

STAFF MEMO

A composite indicator of systemic stress (CISS) for Norway – A reference indicator for the reduction of the countercyclical capital buffer

NO. 4 | 2015

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NORGES BANK

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ISSN 1504-2596 (online only)

ISBN 978-82-7553-877-0 (online only)

A Composite Indicator of Systemic Stress (CISS) for Norway^{†‡}

*A reference indicator for the reduction of the
countercyclical capital buffer*

Yudi Wen[§]

Abstract

This paper constructs a Composite Indicator of Systemic Stress (CISS) for Norway using a portfolio-theoretic framework as in Holló, Kremer and Lo Duca (2012) to facilitate real-time monitoring of the short-term development of systemic stress in the Norwegian financial system. In the aftermath of the global financial crisis, capital requirements are being tightened to make credit institutions more resilient to turmoils in the financial system. As part of the new capital requirements for banks, a counter-cyclical capital buffer has been activated in Norway in the light of Norges Bank's assessment that financial imbalances had been build up over time (Press release 12 December 2013 from the Ministry of Finance). Norges Bank's advice on the level of the buffer is primarily based on four key indicators. However, another type of indicator(s) is needed for the prompt reduction of the buffer in the event of market turbulence and heightened loss prospects for the banking sector, and this paper aims to provide just that.

Keywords: Financial stress index, Financial stability, Systemic risk, GARCH models, Countercyclical capital buffer.

[†] This paper was first submitted as a master thesis for the degree Master of Economic Theory and Econometrics at the Department of Economics in the University of Oslo in May 2015, written under an internship at Norges Bank's Macroprudential Unit in the Financial Stability Department.

[‡] My sincere appreciation goes to my supervisors Karsten Gerdrup and Professor Kjetil Storesletten. Special thanks also go to Ketil Johan Rakkestad, Bjørn Ivar Bakke, Mats Bay Fevolden, Elisabeth Lervik, Gro Medlien, Aleksander Bråthen, and Johannes Skjeltorp, for the advice they gave me on the choice of input data used in the indicator. I must also give my gratitude to all the colleagues at Norges Bank and the University of Oslo with whom I had wonderful discussions with. Among them are Ketil Johan Rakkestad, Bjørn Ivar Bakke, Mats Bay Fevolden, Ragnar Nymo, Harald Goldstein and Yikai Wang.

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1 INTRODUCTION

The recent financial crisis highlighted the importance of systemic risk: the failure of a global financial institution – Lehman Brothers, marked the start of the first truly global financial crisis. The course of events demonstrates how interconnected the financial world has become. Regulators around the globe have come to the consensus that micro-level supervision of individual financial institutions is not enough to safeguard the entire financial system, and have subsequently developed a set of macroprudential policy instruments to make systemic risk more manageable. Among these is the countercyclical capital buffer (CCB), which is meant to be built up in good times and released to absorb banks' losses during periods of distress. Effective use of the CCB requires identification of the “good times” and “periods of distress”. The central bank of Norway, Norges Bank, has identified four key indicators for activating and maintaining the buffer under normal circumstances: credit to GDP ratio, house prices to disposable income ratio, commercial property prices and the wholesale funding ratio of Norwegian credit institutions. To determine when to release the buffer requires another set of indicators as guidance. This paper aims to identify such indicators and combine them into a single composite indicator of systemic stress.

This desired indicator must be able to measure the current state of instability in the financial system as a whole, since the CCB is a rather generic instrument that affects the entire banking sector, which in turn is connected to other parts of the financial system and the real economy. The failure of one bank can be a stressful event, but unless it leads to significant level of *systemic stress*, the CCB will not be a suitable instrument to employ. De Bandt and Hartmann (2000) define systemic risk as “the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially,” and systemic stress is the materialization of this risk (Holló et al. 2012).

Moreover, this indicator should be available on a timely basis, in order for policy makers to monitor the current level of systemic stress in real time. Some may suggest that when a financial crisis occurs, policy makers will know and can respond swiftly. However, stressful events and the “crisis” label do not always go hand in hand. Usually, one or few incidents occur somewhere in the financial system. Policy makers and others may take notice, but these events alone are not enough for them to take action. The same event may trigger a crisis in one scenario, in which markets are in a “nervous” state, but none in another, in which

financial markets are stable; hence the distinction between stress and risk. A true crisis occurs when isolated events trigger waves of responses other than where they have originated.

The first systemic stress indicator that combines the above elements was designed by Holló et al. (2012) for the Euro area. They select 3 raw stress indicators into 5 financial markets – money market, bond market, equity market, financial intermediaries and foreign exchange market, first transform these variables into empirical cumulative distribution functions, then take the average to produce robust market stress variables (subindices). They then compute a dynamic correlation matrix between these subindices using an exponentially weighted moving average (EWMA) model. The final indicator is obtained by weighing the subindices with cross correlations between markets, inspired by modern portfolio theory. This framework aims to capture both the severity of stress in various financial markets (represented by the subindices) and the contagion between them (effects from cross correlations), and has gained popularity among central banks due to its good empirical properties and is recommended by the European Systemic Risk Board (see Detken, Carsten et al, 2014).

Using the framework provided by Holló et al. (2012), Louzis and Vouldis (2012) construct a financial systemic stress index for Greece. They extended the EWMA model used by Holló et al. (2012) for the computation of subindices to a multivariate GARCH model. They also included balance sheet data for the banking sector, making a compromise to obtain a monthly, rather than weekly indicator. Another difference is that they used principal component analysis instead of ordered statistics in the first level aggregation (from raw stress indicators to subindices.)

Cabrera et al. (2014) applied the CISS methodology to Colombia. They too used principal component analysis to obtain subindices. However, as Holló et al. (2012) pointed out, principal component analysis is sensitive to outliers, resulting in less robust market stress indicators. To estimate dynamic correlations, Cabrera et al. (2014) also used a MGARCH model. Their innovation is to use GARCH models to estimate realized volatilities. Previous authors tend to use simple standard deviation or similar volatility measures. GARCH models are better suited for financial market volatility measures due to the heteroskedasticity present in the data. More weights should be given to recent data since volatilities tend to cluster, especially in times of crises.

Iachini and Nobili (2014) used a different set of indicators to construct an indicator of systemic liquidity risk in the Italian financial markets with mostly the same method as Holló et al. (2012). Such an application can prove useful for the liquidity management of central banks, and demonstrates the flexibility of the portfolio-theoretic framework developed by Holló et al. (2012).

The central banks of Jamaica, Sweden and Denmark have also constructed similar CISS indicators for their countries. I will construct a composite indicator of systemic stress à la Holló et al. (2012) for Norway.

The remainder of this paper is structured as follows: Section 2 presents the selected raw indicators from five sectors. Section 3 develops the methodology for constructing the CISS. Main results and empirical evaluation are presented in section 4. Section 5 concludes.

2 SELECTION OF VARIABLES

Ideally, measurement of systemic risk should involve data collected from all sectors that make up a financial system. This includes, as Holló et al. (2012) suggest, financial markets, financial intermediaries and financial infrastructure. Although data could arguably be found for more areas, the need for real-time monitoring means that highly frequent and easily available data materials are preferred. As a result, only market data are used in this thesis, covering several financial markets as well as financial intermediaries.

This section presents variables selected for the construction of the CISS. These variables, or “raw stress indicators”, are grouped into 5 market segments or sectors following Holló et al. (2012) and Cabrera et al. (2014): money market, bond market, equity market, financial intermediaries and external sector. In choosing the raw data used in each sector, this paper follows Holló et al. (2012) whenever possible and plausible, to facilitate comparison with CISS for the Euro area and elsewhere. I use the following set of criteria when selecting variables:

- i) *The set of raw indicators should capture key features of financial stress*

Hakkio and Keeton (2009) characterize the following key features of financial stress:

- i) uncertainty about the fundamental value of assets, ii) uncertainty about the behavior of investors, iii) asymmetry of information, iv) decreased willingness to hold risky assets (flight to quality) and v) decreased willingness to hold illiquid assets (flight to liquidity). In financial markets, these symptoms are often expressed as greater asset price volatilities and wider spreads between rates of return on different types of assets, especially those on riskier assets. Thus a major part of the input series (12 out of 15) used for the Norwegian CISS are volatilities and spreads, as in Holló et al. (2012).

- i) *To satisfy the real-time monitoring purpose of the CISS, data for each series must be available on at least a weekly basis and go sufficiently far back in time.*

One cannot study systemic risk without covering episodes of high stress. The “sufficient” sample length is at least 3 years prior to the financial crisis of 2007-2009 for the following reasons: a) whether the CISS could give signals prior to the financial crisis is crucial for its evaluation and b) a dynamic correlation matrix will be estimated for the five subindices using a diagonal MGARCH-BEKK model. 2-3 years of weekly

data is needed for sound parameter estimation and the computation of the CISS. Even though it is desirable to let the final indicator stretch back to the Norwegian banking crisis in the early 1990s, available data covering various aspects of the financial market go just as far back as late 2003². Certain derivatives which would have been useful in measuring risk, e.g. credit default swaps, are not used in this study due to deficient data length. Balance sheet data, which contain useful information about financial institutions' liquidity and solvency situation, are left out due to low frequency.

- ii) *Variables selected should be close to those used by the ECB to facilitate comparison with other regions' CISS indicators, while at the same time take into account the specificities of the Norwegian financial system.*

Even though variables used in Holló et al. (2012) are meant to be readily available for many countries, one size does not fit all. Fortunately, their work provides a flexible framework on which amendments can easily be made to fit a particular country. Examples of such individual choices can be which market segments to include, the choice of input variables, and subindex weights.

- iii) *Each segment/sector should contain the same number of variables*

This symmetry requirement is related to the Central Limit Theorem (CLT), which states that the average of independent random variables regardless of distribution will become approximately normally distributed as the number of variables increases. The variance of the mean will also be decreasing in the number of variables. However, this motivation is rather weak since raw stress indicators from the same market segment can hardly be considered independent, and that the CLT only applies when the number of variables is sufficiently large (e.g. 30), which is not the case with this exercise.

Nevertheless, it does make sense to have several raw indicators per market segment to incorporate different sources of information and smooth out undesirable noise. Moreover, a symmetrical setup gives each segment equal attention at the outset.

In what follows, a brief description of each variable, its interpretation, and relation to systemic risk is provided, organized by sectors.

² When investment-graded corporate bond data first became available.

2.1 Money market

As a primary source of short-term funding, the money market is non-negligible when assessing the functioning of the financial system, a point that is clearly illustrated by the financial crisis of the late 2000s.

Realized volatility of the 3-month NIBOR: The NIBOR is supposed to reflect the interest rate on short-term unsecured interbank lending in NOK. 6 large banks in Norway report each day the rate at which they believe they are willing to lend unsecured, NOK-denominated funds to each other. Higher volatility of the 3-month NIBOR reflects higher uncertainty in the Norwegian interbank market. Uncertainty often results in flight to quality (e.g. secured lending or riskless bonds), flight to liquidity (e.g. central bank deposit) due to increasing asymmetric information (banks not knowing the liquidity and solvency situation of each other) as pointed out by Louzis and Vouldis (2012). This could increase systemic stress.

Interest rate spread between 3-month NIBOR and 3-month Norwegian Treasury bills

The spread between the NIBOR, an indicative market rate, and the essentially riskless T-bills (equivalent to the TED spread in the U.S.) is often used as a proxy for counterparty risk and liquidity risk in the literature. As Brunnermeier (2009) points out, in the face of higher uncertainty, banks charge higher interest for unsecured loans, while at the same time rushing to first-rate collateral such as Treasury bonds, driving down their yields. The first effect captures flight to quality, and the latter flight to liquidity. Both effects contribute to widening the spread in times of crisis. These symptoms are largely associated with asymmetric information intensifying in episodes of stress, as argued by Hakkio and Keeton (2009).

Spread between 3-month NIBOR and the key policy rate³: unlike the market-determined 3-month Treasury bill interest rate, the key policy rate is determined by the central bank.

³This raw stress indicator differs from that of the ECB – a scaled version of monetary institutions' recourse to ECB's standing lending facility. A Norwegian equivalent of the ECB's choice of input is possible to obtain, but not ideal. Banks can borrow reserves overnight from Norges Bank, normally at a rate 1 % higher than the key policy rate. The loan is referred to as an overnight loan (D-loan). Banks that have a shortage of reserves at the closing of Norges Bank's settlement system must use the standing facility. Intraday loans that are not repaid before the closing of the settlement system are automatically converted into overnight loans. This variable does, to some extent, reflect liquidity strains in the interbank market. However, it is also very much influenced by the liquidity management of the central bank. D-loans were generally more common in the late 90s than the 2000s. The scaling factor employed by Holló et al (2012), total reserve requirements, does not exist in Norway. This makes it difficult to take out the effects of regime shifts. Furthermore, not every D-loan occurs due to a liquidity crisis in the interbank system or a certain bank. Technical problems and operational mistakes may also lead to a bank taking an overnight loan, but stress caused by such factors are often (known to be) temporary and is not

Taylor and Williams (2009) suggest that money market spread like that between the 3-month LIBOR and the federal funds rate reflect counterparty risk and liquidity risk. In the case of Norway, this spread also demonstrates the close link between the liquidity situation of the dollar market and that of the Norwegian money market (contagion), as Norwegian banks commonly use a liquid swap market for Norwegian kroner against US dollar in their liquidity management (Aamdal, 2014). Monetary policy has an important influence on financial markets and therefore should not be ignored when evaluating systemic stress. Lowering the key policy rate by injecting liquidity should help to ease stress in financial markets by lowering the funding costs for banks in distress, even if the extent to which central bank liquidity measures can reduce money market spreads has proven to be limited by the recent crisis (see Taylor and Williams, 2009). Due to the above arguments, this series contains information different from the TED spread so that colinearity should not be a problem.

2.2 Bond market

The bond market is a source of funding for large corporations and the government. Variations in bond yields affect household balance sheets through pension funds and other instruments. Therefore, development in the bond market is important for the evaluation of systemic stress.

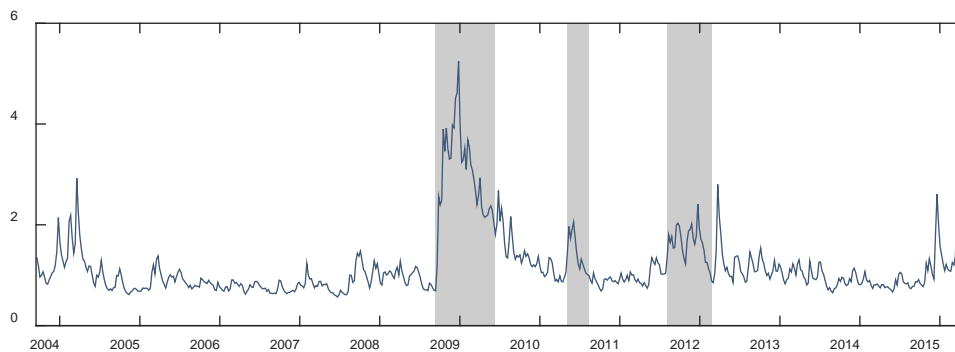
Realized volatility of the Norwegian 10-year benchmark government bond yield: the 10-year government bond is undoubtedly one of the safest NOK-denominated assets. In the face of increased uncertainty, investors will rush to hold it to stay liquid and secure. Moreover, the anticipation that others may increase their holdings also encourages market agents to buy government bonds in order to sell to investors more eager to hold these bonds at a higher price. Unlike some other small countries, Norwegian sovereign bonds are perceived to have close to no default risk, thanks to the sovereign wealth fund. However, when sovereign default risk is intensified in other regions, the Norwegian government bonds could be perceived as a safe haven⁴ for investors pulling out from downgraded bonds. Such contagion was indeed observed during the first Greek crisis in 2010 and later the more general sovereign debt crises⁴ between 2011 and 2012.

perceived to be systemic. Identifying these non-fundamental stress events for multiple years proves too challenging. Using data from large banks may help to smooth the noise, but does not solve the scaling problem.

