

Quantitative Easing and Danish Krone Exchange Rate Volatility

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Abstract

This study uses the GARCH and eGARCH models to examine the relationship between quantitative easing and conditional volatility of the Danish krone while evaluating the asymmetric effects of good and bad news on conditional volatility. This study finds that during the quantitative easing period, an increase of the interest rate differential further reduces exchange rate volatility with the euro but increases exchange rate volatility with the Swedish krona and Norwegian krone. After accounting for the positive relationship between Danish krone appreciation and exchange rate volatility, during the quantitative easing period as the interest rate differential increases, exchange rate volatility declines for the US dollar but increases for the UK pound.

Keywords: Exchange rate volatility, quantitative easing, GARCH, eGARCH

JEL Code: E52, F31

I. Introduction

In response to the global financial crisis of 2007-2008 and lack of conventional monetary policy effectiveness, central banks around the world introduced a variety of unconventional monetary policy tools aimed at restoring financial market stability, avoiding deflation, and encouraging economic growth. These unconventional monetary policy tools included quantitative easing (QE) and negative nominal interest rate policies (NNIR). QE, also known as large-scale asset purchases, is an unconventional monetary policy whereby a central bank buys government bonds or other financial assets in order to increase liquidity and lower interest rates. In theory, the higher levels of liquidity and lower interest rates would encourage banks to loan funds thereby increasing investment and consumer spending. If successful, QE would stabilize financial markets by providing liquidity; avoid deflation by increasing inflation rates, and spur economic growth by encouraging investment and consumer spending.

Prior to the recent financial crisis, economists and central bank officials assumed that a zero nominal interest rate policy represented the lower bound of a nominal interest rate target. If a zero nominal interest rate policy was implemented, it would lead to a liquidity trap. Any additional money supply increases would have no expansionary effect on aggregate demand since households and businesses would have met their liquidity needs. As the negative economic impacts of the financial crisis persisted and the minimal effectiveness of fiscal policy became apparent, several central banks discussed the possibility of implementing a negative interest rate target. Despite liquidity trap concerns, the use of a NNIR policy was first introduced by Denmark Nationalbank in July 2012 to discourage appreciation of its currency and to defend its peg with the euro. In June 2014, the NNIR policy was introduced by the European Central Bank; this action was quickly followed by the Swiss National Bank in January 2015 and the Swedish Riksbank in February 2015. By 2016, the central banks in Bulgaria, Denmark, the euro area, Hungary, Japan, Sweden, and Switzerland had implemented NNIR policies.

Although the implementation of quantitative easing and NNIR policies has led to a growing body of literature, most of the research has focused on a theoretical re-evaluation of the nominal interest rate lower bound assumption (see Buiter, 2009; Dong and Wen, 2017) and empirical assessments of QE and NNIR policy impacts on monetary policy transmission and bank profits (see Bech and Malkhozov, 2016; Kerbl and Sigmund, 2016; Arteta and Kose,

2018). This study adds to the empirical literature by exploring the effects and effectiveness of QE and NNIR policy on exchange rates volatility. This study uses GARCH and eGARCH methods to examine the relationship between quantitative easing and conditional volatility of the Danish krone while evaluating the asymmetric effects of good and bad news on conditional volatility

II. Data

This study uses the daily Danish krone bi-lateral exchange rates with the euro, Norwegian krone, Swedish Krona, the United Kingdom (UK) pound, and the United States (US) dollar from 4 January 1999 through 30 March 2018 (source central banks) to measure exchange rate volatility. The countries using these five currencies account for nearly 70% of Denmark’s exports and imports. The interest rate data used in this study are the daily Denmark Nationalbank certificate of deposit interest rate (source Denmark Nationalbank Statbank) and the daily Denmark 10-year bond rate (source Investing.com). Exchange rate volatility is a measure of the fluctuations of the daily exchange rate change or the variance of the exchange rate return.

