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A Survey of Risk and Ambiguity: An Application to the GARCH(1,1) Model with Exchange Rate Data.

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En studie av risiko og usikkerhet med andvendelse i en GARCH(1,1) model med valuta data.

Author:		ADVISOR:
Student number: 210487	Name: Eduardo Villegas	Mr. Lorán Chollete

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Preface and Acknowledgements

This thesis is submitted for the fulfillment of a 2-year master's program in risk management in the fields of business, finance and economics. It represents 30 ECTS credits (one semester) and was conducted on a full-time basis at the UiS Business School. The degree consists of a total of 120 ECTS credits.

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Thanks is also directed to the Norwegian branch of the SAS Institute for granting access to their software during the duration of this thesis. Although, learning SAS programming has been somewhat of a carousel experience, it would have been difficult to carry out the formal testing without the adequate software at hand. I plan to expand on this experience, once I recover from this work ☺.

Also, many thanks to friends and family for their support and patience in listening to my loud and endless debates of economic theory. Hopefully, you have gained something too!

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Abstract

The assumption of *normality* in many risk management models is not always representative of the *sample* distribution at hand. Applying a uniform approach to a non-uniform population can produce biased and unreliable estimators that can have adverse effects to the consequences of decision-making. Since advancements in both research and statistical tools enable models to be more flexible than before, the purpose of this text is to examine to what extend this can be verified using exchange rate data, which is often characterized by the pronounced leptokurtosis and volatility that is found in such time series. Two GARCH(1,1) models are constructed for each of the three exchange rates in the study; one using the normal distribution, and the other using Student's *t* distribution. The proxy for differences in the dynamics as implied by both approaches is translated in the parameter for persistence. Results support that a distribution with more mass in the tails is superior to the normal distribution for the three exchange rate returns in the study, as defined by information criteria. Also, the persistent parameter is different in all accounts between the two distribution approaches: the estimated persistence using Student's *t* distribution is higher for USD/NOK and USD/YEN, but lower for USD/EUR, compared to estimates using the normal distribution. While these findings cannot be generalized asymptotically, they illustrate the deviation in parameter estimation due to different methodological assumptions, and promote a multidisciplinary approach to problem solving.

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1 Introduction

1.1 Context and Background

Floating [1] capital markets are believed to be efficient operators, reflecting the underlying economic conditions that prevail. This amplification can at best stimulate economic growth and prosperity in one end, and economic decline and loss in the other end. It seems that the increasingly integrated financial markets around the world can only add further to this amplification. For example, in the wake of the credit crunch and market turmoil that followed 2007/2008, it became apparent that globalisation had spread to a level were economies had become integrated to such an extent that a change in some financial value in one part of the world, could have a sudden and severe impact on another *distinct* financial value at another end of the world. With the right motivation, it seemed, markets had a great ability to move together in the same direction. But what was it that caused so many buyers and sellers to make such different valuations to what they had only recently done? Did economic agents not follow economic models? Or could it be that we did not have the adequate models to describe and guide in the given situation? Efficient market hypothesis (EMH) *aficionados* may rightly claim that the re-evaluation of market prices during such a short interval was ultimately due to the introduction and formation of new information. However, if we look beyond EMH theory and a re-calibrate the question to ask how economic agents could avoid being caught so surprisingly by new information, we may encounter theories that may vary in complexity. Assuming economic agents are optimisers, whilst acknowledging that a considerable part of the ex-ante 2007/2008 decision-making in financial markets was less than optimal, given the way market conditions as a whole developed, not forgetting the arguable element

[1] Although, *floating* is used to denote the exchange rate regime since the abolition of the Bretton Woods system, the term is also used intentionally as oppose to *free* (markets), to distinguish that a market may take a number of *n* (continuous) directions, but may still be subject to (government) intervention if *sinking* is occurring or believed to occur, and *sinking* is defined as *not* preferable. *Free* (markets) is thus treated more in a utopian sense. This point is maybe best seen as part of the euro (currency) crisis that is currently being negotiated.

of surprise, then a re-evaluation of risk and uncertainty perceptions, and the methods to process these, may be inevitable in finding suitable answers.

The foreign exchange (FX) market is today the world's largest financial market, operating twenty-four hours a day. In a triennial report on FX activity, BIS (2010) reports that the global FX *daily* trade in April 2010 amounted to $4.0 trillion, up 20% from the $3.3 trillion in April 2007. Also, ECB (2008) state that international capital flows alone have increased faster than product trade. Although, it may seem that currency *trading* may have been less affected by the financial crisis, currency *price* movements are *not* without implications for policymakers and individual agents, in their quest for macroeconomic stability and easy access to capital markets (for the financing of projects). This ancient relation between risk and reward has led to growth in financial products that offer some form of hedge, or insurance, against future developments that may have an adverse effect on investments. However, even a complete *bulletproof* hedge will, more often than not, not come without some price, or cost if you like, that may itself vary. Hence, although this may be a question of weighing marginal cost against marginal gain, the introduction of uncertainty may require a different tool set than that in a setting with full information, as getting the uncertainty element wrong can have devastating consequences that may be unknown at the time of decision. In this regard, the anatomy is maybe best described in that a future event is not fully disclosed until some time, t+1, is realised. By its very nature, this introduces an element of *uncertainty* about some future prospect, since an event cannot be factually described until it is a real outcome in the past. Thus, for an investor who wishes to maximise profits it may be natural to approach uncertainty through some risk mitigation process. Once the investor has formalised a risk profile, a selection of potential investments can be considered. If transaction costs and other operational costs are ruled out, this selection process typically involves targeting the *variance* of an asset in order to deem weather the asset can add value or not. Variance or the measure of volatility if you like, is a popular proxy for risk given

- investors care about volatility as high levels could indicate potential large losses or gains, and as such greater uncertainty, which again can make financial planning increasingly difficult (Gujarati, 2003).

- variance is often a key component in valuation of (risk related) securities such as credit or derivatives; ceteris paribus, prices for both these products may be relatively higher in volatile markets compared to when markets are less volatile (Gujarati, 2003).
- variance is also used in other calculations relating to uncertainty, such as value at risk (VaR).

At this point it may be worthwhile to note that the assumption of a constant variance might have to be relaxed as it may be deemed inappropriate for a time series that demonstrates large and rapid change in volatility across periods (Enders, 2010). Since exchange rate data is believed to display such *time varying volatility*, or *volatility clustering*[2] (Dannenburg and Jacobsen, 2003), it has been pivotal in reaching an applicable model that it has the ability to capture such attributes. The GARCH model is one such model as it is first and foremost designed to address such volatility clustering (Cont, 2005). Also, another feature that might be considered as a proxy for risk is the GARCH model's ability to measure *persistence*. This may be interesting since depending on an investor's horizon for a given investment, shocks can introduce a variety of changes to the underlying economic conditions, such as a change to an assets (cap)ability to liquidate. This is cited as an essential part of the credit crunch that eventually led to the financial crisis[3].

Relying solely on historical data as a mirror for the future has received criticism for being too backward looking, where qualitative data has been seen as more of a forward looking input (BIS, 2006). However, since both approaches mostly rely on computation and ultimately an *estimate*, one way to approach uncertainty may be to create confidence in the risk analysis[4]. This is likely to be of particular importance

[2] As per Mandelbrot (1963) volatility clustering can be explained in that "[…] large changes tend to be followed by large changes - of either sign - and small changes tend to be followed by small changes […]". This phenomenon is also referred to as conditional *heteroscedasticity*.

[3] Please see Chollete (2011) for an informative model of the co-formation of extreme events due to congestion.

[4] Please see Andersen and Häger (2011) for a discussion on objectivity, risk measurement, and creating confidence in the analysis process.

since in order to manage risk to a decent standard, it is likely to be beneficial to understand *what* is to be managed in order to apply efficient risk management tools. In the currency rate example, this means that understanding currency prices can be paramount in order to grasp the exposure that a given economic agent may be subject to.

In both Engle's (1982) and Bollerslev's (1986) original papers on ARCH and GARCH models, respectively, normality was assumed. These authors were, however, not unique in doing so as applying the normality assumption seem to almost have been an "*industry standard"* in many respects. Although the framework has been cited as overly simplistic, its popularity can be explained by the ease of implementation. However, since a given distribution carries certain properties inherent in the methodology, applying a distribution that does not adequately mirror the residuals of the sample can bias the risk management process altogether as it may produce unreliable estimates.

1.2 Educational Purpose

As discussed earlier, decision-making under uncertainty is likely to occur given full information is a scarce good that may not always be fully accessible in any circumstance, yet a decision must be made; be it do nothing or take some new action. As such, this study is motivated by two main questions:

1. How does the literature describe choice and decision under uncertainty? and
2. How can such research be informative to risk management in a GARCH(1,1) framework?

1.3 Overview of this Text

This text is organized in the following way. Section 2 provides a review of the literature on risk and uncertainty. Section 3 describes the data that has been utilized.

Section 4 introduces the econometric considerations, whilst section 5 presents the results together with discussion. Section 6 provides the summary and conclusion.

2 Literature Review

This section starts by introducing the terminology that is often used in the literature to distinguish various definitions of *uncertainty*, before reviewing the theoretical literature on economics and uncertainty.

2.1 Terminology

unˈcertainty, n.;

The quality of being uncertain in respect of duration, continuance, occurrence, etc.; liability to chance or accident. Also, the quality of being indeterminate as to magnitude or value; the amount of variation in a numerical result that is consistent with observation. (OED, 2012)

The above is retrieved from one of the Oxford English Dictionary's (OED) many descriptions on *uncertainty*. In the literature, and in general for that sake, we may encounter a variety of perceptions and definitions associated with the term *uncertainty* to such an extent that the definition of *uncertainty* itself can become somewhat uncertain. For that reason, some sciences have a more profound need to specify and explain this term than do others, e.g. psychology as oppose to accounting, i.e. two subjects could encounter uncertainty in one way or the other, but may have a completely different usage and thus approach to the term. Nonetheless, although we might not evoke too much harm if we put forward the OED description in describing *uncertainty*, it may be useful to reach some formalisation in more detail to promote healthy discussion.

We could say that everything we do *not* know with certainty is uncertain. If we rephrase this definition, we could also say that uncertainty may be present if we do not hold sufficient *knowledge* to *describe* or *assert* some phenomenon fully. The inclusion of both *describe* and *assert* is intentional as it can illustrate that in some situations information that can reduce uncertainty may be *readily* available, yet not part of an agent's knowledge base, whilst in other situations information about some phenomenon may simply not exist (yet). The former is typically referred to as *unacquired* knowledge, and the latter to some *unrealised* outcome[5].

Contrary to what one might think in theory, absence of knowledge does not stop economic agents from taking decisions in the face of uncertainty. An explanation could be that everyday life is full of uncertain events that we may not be able to fully control or even hedge against. If we remind ourselves that *not* taking some *new* action is an action in itself, then we could also add that there must ultimately exist some form of motivation that triggers action. Aristotle claimed that this was happiness[6]. In microeconomics this is often translated into *utility*; a measurable but not always observable quantity that can indicate an individual's level of satisfaction. When *uncertainty* is drawn into the equation, we may describe the base of action as a tradeoff between *risk* and *reward* (or risk-reward tradeoff, as it is also referred to in the finance literature). Implicit in this description is that the values of both *risk* and *reward* are *potential* values that may or may not coincide with their true, but yet unknown, values in relation to some phenomenon. Although, both *risk* and *reward* may describe something that can have an *adverse* or *advantageous* effect on utility[7], risk-reward may best be seen in conjunction with e.g. '*the reward for taking risk x, is...*'. That is, the *reward* follows, or is affiliated with the *risk* that is assigned. And

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[5] Please note that lack of *knowledge* also include lack in knowledge on *how* to process information, and not only the *gathering* of information. An interesting observation is that psychology studies bring this discussion further to include *cognitive* limitations to capacity and time (Bammer and Smithson, 2008).

[6] Aristotle divided happiness into hedonia, which described *pleasure*, and could be short lived; and eudaimonia, which described *satisfaction* of a life well-lived.

[7] E.g. BIS (2001) defines (operational) risk as: "*the risk of direct or indirect **loss** resulting from inadequate or failed internal processes, people and systems or from external events*", while COSO (2004) includes in its definition on enterprise risk management (ERM): "*…identify potential **events** that may affect the entity…*", implying that risk may take any nature not limited to an adverse effect only. Also, a reward may be defined to take the value of any real number. As such it can be utility increasing (+), or utility decreasing (-).

here is maybe where we might find a clue to Knight's definition of risk and uncertainty; the degree of ability to calculate the realization of some reward.

Knight (1921) defines *risk* as some *measurable* quantity, while he defines *uncertainty* as some *unmeasurable* quantity. Again, we are back at *knowledge*, but this time it is more about knowledge of the parameters that form a methodology. Hence, in a Knightian world with probabilities, *risk* is characterised by *known* probabilities, and *uncertainty* is characterised by *unknown* probabilities. As such, while both definitions are ultimately unaware of the true probability[8] (if any) of some random phenomenon, Knight's focus is more on whether there is a (mathematical) claim, or possibility, to form a probabilistic measure, or estimate if you like, of randomness, or not. If such an estimate is *not* able to establish *confidence* or consensus, then according to Ellsberg (1961), we might have *ambiguity*[9]. This notion naturally introduces the matter of *subjectivity*[10]. In fact, Frisch and Barron (1988) define *ambiguity* as "[...] *the subjective experience of missing information relevant to a prediction*", which we could say is somewhat analogous to Knightian uncertainty. This is maybe not the biggest of surprises as both have been used interchangeably in the literature (Ghirardato[11], 2010).