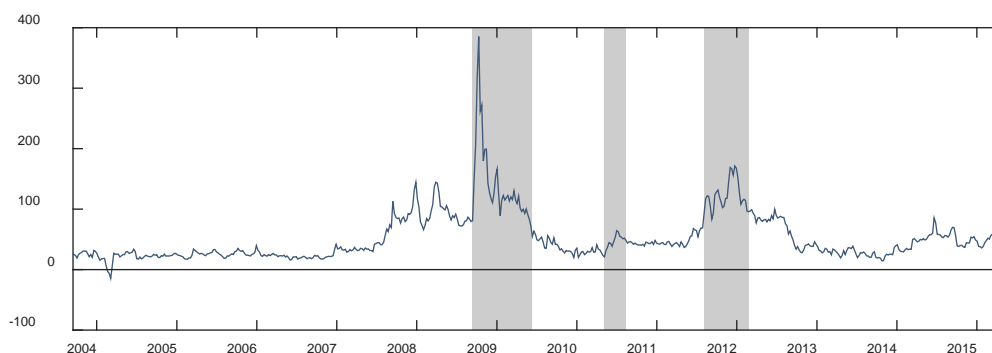
⁴ Such an event is unlikely in normal times, due to the exchange rate risk and liquidity risk associated with entering a small market.

Figure 2.1 Money market variables.

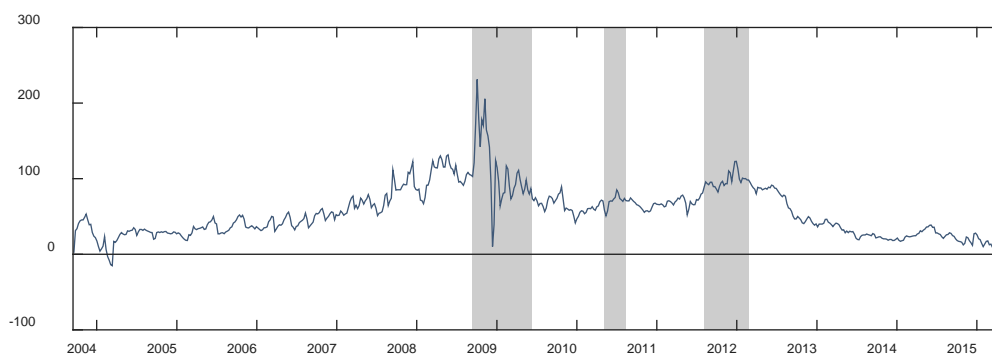
Realized volatility of the 3-month NIBOR. Weekly average of daily GARCH(1,1) volatilities.
15 September 2003 – 1 May 2015



Interest rate spread between 3-month NIBOR and 3-month Norwegian Treasury bills.
Weekly average of daily data. 15 September 2003 – 1 May 2015



Interest rate spread between 3-month NIBOR and the key policy rate.
Basis points. Weekly average of daily data. 15 September 2003 – 1 May 2015



Source: Norges Bank

⁵ During which European periphery countries like Greece, Portugal and Spain had trouble convincing investors of their credit-worthiness (aka. the Euro crisis), and Standard & Poors, a rating agency, downgraded the U.S.

Yield spread between investment-graded non-financial corporations (utilities) and government bonds (5-year maturity): the Norwegian investment-grade corporate bond market is rather small and few issues were made in the early 2000s. In this paper I use a weekly risk premium series for *utilities* from DNB Markets as a proxy for BBB-rated non-financial corporations. DNB Markets' risk premium series for utilities is constructed by subtracting the 3-month NIBOR from a weighted average of yields of investment-graded bonds issued by utility enterprises. A yield spread between proxy investment-graded non-financial corporations and government bonds can be computed by adding back the 3-month NIBOR interest rate to the utilities series and subtracting the government bond yield of the same maturity (5 years). This yield spread contains default and liquidity risk premia which should capture the flight to-quality and flight-to-liquidity phenomena (Holló et al., 2012). A higher spread could thus contribute to higher systemic stress.

10-year interest rate swap spread: the 10-year interest rate swap spread is the difference between the going rate of a 10-year NIBOR swap and the 10-year government bond. The empirical evidence provided by Liu et al. (2002) and Feldhütter and Lando (2008) for the US shows that although counterparty risk (credit risk) is a factor, the convenience yield for holding government bonds (other than receiving the bond yields through a swap contract) accounts for most of the swap spread. The swap spread widens when the swap rate increases, and/or when the government bond yield decreases. The swap rate reflects the borrowing costs for banks and financial institutions. During the U.S. subprime crisis and the global financial crisis that followed, such borrowing costs increased due to higher credit risk and uncertainty. In times of crisis investors also rush to safe and liquid government bonds, which drives down yields. This spread thus captures the flight-to-liquidity and flight to-quality effects (key stress symptoms) in the bond market, adding to systemic stress.

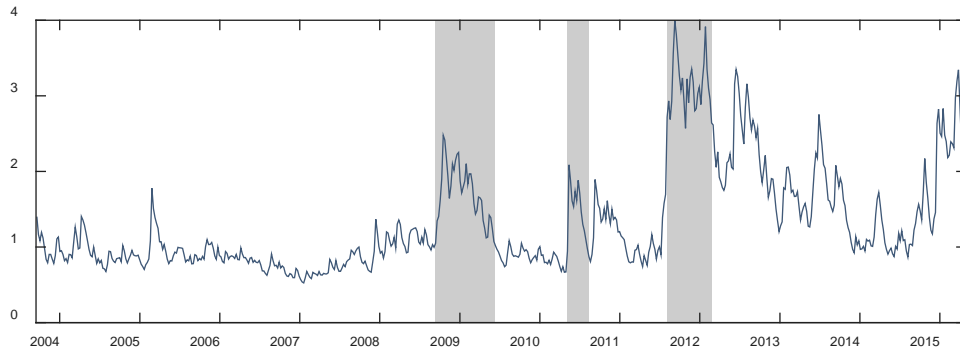
2.3 Equity market

Stress in the equity market erodes funding to firms as well as returns to investors, hurting both the supply and demand side of the real economy; furthermore, it spreads easily to the rest of the financial system and is often the trigger of financial crises (see e.g. Kindleberger and Aliber, 2011). These profound effects are closely linked to the definition of systemic stress.

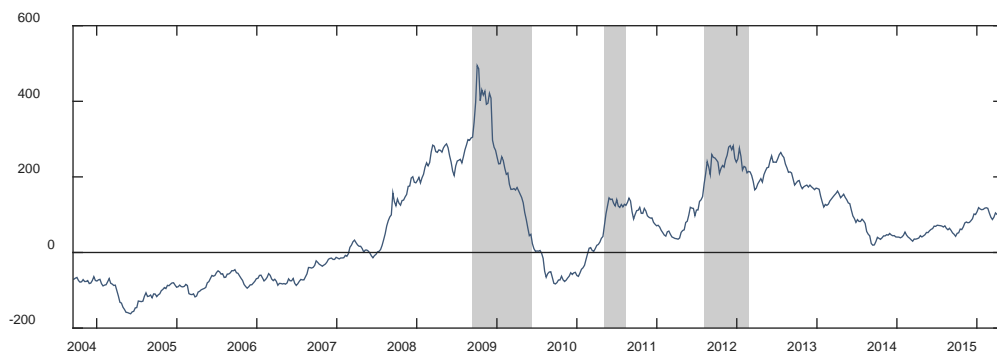
Figure 2.2 Bond market variables.

Realized volatility of the Norwegian 10-year benchmark government bond yield.

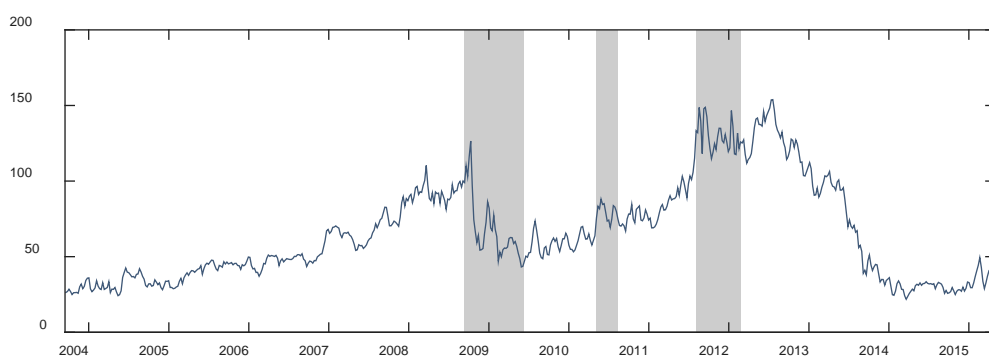
Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015



Yield spread between proxy investment-graded non-financial corporations (utilities) and government bonds (5-year maturity). Basis points. Weekly data. 15 September 2003 – 1 May 2015



10-year interest rate swap spread. Basis points. Weekly average of daily data. 15 September 2003 – 1 May 2015



Sources: DNB Markets, Thomson Reuters EcoWin and Norges Bank

Realized volatility of the Oslo Stock Exchange Benchmark Index (OSEBX): just as in the bond market, higher volatility in the stock market reflects increased uncertainty about fundamentals as well as the behavior of other investors (Hakkio and Keeton, 2009).

CMAX for the Oslo Stock Exchange Benchmark Index (OSEBX): CMAX, or maximum cumulative loss over a certain period of time, was first suggested by Patel and Sarkar (1998) to identify crisis episodes in stock markets. Stock market indices have negative skewness and excess kurtosis: i.e. it takes longer for prices to rise than to drop. An example of this is the stock market crash in October 1987, when the S&P 500 dropped over 20 % in a single day. In times of crisis, such sharp decline of equity prices will be captured by the CMAX, making it a good candidate for an equity market stress indicator (e.g., Illing and Liu, 2006). As in Holló et al. (2012), the CMAX for OSEBX is defined over a moving 2-year window,

$$CMAX_t = \left(1 - \frac{P_t}{\max\{P \in (P_{t-j} | j = 0, 1, \dots, T)\}} \right) \times 100 \%$$

where P_t is the OSEBX stock index at week t ⁶, and $T = 104$ for weekly data.

Stock prices are typically more volatile than bond prices. Therefore, only prolonged periods of large declines can be seen as true equity market crises. In good times, this indicator will be close to zero, as prices generally move up.

Amihud illiquidity measure⁷ for the Oslo Stock Exchange Benchmark Index (OSEBX): the Amihud illiquidity measure is developed by Amihud (2002) to measure illiquidity in the stock market. It is defined here as the weekly average of the daily absolute total return divided by daily turnover:

$$ILLIQ_t = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{dt}|}{Vol_{dt}}$$

R_{dt} is the return on day d in week t , while Vol_{dt} stands for turnover on the same day. D_{it} is the number of trading days in week t . $ILLIQ_t$ can thus be interpreted as the weekly price response per NOK traded, thus serving as a rough measure of the price impact. This raw stress indicator is also used in the Swedish financial stress index by Johansson and Bonthron (2013).

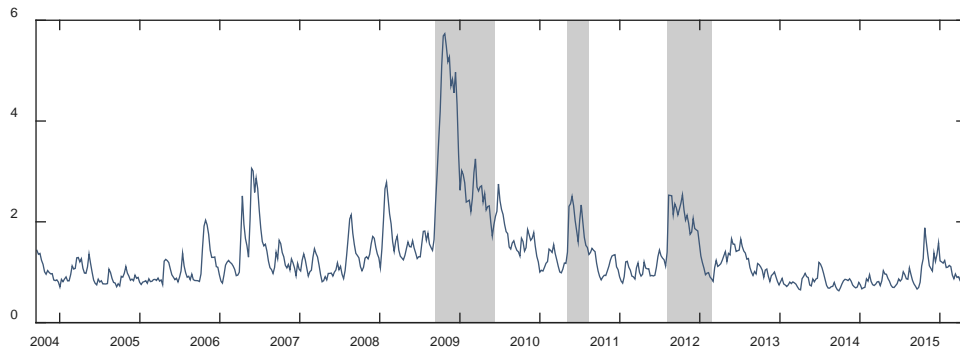
⁶ Here the weekly average value for the stock market index is used to smooth out noise.

⁷ This is another indicator that deviates from the ECB setup. Holló et al. (2012) use the negative of the short-term stock-bond correlation (corrected for a long-term trend). They argue that in times of heightened systemic stress, investors pull their funds out of risky stocks into safe government bonds, thereby driving the return correlation between these two asset classes into negative territory. However, in practice, this indicator is ill-suited for measuring stress in the Norwegian financial market. The short term (4-week or 8-week) correlations are extremely volatile, and seem unable to identify stressful events. A report by Johnson et al. (2013) from Pimco, a global investment management firm, illustrates that the U.S. stock-bond correlation is also highly volatile, and points out that it is an unreliable input for asset allocation decisions.

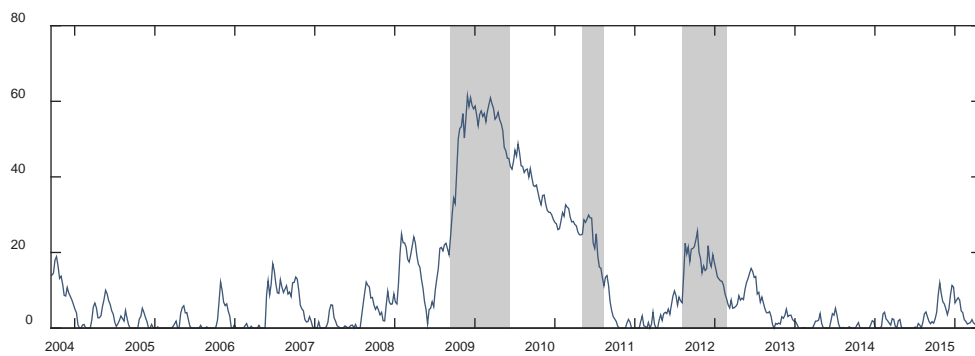
Figure 2.3 Equity market variables.

Realized volatility of the Oslo Stock Exchange Benchmark Index (OSEBX).

Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015

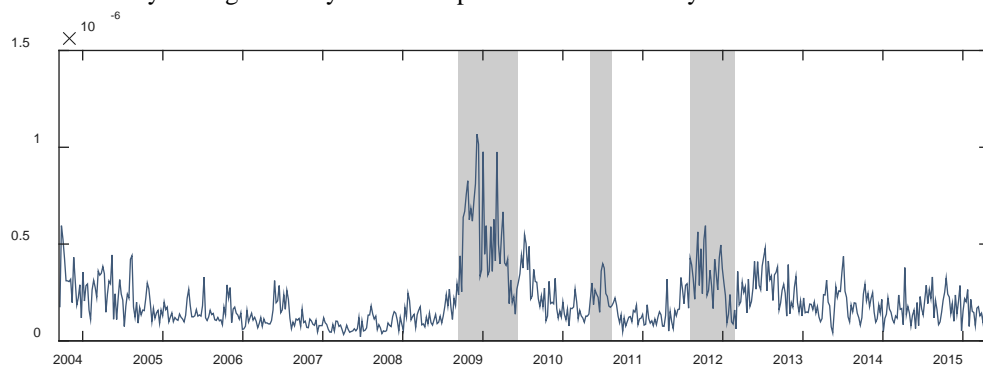


Maximum cumulative loss (C_{MAX}) of the Oslo Stock Exchange Benchmark Index (OSEBX) over a two-year moving window. Percent. Weekly average of daily data. 15 September 2003 – 1 May 2015



Amihud illiquidity measure of the Oslo Stock Exchange Benchmark Index (OSEBX).

NOK per share. Weekly average of daily data. 15 September 2003 – 1 May 2015



Sources: Thomson Reuters EcoWin, Bloomberg and Norges Bank

2.4 Financial intermediaries

The financial crisis of the late 2000s illustrated the importance of monitoring the stress level in the banking sector. Although balance sheet data is helpful for detecting financial strains, they are only available on a monthly basis. As a result, only market data is used in this paper.

Realized volatility of the idiosyncratic stock returns of the banking sector – Oslo Stock Exchange Equity Certificate Index (OSEEX): since market risk is taken care of by volatility of the stock market benchmark index, only idiosyncratic risk of the banking sector, i.e. the risk attributed to bank-specific events, is of interest here⁸. In order to measure this risk, first a suitable banking sector index must be selected. There are three candidates: the equity certificate index (OSEEX), OSE40 Financials, and OSE4010 Banks. The Financial index contains not only banks and insurance companies, but also some real estate enterprises, which are not financial intermediaries and are not as systemically important as the former groups. The largest bank in Norway, DNB bank, represents over 60 % of the Financial index and over 90 % of the Bank index⁹. This is problematic: Kelly et al. (2011) use option market data to show that government guarantee is priced in for systemic banks during crises, times at which the CISS will be of most interest. According to Moody's rating of DNB Bank in March 2015¹⁰, the bank has "dominant position in the Norwegian market", is "Norway's most international bank", and with the Norwegian government as its largest shareholder, "[Moody's] continue to view DNB as the government's flagship financial institution". Thus the financial and bank indices are not the ideal choice here. The Equity Certificate Index, on the other hand, consists of 19 small saving banks which "engage in all ordinary banking business and can provide the same services as commercial banks", according to the Norwegian Saving Banks' Association¹¹. The idiosyncratic return of the banking sector, e_t , is calculated as the residual from an OLS regression of the OSEEX daily returns on market returns over a moving 2-year window (522 business days)¹²:

⁸ Since the estimation of dynamic correlation is essentially a regression, each subindex should not contain the same information to rule out colinearity.

⁹ In fact, DNB was the only bank listed in Oslo Stock Exchange before 2012, after which another much smaller regional bank, SpareBank 1 SR-Bank, followed suit. A third saving bank got listed in as recent as April 2015.

¹⁰ <https://www.dnb.no/portalfont/nedlast/en/about-us/ir/funding/20150326-Moodys-Credit-opinion-DNB-Bank.pdf>.

¹¹ <http://www.sparebankforeningen.no/id/17042.0>

¹² An alternative measure of banking sector-specific stress is the banking sector's β , a measure of relative equity-return volatility as in Illing and Liu (2006). This thesis uses the regression measure to enhance comparability with the Euro area CISS.

$$r_t^{OSEEX} = \beta_0 + \beta_1 r_t^{OSEBX} + e_t$$

The realized volatility of e_t is then used as a input series for the financial intermediaries.

Yield spread between investment-graded financial and non-financial corporate bonds (5-year maturity): due to data limitations, the non-financial sector is represented utilities, and the financial sector by banks. These are weekly data from DNB Markets in the form of risk premia. 5-year is a medium term for bonds, an appropriate horizon for financial stability concerns. Not many Norwegian bond issuers are rated by big international rating agencies like Moody's and Standard & Poors due to high costs. However, DNB Markets has their own ratings for such companies. The overall rating for banks and utilities are A and BBB respectively, which means that unless the banking sector is under distress, this spread ought to be negative. Indeed, the spread peaked in 2008 after the financial crises to close to 100 bps, and again positive during the sovereign debt crises from 2010 to 2012, while remaining largely negative the rest of the time. However, the sign of the spread does not really matter for the CISS, since all raw stress indicators will be transformed into empirical cdfs.

CMAX interacted with the inverse price-book ratio for the financial sector equity market index: CMAX as defined above is computed for the financial sector equity market index OSE40GI. As pointed out earlier, a high CMAX indicates high level of stress in the sector concerned. Since this indicator alone will inevitably be similar to the stock market CMAX in section 2.3, a different source of information is incorporated as in Holló et al. (2012) by interacting it with the financial sector book-price ratio:

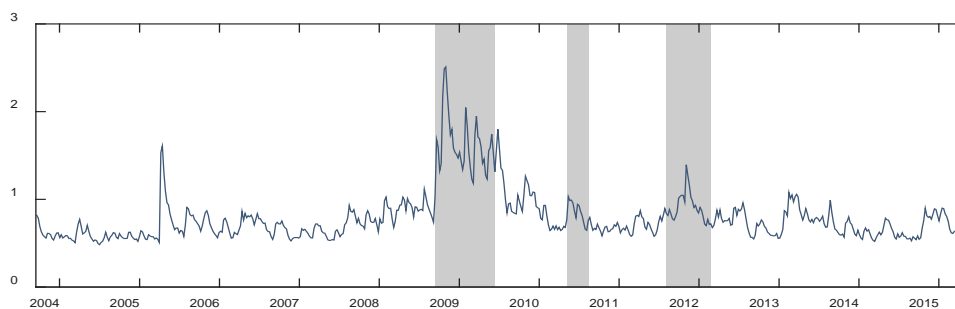
$$Int_t^{financials} = \sqrt{CMAX_t^{financials} \times PB_t^{financials}^{-1}}$$

Since the book value of a firm (in this case, financial intermediaries¹³) reflects its fundamental value, when price-book value is above one, markets have priced in bright future prospects. When financial intermediaries are under distress, markets will revalue these firms so that their stock prices will fall to reflect (new) fundamentals. As the price-book ratio reflects the bullishness of the market, its inverse will serve as a stress indicator. The interacted indicator is thus a geometric average of the CMAX and the inversed price-book ratio, both of which are first transformed into empirical cdfs so that they are on a common scale prior to interacting.

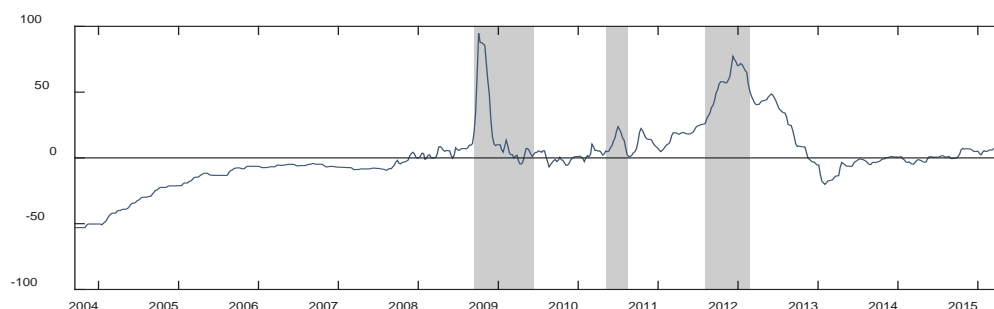
¹³ As mentioned before, this index is dominated by DNB Bank, and other large corporations in the index are insurers, also financial intermediaries.

Figure 2.4 Financial intermediaries variables.

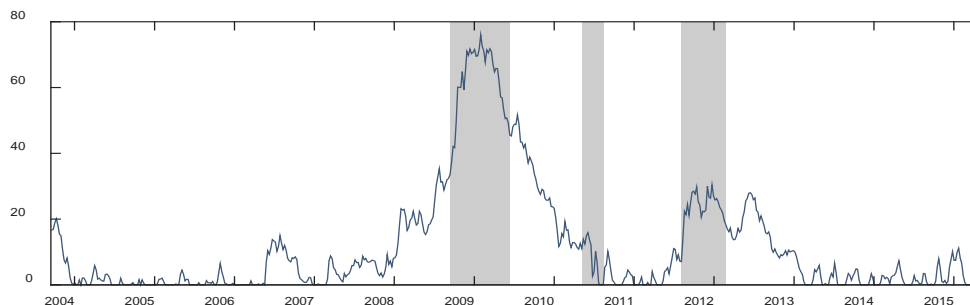
Realized volatility of the idiosyncratic stock return¹⁾ of the banking sector²⁾. Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015



Yield spread between investment-graded financial (banks) and non-financial (utilities) corporate bonds (5-year maturity). Basis points. Weekly data. 15 September 2003 – 1 May 2015



CMAX of the financial sector equity market index (OSE40GI). Percent. Weekly average of daily data. 15 September 2003 – 1 May 2015



Inverse price-book ratio of the financial sector equity market index (OSE40GI). Weekly average of daily data. 15 September 2003 – 1 May 2015



- 1) Idiosyncratic returns are calculated as the OLS residuals from a regression of the OSEEX daily returns on market returns over a moving 2-year window.
- 2) Represented by the Oslo Stock Exchange Equity Certificate Index (OSEEX)

Sources: Thomson Reuters EcoWin, DNB Markets and Bloomberg

2.5 External sector

External shocks can have significant impacts on both financial markets and the market for goods and services. Foreign counterparties represent a source of funding for firms, especially in the banking and petroleum sector; a reduction in these inflows could impose important limitations to economic activity. Moreover, movements in the prices of export goods, in particular that of oil, will have a significant and direct impact on the national income and government revenues. Uncertainty in the external sector can thus increase systemic stress.

Exchange rates (USD/NOK and EUR/NOK) volatilities: the USD/NOK and EUR/NOK exchange rates are important for both Norway's financial sector and its real economy. The Euro area is by far Norway's largest trading partner. The United States is also an important trading partner, but the dollar's impact far exceeds trade with the U.S., due to its status as the global currency. For example, a significant share of Norway's export are commodities, many of which have global benchmarks priced in USD. Excessive volatility in the exchange rates will create undesirable volatility in the income/expenditures of exporters/importers, which complicates their financial planning in the medium term (Cabrera et al., 2014). Moreover, Norwegian banks and mortgage companies (as well as some other large enterprises) have increasingly financed themselves from foreign credit markets¹⁴. According to Norges Bank's Financial Stability Report 2014, over half of Norwegian banking groups' wholesale funding is in foreign currency, mostly USD and EUR. In particular, the report points out that short-term funding in the U.S. money market increases refinancing risk. Thus, higher volatility in the exchange rates may also add to systemic stress.

Oil (Brent Crude) price volatility: the petroleum sector is undoubtedly Norway's most important economic sector, standing for 22 percent of the country's GDP, about 30 percent of the government's total income, and about half of total export in 2013¹⁵. It is then no surprise that the oil price and its fluctuation have profound impact on both the real economy (employment and output, government revenue, industrial structure etc.) and the financial system (Oslo Stock Exchange, monetary policy, exchange rates etc.). Due to the many transmission channels listed above, higher oil price volatility adds to uncertainty in the real economic outlook and increases systemic stress.

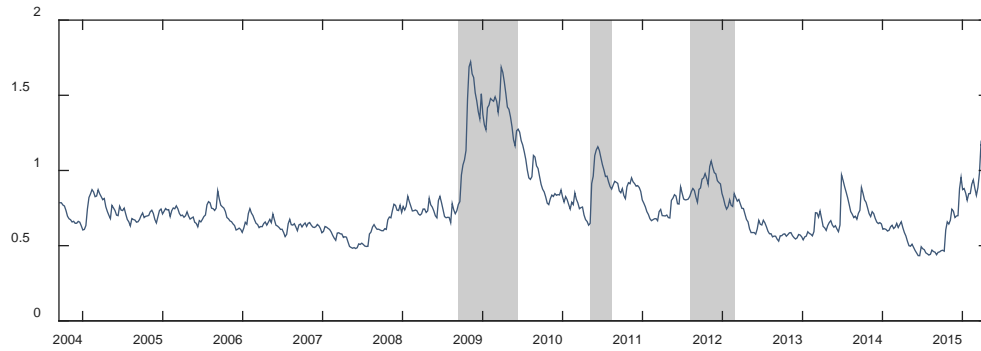
¹⁴ Banks usually hedge themselves against swings in the exchange rates. Non-financial enterprises do so to a lesser extent. This effect thus mitigates but does not eliminate exchange rate risk.

¹⁵ Source: Ministry of Petroleum and Energy <https://www.regjeringen.no/nb/tema/energi/olje-og-gass/verdiskaping/id2001331/>. Page in Norwegian. Retrieved 4. Jan. 2015.

Figure 2.5 External sector variables.

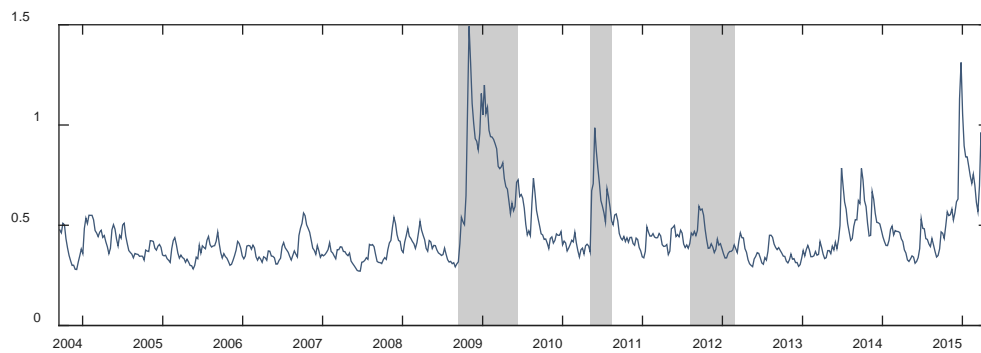
Realized volatility of the USD/NOK exchange rate.

Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015



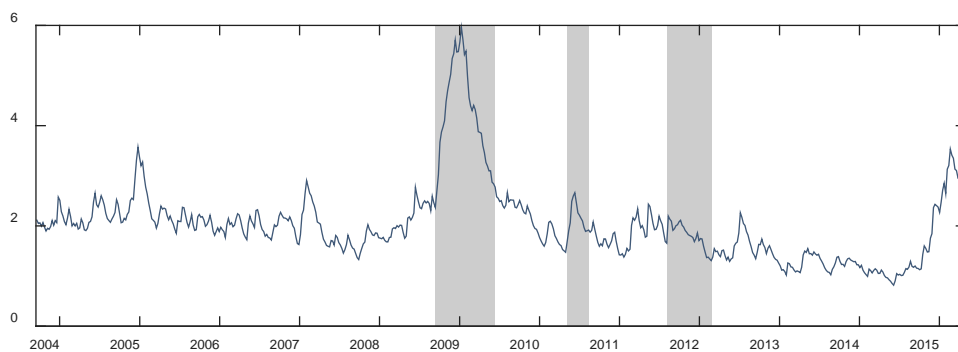
Realized volatility of the EUR/NOK exchange rate.

Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015



Realized volatility of the Brent Crude price.

Weekly average of daily GARCH(1,1) volatilities. 15 September 2003 – 1 May 2015



Sources: Norges Bank and Thomson Reuters EcoWin

3 METHODOLOGY

This section describes how the Norwegian systemic stress indicator is constructed. I adopt a two level aggregation scheme as in Holló et al. (2012) by first putting transformed input variables (empirical cdfs) into 5 subindices, then weighing these subindices, each representing a market segment or economic sector, by their estimated cross correlation. Section 3.1 addresses the computation of realized volatility. Section 3.2 applies order statistics to standardize the raw stress indicators. Subindices are computed in section 3.3. In section 3.4 I discuss the theoretical motivation for aggregating the subindices using modern portfolio theory. Section 3.5 is dedicated to the estimation of a dynamic correlation matrix of the subindices. Section 3.6 presents the final aggregation to a single statistic.

3.1 Estimation of realized volatilities

Volatility, a latent variable, can only be estimated¹⁶, but not observed. In the literature, there is a distinction between realized (historical) volatility represented by, among others, Andersen and Bollerslev (1998), and implied volatility (e.g. Harvey and Whaley, 1992). For the purpose of measuring existing level of stress in the financial system as in this exercise, realized volatility is the more suitable measure. However, implied volatility should work better in early-warning models due to its forward-looking nature.

There are many ways to estimate realized volatility. The most common method is perhaps taking the standard deviation of daily log returns over a moving window. In the recent stress indicator literature, this method is adopted by Iachini and Nobili (2014) for Italy, and Louzis and Vouldis (2013) for Greece. Holló et al. (2012) use a simple measure: weekly average of absolute daily log returns. However, none of these measures take into account the volatility clustering inherent in financial data. Bollerslev et al. (1992) suggest that asset price dynamics are often best modelled with a GARCH(1,1) process. This paper also follows the finance and financial stress indicator literature (e.g. Illing and Liu, 2006) in fitting a GARCH(1,1) model to daily asset price returns, r_t , defined as

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right).$$

¹⁶ For a brief review of estimating volatilities, see chapter 22 of Hull (2012).

Suppose that the expected daily return is zero, the maximum likelihood estimator of the daily variance is simply a simple average of past squared returns.

$$\sigma_t^2 = \frac{1}{m} \sum_{i=1}^m r_{t-i}^2$$

The GARCH(1,1) model incorporates volatility clustering by assigning higher weights to recent observations (similar to EWMA models), as well as mean reversion (by adopting a constant term γV_L):

$$\sigma_t^2 = \gamma V_L + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2$$

The conditional variance is explained by three parts: a long-run average, V_L , yesterday's squared return, and yesterday's conditional variance. The parameters α, β and γ are all positive and sum up to 1. Substituting backwards yields

$$\sigma_t^2 = \gamma V_L \sum_{i=1}^m \beta^{i-1} + \alpha \sum_{i=1}^m \beta^{i-1} r_{t-i}^2.$$

β , the coefficient in front of the recursive past squared returns, is the decay rate: the importance of historical returns decays exponentially over time by β^{i-1} for each past day i . γ indicates the degree of mean reversion. Then daily GARCH(1,1) volatilities can be computed using estimated parameters and return data. Weekly volatility estimates can be obtained by taking the average of estimated daily volatilities.

On the other hand, the simple volatility measure adopted by Holló et al. (2012) is just

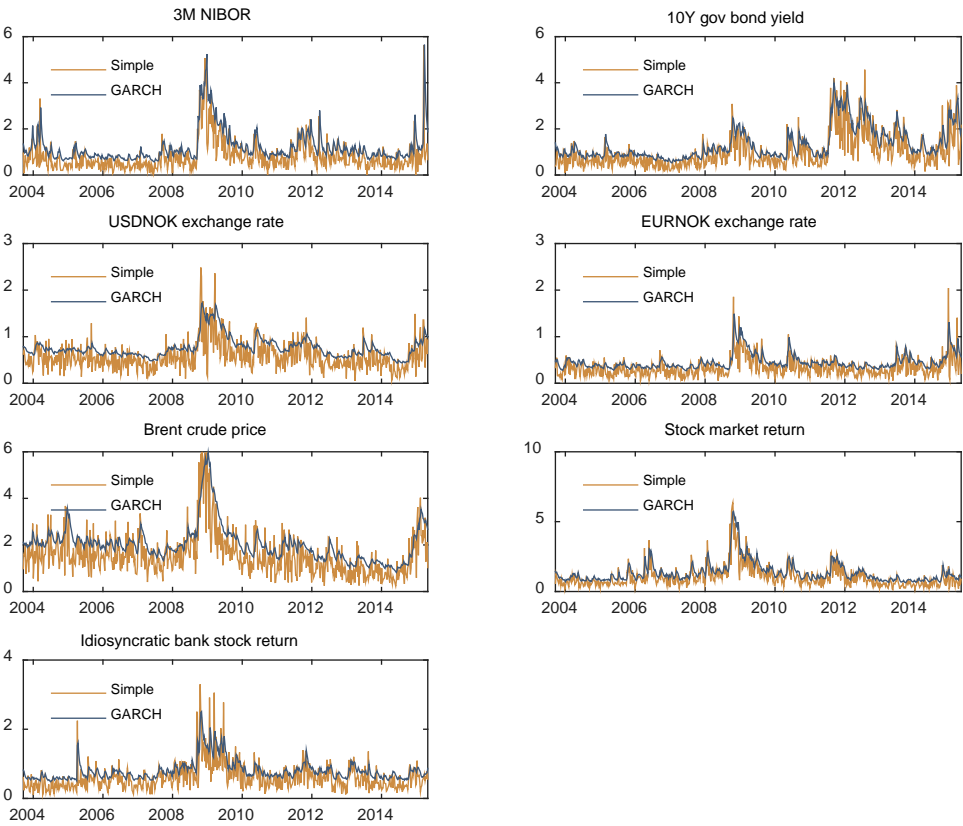
$$\sigma_t^{simple} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} |r_{dt}|$$

Where r_{dt} is the return on day d in week t , while D_{it} is the number of trading days in week t .

Figure 3.1 presents these two volatility measures applied to Norwegian data. It can be seen that GARCH volatilities are a lot smoother than the average absolute return measures, and seem to be able to correct for outliers – extremely high volatility of very short duration. Interestingly, the GARCH volatilities seem to follow the upper bound of average absolute

returns (except for the extremes), and are hence systematically higher than a simple moving average of the former. As stress is built up in markets, volatilities tend to go up quickly. For this reason, these two volatility measures look similar in these episodes. However, as markets move back to normal, volatilities fall slowly, with occasional rebounds. GARCH volatilities appear to decline in a slower and more “cautious” way than average absolute returns.

Figure 3.1 Two volatility measures. Simple weekly average of absolute daily log returns and weekly average of estimated daily GARCH (1,1) volatilities. 15 September 2003 – 1 May 2015



Sources: Norges Bank, Thomson Reuters EcoWin, and author’s own calculations

As mentioned in the introduction, subindices are arithmetic averages of the input series. Statistical properties of each input series are hence inherited by the corresponding subindices. It is not a desire by itself that subindices are smooth, but there are gains if that was the case. First, when calculating the dynamic cross correlations, noisy subindices make it more difficult to evaluate the fundamental interconnectedness between markets – we could be measuring

correlations between noises (e.g. a short-lived sunspot shock in one market), which means that correlations are more likely to change signs, adding noise to the final indicator. Secondly, volatilities in the subindices are also transmitted to the CISS directly in the aggregation. Again, it is not a goal in its own right that the weekly systemic stress indicator should have relatively low unconditional variance. But in practice (that is, if the indicator were used to monitor systemic stress level in real time), knowing that the CISS (taking values between 0 and 1) has an inherent tendency to move up and down by, say, 0.3, in any given week, is not very helpful for policy makers. It would be hard for them to distinguish random movements from fundamental changes in the financial environment in real time. They might need several weeks to see the underlying trend, in order to tell the direction in which markets are heading.

For the reasons above, as well as the fact that GARCH volatilities are more commonly used in the finance literature and by practitioners in financial markets, this paper also adopts this measure.

However, averaging weekly returns also have its merits: it is simple, and does not require estimating a model, which needs more observations to pin down the parameters. Although there are only three parameters in a GARCH(1,1) model, one or two years of data may not be enough to produce credible estimates of these parameters: in normal times, volatilities are more Gaussian like, which means that GARCH models are ill-fitted for modelling volatilities. In other words, we need stressful episodes exhibiting volatility clustering to justify the use of GARCH models. The long timespan (nearly 11 years of weekly data) in this exercise ensures that the above condition is satisfied.

These GARCH volatilities are also estimated recursively to be used to compute a CISS in real time for evaluation purposes (section 4.3). The recursive volatility estimates are similar to the full-sample data, as shown in Figure A.1 in appendix A.

3.2 Transformation of raw data

Any level of aggregation requires that raw stress indicators are put on the same scale. The most common way of doing so is by first subtracting the sample mean and then dividing by the standard deviation, the so-called standardization:

$$z_t = \frac{x_t - \bar{x}}{s_x}.$$

However, this method implicitly assumes that the underlying series is normally distributed, such that the sample mean and variance are sufficient to describe the entire distribution. As can be seen from figure A.2 in Appendix A, none of our raw stress indicators seem to have been drawn from a normal distribution¹⁷. The classical standardization is sensitive to outliers and will lead to significant revisions of the resulting subindices and the final indicator as time evolves. As a policy tool, the systemic stress indicator should be rather robust against outliers, to make recent measurements comparable to past episodes.

Another way of standardizing variables is to use order statistics: first compute the empirical cumulative distribution function (ecdf) of each series; then let each observation take the value of its corresponding ecdf value.

Let the observations of variable X be denoted $x_1, x_2, \dots, x_t, \dots, x_N$. The computation of ecdf involves ordering the sample, i.e. these n observations are ranked from the smallest to the largest value into $x^1, x^2, \dots, x^r, \dots, x^N$. In other words, subscript t denotes time and superscript r denotes rank. The empirical cdf of an observation x_t is then defined as

$$z_t = F_N(x_t) := \frac{r}{N}, \quad x^{r-1} \leq x_t^r < x^{r+1}$$

For $r = 1, 2, \dots, N$. Clearly, $0 < z_t \leq 1$. It takes the value of 1 when x_t happens to be the largest observation ($r = N$). If multiple observations take the same value, this value will take their average ranking. For example, if a certain value occurred twice, taking both the 3rd and the 4th place, it will be ranked $r = (3 + 4)/2 = 3.5$.

¹⁷ Indeed, were such series to have the appearance of white noise over a 11-year period, they must be very poor indicators for stress.

Such a transformation will put every raw series on the same scale (between 0 and 1). In comparison, when an approximately normally distributed random variable is standardized by demeaning and dividing by the sample standard deviation, we can expect that the standardized variable will produce, on average, observations within two standard deviations (or between -2 and 2) 95 % of the time. For non-normal variables, however, it is unclear in what values the standardized variables can take. In other words, we cannot really say that they lie on the same scale. Hence aggregation is not that straight forward as if they were transformed by rank statistics.

In practice we face an expanding sample. This requires the definition of ecdf above to be slightly modified. Let us introduce a recursion period of n weeks. Observations during this period are ranked from 1 to n . Then as time goes by, the sample expands to $n + 1, n + 2, \dots, n + k, \dots, n + T$. If we let $n + T = N$, we can establish the link between recursive and full-sample rank statistics:

$$z_{n+k} = F_{n+k}(x_{n+k}) := \begin{cases} \frac{r}{n+k}, & x^r \leq x_{n+k} < x^{r+1} \\ 1, & x_{n+k} > x^{r+1} \end{cases}$$

x^r is the value ranked r from the previous sample of $n + k - 1$ observations. Each new observation is compared to the existing ordered data then added into the rankings, shifting larger values one rank behind, unless it happens to be the largest one.

Figure A.2 in appendix A shows empirical cumulative distributions for both the full sample and the real-time recursive sample. In contrast to Holló et al. (2012), I am unable to declare that differences between the recursively computed real-time ecdfs and the full sample ecdfs are small. This has to do with our recursion period (Sep. 2003 – Sep. 2006) being exceptionally tranquil from a systemic stress perspective. Although Holló et al. (2012) also used a recursion period of 3 years, their sample (Jan. 1999 – Jan. 2002) included the moderately stressful Dot-com bubble; in addition, the terrorist attack on September 11th 2001 also created some short-lived tension.

We now have 15 standardized raw stress indicators¹⁸ grouped into 5 market segments, ready for aggregation into market indicators.

¹⁸ After interacting the ecdfs of the inversed price-book ratio and CMAX for financial stocks.

3.3 Construction of subindices

With 3 homogenized stress indicators in each market, an intuitive way of aggregation to market indicators, or subindices, is to take their arithmetic average¹⁹. Let i denote market, and let $j = 1, 2, 3$ denote raw stress indicators, then subindex i in week t is simply defined as

$$s_{i,t} = \frac{1}{3} \sum_{j=1}^3 z_{i,j,t}.$$

For a graphical presentation of stress level in each of the five market segments, see Figure A.3 in appendix A.

3.4 Portfolio theory and systemic risk

The previous section completed the first level aggregation into subindices. Before I proceed to estimate dynamic cross correlations and do the final aggregation, some light needs to be shed on the theoretical motivation for doing so.

The aggregation scheme adapted from Holló et al. (2012) is inspired by the way the variance of a portfolio is calculated in modern portfolio theory (MPT). A vector representation of Markowitz (1952) is as follows:

Suppose I have a portfolio consisting of N securities. Let w denote a vector of portfolio weights²⁰ which sum to 1 such that $\sum_{i=1}^N w_i = 1$. Let X be the vector of returns for the N securities in the portfolio, and $\mu \equiv E(X)$ is the expected returns. Then $R = \mu'w$ will be the expected return on the portfolio. Furthermore, let Σ denote the covariance matrix for the returns on the assets in the portfolio.

$$\Sigma = E[(X - \mu)(X - \mu)'] = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1i} & \cdots & \sigma_{1N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \sigma_{i1} & \cdots & \sigma_{ij} & \cdots & \sigma_{iN} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \cdots & \sigma_{Nj} & \cdots & \sigma_{NN} \end{bmatrix}$$

¹⁹ In principal, a weighted average could also be used. However, it is no easy task to empirically determine the relative importance of each raw stress indicator. Hence giving each raw indicator equal weight at the outset seems plausible.

