JYU DISSERTATIONS 787

Juhani Raatikainen

Gimme Shelter

Hedges and Safe Havens in Banking and Equity Markets

JYVÄSKYLÄ UNIVERSITY
SCHOOL OF BUSINESS AND ECONOMICS

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ABSTRACT

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This thesis explores risk management strategies of investors and banks under turbulent or challenging market conditions. The special focus is on the role of gold and crude oil in investor's portfolio choices during market crashes and the business mix choices of banks during negative interest rates. The dissertation consists of introduction and three empirical essays.

The topic of the first essay is to investigate dynamic connections between stock and gold markets and some popular risk measures. My results confirm that gold is a strong safe haven for US equity market investors. In addition, I present new evidence suggesting that the safe haven property lasts longer than usually thought and the strength of the safe haven property increases with the size of the stock price decrease. The latter result challenges previously published research. In addition, the first essay shows that the impact of exogenous shocks, such as, terrorist attacks and geopolitical tensions, have larger and more complicated impact on markets than has previously been understood.

The second essay investigates the relationship between stock, gold, and crude oil markets. One of the key contributions of the second essay is the analysis of the dynamic minimum variance portfolio weights of portfolios consisting of 1) a crude oil, gold, and S&P 500 portfolio, and 2) a crude oil, gold, and S&P 500 Energy IG portfolio. Both crude oil and gold are a safe haven for both portfolios, but gold is better and more efficient during crisis periods. The most important contribution of the second essay is the finding, that when the crude oil futures curve is in contango, the dynamic correlation between the crude oil futures and stock market returns is the highest, and, when the futures market is in normal backwardation the correlation is low or negative.

The third essay analyzes profitability of Finnish cooperative banks during negative interest rates. We use highly confidential monthly data of Finnish cooperative banks over the period 1/2009–12/2018. Our methodological choice is unique: we construct time series of variables of different banking groups, and we apply VAR and DCC-GARCH analysis. We find that profitability of Finnish cooperative banks has not decreased significantly even during negative rates, even though the net interest margin has fallen. Banks' profitability and reactions to low and negative rates differ significantly between different bank size groups. The introduction of negative interest rates has shifted banks' funding structure more to wholesale-based funding. The impact is strongest in the group of the largest banks.

Keywords: Crisis, Safe Haven, Commodity Markets, Equity Markets, Banks, Profitability, Negative Interest Rates

TIIVISTELMÄ (ABSTRACT IN FINNISH)

Raatikainen, Juhani
Anna minulle suojaa: Riskien suojaus ja turvasatamat pankkitoiminnassa ja osakesijoittamisessa
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Väitöskirja tarkastelee osakesijoittajien ja pankkien riskienhallintastrategioita markkinaromahdusten ja muutoin haastavien markkinaolosuhteiden vallitessa. Työssä tutkitaan erityisesti kullan ja raakaöljyn merkitystä osakesijoittajille sekä pankkien liiketoimintastrategioiden muutoksia negatiivisten korkojen periodilla. Väitöskirja koostuu johdannosta ja kolmesta empiirisestä tutkimuksesta.

Väitöskirjan ensimmäinen tutkimus tarkastelee osake- ja kultamarkkinoiden sekä eräiden suosittujen riskimittareiden välisiä dynaamisia yhteyksiä. Tulokset vahvistavat kullan olevan vahva turvasatama Yhdysvaltojen osakemarkkinoille. Tulokset osoittavat lisäksi, että kullan turvasatamaominaisuus säilyy pidempään kuin on yleensä ajateltu ja se on sitä voimakkaampi, mitä suurempi osakekurssien pudotus on. Viimeksi mainittu tulos haastaa aiempaa tutkimustraditiota. Eksogeenisten shokkien, kuten terroristihyökkäysten ja geopoliittisten jännitteiden vaikutus on voimakkaampi ja monimutkaisempi kuin mitä on aiemmin tiedetty.

Järjestyksessä toisessa tutkimuksista mallinnetaan osakkeiden, kullan ja raakaöljyn tuottoja. Yksi keskeisistä kontribuutioista on dynaamisten minimivarianssipainojen analyysi salkuissa, jotka koostuvat 1) raakaöljystä, kullasta ja S&P 500 indeksistä ja 2) raakaöljystä, kullasta ja S&P 500 Energy IG -indeksistä. Sekä raakaöljy että kulta ovat vahvoja turvasatamia osakesijoittajille, mutta kulta on parempi ja tehokkaampi kriisiperiodien aikana. Tärkein tulos on havainto, jonka mukaan, kun raakaöljyn futuurikäyrä on contangossa, dynaaminen korrelaatio raakaöljyn ja osakkeiden tuottojen välillä on korkein, ja, kun futuurimarkkina on backwardation tilassa, korrelaatio on matala tai negatiivinen.

Väitöskirjaan sisältyvistä tutkimuksista viimeisessä analysoidaan suomalaisten osuuspankkien toimintaa negatiivisten korkojen periodilla. Tutkimuksessa käytetään salaista pankkikohtaista kuukausiaineistoa tammikuusta 2009 joulukuuhun 2018. Yleisesti käytetyn paneeliregression sijasta pankit on jaettu koon perusteella ryhmiin ja ryhmäkohtaisia aikasarjoja analysoidaan VAR and DCC-GARCH -malleilla. Tulosten mukaan suomalaisten osuuspankkien tulos ei ole heikentynyt merkittävästi negatiivisten korkojen aikana. Pankkien reaktiot mataliin ja negatiivisiin korkoihin eroaavat pankkiryhmittäin. Negatiivisten korkojen aikana pankit, erityisesti suurimmat pankit, siirsivät varainhankinnan painopistettä tukkumarkkinoille.

Avainsanat: Kriisit, turvasatama, raaka-ainemarkkinat, osakemarkkinat, pankit, voitto, negatiiviset korot

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Jyväskylä 10.3.2024
Juhani Raatikainen

FIGURES

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1 INTRODUCTION

This thesis focuses on risk management of financial agents—especially the role of gold and crude oil in portfolio choices during market crashes and the business mix choices of banks during negative interest rates. In both cases, the key is a change in the portfolio's structure to secure portfolio's value (or returns) when markets fall. A common strategy among investors is decreasing the weight of stocks in the portfolio when the stock market crashes and investing the funds in safer assets. Especially in the case of a severe market crash, gold plays the key role. Similarly, when interest rates are very low or negative and because of that banks' net interest margin (NIM) is consequently low, banks may fight against the fall in the NIM by increasing the share of wholesale funding at negative market rates. They may also invest the funds in bond markets. Other choices include an increase in lending activity to more risky clients, and an increase in other types of non-interest incomes.

This thesis consists of three essays. The first two essays focus on the role of gold and crude oil in a diversified equity portfolio or in a portfolio comprising energy stocks. The background for the underlying risk environment is cyclical market behavior manifesting in bull and bear market conditions. In addition, the long-term structural change aspect is present in the form of financialization of commodities, which gained strength especially during 2003–2008. The first essay models and investigates dynamic connections between the stock and gold markets. It analyzes the dynamic impacts caused by exogeneous shocks, such as geopolitical tensions, on gold and stock markets. The paper seeks the answer to the question of whether gold is a safe haven for equity investors. In addition, it tests how the dynamic correlations between gold price changes and stock returns react to exogenous shocks. The second essay dives deeper and investigates the relationship between stock and gold markets, adding a new element—the black gold: crude oil. This essay specially focuses on the optimal hedging strategy and especially whether gold or crude oil is a hedge or safe haven for stock market investors who either hold a diversified equity portfolio or a portfolio consisting only of energy stocks. In addition, the second essay searches an answer for the question of what role crude oil should play as an investment asset during different market phases.

The third essay examines bank behavior under unconventional monetary policy. In the zero or negative interest rate zone, banks' NIM—the major source of income for most of the banks—decreases or disappears. Bank's strategic choices include, continuing their business without any changes while hoping for an early change in monetary policy, accelerating lending activity, increasing risk in the loan portfolio, increasing non-interest income, changing the funding structure to allow gains of negative interest rates, and increasing non-interest incomes in the business mix. The third essay focuses on behavior of Finnish cooperative banks during the negative interest rate period and the impact of negative rates on the banks' profitability. In addition, it compares the profitability and business mix solutions of banks in different size groups.

The key problem on which this thesis aims to shed light on how economic agents—whether investors or banks—react to unfavorable market conditions. The following subsections present an overview of the thesis' topic and a brief survey of the related literature. The essays are presented in Chapter 2, 3, and 4.

1.1 Research topics and related literature

1.1.1 Gold and stock markets

1.1.1.1 Gold as an investment and as a diversifier

According to Green (2007), there has been an active gold market for over 6,000 years. In the early days, gold served as a store of value, as a material for coins, and later as the anchor of the gold standard. However, gold is also a metal, and it is as a raw material in jewelry, dentistry, and several other industrial processes, especially in electricity. As an investment vehicle, it is, nowadays, also an asset class of its own. As an asset, gold is used for speculative purposes, as a part of an investment portfolio, and as a hedge and safe haven asset in turbulent times.

Since the 1960s, gold has been interpreted in academic literature as a diversifier and a "safe asset". Early research concluded that gold is not an attractive investment per se, because of its too high volatility compared to its return (McDonald and Solnik, 1977; Jaffe, 1989; Chua et al., 1990). However, it was found that gold has low correlation with stocks, and it is an efficient diversifier and a "safe asset" because of that (McDonald and Solnik, 1977; Jaffe, 1989; Chua et al., 1990; O'Connor et al., 2015, and Lucey et al., 2006 offer extensive discussions; for the early research see also Solt and Swanson, 1981; Aggarwal and Soenen, 1988 Johnson and Soenen, 1977 are more skeptical regarding the role of gold).

Jaffe (1989) studied gold as a portfolio diversifier instead of an asset per se. Several early studies confirmed the observation that the dependence between gold price return and stock market return is very close to zero, either measured by correlation coefficient or by the Capital Asset Pricing Model beta (CAPM) (Jaffe, 1989; McDonald and Solnik, 1977; Johnson and Soenen, 1977; Aggarwal and Soenen, 1980; Tschoegl, 1980; Chua et al., 1990, for a more thorough survey of the older studies, see the discussion in Lucey et al., 2006). For example, Jaffe (1989) suggested that the optimal share of gold in a diversified equity portfolio is between 5% and 10%. This aligns with most early studies. However, even some of the early studies reported that there are quite strong regime changes regarding gold returns and the diversifier property (for example, Johnson and Soenen, 1977).

The above sited research is based on data which entails the specific features of the Bretton Woods system and does not yet cover the impact of the Central Bank Gold Agreement[1] and the commodity market financialization. The first analysis based on long time series post the Bretton Woods is Hillier et al. (2006). They analyzed diversification benefits offered by gold and other precious metals. Their data covered the period between January 1, 1986, and April 1, 2004. Hillier

[1] On September 26, 1999, central banks signed the Central Bank Gold Agreement (CBGA1), which defines the maximum amount of gold a central bank is allowed to sell or lease during a year. This agreement has been renewed three times (the current one is the CBGA4). The aim of the agreement is to stabilize the gold market.

et al. (2006) estimated CAPM type equations for precious metals including as regressors stock market returns and variables measuring market risk. The key result was that under normal market conditions, precious metals do not offer significant benefits to diversified equity portfolios. However, under market stress, measured as extremely high GARCH volatility, all precious metals offer efficient diversification. Hillier et al. (2006) concluded that gold should be included in well-diversified equity portfolios, and the optimal share of gold in the portfolio is 9.5%. They also found that gold should be kept passively: Gold is a strategic, not a tactical, asset. These results have been confirmed by Lucey et al. (2006) and Conover et al. (2009). Conover et al. (2009) made two additional findings. First, they argued that instead of a direct investment in gold bullion, an investment in gold stocks is preferable. Second, gains offered by gold are regime dependent, being the highest during periods of monetary policy tightening. Conover et al. (2009) concluded that the weight of gold should be high, around 25%.

Solt and Swanson (1981) and Aggarwal and Soenen (1988) already discovered that the distribution of gold returns is non-normal. Lucey et al. (2006) confirmed this and presented evidence of significant positive skewness of the gold return distribution. Lucey et al. (2006) highlighted the importance of skewness in portfolio selection and applied mean-variance-skewness optimization instead of the mean-variance approach. Their seminal finding was that positive skewness of the distribution of gold highlights the importance of including gold in diversified equity portfolios.

We can divide research on the diversification properties of gold into older and more recent strands. Data used in the latter covered the intensive financialization period 2003–2007, the Global Financial Crisis (GFC), and the period after the crisis. Furthermore, research methods have evolved over time. Regarding research methods, Lucey et al. (2006) were the first to focus on skewness of the return distributions, and they applied the polynomial goal programming by Lai (1991). Emmrich and McGroarty (2013) applied the standard methodological approach and extended the analysis by Jaffe (1989) with data covering 1981—2011. They reported that the risk reduction offered by gold in the 1980s and 1990s did not compensate for the negative mean return of gold during those periods. This contradicts results by the main line of research. However, their key result was that after the Millenium and especially after 2007, gold should be included in equity portfolios. They suggested that the weight of gold in a portfolio should be about 10%. They also found out that equity portfolios have high kurtosis and are negatively skewed, while kurtosis of the return distribution of gold is lower and, depending on the period, either positively skewed or only slightly negatively skewed which increases gains offered by gold as a portfolio diversifier. Hoang et al. (2015) confirmed these results in the case of diversified French equity portfolios. Hoang et al. (2015) used very long time series covering the period 1949–2012 and they applied the stochastic dominance approach. Their results revealed that gold gives highest gains during periods of market turmoil. After 2000, gold became a "volatility reducer" and a diversifier for equity investors. However, gold does not give diversification benefits to bond portfolios. Beckmann et al. (2019)

tested diversification gains offered by gold to Chinese equities with data from 2015—2019. The methodological approach was sophisticated based on several different copulas and CCC-GARCH models in measuring dependencies. Diversification gains were measured by the hedge effectiveness ratio. The key finding was that there is a negative tail dependence between Chinese stock returns and gold returns. Gold offers diversification gains for most of the Chinese industrial sector portfolios.

