Universitetet i Stavanger

University of Stavanger Business School

MASTER'S THESIS

Study program:
Economics and Administration

Specialization:
Applied Finance

Not confidential

Title:
The role of the latest financial crisis in the long-run, short-run and Granger causal relationships between exchange rates and stock prices in Norway from 1999 to 2017.

Author:
Alan Laypanov

Supervisor:
Siri Valseth

Candidate number:
895 751

Abstract

This thesis aims to find out what role the latest financial crisis played with respect to the long-run, short-run and Granger-causal relationships between exchange rates and stock prices in Norway from 1999 to 2017.

Both daily and monthly time series data of exchange rates and stock prices, as well as 2 control variables are divided into three periods: before the crisis, during and after. By introducing 2 control variables I create a multivariate vector error correction model (VECM) which produces more robust coefficients as well as alleviates potential omitted variables bias. The VECM is also capable of giving insight into long-run and short-run dynamics between variables. Granger causality tests are run as well.

The results show that the crisis had a destructive impact on the causal and short-run dynamics between exchange rates and stock prices. Stock prices and exchange rates were cointegrated before the crisis, with both short-run and long-run relationships. Granger causality was running both ways between stock prices and exchange rates. The latest financial crisis in Norway eliminated long-run and short-run relationships for its duration. The long-run relationship has been reinstated after the crisis. The same is not true of the short-run relationship and causality between stock prices and exchange rates. Short-run and causal relationships disappeared after the crisis.

An important implication of this research is that stock and exchange rate markets in Norway became more efficient, which, paradoxically, might suggest that the crisis had some positive influence on the economy.

Table of contents

List of figures and tables

Figures

Tables

List of abbreviations

ADF – Augmented Dickey-Fuller stationarity test

KPSS - Kwiatkowski–Phillips–Schmidt–Shin stationarity test

PP – Phillips-Perron stationarity test

VAR – Vector autoregression

VECM – Vector error correction model

1 Introduction

We are all used to hearing about changes in stock prices in the news. These changes are often said to be due to some political or social change. The reality behind stock price fluctuation seems more complicated to me. Norwegian academia has done a lot of macroeconomic research on changes in stock prices and exchange rates. This research has brought variables like money supply, oil prices and order flows to the forefront of theoretical thinking. This research has paid little attention to the relationship between exchange rates and stock prices. In this paper I attempt to elucidate this relationship. I theorize that changes in stock prices and exchange rates in Norway are connected and I study this connection in detail throughout the paper.

Possible relationship between stock prices and exchange rates has practical implication for governments and investors alike. There are many economic theories explaining theoretical underpinning of this relationship. I am only going to concentrate on few of those theories: flow-oriented, stock-oriented and monetary theories. Flow-oriented models maintain that exchange rates influence how competitive domestic firms are thereby influencing their production and stock prices. Stock-oriented models posit that changes in stock prices affect wealth of investors' thereby changing overall demand for money in the economy. Monetary theories do not expect any causal relationship between stock prices and exchange rates and explain changes in these variables by alluding to fundamental factors of the economy like interest rates, oil prices etc. Mechanisms of these models are going to be elaborated upon later. This paper is going to find out which, if any, theory is more applicable to exchange rates and stock prices in Norway.

There have been several empirical studies looking at the possible interplay between exchange rates and stock prices. These studies used different methodologies and different data frequencies. Some were simplistic – using only pairwise Granger causality; some were a lot more intricate – trying to find not only Granger causality but also examining long- and short-run relationships. This paper is going to attempt bringing together the simplicity of causality tests with a more complex vector autoregressive (VAR) environment allowing for examination of long-run and short-run dynamics.

1.1 Research objectives

This thesis aims to find out what role the latest crisis played with respect to the relationship between exchange rates and stock prices in Norway. The first objective of the thesis is, therefore, to establish whether there is a relationship between exchange rates and stock prices. The second objective is to describe this relationship in terms of its long-run and short-run structure. The third objective is to find out whether there is Granger causality present between these variables and if so what the direction of that causality is. And lastly, this paper aims to show how the latest financial crisis affected the long-run and short-run structure as well as causality between stock prices and exchange rates in Norway from 1999 to 2017.

This paper explores long-run and short-run dynamics between Norwegian exchange rates and stock prices. It does so by running Granger non-causality tests within the framework of a multivariate vector error correction model (VECM) in three different periods: before the latest financial crisis, during the crisis and after the crisis. Time series of exchange rates and stock prices are divided into these three periods to allow for a closer study of the impact of the latest financial crisis on the relationship between stock prices and exchange rates.

Here are the research questions of this paper. Are there long-run and short-run relationships between exchange rates and stock prices in Norway? Is there causality between these variables? In what direction does this causality run? How has the latest financial crisis in Norway changed these dynamics? This thesis shows that the latest financial crisis had a deep, yet not very lasting impact, on the interplay between stock prices and exchange rates. The results of this thesis show that the crisis destroyed the long-run relationship between stock prices and exchange rates for the period of its duration.

1.2 Contributions of this paper

Previous research on the relationship between exchange rates and stock prices is not overwhelming in its magnitude. It is mostly univariate and is not overly focused on crises. Most of it is conducted on the data from Asian and G7 countries. To my knowledge, there is only one Scandinavian country (Sweden) present in the research. Moreover, previous research presents very contradictory results that can hardly be extrapolated on other countries, making this paper interesting and important.

My paper contributes to the literature in several ways. Firstly, it is, to my knowledge, one of the first papers to discuss Norwegian exchange rates and stock prices in the context of Granger causality. Secondly, it is one of the few studies that are based on a multivariate framework. Thirdly, it is one of the few studies that overtly discuss crises effect on dynamics between exchange rates and stock prices. Fourthly, this paper's analysis is based on both daily and monthly data, while much of the previous research only uses one data frequency. The main purpose of this study is to find out the effects of the latest financial crisis on the relationship between exchange rates and stock prices in Norway.

1.3 Hypothesis

I posit that the latest financial crisis has disrupted the way exchange rates and stock prices interact in Norway. I posit that the previous long-run relationship is destroyed and that causality between stock prices and exchange rates disappears. It would be interesting to see how long this disruption lasted and if the relationship comes back and the causality is restored.

1.4 Structure of this paper

This paper proceeds as follows. Firstly, I go through economic theories on possible causation between exchange rates and stock prices. One of the aims of this paper is to find out which theory explains the interactions between exchange rates and stock prices in Norway best. I then go through the previous literature to find common threads and discrepancies that might anchor my research and give it historical perspective. I then present the data that I am going to be working with and justify my choice of variables for the coming regression. I also explain how I divide the time series into before, during and after periods. The next section is devoted the multivariate VECM constructed based on stationarity and cointegration tests. I also discuss Grange causality, lag selection and briefly talk about robustness checks. I then present the results for each period followed by discussion of long-run and short-run dynamics. Finally, I present implication of my research and draw conclusions.

This paper has many tables. Tables representing VECM coefficients as well results of stationarity tests are especially big. I choose therefore to only present significant coefficients in the main body of the paper and place the rest of the tables in appendices.

2 Theoretical review

This paper is not intended as the complete explanation of how exchange rates and stock prices are determined in Norway. The reality of exchange rates and stock prices determination is so complex, that no one research can explain all its intricacies. This paper only attempts to elucidate one of the hundreds (if not thousands) of mechanisms that influence exchange rates and stock prices. To place this paper in the proper theoretical framework I will briefly list some major perspectives on how these variables are determined.

There are several major theories of exchange rate determination. The Purchasing Power Parity theory, echoing the law of one price, maintains that prices in different countries should be equal when exchange rates are considered (Balassa, 1964). If exchange rates are not equal there will be an arbitrage opportunity which will be exploited by traders until the purchasing power parity is achieved between two countries. Another theory is the Interest Rate Parity. It is also based on arbitrage opportunities, however, according to this theory countries should have same interest rates to eliminate arbitrage opportunities (J. A. Frankel, 1979). Another theory is called the International Fisher Effect. This theory deals with differentials of nominal interest rates. It postulates that if one country has lower nominal interest rates than its counterparts, its currency should appreciate in comparison to currencies of countries with higher interest rates (Sundqvist, 2002). Another theory is the Real Interest Rate Differentiation Model, which is very similar to the International Fisher Effect. The only difference is that instead of nominal rates, this model operates with real interest rates (Chan, Karolyi, Longstaff, & Sanders, 1992). The mechanism is the same as in the previously discussed theory.

Undoubtedly all these theories are relevant to exchange rates determination of Norwegian currency. I would, however, like to pay special attention to the Balance of Payments theory and the dichotomy between exports and imports. This is because Norway is small export based open economy. Norway's exchange rates are therefore bound to be influenced by its exports and imports. This theory is based on the current account of a country, which deals with trade of goods. If the account runs a surplus or a deficit that country's exchange rate is not in equilibrium with respect to the currencies of its trading partners. The equilibrium is achieved though appreciation (in case of surplus) or depreciation (in case of deficit) of domestic currency (Johnson, 1972). It is important to note that Norway is both an importing and exporting country, therefore the Balance of Payments theory is very relevant in explaining changes in Norwegian krone. The relationship between exports/imports and exchange rates is a self-reinforcing one. Weaker domestic currencies encourage more exports, since they become cheaper for countries buying them. If, on the contrary, the currency appreciates, imports become cheaper.

As one can see there are a lot of potential ways exchange rates can be determined in Norway. The number of ways stock prices are influenced is a lot more substantial. Countless studies have been carried out on how stock prices react to different news, announcements and so on. It would be impossible to explain all the theories of stock price determination in this paper. I, however, want to emphasize a very relevant detail when it comes to the Norwegian stock market. The Norwegian stock market is very energy driven, energy industry accounts for around 35% percent of all shares on Oslo Stock exchange. What is more, the biggest contributor to the energy industry in Norway and, therefore, its stock market is Equinor (previously Statoil). Equinor being mostly an oil company, is very sensitive to changes in oil prices. This means that the stock market is also very sensitive to the changes in oil prices, which is not surprising when it comes to oil exporting countries like Norway.

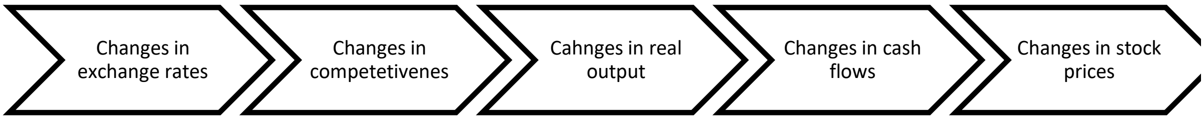
Many different other variables affect exchange rates. Some researchers posit that the long-run exchange rates are largely determined by real oil price, price differentials, and real interest rates differentials (Alstad, 2010). Other researchers stress the role of consumer prices on exchange rate determination (Ulvedal & Vonen, 2016). Oil price shocks also seem to be one of the major determinants as well (Ellen & Martinsen, 2016). Martinsen adds few other determinants to the list presented above: consumer prices, volatility of the exchange rates, foreign currency reserves, and Norway's mainland’s current account (2017). Other researchers focus on information as a determinant and showed that exchange rates immediately react to information about interest rates and GDP (Flatner & Xu, 2015). More relevant to the purposes of this thesis, Martinsen showed that both exchange rates and stock prices react immediately to changes in interest rates and monetary policy (2017). This may hint at a strong relationship between exchange rates and stock prices. Study of this relationship is the exact purpose of my thesis.

Before going any further, it is important to briefly discuss the efficient market hypothesis. There is a well-grounded and much researched argument that stock markets are informationally efficient (Fama, 1970). The efficient market hypothesis assumes that market prices are decided based on all the available information in the market. There are different types of efficient market hypothesis ranging by strength. The weakest form assumes that past stock prices have no bearing on the future prices, yet the prices reflect market information. The semi-strong form assumes quick adjustment of prices to reflect new information. The prices according to the semi-strong form consist of all publicly available information. The strongest form suggests that prices reflect all information, both public and private and prices adjust very fast (Malkiel & Fama, 1970). The amount of time needed for markets to adjust prices in relation to new information is a debated issue. Some seem to suggest that the adjustment is instantaneous (Brown, Harlow, & Tinic, 1988) others tend to propose that there are considerable lags (Wang, 2015). The implications of the efficient market hypothesis might lead us to conclude that there should be a causal relationship between exchange rates and stock returns. Past and future information should be, according to the strong form of efficient market hypothesis, reflected in the prices of stocks. Furthermore, prices of stocks should react to new information with varying time lags. Very short, almost non-existent lags, if we are talking about strong form. Longer lags, when it comes to semi-strong form. Very long, sometimes undetectable, lags, or even random walks when it comes to weak form (Urrutia, 1995). The strong form of the efficient market hypothesis tells us that stock prices are going to adjust to economic changes. Reducing this argument to the topic of my thesis, it is logical to expect that stock prices are going to react to exchange rates as well, since exchange rates are one of the major economic variables. Therefore, it can be assumed, that according to at least the strong form of the efficient market hypothesis, there should be a causal relationship between exchange rates and stock prices. It does not seem possible to extrapolate the nature of this relationship - neither its direction nor strength - based solely on the efficient market hypothesis. Therefore, in the later sections of this theoretical review I am going to present flow and stock models that explicitly predict the direction of causation.

2.1.1 Flow model

The so-called "flow model" is a model of interplay between exchange rates and stock prices. It is one of the most well-known models of co-movements of exchange rates and stocks. According to Dornbusch and Fisher (1980), changes in exchange rates influence international competitiveness of firms operating in the economy. Since country's GDP consists to a large extent of production by firms, the changes in exchange rates affect the real output of the country. Changes in real output then affect cash flows of companies and thereby their stocks. See 1 for an illustration of the process:

Figure 1: Simplified flow model.



The model described above is also called the “goods market hypothesis”. To give a more concrete example, think of a country with one multinational firm. Imagine that the local currency depreciates. The immediate effect of currency depreciation is that exporting goods is going to be cheaper, which in turn will increase demand for country’s products abroad. In other words, depreciation of local currency is beneficial for firms that produce for export. The opposite is true as well: appreciation of local currency can be detrimental for firms that export much of their produce. In case of depreciation, firm’s stocks go up in value; in case of appreciation firm’s stocks are like to plummet. The mechanism is reversed when it comes to importing firms. If the local currency appreciates, firm’s value increases given that the firm is importing its raw materials. If the local currency depreciates, importing firm’s value goes down.

While the direction of stock responses to changes in exchange rates is easily understandable, the strength of this response is dependent on firm’s value’s sensitivity to changes in exchange rates. This sensitivity is going to change due to how much of firm’s overall value depends on exports or imports (Dornbusch & Fischer, 1980). In addition to this, exchange rates influence stock prices and future cash flows by affecting future payables or receivables, since firms transactions like importing raw materials are affected by changes in exchange rates (Pan, Fok, & Liu, 2001). Adler and Dumas (1984) have contributed a lot to the flow model by focusing on domestic firms. According to their research all firms’ stocks are affected by exchange rate dynamics, not only firms with international activities. As long as input, output prices or demand for their products are affected by the exchange rate changes, so will their stock fluctuate (Adler & Dumas, 1984).

Norway is small open economy. Therefore, according to the flow model, we should expect that exchange rate fluctuations are going to cause changes in stock prices. If the Norwegian krone depreciates, then the stock price should go up. If the Norwegian krone strengthens - stock prices should decrease. We should further expect causal relationship running from exchange rates to stock prices. This again is because so much of Norwegian wealth stems from its exporting activities. It is important to emphasize that this model, as all models are, is simplistic. It does not, for example, consider the role Equinor plays in the Norwegian economy. Neither does it distinguish well enough between exporting and importing firms.