²⁰ Portfolio weights can be negative if investors are allowed to short an asset.

where $\sigma_{ij} = \sigma_i \sigma_j \rho_{ij} \forall i, j$, and ρ_{ij} is the correlation between the returns on securities i and j , X_i and X_j .

The variance of the portfolio returns is then defined as

$$\text{Var}(R) = w' \Sigma w = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_{ij} = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i \sigma_j \rho_{ij}$$

Both in the literature and in financial markets, it is common to use variance or volatility as risk measurements. One key message from MPT is that the more an asset's return co-move with that of the rest of the portfolio, the more risk it adds to the portfolio.

Why is this relevant for systemic risk and macroprudential authorities? I believe that the task facing financial stability authorities in some way resembles risk management of a fund. This fund could be so big (e.g. a state pension fund) that it has to hold some securities of every economic sector for diversification purposes. Let us make the simplifying assumption that the fund has a mandate to hold a portfolio of mutual funds managing non-financial equities, financial equities, currencies, commodities and bonds. Unlike ETFs (exchange traded funds), mutual funds are not traded on the open market, and hence cannot be shorted. Therefore, the portfolio weights have to be non-negative and sum up to 1. Similarly, the macroprudential authority cannot simply ignore any particular financial market in their assessment of systemic stress. The risk manager is usually not directly involved in the day-to-day management of a fund, but computes and monitors different measures of risks and exposures. When these measures, for example portfolio variance, exceed the limit set the fund's mandate, the risk manager will have to step in and intervene. In the same vein, macroprudential authorities monitor stress in the financial markets in real time, but has certain policy tools, e.g. the CCB, to intervene in the financial markets when they deem that existing stress in the financial markets is so high and widespread that it impairs the functioning of the financial system and that the real economy and welfare will suffer (De Bandt and Hartmann, 2000). In this analogy, the macroprudential authorities manage the stress, or realized risk, of the financial system, which can be thought of as a "portfolio" of financial markets. Therefore, the portfolio variance measure may just be suitable for measuring systemic stress.

3.5 Dynamic covariance matrix

The previous section presented the theoretical motivation of the systemic stress measurement. In this section, a dynamic covariance matrix is computed for the subindices obtained in section 3.3.

Two classes of models, the exponentially weighted moving average (EWMA) and multivariate GARCH models, are commonly used for estimating dynamic covariance matrices.

Holló et al. (2012) use the EWMA to model each covariance entry in the following way²¹

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1 - \lambda)\tilde{s}_{i,t}\tilde{s}_{j,t},$$

Just as the definition of covariance for random variables X and Y is the expectation of their demeaned product, $Cov(X, Y) = E[(X - \bar{X})(Y - \bar{Y})]$, the computation of a covariance matrix also starts with demeaning. Since the subindices are arithmetic averages of empirical cdfs, their “theoretical” median should also be close to that of a cdf, namely 0.5. For Norwegian data from 15 September 2003 to 1 May 2015, the sample mean of the subindices are indeed very close to 0.5²². Thus, $\tilde{s}_{i,t} = s_{i,t} - 0.5$ denotes the demeaned subindices while $\lambda \in (0,1)$ is a smoothing parameter and take the value of 0.93.

In other words, covariance this week is a weighted average of last week’s covariance and the product of this week’s errors. By substituting backwards, we will obtain

$$\sigma_{ij,t} = \lambda^N \sigma_{ij,t-N} + (1 - \lambda) \sum_{n=1}^N \lambda^{n-1} \tilde{s}_{i,t-n+1} \tilde{s}_{j,t-n+1}$$

Since $\lambda \in (0,1)$, as $N \rightarrow \infty$, the first term vanishes, so we are left with an exponentially weighted moving average of demeaned subindex product pairs. As the relative importance of these products decays at a factor of λ , λ is also called the decay factor.

When it comes to the MGARCH class, BEKK (Baba-Engle-Kraft-Kroner, first developed in Engle and Kroner, 1995) and DCC (dynamic conditional correlation, first proposed by Engle, 2002) are the two most widely used variants of conditional covariances and correlations.

²¹ Note that the variance of a variable is just its covariance with itself ($\sigma_{ii,t} \equiv \sigma_{i,t}^2$).

²² See table B.1 in Appendix B for descriptive statistics of the subindices.

In the recent systemic stress indicator literature, Louzis and Vouldis (2012) as well as Iachini and Nobili (2014) used the BEKK representation, whereas Cabrera et al. (2014) chose the DCC variant. Caporin and McAleer (2012) point out that although traditionally DCC is used to forecast conditional correlations whereas BEKK is used to forecast conditional covariances, one model can do virtually everything the other model can do. They make comparisons of the two models and highlighted that BEKK by construction possesses asymptotic properties under untestable moment conditions, whereas the asymptotic properties of DCC have simply been stated under a set of untestable regularity conditions. Based on their findings, this paper applies the BEKK representation with the simplest specification in which all lags are of order 1 – a BEKK-MGARCH(1,1,1) model.

Before introducing the model, an issue concerning the subindices needs to be addressed. As mentioned in the previous section, we aim to estimate the dynamic covariances of subindices like we would do with asset returns in a portfolio. Despite the conceptual similarities between subindices and asset returns established in section 3.4, the two have very different statistical properties. Asset returns are stationary, a claim that can be established by using e.g. a Dickey-Fuller test on asset returns (finding no unit roots), or indirectly by testing whether asset prices have one unit root. EWMA and MGARCH are regression models, so that stationarity conditions should not be ignored when applying them. However, we cannot reject any of the subindices being a random walk using such tests, even if they are bounded by construction between 0 and 1²³. Fortunately, not passing unit root tests does not mean that the subindices are non-stationary²⁴. To establish stationarity assumptions, we can work with the definition of (weak) stationarity, that *the first and second moment, as well as autocovariances, do not depend on time*. The first part of the definition is easy to satisfy since the subindices are all averages of empirical cdfs and hence possess similar statistical properties, a point supported by the data since the subindices all have means between 0.48 and 0.50, and standard deviations between 0.23 and 0.25 (see Table B.2 in appendix B for more details of the statistical properties of subindices). As to the autocovariances, it is apparent in figure A.3 that they are positive, and could well be time-invariant²⁵. However, what can definitely destroy stationarity is the existence of a *time trend*, which can be directly observed for the bond market. I therefore run an OLS regression for each subindex to detect possible time trends.

²³ Indeed, any series can be scaled to appear to be “bounded” between 0 and 1.

²⁴ Thanks to the non-ignorable possibility of type II error.

²⁵ Note that weak stationarity requires only that the *unconditional* mean and autocovariances be time-invariant. No restrictions are made for its conditional counterpart.

The output is presented in Table B.2 in appendix B: at a 5 % significance level, there exists a time trend in all but the equity market. The coefficient for the money market is rather weak (0.003), but that for the bond market and financial intermediaries are more prominent (0.008 and 0.006 respectively) and they all are highly significant (p -value = 0.0000). I choose to ignore the detected time trend for the external sector (-0.001) despite a p -value within threshold (0.03) since standard error is of the same magnitude (0.001). Highly significant time trends in 3 markets show that demeaning is not enough. For these markets, we need to detrend the subindices before using them to compute covariances:

$$\hat{s}_{i,t} = s_{i,t} - b_i t - a_i, \quad i = 1, 2, 4,$$

where b_i is the OLS coefficient and a_i is the OLS intercept for subindex i .

For the equity market and external sector, demeaning will suffice²⁶:

$$\hat{s}_{i,t} = s_{i,t} - \bar{s}_{i,t}, \quad i = 3, 5,$$

where $\bar{s}_{i,t}$ denotes sample mean of subindex i . This has, in practice, little difference from subtracting from 0.5 since the sample means are so close to that number.

The conditional covariance matrix at week t using the BEKK parameterization is then

$$\mathbf{\Sigma}_t = \mathbf{G}'\mathbf{G} + \mathbf{A}'\hat{\mathbf{s}}_{i,t-1}\hat{\mathbf{s}}'_{i,t-1}\mathbf{A} + \mathbf{B}'\mathbf{\Sigma}_{t-1}\mathbf{B},$$

where parameter matrices \mathbf{A} , \mathbf{B} and \mathbf{G} all have dimension $m \times m$, and \mathbf{G} is lower triangular. As an illustration, a bivariate case ($m = 2$) can be written as²⁷:

$$\begin{aligned} \mathbf{\Sigma}_t &\equiv \begin{bmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{2,t}^2 \end{bmatrix} \\ &= \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \\ &\quad + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \hat{s}_{1,t-1}^2 & \hat{s}_{1,t-1}\hat{s}_{2,t-1} \\ \hat{s}_{2,t-1}\hat{s}_{1,t-1} & \hat{s}_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ &\quad + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} \sigma_{1,t-1}^2 & \sigma_{12,t-1} \\ \sigma_{12,t-1} & \sigma_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \end{aligned}$$

²⁶ It can be argued that no distinction needs to be made since the absence of a time trend implies $b_i = 0$ and $a_i = \bar{s}_{i,t}$. Errors made by detrending the external sector if there were no time trend would be very small.

²⁷ Here I make use of the fact that $\sigma_{ij} = \sigma_{ji}$.

Even for the simplest MGARCH model shown above, without restrictions, we will have to estimate 11 parameters. For m variables, the fully parameterized model includes $2.5m^2 + 0.5m$ parameters. In our case, there are 5 subindices, so the full model has 65 parameters. With weekly data, we would need more than a year's observations just to pin down these parameters, let alone sound estimates. To cope with this "curse of dimensionality", matrices \mathbf{A} and \mathbf{B} are restricted to be diagonal as in Ding and Engle (2001), reducing the number of parameters to be estimated to 25.

By expanding the expression, we can also see that each covariance entry consists of a constant term, weighted error products, as well as weighted covariances. Therefore, the EWMA model is just a special case of the BEKK model – a scalar BEKK where $\mathbf{A}' = \sqrt{1 - \lambda} \mathbf{I}$, $\mathbf{B}' = \sqrt{\lambda} \mathbf{I}$ and the constant matrix $\mathbf{G}'\mathbf{G} = \mathbf{0}$.

At this stage, comparing the EWMA and BEKK is easy: the EWMA is very simple, with only one parameter, the decay factor λ . Very often, even this parameter is not estimated, but imposed at the outset, equal to 0.94 as advocated by RiskMetrics™, a financial risk management company (for their VaR models). By eliminating the constant term, the EWMA model rejects the possibility that there exist any degree of mean reverting behavior in the covariances ($\gamma = 0$ in the GARCH(1,1) model introduced in section 3.1), unless the long-run average V_L happens to be zero. Despite the EWMA being extremely parsimonious, with over 11 years of data (over 600 weekly observations) and good computing power provided by programs such as Matlab, a parametric model should be preferred to a simple model that imposes too many parameter restrictions at the outset with little theoretical foundation.

Due to the one-to-one relationship between covariances and correlations, $\sigma_{ij} = \sigma_i \sigma_j \rho_{ij}$, we can transform the estimated dynamic covariance matrix from the BEKK model into a dynamic correlation matrix \mathbf{C}_t :

$$\mathbf{C}_t = (\text{diag}(\boldsymbol{\Sigma}_t))^{-\frac{1}{2}} \boldsymbol{\Sigma}_t (\text{diag}(\boldsymbol{\Sigma}_t))^{-\frac{1}{2}}.$$

This dynamic correlation matrix will be used in the final aggregation.

3.6 Aggregation

In this section, we compute the final CISS indicator using the subindices and dynamic covariance matrices constructed in previous sections.

For final aggregation, we follow Holló et al. (2012):

Let $\mathbf{w} = (w_1 w_2 w_3 w_4 w_5)$ denote the weights on each market segment²⁸. Let $\mathbf{s}_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t}, s_{5,t})$ denote the subindices at week t . Let \mathbf{C}_t denote the dynamic correlation matrix between the 5 subindices at week t :

$$\mathbf{C}_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{pmatrix}$$

Our composite indicator of systemic stress is defined as

$$CISS_t = (\mathbf{w} \circ \mathbf{s}_t) \mathbf{C}_t (\mathbf{w} \circ \mathbf{s}_t)'$$

Where \circ denotes the Hadamard product, or element wise multiplication. So $\mathbf{w} \circ \mathbf{s}_t$ represents the weighted subindices:

$$\mathbf{w} \circ \mathbf{s}_t = (w_1 s_{1,t} \ w_2 s_{2,t} \ w_3 s_{3,t} \ w_4 s_{4,t} \ w_5 s_{5,t})$$

We can expand the expression and get:

$$CISS_t = \sum_{i=1}^5 \sum_{j=1}^5 w_i w_j s_{i,t} s_{j,t} \rho_{ij,t}.$$

Comparing this result with the variance of the portfolio returns from section 3.4,

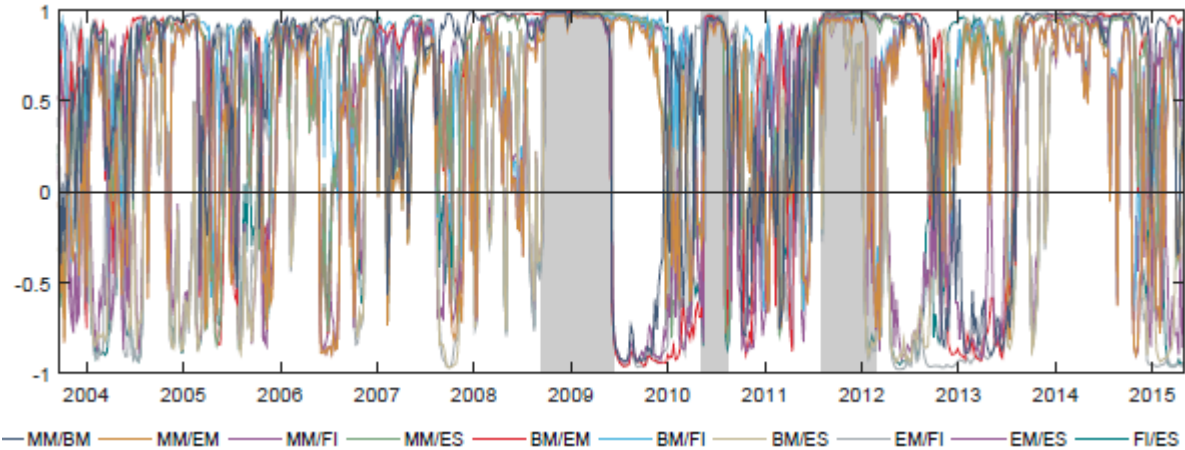
$$Var(R) = \mathbf{w}' \Sigma \mathbf{w} = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_{ij} = \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_i \sigma_j \rho_{ij},$$

²⁸ This thesis assumes equal weights for all markets. Holló et al. (2012) point out that using equal weights and roughly estimated real-impact weights from VAR models produce similar results.

we will understand why the average stress is not weighted by the covariance matrix, but the correlation matrix: the subindices themselves are already risk measures, analogous to the volatility of each asset (class) in a portfolio. The $\sigma_{i,t}$ estimated from the BEKK model is essentially the volatility of stress indicators (which consists of, among other things, volatilities), which makes little sense. In addition, since the subindices have very similar statistical properties by construction, their sample standard deviations are nearly identical²⁹. Whether to include the $\sigma_{i,t}\sigma_{j,t}$ term would not really matter as a consequence.