1.1.1.2 Gold as a hedge and a safe haven

The cornerstone of the first and second essays is the seminal work by Baur and Lucey (2010) and Baur and McDermott (2010), who started a new strand of research focusing on the gains that gold can offer during stock market turbulence. Baur and Lucey (2010) defined diversifier as an asset having low correlation with another asset or a portfolio. A hedge is "an asset that is uncorrelated or negatively correlated with another asset or portfolio on average". They defined a safe haven as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil". Baur and McDermott (2010) modified Baur and Lucey's (2010) original definition of a safe haven asset to make a distinction between strong and weak safe haven property in the following way: "A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with an asset or portfolio in certain times only, e.g. in times of falling stock markets." Almost all of the above-sited literature focus on hedging property based on low correlation (e.g., diversifier property). In the following paragraphs, we focus on the safe haven property.

Baur and Lucey (2010) and Baur and McDermott (2010) estimated the following type of equations:

$$r_{gold,t} = a + c_1 r_{stock,t} + c_2 r_{stockq5,t} + c_3 r_{stockq2.5,t} + c_4 r_{stockq1,t} + \varepsilon_t \qquad (1)$$

in which r refers to return, t to time and q5, q2.5 and q1 to 5%, 2.5% and 1% return quantiles. If return is larger than the quantile threshold τ ($\tau = 1\%, 2.5\%, 5\%$), the value of the variable $r_{stock\tau,t}$ is zero. The strong (weak) safe haven property implies that the (sum) coefficients c_2, c_3, and c_4 should be negative (zero). While Baur and Lucey (2010) applied the above formula, Baur and McDermott (2010) further included bond returns and bond return quantiles as regressors. The above Baur and Lucey (2010) and Maur and McDermott (2010) formulation assumes that stock market information flows from the stock and bond markets to the gold market, but there are no information flows or feedback from the gold markets to the stock or bond markets. Residual variance is estimated with a GARCH model. This approach and its modifications have become standard tools in this strand of literature.

Baur and Lucey (2010) used daily data covering 1975–2005 and Baur and McDermott (2010) used daily, weekly, and monthly data covering 1979–2009. Baur and Lucey (2010) data included the US, UK, and German stock and bond markets, while Baur and McDermott's (2010) data included 53 international stock markets. The key result by Baur and Lucey (2010) was that gold is a hedge and safe haven for stock markets but not for bonds. However, the safe haven property is short-lived, lasting about 10–15 days. Baur and McDermott (2010) found that gold is both a hedge and strong safe haven for the major European stock markets and for the US stock market but not for Canadian, Australian, and Japanese stock markets or major emerging markets. Baur and McDermott (2010) confirmed the finding by Baur and Lucey (2010) that the safe haven property is rather short-lived, and, for example, it is found in daily data but not in monthly data. In addition, Baur and McDermott (2010) reported that the safe haven property varies with the nature of the stock market crisis. For example, gold served as a safe haven asset during the 1987 crisis and the Global Financial Crisis (GFC), but not during the Asian crisis (not even for the US market). A seminal, important finding by Baur and McDermott (2010) is that under extreme uncertainty, gold loses its safe haven property, and both gold and stock prices move in the same direction.

The papers by Baur and Lucey (2010) and Baur and McDermott (2010) started a line of active research on testing the hedge and safe haven properties of gold and whether some other asset or commodity would offer more efficient shelter against "stormy weather" in financial markets. With only a few exceptions, the methodology follows the above two seminal papers. Hood and Malik (2013) confirmed the results by Baur and Lucey (2010) and Baur and McDermott (2010) with daily US data covering 1995–2010. They also confirmed the finding by Baur and McDermott (2010) that gold is not a safe haven under extremely high volatility. Hood and Malik (2013) offered a new interesting finding showing that VIX is a very strong safe haven and should be preferred to gold. Baur and McDermott (2016) used daily data covering the period 1970–2013 of the MSCI World Index and S&P500 Composite Index returns. They tested the hedge and safe haven properties of gold, silver, the CRB Commodity Price Index, and trade-weighted Swiss franc and US dollar indices. The key result was that gold, and the US 10-year bond are strong safe havens, but gold is the riskier one. They also suggested that investors irrationally prefer gold to bonds during turbulent times because of the historical narrative of gold as a currency, store of value, and "safe asset".

In several recent papers, more sophisticated methods–including regime dependent models, copula models, and quantile regression models—have been applied, substituting, at least partly, the original Baur and Lucey (2010) and Baur and McDermott (2010)-type regressions. Flavin et al. (2014) applied Markov switching model, decomposing shocks into idiosyncratic and common shocks. Their sample consisted of daily US stock market data from the 1980–2012. They tested gold and the US 10-year and 1-year bonds as hedges and safe havens. Both gold and the 10-year bond classified as safe havens in the long run. During turbulent times, gold has higher expected returns, and its variance is insulated from contagious effects. However, it also has a higher risk compared to the 10-year bond. Flavin et al. (2014) suggested that the choice between these two safe haven instruments is based on the investor's risk preferences. Areal et al. (2015) tested safe haven properties of gold and two gold substitutes — a value-weighted portfolio of gold mutual funds and an index of US gold mining companies — with an AR-DCC-GARCH model. Their sample consisted of daily observations between 1976 and 2013. The key result was that gold is always a safe haven, but the gold proxies are only diversifiers. An interesting finding was that correlations between stock returns and returns of the gold proxies decrease during bear markets but not during extreme volatility periods. Liu et al. (2016) applied the copula approach to test the safe haven properties of gold and the US dollar trade-weighted index. Weekly data covered 2000–2013 and market coverage was the UK, German, Switzerland, the US, Canada, Australia, and Japan. Both gold and the US dollar serve as safe haven assets, dollar being the preferred asset. They also found that the US dollar and gold have positive tail dependence and should, consequently, never be used jointly. Bredin et al. (2017) focused on portfolio downside risk by using Value-at-Risk analysis. Their data covered 1980–2014, and they applied the analysis on daily, weekly, and monthly returns of the US S&P 500 Index. Bredin et al. (2017) confirmed the general conclusion that gold is a safe haven but only for a short period of time, about 15 days (Shahzad et al., 2022 confirmed the same result for the G7 countries with a DCC-GARCH model). However, when compared to the main line of research, Bredin et al. (2017) found that the safe haven property is much stronger than suggested by the other studies. Compared to several other studies, they highlighted more costs of hedging with gold. If gold is used as a safe haven asset, significant expected risk-adjusted return has to be sacrificed. An interesting finding was that the key of the safe haven property is the low kurtosis of the gold return distribution, not the skewness property. This contradicts the conclusions by Lucey et al. (2006) and Emmrich and McGroarty (2013), according to which the skewness is the key for protection.

While most of the research papers conclude that gold is a (strong) safe haven, but only for a period of about two weeks, there are some contradicting results regarding the length of the period. As already discussed above, Flavin et al. (2014) found gold to be a safe have in the long run. Bredin et al. (2015) focused on the US, UK, and German markets with a wavelet model. Their data covered 1980 — 2013. They found gold to be a hedge and, since the 1987 crisis, a strong safe haven for equities for long periods up to one year. Dee et al. (2013) reported the same result in the case of the Chinese stock markets. Michis (2014) also applied wavelet-based analysis to US, UK, and German data and found that gold is not a safe haven, but it is a diversifier in the long run for periods over 32 months.

The key result of the main line of research is that gold is a hedge and a safe haven in almost all developed countries at least for short horizons. Nevertheless, there is evidence challenging this conclusion. Ciner et al. (2013) did not find gold to be a safe haven for equities at all. Chen and Lin (2014) applied the traditional quantile regression approach to the US sectoral stock market indices with time series covering 1968–2002. They found that gold is a safe haven only in two of the four crisis periods (see also Baur and McDermott, 2010). This result may at least partially be related to the data period, which excludes the financialization period, the GFC, and the post-financialization period. This finding aligns with Bredin et al. (2015), who found that gold was a safe haven only after 1987. The second interesting point worth more research is the positive tail dependence between the returns of gold and stock markets during extremely severe stock market crisis. Evidence of this is reported in Baur and McDermott (2010), Hood and Malik (2013), Areal et al. (2015), Choudhry et al. (2015), Drake (2022), Iqbal (2017), Shahzad et al. (2017), Tiwari et al. (2018), Liu (2020), and Balcilar et al. (2020). In the case of the Chinese market, the opposite results were found by Beckmann et al. (2019), as well as Reboredo et al. (2021), who reported that spillovers between gold and stock returns are a positive function of the TED Spread and a negative function of VIX). The third point discovered by Chen & Lin (2014) is that gold is a safe haven only for the small-cap firms. A more negative view was offered by He et al. (2018), who concluded that gold is a hedge but never a safe haven. They applied a Markov switching model to US and UK data and found that gold is not a safe haven in the high or low volatility regime. Almost all research in this strand of literature focus on aggregate stock market indices, and the question of which type of companies and against which types of risks gold offers the hedge and the safe haven property is, with the exception of Chen and Lin (2014), neglected.

The behavior of gold's hedging and safe haven properties during crisis periods and on the far end of the loss distribution is a critical question. As discussed in the beginning of the previous chapter, gold is a safe haven only in some, but not in all financial crisis, and it loses its safe haven property on the far end of the loss tail (Baur and McDermott, 2010; Hood and Malik, 2013; Areal et al., 2015; Choudhry et al., 2015; Drake, 2022; Iqbal, 2017; Shahzad et al., 2017; Tiwari et al., 2018; Liu, 2020; Balcilar et al., 2020). One way to shed more light on this problem is to study the impact of investor stress and uncertainty on gold price behavior. Li and Lucey (2017) estimated the impact of the Economic Policy Index (EPU), the Financial Stress Index, stock market volatility (option market implied volatility indices), credit spreads, consumer price inflation, and national consumer confidence indicators on the safe haven properties of precious metals against stock and bond market risk. Their data covered eight developed markets and three emerging markets from 2004—2016. The results were heterogenous regarding markets and which of the precious metals are safe havens (and when). Changes of the EPU index correlate positively with the safe haven properties of precious metals, including, of course, gold. An increase in the EPU Index increases gold's likelihood of being a safe have against stock market falls in France, Japan and India, and against extreme bond market falls in the US, the UK, Germany, France, Italy, and India. Results regarding the impact of the Financial Stress Index showed the extreme (and interesting) heterogeneity of the impacts. For example, in the case of the US, the UK, and France an increase in the Financial Stress indicator decreases the likelihood of gold being a safe haven against stock market falls, but in the case of France and Italy, the impact has a positive sign. The same kind of heterogeneity characterizes results regarding the impact of other indicators, including stock market implied volatilities and credit spreads. Because of the rather limited amount of research focusing on this theme, it is too early to make strong conclusions, but with some caution, we can argue that uncertainty measures have, in most cases significant, impact on gold's safe haven property, and the sign of the impact is country specific (see, for example, Triki and Maatoug, 2021; Reboredo et al., 2021; Su et al., 2022a, 2022b).

Compared to the analysis regarding industrialized countries, results with emerging markets are even more mixed. It seems that the hedge and the safe haven properties of gold are highly country, sector, and maybe crisis specific. Chkili (2016) focused on the BRICS countries during 2000—2014 applying the AR-AGDCC-GJR-GARCH model and concluding that investors should include gold in their portfolios. However, in line with the results by Baur and McDermott (2010), Chkili (2016) classified gold as a diversifier and only sometimes a safe haven for BRICS. Bekiros et al. (2017) applied a sophisticated wavelet and copula-based approach to the BRICS equity markets and confirmed the findings by Chkili (2016): Gold is a diversifier during normal and turbulent times in the short and medium horizons but never a safe haven (see also Chkili, 2017, regarding the Islamic markets). Gürgün and Ünalmis (2014) report that gold is a strong safe haven for nine and a weak safe haven for six countries out of 28 tested countries between 1980–2013. Under the extreme crisis between 2008 and 2013, gold was a strong safe haven for 14 countries and a weak safe haven for seven countries (see also Tiwari et al., 2019; Adewuyi et al., 2019; Ali et al., 2020; Mensi et al., 2021; Mensi et al., 2021; Maghyereh and Abdoh, 2021; Naeem et al., 2021). Li and Lucey (2017) applied the original Baur and Lucey (2010) and Baur and McDermott (2010) regression approach to 11 countries (both developed and emerging), with daily data covering 1994–2016. In addition to gold, they tested the safe haven properties of silver, platinum, and palladium. The key result was that even though gold clearly serves as a safe haven in several cases, there is no unique safe haven asset serving all countries during all crisis periods. Beckmann et al. (2015) used monthly data from 1970–2012 of 18 individual stock markets, and five regional indices. They applied a smooth transition model. Gold serves as a hedge and a safe haven in most but not in all of the cases. In the STR models, the speed of adjustment differs significantly between countries, and especially in large, industrialized countries the speed of transition is very fast.