2.1.2 Stock model

Another model, which is often called “the stock model”, in contrast to the flow model, posits that changes in stock prices influence exchange rate movements. Major contributors to this theory are Branson (1983) and Frankel (1983). The mechanism is not complicated: increases in national stock markets are bound to attract investments from other countries. This, in its turn, is going to increase the demand for country’s’ currency. A poorly performing stock market would signal bad investment opportunities for potential investors that are then going to postpone or withhold their investments, thereby decreasing the demand for country’s currency.

The movements in stock markets are going to affect investors’ wealth and demand for money. They will then change their levels of spending/investing/saving, which again will influence stock market and then the exchange rates (Gavin, 1989). Imagine investors holding domestic and foreign assets in their portfolios. If domestic stock prices start increasing, investors (given that they do not have fixed portfolio weights) are likely to acquire more domestic stocks because they are becoming more valuable. To acquire more domestic assets, investors under budget constraints, would need to rebalance their portfolios by selling foreign assets. This shift of demand from foreign assets to domestic assets in investor’s portfolio is going to cause the domestic currency to appreciate. On the other hand, if the stock market plummets, foreign investors are going to be discouraged from investing and might even sell stocks, therefore bringing demand for domestic currency down. This is going to lead to capital outflows and consequent depreciation of home currency. Exchange rates play a role of balancing demand for and supply of stocks.

Figure 2: Simplified stock model.

This model lends itself for situations of crisis and is therefore particularly relevant for my thesis. During crises, the investment behavior of traders can strongly affect exchange rates and stock prices. It is a common feature of crises that investors resort to herding behavior thereby reducing their investments, for example by stopping acquisition of stocks (Kim & Wei, 2002). Investors can also stop investing in local firms and invest in foreign companies or bonds instead. In other words, they would invest in equities denominated in foreign currencies. This means reduction of demand for local currency. Reduction of demand for money is then going to lead to capital outflows from the local country, which will bring the currency down (Frenkel, 1976). My paper aims to find out whether the above mechanism worked as described during the latest financial crisis in Norway.

The stock model emphasizes the importance of the capital account in how exchange rates are determined. This model shows that there is a negative relationship between stock prices and exchange rates, with the causality running from stock prices to exchange rates. Contrary to the flow model, this model emphasizes capital account in determining changes in exchange rates. Financial value of any firm is based on the present values of its future cash flows. These future cash flows are calculated by taking into consideration certain assumptions and expectations about currency values (Branson, 1983). Exchange rates can therefore be affected by stock prices. In general, the stock model maintains that there is a negative relationship between stock prices and exchange rates. It also maintains that stock prices play a causal role in this relationship (JA Frankel, 1983).

The mechanism explained above is direct in its effect. There is also an indirect mechanism by which stock market influences exchange prices. When domestic stock prices increase, people who hold domestic stocks experience growth in wealth. Growth in wealth is linked to increases in monetary transaction, which means that investors will demand more money for their investments (MacDonald & Taylor, 1992). The growth in demand for money raises domestic interest rates. Higher interest rates attract foreign investors and, thereby, increase demand for local currency, which, of course, leads to currency appreciation. When it comes to my thesis, the portfolio balance model, suggests that changes in stock prices cause changes in exchange rates. What is more, it should be expected that the relationship between stock prices and exchange rates is inverse (Frenkel, 1976).

Based on the efficient market hypothesis, I conclude that it is logical to expect some relationship between stock prices and exchange rates. The efficient market hypothesis tentatively hits at a causal relationship (running one way or both ways) without being sufficient to decide upon the direction of causation or type of the relationship. This is where the flow model and stock models come in to fill the theoretical vacuum.

Table 1: Summary of predictions of different theories.

	Flow model	Stock model
Predictions	- Changes in exchange rates cause changes in stock prices. - Positive correlation.	- Changes in stock prices cause changes in exchange rates. - Negative correlation.

Table 1 below presents a simplified summary of theoretical models that guide the relationship between exchange rates and stock prices. There are two primary models: flow and stock model. These models have different predictions when it comes to the relationship between stock prices and exchange rates.

According to the flow model changes in exchange rates are going to cause changes in stock markets. Furthermore, the changes will have the same sign. In other words, depreciation of domestic currency will lead to raise in stock prices, while depreciation will cause stock prices to fall. Stock model gives contrasting view on the relationship between exchange rates and stock prices. This model is the exact opposite of the flow model: changes in stock prices cause changes in exchange rates, and the nature of the relationship is negative. In other words, the fall in exchange rates brings about appreciation of the domestic currency, while the upward movement in stocks will cause apreciation.

3 Literature review

Possible Granger causality between changes in stock prices and exchange rates began receiving academic attention in the late 1960ies. I found around 50 relevant studies on the topic. The landmark studies are by Fama (1981), Sims (1972), Frankel (1983), Dornbusch and Fischer (1980), and Granger (1969). The first four authors are mostly concerned with developing theoretical basis for the interplay between exchange rates and stock prices, while the last two authors have tremendous contributions to the methodology of causality research as well as some empirical studies. These studies are present in pretty much every literature review on the topic. The leading authority that stands out from all the researchers seems to be Granger himself. This is not surprising since the man is responsible for the very methodology that most of the other studies are based on.

As this paper is going to show there is no consensus in previous literature on the direction of causality between exchange rates and stock prices. Perhaps this is because previous research has focused on many different countries. All these countries vary in terms of culture, history, politics and everything else that can influence exchange rates and stock prices. Surprisingly, even when academics studied the same country their results were still astonishingly different. Later in the literature review I am going to illustrate this point with a curious case of Japan.

Finding whether crises influence causal relationship between exchange rates and stock prices or not, is one of the goals of this thesis. Of all the relevant studies done on possible Granger casual links between exchange rates and stock prices there are only 5 that directly address financial crises and their possible influence on causality between exchange rates and stock prices.

The most relevant study is by Lin (2012). This study explicitly addresses the question of how crisis influences causal relationships between exchange rates and stock prices. It studied Asian countries from 1986 to 2010. It shows that crises make co-movement between exchange rates and stock prices stronger. Thailand, India, Indonesia, Korean, Philippines and Taiwan display causal relationship running from stock prices to exchange rates. The relationship gets stronger during the crisis (Lin, 2012). This suggests that the relationship between exchange rates and stock prices in Norway might get stronger during crisis. Another relevant study is by Pan, Fok and Liu (Pan et al., 2001) based on Asian countries from 1988 to 1998. Its most interesting result is that crisis seems to eliminate Granger causality running from exchange rates to stock prices in Hong-Kong, Japan, Malaysia and Thailand. Furthermore, no country displayed causal relationship from stock prices to exchange rates (Pan et al., 2001). Even though results are robust authors mention that "it appears that no one single theory can completely explain our results" (ibid, p. 514). This echoes the sentiment shared by other researchers that there is no consensus on what model has the most explanatory power. Based on this study I may expect that the latest financial crisis in Norway might eliminate any causal relationship between exchange rates and stock prices.

Granger, Huangb and Yang (2000), present another relevant study, focusing on Asian countries during the Asian flu crisis from 1986 to 1997. There is causality running from exchange rates to stock prices in Japan and Thailand. In contrast, stock prices cause exchange rates in Taiwan. Korean and Malaysian data show strong feedback between exchange rates and stock prices.

Singapore, however, shows no recognizable pattern (Clive WJ Granger et al., 2000). This does not provide direct conclusions on how financial crises influence casual relations between exchange rates and stock prices either. A study by Phylaktis and Ravazzolo (2005) is different because it focuses on long-run causality during 18 years from 1980 to 1998. Unlike other studies, it shows that there is no long-run causality between exchange rates and stock prices in Hong-Kong, Indonesia, Malaysia, Philippines, Singapore and Thailand. There is another research that resembles the research by Phylaktis and Ravazzolo, which is done by Ramasamy and Yeung (2005). The resemblance lies in the fact that this research has not shown any causality between stock prices and exchange rates in Asian countries in period from 1997 to 2000. This study can perhaps be criticized because of the very short period but given the fact that there are so few studies done on data from countries experiencing financial crisis, it certainly cannot be overlooked. Results from Hong-Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan and Thailand are inconclusive (Ramasamy & Yeung, 2005). This study functions as a warning that Granger causality test should be used with caution.

Evidently, previous research is inconclusive when it comes to crises' influence on causality between stock prices and exchange rates. This argument is supported by Wu's study (2001) on data from Singapore. It is especially interesting, because its results fall squarely between two models, flow model and stock model. The causation between exchange rates and stock prices runs from exchange rates to stock prices (Wu, 2001). This is the direction of causation predicted by the flow model. However, the relationship itself is negative, which is not in line with the flow model. Instead the negative relationship follows predictions of the stock model. This interesting nuance once again shows that theories of causation between exchange rates and stock prices are not set in stone and are only theoretical sketches of many possible relationships that are present in real life. Previous studies collectively emphasize a vast gap present between economic theories and reality.

Other studies present bi-directional causality, and thereby support both models at the same time. Bahmani-Oskooee and Sohrabian studied US data from 1973 to 1988 and found that causality runs in both directions between exchange rates and stock prices (1992). A research based on data from Sri Lanka and Bangladesh from 1994 to 2000 yielded the same result of bidirectional causality (Muhammad, Rasheed, & Husain, 2002). Lastly, a study done in Turkey between 2001-2008 showed the same bidirectional casualty (Aydemir & Demirhan, 2009). This suggests that different models can be present simultaneously. It is important to remember that there are many factors influencing both exchange rates and stock prices. The relationship between these two variables varies across countries and across time.

And finally, there are many studies that show no causality whatsoever (Bhattacharya, 2012; Chamberlain, Howe, & Popper, 1997; Griffin & Stulz, 2001; Morley & Pentecost, 2000; Nieh & Lee, 2002; Rahman & Uddin, 2009; Ramasamy & Yeung, 2005). This further strengthens the idea that reality does not neatly conform to any theoretical disposition, which means that there is no way to extrapolate results from previous research to Norway. This makes my research even more pertinent.

Most striking is that studies based on the same country from the same time do not agree with each other. Consider research done by Griffin and Stulz (2001) based on data from Germany from 1975 to 1997. The results of this study showed that there was no causality between exchange rates and stock (Griffin & Stulz, 2001). Compare this study to the study by Ajayi, Friedman and Mehdian (1998) done in the same country in the overlapping period from 1985 to 1991 that showed causality running from stock prices to exchange rates. Time periods overlap, the country being studied is the same. Yet results are so different. The difference in results might be due to differences in data frequency (monthly in the research by Griffin and Stulz, and daily by Ajayi et al). The difference in methods can also account for differences in results (Griffin and Stutz used OSL regression, while Ajayi et al used a more complex method of Granger test). Here is another example. Two studies under consideration: one by Rahman and Uddin (2009) and another by Lin (2012). The subject of the study is the same – India. Time periods overlap: Rahman and Uddin studied data from 2003 to 2008, while Lin studied data from 1986 to 2010. Again, the results are not the same: Rahman and Uddin find no causality (2009), while Lin demonstrates causality running from stock prices to exchange rates getting stronger during crisis (2012). Data frequencies are the same this time – both studies are based on monthly data. Methods are different: Rahman and Uddin used Johansen bivariate cointegration test, while Lin used Granger test and autoregressive distributed lag model. Another example, Morley and Pentecost (2000) studied Italy from 1982 to 1994 using Engle-Ganger cointegration test, which revealed no causality. While Yang and Doong (2004) studied the same country in the overlapping period from 1979 to 1999 using VAR model with Granger test and finding causality running from stock prices to exchanger rates. Different methods seem to provide opposing results. This presents an econometric challenge, since such result might indicate that one econometric technique is less suited for testing for causality than another.

The case of Japan is representative of vast differences between empirical studies. Granger, Huangb and Yang studied Japan from 1986 to 1997 and found that exchange rates cause stock prices (2000). Ajayi and Mougoue (1996) studied Japan from 1985 to 1991 and found that in the short-run stock prices cause exchange rates and the relationship is negative. They also found that in the long-run the direction of causation is the same, but the relationship is positive (Ajayi & Mougouė, 1996). Yang and Doong (2004) studied Japan from 1979 to 1999 and showed that causality is running from stock prices to exchange rates. Morley and Pentecost (2000) studied the same country from 1982 to 1994 and found no causality. Chamberlain, Howe and Popper (1997) are other researchers that studied Japan in 1993 and, similarly to Morley and Pentecost, found no causation. Grifiin and Stulz (2001) studied Japan, from 1975 to 1997, again finding no causality. Nieh and Lee (2002) studied Japan from 1993 to 1996 and found no causation between stock prices and exchange rates.

This curious case of Japan is very illustrative of research in general. Seven papers are written about the causality between exchange rates and stock prices in the overlapping periods from 1975 to 1997. Three papers showed causality. Of those three papers, two showed causality running from exchange rates to stock prices, just as the flow model would predict; another one paper showed causality running from stock prices to exchange rates, supporting the stock model. The other four papers showed no causality, supporting the monetary model. These are big discrepancies in the literature that can neither be overlooked nor explained away. A reasonable and demotivating question is then: can we test for causality at all? It seems like the results are neither reliable nor reproducible. There is no consensus on what methodology is best suited to this type of research. Econometrics is a complicated field that is still developing. Perhaps, the lack of time-proven methodologies that can be applied to a vast range of time series makes it impossible to come to the same results.

All in all, previous empirical review studies present a rather chaotic picture. There is no consensus on anything, except that we could expect causal relationship between exchange rates and stock prices. The nature of the relationship, the strength and the direction vary from study to study. The same can be said about the role of crises in this relationship – it is impossible, based on the previous empirical research, to conclude whether crises introduce causal relationship, reverse it, make it stronger, make it weaker, or eliminate it. The choice of data seems to fall between monthly or daily. Methods used are very diverse as well, betraying that there is no one method that suits best for testing causality. It seems to me that the only thing that can justifiably be expected is that some causal relationship is going to be present. When it comes to whether crises are going to change this relationship remains to be tested.

The purpose of the theoretical and literature review was two-fold. Firstly, I intended to present workable theoretical models of whether exchange rates cause stock market prices, or stock market prices cause exchange rates. Secondly, I wanted to survey previous empirical research to find support for the models. All the models are supported by the research, even though the research presents very different results. The main drawback of previous research is that it does not make me more capable of answering the major research question of this paper: how do crises influence the causal relationship between exchange rates and stock prices? Since no definitive answer to this question can be gathered from previous research, I must conduct my own tests based on Norwegian data. The remaining chapters of this paper are going to deal with methodology, results and their discussion.

4 Data

This paper is going to use both daily and monthly data. Using daily and monthly data has several advantages. Firstly, using two different frequencies will hopefully give more insight into the relationship between exchange rates and stock prices. Secondly, comparing results of regression analysis based on daily data and monthly data can serve as a robustness check.

Research data for this article consists of nominal exchange rates taken from Norwegian Central bank (Norges Bank) expressed in Norwegian kroner for 1 Euro, stock prices taken from Norwegian Stock exchange (Oslo Børs) and proxied by the values of OSBX index, oil prices taken from DataStream, and interest rates expressed as 3 month-maturity treasury bills taken from Norwegian Central bank (Norges Bank).

Nominal exchange rates are used to not complicate the results by considering inflation, which would be already present in the real effective exchange rates. The OSBX index is chosen because it is the biggest index with the most observations to be found in the Norwegian stock statistics. Treasury bill prices for 3-month maturity are chosen, because 3-month maturity is the shortest available maturity that can give insight into financial fluctuations much better than bills with longer maturities. Oil prices are collected as daily values and then averaged into monthly values with the use of statistical software. Granted, such transformations might not be ideal, but they are necessary since the analysis in this paper is carried out on both daily and monthly data.