Correlation $\rho_{ij,t}$, measures how stress in different markets relates to each other (in a linear fashion). If the stress level in different financial markets are highly correlated, when one market is suddenly under distress, instability could quickly spread to other markets, increasing systemic stress. Figure 3.2 shows that, for Norwegian data from September 2003 to April 2015, there were five episodes with longer duration in which all correlations were close to 1. Three of these episodes correspond to crisis which had an impact on the Norwegian financial system³⁰: the global financial crisis from 2008 Q3 to 2009 Q2, the Greek crisis in summer 2010, and the sovereign debt crisis 2012 Q3 – 2013 Q1. Other episodes were end of 2006 to summer 2007 (subprime crisis in the U.S.) and large parts of 2014. The dynamic correlation matrix represents how widespread financial market stress is. For plots of individual cross-correlations, see Figure A.4 in appendix A.

Figure 3.3 Cross correlations of subindices.
15 September 2003 – 1 May 2015



Source: author’s own calculations

²⁹ Between 0.0021 and 0.0025 for data up to 17 April 2015. For more details, see table B1 in appendix B.
³⁰ Note that they might not have had much impact on the real economy.

As argued in section 3.3, the subindices measure stress level in each of the five market segments. In other words, they represent the severity of financial market stress.

Since the CISS indicator is a (weighted) product of the two, it takes into account both the severity and widespreadness of stress in different financial markets. This way it differs from many other indicators that does not take contagion (correlation) directly into account and miss a significant component of systemic stress.

It should be pointed out that the CISS is by construction a variance-equivalent measure. Traditionally, it is the standard deviation, or volatility, that is used as risk/stress measures. It is therefore more intuitive to define systemic stress as $CISS_t = \sqrt{(\mathbf{w} \circ \mathbf{s}_t) \mathbf{C}_t (\mathbf{w} \circ \mathbf{s}_t)'}'$, as in Cabrera et al. (2014).

Holló et al. (2012) argue that they choose the variance equivalent formulation over its volatility equivalence because the variance, or the square of the systemic stress measure, differentiates better between episodes of stress and calmer periods. However, if the goal was to best distinguish the most stressful periods based on the same information, we may just as well transform the volatility equivalent CISS by the power of 4, or apply any other monotonically increasing transformation that creates higher variations. Nevertheless, I follow the notation used by Holló et al. (2012) as their paper serve as a benchmark for many other central banks, to facilitate comparison other countries' systemic stress level.

We can explore the properties of the CISS further by looking at special cases of the correlation matrix. In this study, the average correlations are positive between any two markets

$$\mathbf{C}_t^{average} = \begin{pmatrix} 1.00 & 0.59 & 0.41 & 0.63 & 0.31 \\ 0.59 & 1.00 & 0.26 & 0.53 & 0.19 \\ 0.41 & 0.26 & 1.00 & 0.57 & 0.30 \\ 0.63 & 0.53 & 0.57 & 1.00 & 0.35 \\ 0.31 & 0.19 & 0.30 & 0.35 & 1.00 \end{pmatrix}$$

A natural benchmark would be to assume zero correlation between any two markets at all times. I.e. $\mathbf{C}_t = \mathbf{I}$ for all t. Then we will simply get the sum of weighted subindices squared:

$$CISS_t^{zero\ corr} = (\mathbf{w}' \mathbf{s}_t)(\mathbf{w}' \mathbf{s}_t)' = \sum_{i=1}^5 (w_i s_{i,t})^2.$$

With equal weights, this CISS becomes:

$$CISS_t^{zero\ corr} = w^2 \sum_{i=1}^5 (s_{i,t})^2,$$

proportional to the weekly variance of subindices. The zero correlation case collapses to some kind of measure of the variance of raw stress indicators, which is hard to interpret.

As can be seen from Figure A.5. in appendix A, the resulting series is rather small compared to the CISS, especially during crises.

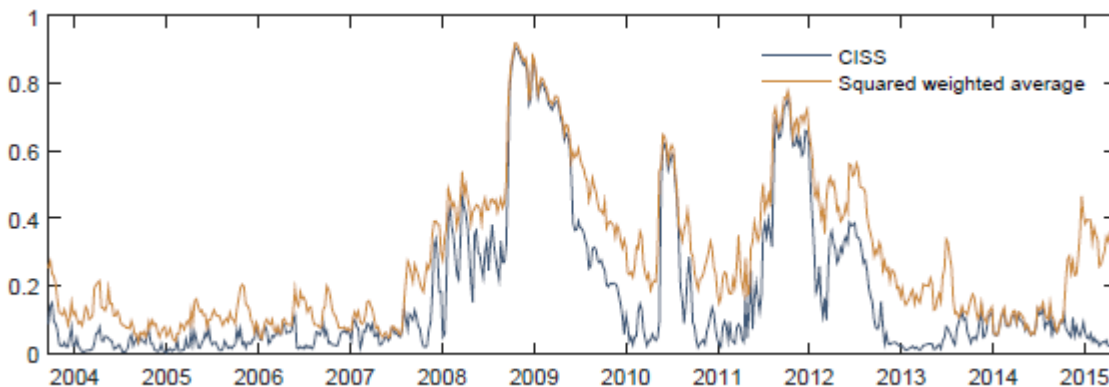
Holló et al. (2012) choose another benchmark – that of perfect correlation. In other words, we let every element of \mathbf{C}_t be 1. By expanding and collecting terms, in the end we are left with

$$CISS_t^{perfect\ corr} = \left(\sum_{i=1}^5 w_i s_{i,t} \right)^2$$

which is simply the square of a weighted average of the subindices. Naturally, the volatility-equivalent CISS would be just the weighted average. The difference between no correlation and perfect correlation is essentially whether the square lies inside or outside the sum.

The benefit of choosing perfect correlation as a benchmark is that it defines an upper bound for the CISS. In other words, $CISS_t^{perfect\ corr}$ defines the maximum value the CISS indicator can possibly take, given subindices and weights. The zero correlation scenario, on the contrary, does not provide a lower bound since negative correlation can reduce the CISS further.

Figure 3.4 CISS versus the squared weighted-average of subindices (“perfect correlation”) 15 September 2003 – 1 May 2015

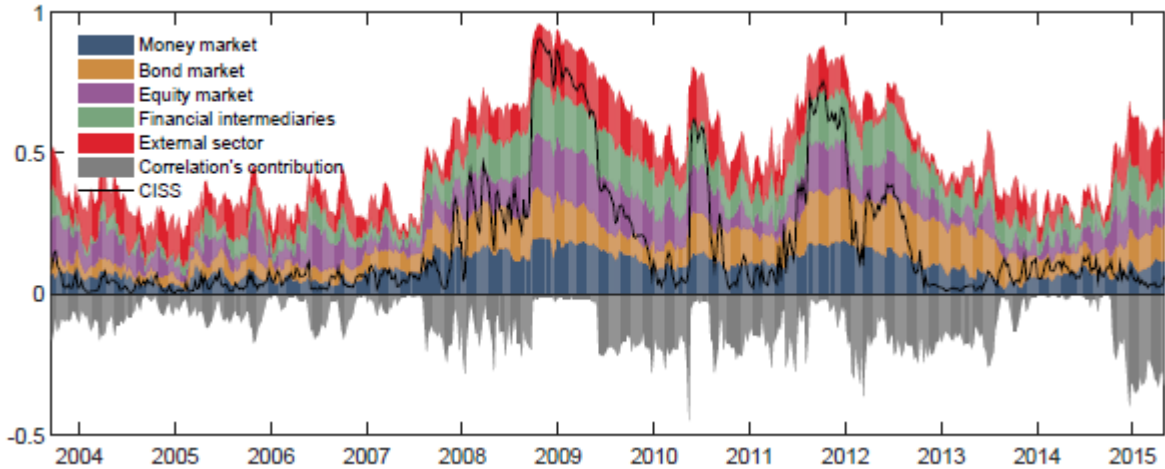


Source: author’s own calculations

Based on this benchmark, Holló et al. (2012) suggest an excellent way of decomposing the CISS into contributions coming from each of the subindices (with weights) and the overall contribution from the cross-correlations defined as the difference between the squared weighted average of the subindices and the real CISS.

$$\text{Correlation's contribution} = CISS_t^{perfect\ corr} - CISS_t$$

Figure 3.5 Decomposition of the Composite Indicator of Systemic Stress for Norway. 15 September 2003 – 1 May 2015



Source: author's own calculations

Such decomposition may prove helpful for the real-time monitoring exercises of macroprudential authorities, since they can at a glance perceive in which markets stress have arisen and how widespread stress is.

4 EVALUATION

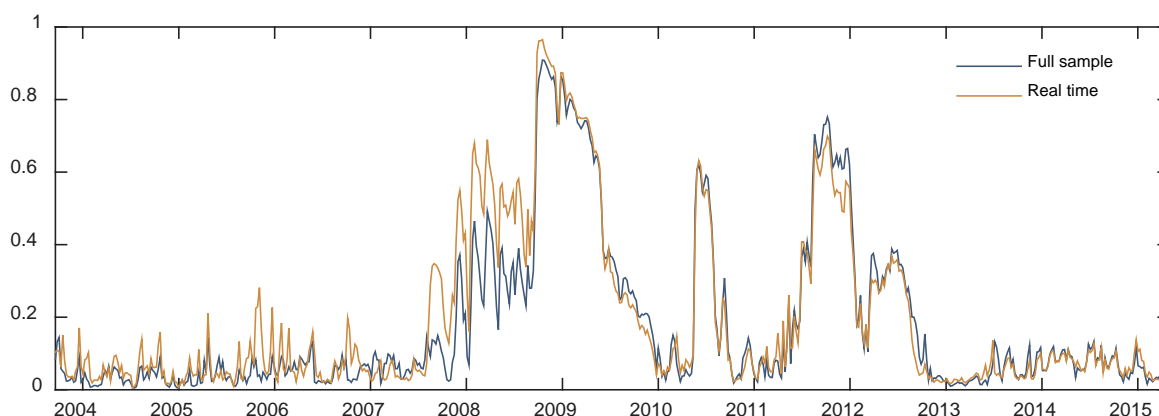
Four different measures are used to evaluate the systemic stress indicator for Norway: Section 4.1 performs robustness checks by recursion as well as comparing the Norwegian CISS with that of other Scandinavian countries and the Eurozone. In section 4.2, event identification is conducted with the recursively estimated real-time CISS. The last section is dedicated to investigating the relationship between the Norwegian CISS and Norway's real economy.

4.1 Robustness

In section 3.2 I argued that transformation by order statistics makes the subindices, and hence the CISS a more robust measure. Here, robustness refers to not being sensitive towards outliers, and hence not prone to significant revisions as new information arrives.

A recursively computed CISS in real time is shown in Figure 4.1 against the full sample CISS. It can be seen that deviations are reasonably small. Not surprisingly, the largest deviations occurred one year prior to the financial crisis: since the financial system was rather stable from the beginning of the series, September 2003, to summer 2007 (just between the Dot-com bubble and the global financial crisis), the U.S. subprime crisis in the second half of 2007 appeared more stressful than it seemed after the truly systemic global financial crisis. Such deviations must be seen in the light of the lack of data and the particular tranquility of the financial system during my recursion period from September 2003 to September 2006. Weeks after Lehman collapsed, the difference between the recursive and full sample CISS became marginal. After the financial crisis, only one large discrepancy occurred in the

Figure 4.1 Recursive¹⁾ versus full-sample computation of the CISS²⁾.
15 September 2003 – 27 March 2014



1) Recursion starts on 15 September 2006.

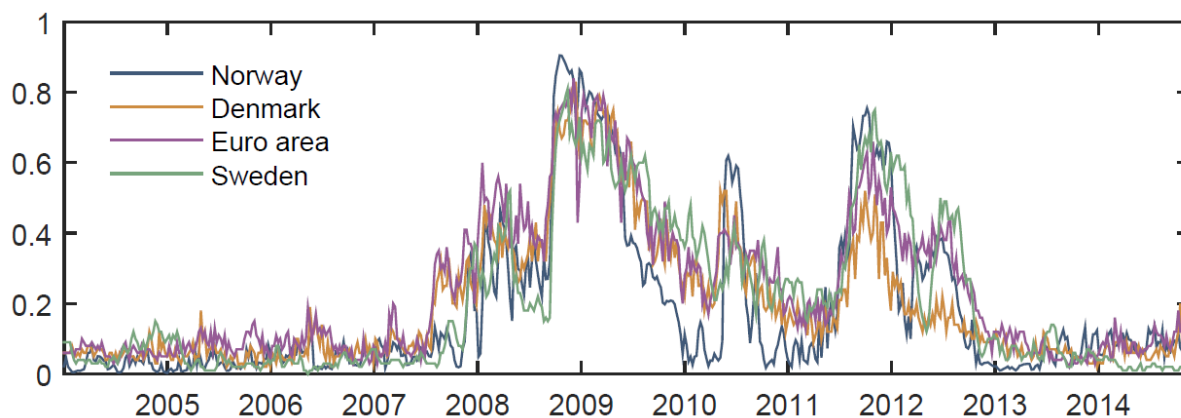
2) Note that the discrepancies do not disappear entirely even towards the end of the sample period because 7 of the 15 input series for computing the CISS are volatilities which also are recursively estimated.

Source: author's own calculations

second half of 2011. The question is how severe the sovereign debt crisis was. Given that subindices are robust after the first crisis (due to transformation to empirical cdfs), the more likely source of these discrepancies is cross-correlations. In other words, the real-time CISS may have underestimated the degree of contagion in that episode.

Figure 4.2 Composite indicator of systemic stress for selected countries.

1 January 2004 – 21 November 2014.



Sources: Danmarks Nationalbank, ECB, the Riksbank, and author's own calculations

Another robustness check can be to compare the CISS for Norway with that of countries or regions similar to Norway. Figure 4.2 illustrates that the Norwegian CISS behaves similarly to systemic stress indicators in Sweden, Denmark and the Euro area. One unique feature of the Norwegian CISS is that it is smoother on a weekly basis, most likely due to using GARCH volatilities as input.

