190]	[0.126]	[0.154]
Observations	993	993	993	993	993	993
R-squared	0.035	0.034	0.028	0.023	0.024	0.025

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33. Cont'd

VARIABLES	Model 11	Model 12	Model 12-1	Model 12-2	Model 12-3	Model 12-4
Bitcoin (USD) (t-1)	-0.028	0.050	0.086*	0.037	0.026	0.031
	[0.695]	[0.371]	[0.072]	[0.442]	[0.628]	[0.509]
Spread (t-1)	0.005**	0.005**	0.004**	0.004**	0.004**	0.004**
	[0.012]	[0.019]	[0.027]	[0.047]	[0.032]	[0.046]
Bid-Ask Spread (t-1)	0.000	0.000	0.000	0.000	0.000	0.000
	[0.730]	[0.967]	[0.900]	[0.940]	[0.881]	[0.945]
Trading Volume (t-1)	0.001	0.000	-0.000	-0.001	-0.001	-0.001
	[0.730]	[0.927]	[0.933]	[0.740]	[0.880]	[0.905]
Regulation	-0.011	-0.022	-0.015	-0.022	-0.017	-0.017
	[0.727]	[0.402]	[0.650]	[0.419]	[0.581]	[0.576]
S&P500 (t-1)	0.340	0.310	0.325	0.313	0.307	0.319
	[0.120]	[0.159]	[0.142]	[0.160]	[0.165]	[0.151]
SHSZ300 (t-1)	0.033***	0.034***	0.034***	0.034***	0.033***	0.034***
	[0.003]	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]
NIKKEI (t-1)	0.332**	0.362***	0.386***	0.361**	0.363**	0.362**
	[0.018]	[0.009]	[0.006]	[0.011]	[0.010]	[0.011]
EURO STOXX50 (t-1)	-0.147	-0.140	-0.148	-0.128	-0.127	-0.138
	[0.344]	[0.368]	[0.344]	[0.411]	[0.411]	[0.374]
KOSPI (t-1)	-0.082	-0.104	-0.120	-0.098	-0.101	-0.095
	[0.685]	[0.600]	[0.548]	[0.627]	[0.616]	[0.637]
10% Soar (t-1)		-0.034*	-0.029			
		[0.070]	[0.114]			
20% Soar (t-1)		0.056		0.025		
		[0.252]		[0.590]		
10% Crash (t-1)		-0.008			-0.016	
		[0.508]			[0.244]	
20% Crash (t-1)		-0.042				-0.052
		[0.390]				[0.283]
Soar (t-1)	-0.006					
	[0.633]					
Crash (t-1)	-0.025***					
	[0.004]					
Constant	0.004**	0.002*	0.002	0.002	0.002	0.002
	[0.010]	[0.083]	[0.115]	[0.206]	[0.138]	[0.169]
Observations	995	995	995	995	995	995
R-squared	0.032	0.030	0.024	0.020	0.020	0.021

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33. Cont'd

VARIABLES	Model 13	Model 14	Model 14-1	Model 14-2	Model 14-3	Model 14-4
Bitcoin (USD) (t-1)	-0.036	0.026	0.058	0.014	0.011	0.011
	[0.605]	[0.642]	[0.216]	[0.759]	[0.828]	[0.808]
Spread (t-1)	0.005**	0.005**	0.004**	0.004**	0.004**	0.004**
	[0.011]	[0.018]	[0.023]	[0.036]	[0.028]	[0.037]
Bid-Ask Spread (t-1)	0.000	-0.000	0.000	-0.000	0.000	-0.000
	[0.797]	[0.950]	[0.956]	[0.997]	[0.944]	[0.999]
Trading Volume (t-1)	-0.001	-0.002	-0.002	-0.003	-0.003	-0.002
	[0.904]	[0.702]	[0.563]	[0.435]	[0.537]	[0.585]
Regulation	-0.010	-0.022	-0.013	-0.021	-0.015	-0.015
	[0.765]	[0.411]	[0.696]	[0.428]	[0.634]	[0.633]
XRate CNY-USD (t-1)	0.147	0.085	0.125	0.160	0.164	0.173
	[0.836]	[0.906]	[0.861]	[0.821]	[0.818]	[0.808]
XRate JPY-USD (t-1)	-0.144	-0.146	-0.195	-0.188	-0.194	-0.190
	[0.602]	[0.574]	[0.463]	[0.480]	[0.470]	[0.479]
XRate EUR-USD (t-1)	0.442	0.519*	0.484	0.477	0.462	0.462
	[0.150]	[0.080]	[0.109]	[0.124]	[0.136]	[0.137]
XRate KRW-USD (t-1)	0.123	0.138	0.132	0.117	0.120	0.105
	[0.657]	[0.615]	[0.633]	[0.674]	[0.665]	[0.705]
10% Soar (t-1)		-0.032*	-0.024			
		[0.091]	[0.179]			
20% Soar (t-1)		0.064		0.035		
		[0.183]		[0.451]		
10% Crash (t-1)		-0.005			-0.011	
		[0.709]			[0.405]	
20% Crash (t-1)		-0.051				-0.057
		[0.308]				[0.250]
Soar (t-1)	-0.007					
	[0.585]					
Crash (t-1)	-0.022**					
	[0.010]					
Constant	0.004***	0.003*	0.003*	0.002	0.002*	0.002*
	[0.006]	[0.051]	[0.069]	[0.125]	[0.084]	[0.096]
Observations	1,039	1,039	1,039	1,039	1,039	1,039
R-squared	0.019	0.019	0.012	0.010	0.009	0.011