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[8] This should hold even if the probability is 0 or 1, given we define probability as an (calculated) *estimate* of some unknown value. If, however, we knew the true value, randomness would no longer be part of our estimate, in which case an estimate could be seen as obsolete.

[9] To the degree that Knight uses the word *ambiguity* in his 1921 paper, it is more in relation to describing confusion, as oppose to defining a specific notion for it.

[10] But as Ellsberg also adds: "[…] *it should be possible to identify 'objectively' some situations likely to present high ambiguity* […]", e.g. when there is wide agreement that it should be obvious that an estimate may be flawed.

[11] Contributing author to the *Encyclopedia of Quantitative Finance (2010)*, see list of references for further details.

2.2 Theory

The three theories that are discussed here on risk and ambiguity could be characterised as i) an academic student economics text, ii) a behavioural descriptive text, and iii) a normative text.

2.2.1 Management of Risk

The book where our chapter is retrieved from, *Microeconomic Theory* (Mas-Colell, et al., 1995) is often characterised as one of the more detailed and mathematical intensive of a variety of graduate text books that are commonly referred to in (economics) graduate courses. The book's chapter 6, *Choice Under Uncertainty*, is no exception. It offers insight into how we may manage choice under uncertainty in that it presents a way to systemise *risky* alternatives, and how to make *consistent* choices among them.

The *risky* alternatives facing an economic agent are referred to as *lotteries* and may initially be *simple* or *compound* lotteries. A central feature in preference building in this respect is the *consequentialist* premise, stating that the decision maker is concerned with the *reduced* lottery over the final outcome regardless of the lottery structure[12]. This means that any lottery, no matter how complex, can be represented by a simple lottery with the same ultimate distribution over outcomes. Thus, in essence a simple or reduced lottery is the list $L = (p_1, \dots, p_N)$ with $p_n \geq 0$ for all n and $\sum_n p_n = 1$, where p_n is the probability of outcome n occurring. For much of the text these probabilities are assumed to be *objectively known, s*imilar to probabilities arising from a lottery based on, as the authors put it, *"the spin of an unbiased roulette wheel*". As such, given the assumptions of the model, if an economic agent has inconsistent preferences over lotteries, this will *not* first and foremost be due to ambiguity, but rather a consequence of sub-optimal information processing, according

[12] Although this may be true, it may be argued that a path consisting of a compound lottery, given substantially many lotteries, may be perceived as more *treasonous* compared to one that only has a few lotteries, or even just a simple lottery.

to the authors. Although ambiguity is briefly mentioned in the section that relates to comparison of distributions and application of stochastic dominance in order to address optimal choice under uncertainty, information processing seems to be a central aspect of the theory throughout. When ambiguity is discussed in the reminder of the chapter, the authors refer to *subjective probability theory* as a potential bridge to fill the gap between known and unknown probabilities, albeit adding that more research may be necessary to assess whether this makes for an adequate substitute.

The theory that the Mas-Colell, et al. text presents, may receive criticism for the assumptions it imposes, e.g. probabilities that are objectively know, the consequentialist premise etc., but it could surely receive as much praise for including them in their presentation as well. Yes, it is not *perfect* (which model per definition is?!), and it may collide with other theories that have more relaxed assumptions, but the chapter appears nonetheless as informative as it introduces usable and thus valuable knowledge in relation to *uncertainty*, be it in an academic setting for understanding and building on knowledge, for an economic entity that may have the resources to pursue the methodology as part of a strategic tool box, or just for a private person's general curiosity. One may argue that this should more than make up for the strong assumptions that follow the theory in question, although one could also argue that it could have been interesting to expand the text to include other theories and aspects of *uncertainty* that have shed the light of academia. Two such alternative texts are discussed next.

2.2.2 Behavioral Choice Description

Itzhak Gilboa's (2009) description of uncertainty is in large consistent with the perception of uncertainty as some unknown probability. Nonetheless, he brings forward an interesting discussion on asymmetric beliefs to add in understanding how one might deal with choice under uncertainty. The following example due to Schmeidler(1989) may illustrate this better: Imagine two coins A and B, where only the probability of A is known. Given a fair toss, the probability of either heads (H) or tails (T) at the end of the toss is about 50% for coin A. Then there is coin B, which we know nothing about. If we have symmetric beliefs we may assign the same probability to coin B as for coin A. However, whilst the probability structure of coin A is based on empirical frequency, the probability structure of coin B would be non-verifiable as it would have been assigned by default. As such, in both theory and in practice the probability of $H's$ or T's for coin B can be anywhere between 0 and 100%. According to Gilboa, when people are faced with a bet that has a known probability of 50% against another bet with unknown probabilities, they will prefer the former rather than the latter alternative. Gilboa argues, as Ellseberg (1961) did, that this would imply that people are *not* necessarily (subjective) probabilistic rule driven expected utility maximizers when faced with unknown elements in choice. If they were, the author says, people's probabilities would have to reflect a higher likelihood of an outcome of H's for coin A than for coin B, and a higher likelihood of T's for coin A than for coin B. However, this would not be possible if the probabilities for both H's and T's for each coin would have to add up to 1. It is in this context that the author questions Bayesianism, whose foundation is that all uncertainty can be quantified in a probabilistic manner. This notion, however, would not be compatible with preferences for known versus unknown probabilities. Hence, the introduction of non-additive probabilities, which carry weaker assumptions compared to Bayesianism.

Formally, if we denote the non-additive probability by v and A and B are *disjoint*, then our non-additive measure does not need to satisfy $v(A \cup B) = v(A) + v(B)$. This means that in relation to coin B from our previous example, we may have that

$$v(H) + v(T) = .4$$

while

$$v(H \cup T) = 1$$

Furthermore, the following properties will have to be satisfied:

i. $v(\emptyset) = 0$;
ii. $A \subset B$ implies $v(A) \leq v(B)$;
iii. $v(S) = 1$.

According to the author, this framework may explain preference for betting on a coin with known probabilities, as the preference order is no more than a ranking of events. For a multi outcome setting with non-additive probabilities, Gilboa shows why a typical Riemann integral may not be sufficient, and refers to the Choquet (1954) integral as a possible solution for solving the problem of ambiguity that is found in the Riemann model. As such, Gilboa's presentation of decision theory provides insight into how choice ordering can be explained in a setting with uncertainty when there are violations of expected utility theory (EU). The focus on the behavioural aspects of the economics (of the problem) is not only gainful for those instances were increased accuracy can be attained, but it is also gainful in an informative manner in that the theoretical description has a closer 'fit' to the behavioural phenomenon in question.

2.2.3 Choice and Decision Making

Manski's (2007) analysis of decision making and welfare maximization is largely based on an econometric approach to uncertainty. The setting that is examined in particular is one with a decision making planner with knowledge about the choice set, but with limited knowledge about the outcome of choice[13]. Thus, according to Manski the planner faces an identification problem, and hence treatment choice under ambiguity[14]. Manski specifies this further and adds that since the planner has *partial knowledge* of the distribution of treatment response, she may not be able to determine optimal treatment choice. This, therefore, may lead to a sub-optimal outcome.

Formally, the choice set is denoted C. This is the set the decision maker must choose an action from with the intent to maximise an objective function: $f(\cdot): C \rightarrow R$. In

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[13] Here we can only assume that choice reflects more than one option. If number of options in the set is *n*, then we have that $1<n$. 'Do-nothing' or applying some new innovation could be two such minimum options consistent with the above definition.

[14] For productive purposes, Manski makes the explicit distinction that we see this from an ex-ante planner's perspective as opposed to from an ex-post researcher who analyse treatment choice.

words, this means that action is mapped into real-valued outcomes. Since the planner knows C and only that $f(\cdot) \in F$, where F represents some possible objective functions, the planner faces a problem of choice under *ambiguity*. Manski offers further insight into the ambiguous state of nature: *First*, the planner should *not* choose a *dominated* action. If there exists a feasible action $c \in F$ that is equally as good as some other feasible action $d \in F$, for *all* objective functions in F and strictly better for some functions in F, then action d is said to be dominated. *Second*, given we have two *undominated* actions c and d, then either they are equally as good, making the decision maker indifferent between them, or the decision maker is not able to order the two actions as either action (say action c) may yield a better or worse outcome than the other action, (say action d). The bottom line is that the decision maker is not able to identify which is the better choice of action. Please note that although the decision maker cannot order the two undominated actions, she is assumed to be an optimiser and she should thus not be indifferent between the two actions because choosing one over the other may yield vastly different outcomes. Formally, we have either$[g(c) = g(d),\ all\ g(\cdot) \in F]$ or $g'(\cdot) \in F$ and $g''(\cdot) \in F$ such that $g'(c)\ \ g'(d)$ and $g''(c)\ \ g''(d)$. Manski argues that there are no unambiguously correct answers to the latter state as the problem itself contain an ambiguous element. *Third*, Manski describes a further definition of choice under ambiguity in that action must not only be undominated, but also *exclusive*. This means that the planner cannot order between a subset of equally applicable maximising actions, yet she can only apply one (unique) treatment[15]. *Fourth*, contrary to general optimisation theory, expansion of the choice set may decrease welfare as there may be a positive correlation between ambiguity and the total number of actions available in a choice set. This makes intuitive sense as introducing an additional action, say e, that is neither dominated nor dominates other actions in the initial set, may further blur the maybe already blurred road map of preferred action: action e might be chosen, although it may turn out that

[15] Choosing a combination of actions that collectively form an action is not necessarily ruled out as it may also be part of the choice set that the planner has knowledge about. However, it may be worthwhile to note that a choice that includes combined actions of other actions in the set, naturally expands the total choice set compared to a set of actions that do not hold combined action.

$f(e)\ f(c)$. As such, expansion of the choice set may bring a welfare reducing characteristic.

Although Manski's text does not discuss risk in a strict Knightian sense, one can still get the impression that applying any sufficiently strong assumptions to a dataset may invoke an increased likelihood of distortion of the (true) data representation: If we define e from above as some additional assumption introduced to the decision-making problem (where action could be expressed as *information*), then a decision that includes e may potentially curb the prospect of an outcome. But Manski also adds that decision-making with partial information may not always result in a binominal representation, e.g. success or no success, for all or part of a population, as the author shows that a solution can also be fractional and optimal at the same time. From an asset management perspective this is closely related to the theory of portfolio diversification, in that a multiple number of assets are acquired as a hedge against uncertainty, instead of settling with only one asset.

3 Data

The data in this text has been sourced online from the Federal Reserve Bank of St. Louis[16] in its entirety, and consist of a discrete time series where the observations are daily New York City *midday* buying quotes for the period between 7th January 1975 and 30th December 2011. The observant reader may verify that only data *after* the floating exchange rate regimes were implemented is included. The maximum possible observations are thus 9,292. The variables are defined as follows[17]:

- Variable (nok): Currency pair $\frac{USD}{NOK}$, is the amount of USD for one unit of NOK.
- Variable (yen): Currency pair $\frac{USD}{JPY}$, is the amount of USD for one unit of JPY.

[16] The Federal Reserve Bank of St. Louis is one of 12 regional Reserve Banks in the USA, reporting to the main central bank, the Board of Governors of the Federal Reserve System, or the Fed as it is also referred to.

[17] Names in brackets denote how the variables are defined in SAS.

- Variable (eur): Currency pair $\frac{USD}{EUR}$, is the amount of USD for one unit of EUR[18].

From the above description; since *all* values are expressed in USD, we could for simplicity say that the *home* currency is set to USD. That is, the amount of USD that would have to be paid in exchange for *one* unit of foreign currency[19]. As such, the *foreign* currency is here represented by NOK, JPY, and EUR[20].

4 Methodology (Econometric Considerations)

Fitting an adequate GARCH(1,1) model to the data will be a central aim of the methodology[21]. The following gives a short introduction to the GARCH(p,q) model, whose equations will be referred to throughout, before introducing econometric considerations that will be applied in the process.

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[18] Please note that the Euro as we know it today was only introduced in January 1999, and thus data prior to this time is not available. Subsequently, there are missing values for the currency pair $\frac{\text{USD}}{\text{EUR}}$.

[19] This text adopts the Federal Reserve Bank of New York best practice on currency pairs as per their Currency Pair Matrix (2005), which states that: "*The numerator of the Currency Pair Fraction is defined as the "Numerator Currency," and the denominator of the Currency Pair Fraction is defined as the "Denominator Currency." Each Currency Pair Fraction is expressed as the amount of Numerator Currency per one unit of Denominator Currency*".

[20] NOK=Norwegian Kroner, JPY= Japanese Yen, and EUR=European Euro. Also, USD= United States Dollars.

[21] Although, there are other models that acknowledge that volatilities and correlations are not constant, such as the autoregressive conditional heteroscedasticity (ARCH) and the exponentially weighted moving average (EWMA) models, Bodie et al. (2009) note that the GARCH model is "[…] the most widely used model to estimate the conditional (hence time-varying) variance of stocks and stock-index returns […]".

