LUND UNIVERSITY
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Neighbours, but yet different? Scandinavian stock market volatility and its drivers under different regimes

A GARCH-MIDAS approach

by

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May 2019

Master's Programme in Economics

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Abstract

This study is an initial attempt to investigate the differences and similarities of the stock market volatilities in Scandinavia with respect to their drivers. Using the GARCH-MIDAS (Mixed Data Sampling) framework, this paper evaluates the explanatory value of various variables originating from different areas, covering the period from February 1998 to December 2018. Considered categories include business cycle indicators, monetary policy, economic policy uncertainty indices and oil shocks. A principal component analysis is used to proxy the state of the U.S. economy. To gain a deeper insight into the dynamic volatility behaviour, this study focuses on different regimes, namely the Pre-GFC and the Post-GFC era. The Danish equity market shows overall the greatest exposure to the business cycle and monetary policy. While for Denmark the link between the real economy and the market volatility (slightly) increased after the GFC, a reverse trend can be seen for Norway. Among the economic policy uncertainty variables, both the American and the Swedish index affect the markets of Scandinavia, while no such link can be found for the European version. Real oil prices are of no explanatory value for no subsample considered and a declining exposure to oil shocks is revealed. While statistically relevant for the full sample across all countries, the proxy for the U.S. economy is only significant for Denmark when discarding the period of the GFC.

Keywords: Scandinavia, Stock market, Volatility, GARCH-MIDAS

Acknowledgements

I wish to thank my supervisor Hossein Asgharian for his support throughout the thesis. Advice given by Duc Hong Hoang regarding the MATLAB code has also proven to be of great help. I would also like to acknowledge the support provided by my family and my friends here in Lund and also in Germany during the preparation of this research paper. This thesis would not have been possible without the financial support by the German national academic foundation.

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1 Introduction

In landmark studies, Engle (1982) and Bollerslev (1986) introduced the autoregressive conditional heteroscedasticity (ARCH) model and the respective generalized ARCH (GARCH) model, both helping financial econometrics to make enormous progress. The main feature of these models is their ability to capture some of the well-known stylized facts of financial return, such as volatility clustering. However, from a theoretical point of view (see for example, Ross, 1976; Chen et al., 1986), stock returns are also subject to changes of economic fundamentals. Yet, as the sample frequency of many macroeconomic variables differs from the one of financial returns, one main theoretical question of the past was how to incorporate those variables in the standard volatility frameworks. In a pioneer contribution, Ghysels et al. (2006) propose a new method called mixed data sampling (MIDAS), which solves the aforementioned problem and therefore allows for considering data sampled at different frequencies. Engle et al. (2013) use this framework and introduce the GARCH-MIDAS model in which the conditional volatility is split up into a respective short-term and long-term part. The GARCH-MIDAS framework effectively combines the two-component approach first introduced by Engle and Lee (1993) with the MIDAS methodology of Ghysels et al. (2006).

As a response to this promising model framework, several studies have used this approach to directly examine the predictive power of macroeconomic variables on forecasting financial volatility of various assets (see for example, Magrini and Donmez, 2013; Fang et al., 2018; Walther and Klein, 2018). Yet, few attempts have been made to investigate the link between macroeconomic fundamentals and stock market volatility in small open economies. Salisu and Ndaku (2017) apply a GARCH-MIDAS model to the European equity market, including (among others) countries such as Turkey, Austria or Finland. Virk and Javed (2017) explore the dynamic correlation pattern between large and small equity markets in Europe. The research by Virk and Javed (2017) moreover indicates that one has to take the dynamic economic setting into account when investigating the link between the stock market volatility and macroeconomic fundamentals. Kejlberg (2018) explores solely the variance contributions of several macroeconomic variables to the Swedish equity market using a GARCH-MIDAS framework.

The aim of this thesis is to close the apparent gap and to gain a better understanding of the stock market volatility of small open economies. This is done by analysing the Scandinavian equity market using daily data covering the period from 1998 to 2018. In particular, by considering various variables originating from different areas, this paper seeks to address the following questions: Firstly, what macroeconomic variables show the best explanatory value for the volatility of each equity market and are there any prominent differences among the countries? Secondly, did the importance of some drivers change during specific periods? Thirdly, which economy shows the greatest exposure to the state of the U.S. economy? While some studies focus on the overall contribution of variable categories (see for example, Virk and Javed 2017), this study wants to provide an in-depth analysis of individual drivers.

For resolving the aforementioned issues, this paper applies the previously introduced GARCH-MIDAS approach. Additionally, the data sample was split into respective subsamples, namely into pre-financial crisis (Pre-GFC) covering the period from February 1998 to November 2007 and into post-financial crisis (Post-GFC), which lasted from January 2010 to December 2018. Moreover, for improved comparability purposes, the GARCH-MIDAS model was fit to the full sample. This procedure helps to shed light on answering the question if the importance of some drivers is subject to changes of the underlying dynamic economic setting.

This thesis is divided into four main sections. Chapter 2 discusses the relevant literature, while Chapter 3 introduces the methodology used. The remaining sections present the data and the empirical results, before Chapter 5 concludes.

2 Literature Review

In an attempt to explain changes of stock market volatility over time, Schwert (1989) investigates the link between macroeconomic variables and the U.S. stock returns. Using different variables such as the industrial production growth or the short-term interest rates, Schwert (1989) reports that macroeconomic volatility contains only little value for predicting fluctuations of the stock market. In the same year, Fama and French (1989) offer empirical evidence for a countercyclical behavior of risk premiums which partly contradicts Schwert's (1989).

Inspired by these results, a number of studies tried to shed light on the channel between the stock market volatility and the respective changes of macroeconomic variables. Yet, the results are mixed and there is no clear consensus on what drives the equity volatility the most. While Glosten et al. (1993) find risk free rates to influence the volatility, Whitelaw (1994) reports a statistical significance of the commercial paper-treasury spread. He therefore concludes that return volatility is affected by monetary policy which opposes the findings by Schwert (1989). Hamilton and Lin (1996) as well as Perez-Quiros and Timmermann (2000) stress the importance of the level of the economy for forecasting the stock market volatility. For the UK, Morelli (2002) reports only limited value of macroeconomic fundamentals for explaining fluctuations of the respective stock market. Unlike Schwert (1989) and Morelli (2002), Liljeblom and Stenius (1997) reveal a surprisingly strong relation between macroeconomic variables and the Finnish stock market volatility. Partly in line with this finding, Chinzara (2011) notes that while macroeconomic fundamentals can significantly describe stock market volatility, surprisingly no such link can be found for the industrial production.

In reviewing the literature of exploring the effects of oil price shocks on stock market volatility, empirical evidence suggests that the oil price is of explanatory value (see for example, Sadorsky, 1999; Papapetrou, 2001; Masih et al., 2011). Analysing the impact of oil price shocks in 14 countries, Park and Ratti (2008) show that effects vary for the different stock markets. While for Sweden and Denmark oil price shocks have a negative impact, a reverse effect is found for Norway, an oil-exporting country. All of these studies however treat oil price shocks as exogenous, an aspect first forwarded by Kilian (2009). In his pioneering work, Kilian (2009) argues in favor of an endogenous model and decomposes oil price shocks into three parts, namely oil supply shocks, aggregate and specific demand shocks. Overall, however, these studies strengthen the idea that one should also consider oil price movements in volatility models.

Apart from macroeconomic fundamentals, empirical evidence also suggests that economic policy uncertainty (EPU) can also explain stock market volatility. Becker et al. (1995) show that both the UK and the U.S. market react to public information from the U.S. This result is consistent with the findings by Albuquerque and Vega (2008) who analyse the impact of U.S. news on small open economies. Considering the Portuguese stock market, they find a significant effect. Bolstering the insights from a technical perspective, Pástor and Veronesi (2012) provide a theoretical framework for the link between government policy news and stock prices. Taken together, these findings therefore suggest a role for EPU in explaining stock market volatility.

There were two main limitations of the studies discussed so far both related to the methodology used. Firstly, previous research overlooked the fact that it might be fruitful to consider volatility as a variable that consists of components each of which changing differently over time. Secondly, most early studies have been carried out applying a vector autoregressive model (VAR). This practice resulted due to the lack of approaches available to include macroeconomic variables directly in a volatility model. Consequently, it is possible that some macroeconomic information for predicting volatility was lost due to these two aspects. Tackling the first theoretical issue, Engle and Lee (1993) propose to split up the volatility component of a GARCH model into a short- and a long-run part. Their research is in line with other studies suggesting to consider component models (see for example, Ding and Granger, 1996; Gallant et al., 1999). These insights are important as they offer a new way of conceptualizing the link between macroeconomic volatility and the respective fluctuation of equity.

Even though all of this research indicates that considering macroeconomic volatility can be beneficial, the majority of studies fail to explain why certain macroeconomic drivers seem to be more important for some economies than for others. For instance, Errunza and Hogan (1998) find that while return volatility in the equity markets of Germany and France are significantly affected by the monetary policy, the respective counterparts for the Netherlands and Italy are influenced more by industrial production. In an attempt to solve this problem, Engle and Rangel (2008) introduce a Spline-GARCH model. This model allows the volatility to change with respect to time and is based on a two-component framework for the daily return fluctuation. By analyzing fifty countries, Engle and Rangel (2008) find evidence for a link between macroeconomic and stock market volatility.

The methodology used in this paper is based on two main pioneering contributions. Ghysels et al. (2006) propose a new method called MIDAS. This approach solves the puzzle of considering several variables sampled at different sample frequencies in one framework. Introducing the GARCH-MIDAS model, Engle et al. (2013) combine a two-component model with the MIDAS approach. These two concepts advanced research enormously, as one can now consider various macroeconomic variables directly in a GARCH-Model. In their research, Engle et al. (2013), revisiting the work by Schwert (1989), show that up to 35% of the daily fluctuation of the stock return can be explained through inflation and industrial production volatility.

As theoretically speaking a number of macroeconomic fundamentals can potentially be linked to return volatility, considering several variables in a GARCH-MIDAS approach is attractive. Yet, this approach is challenging due to the computational efficiency. In a new approach, Asgharian et al. (2013) compromise the predictive value of various macroeconomic fundamentals using a principal component analysis (PCA) and apply a GARCH-MIDAS framework. This work made a valuable contribution as it effectively incorporates several macroeconomic explanatory variables in one volatility framework.

As the GARCH-MIDAS model is not restricted to macroeconomic fundamentals, various variables can be considered to explain stock market fluctuations. Recently, Asgharian et al. (2018) explore the role of EPU for stock market volatility in the U.S. and UK and report a positive link between U.S. news and stock market volatility in both markets. This study is of high value as it is one of the first studies investigating how EPU can explain the volatility and correlation of different stock markets.

Despite these studies, there still remain aspects that need to be explored. First and foremost, more research has to be done to better understand the dynamic behavior of the link between return and macroeconomic volatility. As the work by Virk and Javed (2017) suggests, the aforementioned relationship is unstable and subject to change with respect to different time periods observed. Second, while including macroeconomic fundamentals often provides better in-sample fits, results for the predictive power of these additional variables are mixed. Some researchers claim a better forecast performance when considering macroeconomic variables (see for example, Engle et al., 2013; Albu et al., 2015), while others report rather disappointing results (for instance Asgharian et al., 2015; Maio and Philip, 2015). Further research should be undertaken to investigate these surprising and partly contradictory findings. On top of that, empirical evidence points out that some macroeconomic forces are differently important than others, depending on what economy one analyses. Virk and Javed (2017) find that large markets are more sensitive to shocks in monetary policy, while smaller economies are more affected by changes in the business cycle. Contrary to expectations, Girardin and Joyeux (2013) apply a GARCH-MIDAS model to the Chinese stock market and find no link between the real business activity and long-term volatility.

This paper addresses some of the aforementioned questions. By providing further empirical evidence on the importance of macroeconomic drivers for the rather small open economies of Scandinavia, this study complements existing literature. Additionally, by considering different subsamples, the results of this paper add valuable insights on the dynamic relationship between economic drivers and stock market volatility. Lastly, it is to my best knowledge the first paper that analyses the differences among the three Scandinavian equity market with respect to their exposure to various drivers using a GARCH-MIDAS approach.

3 Methodology and Data

3.1 GARCH-MIDAS framework

In line with Engle et al. (2013), this paper uses a GARCH-MIDAS approach. The return on day i of month t is modelled in the following way:

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot g_{i,t}} \cdot \epsilon_{i,t} \qquad \forall\, i = 1, 2, \dots, N_t$$
$$\epsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1) \tag{1}$$

where $\Phi_{i-1,t}$ denotes the information set available up to trading day $i-1$ of month t with N_t representing the last trading day of the respective month. Following Engle and Lee (1993), the conditional variance $\sigma_{i,t}^2$ is split into two parts, e.g.

$$\sigma_{i,t}^2 = \tau_t \cdot g_{i,t} \tag{2}$$

where the short-term component $g_{i,t}$ is assumed to follow a GARCH (1,1) process first introduced by Bollerslev (1986):

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{3}$$

For stationarity and non-negativity, $\alpha + \beta \ \leq 1$ must hold. The long-term part τ_t is specified in the light of the MIDAS framework proposed by Ghysels et al. (2006):

$$\tau_t = m_{RV} + \theta_{RV} \sum_{k=1}^{K} \varphi_k(w_1, w_2) RV_{t-k}$$
$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{4}$$

RV_{t-k} denotes the realized volatility (RV) with K indicating the number of days, weeks or months etc. used in the smoothing process. It is important to note that it is possible to let τ_t vary during the time span considered. Yet, the approach taken in this paper refrains from this possibility and keeps τ_t fixed as Engle at al. (2013) report similar results for both approaches.
Moreover, this paper analyses the explanatory value of lagged economic variables for τ_t. Hence, (4) can be written as:

$$log\,\tau_t = m_x + \theta_x \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{t-k} \tag{5}$$

where X_{t-k} denotes the additional explanatory variables used. As some of the variables can take negative values, the log form is needed to ensure non-negativity of the conditional variance. If θ_x is set to zero, the GARCH-MIDAS model reduces to a standard GARCH (1,1) framework with a constant long-term variance component. In that sense, the GARCH-MIDAS model implicitly incorporates the standard GARCH (1,1) approach (Conrad and Loch, 2015). Additionally, one has to specify a weighting scheme for $\varphi_k(w)$. As used by Engle et al. (2013) as well as by Asgharian et al. (2013), this paper applies the following functional form:

$$\varphi_k(w_1, w_2) = \frac{\left(\frac{k}{K}\right)^{w_1-1} \left(1 - \frac{k}{K}\right)^{w_2-1}}{\sum_{j=1}^{K} \left(\left(\frac{j}{K}\right)^{w_1-1} \left(1 - \frac{j}{K}\right)^{w_2-1}\right)} \tag{6}$$

To answer the question to what extent movements of the underlying low-frequency variable X can explain fluctuations of the conditional variance $\sigma_{i,t}^2$, variance ratios (VR) as introduced by Engle et al. (2013) and also used by Kejlberg (2018) will be calculated:

$$VR(X) = \frac{Var(\log(\tau_t^x))}{Var(\log(\tau_t^x * g_{i,t}^x))} \tag{7}$$

As the log-transformation (5) is applied, one has to adjust the originally introduced version of the VR accordingly. Not only is it of interest, what share fluctuation of the long-term component $\log \tau_t$ has on corresponding movements of the conditional variance, but also what additional insights marginal effects might provide. In their paper, Engle et al. (2013) approximate the effect a 1% increase of the low-frequency variable has on the conditional market volatility by computing:

$$e^{\theta * \varphi_k(w_1, w_2)} - 1 \tag{8}$$

It is important to note, that before applying (8), one has to rescale the coefficient θ into percentage units by multiplying with 10^{-2}.

3.2 Data description

This paper analyses the daily closing stock prices of the respective stock market indices for Denmark, Norway and Sweden covering the period between Feb 1998 and Dec 2018. As three years will be needed for estimating the GARCH-MIDAS model, the analysis of the explanatory value of the additional variables only applies to the period from Feb 2001 to Dec 2018.

Moreover, the sample was divided into two subsamples, therefore accounting for the possibility that the return volatility behaviour changes when the economic environment differs. Two regimes are considered, namely the Pre-GFC and the Post-GFC. For estimating the GARCH-MIDAS model for the Post-GFC, the time period of the GFC was excluded, as it is expected that in-sample results are distorted otherwise.

This study investigates the explanatory value of several variables for the return volatility in Scandinavian countries. All variables were sampled at a monthly frequency and were seasonally adjusted when possible. The choice for a monthly period for K results from two considerations. First, as this study aims at investigating a great number of different variables with respect to their usefulness in a GARCH-MIDAS framework, a monthly sample period fits best for the purpose of the study. Second, a monthly time span for K is also reasonable bearing in mind the sample period, especially for the subsamples.

The variables investigated in this study can be broadly categorized into business cycles variables, monetary policy variables, EPU indicators and oil shocks. In particular, the following variables were analysed:

Business cycle variables:

- *Monthly growth rate of the Industrial Production Index (IPI)* serves as a proxy for the growth rate of the gross domestic product (GDP) which is sampled at a quarterly frequency (and is therefore not considered here). The growth rate of the IPI was calculated as the log difference of two consecutive periods.

- *Consumer Price Index (CPI)* was used to calculate the *Inflation*.

- *Interest Rate Term Structure* (IRTS) was calculated as the spread between a 10-year U.S. government bond and a 3-month U.S. treasury bill.

- *Monthly change of the Unemployment Rate (UR)* was calculated as the log difference of two consecutive unemployment rates.

- *Default Spread (DS)* was calculated as the yield difference between Baa and Aaa Moody’s corporate bonds (same maturity). Although the DS is strictly speaking a financial rather than a business cycle variable, the DS can serve as an indicator for the business cycle which explains its categorisation in this paper.

Monetary policy variables:

- *Change of the U.S. Dollar Exchange Rate (USDEX)* against the local currency of the country. The respective change was obtained by using the log difference.

- *Growth rate of the M3 (broad) Money Index* was calculated as the respective log difference of two consecutive data points.

EPU indicators:

- *American Economic Policy Uncertainty (AEPU) Index* introduced by Baker et al. (2016). The AEPU index is based on articles in 10 American newspapers and represents a measure of uncertainty.

- *European Economic Policy Uncertainty (EEPU) Index* is the European counterpart of the AEPU and covers articles of 10 newspapers in five different European countries.

- *Swedish Economic Policy Uncertainty (SEPU) Index* which was recently introduced by Armelius et al. (2017).

For all three indicators, the respective log difference of the index value was obtained. Higher uncertainty is associated with a percentage increase of the underlying index.

Oil shocks:

Following the methodology suggested by Kilian (2009), oil shocks were decomposed into three different components:

- *Oil specific demand shocks* were measured by real crude oil prices (based on refiner acquisition cost of imported crude oil). In order to generate real prices, the U.S. CPI was used to deflate the nominal prices.