Empirical literature has found that daily returns of financial assets such as stocks, bonds and exchange rate returns are not normally distributed but are heavy-tailed and skewed distributions (select articles include Black, 1976; Merton, 1980, Nelson (1991), Bekaert, 2000). The underlying premise is that negative shocks increase conditional volatility more than positive shocks, hence there is asymmetry on the impact of good and bad news on the riskiness of returns. Figure 1 shows that for all five currencies, the Danish krone exchange rates have stochastic trends or are nonstationary. The bi-lateral exchange rate variances exhibit volatility clustering, where periods of low volatility are followed by periods of low volatility and periods of high volatility are followed by periods of high volatility.

Figure 1: Exchange rates with evidence of volatility clustering

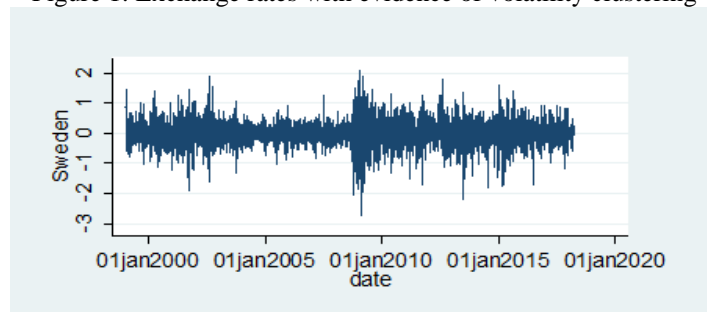
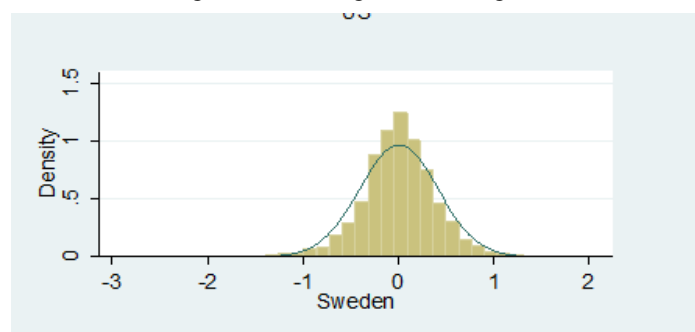


Figure 2 shows that the exchange rate volatility is not normally distributed. The distributions are more peaked than a normal distribution and have fatter tails or excess kurtosis.

Figure 2: Exchange rates histograms



The test results in Table I confirm that the exchange rate changes are not normally distributed and exhibit autocorrelation in squared returns.

Table I: Heteroskedasticity and Normality tests

Currency	BP	White	Skewness	Kurtosis	LM
Euro	134.64***	114.99***	3.18	15.00***	166.33***
Norway Krone	145.59***	52.84***	1.84	2.92*	48.31***
Swedish Krona	76.76***	102.09***	1.26	10.93***	243.38***
UK Pound	81.10***	98.46***	8.52**	6.75***	145.683***
US dollar	37.73***	78.76***	3.49	34.24***	131.853***

The Breusch-Pagan (BP) and White test for heteroskedasticity. Skewness and Kurtosis test for normality. LM test for autoregressive conditional heteroskedasticity (ARCH). *** p < 0.01, **p < 0.05, *p < 0.10

III. Methodology

The preliminary test of the Danish krone exchange rate returns data supports the use of the GARCH and eGARCH models that account for heavy-tailed and skewed distributions. Improving on the autoregressive conditional heteroskedastic (ARCH) model developed by Engle (1982), Bollerslev (1986) developed the generalized ARCH (GARCH) model for data that exhibit heteroskedasticity and volatility clustering. Since the GARCH model allows for the variance to change over time in response to market shocks, the GARCH model is frequently used to evaluate stock price return volatility and exchange rate volatility. This study uses GARCH and EGARCH models which account for volatility clustering and non-normal error distributions to simultaneously estimate a mean equation and a variance equation for the exchange rate returns. The mean equation is a function of the previous day's exchange rate return. The variance equation includes the internal shocks of the previous day's residual variance (L1.garch) and the previous day's squared residual (L1.arch), and exogenous monetary policy shocks associated with the nominal interest rate policy. Dummy variables are used to model QE and NNIR policy shocks over time.