4.1 The GARCH(p,q) model

The generalized ARCH (GARCH) model by Tim Bollerslev (1986) extends Robert Engle's (1982) autoregressive conditional heteroscedasticity (ARCH) model to incorporate lagged conditional values of the variance to explain the variance, or as Enders (2010) describes it: "[…] *GARCH(p,q) allows for both autoregressive and moving-average components in the heteroscedastic variance*". Using Bollerslev's (1986) original notation, the GARCH model can be described in the following way:

We have an initial model of interest[22],

$$y_t = \boldsymbol{x}_t'\boldsymbol{b} + \varepsilon_t, \tag{4.1}$$

which we can write,

$$\varepsilon_t = y_t - \boldsymbol{x}_t'\boldsymbol{b}, \tag{4.2}$$

where y_t is the dependent variable, $\boldsymbol{x}_t$ is a vector of explanatory variables, $\boldsymbol{b}$ is a vector of unknown coefficients, and ε_t is a real-valued discrete-time stochastic process. To see how the ε_t's in the GARCH (*p*,*q*) can be "*innovations in a linear regression*" as Bollerslev (1986) puts it in his 1986 paper, the GARCH defines the value of ε_t conditional on some information set ψ_t at time t, as normally distributed with zero mean and (conditional) variance h_t,

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \tag{4.3}$$

where, (4.4)

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

[22] (4.2) could for instance be and ADL(1,1): $Y_t = \beta_0 + \beta_1 Y_{t-1} + \gamma_1 X_{t-1} + \varepsilon_t$. (3.2) is also typically referred to as *the mean equation*.

and,

$$p \geq 0, \qquad q > 0,$$

$$\alpha_0 > 0, \qquad \alpha_i \geq 0, \qquad i = 1, \dots, q,$$

$$\beta_i \geq 0, \qquad i = 1, \dots, p.$$

Although (4.3) and (4.4) are central descriptions of the GARCH (*p*,*q*) process, the way in which the mean equation (4.1) is fitted will have implications for the output in (4.4). From (4.4) we can see that the conditional variance is allowed to depend on the lagged squared values of the disturbance (q), and the values of the lagged conditional variance itself (p). The weights that GARCH(*p*,*q*) assigns each variable are expressed by α_i and β_i. The values of both p and q may vary depending on the data and data modeller, but GARCH(*p*=1,*q*=1), or GARCH(1,1) as is the usual notation, is by far the more popular model. Please note that a GARCH(0,1), is simply an ARCH(1), or ARCH(q=1) model. Put differently, if the β_i's equal zero then the model reduces to an ARCH(q) model, given there are ARCH effects present in the data set. Since we have that $q > 0$, checking for ARCH effects is thus paramount before considering fitting a GARCH(*p*,*q*) model. However, before we can fit an adequate GARCH(1,1) model, the mean equation, (4.1), need to be modelled.

The GARCH(1,1) model measures volatility persistence measured by the parameter λ where,

$$\lambda = (\alpha_1 + \beta_1) \tag{4.5}$$

As λ increase and approach unity, past shocks have stronger effect on the current variance. However, as Enders (2010) notes, α_1 and β_1 transfer volatility in different ways since α_1 has less autoregressive persistence than β_1. In short, α_1 transfer relatively more volatility over a shorter period, than β_1, which transfers volatility more spread over a longer period.

4.2 Statistical Software

SAS 9.2 is used for calculating all estimates in tables and figures, except for LR-tests which are carried out using SAS 9.3. Also, since SAS has a variety of options for processing data, the SAS procedure that have been used in conjunction with the described methodology will briefly be described under each section were this is applicable. These descriptions will be marked with a vertical line on each side of the text[23]. Excel 2007 student version was used in the preliminary stages of data handling.

4.3 Specification of the Mean Equation

De Vries and Leuven (1992) describe a list of stylized facts in conjunction with nominal exchange rate returns. In particular, they highlight statistical aspects such as *nonstationarity*, *fat tails*, and *volatility clusters*, and advice this be seen in relation to *unit roots* and *no fundamentals*; where the latter two descriptions are best seen as a result of the *no arbitrage* condition[24], e.g. a (predictive) structural model of nominal exchange rates, implying arbitrage opportunities by its very nature, should, given economic theory and technological advancements in market monitoring and trade execution, at best only suggest a short (instantaneous) time lasting arbitrage opportunity with limited scope. Hence, a structural model should arguably not be a better predictor than a random walk model. This point is shown empirically by Meese and Rogoff (1982), and Enders (2010) adds that this is also the general finding in relation to high frequency data and nominal exchange rates. Hence, this text will first and foremost apply an *atheoretic* Box-Jenkins (1976) methodology in the *univariate* AR(I)MA[25] approach to model the mean equation by OLS[26]. In short this method

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[23] Please refer to Appendix 2 for a list of programming commands used in this text.

[24] This is similar to the *efficient market hypothesis* (EMH), where (stock) prices, in essence, are regarded as randomly generated values, making profitable speculation difficult to integrate as part of a structural model (Gujarati, 2003).

[25] As the series will be *differenced* at least once from the *raw* exchange rate levels given (3.1), I(d) may be obsolete. However, as there will not be any profound diagnostic checking on the *raw* data, it *cannot*

consists of three stages: *identification*, *estimation*, and *diagnostic checking*. A lot of the literature on exchange rate returns supports and follow this method, particularly in relation to forecasting. As a final note on the Box-Jenkins method, it could be worthwhile to remind the reader that this method is based on the principle of *parsimony* in model selection.

In general, the SAS ARIMA and AUTOREG procedures will be used to specify the mean equation and construct the GARCH(1,1), respectively. The ARIMA procedure follows the Box-Jenkins methodology closely, and it is as such a natural choice. The AUTOREG Procedure offers various solutions, including ARCH and GARCH estimation.

4.3.1 The Dependent variable

FX *spot* transactions grew 48% from April 2007 to April 2010, and was as such the main contributor to the increase in daily FX trading in that interval. Trade by financial institutions and reporting dealers accounted for 87% of total FX trade, leaving the remainder 13% for non-financial entities[27] (BIS, 2010). This suggests that the relevant variable in the mean equation should be exchange rate *return* rather than the nominal exchange rate *level*, as a considerable amount of FX valuation seems to be motivated

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be concluded that they follow any *random walk* process. Subsequently, it cannot be concluded, at this stage, that the lognormal exchange rate return is stationary by default. Hence, the *integrated process* part of the ARIMA is written in parenthesis as per general findings in the literature on exchange rate levels that they are nonstationary. As such, it is not expected that the lognormal exchange rate return will have to be ‘differenced’ further. However, before formal testing has been applied and analyzed, we *cannot* fully exclude that the data may have to undergo some form of *transformation* to satisfy methodological requirements.

[26] While the GARCH regression is *estimated* by maximum likelihood estimation (MLE), the mean equation can be *fitted* using OLS.

[27] The report defined non-financial entities as ‘*non-financial **end users**, such as corporations and governments*’ (BIS, 2010). Please refer to the report for further details.

by capital movement. Further to this, applying the first differences of the exchange rate enables the series to become stationary and thus subject to standard time series analysis given the nominal exchange rate is a random walk process. As such, the dependent variable of interest is denoted as:

$$\boldsymbol{y}_t = \boldsymbol{s}_t - \boldsymbol{s}_{t-1} \tag{4.6}$$

where $s_t = \ln(S_t)$, i.e. the natural logarithm of the spot rate S at time t, making $y_t$the first difference of the natural logarithm of the nominal daily exchange rate[28]. Another advantage with using exchange rate returns, as oppose to levels, is the unit free measure that can facilitate comparisons across currency pairs (e.g. performance, etc.).

The variables for log normal return will as such be denoted as dlnok, dlyen and dleur.

4.3.2 Normality

While Bollerslev's (1986) original GARCH model follows Engle's (1982) ARCH model in *assuming* normality, the model itself is not restricted to only one distribution. Testing for normality is important because can assess whether a variable is subject to standard statistical inference, or hypothesis testing if you like, or not, alternatively, if other measures need to be explored. The literature describes a number of normality tests. In order to diagnose the degree of strength related to the normality assumption this text will use the Jarque-Bera (JB) test of normality where the test statistic T_n, can be described as,

$$T_n = n\left[\frac{skewness^2}{6} + \frac{(kurtosis-3)^2}{24}\right] \sim \chi^2(2) \tag{4.7}$$

[28] Please note that y_t is close to the rate of return r at time t: $r_t = \frac{S_t - S_{t-1}}{S_{t-1}}$. This text uses the logarithmic model as this is a fairly usable method to apply when manipulating data.

where n is number of observations, and $\sim\chi^2(2)$ denotes that that statistic T_n follows a chi-squared distribution with 2 df[29]/[30]. The null hypothesis is normality. SAS provides additional normality test like the Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling tests. A common factor that these test share with the JB test of normality is that that hypothesis is formally,

H_0: Normality	H_A: Non-normality

If the null hypothesis cannot be rejected, then estimation is likely to perform well given the normality assumption. However, in the case that the null hypothesis is rejected, then here are a number of options that can be applied to account for non-normal distributions. Some of these theories centre on the distributional shape in that they have more mass in the tails than do the standard normal distribution. Examples of such fat-tailed distributions are Student *t* or the Cauchy distributions.

The SAS ARIMA Procedure does not have an option to the standard normal distribution. The SAS AUTOREG Procedure, which will be used for the GARCH estimation, however, offers the option to use the Student's *t* distribution in the MODEL statement, relating to the GARCH estimation. The command is done explicitly. As such the mean equation will be conducted with the normal distribution only, whilst the Student's *t* distribution is applicable for the GARCH estimation. Also, the degrees of freedom for the Student *t* distribution are expressed through TDFI in SAS, which is formally the inverse of the degrees of freedoms and is an estimated parameter.

[29] Skewness is formally defined as: $SK = \frac{[(y-\mu)^3]}{\sigma^3}$.

[30] Kurtosis is fomally defined as: $K = \frac{[(y-\mu)^4]}{\sigma^4}$. A distribution with a kurtosis value in execess of +3 is said to have heavy tails due to more mass in the tails compared to a normal distribution.

4.3.3 Correlograms and ACF and PACF[31]

Without going into the architectonic or computational details of the autocorrelation function (ACF)[32] and the partial autocorrelation function (PACF)[33], these tools are useful in the *identification* part of the Box-Jenkins methodology. Because the shape and form of an ACF and a PACF is thought to be informative of characteristics related to some particular process (e.g. *tentative* order of AR(p) and/or MA(q) in an ARMA(p,q)), these tools are used as preliminary tests before further exploration and testing is applied. A typical *stationary* process exhibits an ACF (correlogram) that reduces to zero at a *geometrical* pace and remains close to zero for the reminder of the lags. As such, the *sample* ACF can act as a *simple* test of stationarity.

The SAS ARIMA Procedure is used to run both ACF and PACF, where the values and (correlogram) plots are generated automatically by inducing the IDENTIFY statement.

4.3.4 White Noise Test

A formal test for white noise is found in Ljung-Box (1978). Because the *LB* statistic, or *Q* statistic, as it is also referred to[34], is a test to ascertain whether the *joint hypothesis* (of a group of autocorrelations) is simultaneously significantly different

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[31] The correlogram of PACF is formally referred to as a *partial correlogram*.

[32] In short, an ACF value at lag *k* is the ratio of sample covariance (at lag *k*) to sample variance (Gujarati, 2003).

[33] A PACF value at lag *k* is (on the other hand) maybe best described as the *ceteris paribus* (individual) correlation between *t* and a *k* lag, as the PACF *controls* or '*nets'* out the correlation of any intermediate lags that are less than lag *k*.

[34] Not to be confused with the much similar *Q* statistic based on Box-Pierce (1970), or Box-Pierce *Q* statistic as it is also referred to. In short, the LB-*Q* statistic is believed to have more power over the BP-*Q* statistic.

from zero, the statistic can also be used in an informative manner to ascertain whether the residuals of an ARMA(p,q) behave as a white noise, or not. The general idea is that if the LB-Q statistic(s) is *not* significantly different from zero, then this is a sign that the estimated model may 'fit' the data well (Enders, 2010), as there may not be any more information in the series to model. Formally, the hypothesis is written

H_0:	White Noise	H_A:	No White Noise

The SAS ARIMA Procedure generates the LB-Q statistic by default in the IDENTIFY statement. Since the LB-Q statistic follows an asymptotical *chi-square* distribution the SAS output refers to the LB-Q statistic as a *chi-square* statistic with the corresponding *chi-square* value and the related p-value for a group of autocorrelations.

4.3.5 Model Adequacy

Although the goodness-of-fit assessment will be conducted as results are generated, not forgetting the underpinning economic theory, both the Aikaike Information Criterion[35] (AIC) and the Schwarz Bayesian Criterion[36] (SBC) will play central roles in the selection process. The idea is that the competing model with the lowest information criteria is the preferred model, or as Enders (2010) points out: "*as the fit of the model improves, the AIC and SBC will approach* $-\infty$". Some characteristics that may be worth mentioning is that as oppose to the R^2criteria, AIC and SBC have in common that they impose a penalty for adding more explanatory variables, which for some models may naturally introduce some sort of trade-off. Also, the SBC is thought to select the more parsimonious model over the AIC, given $n >\approx 7$ since then $\ln(n) > 2$ holds (please refer to the two computations that SAS utilizes as per below to inspect further). Finally, Enders (2010) points out that SBC has superior

[35] (Akaike, 1974).

[36] (Schwarz, 1978).

large-sample properties, whilst AIC can perform better in small samples, comparing both criteria.

The ESTIMATE statement of the SAS ARIMA Procedure generates both the AIC and SBC by default. This SAS procedure has the following computational description for each information criteria

$$AIC = -2\ln(L) + 2k \tag{4.8}$$

"*where L is the likelihood function and k is the number of free parameters,*

and

$$SBC = -2\ln(L) + \ln(n)k \tag{4.9}$$

where n is the number of residuals that can be computed for the time series" (SAS OnlineDoc, version 7-1, 2008).