- *Oil supply shocks* were measured by monthly percentage changes of the world crude oil production (measured in thousands barrels per day and averaged over months). To obtain the percentage changes, the difference between the log transformed values was calculated.

- *Oil aggregate demand shocks* were measured by using the index of global real economic activity first introduced by Kilian (2009). This study used the corrected and updated version of the dataset, as discussed in Kilian (2019b).

Data for the U.S. term spread was obtained from Bloomberg, while data for the EPU indicators was downloaded from the website for economic policy uncertainty run by Baker et al. (2019). The respective data for oil specific demand and supply shocks was extracted from the U.S. Energy Information Administration (2019a; 2019b), while Lutz Kilian's index was retrieved from his personal website (2019a). The remaining variables were downloaded from Thomson Reuters Datastream. Theoretical relevance and empirical evidence were criteria for investigating the above-explained economic variables. Nonetheless, the choice of the drivers was restricted by the availability of time-series data for the period analysed.

3.3 Estimation method

3.3.1 Estimation approach for GARCH-MIDAS

Taking the estimation strategy into account, all parameters of the GARCH-MIDAS framework were obtained by maximizing the following log-likelihood function (LLF):

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left[\log(2\pi) + \log(\tau_t g_{it}) + \frac{(r_{i,t}-\mu)^2}{\tau_t g_{it}}\right] \tag{9}$$

This method was also taken by Kejlberg (2018). Under a few assumptions, Wang and Ghysels (2015) show that maximizing the LLF yields consistent and asymptotically normally distributed parameters for the GARCH-MIDAS model.

Choosing the appropriate weights w_1 and w_2 for the beta lag polynomial (6) is crucial for the analysis undertaken. Figure 1 in Appendix A therefore compares weights assigned given different choices for w_1 and w_2. As it can be seen from the figure, the function can vary and is flexible with respect to its shape. This is common for this specific type of weighting function (Ghysels et al., 2007). By assigning a value of three to w_1, one can observe that some observations further away get higher weights than observations occurring more recently. To exclude this counterintuitive results to happen, $w_1$was set to one which ensures that more recent observations will be given a higher weight and vice versa. This procedure is in line with the approach taken by Asgharian et al. (2013) and Engle et al. (2013) (for their estimation of the GARCH-MIDAS model with RV).

Another aspect that needs to be considered is the choice of the number of K. To recall, K represents in this study the number of months used in the MIDAS framework (4). Following Asgharian et al. (2013), who show that the optimal choice is around 36 lags, this paper set K to 36, hence considering 36 months or three so-called MIDAS-years.

For estimating the GARCH-MIDAS model, this paper assumed 22 trading days per month. Virk and Javed (2017) also consider in their study the same number of days. If one month has fewer trading days, the respective monthly average was taken to close the gap. In the case of more than 22 trading days, the last trading day of the month was discarded from the observation set.

Preliminary results were obtained by using STATA while the GARCH-MIDAS analysis was carried out using MATLAB.[1]

[1] This paper uses MATLAB version R2019a and the MIDAS MATLAB toolbox (version 2.3.0.0) by Qian (2017) for estimating the GARCH-MIDAS framework.

3.3.2 Principal component analysis

The objective of this study is to explore the similarities and differences between the Scandinavian equity markets with respect to their exposure to several economic drivers. However, the analysis of macroeconomic fundamentals for stock market movements is not restricted to country specific variables. Among others, it also includes common variables that are related to the state of the U.S. economy, namely DS, AEPU and IRTS. By exploring the combined effect of these variables on the market volatility of the different countries in Scandinavia, one can also answer the question which stock market shows the greatest dependency on the U.S. economy. As stated by Asgharian et al. (2013), including several variables in the respective MIDAS equation of (5) might cause computational and optimisation issues. For this reason, this study adopts the approach taken in their paper and apply a PCA to reduce the number of variables in an efficient manner. This is also in the spirit of the work by Stock and Watson (2002) who use the aforementioned method without a loss of efficiency in their regressions. As the U.S.-related variables DS, AEPU and IRTS are of different scale, the principal components were constructed based on the correlation among them, therefore following the procedure by Asgharian et al. (2013).

4 Results and analysis

4.1 Preliminary results

Table 1 reports summary statistics for the Scandinavian equity markets. All three equity markets have a small positive mean daily return for all time periods considered. The Danish stock market is the least volatile market as it has the lowest daily variance among all countries analysed. Interestingly, the markets showed greater fluctuations before the GFC than afterwards. This could partly be explained by more regulated financial markets after the GFC. All three equity markets show the typical positive excess kurtosis, but only the series for Denmark and Norway exhibits negative skewness. For the full sample as well as for the time period before the GFC, the financial data for Sweden shows a skewness very close to zero. This means that both large positive and large negative returns occurred equally often in the respective period. Almost all financial returns are not normally distributed as stressed by the presented p-values of the Jarque-Bera test. The only exception is the time period before the GFC in Sweden, for which the normality assumption cannot be rejected. This is atypical and results probably from the close-to-zero skewness of the series. Not surprisingly, squared returns show both highly significant autocorrelation and greater persistence than daily returns. This a well-known fact and is commonly observed in financial studies. However, the full sample of financial returns for Denmark demonstrate significant autocorrelation at all four lags. Similarly, the Swedish series for the whole period has significant autocorrelation values at lags two to four. These results are counterintuitive and contradicts the efficient market hypothesis, as one could use these autocorrelation patterns in a profitable way (Cont, 2001). The large positive autocorrelation values for the squared returns are examples of the well-known volatility clustering. In times of large price fluctuations, large price movements are more likely to occur and vice versa. One could argue in favour of modelling the financial returns for the full sample period for Denmark and Sweden. Yet, this paper does not follow this approach for two reasons: First and foremost, this paper focuses on the subsamples Pre-GFC and Post-GFC. For these time periods, the autocorrelation values do not indicate a need for modelling the returns. Secondly, the full sample is analysed for comparison reasons. Modelling the financial returns only for Denmark and Sweden would interfere with this purpose. This is in line with the approach undertaken by Virk and Javed (2017), who also find autocorrelation in the data for the French equity market.

Table 1 in Appendix A shows the unconditional pairwise correlation of equity returns for the full sample, the Pre-GFC as well as the Post-GFC. Unlike the results presented in Virk and Javed (2017), who report high values for several stock markets (among others, Germany and France), almost all financial returns considered in this study are uncorrelated with each other. The only exception can be found in the bivariate correlation between Sweden and Norway. The findings indicate that these two markets show a greater co-movement behaviour after the GFC (the correlation increased to a value of approximately 0.31). However, these values are still considerably lower than the ones reported by Virk and Javed (2017) for different European equity markets. This is a surprising result, taking both the trade relationships among Denmark, Norway and Sweden and their geographical proximity into consideration. A possible explanation for this might be that unlike the countries within the EU, the Scandinavian countries do not have the same currency and are also independent with respect to their monetary policy.

Figure 2 in Appendix A displays the squared daily returns of the different Scandinavian equity markets. The volatility fluctuates over the analysed period and displays patterns of volatility clustering. One can observe an increased level of RV at the beginning of the sample (around 1998) which is probably caused by the Asian crisis. In the period thereafter, the Swedish stock market shows a higher level of RV than its Scandinavian counterparts. As expected, the greatest spikes occur during the peak of the GFC (2008). Interestingly, the RV of the Norwegian market is twice as high as for example of the Swedish market, indicating that the GFC had a larger impact on the former. Afterwards, the figure shows a declining trend for the RV only interrupted with short volatile periods. The last noticeable fluctuation (around 2016) could be a result of the market uncertainties due to the United States presidential election.

Figures 1 to 5 in Appendix B show the time-series plots for the variables of the different categories, while Tables 2 to 4 in Appendix A report the bivariate correlation between these variables and the RV. All variables were sampled at a monthly frequency. Across all markets, the RV is correlated the most with the DS (positive correlation). As expected, the EPU indicators are positively correlated with the RV. The only exception is the SEPU for the Danish stock market which shows a (weak) negative correlation with the respective RV. Despite being positive across all countries, the comparable high correlation between the UR and RV in Denmark stands out. The positive correlation between USDEX and RV is interesting because this implies that if the local currency depreciates (against the U.S. Dollar), the corresponding RV tends to be higher. However, as correlations do not make any statements about the direction of the effect, it could also be the case that higher RV causes the local currency to depreciate which is intuitive. The co-movement between higher real oil prices and inflation was also expected. The high correlation among all three EPU indices is not surprising and shows that countries and their economies are intertwined.

Table 5 in Appendix A presents the results of the PCA. The first panel shows the correlation between the U.S.-related variables and the corresponding principal components constructed. In contrast to the second and third component, the first one is highly correlated with all three U.S. –related variables. Moreover, it explains roughly 60% of the variance of the underlying variables. For these reasons, only the first principal component $PC1$ will be considered. Figure 3 in Appendix A illustrates the $PC1$ variable. The purpose of generating the $PC1$ variable was to obtain a proxy for the U.S. state of economy. To verify if the $PC1$ incorporates the necessary information, the grey shaded area in the respective figure represents the U.S. recessions as dated by the Federal Reserve Bank of St. Louis (2019). As can be seen from Figure 3 in Appendix A, the constructed $PC1$ significantly increases in times of a recession. In periods of an economic upswing, the corresponding value drops. Hence, one can conclude that the $PC1$ variable captures valuable information about the U.S. economy. Therefore, the $PC1$ will be called hereafter PC_{USA}.

Table 1: Descriptive statistics

Notes: This table reports descriptive statistics, test statistics for normality as well as autocorrelation values for daily log returns of the Danish, Norwegian and Swedish stock market for the full sample (Feb 1998 – Dec 2018), for the Pre-GFC (Feb 1998 – Nov 2007) as well as for the Post-GFC (Jan 2010 – Dec 2018). The * indicates statistical significance at the respective 5% significance level.

Description	Denmark			Norway			Sweden		
	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC
Mean daily returns (%)	0.027	0.035	0.044	0.033	0.048	0.034	0.015	0.022	0.017
Variance daily returns	1.613	1.362	1.257	2.298	1.861	1.432	2.235	2.499	1.354
Skewness	-0.281	-0.332	-0.245	-0.508	-0.403	-0.179	0.051	0.076	-0.349
Kurtosis	7.948	4.988	5.762	9.378	5.767	5.483	6.950	5.909	7.057
JB- test p-value	0.000*	0.000*	0.000*	0.000*	0.000*	0.001*	0.000*	0.121	0.000*
Autocorrelation daily returns	0.034*	0.032	0.020	-0.004	0.021	-0.019	-0.019	0.002	-0.046*
	-0.020*	-0.026	-0.007	-0.019	0.009	-0.006	-0.036*	-0.024	-0.023
	-0.027*	-0.034	-0.011	-0.020	-0.030	-0.019	-0.035*	-0.034	-0.011
	0.017*	0.012	-0.044	0.013	0.074*	-0.066*	-0.009*	-0.005	-0.070*
Autocorrelation squared daily returns	0.215*	0.243*	0.147*	0.279*	0.236*	0.154*	0.179*	0.177*	0.142*
	0.291*	0.272*	0.199*	0.312*	0.292*	0.250*	0.225*	0.240*	0.199*
	0.222*	0.189*	0.219*	0.342*	0.239*	0.209*	0.209*	0.159*	0.197*
	0.236*	0.161*	0.087*	0.361*	0.171*	0.152*	0.168*	0.139*	0.159*

4.2 GARCH-MIDAS results

4.2.1 Realized volatility

Table 2 reports the estimated parameters for the GARCH-MIDAS model for all three Scandinavian countries for the full sample, for the Pre-GFC as well as for the Post-GFC. All models were estimated with the respective RV in the MIDAS equation for the long-term variance component. By the nature of the RV measurement, the non-negativity constraint is already met. Therefore, the log form of τ_t is not needed in this step.

With Sweden as an only exception after the GFC, all parameters for μ are significantly different from zero at the respective 1% level. Taking the short-term component $g_{i,t}$ into consideration, all estimations for α and β are highly significant for all samples considered. The high and positive values for β indicate the well-known volatility clustering pattern which means that high levels of volatility in the previous period carries over to the next period and vice versa. Moreover, confirming the results provided by Engle et al. (2013), the sum of α and β in the respective model specification is well below one. Similar results are also reported by Asgharian et al. (2013) and Girardin and Joyeux (2013).

All of the results for the coefficients θ for the long-term variance component τ_t show the expected positive sign and are significant at the respective 1% level. The positive values of θ suggest that higher levels of RV lead to higher conditional variance $\sigma_{i,t}^2$. Interestingly, while the coefficients for θ for Denmark and Norway remain approximately at the same level throughout the different samples, the corresponding value for Sweden dropped to 0.20 for the Post-GFC. All respective weights w_2 are statistically significant. The comparable high values for w_2 for all samples considered imply a fast decaying weighting function. Figure 4 in Appendix A plots the optimal weights for each country and sample.

Table 2 also provides the respective values for the Bayesian information criterion (BIC) and the VR. According to reported statistics for the BIC, the model fits the Danish stock market for both the full sample and the Pre-GFC period the best. After the GFC, the GARCH-MIDAS framework for Norway shows the best model fit. For the full sample as well for the period before the GFC, the GARCH-MIDAS model for Sweden displays the highest VR. This means that the long-term component τ_t with the RV can explain the expected volatility the most for these periods. Surprisingly, for the Post-GFC, this strong link becomes much weaker as indicated by a value of only 0.96. A noteworthy aspect is that the link between co-movements of the long-term variance with the RV and the total variance differs with the sample observed. Additionally, while for the Swedish stock market the relationship became less present after the GFC, the opposite holds for the Norwegian equity market. In contrast to these two countries, the corresponding values for Denmark stay throughout all samples at a comparably low value.

Figures 5 to 7 in Appendix A graphically illustrate the above-mentioned insights. For the full sample, the long-run variance (with the RV) follows the movements of the total variance comparably well. As indicated by lower VR values, the fit gets worse for Sweden after the GFC. The corresponding plot shows a rather flat curve. This is in contrast to Norway for which the secular volatility mimics the overall fluctuation better after the GFC.

Table 2: Estimated results for the GARCH-MIDAS model with RV

Notes: This table reports the estimated parameter for the GARCH-MIDAS model with RV of the Danish, Norwegian and Swedish stock market for the full sample (Feb 1998 – Dec 2018), for the Pre-GFC (Feb 1998 – Nov 2007) as well as for the Post-GFC (Jan 2010 – Dec 2018). ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level. BIC is the Bayesian information criterion, and VR is the variance ratio. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2) RV_{t-k}$.

Denmark								
Period	$\mu * 10^3$	α	β	θ	w_2	$m * 10^3$	BIC	VR
Full sample	0.708***	0.124***	0.791***	0.025***	8.234***	0.054***	-27668.900	0.147
Pre-GFC	0.670***	0.092***	0.840***	0.024***	5.357**	0.042***	-10746.400	0.125
Post-GFC	0.712***	0.131***	0.734***	0.022***	6.524***	0.052***	-9377.040	0.118

Norway								
Period	$\mu * 10^3$	α	β	θ	w_2	$m * 10^3$	BIC	VR
Full sample	0.894***	0.124***	0.810***	0.030***	8.248***	0.005***	-26712.700	0.251
Pre-GFC	1.315***	0.144***	0.747***	0.029***	7.242**	0.047***	-10252.300	0.100
Post-GFC	0.650***	0.167***	0.656***	0.030***	14.798***	0.031***	-9604.910	0.350

Sweden								
Period	$\mu * 10^3$	α	β	θ	w_2	$m * 10^3$	BIC	VR
Full sample	0.568***	0.105***	0.842***	0.032***	10.597***	0.041***	-26841.000	0.355
Pre-GFC	0.800***	0.113***	0.800***	0.033***	6.577***	0.028***	-9986.430	0.411
Post-GFC	4.654**	0.123***	0.814***	0.020**	11.829*	0.054***	-9543.460	0.096

4.2.2 Business cycle variables

Table 3 compares the results obtained from the GARCH-MIDAS estimation of the different business cycle variables for the specific sample periods, e.g. full sample, Pre-GFC and Post-GFC. Focusing first on the conditional mean daily return μ, all estimations report a statistically significant and slightly positive coefficient. Turning to the short-term component $g_{i,t}$, the respective values for α and β are highly significant for all samples considered. As seen in the previous estimations, the sum for these two parameters is in most cases below one.

Unlike the short-term component $g_{i,t}$, results for the long-term component $\log \tau_t$ differ with respect to the sample considered. This is not surprising, as the link between macroeconomic environment and stock market volatility can change when the economic setting differs. Considering the full sample first, it is remarkable that the DS[2] proves to be the only variable that is significant for all countries. As expected, higher values for DS causes the conditional volatility to increase. Moreover, the model fit is the best according to the BIC statistics and the respective VR values are high. A corresponding plot is provided in Figure 8 in Appendix A. Interestingly, despite its overall good fit, the long-term component with the DS lags behind the total volatility which is clearly not a wanted outcome.

Results reported for the full sample also highlight the differences among the Scandinavian countries. It seems as if the Danish stock market is more exposed to business cycle variables than the Norwegian and Swedish counterparts are. Estimations for Denmark imply a high exposure to a great variety of variables. Apart from the inflation rate, all macroeconomic variables are highly significant and show the expected sign for the coefficient. The negative value for the IPI supports the findings by Officer (1973), Schwert (1989) and Engle et al. (2013) stating that the market volatility is lower in times of economic growth. A positive relationship between the changes of the UR and the stock market volatility is also found by Conrad and Loch (2015), yet considering a quarterly frequency for the UR.

As opposed to Denmark, the reported results for Norway and Sweden are rather disappointing. Despite the DS, none of the variables are significant for the Norwegian stock market. For Sweden, only the IRTS seems to affect the corresponding stock market volatility besides the DS. Yet, its positive value is counterintuitive as a widening yield curve serves an indicator for a more optimistic outlook and is therefore often associated with an expected economic expansion. A possible explanation is given by McQueen and Roley (1993). In their view, positive news in times of an economic upswing may have an adverse effect on the performance of the equity market as discount rates increase.

[2] Due to estimation problems of the $\log \tau_t$ in combination with the DS, the model considered does not entail the log transformation.

For the Pre-GFC, some interesting insights can be gained. The DS remains highly significant for all equity markets analysed. In a similar vein to the full sample, the DS variable performs the best according to the BIC statistics. Figure 9 in Appendix A gives a graphical illustration. Interestingly, the monthly growth rate of the IPI becomes insignificant for Denmark. While the monthly change of the UR keeps its positive coefficient, its magnitude drops. Applying (8) yields that an increase of 1% in the UR accelerates the corresponding market volatility by approximately 3.10% (compared to roughly 4.30% for the full sample). Additionally, the VR suggests a worse explanatory value for the UR for the period before the GFC than for the full sample. The corresponding weight w_2 indicates that the market volatility is affected by more recent developments in the labour market. As opposed to the monthly changes of the UR, the IRTS shows a greater impact on the Danish stock market volatility.