The COVID-19 crisis has offered new data to be analyzed. Salisu et al. (2021) analyzed the S&P 500 Composite Index, and 11 sectoral index returns with a sample covering 2.1.2019–27.7.2020, which is divided into pre-COVID and post-COVID periods. Analysis was based on CCC-GARCH correlations. The key results were that the optimal portfolio share of gold, as also the hedge effectiveness of gold, are significantly lower in the post-COVID period (see also Będowska-Sójka and Kliber, 2021). Gold is a safe haven for most of the sectors, but not for all. Akhtaruzzaman et al. (2021) focused on the S&P 500 Composite Index, Euro STOXX 50 Index, Nikkei 225 Index, and China FTSE A50 Index returns during period 31.12.2019–24.4.2020 with intraday data. The analysis was based on DCC-GARCH correlations. They confirmed the results by Salisu et al. (2021) regarding gold's safe haven property during the pre-COVID but not in the post-COVID period and that gold was an efficient hedge during the pre-COVID period. However, contrary to the finding by Salisu et al. (2021), Akhtaruzzaman et al. (2021)

found that the optimal portfolio weight of gold increased in the post-COVID period. Choudhuryet al. (2022) tested gold's safe have property for the US and Emerging stock markets during SARS, Ebola, ZIKA, Swine flu, and COVID-19 crises. The key result was that gold serves as a weak safe haven, but the US government bonds, and the Japanese government bonds offer better safer haven properties. Regarding a broad picture of how the gold price reacts to infectious diseases, Balcilar et al. (2022) and Bouri et al. (2022) offer evidence over a period of 700 years.

Results regarding gold vs. gold stocks are mixed (Daskalaki, 2021, offers an excellent survey of commodity stocks in general, including gold stocks, see also Conover et al., 2009; Areal et al., 2015; Reboredo and Ugolini, 2017; Troster et al., 2019). Baur et al. (2021) analyzed the safe haven properties of 609 individual gold mining companies and gold bullion on daily data covering 1997—2018. The key result was that during the most severe crises, the flight-to-quality goes from equities, including the gold mining shares, to gold bullion. However, during situations which could be classified as normal bear markets, flight-to-quality goes from stocks, excluding the gold stocks, to gold stocks and gold bullion. The GFC is an example of the most severe crisis, while the 9/11 did not cause sell-off of the gold mining stocks. The broader is the flight-to-quality that is, if a large number of different mining shares are bought, impact on the gold price is weaker. On the other hand, if only gold bullion, but not gold stocks are bought, the impact on gold price is stronger. In the latter case, the valuation of gold stocks may be too low compared to the price of gold.

The observation by Baur et al. (2021) that during the most severe crisis, there is a sell-off of shares of gold mining companies in exchange for gold bullion (or gold futures) raises an important point. It seems that this kind of behavior reflects a distrust for the whole financial market. Baur and McDermott (2016) analyzed why gold is a safe haven. Gold is not a risk-free asset like AAA-rated government bonds (if held for their full maturity). The flight-to-quality—from equities to gold—is actually an exchange of equity risk to gold price risk. Baur and McDermott (2016) offered several behavioral reasons for gold's role during crisis periods. First, there is a history-based narrative according to which gold is, or at least has been, a "safe asset" and a store of value. This may be partly related to the past gold standard periods. Another narrative is that gold is safe because it is a physical commodity, while the financial system is fragile. In addition, physical gold is shiny and beautiful and has a glorified image in investors' minds. Especially under stress, investors have a tendency to make decisions based on a very narrow information set. This leads to them choosing gold as the "safe asset". The short safe haven period reported by most of the studies may reflect decision-making based on the Prospect Theory and the related Disposition effect. There is profit taking of the gold positions after about two weeks. If the analysis by Baur and McDermott (2016) explains gold's role as a safe haven, then it is a kind of self-fulfilling prophecy, and it holds as long as investors believe in gold.

According to the above evidence, gold is a safe haven for most of the markets for short periods and according to some studies, only for some, but not all crises. One additional mechanism not discussed in academic literature is the squeeze in funding opportunities during financial crisis and the gold lease market (to my knowledge, the gold lease market is analyzed only in Lucey and O'Connor, 2013, and in Theal, 2009). During some crisis, there is a shortage of even short-term corporate funding. One way to obtain short-term funding in these kinds of situations is borrowing gold and selling it. This implies that briefly after the crisis starts, gold borrowing increases, the gold lease rate jumps, and there will be a significant increase in gold selling, pressing the price down. This fits, for example, to GFC (FIGURE 1[2]). The first essay in this thesis has an implicit connection to this topic via the interest rate connection it analyzes.

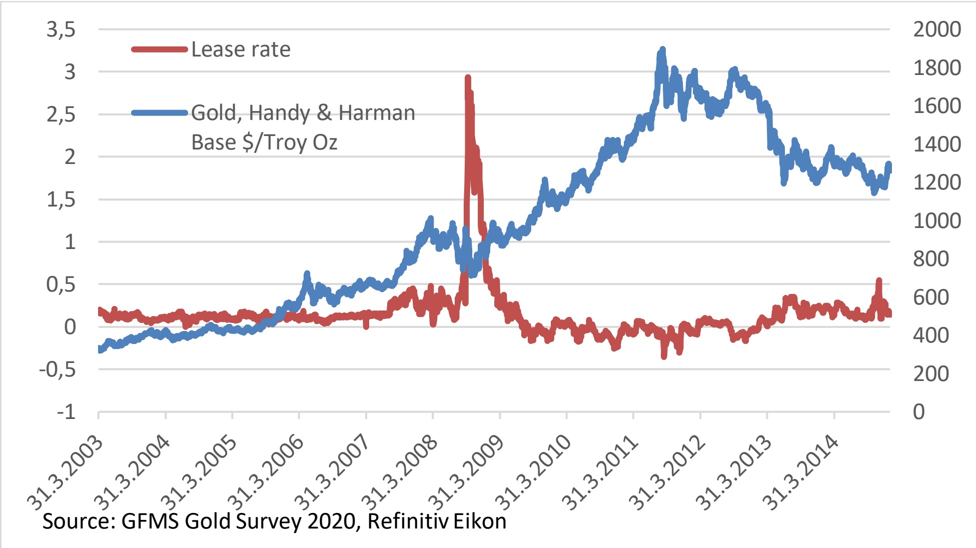

FIGURE 1 Gold price and the three-month gold lease rate during the GFC

1.1.2 Gold, oil, and stocks

The second essay in this thesis adds crude oil to the gold–stock nexus. While the role of gold is a combination of acting as a raw material to noncyclical industrial processes, and serving as an asset class, a diversifier, a hedge, and a safe haven, the role of crude oil is more heavily tied to aggregate economic activity. This, of course, complicates the connection between crude oil and stock returns, not to mention the connection between crude oil and gold. In the following sections, I first briefly discuss the research on the impact of crude oil price changes on stock returns, and then I will focus on the dynamic connectedness between crude oil, gold, and stock returns. The number of studies in this strand of literature is huge, and results are heterogenous depending on country and industry characteristics. In the following, I limit the discussion only to the research most relevant for the focus of this thesis.

2 The time frame in FIGURE 1 ends in 2015, because of end of public fixings for the Gold Forward Offered Rate (GOFO) and the gold lease rates.

1.1.2.1 Oil and stock markets: fundamentals

Research estimating the impact of oil price shocks or, in most of the cases, the impact of oil price changes on stock returns is voluminous starting from the 1990s. The origin this research strand is the *discounted cash flow model,* and it is closely related to research on the impact of oil price changes on macroeconomic activity (Smyth and Narayan, 2018, and Degiannakis et al., 2018, offer excellent and up-to-date surveys).

The discounted cash flow model gives five channels through which oil and equity prices are connected (Jones and Kaul 1996; see also the discussion in Smyth and Naraya 2018, and in Degiannakis et al., 2018). First, if oil price increases (decreases), the production costs of non-oil producing firms increase (decrease), and, and thus the expected corporate cash flows decrease (increase). Second, oil price increase has an impact on inflation and inflation expectations and consequently on interest rates and the discounting factor of the discounted cash flow formula. Expectations regarding the future monetary policy are tied to this inflation channel hypothesis. While the above two channels imply a negative relationship between oil price change and stock returns (at least for non-oil producers), the impact through the third channel is not clear. Changes in oil price or in oil price volatility have an impact on corporate risk premia, which is part of the discounting factor in the discounted cash flow formula. This is the case especially in a high or strongly surging oil price regime. In addition to the above three direct channels, there are two indirect channels. When oil price increases, it has a negative impact on all or at least on most of the commodity and service prices. This implies a decrease in consumers' purchasing power, which decreases aggregate demand and aggregate output, which hits the stock market. On the other hand, this can be interpreted as a worsening of the terms of trade for an oil-importing country and an improvement of the terms of trade for an oil-exporting country. Degiannakis et al. (2018) called this the output channel. The fifth channel works especially in oil-exporting countries. An oil price increase causes a wealth transfer from the oil-importing countries to the oil-exporting countries, which increases aggregate output and government incomes in the oil-exporting countries, either via taxation or directly, if the government owns oil-exporting companies. This usually leads to a growth in government expenditure, which increases domestic companies' expected cash flows and stock price. Degiannakis et al. (2018) called this the fiscal channel.

1.1.2.2 Oil and stock prices

Empirical research on the oil–stock nexus focuses on the discounted cash flow hypothesis with VAR, VECM, TVP-VAR and Markov switching models. Most of the studies found a significant negative relationship between oil price changes and stock returns in oil-importing countries (for example, Jones and Kaul, 1996, in the case of the US, Canadian, the UK, and Japanese markets, Sadorsky, 1999, in the case of the US markets, Papapetrou, 2001, in the case of Greek markets, Ciner, 2001, in the case of the US markets, Miller and Ratti, 2009, in the case of the US, the UK, German, French, Italian, Canadian markets, Park and Ratti, 2008, in the case of 11 European markets, Filis, 2010, in the case of Greek markets, Ciner, 2013, in the case of the US. markets, to mention a few).[3]

In the case of oil-exporting countries the result is the opposite: An increase in the crude oil price has a positive impact on stock prices and vice versa (Bjorland, 2009; Hammoudeh and Choi, 2006; Park and Ratti, 2008; Mohanty et al., 2011; Arouri et al., 2011; Arouri and Rault, 2012; Gil-Alana and Yaya, 2014; Smyth and Narayan, 2018; Siddiqui et al., 2020, to mention a few). Saudi Arabia is a well-known exception of this positive correlation (Arouri et al., 2011; Arouri and Rault, 2012; Ajmi et al, 2014).[4]

Applications of Markov switching models and quantile regression models shed more light on the oil–stock nexus. For example, Lee and Chiou (2011) applied a two–regime Markov switching model on the S&P 500 Index returns, finding that the negative impact of oil price change on stock returns holds only in the low (oil) volatility regime (see also Reboredo and Rivera-Castro, 2014). Chang and Yu (2013) reported that oil shocks affect the S&P 500 Index returns positively only in the high (stock) volatility regime and negatively in the low volatility regime (see also Balcilar et al., 2015, with somewhat differing results). In addition, for example Mokni (2020) showed with a time-varying quantile regression model, that during the GFC in the US and some years after it (2008–2015), in the lowest and middle quantiles, an oil price increase pushes stock returns down, and a decrease in oil price increases stock returns. This should imply, at least on average, a negative correlation between oil price changes and stock returns during this period.[5]

1.1.2.3 Oil price shocks and stock prices

The above-cited research examines the relationship between oil price changes and stock returns. Oil price changes are measured simply as price changes (usually logarithmic differences) or as shocks to a VAR or VECM system. However, maybe an even more interesting question is how stock returns react to oil market shocks caused by drastic, major changes in either the demand or supply of oil. The seminal articles by Kilian (2009), Kilian and Park (2009), and Hamilton (2009a,

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3 Sectoral- and firm-level research is beyond the scope of this thesis. Good examples of that strand of research are Huang et al. (1996), Sadorsky (2001), Lee and Ni (2002), El-Sharif et al. (2005), Hammoudeh and Li (2005), Boyer and Filion (2007), Kilian and Park (2009), Gogineni (2010), Nandha and Faff (2008), Nandha and Brooks (2009), Arouri and Nguyen (2010), Elyasiani et al. (2011), Narayan and Sharma (2011), Moya-Martínez et al. (2014), Lee et al. (2012), Huang et al. (2015), Zhu et al. (2016), You et al. (2017), and Waheed et al. (2017) at the sectoral-level and Huang et al. (1996), Boyer and Filion (2007), Scholtens and Wang (2008), Naryan and Sharma (2011), Ciner (2013), Phan et al. (2015), Tsai (2015), Gupta (2016), Waheed et al. (2017), Ma et al. (2019), Zhu et al. (2019), and Nguyen et al. (2020) at the firm-level, to mention a few.

4 The focus of this thesis is on developed markets. However, for an interested reader Smyth and Naraya (2018), and Degiannakis, et al. (2018) offer excellent surveys and Basher and Sadorsky (2006), Nandha and Hammoudeh (2007), Aloui et al. (2012), Reboredo and Rivera-Castro (2014), You et al. (2017), Yildirim et al. (2019) and Stoupos and Kiohos (2021) are good examples of work in this field.

5 For other works with the quantile regression technique, see Lee and Zeng (2011), Zhu et al. (2016), Nusair and Al-Khasawneh (2018), Tchatoka et al. (2019), Chang et al. (2020), Wang et al. (2020), and Dawar et al. (2021).