4.3.6 Testing for ARCH Effects

There are a number of tests that can be used to look for the presence of *heteroscedasticity*. This text uses a Lagrange multiplier (LM) approach suggested by Engle (1982), where the squared residuals are checked for ARCH effects. Please note that the test assumes white noise in the disturbances. Formally the test is expressed

H_0: Homoscedasticity	H_A: Heteroscedasticity

The SAS AUTOREG Procedure generates the LM statistic and corresponding *p*-value upon instruction in the MODEL statement.

4.4 GARCH (1,1) Estimation

With today's sophisticated (statistical) software modelling a GARCH(*p*,*q*) process is likely to be less complicated than when Bollerslev concluded his 1986 paper. The procedure is fairly straight forward: Once the mean equation is specified, the GARCH(*p*,*q*) can be regressed on the information contained in the mean equation. Parameters are created similar to any other standard regression. Please note that since GARCH(*p*,*q*) introduces conditional variance this in itself may alter the *original* mean equation, since the dynamics could have been altered in that information may have been used differently. Also, GARCH is estimated using MLE.

Model adequacy of the GARCH(1,1) is conducted as per 4.3.5, which is applicable since the SAS computation for AIC and SBC uses the log likelihood function.

The SAS AUTOREG Procedure is utilised for this purpose, specifying the GARCH(1,1) model under the MODEL statement. As per Bollerslev (1986) this procedure utilises MLE by default for a GARCH(*p*,*q*) operation.

4.5 Likelihood Ratio Test

The GARCH model is estimated using MLE and it is as such appropriate to use the likelihood ratio (LR) test in order to test for *joint* significance of the GARCH coefficients. The LR test is somewhat analogous to the F test. In large samples the LR test statistic follows a chi-square distribution with equally as many degrees of freedom as the number of restrictions imposed by the null hypothesis. Since the GARCH coefficients are generated with their own individual significance values, and persistence is defined as per (4.5), the hypothesis is formally,

$$H_0: \alpha_1 + \beta_1 = 0 \qquad\qquad H_A: \alpha_1 + \beta_1 \neq 0$$

The SAS 9.2 AUTOREG Procedure does not have this feature, and the SAS 9.3 AUTOREG Procedure is used instead for this purpose since it offers both LR and

Wald tests. The test is explicitly programmed using the TEST statement. SAS 9.3 also has the option. Also, as Gujarati (2003) notes, the LR and Wald tests give identical answers, asymptotically.

5 Empirical Results and Discussion

5.1 Descriptive Statistics and Normality

Table 1 present the descriptive statistics for the log normal return series of the three currency pairs ($\boldsymbol{y_t}$). Since SAS reports kurtosis as *excess* kurtosis, we can see from Table 1 that the three series have positive kurtosis, indicative of heavy tails. This is expected since the three series are (exchange rate) returns, which are typically characterized by leptokurtic distributions. As such, using a normal distribution may *not* be adequate. Also, the three series are skewed. The deviation from the normal distribution in kurtosis and skewness is supported by the Jarque-Bera normality test in that under the methodological specifications, results show

- *Reject*, the null of normality in all three variables' residuals.

The normality assumption is thus *strongly* questionable on all three accounts ($\boldsymbol{y_t}$). Although, these results do not deviate much from what is reported in the literature on (time series) return data, as stated earlier, applying the normal distribution to the data, given our results, could (severely) underestimate the frequency and magnitude of events.

Panel (e) in Figures 1, 2, and 3, illustrate the distribution of residuals for the daily log returns by a red-dashed line and a histogram. Although, the distributions for all three variables are *not* abnormally different to the well-known bell-shaped normal, or Gaussian if you like, distribution, they are sufficiently different in form as per above, in that they are both taller and slimmer in body compared to the Gaussian distribution. The blue line is the normal distribution based on the sample mean and standard deviation. The JB statistics and excess kurtosis together with the visual inspection of the three distributions, suggest that the Student's *t* distribution could be applicable[37].

Table 2 provides the measurement of co-movement between the dependent variables using the Pearson correlation method. Please note that the calculations are the *pairwise* computations. Statistics that might be noticeable at first glance is the relative high correlation between dlnok and dleur, whilst dlyen has a relative lower relation to both dlnok and dleur.

5.2 Results for the Mean Equation

This section relates to the analysis and model description of the mean equation.

5.2.1 Visual Inspection

Panel (a) in figures 1,2, and 3, show the nominal *raw* exchange rate levels for currency pairs $\frac{USD}{NOK}$, $\frac{USD}{JPY}$, and $\frac{USD}{EUR}$, respectively. The three *nominal* series resemble characteristics typical of a random walk process[38]. Also, a closer inspection of $\frac{USD}{JPY}$ may lead to the suspicion of the series exhibiting some sort of upward "trend" such as a stochastic trend, since over the sample period it looks like it grows more compared to for instance series $\frac{USD}{NOK}$. This might suggest $\frac{USD}{JPY}$ could be a random walk with drift. None of the series seem to revert to a long run mean.

Panel (b) in figures 1,2 and 3 show the graphical composition of the dependent variable for each currency pairs. From a visual point of view, the three series appear to be stationary as both the mean and variation around the mean seem to be *relative*

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[37] Please note as per the methodology earlier that Student's *t* will only be utilized during the GARCH(1,1) estimation since the ARIMA Procedure of SAS does not have this option. As such the next section relating to the mean equation is under the normality assumption.

[38] The ACF's and PACF's of the nominal exchange rate levels have been included in Appendix 2, where figures A1-1, A1-2, and A1-3, strongly support the suspicion of the levels series being random walk, from a visual point of view that is.

constant. As such, there does not seem to be any structural brakes in the three series either. Also, although some skeewness is expected, there should not be any extreme or abnormal tendency either way as it looks like there may *roughly* be as many points above as below the mean. As such, the data for the three currency pairs are likely to form bell-shaped symmetric-like distributions *similar* to a normal distribution, but with a higher concentration around the mean and with more outliers.

Following the Box-Jenkins methodology as per above, the (sample) ACF plot in panel (c), figures 1, 2, and 3, for the change in log returns for the three currency pairs, all show that the autocorrelations decrease rapidly an hover around zero, and may as such support the suspicion that the log return data for all three time series are stationary since these are typical properties of a *white noise* random process. The PACF plots in panels (d) figures 1, 2 and 3, have similar properties to the ACF plots, further strengthening the suspicion of stationarity in the three log return series. Also, since all three ACF's and PACF's show quadratic decay from the current observation (lag 0) with no obvious sufficiently large visual spikes in other autocorrelations in either direction (+/-), the suspicion of stationarity may extend to include a stationary process due an ARMA(0,0) model, or a pure random process if you like, as discussed in the methodology section. This would typically look like,

$$y_t = \mu_t + \varepsilon_t \tag{5.1}$$

However, although a visual inspection is of great help it also has clear limitations, and in order to describe the data with greater certitude formal testing and results are incorporated as part of the wider analysis.

5.2.1 Formal Test of dlnok

Although a visual inspection of the three series gave strong indication that the models could be pure random processes such as (5.1), the suspicion need not only be weighed against results from empirical data, but it could also be beneficial to gain some insight into the dynamics of a series since in many cases empirical data deduction will, at least in the preliminary stages, not be a clear-cut binominal assessment with *one* correct answer in relations to some *real* phenomenon.

As an obvious first candidate is, nonetheless, the construction of an ARMA(0,0) model, which is shown in the second column of Table 3. Under the (methodological) specifications results show:

- *Fail* to *reject* the null hypothesis of the intercept *not* being significantly different from zero.
- *Fail* to *reject* the null hypothesis of white noise.

As such, these results are informative of an intercept that may not add much to the model, and a LB-*Q* statistic that indicate that the ARMA(0,0) model may 'fit' the data well, although it is noted that LB-*Q*(48) statistic is significant at the 5% level. However, from an overall perspective, including the visual inspection, it may be safe to suggest that the ARMA(0,0) model is likely to be a white noise process. This could conclude the mean selection process, but since a white noise process does not necessarily exclude another white noise by default, other ARMA(*p*,*q*) models are constructed and tested to assess the overall fit of competing models.

Additional models ARMA(1,0), ARMA(0,1), ARMA(1,1), ARMA(1,1), ARMA(2,0), ARMA(0,2), and ARMA((2),(2)), are constructed and presented in Table 3, column 3 to 5; and Table 4, columns 2 to 5, respectively. As per results for ARMA(0,0), above, results show that all the seven models *fail* to *reject* the null of the intercept *not* being significantly different from zero: the low t-values shift between -0.23 and -0.24 and there are similar tendencies in the *p*-values. Except from ARMA(1,1), which have an autoregressive (AR) and moving average (MA) term that are both *only* significant at the 10% level, none of the AR or MA terms in Table 3 are significantly different from zero. The LB-*Q* statistics for the models in Table 3, show that the statistics decrease as we move along from columns 2 to 5. A similar pattern is somewhat more difficult to detect in the *p*-values of the LB-*Q* statistics. Nevertheless, in the table, ARMA(0,0) have always lower LB-*Q* *p*-values than ARMA (1,1); and ARMA (1,0) have always lower LB-*Q* *p*-values than ARMA (0,1). As such, although adding a term may lower the LB-*Q* statistic and thus possibly increase the likelihood of white noise, an opposite pattern can be detected in the SBC value. The patterns in Table 4 are maybe more complicated and ambiguous than for the models in Table 3. However, results show that except for the coefficients for an AR or MA of order 2, all estimated coefficients are *not* significantly different from zero. Also, the estimates that are significantly different from zero are all significant at the 1% level. Moreover, since ARMA(2,0) and ARMA(0,2) suggest that including the second lag is significant in relation to both AR and MA, this is (subsequently) combined in both ARMA(2,2) and ARMA((2),(2)). Although, ARMA(2,2) is consistent in relation to the *insignificance* of the AR and MA of orders 1, both ARMA(2,2) and ARMA((2),(2)) have increased significance for inclusion of the AR and MA of orders 2, compared to ARMA(2,0) and ARMA(0,2) even though the coefficients for the combined AR and MA of orders 2 are close to 1(!). The AIC values for the models in Table 4 are all higher than any AIC values in Table 3, slightly favouring any model with a combined AR and MA of order 2. For the respective four LB-*Q* statistics, all values in Table 4 are lower than those in Table 3, and all *p*-values in Table 4 are less significant than any other *p*-value in Table 3. Another noticeable treat may be that ARMA((2),(2)) has a slight jump for the first two LB-*Q* statistics, before ‘settling’ between the LB-*Q* values of ARMA(2,0) and ARMA(0,2) on one end, and ARMA(2,2) on the other end. Also, ARMA(2,2), which is the preferred AIC model, has the lowest value of any of the eight dlnok mean equation models of Tables 3 and 4 in terms of the LB-*Q*(6) statistic, nevertheless, although it may be expected that it also has a *higher p*-value to any other comparable value in Table 3, the noteworthy part may be that it has the lowest comparable *p*-value in Table 4. These two latter observations may not mean much, but put in a context where a relative higher LB-*Q* statistic is in general associated with a lower *p*-value, these results may be informative.

The ARMA(*p*,*q*) models with the *combined* AR and MA of orders 2 are the preferred AIC models of any of the eight dlnok models in Tables 3 and 4. Nevertheless, the ambiguity of comparing the two models, where eliminating the first lags increases the AIC value whilst lowering the SBC value is worrying, especially since the coefficients for the second lags are significant and close to 1. In line with the theory that was discussed earlier in relation to a structural model, and given Enders’ (2010) discussion that it may be overoptimistic to believe that stock return data may be directly influenced by an event in the past whilst an intermediate event may not, it would make sense to focus on the first lags. However, since none of the coefficients of the first lag *only* models are *not* significantly different from zero these models are maybe not optimal. The ARMA(0,0) on the other hand is the preferred model by the large-sample superior and parsimonious SBC. Out of the four models in Table 3 the ARMA(0,0) is also the preferred AIC model. As such, it is believed that the ARMA(0,0) describes the dlnok process adequately.

Please note that the intercept is kept thus far as there may be advantages in including this term in running the GARCH(1,1) model.

5.2.2 Formal Test of dlyen

As with variable dlnok, an obvious first candidate for dlyen is the ARMA(0,0). Three more models are constructed: ARMA(1,0), ARMA(0,1), and ARMA(1,1). No additional models are formally presented, re. Table 4 for dlnok, as much of the same discussion concerning Table 4 is applicable to comparable models for dlyen. Under the (methodological) specifications results show:

- *Reject* the null hypothesis of the intercept *not* being significantly different from zero.
- *Fail* to *reject* the null hypothesis of white noise.

These results are informative in that the mean value is believed to aid in explaining the series process at the 5% level of significance for all four models. Also, the white noise hypothesis cannot be rejected at the 1% level of significance for any of the models. The latter statistics are noteworthy, but this may have to be seen in relation to the ACF and PACF in Figure 2, panels (c) and (d), suggesting white noise overall. None of the lag coefficients of any AR or MA order are significantly different from zero. As such, the AIC's preferred, but indecisive relation to the ARMA(1,0) and ARMA(0,1) may be of less importance. The SBC clearly picks ARMA(0,0) over any other model. The overall values of the AIC and SBC *combined* supports this too.

