# Natural disaster effects on exchange rates, a preliminary study

Johan van Donk - 482674

August 15, 2020

Supervisor: dr. Agnieszka Markiewicz
Second assessor: Riccardo Silvestrini

ERASMUS UNIVERSITY ROTTERDAM
Erasmus School of Economics

Bachelor Thesis International Economics

**Abstract**

In this article we investigate the impact of a natural disaster on the foreign exchange rate for a group of Asian-Pacific nations. We employ several ARCH based models to assess the short term consequences. The results are indicative of both volatility as well as price effects. The traded volume for retail investors also seems to respond to a natural disaster. While there has been evidence of a natural disaster disproportionally affecting returns, this result depends on the country and model estimated. On the long term, the Japanese yen seems to initially appreciate in value and thereafter slowly depreciate in value.

# Contents

# 1 Introduction

Throughout history, major natural disasters have had a lasting impact on societies across the world, in major part because of their severe fallout. Due to the tragic loss of human lives in the North Sea flood of 1953, The Netherlands advanced with the Delta Works flood protection project, changing the country's landscape for years to come. According to the Intergovernmental Panel on Climate Change(Masson-Delmotte et al. (2018)), such extreme weather scenarios will likely become more commonplace as greenhouse gases are continuing to build up. Ex-post analysis of the impact of such events on social and economic costs combined with political pressure have forced policy makers to earmark budgets for natural disaster warning systems. Although the prediction and mitigation of natural disasters is rightfully reserved to the fields of geography and meteorology, the subsequent economic consequences are within the scope of research for this thesis.

The empirical academic literature regarding the economic consequences of natural disasters has been mainly focussed on long term fluctuations in macroeconomic variables such as GDP (see Skidmore and Toya, 2002 and Noy, 2009 among many others). Although shorter term effects have also been investigated, to the best of our knowledge there is little empirical literature on the effects on foreign exchange rates. Current research has been mainly devoted on establishing a theoretical framework. Therefore our main research will focus on the effects of natural disasters on the exchange rate. Led by the theoretical model of Farhi and Gabaix (2016) we consider the following hypotheses[1]:

- Currency spot prices are influenced by rare natural disasters ($H_1$)
- Volatility of foreign exchange rates increases following a disaster ($H_2$)
- Increase in volume traded ($H_3$)
- Developed nations differ in their experienced exchange rate fluctuations in comparison to their underdeveloped counterparts ($H_4$)

In the remainder of the thesis we first establish the existing academic literature, followed by the utilized methodology. Thereafter we highlight the data used and results. We conclude with a short discussion.

[1] For a full derivation, we refer to the relevant section in the literature review.

## 2 Literature Review

The severe impact of natural disasters on the affected region's infrastructure has inspired a wealth of articles estimating the effects on long term economic variables. One such article is Skidmore and Toya (2002), which investigates whether natural disaster promote long-run growth. Accounting for several factors such as demographic, geographical and continent-specific factors, the authors find a robust correlation between disasters and long-run economic growth. An important distinction to make here is that the effect is positive for climatic disasters (such as typhoons and storms), whereas the effect appears to be negative for geologic disasters such as earthquakes. Furthermore, insurers and government assistance programs seem to be, for various reasons, insufficient to completely account for disaster damages, which results in part of the burden being shouldered on the individual.

According to Noy (2009), natural disasters not only affect GDP, but in addition the GDP growth rate over time(also indicated by a theoretical model as described in Albala-Bertrand (1993). The effect here is yet again dependent on several variables, which in this case entails the size of the economy, development level and severity of the disaster(property damage, human loss). The author finds that smaller and less developed nations face higher costs to GDP growth than their more developed and larger counterparts. This vulnerability is in part explained by the strength of (economic) institutions and diversification of the economy.
With an indication of long-term economic effects and part of the economic fallout being shifted on the individual, could foreign disaster relief(such as private fundraisers and family overseas) be an influencing mechanism regarding the foreign exchange rate ?

Although not explicitly the aim of the paper, Yang (2008) provides insights on the impact of hurricanes on short term international financial flows. Such flows, described as official development assistance (ODA), potentially act as a buffer to caused economic losses. ODA are defined as lending from multilateral institutions, bank and trade-related lending, migrants' remittances, foreign direct investment, and portfolio investment. Results indicate a net increase of ODA in poorer countries following a hurricane, fuelled by migrant's remittances to family members. Whereas for richer countries, even though lending from multilateral institutions increased, a total ODA effect of zero can not be rejected. Short term effects on macroeconomic variables have also been observed in a sample of Caribbean island nations by Rasmussen (2004).

Even though the articles as described above give us insights on affected macroeconomic fundamentals, foreign exchange markets are in part also influenced by investment and trading decisions of financial agents acting on capital markets. An obvious example of the short term effect of a natural disaster on capital markets are the stock prices of insurers( Yamori and Kobayashi (2002)). The effect here indicates a negative impact on stock values for the insurance industry in Japan following a major earthquake. A wider scope of research in this field is proposed by Wang and Kutan (2013) who not only consider the effects on the insurance industry, but the composite index as a whole. In both the studied countries (USA and Japan) effects of natural disasters on stock returns is restricted to insurance stocks, with no robust spillover effect on the composite index. Although there seems to be some evidence in favour of natural disaster effects on composite returns(A. Worthington and Valadkhani (2004)), results in line with Wang and Kutan (2013) are observed on Australian capital market returns by adopting GARCH based models A. C. Worthington et al. (2008).

A comprehensive theoretical model describing the dynamics on the foreign exchange markets as a result of rare disasters has been put forward by Farhi and Gabaix (2016). By linking the stock, option and foreign exchange markets, the researchers assess that the probability of disasters and exposure of each country to these events can (partially) explain observed “excess volatility”(Meese and Rogoff (1983)). Disasters in this article are not only restricted to natural disasters, but also events like war and political crises. In their model, disasters pose a negative shock to the (future) productivity of the affected nation. With the current exchange rate being influenced not only by current export levels, but also expectations of future exports, such a negative shock to productivity will also affect exchange rates. Decreases in exports will also result in decreased demand for the respective currency, and hence a depreciation in currency value. Vice versa, this linkage between the exchange rate and disaster risk states that countries with higher “resilience”(i.e., low risk profile) experience a lower exchange rate(i.e an appreciated currency value in price notation)[2]. We therefore formulate the hypothesis ($H_1$) that a natural disaster will influence the currency spot prices through the productivity mechanism.