2009b) identify different types of oil price shocks having specific impacts on stock markets and the macroeconomy. Kilian and Park (2009) divided oil price shocks into three types. Changes in global aggregate economic activity cause changes in the demand for oil. This shock is called an aggregate demand shock. The second type of shock is oil market specific change in demand for oil—a precautionary demand shock (Kilian and Park, 2009). For example, precautionary demand increases oil price if there is uncertainty of the future supply of oil relative to its demand. Such a situation could be caused by an unexpected rise in demand or by an unexpected decline in supply, or both. One typical case to be classified as a precautionary demand shock (also called a speculative demand shock) would be an increase in political tensions, for example in the Middle East, such as the Arab Spring, which increases uncertainty regarding the future oil supply. Under these kinds of circumstances, precautionary demand for oil surges as a reaction to the expected future oil scarcity. This is also reflected in the convenience yield. The third type of oil price shock is a shock caused by the supply of oil. Kilian and Park (2009) called this an oil supply shock. Kilian and Murphy (2014) extended the model to include a fourth shock—the residual oil price shock—which is caused by other reasons not accounted for by the above three shocks (for example, shocks caused by changes in climate, changes in inventory technology, and political decisions such as the release of the US Strategic Petroleum Reserve).

Kilian and Park (2009) analyzed the impact of oil price shocks on the US stock market. Their monthly data covered 1973–2006, and the analysis was conducted with VAR models. Stock market return was measured by the CRSP value-weighted stock portfolio. The key results were the following. First, supply-side shocks are less important and have only a minor impact.[6] Second, precautionary demand shocks have a very sharp and strong negative impact on the stock returns. Furthermore, regardless of the cause of the precautionary demand shock—such as rise of political tensions in the Middle East, an outbreak of a war increasing geopolitical tensions, or a terror attack having possible serious global consequences—it transfers to the oil market very sharply and strongly. Third, aggregate demand shocks have a positive impact on the stock market returns. Compared to the precautionary shocks, the impact is not as sharp, but its impact lasts much longer. Later, several other studies confirmed the Kilian and Park (2009) findings with, of course, some country-specific variations (Apergis and Miller, 2009; Basher et al., 2012; Abhyankar et al., 2013; Gupta and Modise, 2013; Wang et al., 2013; Cunado and Carcia, 2014; Güntner 2014; Kang et al., 2015; Sim and Zhou, 2015; Kang et al., 2017; Zhang 2017; Zhu et al., 2017; Li et al., 2017; Yildirim et al., 2019; Escobari and Sharma 2020; Das et al., 2020; Broadstock and Filis, 2020). Additional results are presented, for example, in Zhu et al. (2017) who showed that oil market shocks have an impact on stock returns only in the high volatility regime. Precautionary demand shock has a negative impact on stock returns and a demand shock a positive impact.

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6 Results regarding the impact of oil supply shocks are somewhat mixed; see, for example, Kilian and Park (2009), Gupta and Modise (2013), Kilian and Murphy (2014), Cunado and Gracia (2014), Kang et al. (2016), Antonakakis et al. (2017), Li et al. (2017), and Huang and Mollick (2020).

1.1.2.4 Dynamic correlations and copula functions: oil, gold, and stocks

The above-cited research suggests that the oil–stock and gold–stock nexus is intricate, varying in time, regime dependent, asymmetric, and probably bidirectional. A quite recent strand of research—including the second essay in this thesis—attacks this time-varying relationship with methods based on dynamic conditional correlations, copula-based methods, and other dynamic measures of connectedness.

Ewing and Thomson (2007) offered the first dynamic correlation analysis, followed by Bhar and Nikolova (2010), who focused on the Russian market, and Cifarelli and Paladino (2010), focusing on oil price changes, exchange rates, and stock returns with a CCC-GARCH model. Choi and Hammoudeh (2010) were the first to apply a DCC-GARCH model on Brent and WTI crude oil, copper, gold, silver, and the S&P 500 Composite Index.

Good examples of the voluminous research on the oil–stock dynamic correlation are Choi and Hammoudeh (2010), Filis et al. (2011) and Chang et al. (2013), Arouri et al. (2011), Creti et al. (2013), Degiannakis et al. (2013), Creti et al. (2014), Sadorsky (2014), Mensi et al. (2015), and Basher and Sadorsky (2016), Pan et al. (2016), and Singhal and Ghosh, (2016), to mention a few. The second essay in this thesis belongs to this strand of research, although it expands the problem setup to also cover gold. Although there is some variation in the results, we can draw some general conclusions. First, oil–stock correlations vary significantly in time. Second, slightly surprisingly, there are no significant systematic differences between oil-stock correlations of oil-exporting and oil-importing countries (see especially Filis et al., 2011). Oil–stock correlations are positive most of the time, and most of the correlations dip drastically during financial crises and around 2003, which coincides with an over 32% oil price slump. With only a few of exceptions, correlations have a slight positive trend during the 2003–2008 strong bull market, during which high economic growth, especially in the emerging economies, caused an exceptional oil price surge (regarding the nature of the oil price surge during that period, see Kilian and Hicks, 2013, and Kilian and Murphy, 2014). During the GFC oil–stock correlations dropped and then jumped in 2009 to drop again during the European debt crisis.[7]

The behavior of the dynamic correlations and optimal hedge ratios are at least partially explained by the major economic events and regimes (for example, Chkili et al., 2014;[8] see also Filis et al., 2011), and economic and political uncertainty (for example, Badshah et al., 2019). For example, Chkili et al. (2014) reported interesting results. They tested the impacts of five major financial and geopolitical events on the oil–stock correlations: the first Gulf War in 1991, the Asian financial crisis in 1997, the Russian and Brazilian economic crisis, the 9/11 terrorist attack, and the GFC. The first Gulf War, the 9/11 attack, and the GFC

[7] The connection between oil price changes and sectoral stock returns is heterogeneous and time varying as should be expected. Degiannakis et al. (2013), Broadstock and Filis (2014), Dutta (2018), Hamdi et al. (2019), Ma et al. (2019), and Mensi et al. (2022) are examples of sectoral research.

[8] The first essay in this thesis applies the same approach as Chkili et al. (2011), but on gold–stock return correlations.

have a significant negative impact on the oil–stock correlation, and all five events have a significant negative impact on the volatility of the correlations. Badshah et al. (2019) tested with dynamic conditional commodity–stock correlations the impact of economic policy uncertainty on commodity–stock return correlations. Regarding crude oil and gold, they reported new results revealing that economic policy uncertainty increases the oil–stock correlation and decreases the gold–stock correlation. The latter result aligns in with Troster et al. (2019), Triki and Maatoug (2021), and Su et al. (2022b).

One line of research estimates the impacts of oil price shocks, as defined by by Hamilton (2009a; 2009b), Kilian (2009), and Kilian and Park (2009), on dynamic oil–stock correlations. Filis et al. (2011) were the first in this strand of research. The key results were as follows i) the aggregate demand-side shocks increase oil–stock correlations positively, ii) the precautionary demand shocks push correlations into the negative direction, and iii) the supply-side shocks have no impact on the correlation structure (Filis et al., 2011). However, Filis et al. (2011) identify the shocks on an ad hoc basis, which may simplify things too much. Broadstock and Filis (2014) strictly followed the Hamilton (2009a, 2009b), Kilian (2009), and Kilian and Park (2009) method to estimate the dynamic correlations between oil price shocks and stock market returns. Their results revealed that the dynamic correlations have been time varying. During the financialization and high Chinese lead growth period (2003–2008) the correlation between aggregate demand shock and the U.S stock returns were positive (both oil and stock prices surge) and during the GFC period, the aggregate demand shock and oil market specific shock correlated strongly (and positively) with the US stock market returns.[9]

Compared with the above, surveyed research on the connections between oil price changes (or oil price shocks) and stock returns research on the connections between gold and oil are somewhat scarce. To my knowledge, Melvin and Sultan (1990) were the first to start this research strand. They reported a positive relationship between oil and gold price changes. Melvin and Sultan (1990) argued that the underlying reason is that when oil price surges, the export revenue of oil-exporting countries increases, and part of that revenue stream is invested in gold, which acts as a portfolio diversifier. Narayan et al. (2010) confirmed the

[9] One important line of research is the application of copula functions to estimate nonlinear and tail dependence between the oil price changes and stock returns. Pioneers in this strand of research are Geman and Kharoubi (2008), Zohrabyan (2008), Suckharoen et al. (2014), and Mensi et al. (2017). Further examples of work in this line are Aloui et al. (2013) focusing on the CEE countries, Nguyen and Bhatti (2012) focusing on China and Vietnam, Nguyen et al. (2020), focusing on Vietnamese market, Li and Wei (2018) on the Chinese market, Jammazi and Reboredo (2016) on the global market (MSCI World Index), Wen et al. (2012), and Yu et al. (2020) on Chinese and the US market, Liu et al. (2019), and Ji et al. (2020) on BRICS markets, Avdulaj and Baruknik (2015), Aloui and Aïssa (2016), and Gong et al. (2022) on the US market, Fenech and Vosgha (2019), and Mokni and Youssef (2019) on the Gulf Corporation Council stock markets, Shahzad et al. (2018) on Islamic Markets, Reboredo and Ugolini (2016) focusing on five developed markets and the 5 BRICS markets, Kayalar et al. (2017) on 10 markets including both developed and emerging markets, Hamma et al. (2019), focusing on 11 markets including both oil-exporting and oil-importing countries, and developed and emerging economies, to mention a few.

positive relationship. They also provided an additional second mechanism for the result. When oil price increases, it feeds inflation, and investors buy gold as a hedge against inflation (see also Tiwari and Sahadudheen, 2015). Reboredo (2013) offered a third channel through which oil and gold prices are connected. Increasing oil prices have a negative impact on economic activity (at least in the oil-importing countries at the end of a high growth period), causing investors to hedge against a financial market downturn by buying gold. Reboredo (2013) applied a copula approach, revealing that oil and gold price changes have a significant average positive dependence. However, on the left tail, there is no dependence, implying that gold may act as a hedge or a weak safe haven for oil during bear markets (for other examples of early research, see Sari et al., 2007, Soytas et al., 2009, Le and Chang, 2011, Kumar, 2017, Kang et al., 2017, Kanjilal and Ghosh, 2017, to mention a few, Hernandez et al., 2019, Salisu and Adediran, 2020, Mensi et al., 2020, Rehman and Vo, 2021, Youssef and Mokni, 2021, Wang et al., 2022, Tanin et al., 2022, and Cui et al., 2023 are examples of more recent work on the safe haven property of gold for oil).

1.1.3 Determinants of bank profitability

Conventional wisdom is that when interest rates fall, banks' key income source—the spread between loan and borrowing rates (the NIM)—falls. In the case of zero or negative interest rates, the fall in incomes may be extreme. When investors expect the end of a bull market, they change portfolio structure from stocks to safer assets, especially to government bonds and gold. The logic in banking is the same—to search alternative ways to do business: diversify into sources of noninterest income, increase, if possible, wholesale funding to gain from negative interest rates, or increase the share of higher risk clients in the loan portfolio.

1.1.3.1 Research on bank profitability before the era of negative interest rates

Up to the 21'st century, both the US and the European banking environments were strongly geographically segmented. In the US banking was restricted to the state level, and banks were not allowed to have business across the state border until the implementation of the 1994 Riegle–Neal Interstate Branching Act in June 1997. One major step in changing the competitive environment was also the Gramm–Leach–Bliley Act in 1999, which repealed major parts of the 1993 Glass-Steagall Act and removed the separation of the banking and investment banking and trading operations. In Europe, the European Economic Community (EEC) adopted the single banking license in December 1989, allowing a bank to operate inside the entire EEC area with a single license granted by any of the member countries. However, the market environment changed very slowly adapting to the European integration process first, the European Union (EU) in 1993, and later enlargements of the union. A major step was the 1999 establishment of the European Monetary Union. At the same time as the above-discussed processes, financial markets developed significantly and integrated globally. For that reason, research on banking has to be divided into early research and modern research. The dividing point in time is somewhere near the Millennium.

Early research focused on the impact of competition (actually, a lack of competition—market concentration) on bank behavior. Good examples of that structure-conduct-performance (SCP) research are Liang (1989), Ho and Saunders (1981), Allen (1988), Molyneux and Thornton (1992), Angbazo (1996), Saunders and Schumacher (2000), Maudos and de Guevara (2004), and Staikouras and Wood (2004), and the literature cited in the articles, Menicucci and Paolucci (2016), present a comprehensive survey of the early research. The key results from the early research are as follows. The more segmented the market is geographically or by activity, the more market power banks have, which is priced in larger interest rate margins. Credit risk and interest rate risk, the latter measured by the volatility of market interest rates, widens the margin between loan and deposit rates (Sauders and Schumacher, 2000; Maudos and de Guevara, 2004). While the conventional analysis of early research reports that higher concentration measured, for example, by the Lerner or Herfindahl Index predicts higher net interest margin, for example Staikouras and Wood (2004) did not find any evidence in favor of this SCP hypothesis. Staikouras and Wood (2004) reported that lower loan-to-assets ratio, a higher difference in size between interest sensitive assets and interest sensitive liabilities, and lower credit risk imply higher profitability. In addition, Staikouras and Wood (2004) argued that macroeconomic and market factors have a higher impact on bank profitability than was understood at that time (see also the important studies by Albertazzi and Gambacorta, 2009; Adrian et al., 2010; Detragiache et al., 2018, on the impact of business and financial cycles). Other topics in the early research are benefits of diversification (discussed below later) and the impact of a capital buffer.

The results of empirical banking research depend on competitive environment, regulation, financial market development, and stages of macroeconomic and financial cycles. Because of that, research using data after the European monetary and financial market integration and after the cross-state banking and overturning of the Glass–Steagall Act gives us more relevant information than the earlier research. Moreover, research methods evolved significantly after the Millennium, and sophisticated panel regression techniques, especially dynamic models following the Arellano–Bond approach, gained popularity. Country coverage in this strand of research is wide; while some studies focus only on one specific country, some use very wide country coverages, including both developed and developing countries (for the country coverages, see, for example, Tan, 2016, Table 1, and Petria et al., 2015). In the following, we discuss only those factors relevant to the topic of the third essay—the impact of negative interest rates on bank profitability.