5.2.3 Formal Test of dleur

Four models are constructed for dleur as per Table 6: ARMA(0,0), ARMA(1,0), ARMA(0,1), and ARMA(1,1). As with dlyen no additional models are formally presented as much of the same discussion concerning Table 4 in relation to dlnok is applicable to comparable models for dleur. Based on the (methodological) specifications results show:

- *Fail* to *reject* null hypothesis of the intercept *not* being significantly different from zero.
- *Fail* to *reject* the null hypothesis of white noise.

These results suggest that the mean (intercept) does not add much to the model in any of the four models in Table 6. While we cannot reject white noise at the 5% significance level for ARMA(0,0), the same applies to models ARMA(1,0), ARMA(0,1), and ARMA(1,1) at the 1% level of significance. As with dlyen, none of the dleur lag coefficients of any AR or MA order are significantly different from zero. This may explain that both AIC and SBC suggest ARMA(0,0) over any other model in the table.

Similar to with dlnok the intercept is kept as the there may be advantages in including it in the GARCH(1,1) regression.

5.3 ARCH Effects

Table 7 shows the LM statistics for lags 2, 4, 8 and 12 for variables dlnok, dlyen and dleur. Under the (methodological) specifications results show:

- *Reject* the null hypothesis of homoscedasticity in favour of the alternative hypothesis of heteroscedasticity.

This applies to all three variables since $p < 0.0001$ up to lag 12 for all three variables[39].

5.4 GARCH(1,1) Estimates with Normally Distributed Residuals

5.4.1 GARCH(1,1) estimate for dlnok (Normal Dist.)

The results from the GARCH(1,1) estimation for dlnok in the second column of Table 8, show that that the intercept of the mean equation add little or no value to the model as it is not significantly different from zero. This is maybe not the biggest of surprises given we had similar results under the ARIMA mean specification section. The coefficients for the conditional variance estimate, on the other hand, are all highly significant. As such, a GARCH(1,1) estimate is run without the intercept term in the mean equation. Results are shown in the second column in of Table 9. If we compare both models, with and without an intercept, it may appear that the differences are minuscule. However, removing the intercept increase the significance of all estimated parameters of the conditional variance model. This is also reflected in lower AIC and SBC values, suggesting a GARCH(1,1) model without an intercept in the mean equation is a better description of the series. Formally, the GARCH(1,1) model for dlnok with normally distributed residuals is,

$$y_t = \varepsilon_t \tag{5.2}$$

and

$$h_t = 3.1855E^{-7} + 0.0658\varepsilon_{t-1}^2 + 0.93h_{t-1} \tag{5.3}$$

with $\lambda = 0.9958$.

[39] Please note that as long as a tests may suggest ARCH effects present in the data, GARCH may also be considered; since the LM statistic is significant for all 12 orders this may further suggest using the more parsimonious GARCH model (p>0) instead of an ARCH model.

5.4.2 GARCH(1,1) Estimate for dlyen (Normal Dist.)

Column three of Table 8 show the results for the GARCH(1,1) estimation for dlyen. As with dlnok, the GARCH(1,1) estimate show that, under the (methodological) specifications, both the AR and MA components of the *heteroscedastic* variance are significantly different from zero. The intercept of the mean equation, however, is *only* significant at the 10% level. Since this may be a relative high number in this respect, a new regression with an omitted intercept is applied to see how the AIC and SBC may react. The results are shown in the third column of Table 9. The new model generate increased *t*-values for all GARCH terms. Although AIC increase with 0.548, SBC lowers with 6.59. The increased *t*-values and improved SBC suggest a model *without* intercept is a better description of the time series process. Formally, the GARCH(1,1) model for dlyen with normally distributed residuals is,

$$y_t = \varepsilon_t \tag{5.4}$$

and

$$h_t = 9.4756E^{-8} + 0.044\varepsilon_{t-1}^2 + 0.9563h_{t-1} \tag{5.5}$$

with λ = 1.0003.

5.4.3 GARCH(1,1) Estimate for dleur (Normal Dist.)

The dleur GARCH(1,1) estimation results are shown in the fourth column of Table 8. As with the GARCH(1,1) for dlnok, and to some extent dlyen, the intercept term of the mean equation adds little value as it is not significantly different from zero. A new GARCH(1,1) model is applied without this term and the results for this model are shown in the fourth column of Table 9. There is little difference in the GARCH coefficient. Nevertheless, contrary to what has been the case for GARCH(1,1) models for dlnok and dlyen, where all *t*-values increased as a result of omitting the intercept term in the mean equation, the GARCH(1,1) models for dleur are not as clear cut. Both the intercept and MA terms of the GARCH(1,1) have a slight reduction in their *t*-values, compared to the model in Table 8. However, although the AIC increases slightly, the SBC value improves substantially to suggest the GARCH(1,1) model *without* the mean intercept term is the better description of the series. Formally, the model with normally distributed residuals is,

$$y_t = \varepsilon_t \tag{5.6}$$

and

$$h_t = 1.1906E^{-7} + 0.0283\varepsilon_{t-1}^2 + 0.9693h_{t-1} \tag{5.7}$$

with λ = 0.9976.

5.5 GARCH(1,1) Estimates with Student *t* Distributed Residuals

5.5.1 GARCH(1,1) Estimate for dlnok (Student's *t* Dist.)

The results for the GARCH(1,1) estimates with the Student *t* distributed residuals for dlnok, are similar to the estimations with the normality assumption in Table 8 in that the null hypothesis of the mean is rejected as it is not significantly different from zero. Also, the GARCH terms are all significant. The second column of 11 thus show the GARCH estimation *without* the intercept in the mean equation. All GARCH terms are significant as before, and both AIC and SBC suggest using the model *without* the intercept in the mean equation just as was found for the dlnok GARCH estimation with the normality assumption. Formally, the GARCH(1,1) model for dlnok Student *t* distributed residuals is,

$$y_t = \varepsilon_t \tag{5.2}$$

and

$$h_t = 2.4073E^{-7} + 0.0856\varepsilon_{t-1}^2 + 0.9164h_{t-1} \tag{5.3}$$

with λ = 1.0002.

5.5.2 GARCH(1,1) Estimate for dlyen (Student's *t* Dist.)

Column three of Table 10 show the results for the GARCH(1,1) estimation with a Student *t* distribution for dlyen. The intercept of the mean equation is as usual is not statistically different from zero and could be suppressed. However, the intercept of the GARCH term, α_0, is also *not* statistically different from zero, which was not found in the GARCH estimates under the normality assumption. The two other GARCH terms are significant. In the third column of Table 11 the results of the GARCH(1,1) regression with Student *t* residuals and no intercept in the mean equation are shown. While α_1 and β_1 are significant, we cannot reject the null hypothesis of the GARCH intercept, α_0, although the significance has almost reduced with half. Both AIC and SBS suggest the model *without* the intercept is the better model. Formally, the GARCH(1,1) model for dlyen is,

$$y_t = \varepsilon_t \tag{5.4}$$

and

$$h_t = 1.6887E^{-8} + 0.0541\varepsilon_{t-1}^2 + 0.9522h_{t-1} \tag{5.5}$$

with λ = 1.063.

5.5.3 GARCH(1,1) Estimate for dleur (Student's *t* Dist.)

Estimation results for the dleur GARCH(1,1) with a Student *t* distribution are shown in the fourth column of Table 10. As before the intercept in the mean equation adds little value as it is not significantly different from zero. All GARCH terms are significant, although it is noted that α_0 is only significant at the 10% level. A new GARCH(1,1) model is constructed without the mean equation intercept term and the results are shown in the fourth column of Table 11. There is little difference in the GARCH coefficients. Also, α_0 remains significant at the 10% level, whilst the other GARCH terms are statistically significant from zero. However, the AIC and SBC values are both lower in the model *with* the intercept term present in the mean equation. This could raise *ambiguity* in that the first regression results suggest 'removing' the intercept of the mean equation, whilst the second regression results suggest that 'removing' the intercept term in the mean equation does not improve the model. Although, AIC does not change much it is the larger increase in the SBC that is of particular interest in the second regression. Also, although α_0 remains significant at the 10% level, as noted above, the significance level for the coefficient decreases in the second regression, albeit not the largest of changes. In the dlyen GARCH comparison between the results in Table 8 and Table 9 the decrease in the SBC value was ultimately the deciding factor. By the same token we should choose the dlyen model in Table 10 over the model in Table 11. However, looking back at the other results for dlyen, and for the other variables, it is difficult to assert that the model should have an intercept in the mean equation. But, as using the Student's *t* distribution should give some form of advantage in relation to accuracy given the heavy tails that were found in the data, the methodological specifications suggest the model with the mean equation[40],

$$y_t = 0.000147 + \varepsilon_t \tag{5.6}$$

and

$$h_t = 1.4405E^{-7} + 0.0302\varepsilon_{t-1}^2 + 0.9669h_{t-1} \tag{5.7}$$

with λ = 0.9971.

[40] Please note that 'removing' the GARCH intercept, α_0, is not possible in the AUTOREG Procedure of SAS 9.2, unless the Integrated GARCH is applied explicitly. Although, it could be interesting to go down that route, it will not be pursued further in this study.

6 Conclusion

6.1 Summary and Conclusion

The main purpose of this study was to examine how research on risk and uncertainty could be informative of risk management in an applied form for highly volatile data. This was a particular objective given the ex post 2007/2008 economic and financial *trauma* that hit both governments and people across numerous countries.

The log normal return of three distinct exchange rates was used to construct GARCH(1,1) models with two different distributions i) normally distributed residuals, and ii) Student's *t* distributed residuals. While the GARCH(1,1) model was superior to any ARMA(*p*,*q*), rejecting the hypothesis of constant variance, the fit criteria also suggests that *all* comparable[41] GARCH(1,1) models that were constructed using Student's *t* distribution were superior over the GARCH(1,1) models using the normal distribution. This supports the idea that assuming normality may not be optimal in modeling market returns, given the heavy tails that is characteristic of such data. Also, the difference in the estimates of the GARCH(1,1) model can naturally transfer onto the value of persistence, which was different for all comparable models. For example, using short mean-reversion as a selection criteria among the final six GARCH(1,1) models, would indicate that $\frac{USD}{NOK}$ is the preferred choice under the normal distribution, while $\frac{USD}{EUR}$ is the preferred choice under Student's *t* distribution. The differences may seem small, but they are nonetheless differences that can have severe implications for decision-making under uncertainty that is dependent on the accuracy of such estimates to make informative decisions. This applies as much to the human side of things as any algorithmic system that can generate executions in the thousands per second, since the basis for decision making in areas such as valuation or forecasting, can be flawed. Research suggests that diversification through a fractional option could be a solution, but as much as this may be efficient in many ways, it might not always be available. Also, relying too much on an overconfident *dogma* of a mean-variance framework, where market returns are assumed to be independently and normally

[41] I.e. Final dlnok (normal) GARCH(1,1) vs. Final dlnok (Student *t*) GARCH(1,1), etc.

distributed, can potentially in any case generate fractional solutions that are themselves flawed. In which case incorporating a behavioral approach to market returns is a possible solution. As such, although extreme events are rare and difficult to predict, there is no reason, with the progress and innovation that is representative of today's statistical software, that behavioural economics should not get wider appreciation. This could aid in creating the confidence and consensus in risk management that financial markets, at times, so badly need.

6.2 Extensions and Final Comments

While the ever extending family of ARCH and GARCH models offer features that would be interesting to include in an extended study, other possible extensions could include forecasting and a linear and non-linear measure of correlation between the exchange rates. Also noted is the restriction in the Box-Jenkins methodology of the SAS ARIMA Procedure, which did not have an option to apply the Student's *t* distribution, like in the GARCH estimation with the AUTOREG Procedure. A final observation that might be worthwhile to mention, is the evident increase in level of sophistication that was experienced in the brief move from SAS 9.2 to SAS 9.3, in conjunction with the LR statistics. Similar progress is currently underway in academia, challenging earlier research, and to some extent, general conviction. If there can be better models that describe real phenomenon better and produce more accurate estimates for the greater good, then future developments are promising.

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List of Tables

Table 1: Descriptive statistics

	dlnok	dlyen	dleur
N	**9292**	**9292**	**3266**
Min	**-0.0681766**	**-0.0355715**	**-0.0300310**
Max	**0.0644395**	**0.0563021**	**0.0462079**
Mean	**-0.000015994**	**0.000146753**	**0.00003257**
Median	**0**	**0**	**0**
Variance	**0.000045725**	**0.000044354**	**0.000043392**
Skewness	**-0.3096940**	**0.4850068**	**0.1175524**
Kurtosis[42]	**7.2707166**	**4.5539417**	**2.0896020**
JB Normality Test	**20589.7507**	**8382.4763**	**598.8546**
p-value	<[0.0001]***	<[0.0001]***	<[0.0001]***

Notes: Numbers in parentheses and square brackets are t-statistics and *p*-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values computed using SAS software.

Table 2: Pearson correlation matrix; dlnok, dlyen, dleur.

	dlnok	dlyen	dleur
dlnok	**1.00000**	**0.034637**	
		[<.0001]***	
dlyen	**0.34637**	**1.00000**	
	[<.0001]***		
dleur	**0.81622**	**0.25739**	**1.00000**
	[<.0001]***	[<.0001]***	

Notes: Numbers in square brackets are *p*-values. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values computed using SAS software.

[42] Please be advised that SAS software reports the kurtosis value as *excess kurtosis* as 3 is subtracted from the output displayed, e.g. for variable dlnok the kurtosis is reported as 7.267, which is the *excess kurtosis*, as oppose to the *real* sample kurtosis which is: 7.267+3 = 10.267.