Our justification of the second hypothesis ($H_2$), volatility of foreign exchange rates increases following a disaster, also stems from the Farhi and Gabaix framework. Although

[2] see page 14 of article

disaster risk can up to a degree be predicted drawing upon historical data, it in addition contains a random element. In other words, the exact fallout of a disaster can not be perfectly predicted, there is a stochastic process. Therefore, hedging for this risk would result in higher premiums on put options in comparison to equivalent call options[3]. Empirically, a potential explanation for these premiums could be higher volatility following a disaster (potential price discovery process). Furthermore, interventions by the central bank following such periods of turmoil on foreign exchange rate markets seem not necessarily be able to subdue volatility (Dominguez (1998)).

The increase in volume traded hypothesis ($H_3$) follows from the definition of our volume metric. Our volume metric mainly relies on movements of retail investors, who in addition can trade on leverage. Our speculation here is that retail investors, regardless of their time spent monitoring positions, either set or are forced to set stop-loss orders to protect against unbearable losses. In so, volume will increase if a disaster causes price swings in the spot market, as those stop-loss orders will be triggered.

Based on the implications of Noy (2009), where development level influences the long term consequences of a natural disaster, we formulate our fourth hypothesis. As development level seems to matter for fallout effects on macroeconomic fundamentals, we also expect it to be a factor on the foreign exchange market as spot rates are in part determined by fundamentals.

# 3 Methodology

## 3.1 Short term effects

### 3.1.1 Cumulative abnormal average returns

As our aim is to shed light on the effects of a natural disaster on exchange rates, different approaches are needed to describe multiple dynamics at play on the foreign exchange market. As a primer we first examine the immediate effects of a natural disaster on the key factor, price($H_1$). The cumulative (average) abnormal returns (hereafter defined as "CAAR") approach is employed here, which assumes a linear relationship between

[3] see page 25

currency's return and the market return. We define returns here as following:

$$return = \frac{FX_{spot,t} - FX_{spot,t\text{-}1}}{FX_{spot,t\text{-}1}} \tag{1}$$

First we define the proportion of the return that can not be explained by the standard market model (abnormal return).

Abnormal return for currency i on time t is defined as the following:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t}) \tag{2}$$

Where $\mathrm{AR}_{\mathrm{i,t}}$ is the abnormal return of the respective currency ($i$) on time $t$, $\mathrm{R}_{\mathrm{i,t}}$ the total return (equation 1), $\alpha_{\mathrm{i}}$ "the risk free rate" [4] , $\beta_{\mathrm{i}}$ the correlation to the market and $\mathrm{R}_{\mathrm{m,t}}$ is our market return. As there is no traditional overarching market index such as in equity markets, we take the USDX index for USD denominated currency pairs and the ECB Nominal effective exchange rate[5] for EUR denominated currency pairs as close proxies of market returns. The USDX measures the relative strength of the USD against a weighted basket of other currencies. An increase in the USDX (USD relatively appreciates against all other currencies) will predict a higher exchange rate for the respective currency(depreciation) when $\beta$ is positive. Currencies with a negative $\beta$ on the other hand would appreciate in value with the same movement of the USDX. The same goes for the ECB index and EUR denominated currency pairs. Therefore the indices will act as an ad hoc equivalent of market returns in the CAPM framework. The OLS estimation window for parameters $\alpha_{\mathrm{i}}$ and $\beta_{\mathrm{i}}$ consists of 180 trading days preceding the event ($\mathrm{t}_{-200}$,$\mathrm{t}_{-20}$). There is an additional 20 days buffer between the estimation and event window to mitigate short term momentum effects.

To estimate the short term effect of a natural disaster on exchange rate, we define a so called "event window" which consists of several trading days following the disaster. In so, we are interested in the cumulative average abnormal return spanning this period, the CAAR. The cumulative abnormal average return follows from the equation:

$$CAAR = \frac{1}{n}\sum_{i=1}^{n}\sum_{t=t_1}^{t_2} \mathrm{AR}_{i,t} \tag{3}$$

[4]As is defined in the CAPM framework,

[5]Trade based against EER-38 group of trading partners

Herein, $t_1$ is the beginning of the event window, $t_2$ the end. $N$ is the subsample size, the amount of observations that fall within the event window. Following the evidence of event-induced volatility(see figure 1), to test for significance of the CAAR we employ the standardized cross-sectional test as described in Boehmer et al., 1991. To captivate possible monetary interventions days after the natural disaster , multiple event windows are investigated. In the conventional CAAR framework the event window also consists of time periods before the actual event, which accounts for predictions and/or information leakages being priced in. However as we deal with events which are near impossible to predict in the near future (natural disasters), at most we estimate an event window which is lower bound at $t_{-1}$.

Important underlying assumptions of the CAAR method (as described in Binder, 1998 )which we have not reviewed yet are the following:

- Serial uncorrelated observations (independently distributed)
- Linear relationship between currency return $R_{i,t}$ and the market return $R_{m,t}$
- Normal distributions of returns

To see whether the first assumption holds, we use the Breusch–Godfrey statistic in Table 1 which suggest serial uncorrelated observation with one lag $t_{-1}$. There is little evidence for rejection of the second assumption, as it is unlikely that returns follow a parabolic or polynomial function of the market return. Normal distribution of the returns seems to hold up by looking at Figure 3 and Table 12.

### 3.1.2 Event induced volatility

Although the BMP test statistic accounts for event induced volatility in our CAAR framework, we still do not know the precise volatility effect of shocks on the exchange rate($H_2$). Simply put, does volatility behave differently following a negative shock (a natural disaster) in comparison to a positive shock (fiscal expansion)? If these effects are known, an assessment can be made whether monetary intervention leads to mitigation of turmoil caused by natural disasters. We first start by investigating whether there are any of these autoregressive conditional heteroskedasticity (ARCH) effects on the returns by using Engle's LM test see Table 10. Evidence suggest a rejection of the $H_0$ = No ARCH effects. The standard Dickey-Fuller test on both daily as well as minute based spot price data fail to reject the hypothesis of an unit root at the 5% confidence level for some periods, the results are mixed. Therefore in the following estimations we take the first difference of the natural logarithm of the spot price.

$$y_t = ln(Y_t) - ln(Y_{t-1}) \tag{4}$$

Here $Y$ is the spot price. We continue by estimating a GARCH (p, q)[6] model on the currency returns to get more precise estimates of the ARCH effects.

$$y_t = c + \epsilon_t \tag{5}$$

$$\sigma_t^2 = \sum_{i=1}^{p} \gamma_{\mathrm{i}} \epsilon_{t-i}^2 + \sum_{i=1}^{q} \delta_{\mathrm{i}} \sigma_{t-i}^2 \tag{6}$$

Here, the value of the return $y$ on period $= t$ equals a constant $c$ and the error term $\epsilon$. Volatility $\sigma$ is defined as a combination of previous periods error term $\epsilon_{t-1}$ and volatility $\sigma_{t-1}$. A significant parameter $\gamma$ indicates that a past shock influences current volatility, whereas a significant $\delta$ indicates influence of past volatility on current volatility. If the sum of ($\gamma + \sigma$ ) is approaching 1, there is evidence of persistence in the conditional variance Stock and Watson, 2015. In other words, periods of high volatility are likely to be persistent over time.