Compared to the findings for the full sample, estimation results for Norway provide evidence in favour of an increased exposure to macroeconomic variables as both the UR and the IRTS report a strong statistical performance. The negative coefficient for the monthly UR is counterintuitive and might also be explained by the hypothesis forwarded by McQueen and Roley (1993). The high weight results in a rapidly decaying weighting function which stresses the importance of recent observations. This supports the explanation provided for the unexpected negative sign for the UR. If recent news about the labour market has been good, market participants adjust the discount rate causing the market to be more volatile.

Consistent with the findings for the full sample, the Swedish stock market is influenced only by the IRTS. Its magnitude and the relationship remains approximately the same. The positive sign for the IRTS coefficient could also be explained by revised growth expectations and discount rates. While highly significant for Norway and Denmark, the monthly changes of the UR do not seem to have an impact on the stock market volatility.

For the Post-GFC, the Danish stock market shows the strongest link with business cycle variables among all Scandinavian countries. Apart from the UR, all variables are highly significant with the expected sign for most of them. Interestingly, a greater IRTS increases the conditional volatility. A striking aspect of the data is the high magnitude of the IPI, inflation and the IRTS. A respective 1% increase of the monthly IPI rate, causes the market volatility to decrease by 8.10%. On the contrary, the IRTS has, with the same movement, an enlarging impact of approximately 2.50%. The positive relationship between inflation and market volatility is in line with results reported for the U.S. market by Engle et al. (2013). As already seen for the full sample and the Pre-GFC, the DS keeps its statistical strong performance and shows the best fit and explanatory value according to the BIC and VR. The long-term component with the DS therefore captures overall stock market movements reasonably well as it can be seen in Figure 10 of Appendix A. Surprisingly, while relevant in the Pre-GFC period, the UR loses its significance for the Post-GFC era.

As opposed to the Danish stock market, it seems as if the Swedish and Norwegian equity markets disconnected from the business cycle after the GFC. Besides the DS, which outperforms all other variables under consideration for both countries, one can reject the null hypothesis of insignificance only for the UR for Norway. The positive relationship is as expected and a 1% upwards movement leads to a corresponding increase by 2.70% of the $\sigma_{i,t}^2$. Remarkable are the very high VR values for both the DS and the UR (for Norway) indicating that fluctuations of these variables can explain movements of the total volatility reasonably well (see Figure 10 in Appendix A).

In summary, the above-outlined results provide several important insights into the link between business cycle variables and stock market movements in Scandinavia. First, the reported empirical evidence suggests that the stock market volatility behaviour changes dynamically over time, therefore responding to different economic settings. Second, the DS proves to be the only variable that is significant for all samples. Its coefficient is of the expected sign and both the VR and BIC report a comparably well fit. Third, the Danish stock market seems to be affected the most by the economy. Considering the outcomes for both samples, it can be conceivably hypothesised that its exposure to the business cycle (slightly) increased after the GFC. In contrast to Denmark, the markets of Norway and Sweden seem to be influenced less by economic activities. While in the case of Denmark more variables affect the stock market volatility after the GFC, the opposite is true for Norway. The result that the inflation rate is insignificant in most samples contradicts Salisu and Ndako (2017) who report overall strong results for most European equity markets. Interestingly, while being significant for all countries before the GFC, the IRTS loses its significance for Norway and Sweden for the Post-GFC period. This might already indicate that the equity markets of these countries are less affected by the U.S. state of the economy. However, this detail will be discussed further in Section 4.2.6.

Table 3: GARCH-MIDAS test results for business cycle variables

Notes: This table reports test results of the GARCH-MIDAS model for the monthly growth rate of industrial production (IPI), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), growth rate of the unemployment rate (UR) and default spread (DS). Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018). The model considered for DS does not entail a log specification. BIC is the Bayesian information criterion, and VR is the variance ratio. ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level.

Full sample

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
IPI	0.69***	0.11***	0.85***	-62.15***	2.78***	-8.83***	-27535.60	0.053
Inflation	0.70***	0.10***	0.87***	-21.73	27.81	-8.82***	-27528.30	0.001
IRTS	0.69***	0.09***	0.89***	-36.90***	6.61**	-7.96***	-27579.10	0.116
UR	0.69***	0.11***	0.83***	25.35***	5.14***	-8.94***	-27554.00	0.141
DS	0.71***	0.11***	0.80***	0.02***	4.86***	0.00***	-27707.00	0.209
				Norway				
IPI	0.86***	0.11***	0.88***	-46.49	3.11	-7.83***	-26577.60	0.014
Inflation	0.86***	0.10***	0.88***	-13.15	48.27	8.44***	-26577.00	0.000
IRTS	0.77***	0.07***	0.93***	-35.86	1.33	-8.76***	-26606.30	0.004
UR	0.86***	0.10***	0.88***	-1.88	38.38	-8.47***	-26576.70	0.000
DS	8.87***	0.11***	0.85***	0.04***	5.28***	0.00***	-26731.80	0.136
				Sweden				
IPI	5.71***	0.09***	0.91***	1.85	49.64	-6.95***	-26723.800	0.004
Inflation	5.70***	0.09***	0.91***	7.98	14.57	-7.05***	-26723.600	0.001
IRTS	0.57***	0.09***	0.90***	18.02**	37.88	-8.54***	-26828.500	0.044
UR	0.57***	0.09***	0.91***	10.35	4.61	-7.04***	-26724.200	0.047
DS	0.58***	0.09***	0.89***	0.04***	5.38***	0.00***	-26853.200	0.311

Pre-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
IPI	0.69***	0.08***	0.89***	-1.07	5.35	-9.10***	-10620.00	0.000
Inflation	0.69***	0.08***	0.90***	-59.15	20.68	-8.99***	-10622.50	0.016
IRTS	0.68***	0.06***	0.94***	-44.00*	11.83	-8.88***	-10701.10	0.144
UR	0.66***	0.08***	0.87***	17.09***	6.83*	-9.11***	-10626.00	0.060
DS	7.44***	0.09***	0.84***	0.03***	7.46***	-0.00***	-10766.60	0.272
				Norway				
IPI	1.25***	0.12***	0.83***	1.26	4.09	-8.75***	-10122.60	0.000
Inflation	1.25***	0.12***	0.83***	-2.04	9.20	-8.75***	-10122.60	0.000
IRTS	1.33***	0.12***	0.81***	-27.59***	1.01	-8.35***	-10247.60	0.073
UR	1.25***	0.12***	0.83***	-11.51**	21.96	0.00***	-10128.90	0.076
DS	1.27***	0.13***	0.78***	0.03***	11.19*	-0.00**	-10252.60	0.135

(continued)

Table 3: Continued

Pre-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Sweden				
IPI	0.82***	0.10***	0.90***	1.71	5.72	-6.82***	-9873.97	0.000
Inflation	0.83***	0.10***	0.90***	-29.10	49.96	-6.59***	-9875.45	0.026
IRTS	0.80***	0.10***	0.89***	18.56**	38.87	-8.57***	-9969.75	0.098
UR	0.82***	0.10***	0.90***	1.92	6.04	-6.84***	-9873.86	0.001
DS	0.80***	0.10***	0.88***	0.06**	5.64**	-0.00	-9972.01	0.217

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
IPI	0.73***	0.11***	0.76***	-216.02***	1.39***	-8.66***	-9377.87	0.231
Inflation	0.74***	0.13***	0.78***	116.66***	33.48	-9.21***	-9382.15	0.075
IRTS	0.69***	0.12***	0.75***	81.77***	1.04***	-10.84***	-9381.90	0.088
UR	0.69***	0.13***	0.78***	-0.77	19.48	-9.14	-9367.83	0.000
DS	0.77***	0.13***	0.67***	0.02***	8.37***	0.00***	-9409.20	0.362
				Norway				
IPI	0.65***	0.09***	0.88***	-0.32	4.99	-9.25***	-9591.07	0.000
Inflation	0.65***	0.09***	0.89***	-44.40	49.43	-9.16***	-9593.42	0.014
IRTS	0.65***	0.09***	0.88***	45.73	1.79	-10.16***	-9593.34	0.033
UR	0.67***	0.12***	0.80***	71.74***	1.34***	-9.52***	-9605.22	0.214
DS	0.67***	0.11***	0.80***	0.02***	29.22	0.00**	-9607.11	0.251
				Sweden				
IPI	0.46**	0.10***	0.87***	11.73	49.98	-9.24***	-9630.68	0.033
Inflation	0.48**	0.11***	0.86***	67.57	33.86	-9.23***	-9626.65	0.016
IRTS	0.46**	0.11***	0.86***	0.14	5.42	-9.14***	-9623.08	0.000
UR	0.47**	0.11***	0.86***	-4.80	45.04	-9.22	-9626.14	0.010
DS	0.46**	0.11***	0.80***	0.02***	19.41***	0.00***	-9648.73	0.338

4.2.3 Monetary policy variables

Table 4 presents the results for the univariate GARCH-Midas model with both monetary policy variables. As expected, results for μ and $g_{i,t}$ suggest overall a high statistical significance. Interestingly, the sum of α and β is often very close to or even one (e.g. for Sweden). This can be taken as a sign that for some model specifications the long-term component $\log \tau_t$ is of no additional explanatory value for the conditional volatility $\sigma_{i,t}^2$ .The reported coefficients for the slope parameter θ are more interesting. Turning to the full sample first, it is interesting to note that none of the variables show a statistical significance for Sweden (as opposed to the Danish and Swedish equity market). The growth rate of the broad money (M3) shows a positive and significant relationship with the corresponding conditional volatility for both Denmark and Norway. An upwards movement by 1% increases the conditional volatility $\sigma_{i,t}^2$ by 13.20% for

Denmark and by 2.90% in the case of Norway. The positive coefficient for both countries is unexpected at first as an expansionary monetary policy should help to stimulate economic growth which in turn should lower stock market movements. It could be argued that the positive relationship is due to changed discount rates and expectations of the market participants. If discount rates drop as a response to higher monetary growth, stock returns start to fluctuate as a response to altered conditions. The idea that monetary policy suffers from a time-lag (the time needed before monetary policy achieves its objectives) also underlines this way of argumentation. Exchange rate changes prove to be significant only for the Danish equity market. Its negative coefficient for θ implies that a deprecating Danish krone causes the expected volatility to move less. As a lower currency exchange rate can help to boost exports which in turn stimulates the economy positively, the reported negative relationship is intuitive. While the corresponding weights w_2 for the significant coefficients θ are comparably high for Denmark, the respective one for Norway (for the M3 index) is very low with a value of only one. The BIC statistics indicate a superior fit of the monetary policy variable for Denmark.

As seen for the macroeconomic variables, different insights are obtained when one analyses subsamples. Considering the Pre-GFC, the most remarkable aspect is the strong significance of the USDEX across all Scandinavian countries. However, while for Denmark the positive relationship remains present, the USDEX seems to affect the equity markets for Norway and Sweden in the opposite way. A drop by 1% results in a corresponding decrease of 0.02% (Norway) and 2.80% (Sweden). Thus, while significant for both countries, the economic effect is much larger on the latter. Moreover, in contrast to Denmark, recent observations have higher weights according to the beta function. Interestingly, the growth rate of M3 shows a poor performance for all markets. Surprisingly, the BIC statistics claim a better fit for Denmark compared to its Scandinavian counterparts. Remarkable is the very high VR value of the USDEX for Sweden. However, the VR does not make any statements about the statistical fit of a variable which can partly explain this apparent inconsistent finding.

For the Post-GFC insightful conclusions can be drawn. Most prominent is the sharp contrast between Denmark and its neighbouring countries regarding the exposure to monetary variables. While both variables remain significant for the former, none of the variables prove to be significant for the latter markets. Striking is the positive coefficient of the USDEX for Denmark. While the respective change of the local currency was related to the market volatility in a negative way for the time before the GFC, reported results indicate a reverse effect after the GFC. This behaviour is in line with the corresponding effects found for Sweden and Norway for the first subsample. A possible explanation for an accelerating effect of a depreciating currency on the stock market volatility might stem from the determination of stock prices (and therefore its returns). A declining local currency affects cash flows negatively as the purchasing power of the currency diminishes. Moreover, market participants might revise growth expectations and even consider adjusting discount rates. Consequently, the respective stocks become more volatile as a response to the adjustments made. Investigating the equity market of Ghana, Adjasi et al. (2008) also report a link between a depreciating currency and an increased market volatility.

Overall, the reported results provide evidence that Denmark’s stock market volatility shows the highest degree of exposure to monetary policy variables among the Scandinavian countries. In contrast to that, Sweden seems to be unaffected. The analysis of the subsamples yield two results. First, the link between the exchange rate and the market volatility became less present after the GFC. Second, supporting the conclusion by Schwert (1989), no strong empirical support can be found for a relationship between monetary policy and stock market returns.

Table 4: GARCH-MIDAS test results for monetary policy variables

Notes: This table reports test results of the GARCH-MIDAS model for the monthly exchange rate change against the U.S. Dollar (USDEX) and the growth rate of the M3 index (M3). Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018). BIC is the Bayesian information criterion, and VR is the variance ratio. ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level.

Full sample

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
USDEX	0.72***	0.10***	0.87***	-9.21**	14.80*	-8.86***	-27532.80	0.008
M3	0.74***	0.10***	0.88***	16.44***	48.99*	-8.92***	-27534.80	0.024
				Norway				
USDEX	0.85***	0.10***	0.89***	3.00	49.22	-8.45***	-26578.80	0.002
M3	0.86***	0.10***	0.88***	102.32***	1.00***	-9.07***	-26580.20	0.013
				Sweden				
USDEX	0.57***	0.09***	0.91***	8.75	1.14	-7.09***	-26723.30	0.012
M3	0.57***	0.09***	0.91***	39.60	2.37	-7.16***	-26724.00	0.102

Pre-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
USDEX	0.72***	0.09***	0.88***	-25.07**	9.72	-9.23***	-10627.60	0.070
M3	0.69***	0.08***	0.89***	1.05	5.20	-9.11***	-10620.20	0.000
				Norway				
USDEX	1.28***	0.12***	0.83***	0.83**	1.00***	-8.67***	-10127.80	0.044
M3	1.25***	0.12***	0.83***	6.92	40.78	-8.80***	-10122.40	0.001
				Sweden				
USDEX	0.83***	0.10***	0.88***	93.67***	1.03***	-8.32***	-9878.81	0.513
M3	0.82***	0.10***	0.90***	14.94	21.37	-6.81***	-9874.68	0.037

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
USDEX	0.72***	0.12***	0.78***	8.19*	50.00	-9.17***	-9372.47	0.034
M3	0.66***	0.12***	0.77***	38.84***	1.48***	-9.27***	-9371.47	0.038
				Norway				
USDEX	0.65***	0.05***	0.95***	-1.53	21.01	-9.54***	-9565.40	0.000
M3	0.65***	0.05***	0.95***	0.27	5.71	-9.61***	-9565.28	0.000
				Sweden				
USDEX	0.40***	0.07***	0.93***	0.04	5.11	-9.49***	-9586.35	0.000
M3	0.40***	0.07***	0.93***	0.20	5.15	-9.45***	-9586.35	0.000

4.2.4 Economic policy uncertainty indicators

Apart from business cycle fundamentals and the monetary policy, market uncertainty could also affect stock return movements. For investigating the impact on uncertainty in Scandinavian equity markets, Table 5 displays the reported estimations for the univariate GARCH-MIDAS model with EPU indicators, e.g. AEPU, EEPU and SEPU. It is expected that higher EPU (measured by a positive percentage change) results in higher volatility and vice versa.

Throughout the samples considered, all coefficients for μ and for the short-term component $g_{i,t}$ are as expected significant at the 1% level. However, the sum of α and β is very often close to one which shows that for some tested model specifications, the long-term component $\log \tau_t$ does not incorporate additional value for explaining movements of the markets.

The main focus of this study is the slope parameter θ. For the full sample, the Scandinavian countries show some similarities. Across all countries, the AEPU seems to be superior compared to its counterparts as it is the only variable being significant for all three markets. The positive coefficient is not surprising and the corresponding BIC and VR also support the strong performance. What is outstanding is the very high VR for Sweden. It seems as if fluctuations of the AEPU can very well capture movements of the expected conditional volatility $\sigma_{i,t}^2$. Figure 11 of Appendix A further supports this. In contrast to Norway and Denmark for which the plots are disappointing, the long-term component with the AEPU accurately follows the total volatility. The rather poor results for the VR for Denmark and Norway, despite significant coefficients for the AEPU, can also be explained given this figure. The VR as defined in (7) is the mere ratio between two variances. If the long-term component varies only a little, the corresponding variance is comparably small which results in a low VR (Conrad and Loch, 2015). This can be seen in Figure 11 in Appendix A. As already observed for the macroeconomic and monetary variables, the Danish market seems to show a higher exposure to a greater variety of variables. Apart from the AEPU, both the EEPU and the SEPU also have an explanatory value for market fluctuations in Denmark. All respective coefficients are positive, which is not surprising and in line with theoretical considerations.

Digging deeper into the specific regimes, namely the Pre- and Post-GFC, different insights can be gained. Interestingly, coefficient reports for the EEPU show very disappointing results; none of the parameter estimation can reject the null hypothesis. Another striking result to emerge from the data is the insignificance for all EPU variables for the Swedish market for both subsamples. Recalling the strong performance of the AEPU for the full sample, this is very surprising. One possible explanation might stem from the sample design which neglects the period of the GFC. It can be argued that the strong positive relationship for Sweden stems especially from this time period. For testing the robustness of the result obtained for Sweden, the GARCH-MIDAS model was estimated using adjusted subsamples (including the GFC). In both cases, the insignificance of the AEPU for Sweden remains present.[3] This gives further

[3] For saving space, reported results are not provided in this study, but are available upon request.

evidence that, in contrast to Denmark and Norway, the AEPU provides no additional value for modeling purposes for Sweden (at least for rather short periods).

For Denmark, the AEPU and SEPU provide convincing results for the Pre-GFC. Remarkable is the aspect that the link between the AEPU and the Danish market volatility diminishes after the GFC. In contrast, the exposure to changes of the SEPU remains approximately the same. A respective 1% increase of the SEPU index accelerates the market volatility by 1.47% before the GFC and by 1.58% after the GFC.