Table 3: dlnok for ARMA(0,0), ARMA(1,0), ARMA(0,1), and ARMA(1,1).

	p=0 q=0	p=1 q=0	p=0 q=1	p=1 q=1
μ	**-0.0000160**	**-0.0000160**	**-0.0000160**	**-0.0000160**
	(-0.23)	(-0.23)	(-0.23)	(-0.24)
	[0.8197]	[0.8177]	[0.8175]	[0.8122]
AR1,1		**-0.01065**		**0.56848**
		(-1.03)		(1.79)
		[0.3049]		[0.0730]*
MA1,1			**0.01127**	**0.58542**
			(1.09)	(1.88)
			[0.2773]	[0.0608]*
AIC	**-66483.1**	**-66482.2**	**-66482.2**	**-66483**
SBC	**-66476**	**-66467.9**	**-66467.9**	**-66461.6**
LB-Q(6)	**11.76**	**10.72**	**10.65**	**7.51**
	[0.0676]*	[0.0572]*	[0.0587]*	[0.1115]
LB-Q(12)	**15.41**	**14.33**	**14.26**	**11.34**
	[0.2199]	[0.2154]	[0.219]	[0.3319]
LB-Q(24)	**34.08**	**33.11**	**33.04**	**29.76**
	[0.0832]*	[0.0793]*	[0.0804]*	[0.1244]
LB-Q(48)	**70.65**	**69.76**	**69.70**	**66.50**
	[0.0183]**	[0.0172]**	[0.0174]**	[0.0256]**

Notes: Numbers in parentheses and square brackets are t-statistics and p-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values computed using SAS software.

Table 4: dlnok for ARMA(2,0), ARMA(0,2), ARMA(2,2), and ARMA((2),(2)).

	p=2 q=0	p=0 q=2	p=2 q=2	p=(2) q=(2)
μ	**-0.0000160**	**-0.0000160**	**-0.0000160**	**-0.0000160**
	(-0.24)	(-0.24)	(-0.23)	(-0.23)
	[0.8123]	[0.8122]	[0.8185]	[0.8184]
AR1,1	**-0.01095**		**-0.03984**	
	(-1.06)		(-1.30)	
	[0.2913]		[0.1950]	
AR1,2	**-0.02812**		**-0.94585**	**-0.89162**
	(-2.71)		(-32.04)	(-13.54)
	[0.0067]***		[<.0001]***	[<.0001]***
MA1,1		**0.01072**	**-0.03573**	
		(1.03)	(-1.05)	
		[0.3012]	[0.2924]	
MA1,2		**0.02744**	**-0.93386**	**-0.87688**
		(2.65)	(-28.60)	(-12.50)
		[0.0082]***	[<.0001]***	[<.0001]***
AIC	**-66487.5**	**-66487.3**	**-66489.1**	**-66488.9**
SBC	**-66466.1**	**-66465.9**	**-66453.4**	**-66467.5**
LB-Q(6)	**3.03**	**3.21**	**2.92**	**3.96**
	[0.5524]	[0.524]	[0.2319]	[0.411]
LB-Q(12)	**6.79**	**6.96**	**7.87**	**8.44**
	[0.7455]	[0.7294]	[0.4463]	[0.586]
LB-Q(24)	**24.48**	**24.67**	**20.88**	**22.99**
	[0.3223]	[0.313]	[0.4042]	[0.4021]
LB-Q(48)	**61.08**	**61.28**	**54.15**	**59.36**
	[0.0675]*	[0.0653]*	[0.1405]	[0.0892]*

Notes: Numbers in parentheses and square brackets are t-statistics and p-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 5: dlyen for ARMA(0,0), ARMA(1,0), ARMA(0,1), and ARMA(1,1).

	p=0 q=0	p=1 q=0	p=0 q=1	p=1 q=1
μ	**0.0001468**	**0.0001468**	**0.0001468**	**0.0001468**
	(2.12)	(2.09)	(2.09)	(2.08)
	[0.0337]**	[0.0365]**	[0.0364]**	[0.0377]**
AR1,1		**0.01559**		**0.29838**
		(1.50)		(0.48)
		[0.1329]		[0.6293]
MA1,1			**-0.01542**	**0.28272**
			(-1.49)	(0.46)
			[0.1374]	[0.6489]
AIC	**-66766**	**-66766.2**	**-66766.2**	**-66764.5**
SBC	**-66758.8**	**-66751.9**	**-66751.9**	**-66743**
LB-Q(6)	**2.81**	**0.55**	**0.57**	**0.31**
	[0.832]	[0.9903]	[0.9893]	[0.9893]
LB-Q(12)	**22.89**	**20.19**	**20.23**	**19.79**
	[0.0287]**	[0.0428]**	[0.0423]**	[0.0313]**
LB-Q(24)	**37.03**	**34.36**	**34.39**	**34.02**
	[0.0435]**	[0.0602]*	[0.0597]*	[0.049]**
LB-Q(48)	**73.04**	**69.93**	**69.97**	**69.54**
	[0.0114]**	[0.0166]**	[0.0165]**	[0.0141]**

Notes: Numbers in parentheses and square brackets are t-statistics and p-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 6: dleur for ARMA(0,0), ARMA(1,0), ARMA(0,1), and ARMA(1,1).

	p=0 q=0	p=1 q=0	p=0 q=1	p=1 q=1
μ	**0.00003236**	**0.00003232**	**0.00003232**	**0.00003231**
	(0.28)	(0.28)	(0.28)	(0.28)
	[0.7789]	[0.7824]	[0.7825]	[0.7822]
AR1,1		**0.01498**		**-0.26624**
		(0.86)		(-0.28)
		[0.3921]		[0.7784]
MA1,1			**-0.01549**	**-0.28374**
			(-0.89)	(-0.30)
			[0.3761]	[0.7631]
AIC	**-23538.2**	**-23536.9**	**-23537**	**-23535.3**
SBC	**-23532.1**	**-23524.8**	**-23524.8**	**-23517**
LB-Q(6)	**11.81**	**11.43**	**11.42**	**11.08**
	[0.0663]*	[0.0435]**	[0.0437]**	[0.0257]**
LB-Q(12)	**17.96**	**17.55**	**17.53**	**17.12**
	[0.117]	[0.0925]*	[0.0931]*	[0.0717]*
LB-Q(24)	**25.58**	**25.12**	**25.10**	**24.67**
	[0.375]	[0.3441]	[0.3453]	[0.3132]
LB-Q(48)	**47.68**	**47.46**	**47.44**	**46.98**
	[0.4857]	[0.4539]	[0.4546]	[0.4322]

Notes: Numbers in parentheses and square brackets are t-statistics and p-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 7: LM archtest; dlnok, dlyen, dleur.

	dlnok	dlyen	dleur
LM ARCH 1-2	**268.5815**	**355.7360**	**75.3465**
	[<.0001]***	[<.0001]***	[<.0001]***
LM ARCH 1-4	**342.8571**	**388.9588**	**111.8198**
	[<.0001]***	[<.0001]***	[<.0001]***
LM ARCH 1-8	**464.6498**	**492.1478**	**174.4662**
	[<.0001]***	[<.0001]***	[<.0001]***
LM ARCH 1-12	**576.8735**	**541.7186**	**227.4305**
	[<.0001]***	[<.0001]***	[<.0001]***

Notes: Numbers in square brackets are p-values. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 8: GARCH(1,1); dlnok, dlyen, dleur (normal distr.).

	dlnok	dlyen	dleur
μ	**-0.000009416**	**0.0000877**	**0.000150**
	(-0.17)	(1.65)	(1.51)
	[0.8637]	[0.0999]*	[0.1317]
α_0	**0.00000031845**	**0.000000093053**	**0.0000001868**
	(16.05)	(8.99)	(2.30)
	[<.0001]***	[<.0001]***	[0.0213]**
α_1	**0.0658**	**0.0436**	**0.0285**
	(33.73)	(27.88)	(7.89)
	[<.0001]***	[<.0001]***	[<.0001]***
β_1	**0.9300**	**0.9567**	**0.9691**
	(589.88)	(27.88)	(261.37)
	[<.0001]***	[<.0001]***	[<.0001]***
AIC	**-68645.352**	**-68228.6**	**-23881.017**
SBC	**-68616.804**	**-68200.052**	**-23856.652**
JB Normality	**6493.1718**	**5119.2215**	**60.4823**
	[<.0001]***	[<.0001]***	[<.0001]***
$\boldsymbol{\lambda}$	**0.9958**	**1.0003**	**0.9976**
LR 0	**2168.3**	**1468.6**	**348.81**
	[<.0001]***	[<.0001]***	[<.0001]***

Notes: Numbers in parentheses and square brackets are t-statistics and *p*-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 9: GARCH(1,1); dlnok, dlyen, dleur (normal distr.).

	dlnok	dlyen	dleur
μ	-	-	-
α_0	**0.00000031855**	**0.000000094756**	**0.0000001906**
	(16.07)	(9.15)	(2.29)
	[<.0001]***	[<.0001]***	[0.0220]**
α_1	**0.0658**	**0.0440**	**0.0283**
	(33.76)	(27.96)	(7.85)
	[<.0001]***	[<.0001]***	[<.0001]***
β_1	**0.9300**	**0.9563**	**0.9693**
	(591.99)	(27.96)	(261.74)
	[<.0001]***	[<.0001]***	[<.0001]***
AIC	**-68647.322**	**-68228.052**	**-23880.883**
SBC	**-68625.911**	**-68206.642**	**-23862.609**
JB Normality	**6505.5406**	**5240.4649**	**60.4823**
	[<.0001]***	[<.0001]***	[<.0001]***
λ	**0.9958**	**1.0003**	**0.9976**
LR	**2168.3**	**1470.6**	**346.75**
	[<.0001]***	[<.0001]***	[<.0001]***

Notes: Numbers in parentheses and square brackets are t-statistics and *p*-values, respectively. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

Table 10: GARCH(1,1); dlnok, dlyen, dleur (Student's *t* distr.).

	dlnok	dlyen	dleur
μ	**0.0000125**	**-0.000029**	**0.000147**
	(0.25)	(-0.60)	(1.47)
	[0.7999]	[0.5452]	[0.1420]
α_0	**0.00000024088**	**0.000000010537**	**0.00000014405**
	(4.58)	(0.83)	(1.90)
	[<.0001]***	[0.4060]	[0.0569]*
α_1	**0.0856**	**0.0537**	**0.0302**
	(13.76)	(12.45)	(5.79)
	[<.0001]***	[<.0001]***	[<.0001]***
β_1	**0.9164**	**0.9527**	**0.9669**
	(170.85)	(291.88)	(170.79)
	[<.0001]***	[<.0001]***	[<.0001]***
TDFI	**0.1804**	**0.2369**	**0.0920**
	(17.72)	(20.36)	(5.28)
	[<.0001]***	[<.0001]***	[<.0001]***
AIC	**-79946.596**	**-79855.751**	**-27658.594**
SBC	**-79910.911**	**-79827.203**	**-27658.576**
JB Normality	**9671.9777**	**6798.6034**	**60.5072**
	[<.0001]***	[<.0001]***	[<.0001]***
λ	**1.002**	**1.0064**	**0.9971**
LR	**1293.1**	**1123.4**	**230.64**
	[<.0001]***	[<.0001]***	[<.0001]***

Notes: Numbers in parentheses and square brackets are t-statistics and *p*-values, respectively. TDFI is the inverse of the estimated degrees of freedom for Student *t*. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

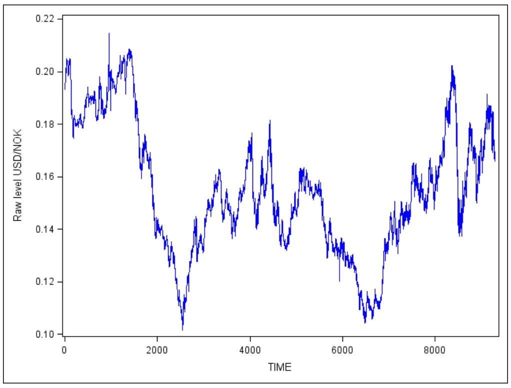
Table 11: GARCH(1,1); dlnok, dlyen, dleur (Student's *t* distr.).

	dlnok	dlyen	dleur
μ	-	-	-
α_0	**0.00000024073**	**0.000000016887**	**0.00000014627**
	(4.58)	(1.24)	(1.91)
	[<.0001]***	[0.2163]	[0.0564]*
α_1	**0.0856**	**0.0541**	**0.0300**
	(13.76)	(12.39)	(5.76)
	[<.0001]***	[<.0001]***	[<.0001]***
β_1	**0.9164**	**0.9522**	**0.9671**
	(170.88)	(286.82)	(170.98)
	[<.0001]***	[<.0001]***	[<.0001]***
TDFI	**0.1803**	**0.2365**	**0.0918**
	(17.72)	**(20.32)**	**(5.31)**
	[<.0001]***	[<.0001]***	[<.0001]***
AIC	**-79948.530**	**-79855.449**	**-27658.480**
SBC	**-79919.982**	**-79834.038**	**-27634.115**
JB Normality	**9657.9477**	**6527.8794**	**60.4823**
	[<.0001]***	[<.0001]***	[<.0001]***
λ	**1.002**	**1.0063**	**0.9971**
LR	**1293.7**	**1123.2**	**228.75**
	[<.0001]***	[<.0001]***	[<.0001]***

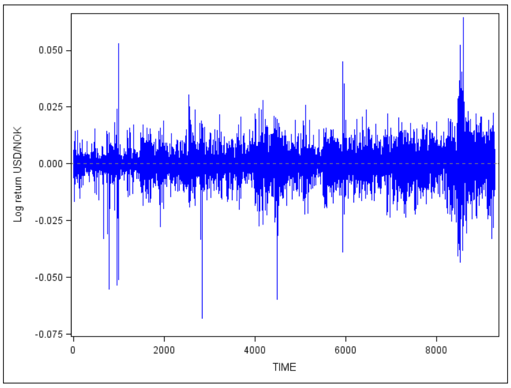
Notes: Numbers in parentheses and square brackets are t-statistics and *p*-values, respectively. TDFI is the inverse of the estimated degrees of freedom for Student *t*. (*) Significant at 10%; (**) significant at 5%; (*) significant at 1%. All values are computed using SAS software.