### 3.1.3 Volatility persistence

In two countries, Japan and New Zealand, we find evidence of return clustering (see Figure 6) as well as persistence in volatility outcomes(see table 6). Even though returns ($y_t$) appear to be serially uncorrelated according to the Breusch-Godfrey test values, large returns in one direction seem to cause an equal counter reaction. Ding et al. (1993) propose an explanation of this phenomena regarding returns of financial indices. In short, even though returns ($y_t$) themselves might not be autocorrelated, their absolute values can be($|(y_t)|$,see figure 6). Therefore one of our assumptions of returns being an i.i.d process does not hold strictly, as any monotonic transformation of ($y_t$) would also be i.i.d, including $|y_t|$[7]. This absolute autocorrelation warrants an other approach, namely estimation by using an Asymmetric Power ARCH model (A-PARCH). We use an A-PARCH(p,q) model of the following form:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-p}| - \gamma\varepsilon_{t-p}\right)^\delta + \sum_{i=1}^{q} \beta_i \sigma_{t-p}^\delta \tag{7}$$

[6] Estimating $p$ and $q$ is done by comparison of the Akaike Information Criterion, see tables (14-17).
[7] assuming a random continuous variable such as $y_t$

$\varepsilon_t = \sigma_t z_t$, where $z_t$ is a standard Gaussian.
Here $\gamma$ indicates an asymmetric shock effect on volatility, while $\alpha$ is the symmetric shock effect. Past influence of volatility is captured by the estimated parameter $\beta$.

## 3.2 ARDL model

To assess ultra short term effects (minutes following a disaster) we will estimate an Auto-regressive distributed lag model(hereafter ARDL). Although immediate disaster effects might occur, these effects could be short lived and therefore dissipate in daily based analysis. As we could only obtain daily based data for the USDX, the above mentioned CAAR method would not be of much use in our case. The parameterization of the ARDL model will be provided by minimization of the Akaike information criterion(AIC) in the STATA ARDL package by Kripfganz, Schneider, et al. (2016) . We estimate an ARDL (p,q) model of the following form:

$$y_t = c_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=0}^{q} \delta_i' x_{t-i} + u_t \tag{8}$$

Where the return($y_t$) is based on it's own $p$ lagged values and lagged $q$ values of the variables matrix $\mathbf{X}$. This variable matrix consists of variables such as the occurrence of a natural disaster, interest and inflation rates. $C_0$ and $u_t$ are respectively the constant and error term.

## 3.3 Longer term effects

Although the physical impact of a natural disaster on its surroundings are direct and potentially severe , Skidmore and Toya, 2002 have proven that such events also seem to affect long term economic variables. Therefore we need to adopt other research methods to identify possible longer term effects. We employ the "Difference in Difference " (Diff-in-Diff) approach as famously implemented by Neumark and Wascher (1992). We consider for each disaster stricken country two counterfactuals and compare whether the results obtained are consistent. Although the exchange rate on one hand hinges on money supply and on the other on (changes in) interest rates, we only account for the interest rate in our Diff-in-Diff. The reason we do not normalize the outcomes by the growth in money supply is due to the fact that money supply can be seen as endogenous. As evidenced by political and monetary policies, central banks potentially adjust their operations in response to extraordinary events such as disasters. Accounting for growth in money supply would therefore filter out the "Disaster effect" in our Diff-in-Diff regression. We do consider the interest rate (mildly) exogenous as we take the immediate interbank lending rate as measure. Our assumption here is that a natural disaster will not influence the level of trust between banks.

We only use Korea, Japan and New Zealand in our analysis, as all countries exhibit roughly the same characteristics(see table 11):

- High comparable level of development
- Well established (financial) infrastructure
- Major traded currencies
- Open foreign exchange markets
- Reliance on Asian-pacific trade

In addition, all data on interest and spot rates are readily available. We assume a linear parallel trend between the different countries in the 3 year period before and after a natural disaster. A longer time period would increase the probability of time-varying factors affecting one country disproportionally (trade wars, political tensions, fiscal/monetary interventions). In our analysis we only consider the 2011 Japan earthquake, as the NZD and KRW do not exhibit similar trends over time. Furthermore, the 2011 Christchurch earthquake is shortly followed by the one in Japan, making the diff in diff estimation window for the NZD too small for for long term analysis. In addition we standardize the exchange rate by the following formula :

$$\frac{FX_{spot}}{FX_{disaster_t}} \tag{9}$$

Simply stated, the spot rate is divided by the foreign exchange rate at the time of the disaster.
Our Diff-in-Diff regression is defined as:

$$Y_{it} = \alpha + \rho T_i + \gamma t + \beta T_i t + \delta X_{it} + \varepsilon_{it}, t = 0, 1 \tag{10}$$

Here the dependable variable($Y_{i,t}$) is the standardized value of the exchange rate. The treatment dummy variable ($T_i$) indicates whether a natural disaster has occured in the country($T_1$), whereas $t$ corrects for time effects and $X_{it}$ for influences of interest rates. The estimated disaster effect equals $\beta$[8].

# 4 Data

To obtain insights into the effect of a natural disaster on an exchange rate, we need several sources of economic and non economic factors. First we make a selection of currencies with 1) a floating exchange rate regime, 2) sufficient amount of data around the disaster time and 3) preferably high trading volumes. These requirements enable us to reliably study exchange rate fluctuations, which becomes more difficult with illiquid and/or fixed markets. Therefore in our analysis we study the currency pairs as outlined in Table 1. All exchange rates follow a price notation. In our datasets, we do not use data involving the Chinese renminbi as there is evidence of a managed float regime and capital movement constraints. Data on exchange rates are obtained by using the FRED Database of the Federal Reserve Bank of St. Louis and Dukascopy database via QuantDataManager. The rates and indices are mostly on a daily basis, however for major currency pairs minute based data is also available.
A measure of the traded volume of the currencies is provided by the Dukascopy database. Due to the decentralized nature of Forex trading and lack of documentation, the "Volume " provided is likely to be a synthetic index composed by Dukascopy. Furthermore the platform's focus on retail investors makes it not indicative of the movements made by institutional investors such as pension funds, trading shops and hedge funds.