Another noteworthy finding retrieved from the respective GARCH-MIDAS model estimation is the change of the coefficient sign for Norway for the Post-GFC. According the results provided below, an increase of the AEPU has a stabilising effect on the conditional market volatility after the GFC, while a reverse effect was found previously. This is in sharp contrast to the other estimation outcomes found and contradicts theoretical consideration. Matching the previous results for w_2, all significant weights imply a slowly decaying weighting function. This finding is in line with the reported estimation results provided by Asgharian et al. (2018) analysing the impact of EPU volatility in the equity markets of the UK and the U.S. The provided VRs suggest that movements of the AEPU can explain corresponding market fluctuation in Denmark and Norway reasonably well for the period before the GFC. The BIC statistics also indicate the best fit. For the Post-GFC, the long-term variance component augmented with the AEPU can explain 27.70% of the overall market movements in Norway. Despite significant, the SEPU has a lower explanatory value for the Danish equity market. To illustrate these findings, plots for the GARCH-MIDAS model with the AEPU changes are provided in Figures 12 and Figures 13 in Appendix A. The graph for Norway for the Post-GFC explains the negative coefficient θ as the long-term component moves countercyclical to the total volatility.

Overall, the results for the EPU indicators give important insights in various ways. The here provided empirical evidence partly supports the research by Pástor and Veronesi (2012) who give theoretical explanations for a link between EPU and stock market volatility. However, the reported results in this section indicate that the link exists mainly for the AEPU (and to some extent the SEPU). The fact that the AEPU shows overall a superior performance compared to its European and Swedish counterpart is in agreement with the findings by Asgharian et al. (2018). Surprisingly, the EEPU does not affect the market volatility of any Scandinavian country in any subsample. Interestingly, taking solely the periods before and after the GFC into account, the Swedish stock market does not show any link to EPU variables.

Table 5: GARCH-MIDAS test results for EPU indicators

Notes: This table reports test results of the GARCH-MIDAS model for the respective monthly percentage changes of the American economic policy uncertainty index (AEPU), the European economic policy uncertainty index (EEPU) and the Swedish economic policy uncertainty index (SEPU). Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018). BIC is the Bayesian information criterion, and VR is the variance ratio. ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level.

Full sample

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
AEPU	0.71***	0.10***	0.85***	15.80***	1.08***	-8.91***	-27553.00	0.026
EEPU	0.71***	0.10***	0.86***	6.46*	1.27***	-8.92***	-27543.30	0.004
SEPU	0.73***	0.11***	0.86***	28.48***	1.37***	-8.88***	-27541.00	0.021
				Norway				
AEPU	0.88***	0.10***	0.88***	16.01***	1.53***	-8.62***	-26594.80	0.014
EEPU	0.85***	0.10***	0.89***	-5.06	1.06***	-8.33***	-26571.50	0.001
SEPU	0.86***	0.10***	0.89***	1.12	17.13	-8.47***	-26578.30	0.001
				Sweden				
AEPU	0.57***	0.09***	0.90***	33.02***	1.05***	-7.56***	-26717.10	0.768
EEPU	0.58***	0.09***	0.91***	10.54	1.77*	-7.30***	-26728.90	0.131
SEPU	0.57***	0.09***	0.91***	13.52	1.11	-6.89***	-26725.60	0.045

Pre-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
AEPU	0.68***	0.09***	0.85***	34.97***	1.06***	-9.11***	-10635.40	0.182
EEPU	0.63***	0.06***	0.94***	-2.11	4.53	-8.46***	-10583.60	0.015
SEPU	0.75***	0.09***	0.86***	28.75***	1.88***	-9.08***	-10628.70	0.069
				Norway				
AEPU	1.30***	0.12***	0.81***	21.47***	1.42***	-8.78***	-10131.00	0.065
EEPU	1.23***	0.12***	0.83***	-0.82	47.02	-8.77***	-10127.10	0.023
SEPU	1.27***	0.12***	0.83***	6.17	4.02	-8.77***	-10124.90	0.010
				Sweden				
AEPU	0.82***	0.10***	0.90***	1.65	4.86	-6.89***	-9873.94	0.006
EEPU	0.81***	0.10***	0.90***	-1.76	9.50	-6.76***	-9875.55	0.042
SEPU	0.82***	0.10***	0.90***	-1.54	29.80	-6.79***	-9877.53	0.044

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
AEPU	0.70**	0.13***	0.77***	5.71	1.93	-9.09***	-9369.62	0.013
EEPU	0.68**	0.13***	0.87***	-2.71	4.83	-2.59***	-9250.98	0.017
SEPU	0.75***	0.12***	0.74***	49.27***	1.12***	-9.13***	-9377.54	0.082

(continued)

Table 5: Continued

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Norway				
AEPU	0.63***	0.05***	0.95***	-31.55***	1.55***	-9.62***	-9599.38	0.277
EEPU	0.65***	0.08***	0.90***	-2.41	7.64	-9.24***	-9590.14	0.014
SEPU	0.65***	0.09***	0.88***	-1.64	9.79	-9.26***	-9591.60	0.003
				Sweden				
AEPU	0.46**	0.10***	0.87***	-12.72	1.43*	-9.29***	-9625.91	0.038
EEPU	0.40**	0.08***	0.92***	-3.88	6.10	-9.38***	-9588.88	0.015
SEPU	0.46**	0.11***	0.86***	-3.24	6.54	-9.21***	-9623.83	0.005

4.2.5 Oil shocks

Table 6 below illustrates the outcomes of fitting an univariate GARCH-Midas model with oil shock variables to the different samples. To disentangle the impacts of the various oil shocks to the market volatility, the analysis follows the suggestions by Kilian (2009) and decomposes the shocks into three components, e.g. oil price, aggregate demand shocks and oil supply shocks.

For the full sample, the parameter estimations for the long-term variance component $\log \tau_t$ reveal mixed results. Changes of the world oil production (oil supply shocks) do not significantly affect the stock market volatility in Scandinavia. In contrast to that, coefficients for aggregate demand shocks show a strong statistical performance, being significant at the 1% significance level. Interestingly, the different markets do not react to respective changes in the same manner. While the reported results below imply a positive correlation for the Danish market, the reverse can be found for Sweden and Norway. As the aggregate demand shock serves as a proxy for real economic activity (Kilian, 2009), a positive coefficient is counterintuitive. If the real economy activity increases (positive change of the aggregate demand shock), the market volatility should decrease. Even though being statistically strong, the economic magnitude of the aggregate demand shock variable is comparably little (in contrast to the reported results for macroeconomic variables for example). A change of 1% increases the conditional volatility of the Danish and Norwegian equity market by only roughly 0.01%. It can be seen from the top panel of Table 6 that changes in the real oil prices affect only the stock markets of Denmark and Sweden, while no such link can be found for Norway. This may be explained by the fact that Norway is an oil-exporting country which may result in an overall lower dependency on oil prices. The negative coefficients of the oil price shock (measured by changes of the real price) found for Denmark and Sweden are consistent with the findings by Park and Ratti (2008). According to the BIC statistics, the aggregate demand shock shows overall the best fit. However its performance with respect to the VR is rather disappointing. Noticeable is the very high value in the case of Sweden for the oil price changes.

Before the GFC, Denmark and Norway showed greater exposure to oil shocks than Sweden; all respective variables are significant for the former markets. Among the oil shocks, the oil supply shocks (world oil production) proves to be the one with the greatest impact. If the world production goes up by 1%, the expected conditional volatility decreases by 7.30% in the case of Denmark and by 10.41% for Norway. A same movement of the real oil prices reduces market volatility in Denmark and Norway only by 1.62% and 1.71% respectively. Similarly to the results obtained for the full sample, the aggregate demand shock has only a very little impact – despite its significance for all three markets. The sensitivity analysis yields only a reduction of less than 1% for all three Scandinavian countries. While the aggregate demand shock variable has the expected negative causal effect, the negative coefficient for the real oil price for Norway is new and surprising as this contradicts the findings by Park and Ratti (2008). This mismatch might emerge from differences in methodology and sample periods used. As opposed to the GARCH-MIDAS framework considered in this study, Park and Ratti (2008) apply a VAR approach. Noteworthy are also the values of the VR for the various oil shocks which show a reasonably well explanatory value for movements of the conditional volatility.[4]

Turning to the Post-GFC, several interesting insights can be gained. First and foremost, it seems as if changes of the real oil price affected the stock market volatility only in the period before the GFC; for the Post-GFC era no such relationship can be found. One possible explanation for the insignificance of the oil price variable after the GFC is provided by Degiannakis et al. (2014). In their view, stock market returns are unaffected by fluctuating oil prices due to effective hedging strategies of companies. Being in accordance with theory, the aggregate demand shock also shows the expected negative sign for all significant estimations. Yet, its impact remains small. Given an underlying movement of 1% of the aggregate demand shock, the stock return fluctuations diminish by less than 1%. Despite its little economic effect, the aggregate demand shock seems to capture a great share of the overall market movements for Denmark and Norway. The VR reports high values of 31.50% and 42.70%.

Comparing both subsamples, a very interesting trend can be revealed. Compared to the Pre-GFC, oil shocks became less important for the Post-GFC era. This can be seen by a drop in the number of significant variables. While a total of 10 variables were significant for the Pre-GFC period, only three remain so after the GFC. This observation could possibly be explained by the developments in the oil market in the past years. Due to excess oil supply, oil prices fell rapidly which might have led to overall lower uncertainties and risks. Counter to this finding, Denmark's equity market became more sensitive to changes of the world production. A 1% higher crude oil supply results in a decrease of roughly 19.00% of expected volatility in the respective market. Besides Denmark, both Sweden and Norway face lower exposure to oil shocks compared to the Pre-GFC period. Recalling the reported results for the Pre-GFC, the former country seems to be affected the least by oil shocks, part of this might be explained by the ecological friendliness of the Swedish economy.

[4] A note of cautious is due here for the BIC statistics of the AGS variable for the Pre-GFC. Its optimisation method varies slightly due to estimation problems. As the sample size differs, a comparative analysis cannot be made for the AGS and the other oil shock variables with respect to their BIC.

Table 6: GARCH-MIDAS test results for oil shocks

Notes: This table reports test results of the GARCH-MIDAS model for the monthly changes of the real oil price (Oil Price), monthly growth rate of world crude oil production (Oil Supply) and oil aggregate demand shocks (AGS Oil) measured by the corrected index of global real economic activity as discussed in Kilian (2019b). Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018). BIC is the Bayesian information criterion, and VR is the variance ratio. ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level. Note that lag K in the MIDAS-equation (5) and the gradient were adjusted for estimating the model with the AGS Oil variable for the Pre-GFC. This approach was taken due to estimation problems of the original model.

Full sample

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
Oil Price	0.69***	0.10***	0.87***	-9.85***	1.49***	-8.85***	-27534.30	0.014
Oil Supply	0.70***	0.10***	0.87***	-12.24	2.75	-8.85***	-27528.80	0.000
AGS Oil	0.72***	0.10***	0.86***	-0.23***	6.87	-8.84***	-27641.70	0.014
				Norway				
Oil Price	0.86***	0.10***	0.88***	-6.15	2.04	-8.42***	-26576.80	0.004
Oil Supply	0.85***	0.10***	0.90***	-5.97	7.28	-7.06***	-26564.20	0.000
AGS Oil	0.85***	0.10***	0.88***	0.52***	1.00***	-8.67***	-26695.20	0.029
				Sweden				
Oil Price	0.57***	0.08***	0.92***	-17.41***	1.27***	-6.61***	-26718.90	0.575
Oil Supply	0.57***	0.09***	0.91***	-21.18	1.99	-6.99***	-26723.00	0.003
AGS Oil	0.57***	0.09***	0.91***	0.39***	1.00***	-8.25***	-26830.30	0.079

Pre-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
Oil Price	0.64***	0.08***	0.87***	-44.65***	1.30***	-8.69***	-10634.80	0.187
Oil Supply	0.67***	0.08***	0.88***	-176.92***	1.54***	-8.92***	-10625.60	0.052
AGS Oil	0.73***	0.09***	0.86***	-0.61***	3.57**	-8.97***	-15304.30	0.184
				Norway				
Oil Price	1.12***	0.07***	0.93***	-2.50*	40.94	-8.24***	-10093.90	0.061
Oil Supply	1.29***	0.13***	0.80***	-250.22***	1.57***	-8.53***	-10136.80	0.094
AGS Oil	1.10***	0.11***	0.85***	-0.37***	4.46	-8.66***	-14613.10	0.047
				Sweden				
Oil Price	0.80***	0.09***	0.90***	-5.64	6.26	-7.02***	-9875.07	0.074
Oil Supply	0.82***	0.10***	0.90***	0.06	5.72	-6.83***	-9873.73	0.000
AGS Oil	0.83***	0.09***	0.88***	-0.80***	1.71***	-8.35***	-14125.30	0.174

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Denmark				
Oil Price	0.69***	0.13***	0.78***	0.27	27.58	-9.13***	-9368.14	0.000
Oil Supply	0.68***	0.13***	0.76***	-76.59**	11.64*	-9.05***	-9375.12	0.062
AGS Oil	0.70***	0.12***	0.71***	-1.20***	7.95***	-9.84***	-9394.64	0.315

(continued)

Table 6: Continued

Post-GFC

Indicator	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
				Norway				
Oil Price	0.65***	0.05***	0.95***	-0.03	5.45	-9.58***	-9565.29	0.000
Oil Supply	0.65***	0.09***	0.88***	15.11	49.98	-9.27***	-9592.19	0.008
AGS Oil	0.70***	0.14***	0.71***	-1.47***	10.22***	-10.12***	-9617.72	0.427
				Sweden				
Oil Price	0.40***	0.05***	0.95***	0.17	5.25	-9.64***	-9584.07	0.000
Oil Supply	0.46***	0.10***	0.87***	-0.03	5.16	-9.21***	-9622.97	0.000
AGS Oil	0.47***	0.11***	0.86***	0.47	1.04	-8.98***	-9623.96	0.010

4.2.6 Exposure to the U.S. economy

Apart from investigating the impact of single economic variables on the respective stock market volatility, it is also likely that the state of the U.S. economy affects the stock market volatility in Scandinavia. For this purpose, Table 7 compares the parameter outcomes of the GARCH-MIDAS model with the PC_{USA}. Not surprisingly, the estimates for the GARCH (1,1) component are all highly significant, yet the corresponding β is the lowest for Denmark. This can be taken as a first indicator, that the long-term component captures movement of the volatility the best for this market. All estimates for θ are significant at the 1% level and the positive sign was expected (recall Figure 3 of Appendix A). Moreover, the link between all three Scandinavian equity markets and the U.S. economy is similarly strong. A 1% increase of the PC_{USA} corresponds to an upwards movement of the respective markets 6.40% for Denmark, 7.50% for Norway and 7.80% in the case of Sweden. Given the BIC statistics, the model fit is the best for the former country, while the VR reports the highest value for the latter. Overall, it can be concluded that all Scandinavian countries seem to show high exposure to the state of the U.S. economy, given the full sample.

As seen in the previous sections, splitting up the sample is beneficial. Surprisingly, none of the estimates for the slope parameter seem to be significant before the GFC. This is very surprising considering the results for the full sample. Additionally, given the VR for Denmark, 12.20% of total movements can be explained by underlying fluctuations of the U.S. economy. This is a high share given the fact that the null hypothesis cannot get rejected for this model specification. As explained above, the VR does not yield any information about the statistical significance of estimators; it is solely a ratio to track the explanatory share of the long-term component $\log \tau_t$ on the total conditional volatility.

Taking the period after the GFC into account, the results are disappointing. The estimates for Norway and Sweden are poor as indicated by the insignificance of the respective θ and the high sum of α and β. The poor VR underlines the fact that the long-term component augmented with the PC_{USA} is of no additional value. As opposed to this, the Danish stock market volatility shows great exposure to the U.S. economy. The coefficient θ is highly significant, and of the expected positive sign. If the U.S. economy performance decreases by 1%, the Danish market volatility reacts by a corresponding drop of 9.70%.

The fact that for none of the subsamples the equity markets of Norway and Sweden show a link to the U.S. economy may be due to the sample design which neglects the GFC. In fact, when including this specific period, the estimates become significant.[5] It is possible therefore, that the main part of the link between the U.S. economy and the Norwegian and Swedish equity market stems from the GFC. On the contrast to that, the Danish market seems to have a greater exposure to the U.S. economic activities as this relationship holds even when discarding the GFC.

Table 7: GARCH-MIDAS test results for the PC_{USA}

Notes: This table reports test results of the GARCH-MIDAS model for the PC_{USA}. The PC_{USA} was constructed based on the monthly default spread (DS), yield spread between 10-years U.S. government bond and 3-month U.S. treasury bill (IRTS), and the monthly percentage change of the American economic policy uncertainty index (AEPU). The corresponding estimates are shown in Table 5 of Appendix A. Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018). BIC is the Bayesian information criterion, and VR is the variance ratio. ***, **, * indicate statistical significance at the respective 1%, 5% and 10% level.

Full sample

Country	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
Denmark	0.71***	0.11***	0.83***	29.68***	8.16***	-9.00***	-27674.40	0.092
Norway	0.86***	0.10***	0.88***	29.38***	9.84	-8.64***	-26692.60	0.043
Sweden	0.57***	0.09***	0.90***	30.96***	9.68	-8.46***	-26834.50	0.172

Pre-GFC

Country	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
Denmark	0.66***	0.05***	0.95***	-25.41	7.04	-9.00***	-10699.30	0.122
Norway	1.25***	0.12***	0.83***	7.75	7.22	-8.74***	-10237.30	0.009
Sweden	0.79***	0.09***	0.90***	1.99	5.38	-8.02***	-9967.50	0.000

Post-GFC

Country	$\mu * 10^3$	α	β	θ	w_2	m	BIC	VR
Denmark	0.72***	0.14***	0.73***	49.08***	7.34***	-9.12***	-9390.04	0.124
Norway	0.60***	0.17***	0.83***	0.45	4.27	-8.84***	-9493.84	0.000
Sweden	0.40***	0.07***	0.93***	-0.23	5.17	-9.55***	-9586.31	0.000

[5] For saving space, reported results are not provided in this study, but are available upon request.

5 Conclusion

This study was set out to assess various potential drivers on its explanatory value and significance for the equity markets of Scandinavia. Furthermore, the aim of this present research was to examine the differences and similarities among the countries regarding their exposure to these variables, whilst also accounting for different economic settings, namely the Post-GFC and Pre-GFC regime.

Insights of various kinds are revealed in this study and could be of significant value for risk managers investing in these markets. Among the business cycle variables, the DS proves to be highly significant across all analysed samples and countries. Moreover, Denmark's equity market shows the highest exposure to monetary policy among Scandinavian countries while the Swedish counterpart seems to be unaffected. Overall, the impact of the exchange rate fluctuation weakened after the GFC. Turning to the EPU indices, one can observe an effect on the respective market volatility, yet their impact is mainly limited to the AEPU index and to the countries of Denmark and Norway. Surprisingly, the EEPU index is of no explanatory value in none of the considered stock markets. Compared to the Pre-GFC, oil shocks became overall less critical during the Post-GFC era. Among the specific shocks, the aggregate oil demand shock turned out to be highly significant for most samples, yet having only a comparatively small impact on the conditional volatility. All Scandinavian countries show close ties to the state of the U.S. economy. Given the full sample, a 1% increase of the PC_{USA} corresponds to an upwards movement of the respective market volatilities by 6.40% for Denmark, 7.50% for Norway and 7.80% in the case of Sweden. Besides the Danish market, this strong relationship diminishes once the period of the GFC is discarded. It can therefore be hypothesised that most of the link for Norway and Sweden stems from this time period.