The GARCH (Bollerslev, 1986) family of models assumes that the market conditions its expectation of market variance on both past conditional market variance and past market innovations. Bollerslev (1986) proposed an extension of the ARCH type models in order to allow longer memory and a more flexible lag structure. Thus, Generalized Auto Regressive Conditional Heteroskedasticity GARCH type models were born. A GARCH (p,q) process is given by:

$$R_t = \alpha_0 + \sum_{i=1}^k \beta_i X_i + \sum_{j=1}^h \psi_j R_{t-j} + \epsilon_t \quad (1)$$

where $\epsilon_t | \Omega_{t-1} \sim N(0, h_t)$

$$h_t = \alpha + \sum_{i=1}^p \beta_i h_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j}^2 \quad (2)$$

where h_t

= $\sigma_t^2 | \Omega_{t-1}$ (conditional variance dependent on the information set ' Ω_{t-1} ')

With the following conditions $p \geq 0, q > 0$
 $\alpha \geq 0, \theta \geq 0, \beta \geq 0$

and: ϵ_t is the residual of the mean equation
 R_t denotes the return of the asset at time t, and
 X 's are explanatory variables.

Equation (1) is called the mean equation while Equation (2) is called the equation for the conditional variance. It can be clearly seen that the GARCH (p,q) models the conditional variance as the function of both the squared innovations and its own past values. Notice that when p=0, Equation (2) reduces to an ARCH(q) model. A limitation of the model is that it

restricts the parameters to be strictly non-negative in order to satisfy the condition of a positive variance. This means that the regular GARCH type models only capture the magnitude of the shocks and tend to neglect its sign.

Proposed by Nelson (1991), the exponential GARCH (EGARCH) model allows for asymmetric volatility effects arising from market shocks (see Bollerslev, 2008 for a summary of ARCH models). By modifying ϵ_t or the residuals of the mean equation such that

$$\frac{\epsilon_t}{\sqrt{h_t}} = z_t \quad (3)$$

where $z_t \sim \text{iid}(0,1)$ and is called the standardized residuals

Furthermore, the EGARCH model is given by:

$$\ln(h_t) = \alpha_i + \sum_{k=1}^{\infty} \beta_k g(z_{t-k}), \beta \leq 1 \quad (4)$$

where $g(z_t) = \theta z_t + \gamma [|z_t| - E|z_t|]$

Simplifying, the EGARCH variance equation becomes

$$\ln(\sigma_t^2 | \Omega_{t-1}) = \alpha_i + \sum_{j=1}^q \gamma_j [|z_{t-j}| - E|z_{t-j}|] + \sum_{j=1}^q \theta_j z_{t-j} + \sum_{i=1}^p \Delta_i \ln(\sigma_{t-i}^2 | \Omega_{t-i-1}) \quad (5)$$

Equation (4) employs the natural logarithm of the conditional variance in order to ensure that the conditional variance remains non-negative. This contrasts with the previous approach of GARCH type models which impose conditions that the variables must be strictly positive so that a linear combination of such will also be positive. Given this freedom, $g(z_t)$ will now be able to accommodate asymmetric volatility.

The parameter denoted by ' θ ' capture the effect of the sign of the innovation. While ' γ ' measures the impact of the current innovation with its long run average, we can say that it captures the magnitude (size) of the innovation. By incorporating an AR process for the conditional variance, to allow for a longer memory, we arrive at Equation (5). However, it is important to note that Stata takes the $E|z_{t-j}|$ as $\sqrt{2/\pi}$ (Stata, 2014). Overall, the EGARCH model, unlike the linear GARCH models, uses the natural logarithm of the conditional variance to relax the non-negativity constraint of the model's coefficients and to allow for the persistence of shocks to the conditional variance.