To identify natural disasters we use the EM-DAT database provided by the Centre for Research on the Epidemiology of Disasters (CRED), consisting of data on the severity of the event (number of people affected, injured, dead, reconstruction costs, etc). With tropical storms and (minor) earthquakes being a common occurrence in some parts of the world (parts of the Caribbean, Asia-Pacific, etc.), people and society have adapted by different construction standards and insurance policies[9]. Therefore, events falling within the "expected" bell curve of seasonal extreme weather or earthquake severity therefore would likely not disturb the exchange rate. Our initial sample also leaves out heat and cold waves, as these events are not characterized by a sudden shock, but are more of a persistent and gradual nature. In addition, their relatively long timespan causes high numbers of casualties(mostly elderly) who would have passed away in the short term

[8] see Appendix for further clarification
[9] example being earthquake proof building codes in Japan Teshigawara (2012)

irregardless. We only keep disasters if their number of affected people, number of deaths and total damages in USD fall above the 95$^{th}$ percentile for the respective country. Furthermore, although we do utilize events pre 1972 in our percentile statistic, we do not consider these natural disasters in our exchange rate analysis. The Bretton Woods era of monetary policy (1945-1971) is characterized by fixed exchange rate regimes, data before 1945 on exchange rates is not within the scope of our research.

Data outlining the similarities of Japan, Korea and New Zealand is provided by the most recent reports of the World Bank and Bank of International Settlements(BIS Triennial Central Bank Survey). As an indication for the openness of capital markets, we use the Chinn-Ito index(Chinn and Ito (2006)). In addition, the ease of doing business metric by the World Bank is used to approximate the quality of the (financial) infrastructure.

# 5 Results

## 5.1 Short term

Figures 1 and 2(see appendix) show an immediate increase in traded volume on the spot market for USD denominated currency pairs, following a natural disaster. In comparison to an equivalent window both Japan and New Zealand experience this effect. In addition there is indication of an immediate increase in volatility for Japan, but this effect does not hold up for New Zealand (see Figures 4 and 5). As put forward in table 1, only the

Table 1: CAAR daily statistics

| Country | Event windows | | | | Breusch–Godfrey |
|---|---|---|---|---|---|
| | (-1,2) | (0,3) | (0,4) | (0,5) | $p$ |
| Japan | -2.40$^{*}$ % | -3.38$^{***}$ % | -5.00$^{***}$ % | -1.87 % | .22 |
| Philippines | .30 % | .41 % | .37 % | .82 % | .69 |
| Thailand | .12% | .53% | .00% | -.41% | .77 |
| New Zealand | -.65% | -.27% | -.66% | -1.07% | .89 |

*Note.* *** p-value < .01, ** p-value <.05, * p-value <.1

Yen/USD exchange rate seems to exhibit abnormal returns with the yen appreciating in value. This result is counter-intuitive with the notions of Farhi and Gabaix (2016), as the problems with a potential nuclear meltdown caused by the 2011 earthquake and subsequent tsunami would induce additional risk in the Japanese markets. This additional risk would have predicted a depreciation of the currency instead. One hypothesis here is that Japanese financial entities(such as insurers and traders) disinvested in their foreign assets to cover for (future) yen denominated liabilities as a result of the disaster. As for the other countries, no conclusive evidence for abnormal returns(Philippines, Thailand, New Zealand) can be found in the above mentioned table.

Table 2: GARCH daily models

| country | c | $\gamma_1$ | $\gamma_2$ | $\delta_1$ | $\delta_2$ | $N$ |
|---|---|---|---|---|---|---|
| New Zealand | .000 | $.117^{***}$ | -.102 | $2.04^{***}$ | | 3998 |
| Japan | .000 | $.118^{***}$ | | $.927^{***}$ | | 3998 |
| Thailand | .000 | $.296^{***}$ | $.309^{*}$ | -.575 | $.772^{**}$ | 4009 |
| Philippines | .000 | $.214^{***}$ | | $.281^{***}$ | | 3063 |

*Note.* *** p-value < .01, ** p-value <.05, * p-value <.1

$$\sigma_t^2 = \sum_{i=1}^{p} \gamma_i \epsilon_{t-i}^2 + \sum_{i=1}^{q} \delta_i \sigma_{t-i}^2 \tag{11}$$

In line with results of Andersen et al. (2001), table 2 indicates evidence of time period lags of volatility influencing current values of volatility(significant positive $\delta$). Shock effects also seem to influence volatility over time($\gamma$ in most cases significant and positive). Although $\gamma_1 + \delta_1$ are in some cases not adding up to 1(Philippines), there is not sufficient evidence for persistence in the conditional variance. The results for all other countries are problematic with $\gamma_1 + \delta_1 > 1$.

Table 3: A-PARCH daily models

| country | $\omega$ | $\alpha_1$ | $\alpha_2$ | $\gamma_1$ | $\gamma_2$ | $\beta_1$ | $\beta_2$ | $\delta$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| New Zealand | .000 | $.044^{***}$ | | $-.221^{***}$ | | $1.01^{***}$ | -.061 | $1.37^{***}$ | 5118 |
| Japan | .000 | $.053^{***}$ | $.058^{***}$ | $-.143^{**}$ | $-.188^{***}$ | .04 | $.850^{***}$ | $1.29^{***}$ | 5118 |
| Thailand | .000 | $.115^{***}$ | | $-.0386^{*}$ | | $.814^{***}$ | .067 | $1.52^{***}$ | 5132 |
| Philippines | .000 | $.032^{***}$ | | -.0406 | | $.966^{***}$ | | $1.66^{***}$ | 3872 |

*Note.* *** p-value < .01, ** p-value <.05, * p-value <.1
Stata output includes the total effect of $\gamma$, multiplication with -1 has already been accounted for. All models chosen by comparison of the AIC. All estimations of $\omega$ are infinitesimally small and for convenience rounded to .000

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-p}| - \gamma\varepsilon_{t-p}\right)^{\delta} + \sum_{i=1}^{q} \beta_i \sigma_{t-p}^{\delta}$$

Therefore looking at table 3, which estimates an A-PARCH model, we find evidence of unexpected drops in the currency price causing volatility ($\gamma$ is significantly negative and relatively large to $\alpha$ in Japan as well as New Zealand). The asymmetric shock effect($\gamma$) for Thailand as well as the Philippines do not appear to dominate. In other words, unexpected appreciations (decline in price notation) are potentially indicative of higher volatility levels. Furthermore, all countries indicate an autoregressive effect of volatility($\beta$).