A limitation of this study is the comparatively small sample size for the considered subsamples. This issue arises as this research analyses recent data and the regimes before and after the GFC. In the years to come, it will be interesting to see if the conclusions turn out to be robust.

As the present study is one of the very first comprehensive assessments of the various drivers of the stock market volatility in the Scandinavian region, some areas might be fruitful for further research. While this paper focused on the specific drivers, one might assess the explanatory value on an aggregate level, e.g. by incorporating various variables at the same time or by using principal components. One could also investigate if the above-mentioned results also hold when the respective volatilities of the analysed variables are considered. Lastly, research could also be conducted to determine the dynamic correlation of the Scandinavian equity markets using a so-called Dynamic Conditional Correlation (DCC)-MIDAS framework as introduced by Colacito et al. (2011).

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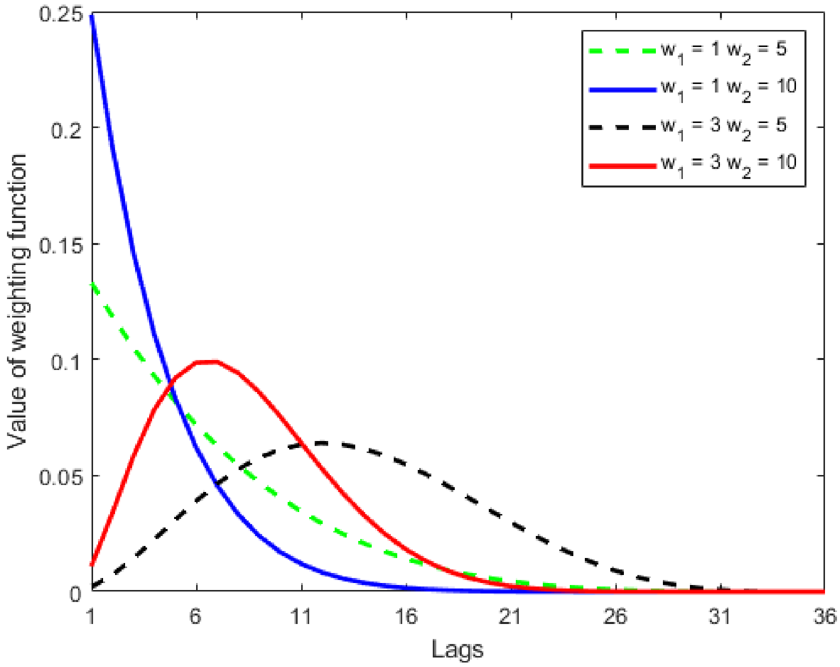
Appendix A

Figure 1: Plot beta lag function for different weights



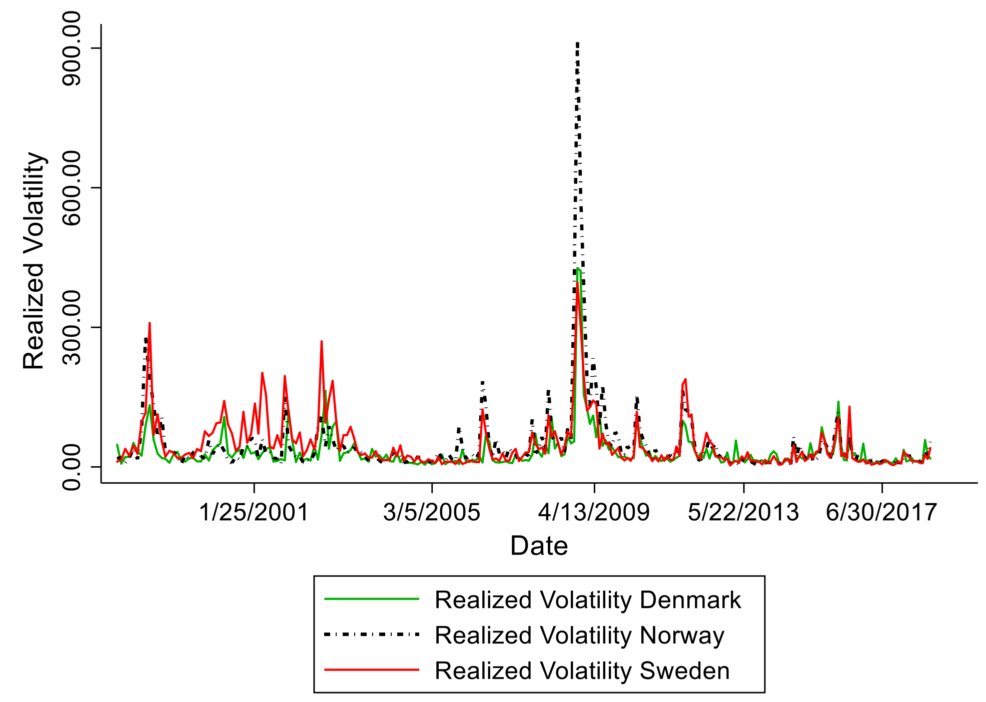
Notes: Given different weights for w_1 and w_2, this figure illustrates the weights assigned to lags 1 to 36 according to the beta lag weighting function. The beta lag function is defined as stated in (6).

Table 1: Pairwise correlation of daily returns in Scandinavia

Notes: This table reports the pairwise correlation of daily log returns in Denmark, Norway and Sweden for the full sample (Feb 1998 – Dec 2018), for the Pre-GFC (Feb 1998 – Nov 2007) as well as for the Post-GFC (Jan 2010 – Dec 2018).

Country		Denmark	Norway	Sweden
Denmark	Full sample	-	0.028	0.002
	Pre-GFC	-	-0.018	-0.012
	Post-GFC	-	0.051	0.004
Norway	Full sample	0.028	-	0.131
	Pre-GFC	-0.018	-	0.120
	Post-GFC	0.051	-	0.313
Sweden	Full sample	0.002	0.131	-
	Pre-GFC	-0.012	0.120	-
	Post-GFC	0.004	0.313	-

Figure 2: Plots of daily realized volatility in Denmark, Norway and Sweden



Notes: This figure shows the realized daily volatility of the Danish, Norwegian and Swedish stock market. Data covers the full sample (Feb 1998 – Dec 2018).

Table 2: Pairwise correlation variables - Denmark

Notes: This table reports the pairwise correlation of the monthly realized volatility (RV), monthly growth rate of industrial production (IPI), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), monthly growth rate of the unemployment rate (UR), default spread (DS), percentage change of the exchange rate against the U.S. Dollar (USDEX), growth rate of the M3 index (M3), monthly percentage change of the American economic policy uncertainty index (AEPU), European economic policy uncertainty index (EEPU) and Swedish economic policy uncertainty index (SEPU), monthly real oil price changes (Oil Price), monthly growth rate of world crude oil production (Oil Supply) and oil aggregate demand shocks (AGS Oil) measured by the corrected index of global real economic activity as discussed in Kilian (2019b). Data covers the full sample (Feb 1998 – Dec 2018).

Description	RV	IPI	Inflation	IRTS	UR	DS	USDEX	M3	AEPU	EEPU	SEPU	Oil Price	Oil Supply	AGS Oil
RV	1													
IPI	-0.119	1												
Inflation	-0.037	0.012	1											
IRTS	0.168	-0.063	0.001	1										
UR	0.230	-0.072	-0.031	0.201	1									
DS	0.613	-0.121	-0.038	0.337	0.383	1								
USDEX	0.108	-0.020	-0.009	-0.027	-0.091	-0.028	1							
M3	0.102	-0.051	0.053	0.004	0.049	0.059	-0.014	1						
AEPU	0.009	0.027	-0.021	-0.022	0.014	-0.020	0.017	0.130	1					
EEPU	0.021	0.022	0.077	-0.007	-0.057	-0.038	0.025	0.139	0.538	1				
SEPU	-0.029	-0.063	-0.116	0.020	-0.082	-0.041	0.034	0.065	0.286	0.211	1			
Oil Price	-0.365	-0.021	0.305	0.005	-0.086	-0.145	-0.144	0.015	-0.083	-0.020	-0.003	1		
Oil Supply	0.052	0.054	-0.046	0.046	-0.029	-0.059	0.043	-0.032	0.004	0.067	0.110	-0.030	1	
AGS Oil	-0.083	-0.011	0.070	-0.000	-0.067	-0.019	-0.032	0.156	0.042	0.011	0.010	0.134	0.069	1

Table 3: Pairwise correlation variables – Norway

Notes: This table reports the pairwise correlation of the monthly realized volatility (RV), monthly growth rate of industrial production (IPI), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), monthly growth rate of the unemployment rate (UR), default spread (DS), percentage change of the exchange rate against the U.S. Dollar (USDEX), growth rate of the M3 index (M3), monthly percentage change of the American economic policy uncertainty index (AEPU), European economic policy uncertainty index (EEPU) and Swedish economic policy uncertainty index (SEPU), monthly real oil price changes (Oil Price), monthly growth rate of world crude oil production (Oil Supply) and oil aggregate demand shocks (AGS Oil) measured by the corrected index of global real economic activity as discussed in Kilian (2019b). Data covers the full sample (Feb 1998 – Dec 2018).

Description	RV	IPI	Inflation	IRTS	UR	DS	USDEX	M3	AEPU	EEPU	SEPU	Oil Price	Oil Supply	AGS Oil
RV	1													
IPI	-0.081	1												
Inflation	0.008	0.034	1											
IRTS	0.127	-0.053	-0.038	1										
UR	0.052	-0.175	-0.011	0.197	1									
DS	0.620	-0.109	-0.029	0.337	0.127	1								
USDEX	0.248	-0.016	-0.013	-0.016	0.113	0.005	1							
M3	-0.074	0.040	0.037	-0.294	-0.105	-0.154	0.038	1						
AEPU	0.096	-0.067	0.091	-0.022	-0.045	-0.020	0.030	-0.013	1					
EEPU	0.120	-0.028	0.228	-0.007	0.028	-0.038	0.003	-0.014	0.538	1				
SEPU	0.064	0.010	0.007	0.020	-0.021	-0.041	0.011	-0.051	0.286	0.211	1			
Oil Price	-0.354	0.010	0.158	0.005	-0.131	-0.145	-0.300	-0.013	-0.083	-0.020	-0.003	1		
Oil Supply	-0.003	0.073	-0.021	0.046	0.057	-0.059	0.082	-0.036	0.004	0.067	0.108	-0.030	1	
AGS Oil	0.007	0.092	0.005	-0.000	-0.045	-0.019	-0.041	0.115	0.042	0.011	0.010	0.134	0.069	1

Table 4: Pairwise correlation variables – Sweden

Notes: This table reports the pairwise correlation of the monthly realized volatility (RV), monthly growth rate of industrial production (IPI), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), monthly growth rate of the unemployment rate (UR), default spread (DS), percentage change of the exchange rate against the U.S. Dollar (USDEX), growth rate of the M3 index (M3), monthly percentage change of the American economic policy uncertainty index (AEPU), European economic policy uncertainty index (EEPU) and Swedish economic policy uncertainty index (SEPU), monthly real oil price changes (Oil Price), monthly growth rate of world crude oil production (Oil Supply) and oil aggregate demand shocks (AGS Oil) measured by the corrected index of global real economic activity as discussed in Kilian (2019b). Data covers the full sample (Feb 1998 – Dec 2018).

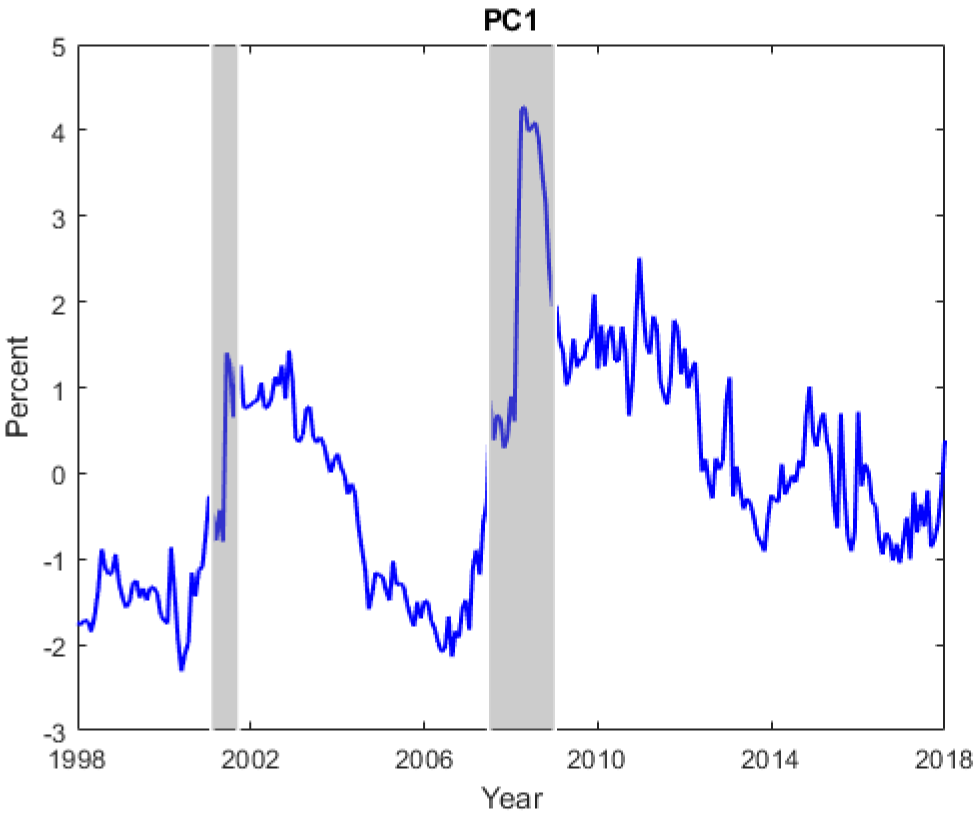
Description	RV	IPI	Inflation	IRTS	UR	DS	USDEX	M3	AEPU	EEPU	SEPU	Oil Price	Oil Supply	AGS Oil
RV	1													
IPI	-0.143	1												
Inflation	-0.002	0.024	1											
IRTS	0.053	-0.052	-0.037	1										
UR	0.073	0.039	-0.060	0.129	1									
DS	0.490	-0.195	-0.128	0.337	0.162	1								
USDEX	0.206	-0.013	-0.043	-0.058	-0.045	-0.014	1							
M3	-0.090	0.043	0.057	-0.283	-0.067	-0.103	-0.009	1						
AEPU	0.162	-0.087	0.032	-0.022	0.096	-0.020	0.053	-0.001	1					
EEPU	0.116	-0.013	0.148	-0.007	-0.062	-0.038	0.050	0.033	0.538	1				
SEPU	0.091	-0.042	-0.154	0.020	0.008	-0.041	0.065	-0.028	0.286	0.211	1			
Oil Price	-0.294	0.069	0.289	0.005	0.008	-0.145	-0.183	0.107	-0.083	-0.020	-0.003	1		
Oil Supply	0.022	0.008	-0.028	0.046	-0.074	-0.059	0.024	-0.023	0.004	0.067	0.108	-0.030	1	
AGS Oil	-0.068	0.047	0.126	-0.000	0.040	-0.019	-0.046	-0.004	0.042	0.011	0.010	0.134	0.069	1

Table 5: Correlation between principal components and U.S.-related variables

Notes: This first panel reports the correlation between U.S.-related variables and the principal components (PC) which were constructed by considering these variables. The U.S.-related variables are the monthly default spread (DS), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), and the monthly percentage change of the American economic policy uncertainty index (AEPU). The second row shows the explained variance of the respective PCs. Data covers the full sample (Feb 1998 – Dec 2018).

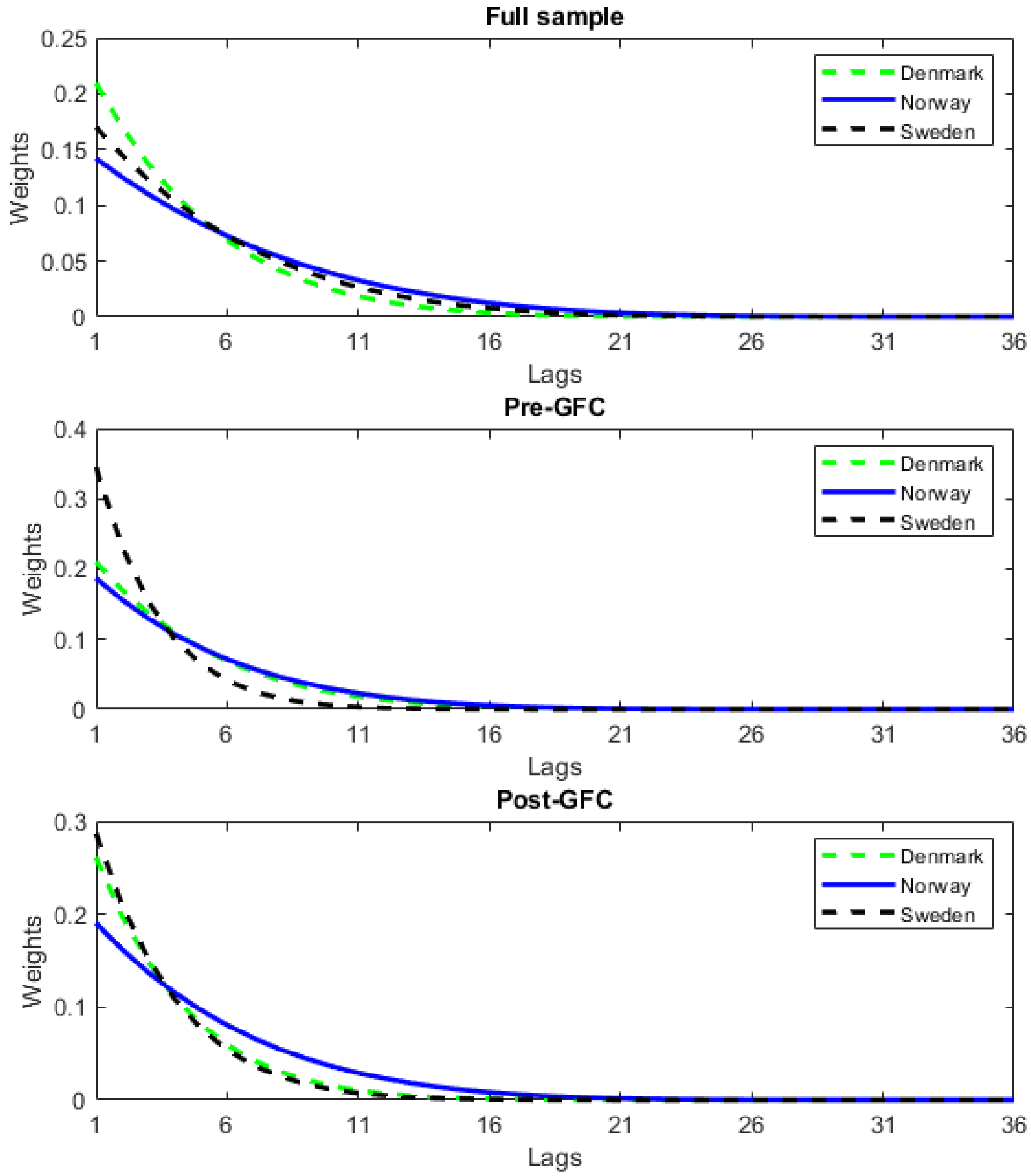
		PC1	PC2	PC3
Correlation	DS	0.603	-0.018	-0.797
	IRTS	0.565	-0.696	-0.443
	AEPU	0.563	0.718	0.410
Fit	Explained Variance	0.598	0.220	0.182