4.1 Choice of variables

The choice of variables is based on theoretical and empirical research. Previous theoretical research suggests that exchange rates are affected by many different variables. I decided to collect as much data as possible on variables presented in the theoretical section of this paper. To finally decide on which variables to include in the final regression, I ran a step wise backward regression on all the possible variables. Those variables were: foreign currency reserves, oil prices, interest rates, inflation and state's debt. A step wise backward regression is an automated econometric tool that aids researchers in selecting the most relevant variables. Economic intuition suggests a long list of possible variables that can be included in the final regression. It is impossible to include all the variables since it would go against the principle of parsimony and overfit the model. A step wise regression is therefore run to limit the number of variables. The step wise regression provided me with two most relevant variables: interest rates, oil prices.

Interest rates are included as control variables to capture the effect of policy interventions and portfolio adjustments. Oil prices are included as a fundamental variable that influences most the Norwegian economy since Norway is a small economy dependent on oil exports. Many studies in previous research have only run pairwise causality tests without bringing other variables into the mix. By introducing 2 control variables I create a multivariate context which produces more robust coefficients as well as alleviates potential omitted variables bias.

4.2 Three periods

Research data covers 3 periods: before the crisis, during the crisis, after the crisis. By dividing data into 3 periods I can pay more attention to each period. This is important because it allows for better understanding of the latest crisis' role in the interplay between exchange rates and stock prices. A disadvantage of this approach is that it leaves very few observations (34 observations) for the shortest period during crisis when it comes to monthly data. This drawback is dealt with by taking great care to treat the shortest period properly in terms of statistical analysis. I do not build regression model with too many variables and I do not use VECM model, since there are too few degrees of freedom in shorter data to begin with. This disadvantage is not present when it comes to daily data (675 observations)

The reason why the data is divided into three periods rests on theoretical and econometric research. To be able to focus on the crisis' role and the relationship between stock prices and exchange rates before, during and after crisis I need to find out when the crises began and when it ended. To do that I consulted previous research on the topic as well as employed statistical methods to find break points in data series that would indicate crisis' beginning and end.

It seems easier to say when the crisis began, than to precisely pinpoint when it ended. The last financial crisis in Norway has its roots in the USA. Already in 2007, the United States were living through a deepening housing crisis. Foreclosures began rising by the mid-2007, subprime mortgages became worthless. February 27th was the day when mortgage giant Freddie Mac announced that it is no longer going to buy the riskiest subprime loans (Freddie Mac (Firm), 2007). Everything went downhill at an ever-accelerating pace after that. In July of the same year Bear Sterns liquidated its hedge funds specializing in investing in securities based on subprime mortgage loans (Hedge Co (Firm), 2008). By September of 2008 situation became so dire that Fannie Mae and Freddie Mac were taken over by the government (Commission & Commission, 2011). Let us assume that the financial crisis in the US began on 27th of February 2007. This alone does not tell us when the crisis began in Norway. Certain researchers maintain that crisis began in 2007, without specifying the date or month (Aalbers, 2009). Some think that the crisis started one year later in 2008 (Sigurjonsson & Mixa, 2011). One extensive study of crises in Norway notes that stock market sopped raising in July of 2007 and started to crash in May 22 (Grytten & Hunnes, 2010). Others go as far as to say that Norway has not experienced the crisis at all (Kriesi & Pappas, 2015).

Neither is there any theoretical agreement on when exactly the global crisis ended. I can at best find the year, but not the date. Some say 2008 (Cecchetti, 2008a, 2008b; Erkens, Hung, & Matos, 2012), others – 2009 (Jeffrey Frankel & Saravelos, 2012; Purfield & Rosenberg, 2010). Since there is no consensus on either the starting of the ending date of the crisis in Norway or the USA, I am going to look at indicators of financial instability and hope that they will guide me to the beginning and ending dates of the crisis.

I am going to test the data for structural breaks using breakpoint test in statistical software. The procedure of testing for structural breaks is based on research by Bai and Perron (Bai & Perron, 1998, 2003a, 2003b), who expanded on research by Andrews (1993). According to these papers structural breaks coincide with the dates of crises. The main reason why I use this procedure is because it is specifically suited for data where multiple structural breaks are present, but where there is no knowledge of the exact location of these breaks. I use the sequential test procedure suggested by Bai (1997) because of how intuitive it is. This procedure tells me that the crisis in Norway lasted from March 2008 to December 2010.

I certainly acknowledge, that neither breakpoint tests of metanalysis of previous studies can give precise dates for when the crisis began and ended. However, combining the two methods gives the most trustworthy results. Based on the discussion above, the periods studied in this paper are going to be selected as follows. Period before the crisis starts in January 1999 and ends in February 2008. Period during the crisis starts in March 2008 and ends in December 2010. Period after the crisis lasts from January 2011 to December 2017.

4.3 Frequency and visual analysis

The data used in this research is both daily and monthly. There are advantages and disadvantages to using only daily or monthly data. Monthly data has fewer observations, which can be detrimental in terms of regression analysis. Daily data can contain a lot of statistical noise skewing results. By basing my research on both daily and monthly data I avoid the disadvantages.

The data was checked for seasonality without finding any persistent seasonal patterns. All data is transformed into logarithmic scale to be more easily comparable. All data are denominated in local currency.

Descriptive statistics for monthly and daily sets of data can be found in Appendix A, Tables 7 and 8. Notice the number of observations for the monthly data during crisis. The number borders on what is acceptable for regression analysis. This challenge is going to be addressed in the methodological section in greater detail again. The reason why only main variables are present in regression based on monthly data for the period during crisis, is that with 34 observations it would be imprudent to fit the model with extra control variables since the degrees of freedom would not allow it.

Figure 3: Exchange rates and stock prices from 1999 to 2017.

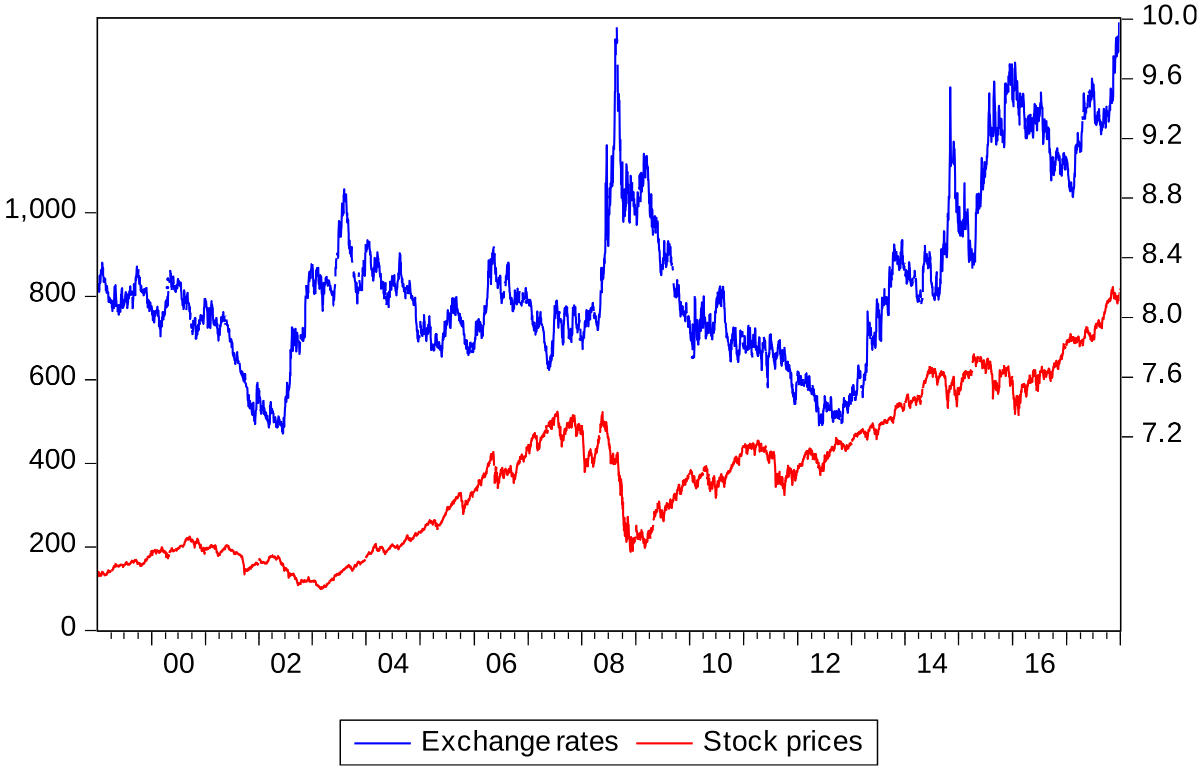


Figure 3 shows values for stock prices (left axis) and exchange rates (right axis) throughout the whole period from in January 1999 to December 2017. There is no visually discernable relationship between exchange rates and stock prices present in the graph. This underlines how important it is to carry out econometric tests to reveal possible hidden relationships. What can be noticed, however, is that exchange rates seem to be more volatile and lacking a clear trend, while stock prices seem to have a trend and less volatility (apart from a big fall in 2008 coinciding with the latest financial crisis).

In general, the data collected for this thesis is similar to previous studies in some respects and different in others. It is similar with respect to logarithmic transformation as well as a choice of monthly and daily frequency. It is different because of control variables as well as the decision to divide the data into 3 distinct periods.

5 Methodology

As the literature review has shown there are many ways to establish causality between two variables. All kinds of models, tests and approaches could be used: VARs, VECMs, different cointegration test, Granger test, Sim's test, modified Sim's test, Toda-Yamamoto model and so on. There are as many, if not more, ways of testing for stationarity, heteroscedasticity, autocorrelation, unit roots, cointegration and stability of time series. The number of choices is compounded by how many information criteria there are to choose from.

In this section of the paper I am going to present my approach to testing Norwegian data on exchange rates and stock prices for causality, short-run and long-run dynamics. I decided to divide the process of testing for causality into several parts: 1) preliminary tests; 2) model selection and estimation; 3) causality tests. Robustness checks are going to be carried out lastly. Preliminary work with time series consists of two components: testing for stationarity and cointegration.

5.1 Stationarity tests

Most methods of regression analysis hinge on the assumption of stationarity. Stationary time series are time series that have a constant mean, constant variance and auto covariance that does not depend on time (Johnston & DiNardo, 1972). There are several reasons why stationarity is desirable in time series data. Firstly, being stationary means being more predictable. Predictability of future behavior has direct implications for extrapolation of results as well as forecasting. Secondly, non-stationary series respond to shocks very differently than stationary series. In stationary series shocks are fleeting, while in non-stationary they may be infinite. This is very relevant since I am studying effects of crisis (a shock) on the causality between exchange rates and stock prices. Thirdly and most importantly, non-stationarity of time series is shown to cause spurious regressions. Financial data is known to usually be non-stationary. This is because this type of data is subject to random variation. To avoid spurious regressions and other problems associated with non-stationarity, time series must be tested for stationarity.

There are different levels, or types of non-stationarity, described as unit roots. The number of unit roots contained in the series shows how further away from being nonstationary the series is. A stationary series has no unit roots and is said to be integrated of order 0, denoted by I(0).

A series with a trend is integrated of order 1, denoted I (1). Time series are seldom integrated in orders higher than 1 (Johnston & DiNardo, 1972).

There are many tests of non-stationarity. The most used ones are Augmented Dickey-Fuller test (ADF), Phillips-Perron (PP) tests and Kwiatkowski, Phillips, Schmidt, and Shin test (KPSS). All these tests have positive and negative sides and they complement each other well. ADF test lacks power according to some researchers (Cheung & Lai, 1995). PP is more powerful since it does not use lagged differences. Null hypothesis for both the ADF and PP is that time series has a unit root. Null hypothesis of the KPSS test, unlike ADF and PP tests, is stationarity. Furthermore, the KPSS test deals better with shorter time series that have deterministic trends (Carrera, Féliz, & Panigo, 2003). Based on the discussion above, I am going to use all three tests to obtain robust results.

5.2 Information criteria and lag selection

Information criteria helps researchers to rank different models based on the explanatory power of these models. Information criterion is one of the most used measures of information loss. It penalizes the model for every new predicting variable so as to achieve the most parsimonious model that still has the most explanatory power (Ivanov & Kilian, 2005). Information criteria are used not only to select best models but decide on the number of lags used in cointegration tests and VECM models.

There are many information criteria: Akaike's, Schwartz, Final Prediction Error criteria, Hana-Quinn to name but a few. All these criteria have positive and negative sides. The most widely used information criterion - Akaike's information criterion has some significant shortcomings. Firstly, it is inconsistent in its results and does not always select the best model. Secondly, it can lead to overfitting models, which should be avoided. Another widely used information criterion is Schwarz information criterion. It includes the strongest penalty for overfitting the model and is more consistent than Akaike's (McQuarrie, Shumway, & Tsai, 1997). Since no information criteria is clearly better I am going to use all of them to assist me in choosing the right number of lags for my model and cointegration tests.

The primary way of choosing the number of lags will be based on autocorrelation. I am going to first run a VECM model for different number of lags. I will then test the residuals of the VAR model for autocorrelation. I will then use the least number of lags that produces residuals with no autocorrelations. I will then, as a precaution and to assure robustness of results, consult information criteria and see if the chosen number of lags minimizes the values of the different information criteria – Akaike's, Schwarz, Final Prediction Error and Hana-Quinn. This approach seems to be rigorous and statistically sound to build a solid foundation for future building of regression models.

5.3 Cointegration tests

Model selection depends on the results obtained from the stationarity and cointegration tests. Different models suit different data. Variables that influence each other are very likely to have some long-run relationship. Cointegration assumes that variables are integrated in order of one. Variables that are stationary are unlikely to have long-run relationships. There is a caveat, however. Two variables that are integrated in order of one separately can have a long-run relationship that makes them I(0) jointly. If this is the case, these variables are said to be cointegrated (Clive W Granger, 1986). I expect Norwegian exchange rates and stock prices to have a cointegrated relationship. I further hypothesize that this relationship is going to be influenced by the latest financial crisis

There are two main approaches to testing for cointegration. Engle-Granger approach and Johansen's test. Idea behind the Engle-Granger test is that cointegrated variables must be I(0) in equilibrium. If they are not stationary in equilibrium, then neither are they cointegrated. The null hypothesis of the test is absence of cointegration, and the test is done finding whether a unit root is present in the equilibrium process. Error correcting model is suggested for testing for cointegration since it is suited for short-run adjustments in the variables. The main drawback of this approach is that is relies on Dickey-Fuller test and is meant for testing of two variables (Sjö, 2008).