Table 4: ARDL returns (1 minute delta)

| parameter | Country | |
|---|---|---|
| | Japan | New Zealand |
| $\alpha$ (constant) | .000 | .000 |
| $\beta_1$(AR (1)) | .005$^{**}$ | .030$^{***}$ |
| $\beta_2$(AR (2)) | -.061$^{***}$ | -.006 |
| $\beta_3$(AR (3)) | -.091$^{***}$ | -.028$^{***}$ |
| $\beta_4$(AR (4)) | .021$^{***}$ | -.021$^{**}$ |
| $\delta_0$ Disaster | .000 | .000 |
| $\delta_1$ lag 1 | .000 | .000 |
| $\delta_2$ lag 2 | .000 | .000 |
| $\delta_3$ lag 3 | .000 | .000 |
| $\delta_4$ lag 4 | .002 | .000 |
| $N$ | 8166 | 6413 |

*Note.* *** p-value $<$ .01, ** p-value $<$.05, * p-value $<$.1

$$y_t = c_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=0}^{q} \delta_i' x_{t-i} + u_t$$

The ARDL framework yields no immediate disaster effects on the exchange rate (Table 4) and highly significant estimations for autoregressive effects up to 4 lags.
In short, volatility in all countries is auto-regressive in nature to a degree and abnormal returns are generally not observed following a severe natural disaster. The only exception here is Japan with a negative abnormal return, which potentially lead to higher levels of volatility. Some signs of asymmetric shock effects on volatility are observed in multiple countries, with negative shocks mainly causing higher levels of volatility.

## 5.2 Longer term

As described in Table 5, The Japanese yen seems to follow a different trajectory than the Korean won in regards to the USD. The yen here seems to be appreciated in value even in the long term, with the effect dissipating slowly(see variable ”did” ). The long term effect, corrected for interest rates seems to be small(at most 1.2 % vs the Korean Won). A comparison against the NZD only yields a significant negative effect(appreciating in value) one year after the disaster(1%), with the t-statistic increasing rapidly over time. This subsequent depreciation in value of the yen following an initial increase could potentially be caused by additional risks and shocks to production being priced in (as described in Farhi and Gabaix (2016)). In short both tables support the hypothesis of a disaster shock causing yen appreciation in the short term(insurance liabilities), followed by longer term depreciation(pricing in of additional risk) . We do have to note that the trajectory of the currency pairs are not strictly parallel before the disaster date. Therefore this result can only be considered exploratory in nature.

Table 5: Diff in Diff Yen-KRW

| | (6 months) std_value | (1 year) std_value | (18 months) std_value | (2 years) std_value |
|---|---|---|---|---|
| monthdiff | -0.000828 | 0.00785*** | 0.00426* | 0.00150 |
| | (-0.24) | (4.67) | (2.41) | (1.04) |
| treated | -0.367 | -0.677*** | -0.207 | 0.158 |
| | (-1.95) | (-4.49) | (-0.86) | (0.98) |
| did | -0.0120* | -0.0122** | -0.00660** | 0.00223 |
| | (-2.47) | (-3.81) | (-3.09) | (0.85) |
| interest | -0.138 | -0.238*** | -0.0780 | 0.0578 |
| | (-2.17) | (-4.67) | (-0.99) | (1.19) |
| Constant | 1.395*** | 1.690*** | 1.201*** | 0.786*** |
| | (7.31) | (10.93) | (4.89) | (4.83) |
| Observations | 12 | 20 | 26 | 36 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Diff in Diff Yen-NZD

| | (6 months) std_value | (1 year) std_value | (18 months) std_value | (2 years) std_value |
|---|---|---|---|---|
| monthdiff | 0.0206 | 0.00518 | 0.00101 | 0.00181 |
| | (1.40) | (1.46) | (0.41) | (1.12) |
| treated | -0.414 | 0.111 | -0.481 | -0.583 |
| | (-0.19) | (0.16) | (-0.94) | (-1.19) |
| did | -0.0334 | -0.00978* | -0.00330 | 0.00202 |
| | (-2.06) | (-2.23) | (-1.24) | (0.76) |
| interest | -0.166 | 0.0765 | -0.164 | -0.193 |
| | (-0.18) | (0.26) | (-0.73) | (-0.91) |
| Constant | 1.443 | 0.880 | 1.481* | 1.546** |
| | (0.64) | (1.22) | (2.80) | (3.07) |
| Observations | 11 | 19 | 26 | 36 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 6 Conclusion and discussion

In conclusion, we find some evidence of natural disasters influencing foreign exchange rates following a natural disaster. Based on the results found in Japan and New Zealand we accept the hypothesis of volume effects($H_3$). Only in Japan we find evidence of abnormal return. Therefore there seems to be weak evidence in support of our initial hypothesis of spot rate effects($H_1$). Furthermore, in case of abnormal returns and spot rate effects (unexpected shocks), we find that volatility effects are likely to be present($H_2$). This volatility effects in addition seems to be heterogeneous with Japan and New Zealand facing negative asymmetric effects (higher volatility following an unexpected negative shock) in comparison to Thailand and Philippines. Whether this effect can in part be attributed to the development level of a country or other factors (investment decisions of economic agents such as insurers, e.g. carry trades) remains a possible avenue for further research. Therefore no credible assessment of ($H_4$) can be made. Longer term effects seem to be lacking robustness with the research methods employed, nonetheless they do find a temporarily appreciation disaster effect which slowly dissipates over time.

There are several important limitations to note in this paper. With Dukascopy's main focus being retail investors, the movements made by institutional investors have yet to be investigated. In addition, our analysis is restricted to four countries in the Asia-Pacific region. A broader investigation consisting of a more substantive sample of disasters could potentially improve the robustness of the results, or reveal other effects. Comparison of *ex ante* and *ex post* portfolio structure of insurers would possibly reveal whether exchange rates are affected by their movements.

# 7 Appendix

DID estimator.

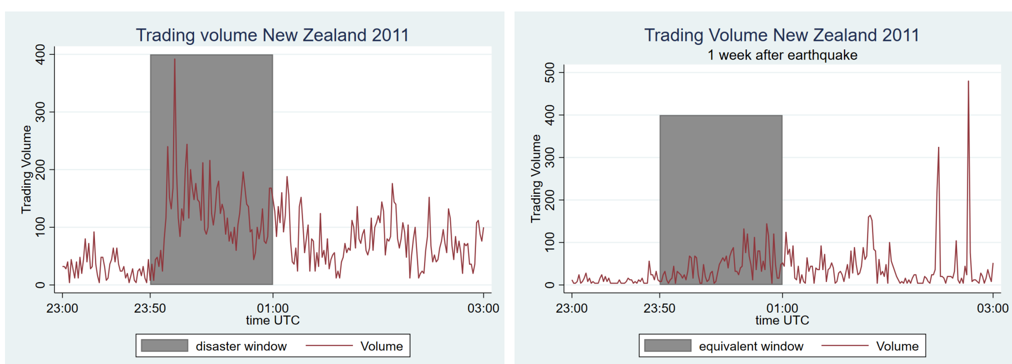
We can estimate the treatment effect by comparing the difference in outcomes of our two groups. Following the notation of the equation described in the "Methods" section, we get the following identity;

$$E\left[Y_i(1) \mid T=1, t=1\right] - E\left[Y_i(0) \mid T=1, t=0\right] -$$
$$\left(E\left[Y_i(0) \mid T=0, t=1\right] - E\left[Y_i(0) \mid T=0, t=0\right]\right)$$

which equals to :

$$((\alpha+\rho+\gamma+\beta)\text{-}(\alpha+\rho))\text{-}((\alpha+\gamma)\text{-}(\alpha)) = \beta.$$