p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 34. Unit Root Test Statistics for Fama (1984) Model

Panel A: CBOE BTC Futures Contracts

Rollover	Nearby			7 Days		
Unit Root Test	ADF	DF-GLS	PP	ADF	DF-GLS	PP
Change in spot	-9.8827***	-4.8564***	-16.6816***	-9.5041***	-9.2639***	-16.6831***
Basis	-5.7320***	-0.3320	-5.9340***	-5.6850***	-0.3601	-5.8364***
Risk premium	-5.2160***	-0.4326	-5.9993***	-5.7349***	-0.3320	-5.9359***

Panel B: CME BTC Futures Contracts

Rollover	Nearby			7 Days		
Unit Root Test	ADF	DF-GLS	PP	ADF	DF-GLS	PP
Change in spot	-9.2851***	-9.0732***	-16.3040***	-9.3170***	-9.1029***	-16.3587***
Basis	-3.9440***	-0.7803	-4.0684	-3.9631***	-0.7873	-4.0850***
Risk premium	-4.2704***	-0.8501	-4.4147	-4.2883***	-0.7139	-4.4295***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 35. Results of Fama (1984) Model

Panel A: CBOE BTC Futures Contracts

Rollover	Nearby			7 Days		
Equation (1): $P_{t-1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	α_1	β_1	F-Stat	α_1	β_1	F-Stat
Coefficient	97.3997**	0.0606***	13.7553***	102.3019**	0.0625***	15.4107***
Standard Error	42.8474	0.0163	-	42.3927	0.0159	-
Probability	0.0237	0.0002	0.0002	0.0164	0.0001	0.0001
Equation (2): $F_t- P_{t+1} =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	α_2	β_2	F-Stat	α_2	β_2	F-Stat
Coefficient	-97.3997**	0.9394***	3308.2470***	-102.3019**	0.9375***	3462.0300***
Standard Error	42.8474	0.0163	-	42.3927	0.0159	-
Probability	0.0237	0.0000	0.0000	0.0164	0.0000	0.0000

Panel B: CME BTC Futures Contracts

Rollover	Nearby			7 Days		
Equation (1): $P_{t-1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	α_1	β_1	F-Stat	α_1	β_1	F-Stat
Coefficient	132.2801***	0.0663***	15.8842***	133.3589***	0.0665***	16.1867***
Standard Error	48.3904	0.0166	-	48.1787	0.0165	-
Probability	0.0066	0.0001	0.0001	0.0060	0.0001	0.0001
Equation (2): $F_t- P_{t+1} =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	α_2	β_2	F-Stat	α_2	β_2	F-Stat
Coefficient	-132.2801***	0.9337***	3151.8007***	-133.3589***	0.9335***	3187.6110***
Standard Error	48.3904	0.0166	-	48.1787	0.0165	-
Probability	0.0066	0.0000	0.0000	0.0060	0.0000	0.0000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 36. Wald Test Results of Fama (1984) Model

Panel A: CBOE BTC Futures Contracts						
Rollover		Nearby			7 Days	
Equation (1): $P_{t-1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$
F-statistic	3484.2530***	5.1673**	3308.2470***	3616.0850***	5.8235**	3462.0300***
df	(2, 313)	(1, 313)	(1, 313)	(2, 314)	(1, 314)	(1, 314)
Probability	0.0000	0.0237	0.0000	0.0000	0.0164	0.0000
Equation (2): $F_t- P_t =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$
F-statistic	6.9956***	5.1673***	13.7553***	7.8213***	5.8235**	15.4107***
df	(2, 313)	(1, 313)	(1, 313)	(2, 314)	(1, 314)	(1, 314)
Probability	0.0011	0.0237	0.0002	0.0005	0.0164	0.0001