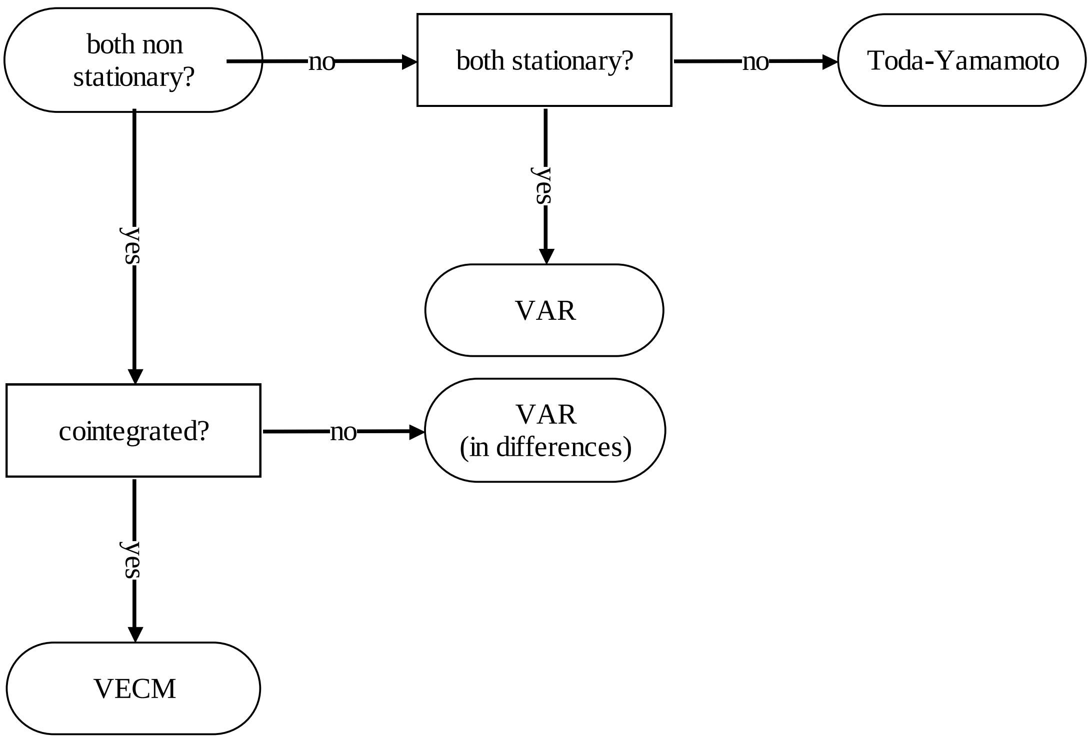
Johansen's test avoids several weaknesses of the Engle-Granger test. The main advantage is that it can be used to establish cointegration between two or more variables. It has some drawbacks too. It is very sensitive to specification errors in shorter samples with many variables (Harris, 1995). This drawback is, however, not very relevant for my research, since the samples before and after the crisis are quite large, while the monthly sample used during the crisis period consists of only two variables, so specification errors are not very likely in this case. Furthermore, the Johansen test is very flexible and deals perfectly well with both I(1) and I(0) variables (Johansen, 1995). The null hypothesis for the Johansen test is absence of cointegration.

Based on the analysis above I am going to use the Johansen's test to test for cointegration between variables in all three periods. Because variables in the periods before and after the crisis are non-stationary and cointegrated, I am going to use a VECM model.

5.4 Vector error correction model and short samples

Different types of data perform best in different types of econometric frameworks. Diagram below presents an easy to understand heuristic approach to choosing a proper framework.

Figure 4 Flow-chart for selecting econometric models.



As stationarity and cointegration tests are going to show, variables before the crisis and after the crises are integrated in order of 1 and cointegrated. This means that the best way to analyze their relationships will be in a VECM model. The general VAR model is well suited for stationary data but gives spurious results when applied to non-stationary cointegrated data. The VECM, which a restricted version of VAR model, is the right model for that type of data (Hayo, 1971). As such the VECM is the same as VAR model with an addition of error correction procedure. It firstly establishes long-run equilibrium between variables. It then detects deviations from that equilibrium that are called errors. Lastly, it calculates how those errors determine short-run dynamics of time series data (Lütkepohl, 2011).

Furthermore, this type of model is well suited for discovering long-run and short-run behaviors. The VECM was developed by Johansen to address weaknesses of previous unidirectional error correction models. There are two main weaknesses of unidirectional models. Firs, those models were only suitable for unidirectional influence between independent and dependent variables. Second, those models required extensive pretesting procedures (Giles & Mirza, 1999). Since my data consists of not only main but also control variables and I am interested in short-run and long-run relationships, the VECM is perfectly suited for carrying out analysis in this paper.

Here are the VECM equations that are going to be used to analyze relationships between stock prices and exchange rates.

$$\Delta ER = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta ER_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta SP_{t-1} + \sum_{i=1}^{n} (\delta_i \Delta CV_{t-1}) + \varphi Z_{t-1} + \mu_t$$

$$\Delta SP = \beta_0 + \sum_{i=1}^{n} \gamma_i \Delta SP_{t-1} + \sum_{i=1}^{n} \beta_i \Delta ER_{t-1} + \sum_{i=1}^{n} (\delta_i \Delta CV_{t-1}) + \varphi Z_{t-1} + \mu_t$$

Where:
ΔER and ΔSP are changes in exchange rates and stock prices; ΔCV are changes in control variables that are foreign reserves, oil price and interest rates; Z is the error correction term

The VECM is going to be used for the data before and after the crisis, since that data is cointegrated. Variables for the period during the crisis are nonstationary but not cointegrated, so there is no need to use the VECM.

Generally speaking, for regression results to be reasonable and have explanatory power, there needs to be at least 10 to 20 observations for every variable (Harrell, 2001). Given the fact that there are only 34 monthly observations in the monthly data during the crisis, I cannot fully justify fitting a regression model with control variables. Control variables are going to be present when it comes to daily data, since that data series has more than 600 observations.

Based on the discussion above and due to the limited monthly sample for the period during the crisis I am not going to fit a vector model, since the limited sample does not provide enough degrees of freedom for vector models (Kilian & Lütkepohl, 2017). I will simply use pairwise Granger causality test on stock prices and exchange rates. This, however, does not apply to daily data since there are enough observations in every period.

5.5 Granger causality

After having tested data for stationarity, cointegration and having built the VECM, I am then going to run Granger non-causality tests. When it comes to data before and after the crisis these tests are going to be run within the framework of the VECM. When it comes to the data during the crisis, I am going to resort to pairwise Granger causality testing for monthly data and will test all 4 variables for daily data.

Causality is important, but very difficult to detect. Knowing causes of events not only gives us more insight into origins and effects, it also lets us plan accordingly. By knowing what causes what, we can prevent, predict or "encourage" the occurrence. This means that the matter of causality is of importance for policy decisions. Therefore, I am going to study the possible causal relationship between exchange rates and stock prices. Finding the nature of this relationship is going to, at least in theory, help policy makers to influence either exchange rates or stock prices.

Granger's definition of causality relies entirely on the assumption that the past causes the future and the future cannot cause the past. This makes intuitive sense. Here is the gist of Granger causality: *variable A Granger-causes variable B, if variable B can be better predicted using historical values of both A and B, than it could be predicted by using historical data of variable B alone* (Clive WJ Granger, 1969). To place this definition into the context of this paper: exchange rates Granger-cause stock prices if stock prices can be better predicted using historical values of both exchange rates and stock prices, rather than by using historical values of stock prices alone. Or: stock prices Granger-cause exchange rates if exchange rates can be better predicted using historical values of both exchange rates and stock prices, rather than by using historical values of exchange rates alone. Granger causality presents a null hypothesis of one variable not being able to forecast another variable.

There are limitations to Granger causality test. The test is sensitive to cointegrated variables. This test can produce spurious results if it is run in a model that does not take cointegration into account. This drawback is dealt with by using an appropriate VECM.

5.6 Post estimation tests

Post estimation step consists of subjecting the model to tests that will show how appropriate it is. This increases the trustworthiness of the results. I am going to test the model for basic assumptions of regressions: normality, autocorrelation, homoscedasticity. If test results show correlation, heteroskedasticity and non-normality it would mean that the result of regression models cannot be trusted, and the model must be changed.

Serial correlation is a strict assumption in the case of my methodology. If the data is normally distributed, homoscedastic and is not autocorrelated, its coefficients are robust. Autocorrelation exists when data in the time series is influenced by its own historical values. In other words, its error terms are correlated over time. Serial correlation means that error terms of two variables are correlated with each other. It indicates that the model is not properly specified. This problem is dealt with by using a VAR model and by adding the right number of lags to eliminate correlation of residuals. There are many sources of correlations. Omitted explanatory variables, misspecification of the mathematical form of the model and errors of measurement are some of them. Whatever the cause, autocorrelation presents a serious econometric problem. Hypothesis tests based on the t-distributions and f-distributions become unreliable. It is therefore important to test for autocorrelation and correct for it if it is present.

The widely used test for auto-correlation is Durbin-Watson test. This test has, however, several drawbacks. A major flaw is that it cannot be used when lagged dependent variables are used. Furthermore, it does not discover higher orders of autocorrelation. I am going to use Breusch-Godfrey test for autocorrelation instead. This test mitigates the drawbacks of Durbin-Watson test and, furthermore, suits VAR models better, since it takes into consideration the fact that variables are endogenous (Hayo, 1971).

When it comes to normality, it is assumed that residuals of regressions are normally distributed. Violation of this assumption makes it difficult to determine whether coefficients are significantly different from 0. Normality is often violated by the presence of extreme outliers, which can have disproportionate influence on predictors via squared errors. It can also pose problems since calculations of confidence intervals and many significance tests are based on the assumptions that residuals are normally distributed. I am going to use the most used test which is the Jarque-Bera test.

Homoscedasticity is when the error term is constant. Heteroscedasticity means that the error term variance is not constant. Heteroscedasticity has several negative effects on regressions. Firstly, it can make significance test either too high or too low. Secondly, standard errors become biased, which can lead to useless confidence intervals (Jarque & Bera, 1980).

Breusch-Pagan test detects linear forms of heteroscedasticity. The null hypothesis of this test is the absence of heteroscedasticity. Alternative hypothesis says that the higher the predicted value of independent variable, the greater the error variance is. Large chi values indicate presence of heteroscedasticity. This test has several strengths. Firstly, it is very simple to run and understand. Secondly, many variables can be teste at once with this test. I am going to use this test to find out whether there is a problem of heteroskedasticity with the analysis in this paper.

All in all, this methodology is going to be used to find answers to the following questions. Firstly, I want to know if there is causality between exchange rates and stock prices. Secondly, I want to know the direction of causality. Thirdly, I want to know how causality was affected by the latest financial crisis. I am going to test the data in three distinct periods: before the latest financial crisis (from January 1999 to February 2008), during the crisis itself (from March 2008 to December 2010), and after the crisis (from January 2011 to December 2017).

6 Results

6.1 Results before crisis (from January 1999 to February 2008)

Before proceeding with further analysis of econometric dependencies between variables it is imperative to establish the order of integration of these variables. This information is going to be important when selecting the appropriate econometric framework later. Three unit root tests are selected for this procedure: the ADF test, the PP test and the KPSS test. This wide selection of tests is going to ensure robustness of results. Furthermore, the tests have different null hypothesis. The PP and ADF test have existence of unit root as their null, while the KPSS test has stationarity as it null hypothesis.

The results of these tests are very conclusive and can be found in Appendix A, Tables 9 and 10. Both daily and monthly variables are integrated in order of 1. As one can see the null hypothesis of unit roots in levels cannot be rejected when it comes to ADF and PP tests, while the null hypothesis of stationarity of KPSS test is rejected at 1% level of significance. In other words, they have unit roots at levels and are stationary at 1st differences.

Before proceeding with cointegration tests it is necessary to choose the optimum number of lags. There are several ways of doing this. Some researchers pre-specify the number of lags according to intuition, having 12 lags for monthly data and 30 lags for daily data for example. Most researchers seem to use information criteria.

As discussed in the methodology section, I am going to focus on the autocorrelation of residuals. I run the VAR model several times with different number of lags starting from 0 and adding one lag every time I run the model. I test the residuals for autocorrelation every time the model is run. As soon as I see that the residuals are not autocorrelated, I settle on the number of lags. The process is iterative and tedious but yields robust results. This “serial correlation” procedure yields 6 lags for monthly data and 12 lags for daily data as the optimum number of lags.

Since the variables are I(1) and the optimum number of lags is chosen, I proceed with the test of cointegration. Results of this test will decide whether variables need to be studied in the VECM (for cointegrated variables) or VAR (non-cointegrated) framework. Johansen-Juselius Cointegration test is chosen as the appropriate test for reasons discussed earlier.

The results of cointegration tests for monthly and daily data are shown in the Appendix A, Tables 11 and 12. Trace and Max-Eigen value statistics are higher than critical values at 5% in cases of zero and 1 cointegrating relationship, indicating that there is at least 1 cointegrating equation when it comes to monthly data. There are 3 cointegrating relationships when it comes to daily data. Tests for both monthly and daily data show that the variables before crisis are integrated of order one. Their cointegration hints at a long-run relationship being present.

Since the variables are cointegrated the best framework for studying their co-movements would be the VECM. This model can give insight into both short-run and long-run dynamics of exchange rates and stock prices.

Table 2: Significant coefficients of the VECM for data before crisis.
Part A: Monthly data.

Monthly data	Exchange rates		Stock prices	
Error correction term	-0.011***	(-4.960)	*insignificant*	
Δ Exchange rate (1 lag)	*insignificant*		1.164**	(2.433)
Δ Exchange rate (2 lags)	-0.375**	(-3.328)	*insignificant*	
Δ Exchange rates (4 lag)	-0.241**	(-2.025)	1.293**	(2.624)
Δ Stock prices (1 lag)	0.068**	(2.141)	0.228*	(1.737)
Δ Stock prices (5 lags)	*insignificant*		0.233*	(1,758)
F-statistic for exchange rate lags	(2.894**)	[0.014]	(3.315***)	[0.006]
F-statistic for stock prices lags	(2.321**)	[0.042]	*insignificant*	

Part B: Daily data.

Daily data	Exchange rates		Stock prices	
Error correction term	-0.001*	(-0.723)	*insignificant*	
Δ Exchange rates (11 lag)	*insignificant*		0.035**	(-0.405)
Δ Stock prices (2 lags)	0.016**	(2.188)	0.063**	(2.490)
Δ Stock prices (4 lags)	0.016**	(2.131)	0.052*	(2.055)
F-statistic for exchange rate lags	(1.187**)	[0.028]	0.932**	[0.050]
F-statistic for stock prices lags	(1.180**)	[0.029]	2.212***	[0.009]

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (...) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis [...] are p-values. Δ Exchange rates are the change in monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices are the change in the monthly closing stock index.*

Table 2 shows pertinent values of significant coefficients from the VECM for monthly and daily data. (Full results with all coefficients are found in Appendix A, Tables 13 and 14). Error correction term captures deviation from the long-run equilibrium between variables, while lagged variables display short-run adjustments in the variables needed to reach the position of long-run equilibrium.

Before discussing these coefficients in detail, it is important to note that the results paint a very similar picture, whether monthly or daily data is used. This suggests that the results are robust and manage to capture the relationship between exchange rates and stock prices.

As seen from Table 2, Part A for monthly data, deviations from the equilibrium are corrected with 1% each month and are tied to the changes in stock prices. In other words, innovations in stock prices are transmitted to exchange rates (indicated by the statistically significant coefficient of -0.011). Changes in exchange rates, however, do not have a long-run effect on the stock prices as indicated by statistically insignificant 0.003 coefficients. As seen from Table 2, Part B for daily data, the picture is similar. Deviations from the equilibrium are corrected with 0.1% each day and follow the changes in stock prices. Daily data shows that innovations in stock prices are transmitted to exchange rates.

To find out whether lagged stock prices and exchange rates exert any influence on each other in the short-run I am going to test joint hypothesis that lagged values of exchange rates and stock prices are jointly equal to 0 using partial F-statistics. Results are given in the last two rows of the Table 2, Part A for monthly data and Table 2, Part B for daily data. As one can see exchange rates are affected by their own lagged values as well as changes in stock prices, while stock prices are affected by changes in exchange rates in the short-run for monthly data. The only difference when it comes to daily data is that stock prices are affected by changes in both exchange rates and stock prices in the short-run.