Figure 3: Plot of the first principal component PC1



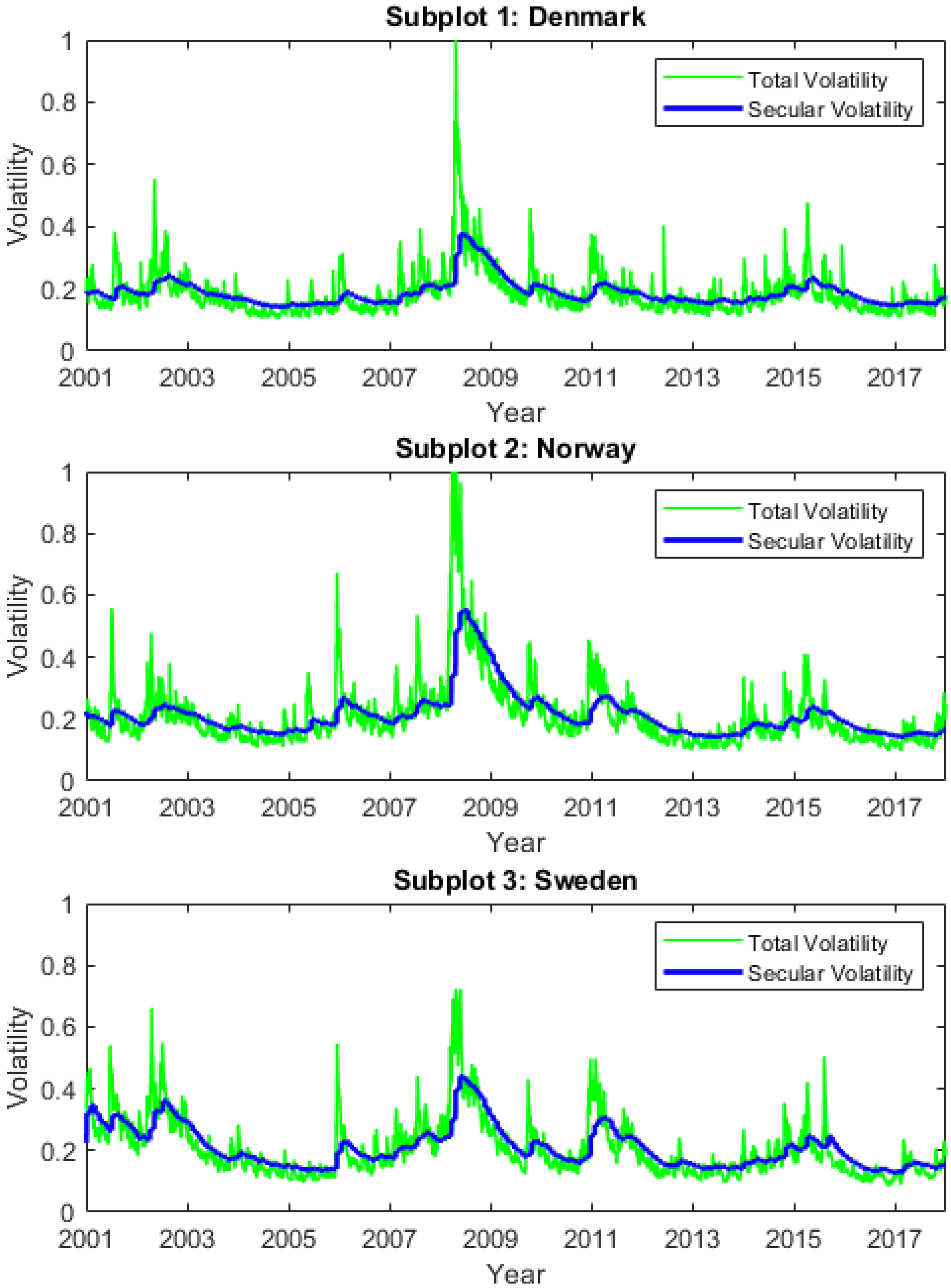
Notes: This figure shows the respective time-series plot for the first principal component (PC1) which was constructed using the monthly default spread (DS), yield spread between 10-year U.S. government bond and 3-month U.S. treasury bill (IRTS), and the monthly percentage change of the American economic policy uncertainty index (AEPU). The corresponding correlations are shown in Table 5. The grey shaded highlights U.S. recessions as dated by the Federal Reserve Bank of St. Louis (2019). Data covers the full sample (Feb 1998 – Dec 2018).

Figure 4: Optimal MIDAS weights for the RV



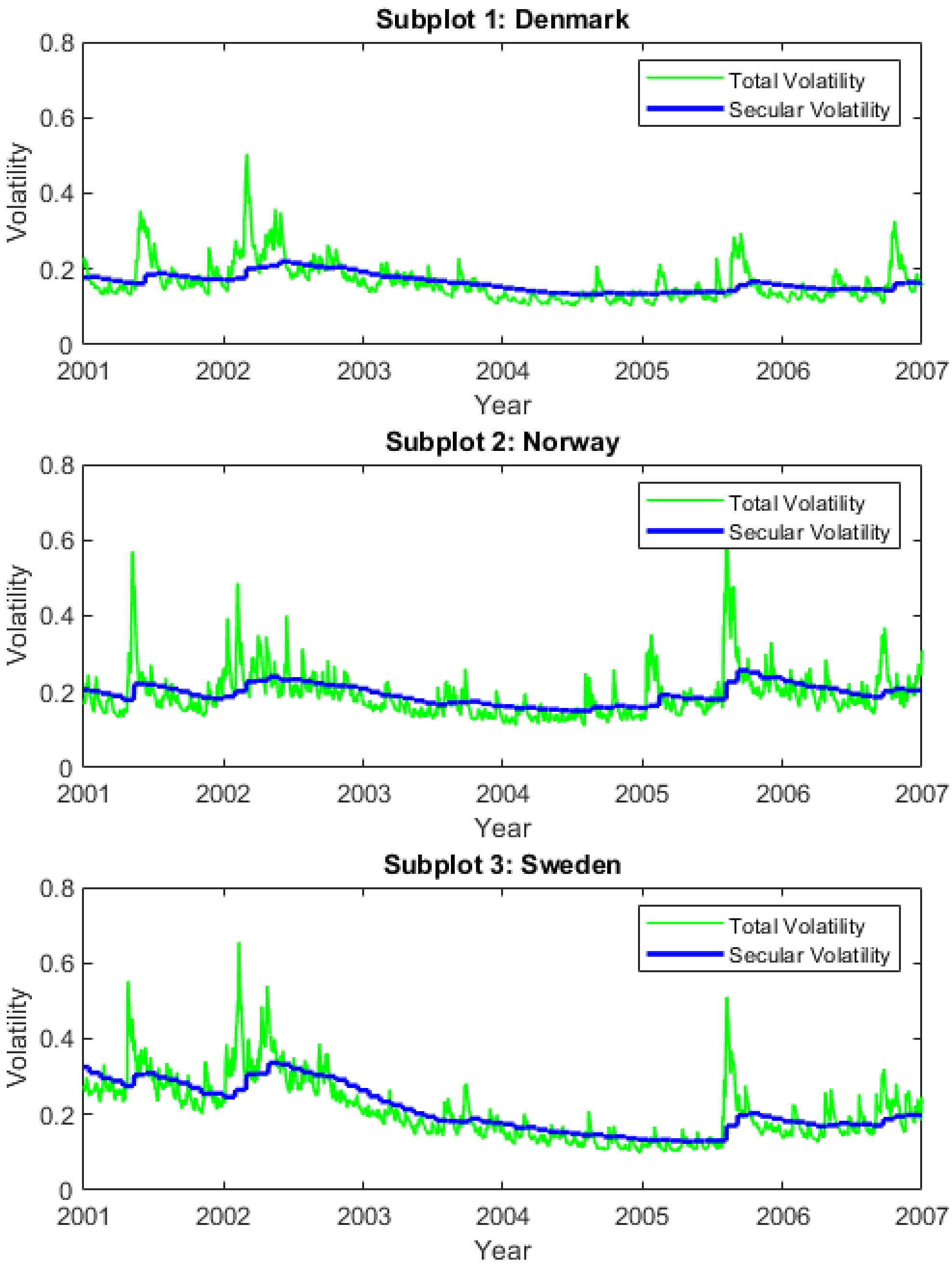
Notes: This figure shows the optimal weights for the RV for the MIDAS equation (4) for Denmark, Norway and Sweden. The corresponding estimates are shown in Table 2. Data covers the full sample (Feb 1998 – Dec 2018), the Pre-GFC (Feb 1998 – Nov 2007) as well as the Post-GFC (Jan 2010 – Dec 2018).

Figure 5: GARCH-MIDAS with RV – Full sample



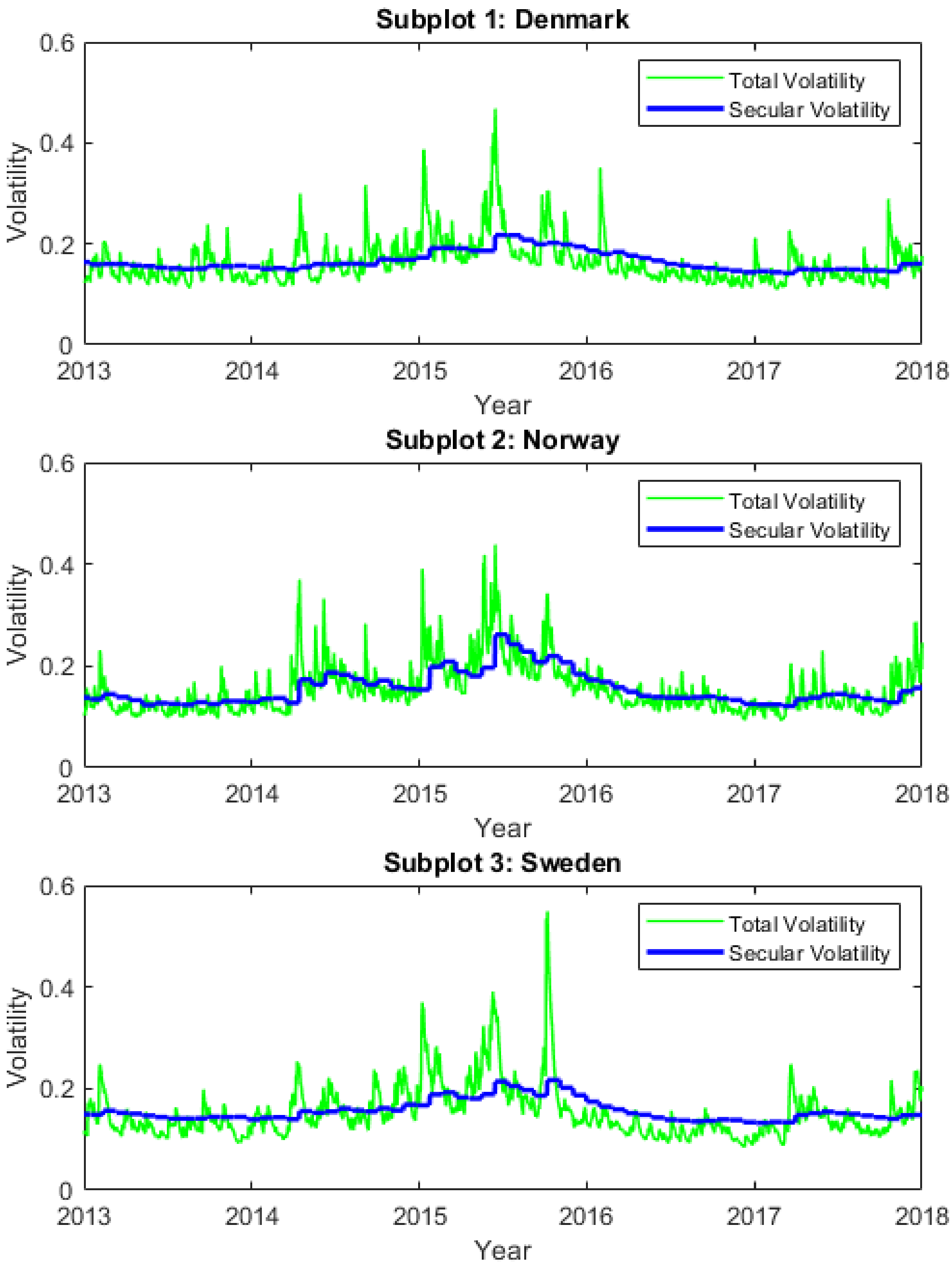
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with RV. Data covers the full sample period (Feb 1998 –Dec 2018). The estimated parameters are shown in the first panel of Table 2. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2) RV_{t-k}$.

Figure 6: GARCH-MIDAS with RV – Pre-GFC



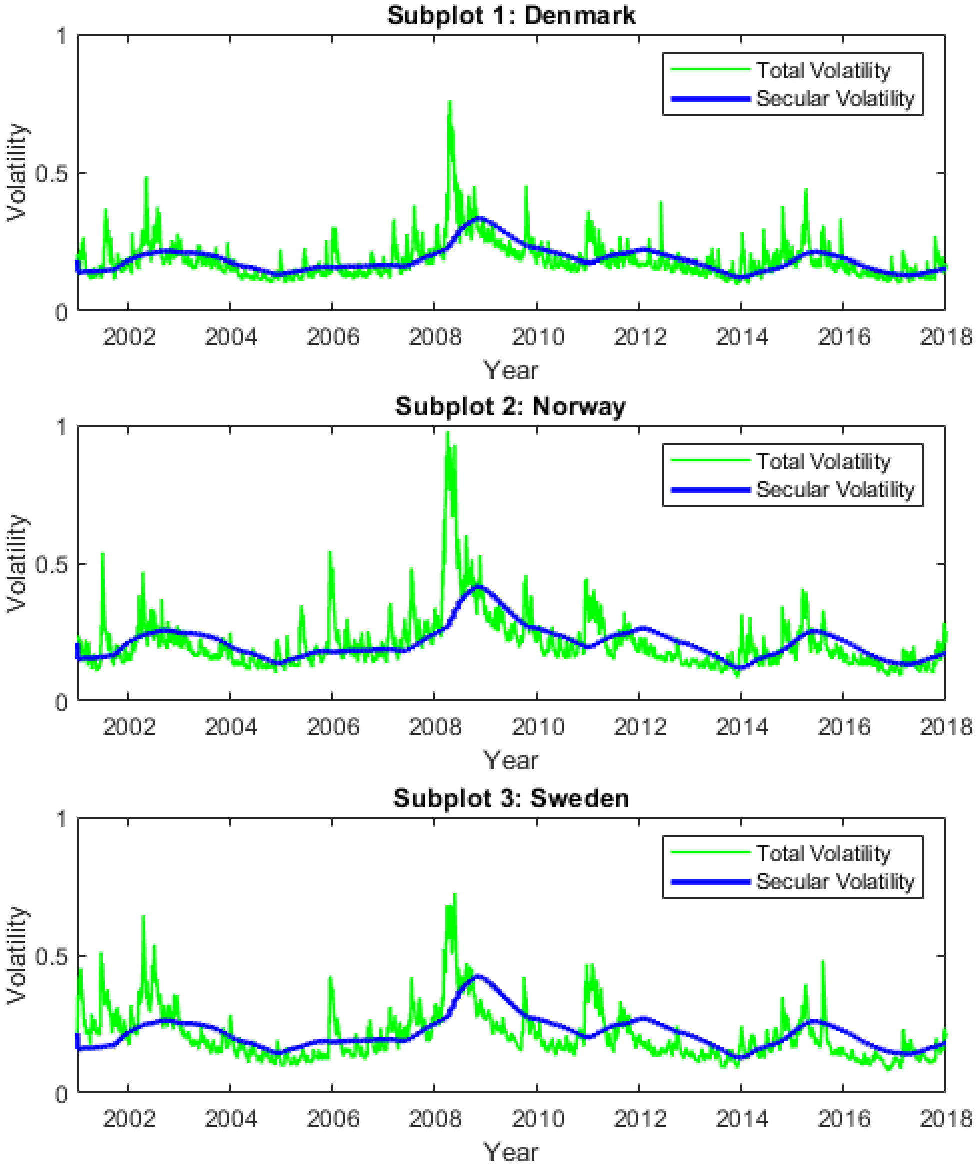
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with RV. Data covers the Pre-GFC period (Feb 1998 – Dec 2007). The estimated parameters are shown in the second panel of Table 2. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2) RV_{t-k}$.