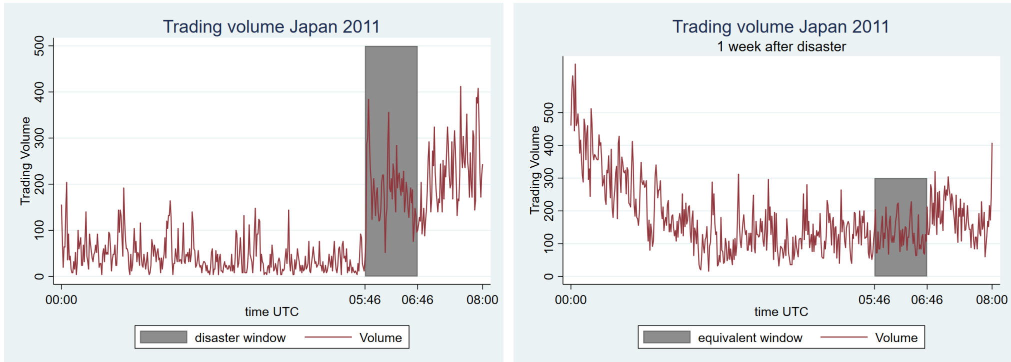
## 7.1 Figures




(a) disaster

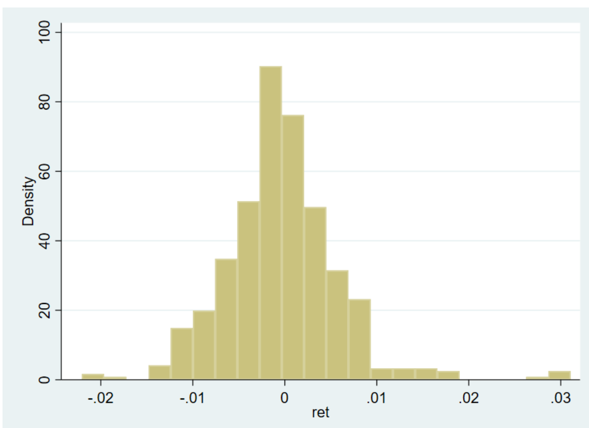
(b) equivalent

Figure 1: NZD volume traded. Disaster window is defined as the one hour period after the impact ($\mathrm{t}_{\text{impact}}$, $\mathrm{t}_{60}$)

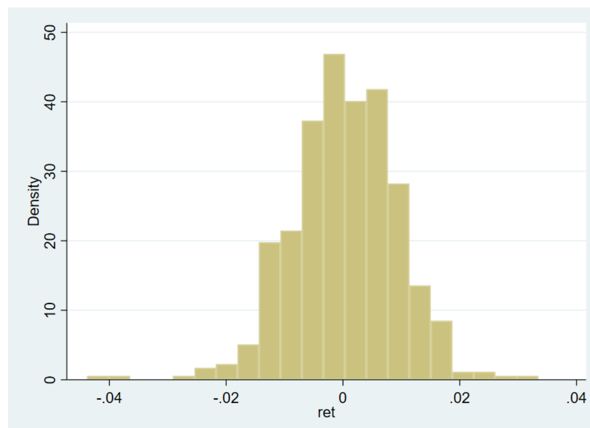



(a) disaster (b) equivalent

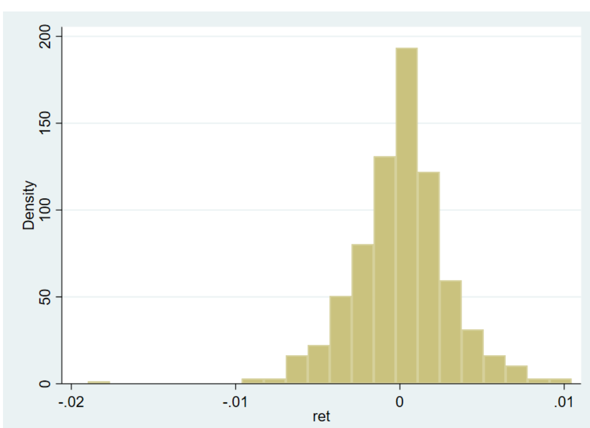
Figure 2: YEN volume traded. Disaster window is defined as the one hour period after the impact ($t_{impact}$, $t_{60}$)