One of the key themes in the third essay is impact of bank size on profitability. Research on this topic before the negative interest era is voluminous. The general conclusion is that larger banks are more profitable, because they can benefit from economies of scale and better diversify their loan portfolio, and usually have better market access (for example, Alp et al., 2010; Athanasoglu et al., 2008;

Gul et al., 2011; Saeed, 2014; Menicucci and Paolucci, 2016). However, the results are somewhat mixed, and some studies report the opposite results (Sufian and Chong, 2008; Kosmidou et al., 2008; Sufian and Habibullah, 2009; Dietrich and Wanzenried, 2011; Trujillo-Ponce, 2013; Tan, 2016). These opposite results may be explained by differences in country coverage, but it is also possible that the impact is nonlinear or dependent on the economic regime. For example, Dietrich and Wanzenried (2011) reported that in Switzerland, small and large banks were more profitable than the middle-sized banks before the GFC, but this result turns to the opposite during the crisis. Results by Petria et al. (2015) suggested that the measure used to measure profitability may also have an impact on the results.

The second factor of interest for the third essay is funding structure. This is usually measured as the ratio of deposits to total assets. Empirical results before the GFC imply that the higher the ratio of deposits, the more profitable the bank is (for example, Naceur and Goaied, 2001; Clayes and Vander Vennet, 2008; García-Herrero et al., 2009; Trujillo-Ponce, 2013; Menucci and Paolucci, 2016; Maudos, 2017). The logic behind this is straightforward: When deposit rates are below market rates, and there is no scarcity of deposits, deposit funding is preferable.

The third core factor in analyzing the impact of negative interest rates is the role of bank's mix[10]. It is usually measured with the ratio of interest income to total income (for example, Dietrich and Wanzenried, 2011), with the Herfindahl–Hirschman Concentration Index of income mix, or some other similar indices (see, for example, Trujillo-Ponce, 2013, p. 573, Equation (1)), or with the ratio of noninterest income to total revenue (for example, Tan, 2016). The early studies focused on bank geographical diversification, bank mergers with insurance companies, and bank diversification to real estate. The first study analyzing bank income diversification between different revenue sources is DeYoung and Roland (2001). Their key result was that an increase in fee-based business increases income volatility without a compensating increase in earnings. DeYoung and Roland (2001) found no evidence in favor of the positive impact of diversification on bank profitability. Demirgüç-Kunt and Huizinga (1999) results already showed a negative impact of income diversification, although their focus was wider than just diversification. After DeYoung and Roland (2001) and Demirgüç-Kunt and Huizinga (1999), clear evidence of the negative impact of diversification on profitability was reported by many studies (Stiroh, 2004; Stiroh and Rumble, 2006; Leaven and Levine, 2007; Mercieca et al., 2007; Goddard et al., 2008; Berger et al., 2010; Doan et al, 2018; Brunnermeier et al., 2020). The logic behind the negative impact is that noninterest incomes—fees, trading revenue, and other sources of noninterest incomes—are more volatile, but do not necessarily offer higher returns than interest income business. In addition, Brunnermeier et al. (2020) reported that noninterest income is positively related to a bank's tail risk and interconnectedness risk.

Although many studies report the negative impact of diversification on bank profitability, several researchers report the opposite result (for example, Saunders and Walter, 1994; Lown et al., 2000; Staikouras and Wood, 2004; Elsas

[10] Of course, also funding structure is also a part of the business mix.

et al, 2010; Dietrich and Wanzenried, 2011; Meslier et al., 2014; Petria et al., 2015; Doumpos et al., 2016; Li et al., 2021). The results by Li et at. (2021) even show that during the COVID-19 pandemic, diversification did not only increase returns, but it also decreased risk. Lee, Yang and Chang (2014) noted that relationship between diversification and profitability is more complicated than previous research has shown. Higher noninterest income raises banks' risk and decreases profitability in developed economies but decreases risk and increases profitability in developing countries. Lee et al. (2014) also reported significant differences in the impacts of diversification based on whether the bank is a savings, cooperative, commercial, or an investment bank (see also, for example, Junttila and Viitala, 2023). Kim et al. (2020) showed that the relationship between bank stability and diversification is U-shaped. According to this U-Shape, there is an optimal degree of diversification. Kim et al. (2020) also reported that during the GFC more diversified banks made the largest losses.

Internal factors alone are not sufficient to explain the determination of bank profitability. Studies have used several macroeconomic and financial market factors. For us, the most important factors are market interest rates and the term structure of interest rates. Flannery (1981) and Hancock (1985) were the first to study the relationship between interest rates and bank profitability. While Flannery found no impact of market interest rates on bank profitability, Hancock (1985) found a significant positive impact. Alessandri and Nelson (2015) examined the impact of the interest rate level and slope of the yield curve on bank profitability. Their key result was that the impact depends on the horizon. In the long run, both the interest rate level and the slope of the yield curve have a positive impact on bank profitability (regarding the yield curve impact, see also, for example, Adrian et al., 2010; Aydemir and Ovenc, 2016, and regarding the impact of the interest rate level in the long run, see also Albertazzi and Gambacorta, 2011; Borio et al., 2015; Aydemir and Ovenc, 2016; Busch and Memmel, 2017; O'Connell, 2023). However, in the short run, the interest rate level has a negative impact. Kohlscheen et al. (2018) reported that the impact of long maturity rates on bank profitability are positive, while short maturity rates have a negative impact. This confirms the Alessandri and Nelson (2015) result regarding the yield curve impact. Results regarding the impact of interest rates in the short run are mixed, probably because of differences in the sample periods (for example, Hancock, 1985; Demirgüc-Kunt and Huizinga, 1999; Albertazzi and Gambacorta, 2009; Trujillo-Ponce, 2013; Aydemir and Ovenc, 2016). Regarding the impact of the slope of the yield curve, Dietrich and Wanzenried (2011) reported an important result revealing that the impact changes depending on economic conditions. Before the GFC, the impact of the slope of the yield curve on bank profitability was positive, but it was insignificant during the crisis.

The asymmetry between short, and long-run reactions of bank profitability to interest rate changes is caused by bank pricing behavior. Gambacorta (2008) showed with Italian data that in the short-run, banks change deposit and loan rates by the same amount as the market interest rates. However, in the long run banks change the loan rate significantly more than they change the deposit rates.

In addition, Gambacorta and Iannotti (2007) reported that banks' reaction to changes in monetary policy is asymmetric so that banks change deposit rates faster in the case of monetary policy tightening.

1.1.3.2 Bank profitability under negative interest rates

The period starting from the GFC and ending in mid-2022 was very exceptional. Monetary policy was very expansionary with low or negative interest rates and huge Quantitative Easing (QE) programs. Specially, the period from 2012 to 2022 with zero interest rates in the US and negative rates in Europe is unprecedented. Figures 2a and 2b present government bond yields in the US and Germany (Germany accurately presents the European interest rate behavior). Based on the survey presented above, low interest rates for a long period should imply a low NIM and low profitability for banks. Furthermore, the yield curve flattened significantly during that period and the impact was amplified because banks did not allow deposit rates to be negative in Europe (at least not the rates applied for households). However, the yield curve had been even flatter during some periods in history, so this would not have been so exceptional if it were not combined with zero rates in the US and negative interest rates in Europe.

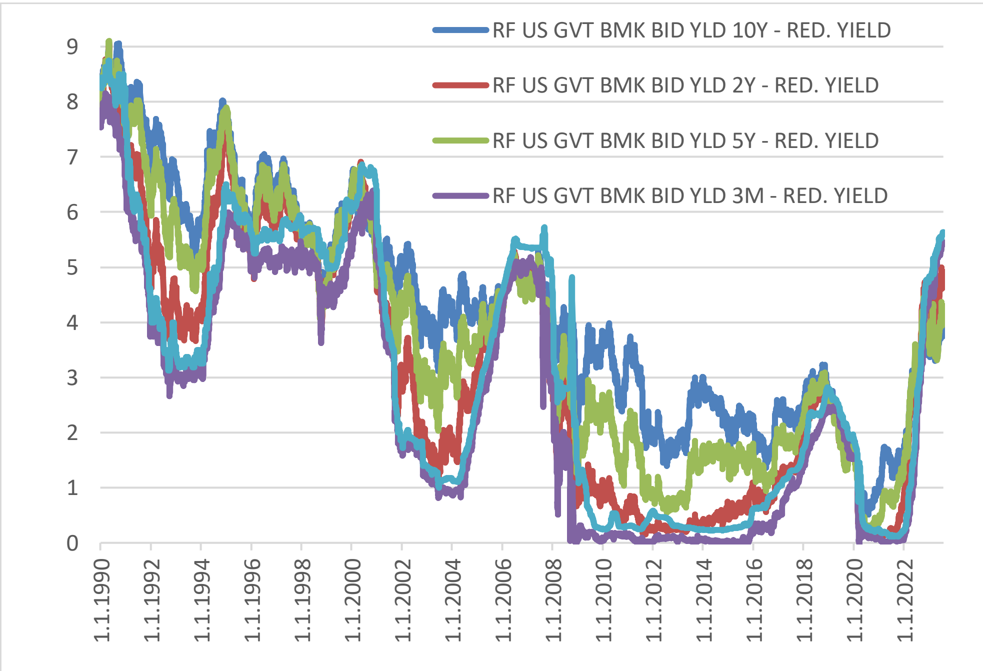

FIGURE 2a. US interest rates (Source: Refinitiv Datastream)

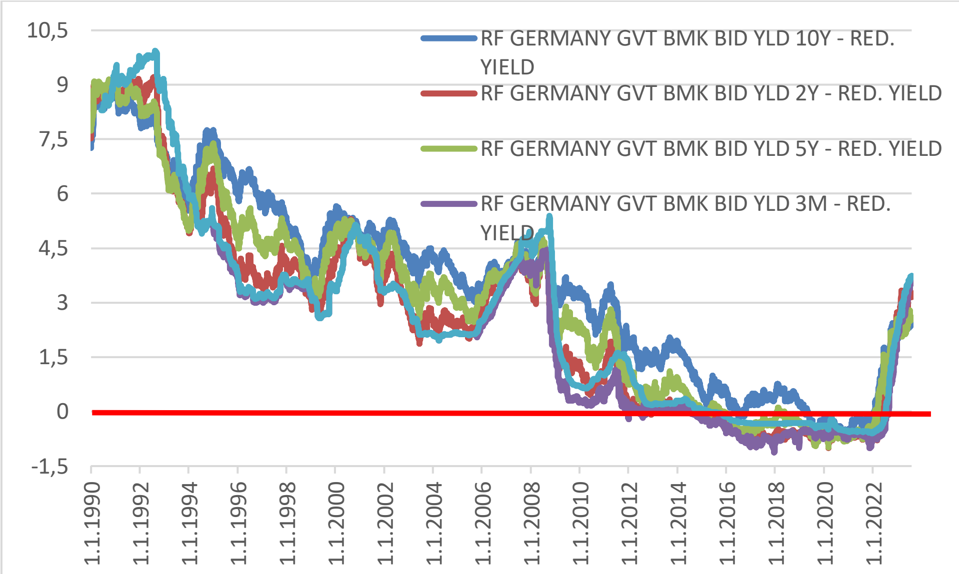

FIGURE 2b. German interest rates (Source: Refinitiv Datastream)

One of the first studies examining the impact of zero rates on bank profits is Bikker and Vervliet (2017). They used US data consisting of 3,582 individual banks from the period 2001–2015. As measures of profitability, they used NIM, return on assets (ROA), return on equity (ROE), and profit reported in banks' income statements. Explanatory variables consisted of the conventional set of bank-specific variables and macroeconomic variables, including short-maturity interest rate (three-month money market rate; a square of the short-maturity rate was also included) and long-maturity interest rate (10-year government bond yield). The model was estimated as a dynamic GMM model following the Arellano–Bond GMM approach. The impacts of the short-maturity interest rate on NIM, ROA and ROE are positive, and the quadratic term has a negative sign. This implies that changes in the money market rate have a stronger impact when interest rates are low. The impact of the long-maturity rate is slightly surprising. On the ROE and profit (measured as in the income statement), the impact is significant and negative, on the NIM the impact is significant and positive, and the impact on the ROA insignificant. These results reveal that when long-maturity rates fall, the NIM falls, but the profit (as reported in banks' income statements) and the ROE increase and the ROA is unchanged. This suggests that banks compensate for the fall in interest rates (and the NIM) by changing the business mix to increase non-interest incomes.

Borio et al. (2017) approached the same problem as Bikker and Vervliet (2019) with slightly older data, covering the years 1995–2012 and 109 large international banks from 14 countries. The results regarding the impact of the short-term interest rate align with Bikker and Vervliet (2019); the impact on profitability (ROA) is positive and strongest when interest rates are low. Instead of testing the impact of a long-term interest rate, Borio et al. (2017) tested the impact of the slope of the yield curve and found it to be significant and positive. In addition, the slope of the yield curve and the level of short-term interest rates are positively correlated. The above results imply that low interest rates and a flat yield curve put pressure on bank profitability.