Panel B: CME BTC Futures Contracts						
Rollover		Nearby			7 Days	
Equation (1): $P_{t-1}-P_t=\alpha_1+\beta_1*(F_t-P_t)+\varepsilon_{1,t+1}$						
	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$	$\alpha_1=0, \beta_1=1$	$\alpha_1=0$	$\beta_1=1$
F-statistic	4000.8910***	7.4726***	3151.8007***	4069.5259***	7.6619***	3187.6109***
df	(2, 300)	(1, 300)	(1, 300)	(2, 302)	(1, 302)	(1, 302)
Probability	0.0000	0.0066	0.0000	0.0000	0.0060	0.0000
Equation (2): $F_t- P_t =\alpha_2+\beta_2*(F_t - P_t)+\varepsilon_{2,t+1}$						
	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$	$\alpha_2=0, \beta_2=1$	$\alpha_2=0$	$\beta_2=1$
F-statistic	8.0422***	7.4726***	15.8842***	8.1939***	7.6619***	16.1867***
df	(2, 300)	(1, 300)	(1, 300)	(2, 302)	(1, 302)	(1, 302)
Probability	0.0004	0.0066	0.0001	0.0003	0.0060	0.0001

*** p<0.01, ** p<0.05, * p<0.1

Table 37. Descriptive Statistics of Mispricing Term and Absolute Value of Mispricing Term

Exchange	CBOE				CME			
Rollover	Nearby		7 Days		Nearby		7 Days	
Error Term	x	abs (x)	x	abs (x)	x	abs (x)	x	abs (x)
Mean	-0.2939	0.3082	-0.3440	0.3567	-0.3193	0.3297	-0.3701	0.3794
Median	-0.2741	0.2779	-0.3169	0.3238	-0.3072	0.3101	-0.3413	0.3444
Maximum	0.6466	0.7049	0.6466	0.7630	0.3705	0.7121	0.3705	0.7629
Minimum	-0.7049	0.0021	-0.7630	0.0119	-0.7121	0.0050	-0.7629	0.0050
Std. Dev.	0.2060	0.1838	0.2185	0.1971	0.1909	0.1724	0.1987	0.1802
Skewness	0.3613	0.3385	0.3667	0.2875	0.2200	0.3021	0.2797	0.2661
Kurtosis	4.1289	2.0015	4.0265	1.8848	3.2911	2.1240	3.4094	2.0116
Jarque-Bera	23.7310	19.2207	21.0208	20.7939	3.5141	14.2957	6.1069	16.0157
Probability	0.0000	0.0001	0.0000	0.0000	0.1726	0.0008	0.0472	0.0003
Observations	317	317	317	317	303	303	305	305

Table 38. Results of Bitcoin Futures Contracts Mispricing Term Unit Root Tests

The error term used for these unit root tests is defined following methodology suggested by MacKinlay and Ramaswamy (1988), Bhatt and Cakici (1990), and Switzer, Varson and Zghidi (2000). Both CME and CBOE's futures contracts daily data are used for the tests and the daily rate of 4-week U.S. T-bill is used for risk-free rate.

Panel A: CBOE Futures Contracts (December 18, 2017 – March 22, 2019)

	Nearby Contracts				Roll-over 7 days before expiration			
	ADF		PP		ADF		PP	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Stat.	-1.80451*	-18.3530***	-1.85708*	-18.3528***	-1.638196*	-17.1532***	-1.7274*	-17.1472***
Prob.	0.0677	0.0000	0.0604	0.0000	0.0957	0.0000	0.0798	0.0000

Panel A: CME Futures Contracts (January 2, 2018 – March 22, 2019)

	Nearby Contracts				Roll-over 7 days before expiration			
	ADF		PP		ADF		PP	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
Stat.	-1.28480	-17.7733***	-1.233471	-17.8079***	-0.792969	-19.8856***	-0.860488	-19.9025***
Prob.	0.1833	0.0000	0.1996	0.0000	0.3719	0.0000	0.3425	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Table 39. Chronology of Major Bitcoin Exchange Hacks

Year	Month	Exchange	Amount Stolen (BTC)
2012	March	Bitcoinica	46,703
2012	May	Bitcoinica	18,000
2012	August	Bitcoin Ponzi	265,678
2012	September	Bitfloor	24,000
2014	February	Mt. Gox	850,000
2014	July	Cryptsy	13,000
2015	January	Bitstamp	19,000
2015	February	BTER	7,170
2016	August	Bitfinex	120,000
2017	December	NiceHash	4,736
2018	April	CoinSecure	438
2018	June	Bithumb	2,016
2018	September	Zaif	5,966
2018	October	MapleChange	919
2019	February	Quadriga	154