Figure 7: GARCH-MIDAS with RV – Post-GFC



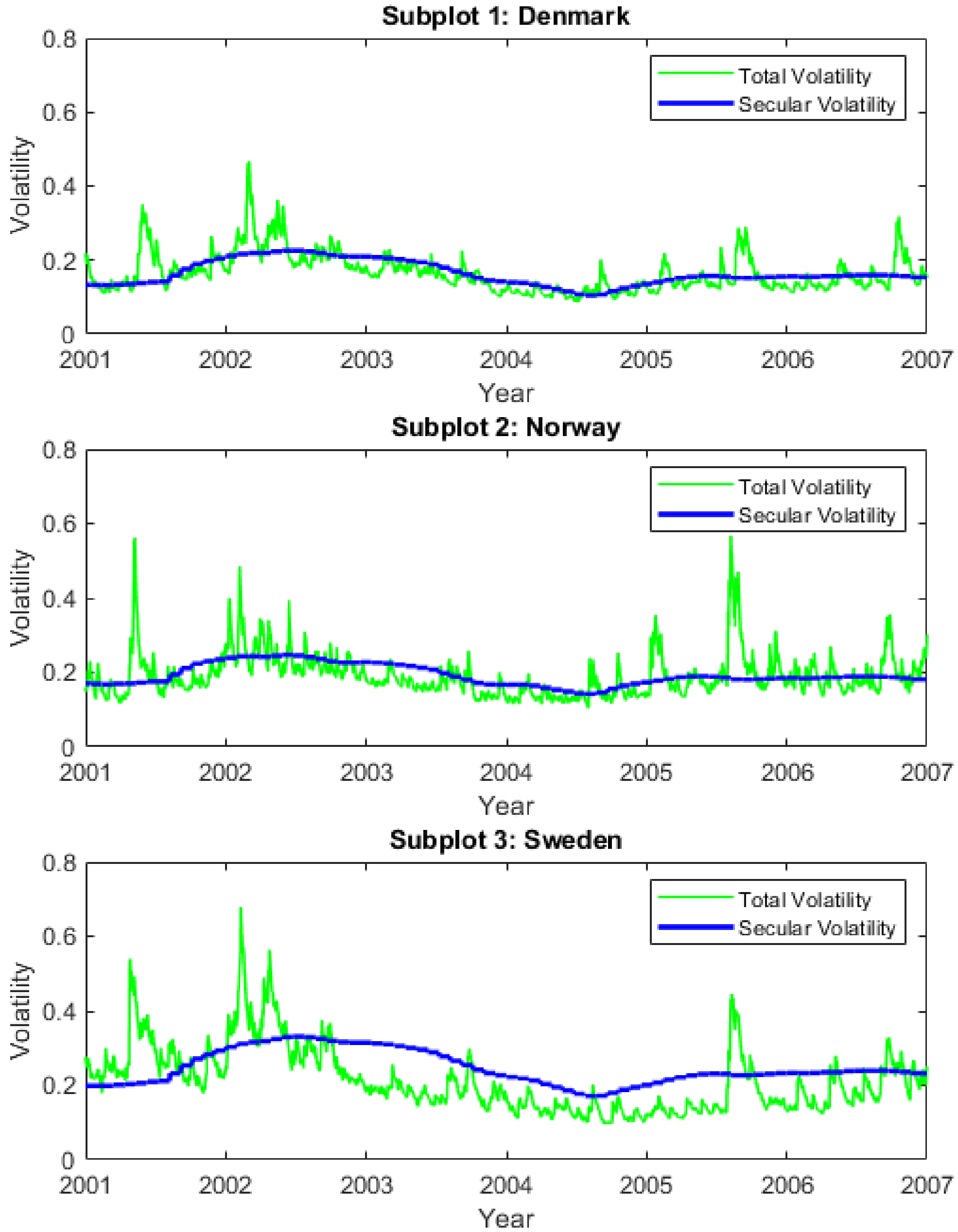
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with RV. Data covers the Post-GFC period (Jan 2010 – Dec 2018). The estimated parameters are shown in the third panel of Table 2. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2) RV_{t-k}$.

Figure 8: GARCH-MIDAS with DS – Full sample



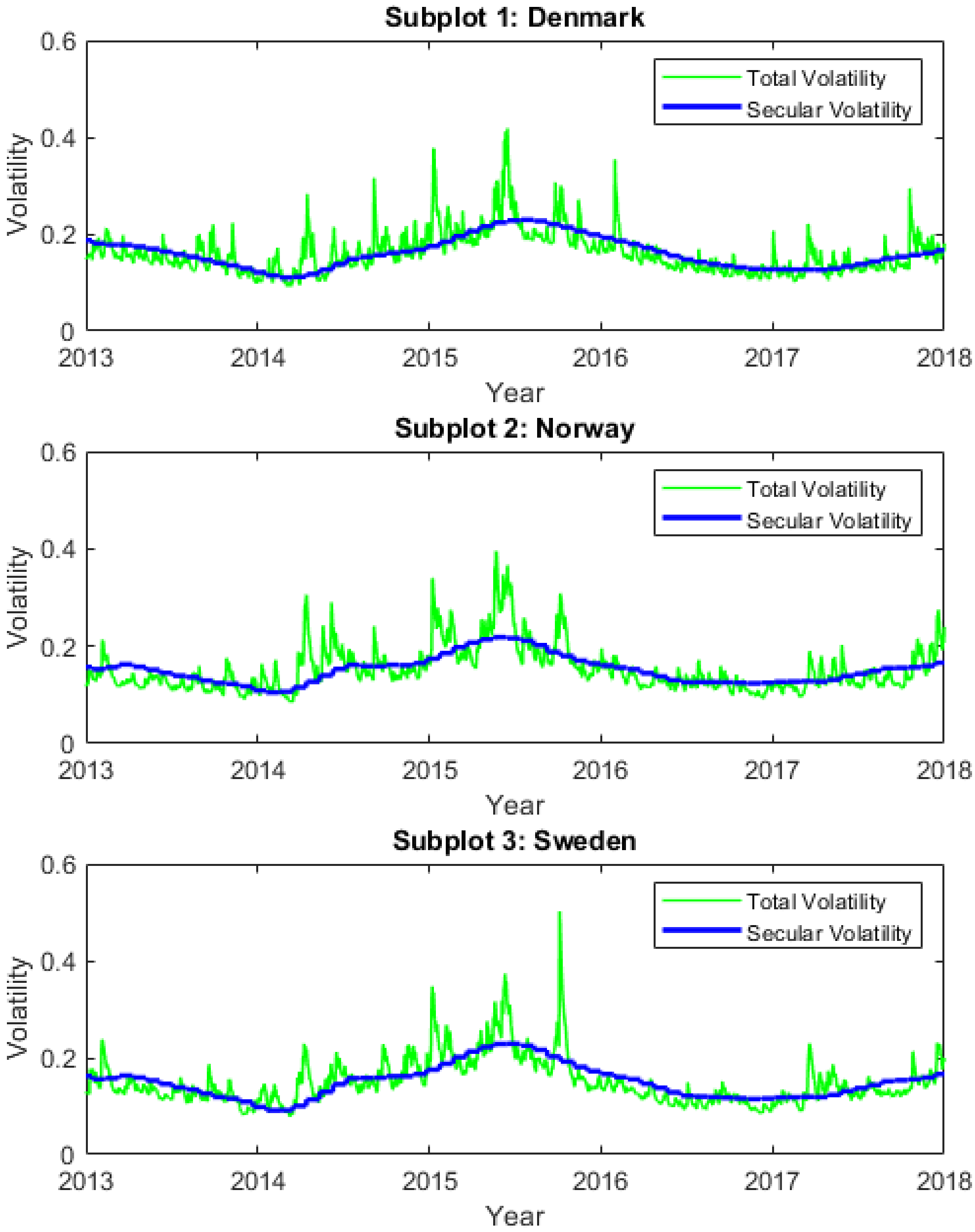
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with DS. Data covers the full sample period (Feb 1998 –Dec 2018). The estimated parameters are shown in the first panel of Table 3. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2) DS$.

Figure 9: GARCH-MIDAS with DS – Pre-GFC



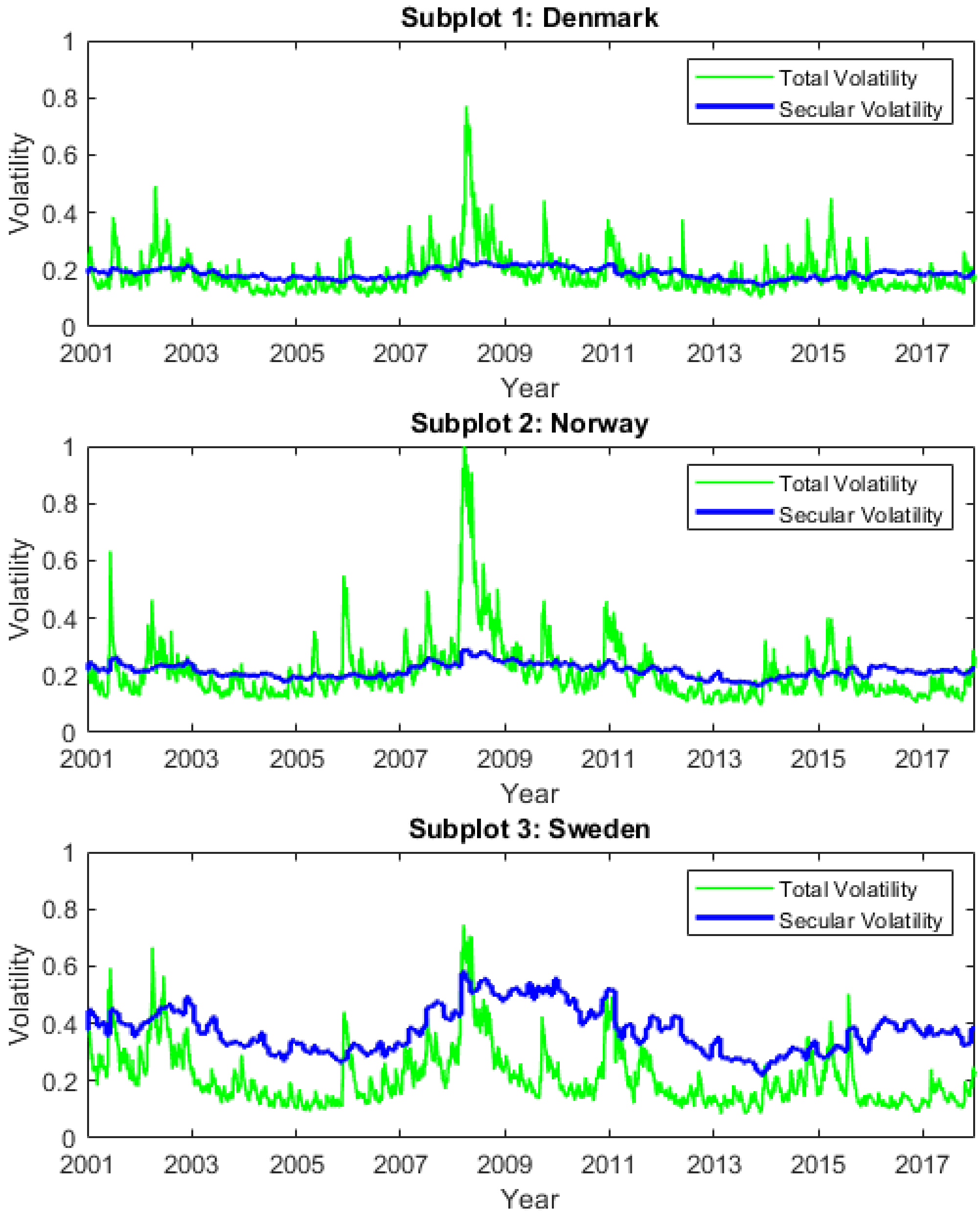
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with DS. Data covers the Pre-GFC period (Feb 1998 – Nov 2007). The estimated parameters are shown in the second panel of Table 3. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2)DS$.

Figure 10: GARCH-MIDAS with DS – Post-GFC



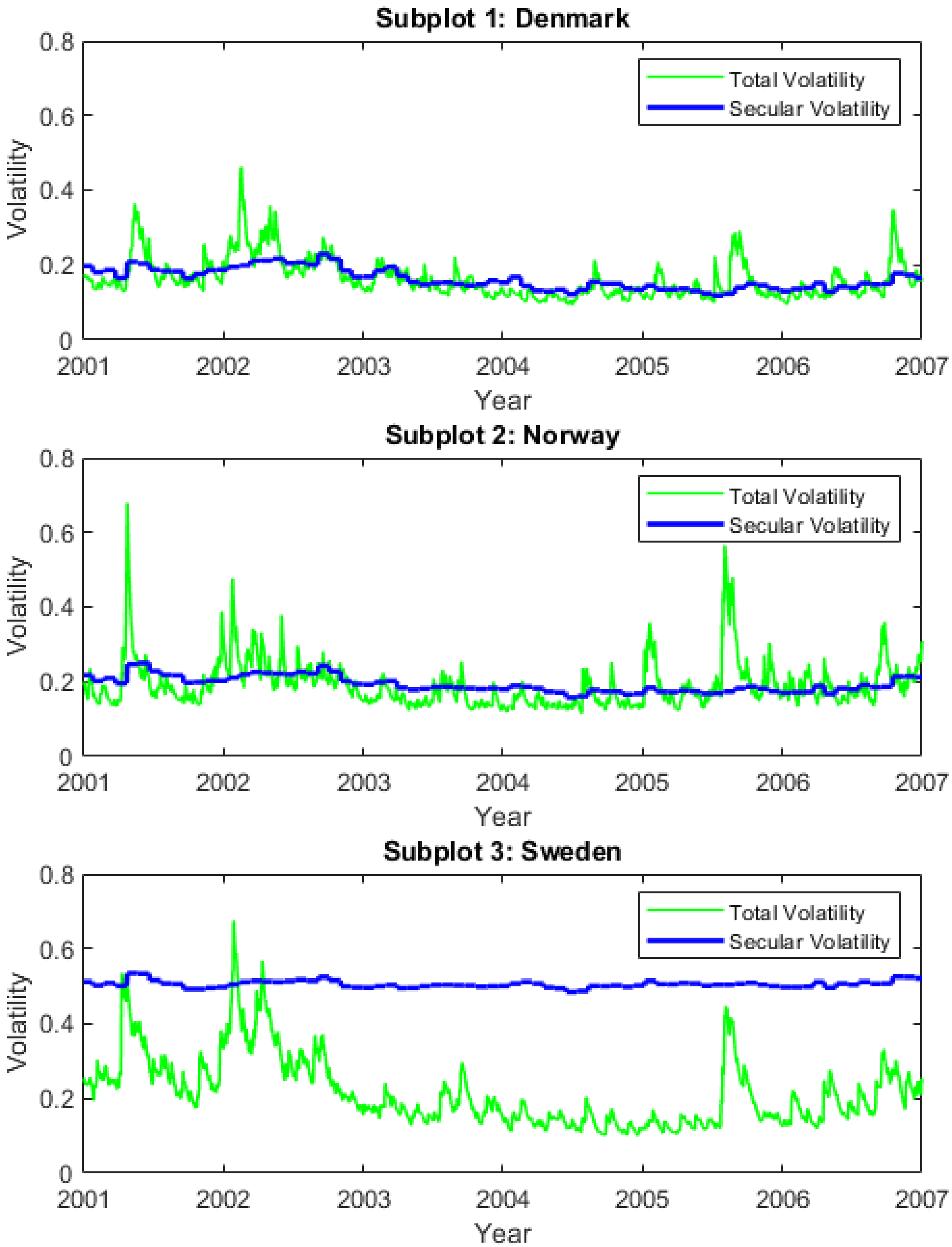
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with DS. Data covers the Post-GFC period (Jan 2010 – Dec 2018). The estimated parameters are shown in the third panel of Table 3. The model considered for the long-run component is $\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(1, w_2)DS$.

Figure 11: GARCH-MIDAS with AEPU – Full sample



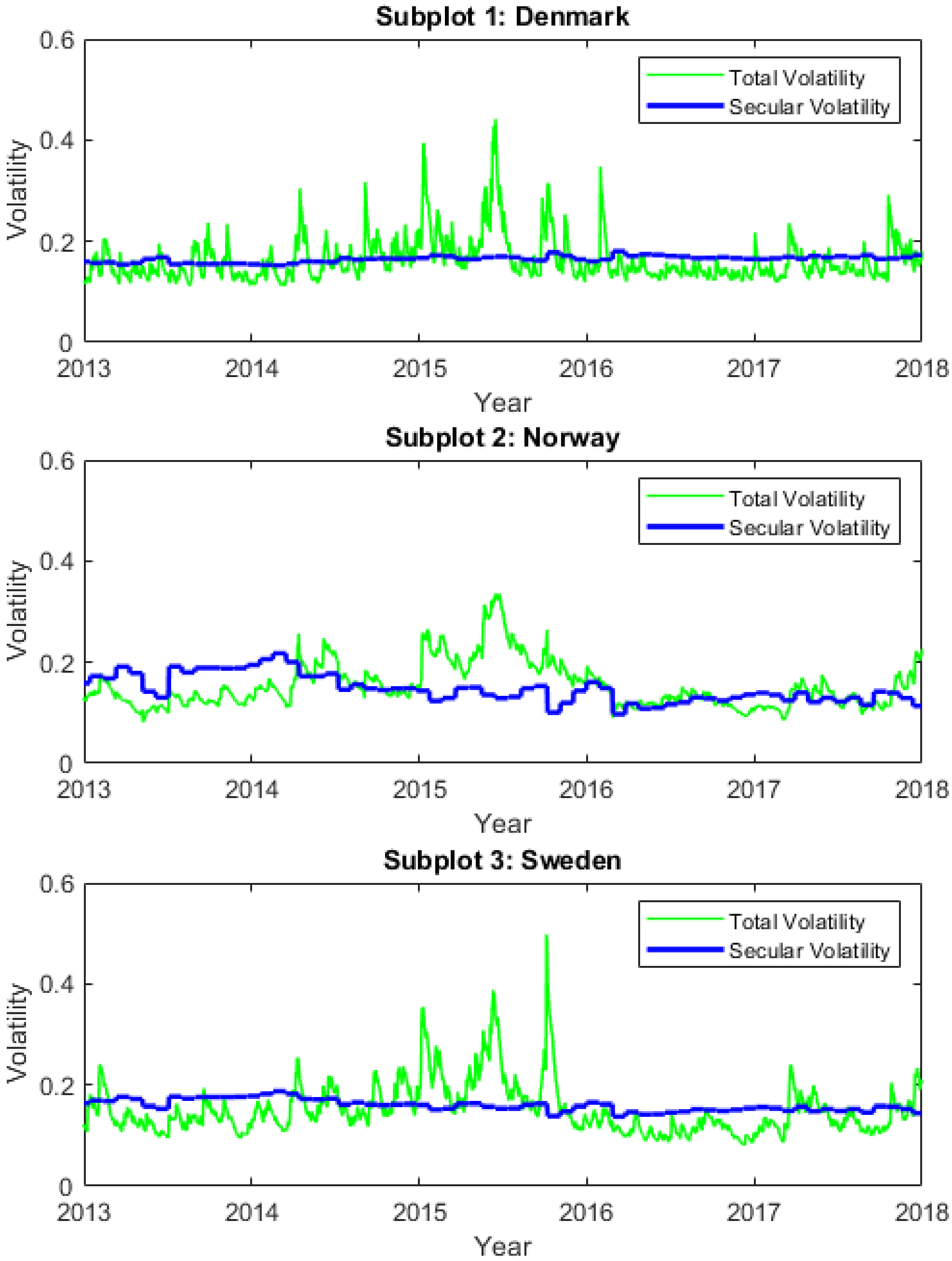
Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with the monthly percentage changes of the AEPU. Data covers the full sample (Feb 1998 – Dec 2018). The estimated parameters are shown in the first panel of Table 5.

Figure 12: GARCH-MIDAS with AEPU – Pre-GFC



Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with the monthly percentage changes of the AEPU. Data covers the Pre-GFC period (Feb 1998 –Nov 2007). The estimated parameters are shown in the second panel of Table 5.