Claessens et al. (2018) analyzed the impact of low interest rates on bank profitability with data consisting of 3,385 individual banks from 47 countries from the period 2005–2013. Profitability was measured with the NIM, interest income margin, interest expense margin, and ROA; the choice of bank-specific and macroeconomic variables follows the main line of this research strand. The interest rate variable was a three-month government bond yield, and the slope of the yield curve was measured with the spread between 10-year and three-month government bond yields. In addition, a country is classified to be either in a low or high interest rate environment based on the level of the short-maturity interest rate during the year in concern. The short-term interest rate has a positive impact on the NIM, and the impact is almost two times stronger in the low interest rate regime. Term spread has a significant positive impact in the low-rate regime, and marginally positive, but not significant in the high-rate regime. For the ROA the short-term interest rate has a marginally positive, but insignificant impact. The results regarding the impact of the slope of the yield curve are interesting: The only statistically significant impacts are a negative impact in the high-rate regime on the largest banks and a positive impact on the smallest banks in the low-rate regime. When interest rates the fall, the NIM falls, and there is an additional marginal impact from the flattening of the yield curve. However, in the high-rate regime, the ROA of the largest banks increase, possibly because of the rise in bond value. On the other hand, in the low-rate regime, the ROA of the small banks fall, probably because of the lower or non-existing business diversification.

Probably the most influential of more recent studies is Lopez et al. (2020), who tested the impact of low and negative interest rates on bank profitability using the data of 5,200 individual banks from 27 advanced European and Asian countries from the period 2010–2017. Lopez et al. (2020) compared the impact of negative interest rates against low, but positive rates (rates between zero and 1%) with a dummy variable technique (dummy, which obtains a value of 1, when the rate is negative). Banks are divided into large and small banks and high-deposit and low-deposit banks. The net interest income of small, high-deposit, and low-deposit banks fall significantly when interest rates are negative (this is also the case with the large banks, but the result is not statistically significant). The impact is strongest for the low-deposit banks. However, net noninterest incomes of large, small, and low-deposit banks increase statistically significantly under the negative interest rate era (the coefficient of the high-deposit banks is not statistically significant). In the case of large and low-deposit banks, this increase in noninterest incomes more than compensates for the decrease in net interest incomes. The ROA of large banks increases statistically significantly; in the case of other bank subgroups, coefficients are positive but not significant. The compensating increase in noninterest incomes comes instead of fees from other noninterest incomes (that is, from an increase in the value of securities the bank holds and an increase in other incomes from securities trading). This effect is (positive and) statistically significant for all subgroups, but strongest for small banks and low-deposit banks. Specially, the reaction of low-deposit banks is about 10 times stronger than in the large bank or high-deposit bank subgroups. The general conclusion by Lopez et al. (2020) was that the impact of negative interest rates on bank profitability has been rather mild, and particularly small and low-deposit banks have met the regime of negative rates with success.

The key result of the above discussed research is that at the aggregate level, negative interest rates decrease the NIM, but this is at least compensated for, by the increase in noninterest incomes. In addition, the impact of negative rates is stronger than the impact of low but positive rates (Bikker and Vervliet, 2017; Borio et al., 2017; Claessens et al., 2018; Lopez et el., 2020; Demilrap et al., 2021). These results are confirmed by several studies, which also offer important additional insights. Scheiber et al. (2016) and Madaschi and Pablos Nuevo (2017) confirmed that negative rates have not caused a decline in bank profitability in Denmark, Sweden, and Switzerland. According to their results, banks' NIM would not have declined during negative rates, because of savings in funding costs. Both Scheiber et al. (2016) and Madaschi and Pablos Nuevo (2017) argued that the decline in funding costs is possible because Danish and Swedish banks rely so much on market funding. Boungou and Mawusi (2023) used the data of 9,638 banks from 41 countries over the period 2009–2018 and showed that negative market rates push bank lending margin (the difference between rates the bank applies to loans and the customer deposit rates) down. Loan rates decrease more and faster than the deposit rates. López-Penabad et al. (2022), with 2,595 individual bank data from 29 European countries over the period 2011–2019, confirmed the above result regarding the NIM but, contrary to other studies, found a significant decline in the ROA.

The results presented above regarding the impact of negative interest rates on bank profitability challenge some of the results discussed in Section 1.1.3.1 (and confirm some other,), showing that the determinants of bank profitability are time varying and regime dependent. Before the GFC, most of the studies showed that larger banks are more profitable, although there are also some studies reporting the opposite results. Especially the research by Lopez et al. (2020) showed that bank size is an important determinant of bank profitability and banks in different size groups behave in different ways (especially regarding the impact of bank size on the results, see Molyneux et al., 2019). This implies that instead of modeling size as one explanatory variable in a panel regression, analysis should be conducted by different size groups. Bank size is not the only factor to consider. For example, Junttila and Viitala (2023) showed that bank size, ownership, and geographical location are highly important factors explaining bank profitability (see also, for example, Windsor et al., 2023). The second factor discussed in Section 1.1.3.1 is the funding structure. Almost without any exceptions, the result before the GFC was that market funding is too expensive, and it pushes profit down. However, the era of negative interest rates turned this result around: During negative rates, a larger share of market funding increases bank profitability (for example, Scheiber et al., 2016; Madaschi et al., 2018; Chen et al., 2018; Lopez et al., 2020; Boungou, 2020). The impact on stability remains to be seen (see, for example, Nguyen, 2023, and the research sited in it.) The third interesting factor is diversification of the business mix. Most of the studies discussed in Section 1.1.3.1 report a negative impact of diversification on profitability, but results are mixed, and the opposite result is reported in several studies. During the era of negative interest rates, diversification to noninterest incomes paid off, as shown, for example, in Lopez et al. (2020). Boungou and Hubert (2021), using the data of 3,637 individual banks in 59 countries over the period 2011–2018 showed that the decrease in net interest income caused by low and negative rates is partially compensated for by the increase in noninterest incomes. In an interesting study, Molyneux et al. (2021) discovered, using the data of 440 Italian banks from the period 2007–2018, that banks' reaction to low and negative interest rates is diversifying incomes to noninterest incomes. Molyneux et al. (2021) disaggregated banks' asset holdings to show that low interest rates and the QE programs increase banks' asset holdings in the categories "assets available-for-sale" and "assets held-to-maturity," but scale down "assets held-for-trading" because of risk adjustment reasons. Altavilla et al. (2017), in a slightly earlier study, found that European banks significantly increased the size of government bond portfolios after the GFC when the European Central Bank's QE program started. They argued that this was probably not done only on economic grounds but also because of government moral suasions. However, even if most of the recent studies find income diversification into noninterest incomes profitable, there some studies report the opposite result (for example, López-Penabad et al., 2022).

1.2 Contribution of the essays

In addition to the introductory chapter, this dissertation consists of three independent articles. Two of the articles are jointly authored. The article in Chapter 2 is co-authored with professor Juha Junttila and with M.Sc. (Econ.) Juho Pesonen, and the article in Chapter 3 is co-authored with professor Juha Junttila and Ph.D. Jukka Perttunen. In both articles my contribution is 80% of the analysis and 50% of the text. To be more specific, in the first co-authored article (Chapter 2) I chose the model to be estimated and advised the estimation process, checked by re-estimation the parameter estimates in Tables 3a and 3b, developed the required mathematics (especially the equations 21-23), and conducted all empirical analysis in chapters 4.2 and 4.3 in the article (including estimation of the DCC-GARCH models[11]). In addition, I participated in writing the text by a 50% contribution. In the second co-authored article (Chapter 3), in the empirical work the analysis based on the DCC-GARCH models is my contribution, and I participated in the writing process with professor Juha Junttila with a 50% contribution. In what follows, I will provide a short introduction to the articles.

[11] In chapter 4 of the article DCC-GARCH models are used instead of the VAR-DCC-GARCH models.

1.2.1 Contribution of the first essay

The first essay sheds light on the following: whether gold is a safe haven for a diversified US equity portfolio, the impact of terrorist attacks and geopolitical tensions on the behavior of stock and gold prices, and whether changes in gold prices give useful information regarding future stock market crashes. The data consisted of Standard & Poor's 500 Composite Index return, gold returns measured by Handy & Harman gold bullion return, and COMEX gold futures return (the near contract) and risk indicators measured by the return of the VIX Index and the three-month US dollar TED spread. The sample covered the period 3.12.1990 –28.2.2014, and three data frequencies—daily, weekly, and monthly—were used. The analysis was based on estimating the VAR-AGDCC-GARCH model by Cappiello et al. (2006) via full information maximum likelihood based on the Bauwens and Laurent (2005) multivariate skewed t-density. Methodologically, the first essay follows the approach by Areal et al. (2015) (see also Mensi et al., 2013). Later, for example, Shahzad et al. (2022) applied the same approach.

Parameter estimates partly confirmed the assumption behind the Baur and Lucey (2010) and Baur and McDermott (2010) regressions according to which information flows from the stock market to the gold market but not the other way around. This holds in the estimated VAR model in the daily and weekly data but not in monthly data. However, one of my key findings is that the dependence between the markets in the form of correlations is stronger than previously thought. The asymmetry term in the GJR-GARCH models indicate that while the stock market volatility increases after a negative return shock, the gold return volatility decreases after a negative gold return shock. This confirms at least partly the finding by Baur and McDermott (2010) and Hood and Malik (2013) that the gold return distribution is positively skewed. However, the remaining skewness revealed by the asymmetry parameter of the t-distribution is negative, dampening the impact in the daily and weekly data.

The behavior of the dynamic gold–stock correlation confirms that gold is a strong safe haven in most of the cases, especially during the dot-com crash, the GFC, and also, to some extent, the European sovereign debt crisis. This aligns with earlier research (Baur and Lucey, 2010; Baur and McDermott, 2010; Hood and Malik, 2013, Baur and McDermott, 2016, to mention a few). The mainstream conclusion is that the safe haven property is short lived—about 10–15 days long. According to my results, the safe haven period is significantly longer (this result is more in line with Flavin, 2014; Bredin et al., 2015, 2017; Dee et al., 2013). One of the key results of previous research is that gold loses its safe haven property, when the stock price decrease is extremely large (Baur and McDermot, 2010; Hood and Malik, 2013; Areal et al., 2015; Choudhry et al., 2015; Drake, 2022; Iqbal, 2017; Shahzad et al., 2017; Tiwari et al., 2018; Liu, 2020; Balcilar et al., 2020). My results challenge this and suggest that the strength of the safe haven property increases with the size of the stock price decrease.

I estimated the impact of terrorist attacks, geopolitical conflicts and developments, and gold market specific events on gold, gold futures, stock market returns, and changes in the TED spread and VIX Index. In most of the cases, terrorist attacks increased the gold price, VIX Index, and the TED spread, and decreased stock prices. This result holds for all horizons (in the daily, weekly, and monthly data), although the impact declined especially in the monthly data. This is in line with earlier research (see, for example, Chesney et al., 2011; Karolyi and Martel, 2010; Guidolin and La Ferrera, 2010). Regarding geopolitical conflicts, there seems to be a clear pattern: Before a conflict, stock prices fall, risk indicators rise, and the gold price increases. When the conflict breaks out, stock price surges, and the risk indicators and gold price fall. This is in line with the findings by Guidolin and La Ferrera (2010) and Brune et al. (2015). A later study by Salisu et al. (2021) explained this behavioral pattern. When geopolitical tensions increase, stock markets react negatively, and investors in search of safe havens increase the demand for gold. When the actual conflict breaks out markets make an opposite correcting movement. This implies that investors have overreacted prior to the outbreak of the conflict (see also the discussion regarding the "War Puzzle" in Brune et al., 2015). Regarding the gold market specific events, the events related to the UK gold sale operation in 1999 negatively impacted the gold price, the Central Bank Gold Agreement has a positive impact, and the rumor that the Central Bank of Cyprus would be forced to sell its gold reserves has a negative impact. Interestingly, this gold market specific shocks have also statistically significant impacts on stock markets and the TED spread, although the impacts are heterogenous. To my knowledge, my analysis in the first essay is the first and still the only one estimating the impact on several markets in a coherent multivariable model. In addition, my analysis of the impacts of gold market specific shocks on financial markets is unique.

In the first essay, I also analyzed whether gold's dynamic correlations between i) gold (spot and futures) and stock market returns and ii) TED spread and VIX provide useful information regarding future stock market crashes. However, the results fail to give a firm confirmation regarding the predictive ability of the correlations.

1.2.2 Contribution of the second essay

The focus of the second essay is the dynamic dependence of gold and oil futures with a diversified US equity market portfolio and a portfolio of energy stocks. The data consisted of the COMEX gold futures contracts (continuous series), West Texas Intermediate (WTI) crude oil futures contracts (continuous), S&P 500 Total Return Index and S&P 500 Energy IG Price Index over the period 11.9.1989–139.2016. We examined whether gold or crude oil is a safe haven, a hedge, or a diversifier for the S&P 500 portfolio and the S&P 500 Energy IG portfolio. Regarding the gold–stock strand of research, the second essay continues the work of the first essay and the literature cited in it regarding the oil–stock strand of literature, the second essay continues to work in line with Choi and Hammoudeh (2010), Filis et al. (2011), Chang et al. (2013), Arouri et al. (2011), Creti et al. (2013), Degiannakis et al. (2013), Creti et al. (2014), Sadorsky (2014), Broadstock and Filis

(2014), Mensi et al. (2015), and Basher and Sadorsky (2016), Pan et al. (2016), and Singhal and Ghosh, (2016), to mention a few.