Table 40. Top 10 Cryptocurrencies by Market Capitalization

Rank	Name	Market Capitalization (As of January 30, 2019)	Initial Release
1	Bitcoin	$60,329,884,225	January 9, 2009
2	Ripple (XRP)	$12,444,402,901	August 11, 2013
3	Ethereum	$11,041,665,977	July 30, 2015
4	EOS	$2,098,395,149	June 26, 2017
5	Tether	$2,034,826,407	October 6, 2014
6	Bitcoin Cash	$1,983,990,236	August 1, 2017
7	Litecoin	$1,889,854,900	October 7, 2011
8	TRON	$1,653,533,859	September 12, 2017
9	Stellar	$1,551,518,489	July 31, 2014
10	Bitcoin SV	$1,119,643,115	November 25, 2018

[Source 1: CoinMarketCap / https://coinmarketcap.com, accessed on Jan 31, 2019]
[Source 2: coinbase / https://www.coinbase.cm/price, accessed on Jan 31, 2019]

Table 41. Estimates of Daily Futures Mispricing Regression with Dummy Variables

Estimation equation: $x = \alpha_1+\beta_1$*hack_cum+ β_2*newcoin

hack_cum constitutes cumulative amount of stolen Bitcoin from December 2017. *newcoin* variable refers dummy variable of new cryptocurrency release. The dummy variable has value of 1 from D-1 to D+5 of new coin releases, otherwise 0. The datasets have two different types of rollover methodologies: nearby and 7 days before expiration, and each methodology is presented in Nearby and 7 Days rows, respectively.

Exchange	Rollover	Variable	Coefficient	Std. Error	t-Stat	Prob		
CBOE	Nearby	Constant	-0.0706 ***	0.0259	-2.7314	0.0067		
		Cumulative Hack	-2.4E-05 ***	0.0000	-9.6612	0.0000		
		New Coin	-0.0325	0.0252	-1.2868	0.1991	R-square	0.2292
	7 Days	Constant	-0.0869 ***	0.0268	-3.2424	0.0013		
		Cumulative Hack	-2.7E-5 ***	0.0000	-10.5906	0.0000		
		New Coin	-0.0538 **	0.0265	-2.0330	0.0429	R-square	0.2636
CME	Nearby	Constant	-0.1288 ***	0.0257	-5.0207	0.0000		
		Cumulative Hack	-1.9E-05 ***	0.0000	-7.8814	0.0000		
		New Coin	-0.0709 ***	0.0243	-2.9113	0.0039	R-square	0.1781
	7 Days	Constant	-0.1402 ***	0.0265	-5.2922	0.0000		
		Cumulative Hack	-2.3E-05 ***	0.0000	-9.3695	0.0000		
		New Coin	-0.0645 ***	0.0246	-2.6260	0.0091	R-square	0.2276

*** p<0.01, ** p<0.05, * p<0.1

Table 42. EGARCH Results of Daily Futures Mispricing Regression with Dummy Variables

Estimation equation: X=C(1)+C(2)*hack_cum+C(3)*newcoin

Variance equation: LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

hack_cum constitutes cumulative amount of stolen Bitcoin from December 2017. *newcoin* variable refers dummy variable of new cryptocurrency release. The dummy variable has value of 1 from D-1 to D+5 of new coin releases, otherwise 0. The datasets have two different types of rollover methodologies: nearby and 7 days before expiration, and each methodology is presented in Nearby and 7 Days columns, respectively.

Exchange	CBOE		CME	
Rollover	Nearby	7 Days	Nearby	7 Days
C(1)	-0.0633	-0.0191	-0.1175	-0.0855
C(2)	-3.0E-05	-3.8E-05	-2.8E-05	-3.4E-05
C(3)	-0.0198	-0.0791	-0.0825	-0.0512
C(4)	-2.2871	-1.9803	-2.2689	-2.2445
C(5)	1.1256	1.1214	1.3440	1.2886
C(6)	0.1823	0.1375	0.2019	0.1737
C(7)	0.6922	0.7620	0.7555	0.7411
Prob. (C(7))	0.0000	0.0000	0.0000	0.0000
	***	***	***	***
R-squared	0.1742	0.1977	0.0186	0.1443

*** $p<0.01$, ** $p<0.05$, * $p<0.1$