Talking about short-run effects further, several coefficients of the lagged variables are statistically significant and different from zero. This means that movements in the exchange rates have a short-run effect on the movements of exchange rates and vice versa. Stock prices coefficients (highlighted in yellow) are positive indicating that an increase in stock prices is going to have a positive effect on exchange rate in the short-run. Significant exchange rate coefficients (highlighted in orange) indicate that an increasing exchange rate (a depreciating Norwegian krone) is also going to have a positive effect on stock prices in the short-run.

The VECM is designed to discover long-run and short-run effects of the variables within its framework. I choose to reinforce insights given by the model by running Granger non-causality tests. This test can show if there is causality in the Granger sense between variables.

Table 3: Granger causality results for data before crisis.
Part A: Monthly data.

	Independent variables			
Dependent variable	X2 – statistics of lagged 1st differenced term [p value]			
	Δ Exchange rates	Δ Stocks	Δ Oil price	Δ Interest rates
Δ Exchange rates	---	13.927** [0.030]	31.138*** [0.000]	19.540*** [0.003]
Δ Stocks	19.890*** [0.002]	---	5.135 [0.526]	7.340 [0.290]
Δ Reserves	3.055 [0.801]	2.590 [0.858]	7.735 [0.258]	3.944 [06841]
Δ Oil price	2.534 [0.864]	3.523 [0.740]	---	1.904 [0.928]
Δ Interest rates	1.970 [0.922]	6.603 [0.359]	8.618 [0.196]	---

Part B: Daily data.

	Independent variables			
Dependent variable	X2 – statistics of lagged 1st differenced term [p value]			
	Δ Exchange rates	Δ Stocks	Δ Oil price	Δ Interest rates
Δ Exchange rates	---	14.129*** [0.002]	9.544 [0.655]	6.317 [0.899]
Δ Stocks	14.908** [0.024]	---	13.104 [0.361]	5.287 [0.947]
Δ Oil price	26.680*** [0.008]	11.404 [0.464]	---	21.328** [0.04]
Δ Interest rates	22.176** [0.035]	16.425 [0.172]	16.002 [0.191]	---

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (...) denote t-statistics and figures in squared brackets [...] denote p-values. Δ denote changes in variables.*

Table 3 shows results of Granger causality test for all variables within the VECM framework for both monthly (Part A) and daily (Part B) data. This paper is limited to exchange rates and stock prices, while other variables are control variables. As shown in the table Granger causality test supports previously obtained results of the VECM model showing bidirectional causality running between exchange rates and stock prices for both monthly and daily data.

Results for the data before the crisis pass all robustness checks as can be seen in Appendix A, Tables 15 and 16.

6.2 Results during crisis (from March 2008 to December 2010)

This sample suffers from a very low number of observations when it comes to monthly data. 34 observations are about the minimum that is allowed for econometric analysis. This problem has already been discussed in detail in previous sections. There are more than enough observations (675) when it comes to daily data, so no such problem is present in the daily sample.

Since there are already very few degrees of freedom I drop control variables and concentrate myself on the only two variables of interest for monthly data: exchange rates and stock prices. I use all four variables: exchange rates, stock prices, oil prices and interest rates for the analysis of daily data. As always, I begin the analysis with unit root tests.

Results in Appendix C, Tables 17 and 18 indicate that both monthly and daily variables are integrated in the order of 1. The next test is Johansen-Juselius cointegration test. Before proceeding with the test, the optimum number of lags is selected by the same procedure as before. As Tables 19 and 20 in Appendix C show there are no cointegrating relationship between variables in either monthly or daily sample. This indicates absence of any long-run relationship.

Theoretically speaking it is possible to test Granger causality within the VAR framework. I choose against it as it would not make practical sense for the monthly sample due to its size. Vector models produce many coefficients and are generally not well suited for shorter samples (Hayo, 1971). No deeper insights can be gathered from the VAR framework when it comes to daily data either, since the model itself is not going to affect Granger test. I therefore use pairwise Granger causality test for monthly data and normal non-pairwise Granger test for daily data to find out if there is causality between exchange rates and stock prices.

Table 4: Pairwise Granger causality test for data during crisis.
Part A: Monthly data.

Ho: absence of causality		
	Independent variables	
Dependent variable	F – statistics of 1st differenced term [p value]	
	Δ Exchange rates	Δ Stocks
Δ Exchange rates	---	2.415 [0.028]
Δ Stocks	1.118 [0.342]	---

Part B: Daily data.

	Independent variables			
Dependent variable	X2 – statistics of lagged 1st differenced term [p value]			
	Δ Exchange rates	Δ Stocks	Δ Oil price	Δ Interest rates
Δ Exchange rates	---	17.471 [0.178]	22.707** [0.045]	25.643 [0.119]
Δ Stocks	8.877 [0.782]	---	28.465** [0.007]	14.427 [0.344]
Δ Oil price	19.881 [0.192]	22.796 [0.442]	---	14.402 [0.346]
Δ Interest rates	17.503 [0.1773]	10.353 [0.664]	31.783** [0.002]	---

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (…) denote t-statistics and figures in squared brackets […] denote p-values. Δ denote changes in variables*

Results of Pairwise Granger causality test are given in Table 4, Part A. The null hypothesis of absence of causality cannot be rejected either in case of causality running from stock prices to exchange rates or from exchange rates to stock prices. The results are robust since they are qualitatively the same for daily and monthly data.

It is important to note that daily data reveals more important information than monthly data. Higher data frequency allows capturing causal effect of oil prices during the crisis. As seen in Table 4, Part B oil prices Granger cause all variables in the sample, further emphasizing how important oil price is for the Norwegian economy.

6.3 Results after crisis (from January 2011 to December 2017)

By now the process is repetitive enough to not go through it in detail again. Tables 21 in Appendix D shows results of unit root tests for monthly data and Table 22 in Appendix D show results of unit root tests for daily data. Variables in both samples are non-stationary in levels, but stationary in first differences. Lag selection procedure gives 4 lags as the optimal number of lags for monthly data; and 2 lags as the optimal number of lags for daily data.

Since the variables are I(1) I proceed with cointegration test. The results are given in Appendix D, Tables 23 and 24. There is at least one cointegrating relationship in monthly data and 3 cointegrating relationships in daily data, which makes the VECM a suitable choice for further analysis of short-run and long-run dynamics.

Table 5: Significant coefficients of the VECM for data after crisis.

Part A: Monthly data.

Monthly data	Exchange rates		Stock prices	
Error correction term	*insignificant*		-0.120**	(-2.265)
Δ Exchange rate (1 lag)	0.327**	(2.250)	*insignificant*	
Δ Exchange rate (2 lags)	-0.103*	(-0.674)	*insignificant*	

Part B: Daily data.

Daily data	Exchange rates		Stock prices	
Error correction term	*insignificant*		-0.001*	(-2.310)
Δ Exchange rate (1 lag)	-0.055**	(-2.045)	*insignificant*	

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis* […] *are p-values. Δ Exchange rates is the change in monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices is the change in the monthly closing stock index.*

As seen from Table 5, Part A for monthly data, deviations from the long-run equilibrium are corrected with 12% each month and are tied to the changes in exchange rates. In other words, innovations in the exchange rates are transmitted to the stock market (indicated by the statistically significant coefficient of -0.120). Changes in stock prices, however, do not have a long-run effect on the stock prices as indicated by statistically insignificant -0.030 coefficient (see Appendix D, Table 25 for full details on monthly data and Table 26 for full details for daily data).

Results in Table 5, Part B paint a very similar picture. Innovations in the exchange rates are transmitted to the stock market. The only difference is that deviations from the long-run equilibrium are with 0.1% each day and are also tied to exchanger rates.

To find out whether lagged stock prices and exchange rates exert any influence on each other in the short-run I am going to test joint hypothesis that lagged values of exchange rates and stock prices are jointly equal to 0 using partial F-statistics. Results are given in the last two rows of Tables 25 and 26 of Appendix D. Talking about short-run effects further, none of coefficients of the lagged variables are statistically significant except two lagged exchange rates coefficients for monthly data and one lagged coefficient for daily data. This suggests that except for lagged exchange rates exerting influence on themselves, there are no other significant dynamics in either monthly or daily samples. This is clearly seen in the last two rows Tables 25 and 26 of Appendix D where null hypothesis of joint short-run coefficients being 0 cannot be rejected.

I now run Granger non-causality test to further elucidate relationships between stock prices and exchange rates.

Table 6: Granger Causality Results based on VECM for data after crisis.
Part A: Monthly data.

	Independent variables			
Dependent variable	X2 – statistics of lagged 1st differenced term [p value]			
	Δ Exchange rates	Δ Stocks	Δ Oil price	Δ Interest rates
Δ Exchange rates	---	2.714 [0.606]	6.841 [0.144]	3.704 [0.447]
Δ Stocks	2.368 [0.668]	---	10.539* [0.032]	1.653 [0.799]
Δ Reserves	1.959 [0.743]	2.944 [0.567]	3.354 [0.500]	5.544 [0.235]
Δ Oil price	1.103 [0.893]	2.350 [0.671]	---	1,742 [0.783]
Δ Interest rates	8.341* [0.079]	3.009 [0.556]	9.738** [0.045]	---

Part B: Daily data.

	Independent variables			
Dependent variable	X2 – statistics of lagged 1st differenced term [p value]			
	Δ Exchange rates	Δ Stocks	Δ Oil price	Δ Interest rates
Δ Exchange rates	---	1.996 [0.368]	39.752*** [0.000]	1.216 [0.544]
Δ Stocks	0.654 [0.721]	---	1.602 [0.448]	0.938 [0.625]
Δ Oil price	3.004 [0.222]	1.966 [0.374]	---	1,777 [0.411]
Δ Interest rates	0.510 [0.774]	3.860 [0.145]	1.306 [0.520]	---

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (...) denote t-statistics and figures in squared brackets [...] denote p-values. Δ denote changes in variables.*

Again, the Granger causality test reinforces results obtained from the VCEM. There is no causality between exchange rates and stock prices as the Table 6, Part A shows. It is also interesting to note that the role of oil prices has diminished after the crisis, since as the Table 6, Part B shows, it now only Granger-causes exchange rates and not all variables as during the crisis.

Results for the data after the crisis pass all robustness checks as can be seen in Appendix D, Tables 27 and 28.

7 Discussion

Unlike previous research that demonstrates casual relationships over the span of many periods, my research groups results into 3 categories: before the crisis, during the crisis, and after the crisis. This allow for a more detailed discussion of the interplay between stock prices and exchange rates. What is more, this paper is based on both daily and monthly data, further increasing the insights that can be gathered about the relationships between stock prices and exchange rates. As evidenced by empirical results of this paper, there are long-run and short-run effects between exchange rates and stock prices before the crisis, no short-run or long-run effects during the crisis and only long-run relationships after the crisis. These results are robust and essentially the same regardless of the data frequency used. This suggests that the relationship between exchange rates and stock prices has been changed by the latest financial crisis in Norway. What is more, this relationship has not been fully reinstated after the crisis.

The discussion section of this paper is going to proceed as follows. I am first going to discuss how the choice of data affected the results. I will then discuss long-run relationships. I will then talk about short-run relationships. Afterwards I will discuss causality as well as try and find out what theoretical models discussed previously explain relationship between exchange rates and stock prices best. Finally, I am going to consider practical implications of this paper.

7.1 Monthly vs. daily data

Some researchers note that lower data frequencies (monthly) explain relationships in data better (Griffin & Stulz, 2001). This is because higher data frequencies (daily) can contain too much noise (Yang & Doong, 2004). Other researchers come to the opposite conclusion, higher frequency data could reveal more insights into time series' behavior (see Granger, Huangb and Yang (2000)). In general studies show that different choices of data frequency give very different econometric results, even though other study parameters are similar (compare for example research by Griffin and Stulz (2001) and Ajayi, Friedman and Mehdian (1998)).

It is therefore noteworthy that my paper does not support these claims. Using daily and monthly data to study relationships between exchange rates and stock prices in Norway yielded qualitatively same results. There was some difference in significance levels and the value of coefficients, which is to be expected. The overall picture presented by different frequencies of data is the same: the latest financial crisis in Norway eliminated long-run and short-run relationships for its duration, however, after the crisis; the long-run relationship has been reinstated.

Daily data did not present the same econometric challenges as monthly data. The period during crisis had very few observations, making regression analysis difficult and using control variables problematic. Daily data had a lot more observations and presented no such problems. This suggests that using daily data in this type of research might be a better decision.

7.2 Long-run relationships

The fact that there is a long-run relationship between exchange rates and stock prices before and after the crisis is not surprising. This finding falls in line with a lot of previous research as well as flow and stock theories. For example, Yang and Doong (2004) too find evidence that stock prices influence future exchange rate movements. The disappearance of long-run equilibrium during crisis is a lot more puzzling.

Test results paint an interesting picture of dynamics between exchange rates and stock prices. Cointegration tests clearly show that time series lose their cointegration properties during the crisis. Some academics argue that well cointegrated stock markets and currency markets are a sign of an advanced economy and that innovations in either market will elicit a response in the other due to the well-structured nature of advanced economies (Ajayi et al., 1998). In that sense it is possible to say that crises made the Norwegian economy less structured.

The finding of absent long-run equilibrium during crisis is consistent with Pan et al (2001) and Nieh and Lee (2002). Nieh and Lee showed that exchange rates and stock prices do not have prediction powers beyond two days, while my research shows that stock prices and exchange rates can predict each other within months before the crisis. The findings in my paper further disagree with research by Gahmani-Oskoee and Sohrabian (1992). Unlike their research, my research shows that there is long-run equilibrium in two periods: before and after crisis. Results of my paper also stand in stark contrast with the results from Lin’s research (2012). Lin’s research suggests that relationship between exchange rates and stock prices intensifies during crisis periods, he also found that long-run relationships are more inclined to occur during crisis.

The exact reason why long-run relationship between exchange rates and stock prices disappears during crisis can only be guessed. Some researchers (Pan et al., 2001) suggested that the lack of long-run equilibrium is a common feature of exchange markets that are based on managed-float currency system. This is not the case with Norway since the currency is free floating. It is also noted that cointegration relations might not be captured by econometric methods due to too much noise in the daily data, which is not the case either since the data used in this paper is not only daily but also monthly. Digging deeper into the reasons why the long-run relationship disappeared, it is necessary to note that positions in foreign assets as well as net trade have a lot of influence on the exchange rates (Kohler, 2010). I posit that Norway, being an oil exporting country, had its net trade balance changed by oil fluctuation in such a way that oil prices started playing a much larger role in determining exchange rates than stock prices. Further research is necessary to pinpoint the detailed mechanism of this happening.

All in all, it is evident that the financial crisis played a disruptive role in the relationship between exchange rates and stock prices. It is argued that crises are often disruptive (Mishkin, 1992) what is more noteworthy is that the crisis did not change the relationship between exchange rates and stock prices permanently. In fact, long-run relationship has been regained shortly after the end of the crisis, which can serve as a testament to how resilient Norwegian economy is.

Proceeding further with exploration of long-run relationships, it is also important to note whether it is exchange rates or stock prices that are responsible for the short-run adjustment toward the long-run equilibrium. In the case of the period before the crisis it is stock prices that are alone responsible for bringing about the equilibrium. While in the case of dynamics after the crisis both exchange rates and stock prices produce short-run adjustments toward the long-run equilibrium. This indicates that exchange rates started playing a bigger role in the relationship after the crisis. This is perhaps due to the fact the crisis was more weakening for stock prices, than exchange rates.