To my knowledge the second essay is the first to include both gold and oil in this type of analysis. At the time of writing the second essay, only Basher and Sadorsky (2016) had included both gold and oil in the analysis. The second contribution is the finding that the correlation between crude oil futures and the S&P 500 Index return increases strongly during financial crises. Even though the methodology and the goal of the essay is different, this result aligns with Mensi et al. (2017) and Gong et al. (2022), who reported strong positive lower tail dependence with copula-based analysis, and with the results by Nusair and Al-Khasawneh (2017), with quantile regression analysis (see also Zhu et al., 2016; Zhu et al, 2016; Chang et al., 2020; Wang et al., 2020; Wang et al., 2020; Dawar et al., 2021), but against the results by You et al. (2017) and Mokni (2020). In addition, the behavior of the correlations is in line with the research strand on the impact of oil market shocks on stock prices discussed Section 1.1.2.3. Recent research on the gold–oil nexus implies that in the extreme low quantile, dependence is positive. Figure 5d in the second essay presents the behavior of the dynamic correlation between gold and S&P 500 Energy IG Index returns. During crisis, the correlation falls into marginally negative territory, which challenges the results by Hernandez et al. (2019) and Salisu and Adediran (2020), even though oil is only a part of the energy index.

One of the key contributions of the second essay is the analysis of the minimum variance portfolio weights of portfolios consisting of 1) a crude oil, gold, and S&P 500 portfolio, and 2) a crude oil, gold, and S&P 500 Energy IG portfolio. In both portfolios, the portfolio weights vary in time significantly, and the weight of gold increases during crisis, while the weights of stocks and oil decrease. An interesting finding is that the weight of gold is always significantly larger in the portfolio including the S&P 500 Energy IG Index. Regarding the safe haven properties of gold, based on the dynamic correlation analysis, gold is a safe haven for both portfolios, and is stronger for the S&P 500 Energy IG portfolio. To my knowledge, these results were new when the essay was written (the closest to our work is Mensi et al., 2017, with Islamic equities). The dynamic hedge ratio analysis reveals that for both portfolios, gold is the better and more efficient hedge during crisis periods. The hedging properties of crude oil are better during the GFC compared to the dot-com crash.

Perhaps the most important contribution of the second essay is the finding that when the crude oil futures curve is in contango, the dynamic correlation between the crude oil futures and stock market returns is the highest, and when the futures market is in normal backwardation, the correlation is low or negative. Later, Ahmadi et al. (2020) reported a closely related result revealing that financial market risks have an impact on the oil market basis (difference between the oil cash price and the oil futures price). The basis rises with financial market turbulence (see also Jiang et al., 2021, on the impact of credit conditions on the oil–stock nexus, and Nguyen and Virbickaitė, 2023, on the impact of interest rates on the oil–stock nexus).

1.2.3 Contribution of the third essay

The third essay analyzes the profitability of Finnish cooperative banks during negative interest rates. The three areas we tested were: i) impact of negative interest rates on bank profitability and differences regarding the profitability measures (NIM, ROA, ROE, and Return on Economic Capital, ROEC), ii) differences between banks in three size groups, and iii) changes in the business mix, especially the funding structure, caused by negative interest rates. We used highly confidential monthly data of Finnish cooperative banks over the period 1/2009-12/2018. Banks were divided into three size groups based on the volume of customer business activities. The Finish cooperative group is unique in the sense that via the central bank of the group even the smallest banks have access to wholesale funding. In the strand of banking research our methodological choice is unique: We constructed time series of variables of different banking groups and applied conventional time-series methods—VAR and DCC-GARCH analyses. This choice allowed us to more accurately model banks' reactions to changes in interest rates.

The first observation was that the profitability of Finnish cooperative banks has not decreased significantly even during negative rates, even though the NIM has fallen. This is in line with Scheiber et al. (2016), Bikker and Vervliet (2017), Borio et al. (2017), Madaschi and Pablos Nuevo (2017), Claessens et al. (2018), and Lopez et al. (2020). However, there are significant differences between bank size-groups and profitability measures. Particularly, the behavior of the risk–adjusted profitability differs from other measures in all bank groups. In addition, our results reveal that the largest banks improved the risk adjusted profitability (ROEC) under negative interest rates significantly more than the other banks. The second observation was that the impact of interest rates on profitability is stronger in the era of negative rates compared to low but positive rates. This confirms with Finnish data the result by Bikker and Vervliet (2017), Borio et al. (2017), Claessens et al. (2018), and Lopez et al. (2020) (see also López-Penabad et al., 2022).

The third general observation is that bank size matters—not only as a dummy variable in a panel regression, as discussed in Section 1.2.3.1, but also in bank behavior and reactions to changes in interest rates, as suggested, for example, by Claessens et al. (2018) and Lopez et al. (2020). In the negative interest rate era, the NIM of the two smaller bank size groups is strongly and positively connected to the market interest rate. However, in the group of the biggest banks, the NIM depends on market interest rates only under low but positive interest rates, and the connection vanishes during the negative rates.

The fourth key finding is that the introduction of negative interest rates has changed banks' business mix, specifically, shifted the funding structure more to wholesale-based funding in all bank size groups, which has had a positive impact on profitability. The impact is strongest in the group of the largest banks, but this positive connection ends in mid-2017. The positive impact of an increase in wholesale funding during negative interest rates on the profitability of large banks has been reported, for example, by Scheiber et al. (2016), Madaschi et al. (2018), Chen et al. (2018), Lopez et al. (2020), and Boungou (2020). However, that this also holds in the case of smaller banks—in our analysis in the groups of the smallest and middle-sized Finnish cooperative banks—is a new result. Furthermore, the observation that the positive impact of increasing the share of wholesale funding vanishes somewhere in mid-2017, is a new result.

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ORIGINAL PUBLICATIONS

I

DYNAMIC CONNECTIONS BETWEEN ASSET MARKETS: SAFE HAVENS AND INDICATORS OF SYSTEMIC FINANCIAL CRISES

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Dynamic connections between asset markets: Safe havens and indicators of systemic financial crises

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ABSTRACT

I find that exogenous structural shocks caused by terrorist attacks, wars, political turmoil, and gold market specific events have a strong role to play in the analysis of dynamic relationships between financial market assets. During and before the crisis periods the interaction between the main 'safe haven' (i.e., the gold market), and the stock markets is much tighter than previously observed. Particularly, some of the gold market specific shocks have long-lasting impacts also on the financial markets. Some events, which may have previously been misinterpreted as minor shocks, have, in fact, had significant impacts on both stock and gold markets. Using a VAR-AGDCC-GARCH model, I also find that the dynamic correlations between many financial market segments increase before the crisis periods, but the conditional correlation between the return on the VIX Index and the change in the TED spread, which measures the dynamic relationship between price risk and credit risk, is the most promising early warning indicator of strong, systemic financial crises. Regarding the role of gold as a safe haven, I present new results. Particularly my evidence suggests that gold serves as a safe haven for significantly longer periods than previously understood. In addition, against the results by mainstream research, the safe haven property of gold gets stronger in the cases of extreme stock market crashes.

Keywords: Gold market; Stock market; Risk; Dynamic correlations; Shocks; Safe haven

JEL Classifications: C32; C58; G01; G12; G14

1. Introduction

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Financial and other economy-wide panics have emerged regularly throughout the modern history of industrialized countries. During the past 15 years, the global economy has undergone the Global Financial Crisis (GFC) from 2009 to 2010, the Euro area sovereign debt crisis from 2010 to 2012, the COVID-19 pandemic, the war in Ukraine, and the market turbulence caused by rapid increase in interest rates, which started in 2022. Usually, these crises manifest themselves as equity market panics and lead to a sharp drop in equity prices worldwide. For example, Bacchetta and van Wincoop (2013) noted that the steep fall in asset prices in 2008 was clearly connected to the enormous spikes in risk, as measured by implied volatility (e.g., VIX in the United States). In the US alone, the VIX quadrupled during the fall of 2008, and the same event was also observed globally in many industrialized and developing countries. Large spikes in implied volatility indices again occurred in May 2010 (Greek sovereign debt crisis), in July/August of 2011 (US debt debate and intensifying European debt crisis), in March 2020 during the COVID-19 pandemic, and, to some extent, when the war in Ukraine started. Hence, the increase in risk was, again, a global phenomenon shared broadly across many countries.

There are several angles from which the impact of risk on financial markets have been studied. I follow the approach focusing on the dynamic connections between equity, bond, and gold markets, but I will extend the analysis to also cover VIX and TED spread as explicit risk measures. My study targets four goals. The first goal is to model dynamic connections between different asset classes. The importance of revealing the underlying dynamic structure is highlighted by the common assumption in the safe haven literature that there is only one-sided causality from equity markets to the gold market (for example, Baur and Lucey, 2010, and Baur and McDermot, 2010, and the research strand following these seminal papers). I will reveal that causality also runs from the gold market to other markets, and the dynamic structure is more complicated than previously thought. The second goal dives further into dynamic modelling, and I will test the impacts of several shocks classified as exogenous terrorist attacks, events produced by political processes, gold market specific events, and stock market crashes. My results reveal that some events, which may previously have been interpreted as minor shocks, have, in fact, had significant impacts on both stock and gold markets.

My third goal is to seek new evidence of the safe haven property of gold for US equity market investors. The number of empirical tests on gold's safe haven property is large (see, for example, O'Connor et al., 2015, and the literature cited in it). There are, of course, country- and period-specific differences in results, but the general result is that gold is a (strong) safe haven for equity market investors, but only for a short period of about 10–15 days (for example, Baur and Lucey, 2010; Baur and McDermott, 2010; Flavin et al, 2014; Areal et al., 2015; Baur and McDermott, 2016, to mention a few). Another even more interesting result is that gold loses its safe haven property under extreme stock price decreases (Baur and McDermot, 2010; Hood and Malik, 2013; Areal, et al., 2015; Choudhry et al., 2015; Drake, 2022; Iqbal, 2017; Shahzad et al., 2017; Tiwari et al., 2019; Liu, 2020; Balcilar et al., 2020). With dynamic conditional correlations I will present the opposite result: the safe haven property becomes stronger with the size of the equity price decrease and its lasts longer than the mainstream research suggests.

My fourth target is testing whether dynamic correlations give guidance regarding future equity market crises. Many previous studies have attempted to extract as simple as possible univariate indicators of systemic risk. For example, Patro et al. (2013) analyzed the relevance and effectiveness of large banks' stock return correlations as a simple indicator of systemic risk. Stock market correlations have been previously proposed as one of several measures to be used as indicators of systemic risks by for example, Lo (2008), Acharya (2009), and Patro et al., (2013). For example, Patro et al. (2013) examined whether a "simple" indicator of systemic risk may be revealed, and they found that stock return correlations are a useful indicator of systemic risk. Thus, the pattern of correlation movements, such as spikes, could be useful as one component when attempting to extract the likelihood of systemic failure. I will also attempt to reveal some new indicators for the systemic risk, but instead of the bank data, from some other financial market return correlations.

I apply asymmetric dynamic conditional correlation models with vector autoregressive models, specifically VAR-AGDCC-GARCH models, as specified by Cappiello et al., (2006). In applying dynamic correlations, I follow the work by, for example, Ciner et al. (2013), Areal et al. (2015), Chkili (2016), and Shahzad et al., (2020). My data consists of daily, weekly, and monthly observations of the S&P 500 Composite Index, gold spot and futures prices, US dollar TED spread, and VIX Index.

My paper proceeds as follows. In Section 2, I provide the background for my main idea in terms of the previous literature regarding the connection between the gold markets, financial markets, and overall extreme conditions and occasions in modern economies. From this perspective, the forward-looking nature of the gold market has not been scrutinized almost at all in the previous literature. First, I give the main previously obtained results on the connections of the gold market to various kinds of shocks possibly hitting the economy. Then, I discuss some of the previous results, particularly regarding the effects of terrorism on the asset markets. In Section 3, I describe my main econometric approach, the DCC-GARCH model, and my version of applying it to the data in this paper, together with the results of estimating the VAR-AGDCC-GARCH model. Section 4 details the results from the analysis of the effects of exogenous shocks on the obtained dynamic relationships between the different financial market sectors from the first stage, Section 5 presents my results regarding gold's safe haven property, and Section 6 contains the analysis regarding the indicator properties of our data in the context of our modelling framework. Finally, Section 7 provides conclusions and suggestions for further research.

2. Asset market linkages during and around crisis periods

Among the key interesting issues in international financial market analysis is the connection between various kinds of asset markets and the relationships between returns and/or risks in them especially during crisis periods in the markets and overall economies. From the hedging perspective, the dynamic connections between the markets and their sensitivity to, for example, general economic conditions are critical in view of possible joint crashes in the markets, and on the other hand, regarding chances of obtaining gains in one market from falling prices and returns in another market. One of the key references on this theme is the study by Hartmann et al. (2004), who focused on asset return linkages during periods of stress by an extreme dependence measure. Their main finding was that even though in the G5 countries the simultaneous crashes between stock markets are much more likely than between bond markets, the widely disregarded cross-asset dependence is crucial. According to their results, the bond-stock contagion is approximately as frequent as the case for vice versa causality (i.e., the contagion from stocks into bonds). Furthermore, the extreme cross-border linkages are very similar to national linkages indicating, that the increasing degree of international integration in the financial markets might not always be advantageous.

However, like Hartman et al. (2004) also noted, most of the recent empirical literature on analyzing the dependence of different asset markets use some form of correlation analysis, often based on (G)ARCH-type models, and many of these studies also scrutinize the directions of international spillovers. Hence, also in my paper, the models belonging to the GARCH family will be analyzed. However, I will make two new openings regarding the analysis of the relationships between the asset markets and overall economy. First, I will scrutinize the role of gold markets in these relationships. Second, in addition to the role of financial market oriented possible systemic risk sources, also the role of extreme occasions, such as terrorist attacks and other types of crisis periods, and specific events regarding the dynamic relationships between these markets will be in my focus. In the next two sub-sections, I first review the most recent literature on the gold market connections to other forms of asset markets and the overall economy. After this, I will also detail some of the most recent other literature, first, on the connection between gold and equity markets during crisis periods and, second, on the effects of clearly exogenous-type (like terrorist attacks) and other kinds of more 'general' shocks in the overall economies on asset market returns or risks.