However, systemic stress measured by the Norwegian index dropped quicker than other regions during the financial crisis and the Greek debt crisis. Norway was indeed less affected by the financial crisis than the others. Looser ties with the Euro may explain the quick drop after summer 2010. Since subindices constructed à la Holló et al. (2012) are robust and all four countries use mostly the same types of information, large deviations from other countries' systemic stress indices are most likely due to differences in correlation estimates. While Sweden and Denmark both adopted the EWMA model proposed by the ECB to calculate the dynamic correlations, this paper makes use of a parametric BEKK-MGARCH

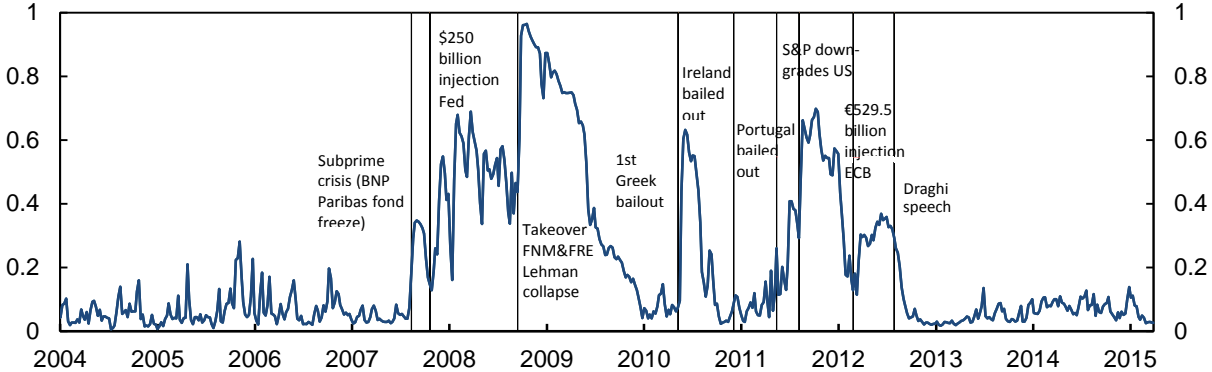
model that is able to capture abrupt changes in conditional correlations. Nevertheless, since 2011, the Norwegian CISS behaves much in the same way as the Euro area and Sweden. A possible explanation is increased contagion from Europe. But that explanation fails to answer why Denmark, whose currency is pegged to the Euro, and have more economic links to the Euro area, behaved so differently in the same period.

More research is needed to explore these cross-country differences. But overall, the Norwegian CISS appears robust and should be viewed as a reliable source of information.

4.2 Event identification

In this section, I match the CISS for Norway with a series of events which marks the heightening/reduction of financial market stress. As the purpose is to evaluate how the CISS responds to these events, it is more meaningful to use the recursively estimated real-time indicator. The results are presented in Figure 4.3.

Figure 4.3 Recursive CISS paired with known financial events.
15 September 2003 – 1 May 2015



Source: author's own calculation

Monitoring the CISS in real time would have given us a small but clear signal of the subprime crisis after sommer 2007 when BNP Paribas had to freeze two of its mortgage backed funds. During the two weeks that saw the federal takeover of Fannie Mae and Freddie Mac and Lehman brothers' collapse, the CISS went up from 0.44 to 0.93. It then went up rapidly during the Greek crisis and when Standard & Poors downgraded the U.S. government, as worries over sovereign defaults went widespread. It went up again in 2012 when people started to loose faith in the Euro. In addition to these stressful events, the Norwegian CISS also responded to policy measures undertaken by the Fed and the ECB (e.g. liquidity

injections and promises like Mario Draghi's "... whatever it takes to preserve the Euro" in July 2012) by entering new lows. The years 2013-2015 saw some remarkably low stress measures. Revisiting the decomposition of CISS in Figure 3.4 gives us the answer: In 2013 and between the end of 2014 and May 2015, average stress level is rather high in the financial system. However, little contagion was detected by correlation estimates. Hence systemic risk was low. In 2014, the situation was the other way round: movements in financial markets were highly correlated (hence the risk of contagion was high), but "nothing happened", i.e., subindices were taking low values. Although the CISS suggest low systemic stress in the last three years, we cannot conclude that the financial system was *stable*. Stability can be characterized by moderate stress level in most of the market segments, *and* little co-movement in the same direction between these segments (low or mixed cross correlations), not the extreme cases above.

The above event identification is by no means a complete account of the global financial system in the past 10 years. I used the word "global" because all the above events were external shocks for Norway. Yet their impact on the Norwegian financial system seem to be profound, as Figure 4.3 clearly illustrates.

It is quite bizarre that the large swings in oil prices in the previous year did not lead to signals of heightened systemic stress. External sector stress has been extremely high in many months, but an oil price shock affects the financial system as well as the real economy through many channels, often with opposite effects. The low level of systemic stress may also have to do with accommodating monetary policies around the globe. I will explore more of the links between the financial system and the real economy in the next section.

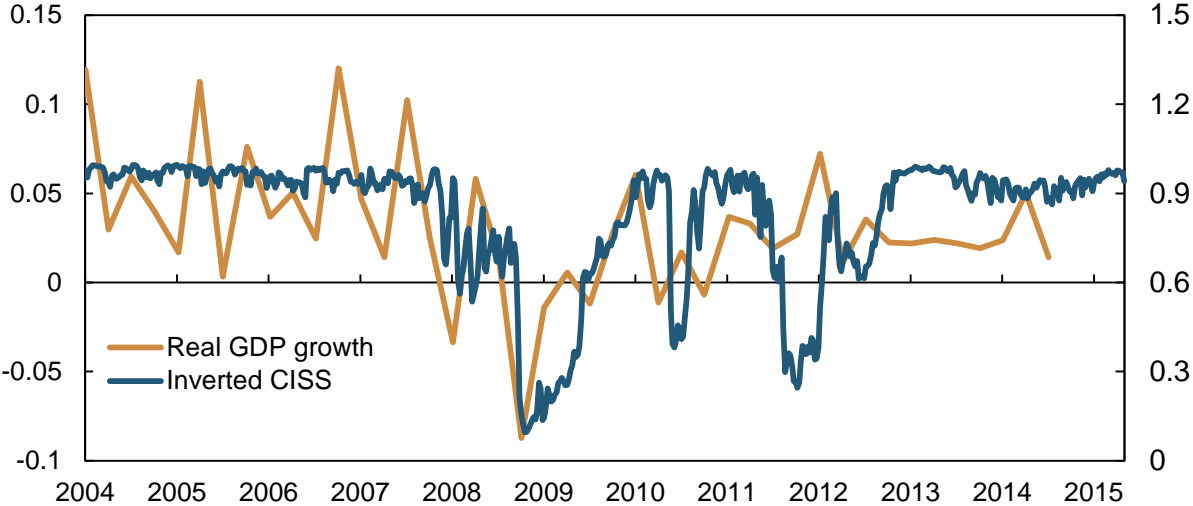
4.3 Relationship with GDP

Systemic stress in financial markets should be inversely related to economic activities. In times of financial turmoil, asset returns are low, leaving people less to spend, and distrust are deeply rooted, so that investors hoard their cash or keep their wealth in low-yielding safe assets. Hence, both demand and supply are negatively affected, leading to a fall in output.

To examine whether this relationship holds, I plot the inverted CISS (i.e., $1 - CISS_t$) with seasonally adjusted real GDP growth for mainland Norway from 2004 Q1 to 2014 Q2. Indeed a close relationship is observed between the inverted CISS and real GDP growth in the first $\frac{3}{4}$

of the sample period. However, since the second half of 2011, the correlation has changed sign – GDP growth was higher in quarters when systemic stress measured by the CISS was high.

Figure 4.4 Inverted CISS and quarterly real GDP growth for mainland Norway.



Sources: Statistics Norway and author’s own calculation

In order to quantify my findings, I calculate the correlation between the CISS and 3-month centered moving average of quarterly GDP growth.

Table 4.1 Correlation between the CISS and GDP growth¹⁾ for mainland Norway.

	2004 - 2014	2004 - 2011	2011 - 2014
Correlation	-0.62	-0.70	0.84

1) 3-month centered moving average. Quarterly.
Sources: Statistics Norway and author’s own calculations

Indeed, the relationship between the CISS and GDP growth is negative on average. Their correlation was highly negative (-0.7) between 2004 and 2011, but since then has experienced a drastic change of sign, to as high as 0.84 between 2011-2014. The latest development could result from measurement errors in GDP. On the other hand, the past 4 years were indeed unusual in that interest rates have been close to zero while growth was stagnant in much of the developed world. The above finding is not the only irregularity we face nowadays: Yields are ultra-low, but savings and demand for safe bonds are high; unemployment is declining and monetary policy loose, but inflation does not kick in... Could it be that the post-crisis world is a different one? This is a question worth asking, but only time (and revised GDP

figures) could show whether the relationship between the CISS and GDP growth has indeed been reversed after 2011. In the meanwhile, this composite indicator is ready to be added into the toolbox of Norwegian macroprudential authorities to monitor the level of systemic stress.

5 CONCLUSION

In this paper I construct a Composite Indicator of Systemic Stress (CISS) for Norway as a reference indicator following recent developments in the literature of systemic risk measurements, in particular the portfolio-theoretic framework proposed by Holló et al. (2012). The Norwegian CISS takes into account stress indicators from the money market, bond market, equity market, financial intermediaries as well as an external sector.

The Norwegian CISS is robust, capable of detecting known stressful events in real time, looks similar to other European countries' systemic stress indicators, but gives stress signals more swiftly, thanks to the BEKK-MGARCH model used in the estimation of dynamic correlations. This indicator should hence be useful for policy makers to monitor systemic stress in real time, increasing the likelihood of timely and successful policy intervention.

This paper provides extended discussions over the theoretical motivations for applying modern portfolio theory in the computation of systemic stress indicators, which the literature so far did not focus on. Another innovation in this paper is that market level stress indicators, or subindices, are not only demeaned, but also detrended in the presence of a significant linear trend, to ensure stationarity of the MGARCH model – an aspect largely neglected in recent literature.

However, the link between the Norwegian CISS and real economic activities, though once strong, has been weakened and perhaps even eroded in recent years (since 2011 Q3). This may raise concerns about whether this indicator will continue to be successful in detecting systemic stress. Nevertheless, when measurement errors in recent GDP figures and ultra-loose monetary policy in the developed world are taken into account, with time, this finding may prove to be insignificant or just an irregularity. In any case, this composite indicator is ready to be added into the toolbox of Norwegian macroprudential authorities for monitoring the level of systemic stress, and hence serve as a reference indicator for reducing or releasing the countercyclical capital buffer.

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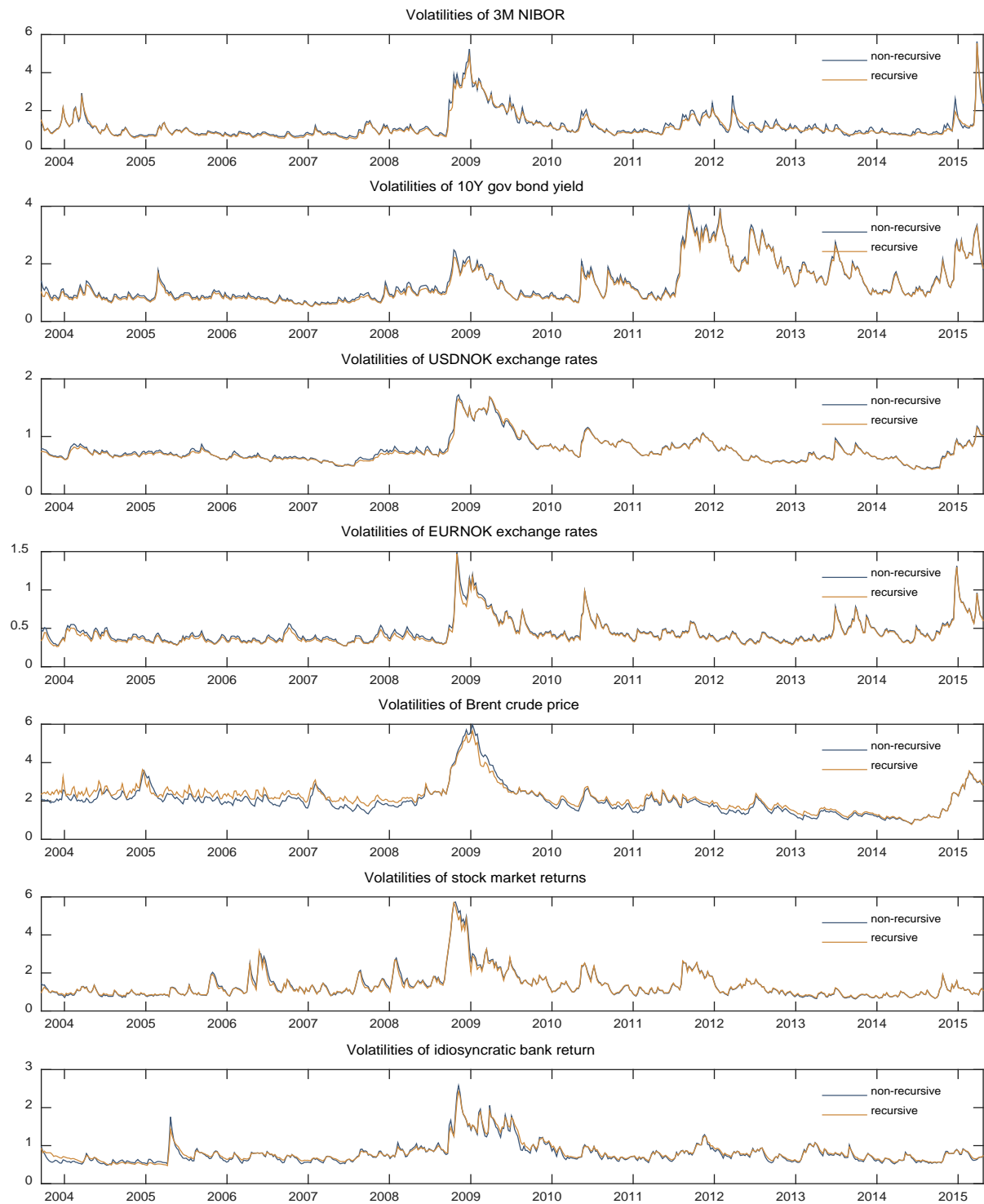
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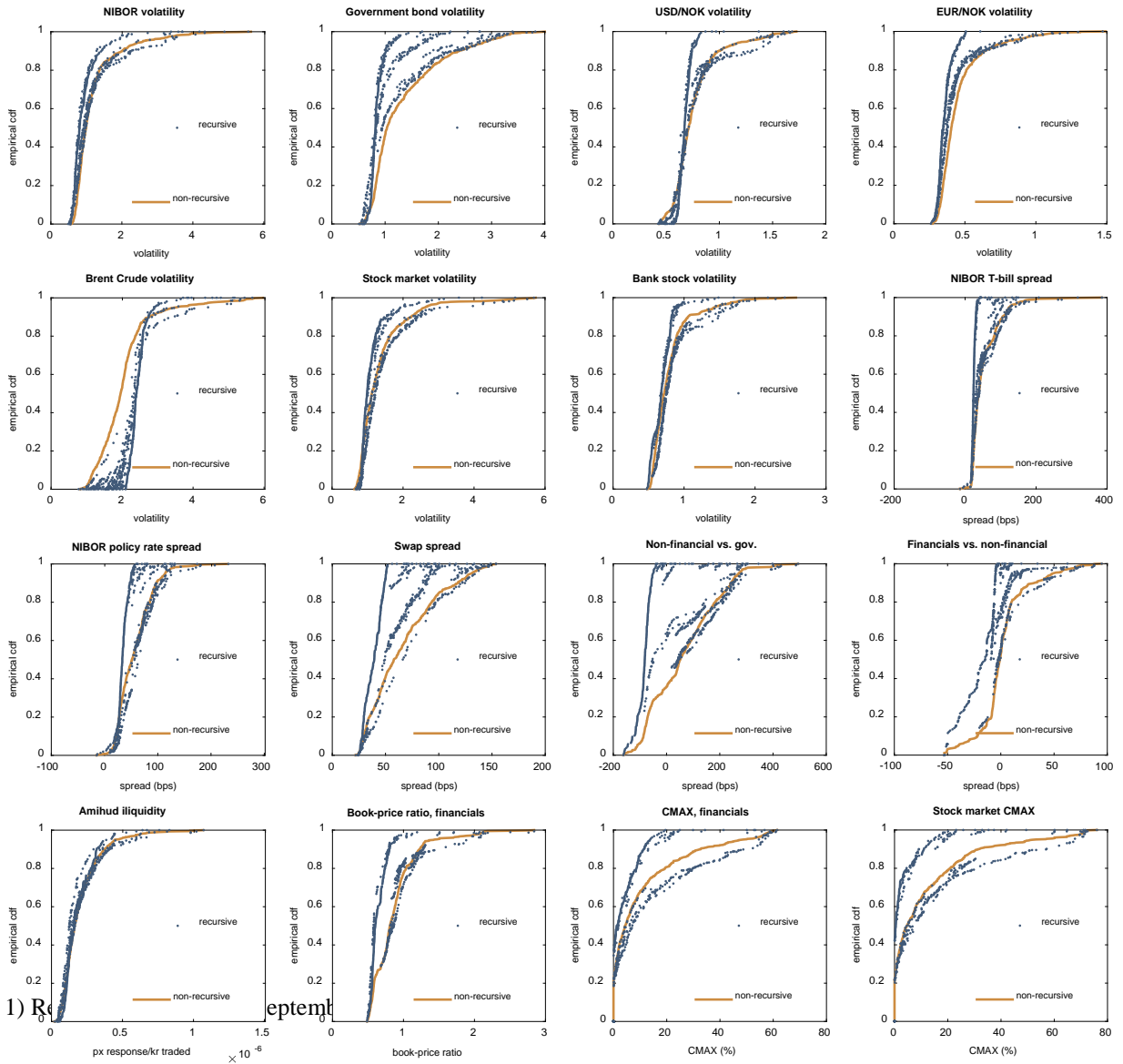
Appendix A: Supplementary Charts