It is interesting to note that Solnik (1987) maintained that the long-run interplay between exchange rates and stock prices can be seen as a barometer for the health of an economy. In this framework we can see that the economy has become healthier since the crisis as the long-run relationship between exchange rates and stock prices has been reinstated.

In general, the results suggest that the interplay between exchange rates and stock prices in the long-run in Norway is linked to the fact that Norway is an export-oriented country. Because Norway has a tremendous export sector, currency appreciation has unfavorable effects on exports and may bring about a downward movement of the stock market. The opposite is true, when the currency depreciates. As the results suggest depreciating krone is inducing a bullish stock market. However, care should be taken to not overgeneralize. As discussed before, oil sector, which is substantial in Norway, very sensitive to changes in oil prices, that in turn affect stock prices and exchange rates.

7.3 Short-run relationships

Short-run dynamics are interesting as well. Before the crisis, stock prices lead exchange rates by one month, while exchange rates lead stock prices by 5 months. The relationship between exchange rates and stock prices is positive. This lead-lag relationship cannot be discerned during crises as there is no long-run equilibrium during that time. It also seems that there is no statistically significant short-run relationship after the crisis.

It is expected that short-run relationships, just like long-run relationships, disappear during the crisis. The fact that they remain undiscernible after the crisis is more intriguing. This can be attributed to the possibility that short-run relationships are more sensitive to the crisis of this proportions and magnitude than long-run relationships.

Furthermore, it can be argued that for a country with a large export sector the favorable effects of currency depreciation on export may bring about increases in the stock market. The opposite is true of import countries (Ma & Kao, 1990). This is reflected in the data before the crisis and explains why there are no short-run effects after crisis. As the economic environment stabilizes, the interplay between stock prices and interest rates becomes less evident. Following the research by Ma and Kao (1990), it could be said that, in the short-run, currency depreciation may have a negative effect on stock markets. This is because domestic counterpart of currency depreciation is inflation, which exerts a dampening effect on the stock market.

These results bring me to a necessary discussion of market efficiency. Markets are said to be efficient if the prices reflect all the available information thereby making speculation impossible, since everything is traded at its fair value (Fama, 1970). Conversely, markets can be said to be inefficient, if there is a prolonged lead-lag relationship between variables that can help financial actors “beat the market”.

What is important here is that the results of this paper indicate that Norwegian stock and currency markets were not very efficient before the crisis, since the changes in the exchange rates could be predicted by changes in stock prices. It can be argued that the results indicate that the crisis has corrected underlying mechanism and made those markets more efficient. This can be seen in the fact that there are no visible short-run relationships between stock prices and exchange rates after the crisis.

7.4 Causality

The Granger causality test displays some noteworthy observations. While exchange rates and stock prices mutually caused each other in the Granger sense before the crisis, the causality disappears as soon as the crisis begins and does not reappear. The fact that bidirectional causality is present before the crisis and is not to be found ever after, once again suggests that the financial crisis weakened the relationship between exchange rates and stock prices.

Results showing dual causality between exchange rates and stock prices before the crisis agree with some papers. For example Osokoee and Sohrabian (1992) show that there is a dual causal relationship between the stock prices and effective exchange rate of the dollar in Sweden. Same results of Granger tests place my paper in disagreement with many other papers.

The general consensus on how exchange rates and stock prices relate to each other before crisis seems to be that currency devaluations cause collapses in stock market (see for example (Kaminsky & Reinhart, 1999). My paper does not show such relationship. Before the crisis the causality was mutual, while there is no causality during or before the crisis.

Results of this paper also stand in stark contrast with prevailing theories about how exchange rates and stock prices influence each other during crisis. Some researchers (Obstfeld, 1996) suggest that self-fulfilling expectations and herding behavior of investors in international markets can make crisis worse and cause currency crisis. This is not the case in Norway, since there is no causality running from stock prices to exchange rates. My assumption is that Norwegian krone was somewhat shielded from the detrimental effects of crisis because Norway is an oil producing country and stock price fluctuations did not affect it too much. It is important to note that oil prices caused all other variables during the latest financial crisis. This suggests that oil prices became more important than usual in influencing stock markets and exchange rates. This is perfectly sensible, when we consider what great role Euinor plays in the Norwegian stock market.

Some research suggests that currencies become fragile because of rumors during crisis (Kaminsky & Schmukler, 1999). Rumors according to their research trigger speculative behavior and hence cause changes in the stock prices. This is not supported by my research, as there is no causality after the crisis. It is my guess that the Norwegian economy is so open and transparent, that it is less susceptible to rumors and speculation than more closed and non-transparent economies.

Other research shows that changes in stock market lead changes in exchange rates, especially during crisis (Clive WJ Granger et al., 2000). Again, this is not the case with Norway. There is a common theme among research showing causality between exchange rates and stock prices during crisis. This research is based on Asian countries, many of which do not have as developed economies as Norway. I posit therefore, that countries without much interference from governments might be doing better in tranquil periods, while countries with more interfering governments do better during crisis. This might be because exchange rate controls provide an extra tool for dealing with crisis. This tool is not present when the currency floats freely.

7.5 Theories explaining the relationship

Some previous research managed to be quite conclusive on the issue of what models are best supported by the empirical results. For example, Rasheed and Muhammad concluded that their research of India and Pakistan provides evidence against the portfolio balance models and does not support any other traditional models (Muhammad et al., 2002). My research, however, is not that conclusive.

When it comes to the period before the crisis the data supports both the flow and portfolio balance model. Goods market theory implies a Granger causality running from exchange rates to stock prices, which is the case before the crisis in Norway. Results show exchange rates significantly lead stock prices. This can be explained in the framework of the flow model in this way: currency appreciation (depreciation) is going to cause more equity inflows (outflows) and thereby influence stock prices by effect of equity flows on prices in the economy. The portfolio balance model is also supported by the data from the period before the crisis. This can be explained by the fact that capital inflows (outflows) are leading to the currency appreciation (depreciation).

The reason why the same models do not hold in the periods after the crisis might be that the size of the Norwegian equity market is not large enough to exert too much influence on the interest rates. It is also possible that crisis has made investors warier of investing abroad. When the size of the equity market is diminished by the crisis, its influence might pale in comparison with other economic factors and can therefore be more difficult to detect.

The interactions between exchange rates and stock prices during the crisis are not exactly explained by either the stock or flow model. There is no evidence of casual relationships between stock prices and exchange rates. Therefore, it is possible to assume that exchange rates and stock prices are determined by other variables during crisis. The same can be true of the period after the crisis. There is a caveat, however. Even though there is no Granger causality between exchange rates and stock prices after the crisis, there is still long-run relationship evidenced by cointegration. This suggests that all other models can be used to explain the interplay between stock prices and exchange rates in Norway after the crisis.

All in all, no single theory completely explains the results presented in this paper. This is in accordance with much of previous research that does not support all the theories either. It seems to me that complexity of real world interactions between stock prices and exchange rates cannot be explained by merely one theory. Much of previous research has come to the same conclusion as well. For example, Fok and Liu note that their results show joint effects from all the theories, and that differences in findings from research to research may be due to differences in exchange rate regimes, the trade size, the degree of capital control, and the size of equity market (Pan et al., 2001). This is the general implication of this research, which is not surprising.

7.6 Practical implications

This research has several practical implications. These implications affect both governments as well as individual investors.

Possible causality between exchange rates and stock prices can help financial managers to gather insight into how their portfolios are going to respond to movements in exchange rates as well as stock prices. As the results for the period before the crisis suggested, there was lead-lag relationship between exchange rates and stock prices. This means that the markets were behaving inefficiently, and it would be, at least theoretically, possible to game the market. The market has become more efficient since the crisis. Again, it is important to not overgeneralize. This lead-lag relationship varies with respect to different industries. Differences between industries are probably even greater after the crisis. The practical implication of this is that it now no longer possible to predict arbitrage opportunities.

Even though, it is not possible to make money by predicting the movements in the market based on exchange rates and stock prices, there is still long-run relationship between stock prices and exchange rates. This implies that there is a lot of insight that can be gathered into how the portfolios are going to behave in the long-run. This is going to affect diversification strategies, hedging and overall financial planning.

When it comes to state agents, the results presented in this paper suggest that they should keep the exchange rates floating and the overall economy open, since it seems that the Norwegian economy recovered quite well from the crisis. The long-run correlations discovered in this paper suggest that governments should stimulate entrepreneurship to attract capital inflows that will solidify the stock market and act as bulwark from future financial crisis.

The evidence showing no causality between exchange rates and stock prices after crisis suggest that the state agencies cannot use exchange rates as policy tools, even if they were to intervene and change the exchange rate regimes. This leaves interest rates as the only viable tools of attracting foreign investment and stabilizing the economic situation.

Digging even deeper, it could be said, that the fact that time series in all periods are non-stationary means that there is no possibility of planned speculation in the foreign exchange or stock market. This is also reinforced by the absence of causality between exchange rates and stock prices.

8 Conclusion

This paper had several research aims dealing with the long- and short-run relationships as well as causality between stock prices and exchange rates during three periods in Norway: before the crisis, during the latest financial crisis and after. I have used multivariate VECM framework where it was appropriate and Granger causality tests where no cointegrating relationships existed to answer these research questions: Are there long-run and short-run relationships between exchange rates and stock prices in Norway? Is there causality between these variables? In what direction does this causality run? How has the latest financial crisis in Norway changed these dynamics?

The results of the analysis of dynamics between both monthly and daily exchange rates and stock prices in Norway from 1999 to 2017 have shown that:

1. There is a long-run relationship between stock prices and exchanger rates before (from January 1999 to February 2008) and after the crisis (from January 2011 to December 2017).
2. The long-run relationship disappears during the crisis (from March 2008 to December 2010). So does the causality.
3. Short-run relationship and bidirectional Granger causality between stock prices and exchange rates present before the crisis disappears during and after the crisis.
4. The latest financial crisis has played an important role in temporarily changing causal dynamics between exchange rates and stock prices.

The thesis of this paper was that the latest financial crisis has deeply changed the interactions between exchange rates and stock prices in Norway. I posited that the previous long-run relationship is going to be destroyed and that causality between stock prices and exchange rates will disappear. This proved to be only partially true.

The crisis did change the relationship between stock prices and exchange rates, but it does not seem that it had long-lasting impact. Stock prices and exchange rates were cointegrated before the crisis, with both short-run and long-run relationships. Granger causality was running both ways between stock prices and exchange rates. The latest financial crisis in Norway eliminated long-run and short-run relationships for its duration. However, after the crisis the long-run relationship has been reinstated. The same is not true of the short-run relationship and causality between stock prices and exchange rates. It seems that short-run and causal relationships disappeared because of the crisis.

In summary, the crisis had a destructive impact on the relationship between stock prices and exchange rates, which was not long-lasting. It further seems that Norwegian economy is recuperating well in terms of exchange rates and stock prices.

There are several broader implications of my research. This paper shows how resilient Norwegian economy proved to be. This resilience can be ascribed to several aspects: the fact that Norway is an oil exporting country seems to play a beneficial role in mitigating the consequences of the crisis. What is probably more important, the economy is resilient due to its openness, which precludes speculation and spreading of rumors. The main implication of my research lies in the fact that the crisis seemed to have corrected informational inefficiency of the exchange and stock market, such that changes in one market can no longer enable investor to game the other market.

8.1 Limitations and future research

One major limitation of this paper is that I use main stock index as the proxy for the stock market. It can be very elucidating to divide the stock market into industries and test whether some industries like oil and gas influence exchange rates more than other industries like agriculture. Something similar has already been done in the past. See for example Japanese industry analysis by (Griffin & Stulz, 2001).

Another limitation of this paper is its choice of data for the beginning and the end of the latest financial crisis. The difficulties of choosing these dates are explained in detail above, but the choice still resembles guesswork.

Future research can fix these limitations by focusing on either stock prices from different industries or stock prices of Equinor, for example. Future research can also experiment with different dates for when the latest crisis began and ended and see how that may change the results.

Bibliography

Aalbers, M. (2009). Geographies of the financial crisis. *Area, 41*(1), 34-42.

Adler, M., & Dumas, B. (1984). Exposure to currency risk: definition and measurement. *Financial Management*, 41-50.

Ajayi, R. A., Friedman, J., & Mehdian, S. M. (1998). On the relationship between stock returns and exchange rates: tests of Granger causality. *Global finance journal, 9*(2), 241-251.

Ajayi, R. A., & Mougouė, M. (1996). On the dynamic relation between stock prices and exchange rates. *Journal of Financial Research, 19*(2), 193-207.

Alstad, G. E. (2010). The long-run exchange rate for NOK: a BEER approach.

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, 821-856.

Aydemir, O., & Demirhan, E. (2009). The relationship between stock prices and exchange rates: Evidence from Turkey. *International Research Journal of Finance and Economics, 23*(2), 207-215.

Bahmani-Oskooee, M., & Sohrabian, A. (1992). Stock prices and the effective exchange rate of the dollar. *Applied economics, 24*(4), 459-464.

Bai, J. (1997). Estimating multiple breaks one at a time. *Econometric theory, 13*(3), 315-352.

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47-78.

Bai, J., & Perron, P. (2003a). Computation and analysis of multiple structural change models. *Journal of applied econometrics, 18*(1), 1-22.

Bai, J., & Perron, P. (2003b). Critical values for multiple structural change tests. *The Econometrics Journal, 6*(1), 72-78.

Balassa, B. (1964). The purchasing-power parity doctrine: a reappraisal. *Journal of political economy, 72*(6), 584-596.

Bhattacharya, B. (2012). Causal relationship between stock market and exchange rate, foreign exchange reserves and value of trade balance in India: An empirical analysis.

Branson, W. H. (1983). A model of exchange-rate determination with policy reaction: evidence from monthly data: National Bureau of Economic Research Cambridge, Mass., USA.

Brown, K. C., Harlow, W. V., & Tinic, S. M. (1988). Risk aversion, uncertain information, and market efficiency. *Journal of Financial Economics, 22*(2), 355-385.

Carrera, J. E., Féliz, M., & Panigo, D. (2003). TESTING THE ORDER OF INTEGRATION WITH LOW POWER TESTS. AN APPLICATION TO ARGENTINE MACRO-VARIABLES. *Journal of Applied Economics, 6*(2).

Cecchetti, S. G. (2008a). *Crisis and responses: the Federal Reserve and the financial crisis of 2007-2008*. Retrieved from

Cecchetti, S. G. (2008b). Monetary policy and the financial crisis of 2007-2008. *CEPR Policy Insight, 21*.

Chamberlain, S., Howe, J. S., & Popper, H. (1997). The exchange rate exposure of US and Japanese banking institutions. *Journal of banking & finance, 21*(6), 871-892.

Chan, K. C., Karolyi, G. A., Longstaff, F. A., & Sanders, A. B. (1992). An empirical comparison of alternative models of the short-term interest rate. *The journal of Finance, 47*(3), 1209-1227.

Cheung, Y.-W., & Lai, K. S. (1995). Lag order and critical values of the augmented Dickey–Fuller test. *Journal of Business & Economic Statistics, 13*(3), 277-280.

Commission, F. C. I., & Commission, U. S. F. C. I. (2011). *The Financial Crisis Inquiry Report, Authorized Edition: Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States*: Public Affairs.

Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American Economic Review, 70*(5), 960-971.

Ellen, S. T., & Martinsen, K. (2016). Oil price shocks and the Norwegian effective exchange rate – an SVAR approach. Retrieved from http://static.norges-bank.no/contentassets/d0d21c7e8c8c4ae5b619569a435a8c63/staff-memo-16_2016.pdf?v=03/09/2017123402&ft=.pdf

Erkens, D. H., Hung, M., & Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of Corporate Finance, 18*(2), 389-411.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25*(2), 383-417.

Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American Economic Review, 71*(4), 545-565.

Flatner, A., & Xu, H. (2015). Which key figures move the foreign exchange market? Staff Memo. Retrieved from http://static.norges-bank.no/contentassets/5b705406836c413c8a961be199b8df24/staff_memo_eng_3_15.pdf?v=03/09/2017123138&ft=.pdf

Frankel, J. (1983). Monetary and portfolio-balanced models of exchange rate determinants: MIT Press, United States.

Frankel, J., & Saravelos, G. (2012). Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis. *Journal of International Economics, 87*(2), 216-231.

Frankel, J. A. (1979). On the mark: A theory of floating exchange rates based on real interest differentials. *The American Economic Review, 69*(4), 610-622.

Freddie Mac (Firm). (2007). Freddie Mac Announces Tougher Subprime Lending Standards to Help Reduce the Risk of Future Borrower Default : Company Also to Develop Model Subprime Mortgages. Retrieved from https://fraser.stlouisfed.org/scribd/?item_id=518857&filepath=/files/docs/historical/fct/freddiemac/freddiemac_pressrelease_20070227.pdf

Frenkel, J. A. (1976). A monetary approach to the exchange rate: doctrinal aspects and empirical evidence. *the scandinavian Journal of economics*, 200-224.

Gavin, M. (1989). The stock market and exchange rate dynamics. *Journal of International Money and Finance, 8*(2), 181-200.

Giles, J. A., & Mirza, S. (1999). Some pretesting issues on testing for Granger noncausality. *Department of Economics, University of Victoria.(Mimeographed.)*.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Granger, C. W. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and statistics, 48*(3), 213-228.

Granger, C. W., Huangb, B.-N., & Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: evidence from recent Asianflu☆. *The Quarterly Review of Economics and Finance, 40*(3), 337-354.

Griffin, J. M., & Stulz, R. M. (2001). International competition and exchange rate shocks: a cross-country industry analysis of stock returns. *The review of Financial studies, 14*(1), 215-241.

Grytten, O. H., & Hunnes, A. (2010). A chronology of financial crises for Norway.

Harrell, F. E. (2001). Ordinal logistic regression *Regression modeling strategies* (pp. 331-343): Springer.

Harris, R. I. (1995). Using cointegration analysis in econometric modelling.

Hayo, B. (1971). Applied econometrics.

Hedge Co (Firm). (2008). Bear Stearns – The domino effect that began with the hedge fund collapse. Retrieved from http://www.hedgeco.net/hedgeducation/hedge-fund-articles/bear-stearns-the-domino-effect-that-began-with-the-hedge-fund-collapse/

Ivanov, V., & Kilian, L. (2005). A practitioner's guide to lag order selection for VAR impulse response analysis. *Studies in Nonlinear Dynamics & Econometrics, 9*(1).

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters, 6*(3), 255-259.

Johansen, S. (1995). Identifying restrictions of linear equations with applications to simultaneous equations and cointegration. *Journal of econometrics, 69*(1), 111-132.

Johnson, H. G. (1972). The monetary approach to balance-of-payments theory. *Journal of financial and quantitative analysis, 7*(2), 1555-1572.

Johnston, J., & DiNardo, J. (1972). *Econometric methods* (Vol. 2): New York.

Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American economic review, 89*(3), 473-500.

Kaminsky, G. L., & Schmukler, S. L. (1999). What triggers market jitters?: A chronicle of the Asian crisis. *Journal of international money and Finance, 18*(4), 537-560.

Kilian, L., & Lütkepohl, H. (2017). *Structural vector autoregressive analysis*: Cambridge University Press.

Kim, W., & Wei, S.-J. (2002). Foreign portfolio investors before and during a crisis. *Journal of International Economics, 56*(1), 77-96.

Kohler, M. (2010). Exchange rates during financial crises.

Kriesi, H., & Pappas, T. S. (2015). *European populism in the shadow of the great recession*: Ecpr Press Colchester.

Lin, C.-H. (2012). The comovement between exchange rates and stock prices in the Asian emerging markets. *International Review of Economics & Finance, 22*(1), 161-172.

Lütkepohl, H. (2011). Vector autoregressive models *International Encyclopedia of Statistical Science* (pp. 1645-1647): Springer.

Ma, C. K., & Kao, G. W. (1990). On exchange rate changes and stock price reactions. *Journal of Business Finance & Accounting, 17*(3), 441-449.

MacDonald, R., & Taylor, M. P. (1992). Exchange rate economics: a survey. *Staff Papers, 39*(1), 1-57.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25*(2), 383-417.

Martinsen, K. (2017). Norges Bank's BEER models for the Norwegian effective exchange rate. Retrieved from http://static.norges-bank.no/contentassets/d98b46b49ba44702b30773772c040f08/staff_memo_7_2017.pdf?v=09/06/2017114854&ft=.pdf

McQuarrie, A., Shumway, R., & Tsai, C.-L. (1997). The model selection criterion AICu. *Statistics & probability letters, 34*(3), 285-292.

Mishkin, F. S. (1992). Anatomy of a financial crisis. *Journal of evolutionary Economics, 2*(2), 115-130.

Morley, B., & Pentecost, E. J. (2000). Common trends and cycles in G-7 countries exchange rates and stock prices. *Applied Economics Letters, 7*(1), 7-10.

Muhammad, N., Rasheed, A., & Husain, F. (2002). Stock Prices and Exchange Rates: Are they Related? Evidence from South Asian Countries [with Comments]. *The Pakistan Development Review*, 535-550.

Nieh, C.-C., & Lee, C.-F. (2002). Dynamic relationship between stock prices and exchange rates for G-7 countries. *The Quarterly Review of Economics and Finance, 41*(4), 477-490.

Obstfeld, M. (1996). Models of currency crises with self-fulfilling features. *European economic review, 40*(3-5), 1037-1047.

Pan, M.-S., Fok, R. C.-W., & Liu, Y. A. (2001). *Dynamic linkages between exchange rates and stock prices: evidence from Pacific Rim countries*. Retrieved from

Phylaktis, K., & Ravazzolo, F. (2005). Stock prices and exchange rate dynamics. *Journal of International Money and Finance, 24*(7), 1031-1053.

Purfield, M. C., & Rosenberg, M. C. B. (2010). *Adjustment under a currency peg: Estonia, Latvia and Lithuania during the global financial crisis 2008-09*: International Monetary Fund.

Rahman, M. L., & Uddin, J. (2009). Dynamic relationship between stock prices and exchange rates: Evidence from three South Asian countries. *International Business Research, 2*(2), 167.

Ramasamy, B., & Yeung, M. C. (2005). The causality between stock returns and exchange rates: revisited. *Australian Economic Papers, 44*(2), 162-169.

Sigurjonsson, T. O., & Mixa, M. W. (2011). Learning from the “worst behaved”: Iceland's financial crisis and the Nordic comparison. *Thunderbird International Business Review, 53*(2), 209-223.

Sims, C. A. (1972). Money, income, and causality. *The American Economic Review, 62*(4), 540-552.

Sjö, B. (2008). Testing for unit roots and cointegration. *Lectures in Modern Econometric Time series Analysis*.

Solnik, B. (1987). Using financial prices to test exchange rate models: A note. *The journal of Finance, 42*(1), 141-149.

Sundqvist, E. (2002). *An empirical investigation of the International Fisher Effect*.

Ulvedal, P. B., & Vonen, N. H. (2016). Pass-through from exchange rate movements to consumer prices. Retrieved from http://static.norges-bank.no/contentassets/1638c1f7840f41288e1ab7e8f2af59ac/staff_memo_3_2016_en.pdf?v=03/09/2017123314&ft=.pdf

Urrutia, J. L. (1995). Tests of random walk and market efficiency for Latin American emerging equity markets. *Journal of Financial Research, 18*(3), 299-309.

Wang, X. (2015). An Empirical Analysis of Lead-Lag Relationship among Various Financial Markets. *Accounting and Finance Research, 4*(2), 60.

Wu, Y. (2001). Exchange rates, stock prices, and money markets: evidence from Singapore. *Journal of Asian Economics, 12*(3), 445-458.

Yang, S.-Y., & Doong, S.-C. (2004). Price and volatility spillovers between stock prices and exchange rates: empirical evidence from the G-7 countries. *International Journal of Business and Economics, 3*(2), 139.

Appendix A: Descriptive statistics

Table 7: Descriptive statistics for *monthly* data.

Before crisis	Exchange rates	Stock prices	Oil	Interest rates
Mean	2.084547	5.395073	3.614145	1.474433
Median	2.091433	5.280794	3.451176	1.698290
Maximum	2.171924	6.236914	4.584495	2.126564
Minimum	1.987444	4.642562	2.737758	0.637106
Std. Dev.	0.036477	0.439828	0.467085	0.495906
Skewness	-0.720037	0.466619	0.339990	-0.475056
Kurtosis	3.879679	2.093304	1.940336	1.623174
Jarque-Bera	13.05172	7.759727	7.265783	12.82582
Probability	0.001465	0.020654	0.026440	0.001640
Sum	229.3002	593.4580	397.5560	162.1876
Sum Sq. Dev.	0.145031	21.08594	23.78035	26.80555
Observations	110	110	110	110

During crisis	Exchange rats	Stock prices
Mean	2.119944	5.808885
Median	2.098195	5.872103
Maximum	2.238543	6.207451
Minimum	2.062553	5.362148
Std. Dev.	0.051197	0.236848
Skewness	0.656334	-0.490040
Kurtosis	2.168834	2.246740
Jarque-Bera	3.419736	2.164606
Probability	0.180890	0.338814
Sum	72.07808	197.5021
Sum Sq. Dev.	0.086496	1.851201
Observations	34	34

After crisis	Exchange rates	Stock prices	Oil	Interest rates
Mean	2.127562	6.292506	4.335249	0.358874
Median	2.120452	6.329882	4.604511	0.471631
Maximum	2.286582	6.691542	4.831103	1.060655
Minimum	1.991142	5.876964	3.409378	-0.494296
Std. Dev.	0.088971	0.209335	0.410929	0.415416
Skewness	0.060062	-0.171397	-0.407700	-0.238604
Kurtosis	1.561970	2.059486	1.605804	2.106136
Jarque-Bera	7.288264	3.507261	9.130316	3.593522
Probability	0.026144	0.173144	0.010408	0.165835
Sum	178.7152	528.5705	364.1609	30.14545
Sum Sq. Dev.	0.657022	3.637141	14.01561	14.32332
Observations	84	84	84	84

Table 8: Descriptive statistics for *daily* data.

Before crisis	Exchange rates	Stock prices	Oil	Interest rates
Mean	2.081015	5.394924	3.693279	1.517400
Median	2.085983	5.277775	3.510500	1.551809
Maximum	2.181547	6.262197	4.969466	1.985131
Minimum	1.977201	4.590767	2.803966	0.916291

Std. Dev.	0.035400	0.436996	0.490506	0.318911
Skewness	-0.749730	0.457699	0.489679	-0.250224
Kurtosis	3.969002	2.109985	2.154213	1.703684
Jarque-Bera	291.1109	148.8807	152.9376	176.3539
Probability	0.000000	0.000000	0.000000	0.000000
Sum	4561.586	11825.67	8095.667	3326.140
Sum Sq. Dev.	2.745638	418.4060	527.1466	222.8342
Observations	2192	2192	2192	2192

During crisis	Exchange rates	Stock prices	Oil	Interest rates
Mean	2.119572	5.812935	4.294652	1.034337
Median	2.101570	5.876306	4.325589	0.985817
Maximum	2.297070	6.259386	4.958851	1.688249
Minimum	2.041480	5.237660	3.531055	0.662688
Std. Dev.	0.053780	0.235412	0.279760	0.220447
Skewness	0.689959	-0.533345	-0.410615	1.358575
Kurtosis	2.709156	2.392838	2.925937	4.362997
Jarque-Bera	55.93402	42.36958	19.12234	259.8938
Probability	0.000000	0.000000	0.000070	0.000000
Sum	1430.711	3923.731	2898.890	698.1774
Sum Sq. Dev.	1.949408	37.35241	52.75109	32.75429
Observations	675	675	675	675

After crisis	Exchange rates	Stok prices	Oil	Interest rates
Mean	2.131374	6.294631	4.323744	0.095560
Median	2.126444	6.339013	4.567572	0.239017
Maximum	2.299962	6.711947	4.853123	1.098612
Minimum	1.983756	5.780558	3.258481	-0.941609
Std. Dev.	0.089384	0.210019	0.411730	0.453540
Skewness	-0.030126	-0.199687	-0.363218	-0.102036
Kurtosis	1.580099	2.094666	1.605649	1.952179
Jarque-Bera	139.6152	67.68236	170.8717	78.77304
Probability	0.000000	0.000000	0.000000	0.000000
Sum	3535.950	10442.79	7173.091	158.5343
Sum Sq. Dev.	13.24649	73.13077	281.0669	341.0475
Observations	1659	1659	1659	1659

Appendix B: Full tables for data before crisis

Table 9: Stationarity tests for *monthly* data before crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-3.263 (12)	-3.245 (12)	-2.672 [1]	-2.627 [2]	0.112*** [8]	0.110*** [8]
Stocks	-0.677 (12)	-1.404 (12)	-0.501 [3]	-1.250 [3]	0.840*** [9]	0.245*** [9]
Oil price	-0.291 (2)	-1.779 (2)	-0.625 [7]	-2.401 [1]	1.118*** [9]	0.206*** [8]
Interest rates	-2.018 (6)	-2.529 (6)	-1.441 [8]	-0.456 [7]	0.619*** [9]	0.171*** [9]
First Difference						
Exchange rates	-5.846*** (8)	-5.807*** (8)	-7.756*** [8]	-7.751*** [8]	0.105 [4]	0.070 [5]
Stocks	-7.088*** (0)	-7.060*** (0)	-7.048*** [4]	-7.014*** [4]	0.174** [3]	0.137 [3]
Oil price	-9.112*** (1)	-9.082*** (1)	-10.779*** [7]	-10.735*** [8]	0.091** [9]	0.080 [9]
Interest rates	-8.785*** (3)	-8.750*** (3)	-5.211*** [4]	-5.491*** [4]	0.326 [8]	0.144 [41]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets [...] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion*

Table 10: Stationarity tests for *daily* data before crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-2.763 (26)	-2.767 (26)	-2.478 [8]	-2.485 [8]	0.356*** [35]	0.335*** [8]
Stocks	-0.335 (0)	-1.109 (0)	-0.389 [11]	-1.168 [11].	4.034*** [39]	1.163*** [9]
Oil price	0.148 (12)	-2.164 (0)	-0.130 [4]	-2.196 [6]	5.767*** [35]	0.939*** [38]
Interest rates	-1.180 (2)	-0.873 (2)	-1.174 [18]	-0.842 [18]	3.183*** [35]	1.153*** [35]
First Difference						
Exchange rates	-23.92*** (3)	-23.93*** (3)	-43.90*** [6]	-43.89*** [7]	0.043 [6]	0.039 [6]
Stocks	-47.46***	-47.45***	-47.52***	-47.51***	0.202	0.155

	(0)	(0)	[11]	[11]	[11]	[11]
Oil price	-46.21*** (0)	-46.23*** (0)	-46.21*** [4]	-46.23*** [3]	0.155 [5]	0.028 [4]
Interest rates	-30.92*** (1)	-30.93*** (1)	-41.44*** [19]	-41.45*** [19]	0.300 [18]	0.191 [18]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets [...] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion.*

Table 11: Johansen-Juselius Cointegration test for *monthly* data before crisis.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	78.759***	38.084**	69.818	33.876
r ≤ 1	54.975**	29.838**	47.856	27.584
r ≤ 2	20.837	11.263	29.797	21.131
r ≤ 3	9.574	8.564	15.494	14.264

*Note: *** and ** denote significance at 1% and 5% levels, respectively.*

Table 12: Johansen-Juselius Cointegration test for *daily* data before crisis.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	29.295***	11.530	29.174	14.849
r ≤ 1	17.764***	9.554	15.304	9.834
r ≤ 2	8.209***	8.199***	5.444	4.855
r ≤ 3	0.010**	0.010	0.093	0.919

*Note: *** and ** denote significance at 1% and 5% levels, respectively.*

Table 13: VECM coefficients for *monthly* data before crisis.