List of Figures

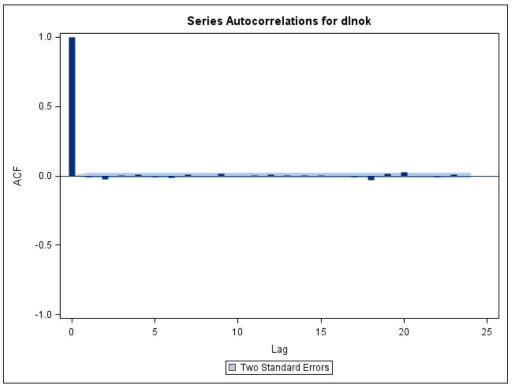
Figure 1: USD/NOK, dlnok; ACF, PACF, distribution.



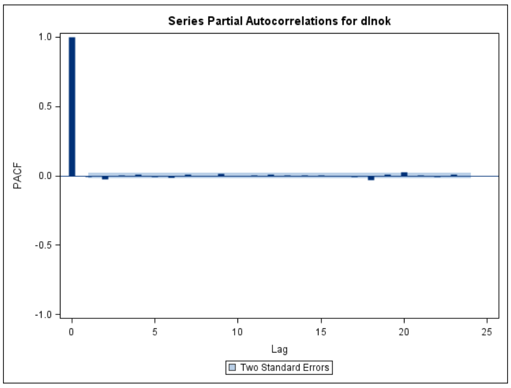
Panel (a)



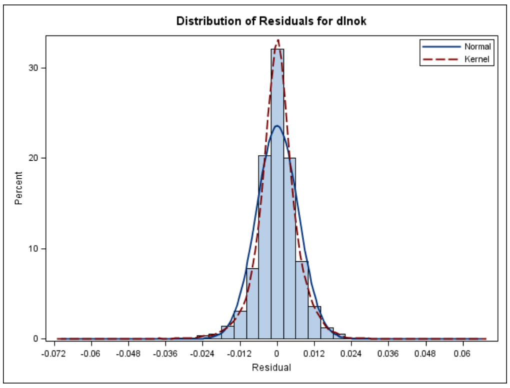
Panel (b)



Panel (c)

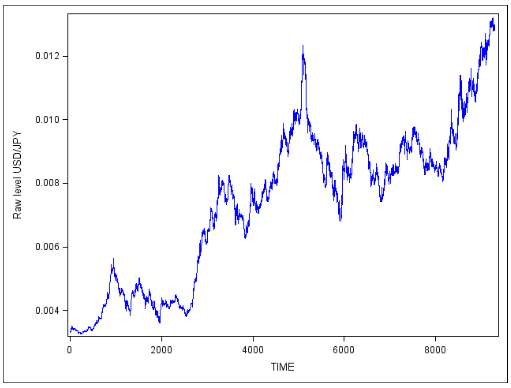


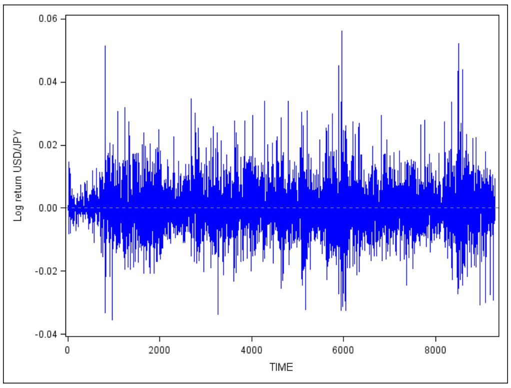
Panel (d)



Panel (e)

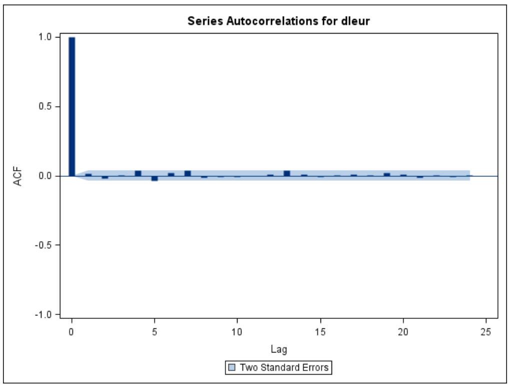
Figure 2: USD/YEN, dlyen; ACF, PACF, distribution.

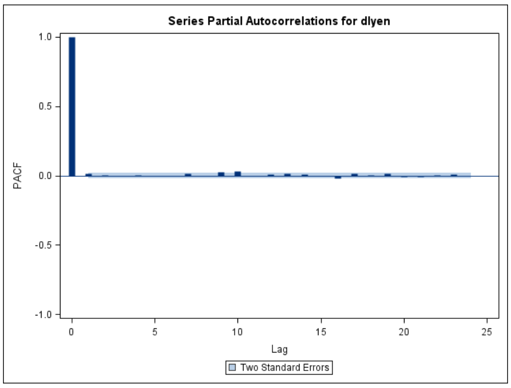




Panel (a)

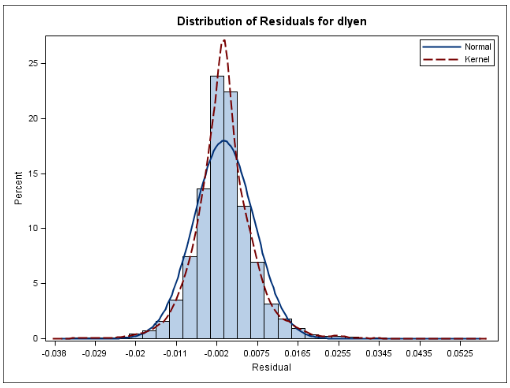
Panel (b)





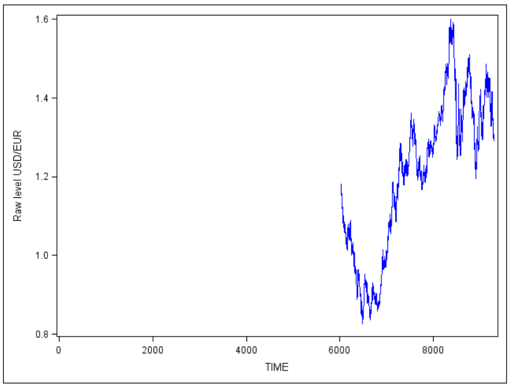
Panel (c)

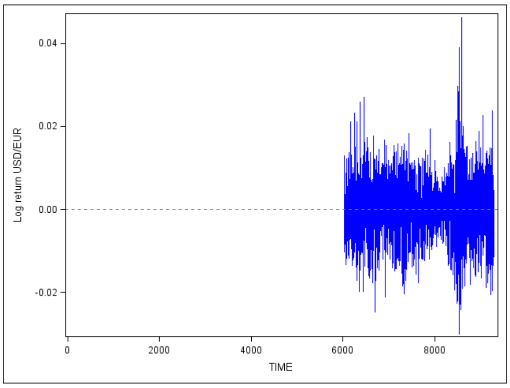
Panel (d)



Panel (e)

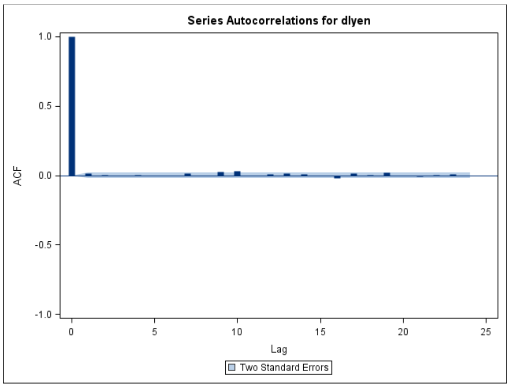
Figure 3: USD/EUR, dleur, ACF, PACF, distribution.

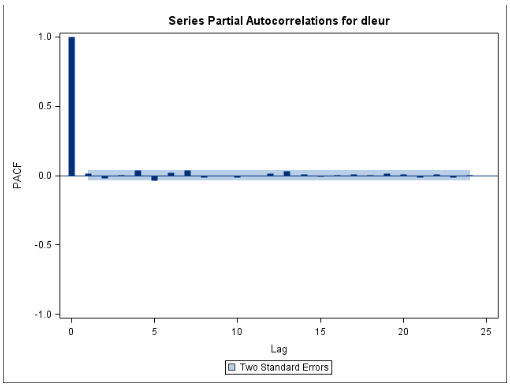




Panel (a)

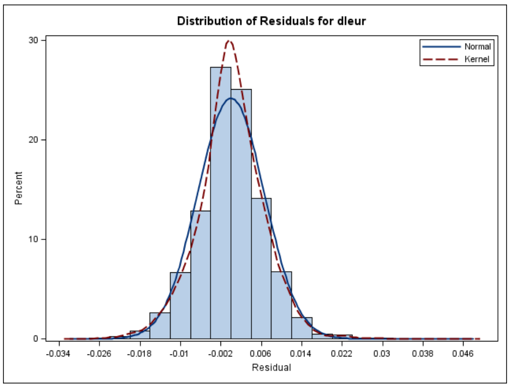
Panel (b)





Panel (c)

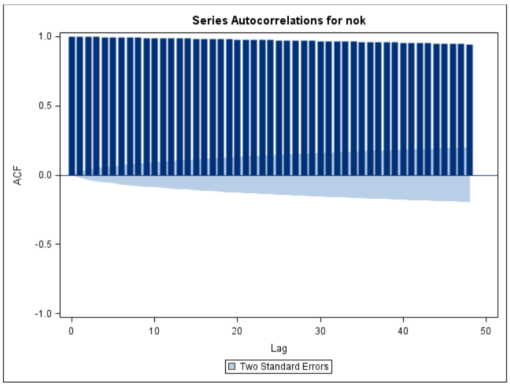
Panel (d)



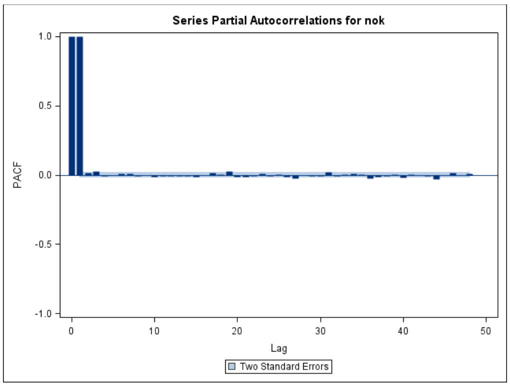
Panel (e)

Apendix 1

Figure A1-1: ACF nok and PACF nok.

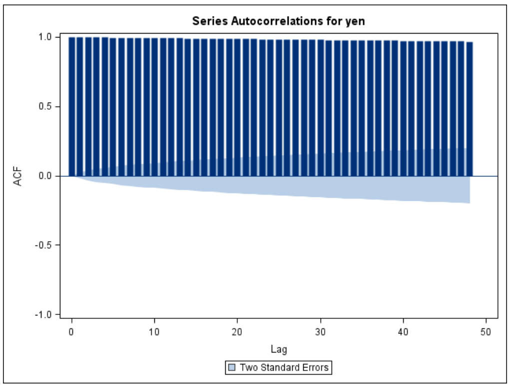


Panel (a)

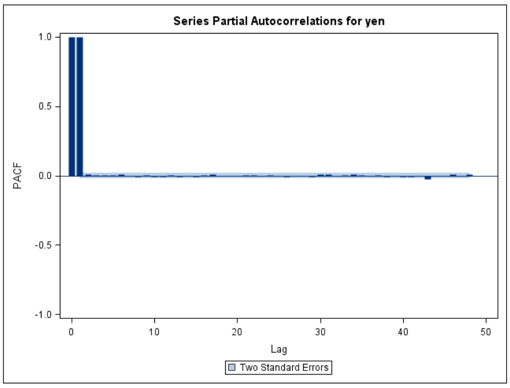


Panel (b)

Figure A1-2: ACF yen and PACF yen.

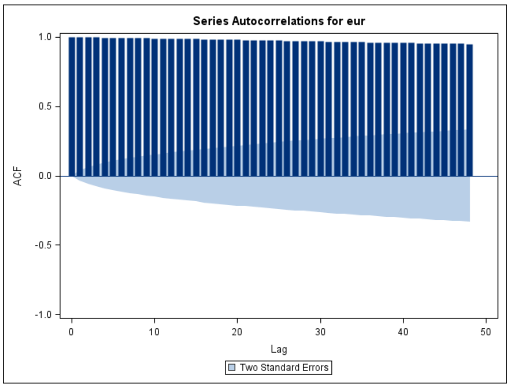


Panel (a)

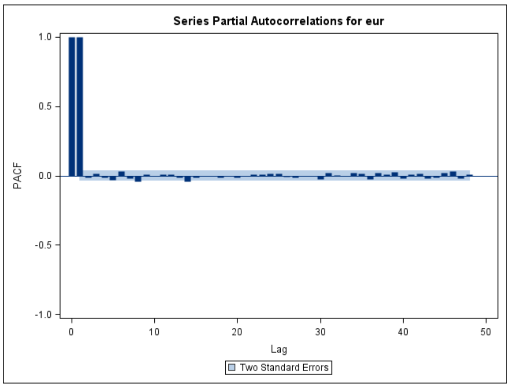


Panel (b)

Figure A1-3: ACF eur and PACF eur.