Figure A.1 GARCH(1,1) volatilities, recursive¹⁾ and non-recursive.
Weekly average of daily data. 15 September 2003 – 1 May 2015



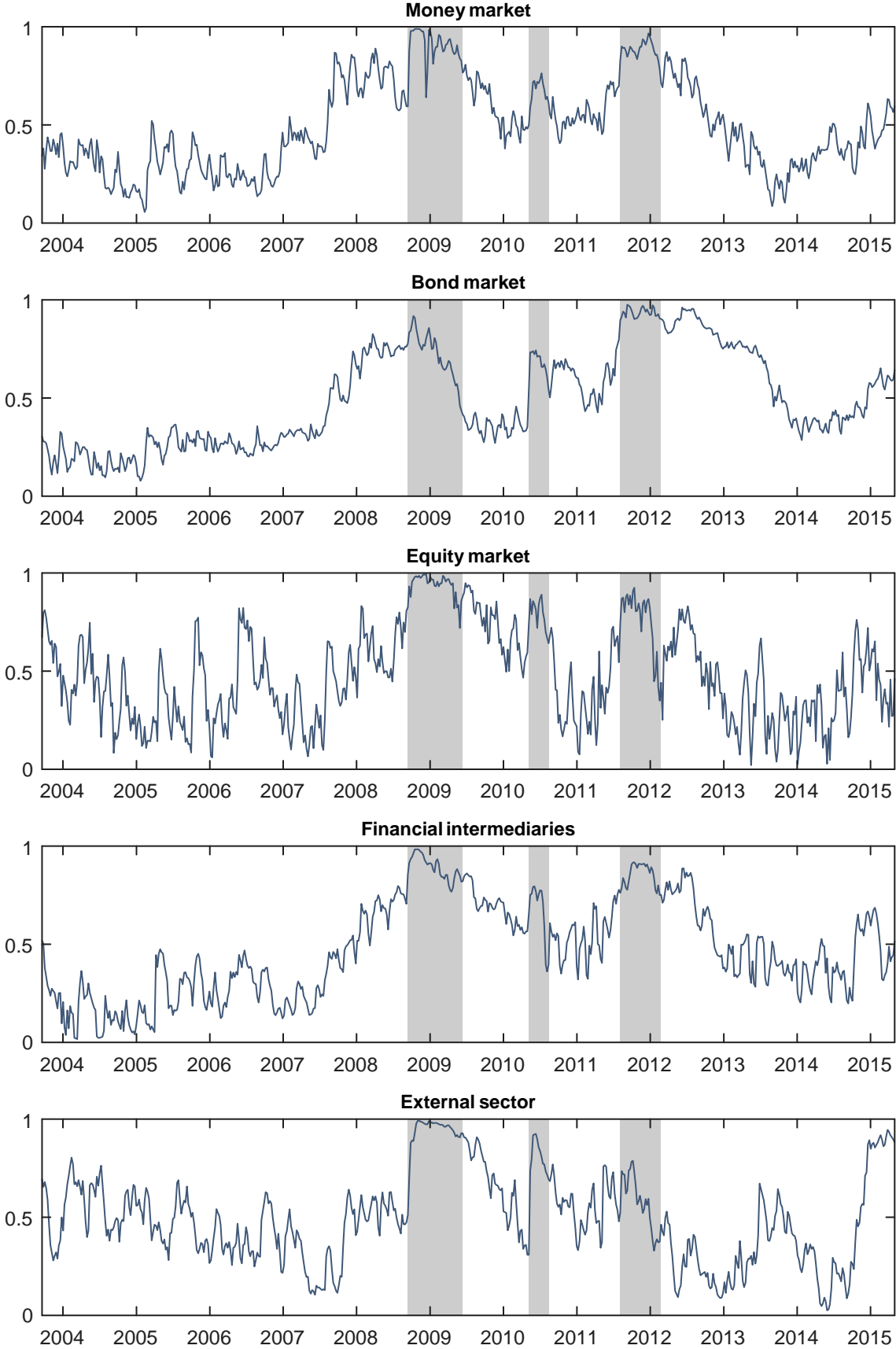
1) Recursion starts on 15 September 2006. GARCH parameters are estimated using data from 2 Jan. 1999.

Figure A.2 Empirical cumulative distribution functions, recursive¹⁾ and non-recursive.
 15 September 2003 – 1 May 2015



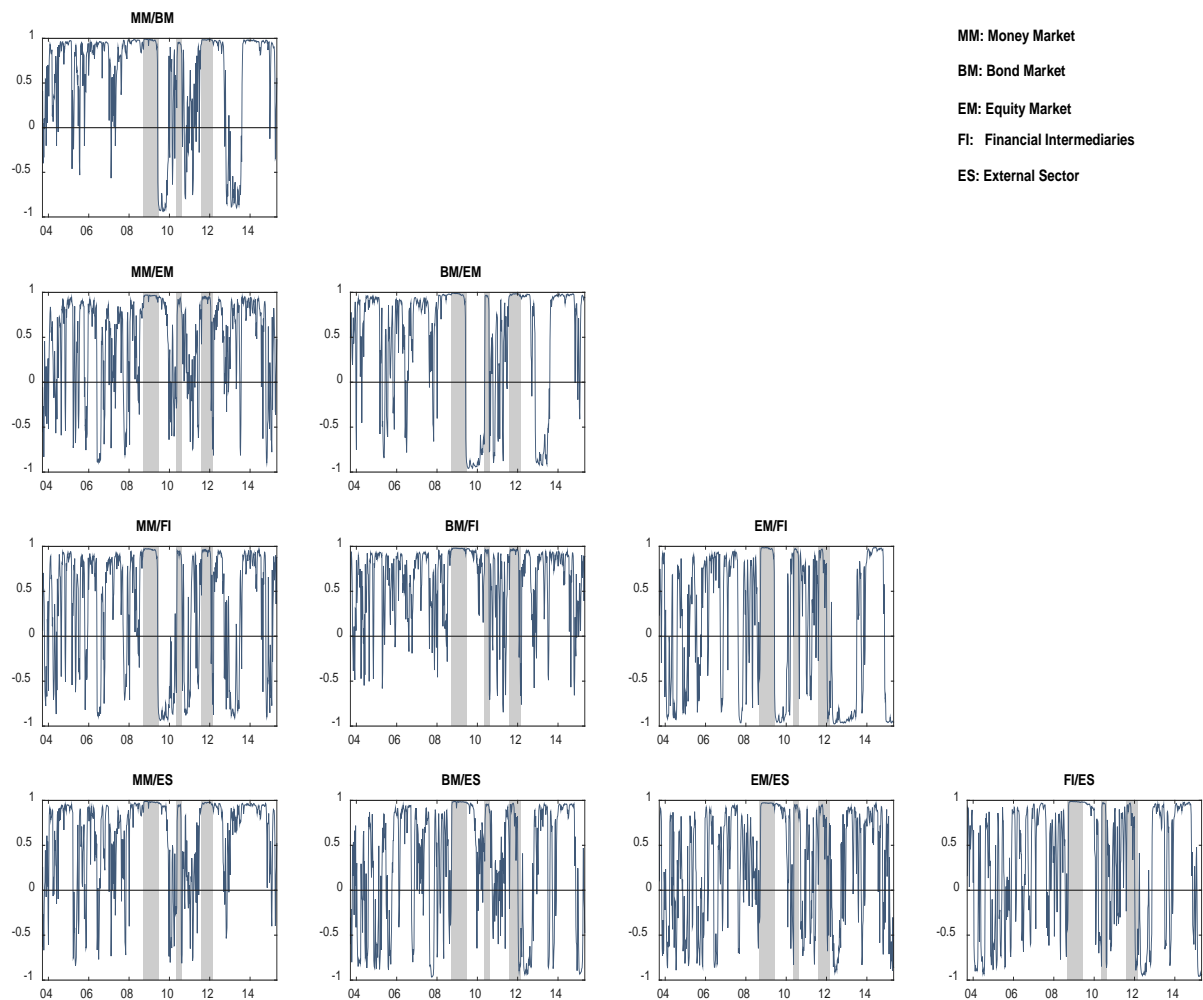
Source: Author's own calculations

Figure A.3 Subindices of the Norwegian CISS.
15 September 2003 – 1 May 2015



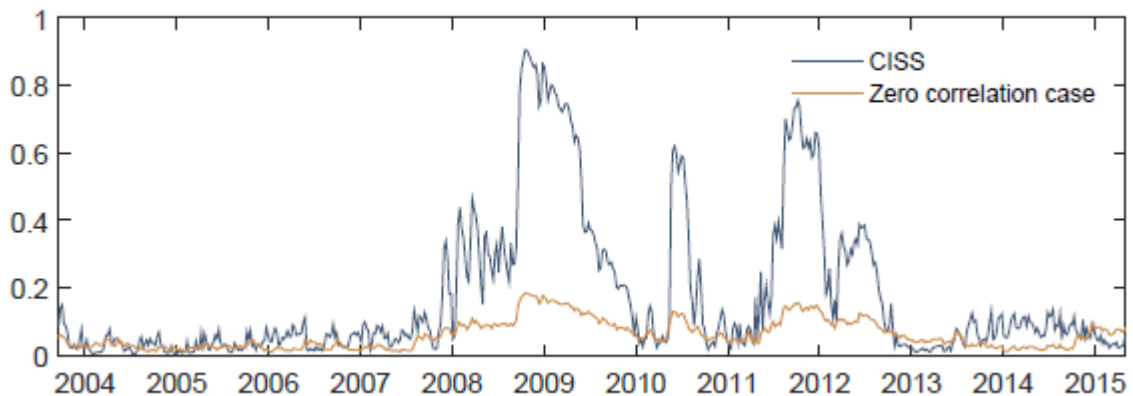
Source: Author's own calculations

Figure A.4 Dynamic cross correlations estimated with a diagonal BEKK-MGARCH model.
15 September 2003 – 1 May 2015



Source: author's own calculations

Figure A.5 CISS versus the zero-correlation case.
15 September 2003 – 1 May 2015



Source: author's own calculations

Appendix B: Supplementary Tables

Table B.1 Descriptive statistics of subindices.

	Max	Mean	Median	Min	Std
Money market	0.990	0.501	0.463	0.056	0.232
Bond market	0.976	0.501	0.438	0.078	0.245
Equity market	0.996	0.493	0.468	0.021	0.248
Financial intermediaries	0.984	0.480	0.450	0.016	0.248
External sector	0.992	0.501	0.485	0.025	0.233

Source: author's own calculations

Table B.2 OLS regression of subindices – detection of time trend.

		Estimate	SE	t-Stat	p-Value
Money market	Intercept	0.3994	0.0183	21.8480	0.0000
	Coefficient	0.0003	0.0001	6.4020	0.0000
Bond market	Intercept	0.2544	0.0162	15.6720	0.0000
	Coefficient	0.0008	0.0000	17.5270	0.0000
Equity market	Intercept	0.4884	0.0201	24.2590	0.0000
	Coefficient	0.0000	0.0001	0.2680	0.7888
Financial intermediaries	Intercept	0.2946	0.0182	16.1920	0.0000
	Coefficient	0.0006	0.0001	11.7680	0.0000
External sector	Intercept	0.5364	0.0189	28.4480	0.0000
	Coefficient	-0.0001	0.0001	-2.1759	0.0300

Source: author's own calculations

Table B.3 Estimated conditional variance models for GARCH (1,1) volatilities.

GARCH(1,1) Conditional Variance Model:				
Conditional Probability Distribution: Gaussian				
	Parameter	Value	SE	t-Statistic
3M NIBOR	Constant	0.028761	0.001966	14.6263
	GARCH{1}	0.883523	0.004528	195.139
	ARCH{1}	0.109843	0.003553	30.9174
10Y gov. bond yield	Constant	0.012878	0.002551	5.04736
	GARCH{1}	0.916743	0.005594	163.867
	ARCH{1}	0.079582	0.005629	14.1382
USDNOK exchange rates	Constant	0.003532	0.001056	3.34565
	GARCH{1}	0.959306	0.005036	190.507
	ARCH{1}	0.035365	0.00409	8.64648
EURNOK exchange rates	Constant	0.004113	0.00073	5.63831
	GARCH{1}	0.912886	0.007623	119.761
	ARCH{1}	0.069311	0.005254	13.1912
Brent crude price	Constant	0.015161	0.004929	3.07556
	GARCH{1}	0.951792	0.004704	202.342
	ARCH{1}	0.045817	0.004644	9.86587
Stock market returns	Constant	0.028922	0.005013	5.76944
	GARCH{1}	0.882024	0.009205	95.821
	ARCH{1}	0.104531	0.008158	12.8131
Idiosyncratic bank returns	Constant	0.015882	0.001855	8.56206
	GARCH{1}	0.906567	0.007998	113.354
	ARCH{1}	0.069364	0.005858	11.8412

Source: author's own calculations