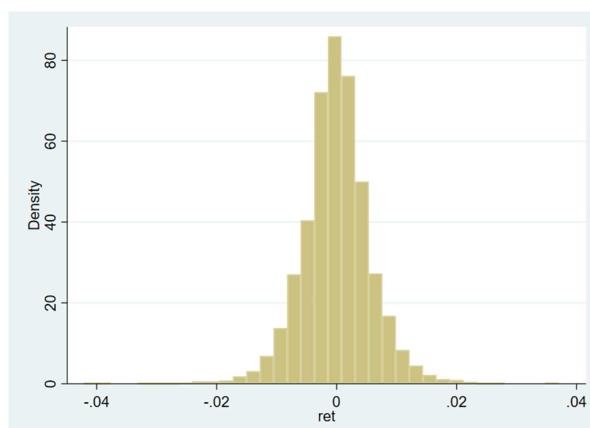

(a) Yen




(b) NZD

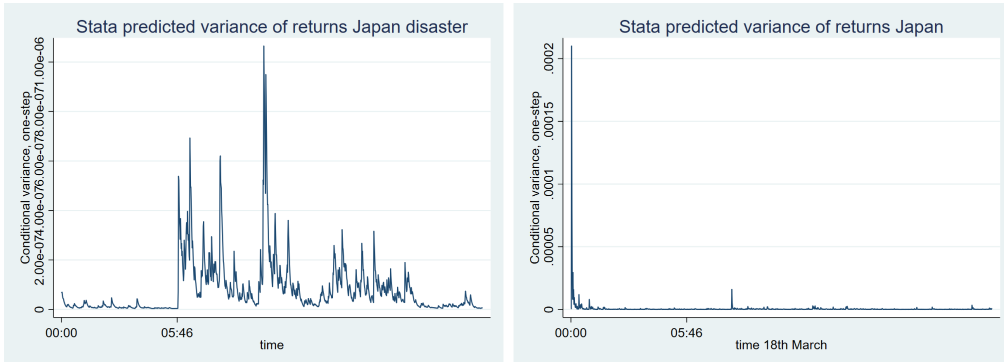



(c) THB



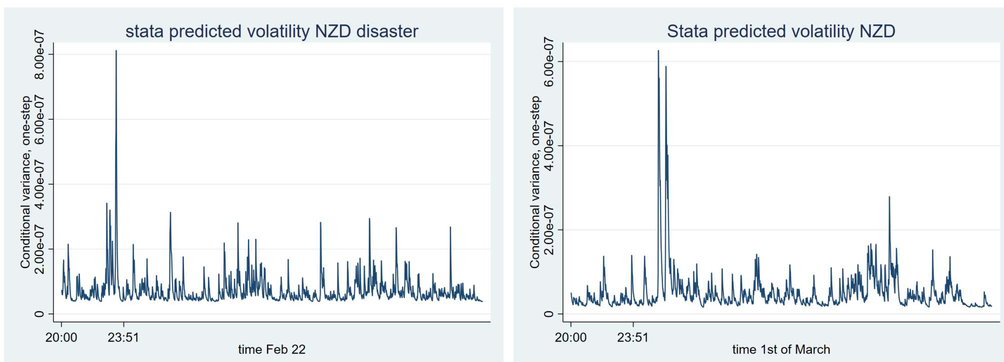

(d) PHP

Figure 3: Histograms of currency returns



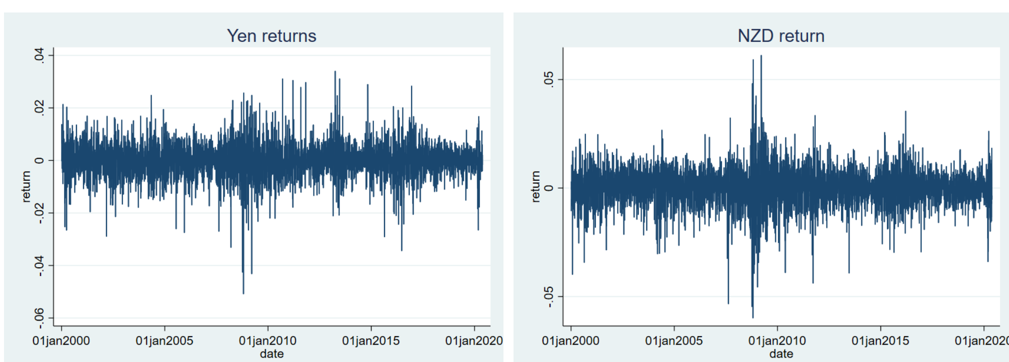

(a) disaster (b) equivalent

Figure 4: YEN Volatility predicted



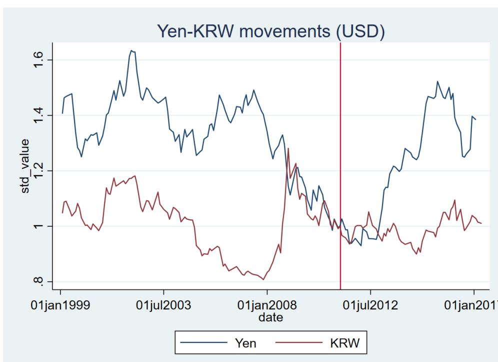

(a) disaster (b) equivalent

Figure 5: NZD Volatility predicted

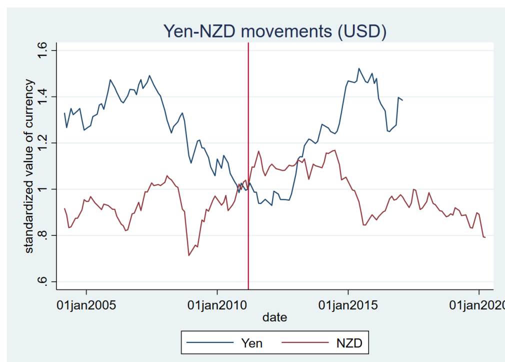



(a) Yen return clustering (b) NZD return clustering

Figure 6: return clustering




(a) Yen vs KRW




(b) Yen vs NZD

Figure 7: red line indicates time of disaster

### 7.2 Tables

Table 7: Descriptive statistics of minutely exchange rates

Volume

| country | mean | SD | min | max |
|---|---|---|---|---|
| New Zealand | 43.27 | 33.58 | 4 | 144 |
| Disaster | 122.42 | 62.38 | 8 | 392 |
| Japan | 129.90 | 45.07 | 64 | 228 |
| Disaster | 182.49 | 66.45 | 40 | 384 |

Close price

| country | mean | SD | min | max |
|---|---|---|---|---|
| New Zealand | .752 | .00042 | .751 | .753 |
| Disaster | .758 | .0028 | .755 | .764 |
| Japan | 81.75 | .042 | 81.68 | 81.82 |
| Disaster | 83.08 | .13 | 82.80 | 83.29 |

Table 8: Natural disasters statistics

| Country | Affected | | Injured | | Dead | | Damages | |
|---|---|---|---|---|---|---|---|---|
| | 95% CI | Skewness | 95% CI | Skewness | 95% CI | Skewness | 95% CI | Skewness |
| Japan | (138 ; 255843) | 7.69 | (7 ; 1600) | 10.16 | (1 ; 99) | 10.28 | (2000; 12.5MM) | 7.65 |
| Philippines | (300 ; 2560374) | 6.64 | (1 ; 2666) | 7.95 | (1 ; 333) | 9.69 | (96 ; 284694) | 13.56 |
| Thailand | (100 ; 6482602) | 3.02 | (2 ; 8457) | 3.58 | (1 ; 164) | 8.96 | (344 ; 1261000) | 7.32 |
| New Zealand | (70 ; 13836) | 4.74 | (2 ; 1500) | 2.26 | (1 ; 181) | 3.54 | (1000; 6.5MM) | 3.70 |

*Note.* Damages are in thousands USD, MM = Millions

Table 9: Statistics of identified events

| Country | Affected | Injured | Dead | Damages |
|---|---|---|---|---|
| Japan(2011) | 362887 | 5933 | 15790 | 210MM |
| Philippines(2013) | 16MM | 28689 | 6293 | 10MM |
| Thailand(2004) | 58550 | 8457 | 8345 | 1MM |
| New Zealand(2011) | 300000 | 1500 | 181 | 15MM |

*Note.* Damages are in thousands USD, MM = Millions

Table 10: LM test

| country | statistic |
|---|---|
| Japan | .000 |
| New Zealand | .000 |
| Philippines | .000 |
| Thailand | .000 |

*Note.* Tested on the first differenced values of spot rates,$y_t$

Table 11: Comparison of indices, Korea, Japan and New Zealand

| | Japan | Korea | New Zealand |
|---|---|---|---|
| Human development index | 0.915 | 0.906 | 0.921 |
| Ease of doing business index | 78 | 84 | 86.8 |
| FX Volume | 17% | 2% | 2% |
| Chinn-Ito index | 2.33 | 2.33 | 2.33 |
| Exported goods value | 57% | 58.4% | 63.54% |

*Note.* FX volume percentage based on all FX instruments traded worldwide (swaps, direct trades, derivatives).