IV. Results and Discussion

The GARCH model results are shown in Tables II and III and the eGARCH model results are shown in Tables IV and V. The variables listed under HET represent the exogenous monetary policy shocks included in the variance equation. Tables II and IV report the results using the dummy QE policy periods and Tables III and V report the results using the interest rate differential and QE policy periods. The variables listed under ARCH represent the internal shock variables.

Both GARCH models find that for all five exchange rates, the previous day's exchange rate return information (L1.arch) and the previous day's exchange rate volatility (L1.garch) positively influence today's exchange rate volatility. The influences of the exogenous monetary policy variables are mixed. In Table II, DQE has a positive and significant influence on exchange rate volatility with the euro, the Swedish krone and the UK pound.

During the QE periods, exchange rate volatility increased with largest volatility for the Swedish krone and the UK pound. DQE has a negative and significant influence on the US dollar exchange rate volatility. DQE did not significantly influence Norwegian krone exchange rate volatility.

Table II: GARCH model results with QE Dummy

	GARCH with DQE				
	Euro	Norway	Sweden	UK	US
constant	.0001 (.0002)	.0079 (.0061)	-.0029 (.0053)	-.0014 (.0067)	-.004 (.0086)
HET					
DQE	.4077*** (.0339)	2.040 (1.4868)	11.79*** (.1686)	10.13*** (.1553)	-.3163*** (.0361)
constant	-9.329*** (.0734)	-5.519*** (1.7536)	-16.12*** (.0010)	-13.94*** (.0001)	-1.121*** (.0920)
ARCH					
L1.arch	.3458*** (.0176)	.1852*** (.01240)	.1909*** (.0129)	.1804*** (.0121)	.1677*** (.0161)
L1.garch	.2671*** (.0352)	.7771*** (.0407)	.7888*** (.0099)	.7966*** (.0113)	.0686 (.0718)
obs	4814	4814	4814	4814	4814

*** p < 0.01, **p < 0.05, *p < 0.10

The Table III results show that when the interest rate differential increases, exchange rate volatility declines for all currencies. When isolating the QE policy periods however the results again are mixed. During the QE periods, euro exchange rate volatility further declined. This suggests that stabilizing the peg by adopting a QE policy reduced euro exchange rate volatility. The QE policy had a negative but small influence on UK pound exchange rate volatility. For the Norwegian krone, Swedish krone, and the US dollar, the interest rate differential significantly increased exchange rate volatility during the QE periods. These results suggest that while Danish Nationalbank QE policy and flattening of the yield curve, achieved the goal of reducing its euro-peg exchange rate risk, exchange rate risk increased with two of its major trade-partners, Norway and Sweden.

For both EGARCH models, appreciation of the Danish krone increases exchange rate volatility (L1.earch_a). For the Norwegian exchange rate, the previous day's exchange rate return information (L1.earch) reduces exchange rate volatility. For all other exchange rates, the results were insignificant. As with the GARCH model, previous day's exchange rate volatility significantly influences today's exchange rate volatility (L1.GARCH). For the EGARCH models DQE increased exchange rate volatility for all currencies except the US dollar. For the US dollar, DQE reduced exchange rate volatility.

For all exchange rates as the interest rate differential increased, exchange rate volatility declined. As with the GARCH model when isolating the QE policy, the interest rate differential influence is mixed. For the Norwegian krone, Swedish krone and UK pound, the interest rate differential significantly increased exchange rate volatility during the QE periods while the interest rate differential further reduced exchange rate volatility for the US dollar. The influence of the interest rate differential during the QE periods was negative but not significant for the euro exchange rate.

V. Conclusions

This study finds that the previous day's exchange rate volatility significantly influences today's exchange rate volatility and that as the interest rate differential increases exchange rate volatility declines. The study also finds that appreciation of the Danish krone increases

exchange rate volatility. This study further finds that during the QE periods, as interest rate differential increases exchange rate volatility declines further for the euro but increases for the Swedish krone and Norwegian krone. After accounting for the positive relationship between Danish krone appreciation and exchange rate volatility, during the QE periods as the interest rate differential increases, exchange rate volatility declines for the US dollar but increase for the UK pound.