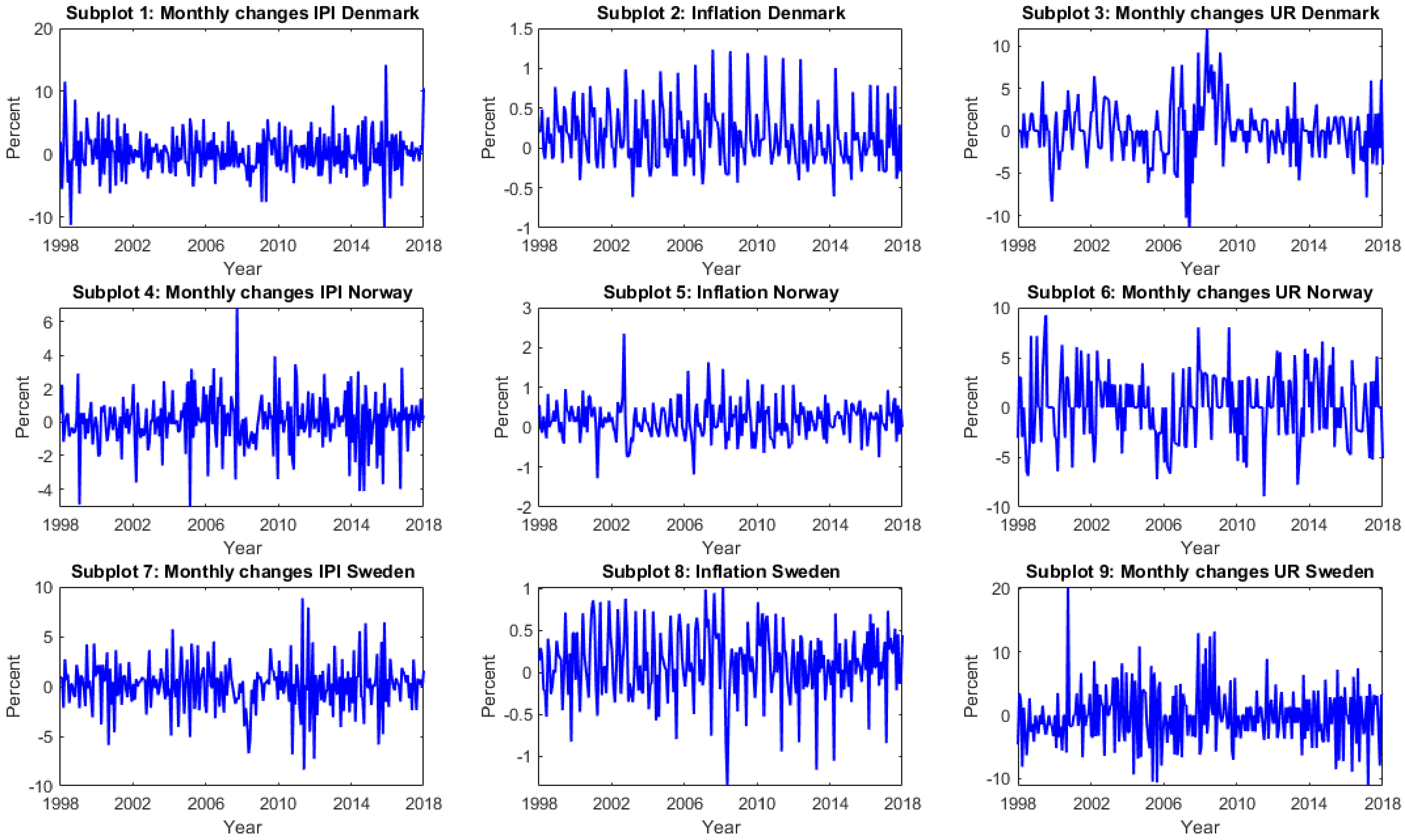
Figure 13: GARCH-MIDAS with AEPU – Post-GFC



Notes: The three panels show the respective conditional volatility and its long-term component for Denmark, Norway and Sweden for the GARCH-MIDAS model with the monthly percentage changes of the AEPU. Data covers the Post-GFC period (Jan 2010 – Dec 2018). The estimated parameters are shown in the third panel of Table 5.

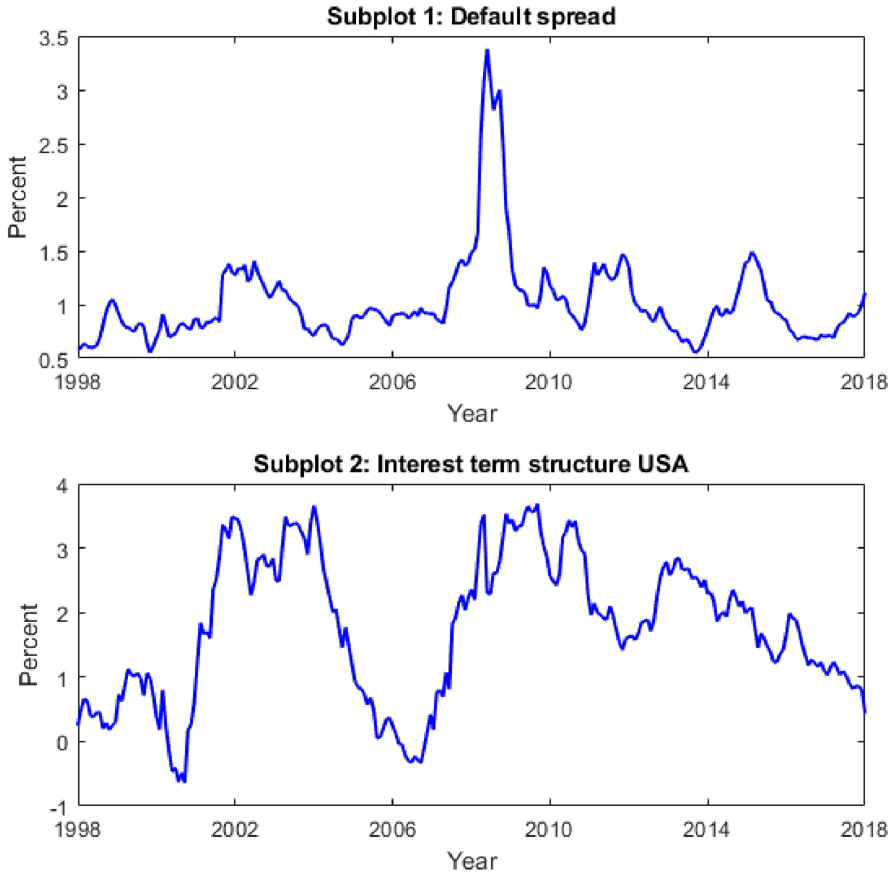
Appendix B

Figure 1: Plots of business cycle variables policy variables



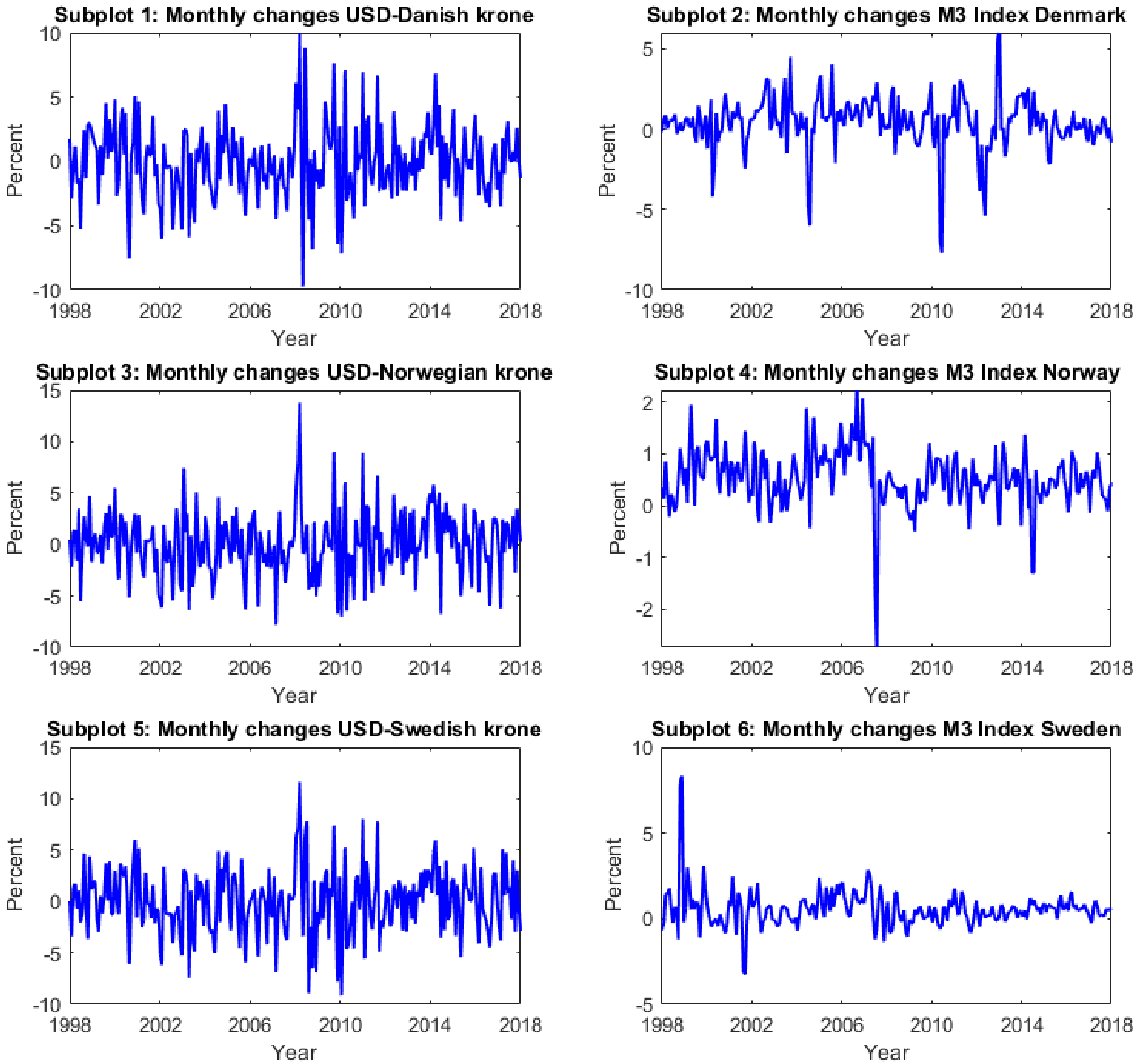
Notes: The nine subplots show the respective time-series plots for the monthly changes of the respective growth rate of the IPI (left side), inflation rate (middle), and the monthly changes of the unemployment rate (right side). Data covers the full sample (Feb 1998 – Dec 2018).

Figure 2: Plots of business cycle variables – common factors



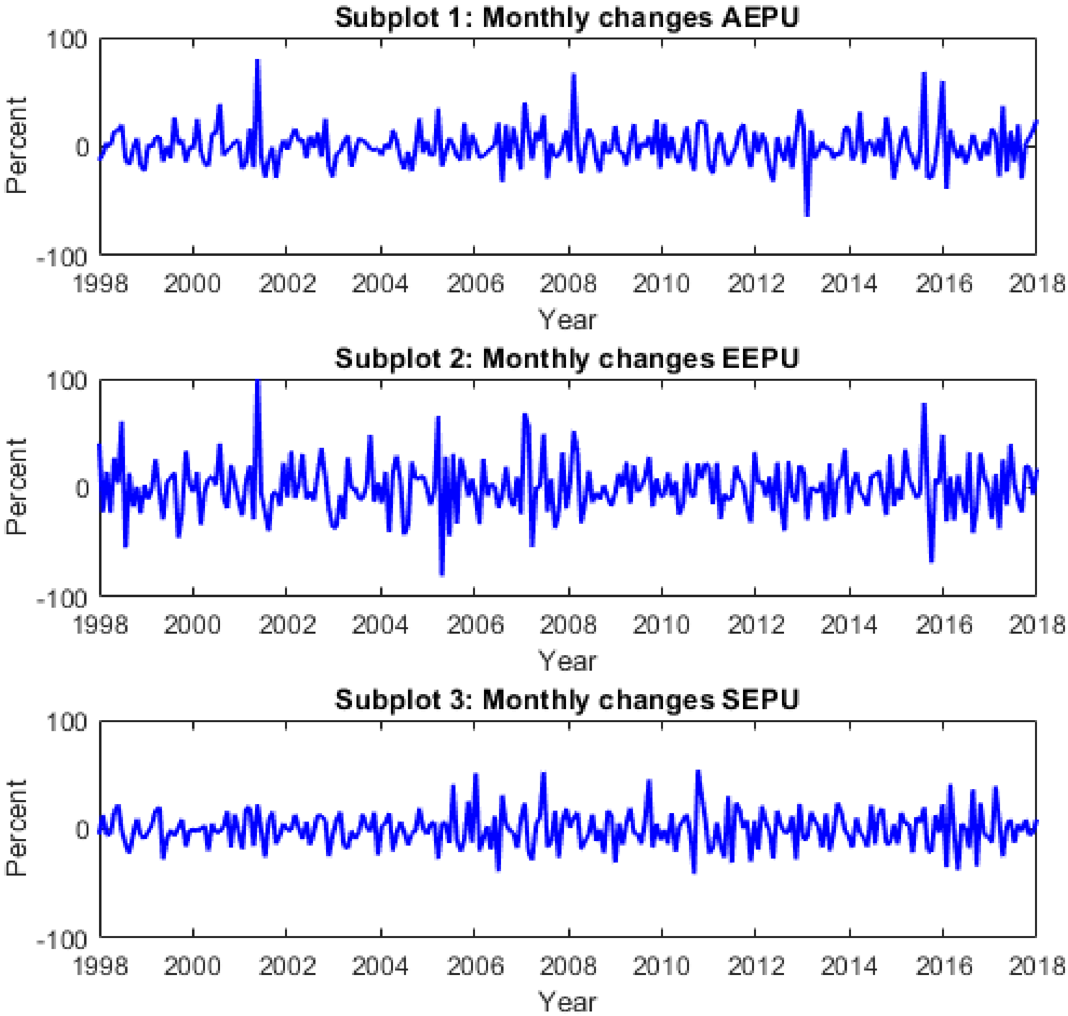
Notes: The two subplots show the respective time-series plots for the default spread and the interest term structure of the U.S. Data covers the full sample (Feb 1998 – Dec 2018).

Figure 3: Plots of monetary policy variables



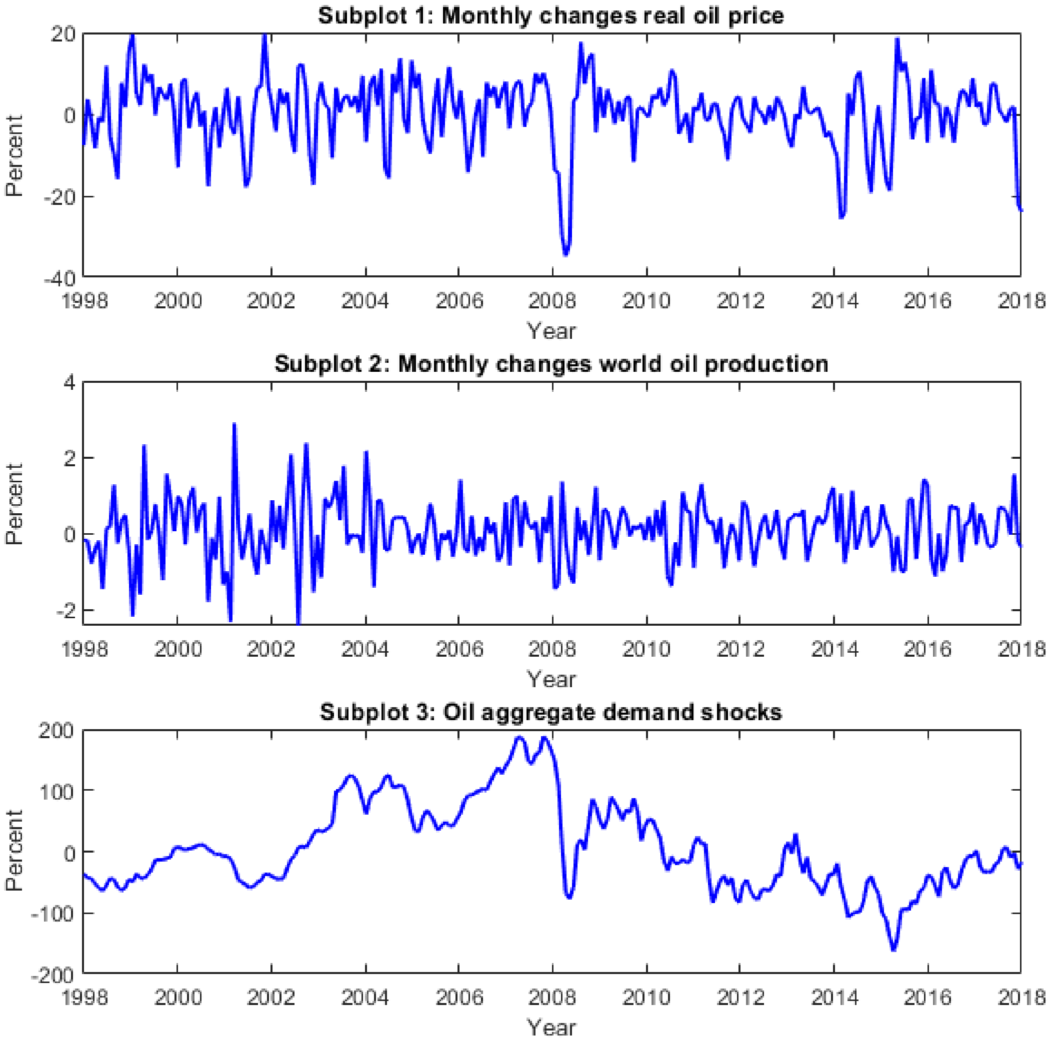
Notes: The six subplots show the respective time-series plots for the monthly changes of the respective local currency against the U.S. Dollar (left side) and the monthly changes of the local M3 index (right side). Data covers the full sample (Feb 1998 – Dec 2018).

Figure 4: Plots of economic policy uncertainty variables



Notes: The three panels show the respective time-series plots for the respective monthly changes of the American economic policy uncertainty index (AEPU), the European economic policy uncertainty index (EEPU) and the Swedish economic policy uncertainty index (SEPU). Data covers the full sample (Feb 1998 – Dec 2018).

Figure 5: Plots of oil shock variables



Notes: The three panels show the respective time-series plots for the monthly changes of the real oil price, monthly growth rate of world crude oil production, and oil aggregate demand shocks measured by the corrected index of global real economic activity as discussed in Kilian (2019b). Data covers the full sample (Feb 1998 – Dec 2018).