Panel (a)



Panel (b)

Apendix 2

Table A2-1: For the interested reader. This is about 1/3 of the amount of SAS programming commands that were used to generate the results *manually*. Further programming is available upon request. SAS 9.2 was used for all results in its entirety, except for the LR tests which were conducted using SAS 9.3.

```
proc import out=fx
datafile="C:\Users\Eduardo\Desktop\UiS MOA\4th semester\FX"
dbms=Excel
replace;
getnames=yes;
run;
proc print;
run;

data fx;
set fx;
label
            nok="Raw level USD/NOK"
            yen="Raw level USD/JPY"
            eur="Raw level USD/EUR"
            dlnok="Log return USD/NOK"
            dlyen="Log return USD/JPY"
            dleur="Log return USD/EUR";
run;

proc contents data=fx;
run;

proc means data=fx;
var dlnok dlyen dleur;
run;
proc corr data=fx;
var dlnok dlyen dleur;
run;
ods graphics on;

proc    arima    data=fx    plots(only)=(series(acf    pacf    series)
residual(normal smooth));
identify var=dlnok stationarity=(ADF) nlag=48;
estimate;
run;

ods graphics off;

proc arima data=fx;
identify var=nok stationarity=(ADF) nlag=48;
estimate;
run;

proc arima data=fx;
identify var=dleur stationarity=(ADF) nlag=48;
estimate q=1;
```

```
run;

proc arima data=fx;
identify var=dleur stationarity=(ADF) nlag=48;
estimate p=1 q=1;
run;

proc arima data=fx;
identify var=dleur stationarity=(ADF) nlag=48;
estimate p=(2) q=(2);
run;

proc arima data=fx;
identify var=dlyen stationarity=(ADF) nlag=48;
estimate;
run;

ods graphics on;
proc arima data=fx;
identify var=dleur stationarity=(ADF) nlag=42;
estimate;
run;
ods graphics off;

proc autoreg data=fx;
model dlnok=/archtest garch=(p=1,q=1) noint normal dwprob method=ml
noint maxiter=1000;
run;
ods graphics off;

proc arima data=fx;
identify var=nok stationarity=(rw);
estimate;
run;

ODS GRAPHICS on;

proc autoreg data=fx;
model dlnok=/archtest dwprob dw=48 garch=(p=1,q=1);
run;

ODS GRAPHICS off;

proc autoreg data=fx;
model dlnok=/ normal garch=(p=1,q=1);
run;

proc arima data=fx;
identify var=nok;
estimate p=1;
run;
identify var=nok;

ods graphics on;
proc univariate data =fx normal;
  var dlnok;
  histogram /normal kernel;
run;

PROC UNIVARIATE DATA=FX NORMAL PLOT;
```

```
VAR pdlnok;
QQPLOT pdlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
RUN;
PROC UNIVARIATE DATA=FX NORMAL PLOTS;
histogram;
VAR pdlnok;
RUN;

title 'Series distributions';
ods graphics off;
proc univariate data=fx noprint;
   histogram dlnok / kernel(c = 0.25
                            l = 1 20 2 34
                            noprint);
run;

ODS GRAPHICS ON;
PROC CAPABILITY DATA=fx NORMALTEST VARDEF=N;
VAR dlnok;
QQPLOT dlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
PPPLOT dlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
HISTOGRAM /NORMAL(COLOR=MAROON W=4) CFILL=BLUE CFRAME=LIGR KERNEL;
INSET MEAN STD /CFILL=BLANK FORMAT=5.2 ;
RUN;
ODS GRAPHICS OFF;

PROC MIXED DATA=FX METHOD=REML;
MODEL pdlnok=/ S DDFM=SATTERTH CL INTERCEPT;
RUN;

data b;
set a;
mse=r-dlnok;
MSE2=mse*mse;
run;

goptions reset=all;
proc gplot data=b;
plot mse2*time;
run;
quit;

proc arima data=fx ;
identify var=dlnok stationarity=(ADF) nlag=48;
estimate  p=3 q=3 maxiter=400;
run;
ods graphics on;
proc gplot data=fx;
plot dlnok * date = 1 /;
run;
ods graphics off;

ODS GRAPHICS ON;
PROC SGPLOT;
HISTOGRAM dlnok/showbins;
density dlnok;
density dlnok/type=kernel;
title'Distribution of dlnok';
run;
ODS GRAPHICS off;
```

```
ODS GRAPHICS ON;
PROC REG DATA = fx PLOTS(maxpoints=10000) = (DIAGNOSTICS FITPLOT);
MODEL dlnok = ;
TITLE 'Results of Regression Analysis';
RUN;
ODS GRAPHICS off;

proc reg data=fx;
model dlnok=/;
run;

proc ttest data=fx;
var dlnok;
run;

DATA fx;
dlnok= TINV(0.95,9);
proc print;
RUN;

proc autoreg data=fx;
model dlnok=/ normal;
run;

proc arima data=fx;
identify var=nok;
run;

proc autoreg data=fx;
model dlnok=/garch=(q=1,p=1);
output predicted=a;
run;

proc gplot data=fx;
symbol1 v=dot i=join;
symbol2 v=none i=r;
plot x*date=1 x *date= 2/overlay;
run;

proc autoreg data=fx;
model x=date/nlag=2 archtest dwprob;
output out=r r=xresid;
run;

ods html body='trend.htm';
proc autoreg data=fx;
model x=date/ archtest dwprob;
output out=r r=xresid;
run;
ods html close;

data fx;
set fx;
xlag1=lag(x);
xlag2=lag(xlag1);
run;
proc autoreg data=fx;
model x=/garch=(q=1,p=1);
run;
```

```
ods rtf file='temp.rtf';
   proc print data=sashelp.class;
   run;
   ods rtf close;

ods rtf style=journal;
proc autoreg data=fx;
model x=date/ archtest dwprob;
output out=r r=xresid;
run;
ods rtf close;

data fx2;
set fx2;
x=log(x)
y=log(y)
z=log(z);
run;

ods graphics on;

ods graphics on;

title'Heteroscedastic Autocorrelated Time Series';

goptions reset=all;
symbol1 i=rlclm;
proc gplot data=a;
plot1 r*time;
run;
quit;
ods graphics off;

ods graphics on;
proc autoreg data=fx;
   model dlnok =/ garch=(p=1,q=1) method=ml;
      output out=a predicted=p residual=r ucl=u lcl=l alphacli=.01;
run;

ods graphics off;

run;
ods graphics off;
proc arima data=fx;
identify var=dlnok nlag=2000 outcov=data2;
run;

ods graphics on;
PROC GPLOT DATA =data2;
PLOT partcorr *lag / VREF =0;
SYMBOL1 C=RED V=DOT H =0.5 I= JOIN;
title2 'Autocorrelation Function dlnok';
RUN;
ods graphics off;

ods graphics on;
proc autoreg data=fx;
model dlnok=/archtest garch=(p=1,q=1) noint normal dwprob method=ml
maxiter=1000;
run;
```

```
ods graphics off;

ods graphics on;
proc autoreg data=fx;
model dlnok=/archtest garch=(p=1,q=1, type=integ, noint)normal dwprob
method=ml noint maxiter=1000;
run;

ods graphics off;

data b;
set a;
mse=r-dlnok;
MSE2=mse*mse;
run;

goptions reset=all;
proc gplot data=b;
plot mse2*time;
run;
quit;

proc arima data=fx ;
identify var=dlnok stationarity=(ADF) nlag=48;
estimate  p=3 q=3 maxiter=400;
run;
ods graphics on;
proc gplot data=fx;
plot dlnok * date = 1 /;
run;
ods graphics off;

ODS GRAPHICS ON;
PROC SGPLOT;
HISTOGRAM dlnok/showbins;
density dlnok;
density dlnok/type=kernel;
title'Distribution of dlnok';
run;
ODS GRAPHICS off;

ODS GRAPHICS ON;
PROC REG DATA = fx PLOTS(maxpoints=10000) = (DIAGNOSTICS FITPLOT);
MODEL dlnok = ;
TITLE 'Results of Regression Analysis';
RUN;
ODS GRAPHICS off;

proc arima data=fx;
identify var=nok stationarity=(rw);
estimate;
run;
ODS GRAPHICS on;

proc autoreg data=fx;
model dlnok=/archtest dwprob dw=48 garch=(p=1,q=1);
run;

ODS GRAPHICS off;
proc arima data=fx;
```

```
identify var=nok;
estimate p=1;
run;
identify var=nok;

ods graphics on;
proc univariate data =fx normal;
  var dlnok;
  histogram /normal kernel;
run;

PROC UNIVARIATE DATA=FX NORMAL PLOT;
VAR pdlnok;
QQPLOT pdlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
RUN;
PROC UNIVARIATE DATA=FX NORMAL PLOTS;
histogram;
VAR pdlnok;
RUN;

title 'Series distributions';
ods graphics off;
proc univariate data=fx noprint;
   histogram dlnok / kernel(c = 0.25
                            l = 1 20 2 34
                            noprint);
run;

ODS GRAPHICS ON;
PROC CAPABILITY DATA=fx NORMALTEST VARDEF=N;
VAR dlnok;
QQPLOT dlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
PPPLOT dlnok /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
HISTOGRAM /NORMAL(COLOR=MAROON W=4) CFILL=BLUE CFRAME=LIGR KERNEL;
INSET MEAN STD /CFILL=BLANK FORMAT=5.2 ;
RUN;
ODS GRAPHICS OFF;

PROC MIXED DATA=FX METHOD=REML;
MODEL pdlnok=/ S DDFM=SATTERTH CL INTERCEPT;
RUN;

proc ttest data=fx;
var dlnok;
run;
DATA fx;
dlnok= TINV(0.95,9);
proc print;
RUN;

proc autoreg data=fx;
model dlnok=/garch=(q=1,p=1);
output predicted=a;
run;

proc gplot data=fx;
symbol1 v=dot i=join;
symbol2 v=none i=r;
plot x*date=1 x *date= 2/overlay;
run;
```

```
proc autoreg data=fx;
model x=date/nlag=2 archtest dwprob;
output out=r r=xresid;
run;

ods html body='trend.htm';
proc autoreg data=fx;
model x=date/ archtest dwprob;
output out=r r=xresid;
run;
ods html close;

data fx;
set fx;
xlag1=lag(x);da
xlag2=lag(xlag1);
run;
proc autoreg data=fx;
model x=/garch=(q=1,p=1);
run;
ods rtf file='temp.rtf';
   proc print data=sashelp.class;
   run;
   ods rtf close;

ods rtf style=journal;
proc autoreg data=fx;
model x=date/ archtest dwprob;
output out=r r=xresid;
run;
ods rtf close;

data fx2;
set fx2;
x=log(x)
y=log(y)
z=log(z);
run;

data fx2;
set fx2;
label        x="USD/NOK"
             y="USD/JPY"
             z="USD/EUR"
             lnx="ln(USD/NOK)"
             lny="ln(USD/JPY)"
             lnz="ln(USD/EUR)";
run;

proc contents data=fx2;
run;

NORMALITY PLOT and TESTS:

PROC UNIVARIATE DATA=FX NORMAL PLOT;
VAR dlNOK;
QQPLOT dlNOK /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
RUN;
ods rtf style=journal;
```

```
PROC CAPABILITY DATA=fx NORMAL;
VAR dleur;
QQPLOT dleur /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
PPPLOT dleur /NORMAL(MU=EST SIGMA=EST COLOR=RED L=1);
HISTOGRAM /NORMAL(COLOR=MAROON W=4) CFILL  = BLUE CFRAME = LIGR;
INSET MEAN STD /CFILL=BLANK FORMAT=5.2 ;
RUN;
ods rtf close;

proc autoreg data=fx;
model dleur=/ normal;
run;

proc arima data=fx;
identify var=nok;
run;

ods rtf style=journal;
proc autoreg data=fx;
model x=date/ archtest dwprob;
output out=r r=xresid;
run;
ods rtf close;

proc arima data=fx;
identify var=nok(1);
run;

proc autoreg data=fx;
model dlnok=/ garch=(p=1,q=1)noint dist=t maxiter=1000;
test _ah_1+_gh_1=0/ type=LR;
run;

proc autoreg data=fx;
model dlnok=/ garch=(p=1,q=1) dist=n maxiter=1000;
test _ah_1+_gh_1=0/ type=LR;
run;

proc autoreg data=fx;
model dlnok=/ garch=(p=1,q=1)noint dist=n maxiter=1000;
test _ah_1+_gh_1=0/ type=LR;
run;

proc autoreg data=fx;
model dlnok=/ garch=(p=1,q=1)noint dist=t maxiter=1000;
test _ah_1+_gh_1=0/ type=LR;
run;

proc autoreg data=fx;
model dlyen=/ garch=(p=1,q=1)noint dist=t maxiter=1000;
test _ah_1+_gh_1=0/ type=LR;
run;
```