Table III: GARCH model results with Interest Rate Differential variables

	GARCH with Interest Rate Differentials				
	Euro	Norway	Sweden	UK	US
constant	.0001 (.0002)	.0080 (.0061)	-.0024 (.0053)	.0002 (.0067)	-.0010 (.0086)
HET					
IntDiff	-.4708*** (.02263)	-3.99*** (.3915)	-4.219*** (.5535)	-3.296*** (.3859)	-.0367* (.0220)
DQEDiff	-.0477* (.0264)	4.778*** (.5067)	5.063*** (.7457)	3.205*** (.4886)	.2369*** (.0282)
constant	-8.418*** (.0512)	-4.59*** (.2254)	-5.379*** (.3403)	-3.621*** (.1897)	-1.065*** (.0920)
ARCH					
L1.arch	.2938*** (.0155)	.1638*** (.0106)	.1824*** (.0126)	.1596*** (.0115)	.1616*** (.0161)
L1.garch	.2054*** (.0286)	.7895*** (.0089)	.7795*** (.0100)	.7881*** (.0120)	.0669 (.0734)
obs	4814	4814	4814	4814	4814

*** p < 0.01, **p < 0.05, *p < 0.10

Table IV: EGARCH model results with QE Dummy

	EGARCH with DQE				
	Euro	Norway	Sweden	UK	US
Constant	-.0002 (.0002)	.0009 (.0063)	-.0053 (.0053)	-.0020 (.0070)	-.0037 (.0086)
HET					
DQE	.2346*** (.0153)	.1181*** (.0132)	.0614*** (.0097)	.0551*** (.0081)	-.2409*** (.0420)
Constant	-4.142*** (.2511)	-1.814*** (.0513)	.2151*** (.0788)	.1860*** (.0598)	-6.455*** (.0780)
ARCH					
L1.earch	.0195 (.0135)	-.1422*** (.01340)	-.0185 (.0117)	.0008 (.0098)	-.0310* (.0167)
L1.earch_a	.5177*** (.0217)	.3191*** (.0196)	.3142*** (.0205)	.3064*** (.0178)	.2936*** (.0265)
L1.egarch	.5116*** (.0298)	.9092*** (.0316)	1.137*** (.0438)	1.133*** (.0273)	.2528*** (.0870)
Obs	4814	4814	4814	4814	4814

*** p < 0.01, **p < 0.05, *p < 0.10

Table V: EGARCH model results with Interest Rate Differential variables

	EGARCH with Interest Rate Differentials				
	Euro	Norway	Sweden	UK	US
constant	-.0001 (.0002)	.00194 (.0064)	-.0047 (.0053)	-.0023 (.0069)	-.0014 (.0086)
HET					
IntDiff	-.2960*** (.0157)	-.0377*** (.0070)	-.0181*** (.0064)	-.0213*** (.0054)	-.0510*** (.0164)
DQEDiff	-.0183 (.0176)	.0956*** (.0159)	.0489*** (.0079)	.0387*** (.0078)	-.1739*** (.0300)
constant	-4.742*** (.2156)	-.2138*** (.0512)	.1938** (.0768)	.1446*** (.0344)	-.5659*** (.0790)
ARCH					
L1.earch	.0174 (.0137)	-.1419*** (.0139)	-.0159 (.0125)	.0007 (.0097)	-.0303* (.0171)
L1.earch_a	.4803*** (.0120)	.3249*** (.0206)	.3193*** (.0214)	.3114*** (.0185)	.2773*** (.0272)
L1.egarch	.3883*** (.0266)	.8599*** (.0337)	1.1129*** (.0431)	1.1088*** (.0266)	.2706*** (.0893)
obs	4814	4814	4814	4814	4814

*** p < 0.01, **p < 0.05, *p < 0.10

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