Monthly data	Exchange rates		Stock prices	
Constant	0.000	(0.120)	0.005	(1.003)
Error correction term	-0.011***	(-4.960)	0.003	(0.347)
Δ Exchange rate (1 lag)	-0.045	(-0.391)	1.164**	(2.433)
Δ Exchange rate (2 lags)	-0.375**	(-3.328)	0.372	(0.798)
Δ Exchange rates (3 lag)	-0.004	(-0.039)	0.761	(1.593)
Δ Exchange rates (4 lag)	-0.241**	(-2.025)	1.293**	(2.624)
Δ Exchange rates (5 lag)	-0.175	(-1.456)	0.756	(1.521)
Δ Exchange rates (6 lag)	-0.236	(-2.085)	-0.171	(-0.365)
Δ Stock prices (1 lag)	0.068**	(2.141)	0.228*	(1.737)
Δ Stock prices (2 lags)	0.045	(1.338)	-0.120	(-0.845)
Δ Stock prices (3 lags)	0.023	(0.703)	0.003	(0.024)
Δ Stock prices (4 lags)	0.035	(1.093)	-0.115	(-0.876)
Δ Stock prices (5 lags)	0.049	(1.534)	0.233*	(1,758)
Δ Stock prices (6 lags)	0.032	(1.114)	-0.150	(-1.239)
F-statistic for exchange rate lags	(2.894**)	[0.014]	(3.315***)	[0.006]
F-statistic for stock prices lags	(2.321**)	[0.042]	(1.168)	[0.333]

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (...) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis [...] are p-values. Δ Exchange rates are the change in* *monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices are the change in the monthly closing stock index.*

Table 14: VECM coefficients for *daily* data before crisis.

Daily	Exchange rates		Stock prices	
Constant	0.000	(0.009)	0.000	(0.000)
Error correction term	-0.001*	(-0.723)	-0.002	(-1.745)
Δ Exchange rate (1 lag)	-0.001	(-0.054)	-0.380	(-0.436)
Δ Exchange rate (2 lags)	-0.045	(-1.752)	-0.068	(-0.782)
Δ Exchange rates (3 lag)	-0.050	(-1.969)	0.029	(0.337)
Δ Exchange rates (4 lag)	-0.048	(-1.843)	0.074	(0.861)
Δ Exchange rates (5 lag)	-0.132	(0.505)	0.008	(0.960)
Δ Exchange rates (6 lag)	0.002	(0.107)	-0.109	(-1.245)
Δ Exchange rates (7 lag)	0.033	(1.290)	-0.053	(-0.604)
Δ Exchange rates (8 lag)	0.003	(0.133)	-0.113	(-1.284)
Δ Exchange rates (9 lag)	0.009	(0.348)	0.072	(0.815)
Δ Exchange rates (10 lag)	0.023	(0.912)	0.140	(1.586)
Δ Exchange rates (11 lag)	-0.020	(-0.802)	-0.035**	(-0.405)
Δ Exchange rates (12 lag)	-0.007	(-0.281)	0.113	(1.292)
Δ Stock prices (1 lag)	-0.009	(-1.187)	0.036	(1.423)
Δ Stock prices (2 lags)	0.016**	(2.188)	0.063**	(2.490)
Δ Stock prices (3 lags)	0.005	(0.728)	-0.022	(-0.882)
Δ Stock prices (4 lags)	0.016**	(2.131)	0.052*	(2.055)
Δ Stock prices (5 lags)	0.002	(0.297)	-0.026	(0.296)
Δ Stock prices (6 lags)	0.004	(0.632)	0.014	(0.557)
Δ Stock prices (7 lags)	0.000	(0.023)	-0.003	(-0.123)
Δ Stock prices (8 lags)	-0.001	(-0.142)	0.029	(1.172)
Δ Stock prices (9 lags)	-0.000	(-0.129)	0.059	(2.376)
Δ Stock prices (10 lags)	0.000	(0.093)	-0.042	(-1.682)
Δ Stock prices (11 lags)	-0.007	(-0.945)	0.030	(1.203)
Δ Stock prices (12 lags)	0.005	(0.756)	-0.017	(-0.716)
F-statistic for exchange rate lags	(1.187**)	[0.028]	0.932**	[0.050]
F-statistic for stock prices lags	(1.180**)	[0.029]	2.212***	[0.009]

*Note: *** and ** denote significance at 1% and 5% levels, respectively. Figures in parenthesis (…) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis […] are p-values. Δ Exchange rates are the change in monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices are the change in the monthly closing stock index.*

Table 15: Correlation, homoskedasticity, normality for *monthly* data before crisis.

Breusch-Godfrey Serial Correlation test Ho: no serial correlation	
Observations r2	3.484 (0.746)

Normality test Ho: normally distributes	
Jarque-Bera	1.803 (0.405)

ARCH Heteroskedasticity test Ho: homoskedasticity	
Observations r2	3.375 (0.760)

Note: Figures in parenthesis (...) indicate p-values

Table 16: Correlation, homoskedasticity, normality for *daily* data before crisis.

Breusch-Godfrey Serial Correlation test Ho: no serial correlation	
Observations r2	1.008 (0.603)

Normality test Ho: normally distributes	
Jarque-Bera	1.562 (0.588)

ARCH Heteroskedasticity test Ho: homoskedasticity	
Observations r2	2.416 (0.1201)

Note: Figures in parenthesis (...) indicate p-values

Appendix C: Full tables for data during crisis

Table 17: Stationarity tests for *monthly* data during crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-1.201 (0)	-1.982 (1)	-1.394 [2]	-1.599 [0]	0.228*** [4]	0.160*** [4]
Stocks	-2.077 (1)	-2.610 (5)	-1.503 [3]	-1.457 [2]	0.164*** [4]	0.141*** [4]
First Difference						
Exchange rates	-2.903*** (3)	-3.939** (1)	-4.165*** [1]	-4.315*** [0]	0.241 [2]	0.097 [0]
Stocks	-3.221** (1)	-2.111* (3)	-3.289** [1]	-3.531* [1]	0.199 [3]	0.080 [2]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (…) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets […] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion.*

Table 18: Stationarity tests for *daily* data before crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-1.406 (0)	-2.836 (0)	-1.405 [3]	-2.838 [3]	1.974*** [21]	0.308*** [21]
Stocks	-1.132 (7)	-1.341 (7)	-1.204 [16]	-1.391 [17]	0.588*** [22]	0.497*** [22]
Oil price	-0.688 (4)	-3.151* (0)	-1.673 [5]	-3.185* [9]	1.060*** [21]	0.266*** [21]
Interest rates	-2.875* (1)	-2.033 (1)	-3.102** [8]	-2.083 [8]	1.359*** [21]	0.335*** [21]
First Difference						
Exchange rates	-26.17*** (0)	-26.21*** (0)	-26.19*** [5]	-26.24*** [6]	0.160 [5]	0.059 [6]
Stocks	-9.897*** (6)	-10.01*** (6)	-26.90*** [17]	-26.99*** [18]	0.330 [17]	0.094 [19]
Oil price	-11.33*** (3)	-11.66*** (3)	-26.63*** [4]	-26.88*** [7]	0.708 [5]	0.211** [9]
Interest rates	-23.14*** (0)	-23.29*** (0)	-23.04*** [10]	-23.18*** [13]	0.548 [6]	0.081 [9]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (…) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets […] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion.*

Table 19: Johansen-Juselius Cointegration test for *monthly* data during crisis.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	10.138	7.269	15.494	14.264
r ≤ 1	2.869	2.869	3.841	2.841

*Note: *** and ** denote significance at 1% and 5% levels, respectively.*

Table 20: Johansen-Juselius Cointegration test for *daily* data before crisis.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	47.522	24.091	47.856	27.584
r ≤ 1	23.431	16.693	29.797	21.131
r ≤ 2	6.738	6.575	15.494	14.264
r ≤ 3	0.162	0.162	3.841	3.841

*Note: *** and ** denote significance at 1% and 5% levels, respectively.*

Appendix D: Full tables for data after crisis

Table 21: Unit root tests for *monthly* data after crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-0.292 (1)	-2.704 (1)	-0.059 [1]	-2.300 [1]	1.028*** [7]	0.137*** [6]
Stocks	0.041 (0)	-2.527 (0)	-0.038 [3]	-2.641 [1]	1.058*** [7]	0.104*** [6]
Oil price	-1.478 (1)	-1.928 (1)	-0.925 [0]	-1.645 [1]	0.922*** [7]	0.142*** [6]
Interest rates	-0.042 (2)	-3.303* (3)	-0.574 [3]	-3.942* [4]	1.096*** [7]	0.125*** [6]
First Difference						
Exchange rates	-6.365*** (0)	-6.419*** (0)	-6.154*** [4]	-6.202*** [4]	0.162* [1]	0.072 [2]
Stocks	-5.554*** (2)	-5.642*** (2)	-8.047*** [4]	-8.077*** [5]	0.118 [3]	0.076 [4]
Oil price	-6.151*** (0)	-6.136*** (0)	-5.920*** [6]	-5.894*** [6]	0.202 [0]	0.199 [0]
Interest rates	-9.134*** (1)	-9.100*** (1)	-10.649*** [2]	-10.370*** [1]	0.052 [2]	0.044 [2]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets [...] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion.*

Table 22: Unit root tests for *daily* data after crisis.

	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)		Kwiatkowski-Phillips-Schmidt-Shin (KPSS)	
	Ho: has unit root		Ho: has unit root		Ho: stationary	
Level						
Variable	Constant without trend	Constant with trend	Constant without trend	Constant with trend	Constant without trend	Constant with trend
Exchange rates	-0.859 (0)	-3.277* (0)	-0.764 [10]	-3.120 [7]	4.871*** [32]	0.419*** [32]
Stocks	0.222 (5)	-2.950 (5)	-0.195 [19]	-3.130* [15]	4.723*** [33]	0.329*** [32]
Oil price	-1.528 (0)	-1.274 (0)	-1.548 [9]	-1.395 [9]	4.357*** [32]	0.201*** [32]
Interest rates	-2.412 (1)	-2.904 (1)	-2.242 [14]	-2.613 [12]	4.063*** [32]	0.382*** [32]
First Difference						
Exchange rates	-40.71*** (0)	-40.72*** (0)	-40.88*** [11]	-40.87*** [11]	0.074 [10]	0.055 [10]
Stocks	-21.26*** (4)	-21.28*** (4)	-41.79*** [19]	-41.83*** [20]	0.107 [19]	0.054 [19]

Oil price	-38.18*** (0)	-38.19*** (0)	-38.14*** [6]	-38.16*** [5]	0.157 [9]	0.086 [9]
Interest rates	-36.14*** (0)	-36.15*** (1)	-35.96*** [17]	-38.98*** [17]	0.123 [14]	0.057 [14]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) represent optimum lag length selected based on Akaike Info Criterion. Figures in brackets [...] represent the Bandwidth used in PP and KPSS tests selected based on the Newey-West Bandwidth criterion.*

Table 23: Johansen-Juselius Cointegration test for *monthly* data.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	79.605***	32.020*	69.818	33.876
r ≤ 1	47.584*	25.807*	47.856	27.584
r ≤ 2	21.777	13.143	29.797	21.131
r ≤ 3	8.633	8.552	15.494	14.264

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.*

Table 24: Johansen-Juselius Cointegration test for *daily* data.

Hypothesized No. of CE(s)	Trace Statistic	Max-Eigen Statistic	Critical Values (5%)	
			Trace	Max-Eigen
r = 0	45.108***	28.486**	25.656	12.716
r ≤ 1	16.622*	9.855**	12.810	8.059
r ≤ 2	6.766*	6.594*	4.043	3.588
r ≤ 3	0.174*	0.171*	0.015	0.015

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.*

Table 25: VECM coefficients for *monthly* data after crisis.

	Exchange rates		Stock prices	
Constant	0.002	(1.447)	0.011**	(2.173)
Error correction term	-0.030	(-1.434)	-0.120**	(-2.265)
Δ Exchange rate (1 lag)	0.327**	(2.250)	0.185	(0.511)
Δ Exchange rate (2 lags)	-0.103*	(-0.674)	0.047	(0.123)
Δ Exchange rates (3 lag)	0.126	(0.856)	-0.435	(-1.180)
Δ Exchange rates (4 lag)	-0.198	(-1.371)	0.353	(0.976)
Δ Stock prices (1 lag)	0.062	(1.177)	-0.091	(-0.686)
Δ Stock prices (2 lags)	-0.042	(-0.805)	0.090	(0.685)
Δ Stock prices (3 lags)	-0.043	(-0.814)	-0.165	(-1.235)
Δ Stock prices (4 lags)	0.012	(0.227)	-0.107	(-0.804)
F-statistic for exchange rate lags	(1.670)	[0.169]	(0.592)	[0.669]
F-statistic for stock prices lags	(0.678)	[0.609]	(0.703)	[0.592]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis […] are p-values. Δ Exchange rates is the change in monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices is the change in the monthly closing stock index.*

Table 26: VECM coefficients for *daily* data after crisis.

	Exchange rates		Stock prices	
Constant	0.000	(0.000)	0.001	(0.005)
Error correction term	-0.001	(-1.068)	-0.001*	(-2.310)
Δ Exchange rate (1 lag)	-0.055**	(-2.045)	0.023	(0.385)
Δ Exchange rate (2 lags)	-0.004	(0.171)	0.037	(0.632)
Δ Stock prices (1 lag)	0.007	(0.625)	0.011	(0.433)
Δ Stock prices (2 lags)	-0.013	(-1.172)	-0.029	(-1.168)
F-statistic for exchange rate lags	(2.128)	[0.119]	(0.262)	[0.769]
F-statistic for stock prices lags	(0.870)	[0.418]	(0.768)	[0.464]

*Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis (...) are t-statistics. F-statistic is the partial F-statistic testing for the joint significance of the lags on the right-hand side variables. Figures in parenthesis* […] *are p-values. Δ Exchange rates is the change in monthly foreign exchange rate, measured in terms of local currency. Δ Stock prices is the change in the monthly closing stock index.*

Table 27: Correlation, homoscedasticity, normality for *monthly* data after crisis.

Breusch-Godfrey Serial Correlation test Ho: no serial correlation	
Observations r2	5.125 (0.274)

Normality test Ho: normally distributed	
Jarque-Bera	0.998 (0.606)

ARCH Heteroskedasticity test Ho: homoskedasticity	
Observations r2	5.561 (0.234)

Note: Figures in parenthesis (...) indicate p-values

Table 28: Correlation, homoscedasticity, normality for daily data after crisis.

Breusch-Godfrey Serial Correlation test Ho: no serial correlation	
Observations r2	0.026 (0.986)

Normality test Ho: normally distributed	
Jarque-Bera	0.208 (0.509)

ARCH Heteroskedasticity test Ho: homoskedasticity	
Observations r2	10.787 (0.793)

Note: Figures in parenthesis (...) indicate p-values