Table 12: normality tests of returns , Jarque-Bera test

| country | N | $\chi^2$ | df | $p$ |
|---|---|---|---|---|
| New Zealand | 497 | 1.040 | 2 | .595 |
| Japan | 493 | 4.540 | 2 | .103 |
| Philippines | 3788 | 3.957 | 2 | .138 |
| Thailand | 518 | 4.231 | 2 | .121 |

*Note.* We exclude returns around disaster dates, as those are potentially abnormal, and therefore problematic.

Table 13: GARCH model selection Japan daily

| Model | $N$ | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| **(1,1)** | 3,998 | . | 14641.76 | 4 | **-29275.52** | -29250.35 |
| (1,2) | 3,998 | . | 14643.6 | 5 | -29277.21 | -29245.74 |
| (2,1) | 3,998 | . | 14647.79 | 5 | -29285.58 | -29254.11 |
| (2,2)* | 3,998 | . | 14644.24 | 5 | -29278.48 | -29247.01 |
| (1,3)* | 3,998 | . | 14644.78 | 5 | -29279.55 | -29248.08 |

*Note.* * Model is impeded by either no convergence or uphill trajectory of log likelihood

Table 14: GARCH model selection New Zealand daily

| Model | N | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| (1,1) | 3,998 | . | 13537.39 | 4 | -27066.79 | -27041.62 |
| (1,2) | 3,998 | . | 13538.79 | 5 | -27067.58 | -27036.11 |
| **(2,1)** | 3,998 | . | 13538.04 | 5 | **-27066.08** | -27034.61 |
| (2,2) | 3,998 | . | 13546.86 | 6 | -27081.72 | -27043.96 |
| (1,3)* | 3,998 | . | 13535.59 | 5 | -27061.18 | -27029.71 |

*Note.* * Model is impeded by either no convergence or uphill trajectory of log likelihood

Table 15: GARCH model selection Thailand daily

| Model | N | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| (1,1) | 4,009 | . | 17121.66 | 4 | -34235.32 | -34210.13 |
| (1,2) | 4,009 | . | 17123.13 | 5 | -34236.25 | -34204.77 |
| (2,1) | 4,009 | . | 17123.4 | 5 | -34236.81 | -34205.32 |
| **(2,2)** | 4,009 | . | 17123.4 | 6 | **-34234.8** | -34197.02 |
| (1,3)* | 4,009 | . | 17123.8 | 5 | -34237.6 | -34206.12 |

*Note.* * Model is impeded by either no convergence or uphill trajectory of log likelihood

Table 16: GARCH model selection Philippines daily

| Model | N | ll(null) | ll(model) | df | AIC | BIC |
|---|---|---|---|---|---|---|
| **(1,1)** | 3,063 | . | 11503.23 | 4 | **-22998.46** | -22974.36 |
| (1,2) | 3,063 | . | 11509.81 | 5 | -23009.62 | -22979.49 |
| (2,1)* | 3,063 | . | 11509.27 | 4 | -23010.54 | -22986.43 |
| (2,2) | 3,063 | . | 11518.72 | 6 | -23025.44 | -22989.28 |
| (1,3) | 3,063 | . | 11523.11 | 6 | -23034.22 | -22998.06 |

*Note.* * Model is impeded by either no convergence or uphill trajectory of log likelihood

# References

Albala-Bertrand, J.-M. (1993). Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development*, *21*(9), 1417–1434.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American statistical association*, *96*(453), 42–55.

Binder, J. (1998). The event study methodology since 1969. *Review of Quantitative Finance and Accounting*, *11*(2), 111–137.

Boehmer, E., Masumeci, J., & Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance [ID: 271671]. *Journal of Financial Economics*, *30*(2), 253–272.

Chinn, M. D., & Ito, H. (2006). What matters for financial development? capital controls, institutions, and interactions. *Journal of development economics*, *81*(1), 163–192.

Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance*, *1*(1), 83–106.

Dominguez, K. M. (1998). Central bank intervention and exchange rate volatility. *Journal of International Money and Finance*, *17*(1), 161–190.

Farhi, E., & Gabaix, X. (2016). Rare disasters and exchange rates. *The Quarterly Journal of Economics*, *131*(1), 1–52.

Kripfganz, S., Schneider, D. C. et al. (2016). Ardl: Stata module to estimate autoregressive distributed lag models.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., et al. (2018). Global warming of 1.5 c. *An IPCC Special Report on the impacts of global warming of*, *1*.

Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of international economics*, *14*(1-2), 3–24.

Neumark, D., & Wascher, W. (1992). Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws. *ILR Review*, *46*(1), 55–81.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, *88*(2), 221–231.

Rasmussen, M. T. N. (2004). *Macroeconomic implications of natural disasters in the caribbean*. International Monetary Fund.

Skidmore, M., & Toya, H. (2002). Do natural disasters promote long run growth? *Economic inquiry*, *40*(4), 664–687.

Stock, J. H., & Watson, M. W. (2015). *Introduction to econometrics*.

Teshigawara, M. (2012). Outline of earthquake provisions in the japanese building codes. *Preliminary reconnaissance report of the 2011 Tohoku-Chiho Taiheiyo-Oki Earthquake.Geotechnical, geological and earthquake engineering*, *23*, 421–446.

Wang, L., & Kutan, A. M. (2013). The impact of natural disasters on stock markets: Evidence from japan and the us. *Comparative Economic Studies*, *55*(4), 672–686.

Worthington, A., & Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: An empirical application using intervention analysis. *Applied Economics*, *36*(19), 2177–2186.

Worthington, A. C. et al. (2008). The impact of natural events and disasters on the australian stock market: A garch-m analysis of storms, floods, cyclones, earthquakes and bushfires. *Global Business and Economics Review*, *10*(1), 1.

Yamori, N., & Kobayashi, T. (2002). Do japanese insurers benefit from a catastrophic event?: Market reactions to the 1995 hanshin–awaji earthquake. *Journal of the Japanese and international economies*, *16*(1), 92–108.

Yang, D. (2008). Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. *The BE Journal of Economic Analysis*, *8*(1).