2.1. Gold and equity markets

The origin of the research on gold in connection to equity markets dates back to the 1970s and 1980s, when research focused on the role of gold as a diversifier (Jaffe, 1989; McDonald and Solnik, 1977; Johnson and Soenen, 1977; Aggarwal and Soenen, 1980; Tschoegl, 1980). Baur and Lucey (2010) and Baur and McDermot (2010) started a new strand of research focusing on the gains, that gold can offer during stock market turbulence. Baur and Lucey (2010) defined a diversifier as an asset having low correlation with another asset or a portfolio. A hedge is "an asset that is uncorrelated or negatively correlated with another asset or portfolio on average". They defined a safe haven as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil". Baur and McDermot (2010) modified Baur and Lucey's (2010) original definition of a safe haven asset to make a distinction between strong and weak safe haven property in the following way: "A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with an asset or portfolio in certain times only, e.g. in times of falling stock markets." In the following, I will focus on the safe haven property.

Baur and Lucey's (2010) and Baur and McDermott's (2010) methodological approach, which is the most popular approach in this strand of research, is based on regressing the return of gold on the 50%, 5%, 2.5%, and 1% "quantiles" of equity market returns and possibly on some other variables (bond yields, some risk measures, etc.).[1] In addition, other methodologies are applied, such as dynamic conditional correlation models, often with VAR models (for example, Chikili, 2016, Salisu et al., 2021; Akhtaruzzaman et al., 2021), copula methods (for example, Bekiros et al., 2017), and quantile regression techniques (for example, Shahzad et al., 2017, 2019). There are some country-, equity market segment-, and period-specific variations in the results, but the general result is that gold is a strong safe haven for most of the equity markets, but only for a short period of 10–15 days (Baur and Lucey, 2010: Baur and McDermott, 2010; Hood and Malik, 2013; Flavin et al., 2014; Gürgün and Ünalmis, 2014; Areal et al., 2015; Baur and McDermott, 2016; Liu et al., 2016; Li and Lucey, 2017; Bredin et al., 2017; Shahzad et al. 2017, just to mention a few).[2]

A crucial and interesting finding is positive tail dependence between the return of gold and stock markets during extremely severe stock market crisis. This implies that gold is not a safe haven, when the stock price decrease is extremely large. Evidence of this is reported in Baur and McDermott (2010), Hood and Malik (2013), Areal et al. (2015), Choudhry et al. (2015), Drake (2022), Iqbal (2017), Shahzad et al. (2017), Tiwari et al. (2019), Liu (2020), Balcilar et al. (2020). Although this result is confirmed by a large number of studies, no effective explanation has been given. Furthermore, it seems to contradict the results suggesting that the safe haven property of gold is stronger under high uncertainty (for example, Li and Lucey, 2017; Triki and Maatoug, 2021; Reboredo et al., 2021; Su et al., 2022a, 2022b). In my empirical work I will challenge this result.

2.2. The effects of terrorism on asset markets and the general economy

The research on terrorist attacks as social phenomena and the impacts of terrorist attacks on financial markets activated only after the 9/11 terrorist attacks. The key results regarding equity markets are the following. On average, terrorist attacks cause a significant negative stock market reaction. There are significant country- and case-specific differences in how strong the market reaction is. Furthermore, the US market is the most resilient market. Regarding sectoral reactions, the airlines and insurance sectors react to the largest number of attacks, while the banking sector is the most stabile sector (see, for example, Chesney et al., 2011; Karolyi and Martel, 2010; Enders et al., 1992; Bonturi et al., 2002; Abadie and Gardeazabal, 2003; Fraser and Carbonnier, 2022).

Both wars and terrorist attacks are violent events, but they are not alike. Terrorist attacks are usually sudden, unexpected, and short-lived, while wars last longer and are often more predictable. Research on stock market impact of wars is rather new. Leigh et al. (2003) and Rigobon and Sack (2005) are among the first studies in this strand of research. Both of the papers focus on the 2003 Iraq War, and both apply a

[1] Also 50%, 10%, 5%, and 1% quantiles are often used.
[2] For the opposite results, see Ciner et al. (2013), Chen & Lin (2014), and Bekiros et al. (2017).

measure of probability of the war or ousting Saddam Hussein. The results revealed that an increase in war risk increases the oil price and causes a fall in stock and bond prices and a widening of corporate bond spread. In addition to the US market, Leigh et al. (2003) examined the impacts on 45 international stock exchanges, of which 32 reacted significantly and negatively. While Leigh et al. (2003) and Rigobon and Sack (2005) tested the impact of an increase in probability of the armed conflict, Guidolin and La Ferrera (2010) tested the impact after the outbreak of the conflict. The hypothesis is that when the tension increases the market (over) reacts negatively, and because of that there is a tendency to ex-post positive stock price reactions. With a news-based probability measure of armed conflicts, Brune et al. (2015) confirmed this pattern – stock prices decrease when the probability of war increases, and stock prices increase after the breakout of a war – which they call the "war puzzle". An additional interesting finding by Rigobon and Sack is that the gold price does not react to an increase in the risk of a war. Regarding the reaction of the gold price to terrorist attacks Cesney et al. (2011) has shown that the gold market has a tendency for negative reactions, which contradicts its role as a safe haven.

Eckstein and Tsiddon (2004) constructed an index of terror activity and included it as one of the variables in a VAR model for per capita GDP, consumption, investment, and exports. Their main result was that terrorism activity has had a large negative and statistically significant impact on the short-run dynamics of Israel's economy from 1980 to 2003. This empirical result also supported their theoretical model that guided them to expect that changes in the terror activities affect the entire economic activity and not just some sectors of the economy[3]. Another attempt to analyze the overall effect of terrorism on stock markets is the paper by Karolyi and Martell (2010), which used an official list of terrorism-related incidents between 1995 and 2002 and event study methods to reveal evidence of a statistically significant negative stock price reaction of -0.83 % in the US market. Moreover, the impact of terrorist attacks differs according to the home country of the target firm and the country in which the incidents occurred. Attacks in wealthier and more democratic countries are associated with larger negative share price changes, and human capital losses, such as kidnappings of company executives are associated with larger negative stock price reactions than physical losses, such as bombings of facilities and buildings.

Among the most intensively examined specific terror attacks are the WTC attacks in September 2001. Drakos (2004) analyzed the effect of the 9/11 attacks, specifically on a set of airline stocks listed at various international stock markets. Using daily closing price data for 13 airline stocks covering the period from 12.7.2000 to 26.6.2002, he reported a structural break in the estimated traditional Campbell et al. (1997) market model beta for airline stocks. In addition, based on his results, the idiosyncratic risk had also substantially increased due to the attacks. Hence, the 9/11 events seem to have had significant effects on portfolio diversification and the ability of airlines to raise capital through market-based financing channels. Carter and Simkins (2004) scrutinized the same terror attack, but they found that the event had a much more thorough effect on the US economy and society in general. Other examples

[3] Other more generally oriented studies examining the effects of terror attacks are, for example, Eldor and Melnick (2004), Chesney et al. (2011), and Kollias et al. (2011).

of research on the 11/9 attack are Nikkinen et al. (2008), Straetmans et al. (2008), and Hon et al. (2004), to mention a few.

In addition to the specific role of terrorism in affecting the dynamic relationships between the financial market sectors, in this paper, I will also analyze the effects of some other extreme events in the economy and financial markets. Details of the specific events and periods, and some previous results on their effects, will be discussed in Section 4 and Appendix A. However, before that I will describe my data set and the background of my main econometric approach, that is, the VAR-AGDCC-GARCH model.

2.3. Indicators of systemic risk

Many previous studies have attempted to extract as simple as possible, basically univariate indicators of systemic risk.[4] For example, Patro et al. (2013) analyzed the relevance and effectiveness of large banks' stock return correlations as a simple indicator of systemic risk. Stock market correlations have previously been proposed as one of several measures to be used as indicators of systemic risks, for example, by Lo (2008) and Acharya (2009). Patro et al. (2013) highlighted the strong correlations among banks as a necessary condition for systemic failures because a single event is unlikely to cause broad-based dislocation over a relatively short period if correlations are low. They selected bank holding companies (BHCs) and investment banks with total assets in excess of $100 billion as of the last quarter of 2006 and examined their daily stock return correlations in connection to the 2008 crash. Because the large banks are highly leveraged, the correlations among their stock returns should be an economically significant indicator. They estimated the correlations for quarterly, yearly, and other sub-period horizons from 1988 to 2008 and found that the average mean and median stock return correlations among the 22 banks had shown an upward trend and had tripled from 1988 to 2008. This supported the results of Acharya (2009) that suggested that prudential regulation should also consider the correlated risk of banks with other banks. In addition, Patro et al. (2013) examined whether the increase in correlations had been driven by systematic risk or idiosyncratic risk by using the Fama-French three-factor model and a four-factor model. They also analyzed, as an alternative, the role of default correlations based on default probabilities produced by reduced-form, structural, and hybrid credit risk models and found that as the subprime crisis began to unfold in 2007, the default correlations did not actually increase but, in fact decreased. Overall, the main objective of Patro et al. (2013) study was to examine whether a "simple" indicator may be revealed, and they found that stock return correlations are a useful indicator of systemic risk. Thus, the pattern of correlation movements, such as spikes, could be useful as one component when attempting to extract the likelihood of systemic failure. I will also attempt to reveal

[4] In general, the *systemic risk* is defined as being connected to a situation wherein the entire financial system, including several markets and institutions, is simultaneously globally distressed (see also, e.g., Patro et al., 2013). What makes systemic crises differ from the bubble-type market crashes is that when the markets collapse systemically, the negative consequences for the macroeconomy at the global level are much more severe and long-lasting, as was seen after the 2008 subprime crises.

some new indicators of the systemic risk, but instead of the bank data, from some other financial market return correlations.

Methodologically the study by Girardi and Ergün (2013) is somewhat related to my study. They used a multivariate GARCH model to estimate the Conditional Value-at-risk (CoVaR) measure of Adrian and Brunnermeir (2016) for the systemic risk.[5] Compared to the original Adrian and Brunnermeier (2016) measure, they changed the definition of financial distress from an institution exactly at its VaR to being at most at its VaR value, enabling them to consider more severe distress events in the markets. They found that during their sample period from June 2000 to February 2008, depository institutions were the largest contributors to systemic risk, followed by broker-dealers, insurance companies, and non-depository institutions. They also found that the time series of their systemic risk measure could potentially have information that is different from the information in the time series of the specific institution's VaR, and the institution's leverage, size, and beta play an important role in explaining their contributions to systemic risk. In addition, their pre-crisis analysis showed that the systemic risk of all industry groups increased substantially during the 12 months before June 2007.

My main innovator for the part of previous research is the study by Patro et al. (2013). However, the aim of my paper is to reveal a new and simple forward-looking measure for the emergence of increasing systemic risk in the global financial markets and economy from a more general financial sector data. Hence, instead of focusing merely on stock markets (and specifically the banking sector), interest yielding assets, or any other financial market segments, I will focus more on, for example, the role of gold markets, because gold has previously often been found to serve as a safe haven asset in times of extreme global conditions, such as during and right after the September 11 attacks in 2001. For this purpose, I analyze the connections of significant, sudden, and usually unpredicted financial market and politically or otherwise-based shocks to the time-varying conditional correlations between the returns from gold and some other asset markets.

3. Data and econometric approach

3.1. Data

My aim is to analyze the behavior of the gold and stock markets in a consistent framework and to study whether crash risk may be forecasted by simple indicators

[5] Girardi and Ergün (2013) used the CoVar method, as described in the working paper version of Adrian and Brunnermeier (2016), which has since then been published in the AER. Other recent approaches for quantifying systemic risk are, for example, the principal component analysis and Granger causality (see Billio et al., 2012), multivariate extreme value theory (Zhou, 2010), the use of credit default swap and equity return data (Huang et al., 2009, and Segoviano and Goodhart, 2009, in a multivariate setting), and the calculation of the so-called Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES) measures (Acharya et al., 2017, and Brownlees and Engle, 2017). Finally, as a macro-level systemic risk indicator, Allen et al. (2012) introduced the so-called CATFIN measure that indicates the effects of systemic risk, considering the role of the banking sector as a whole. Their calculations imply that high levels of systemic risk in the banking sector impact the macroeconomy, especially through aggregate lending activity, and that a conditional asset pricing model shows that CATFIN is actually priced for both financial and non-financial firms.

based on market volatilities and correlations. I focus on the US market, and I measure the stock market prices by the Standard & Poor's 500 Composite Index (the total return index). Gold market prices and returns are based on the Handy & Harman gold bullion prices traded on COMEX and on the COMEX gold futures contract prices (near contract, a continuous series constructed by Datastream). In addition to these, I include two forward-looking financial market variables into my model: the VIX Index and the TED spread. The VIX Index measures the future stock price volatility implied by the Standard & Poor's Index option trades and the latter, calculated as the difference between the three-month US dollar Libor rate and the respective US government t-bill rate, is commonly used as an indicator of interbank credit risk. My sample consists of daily observations from the period 3.12.1990–28.2.2014, and the data are collected from Datastream.

Figures 1a and 1b depict the time series behavior of our data set. I plot first the observations on the gold market spot prices together with the S&P500 Index (Figure 1a) and then, the observations on the VIX Index and the TED spread (Figure 1 b).

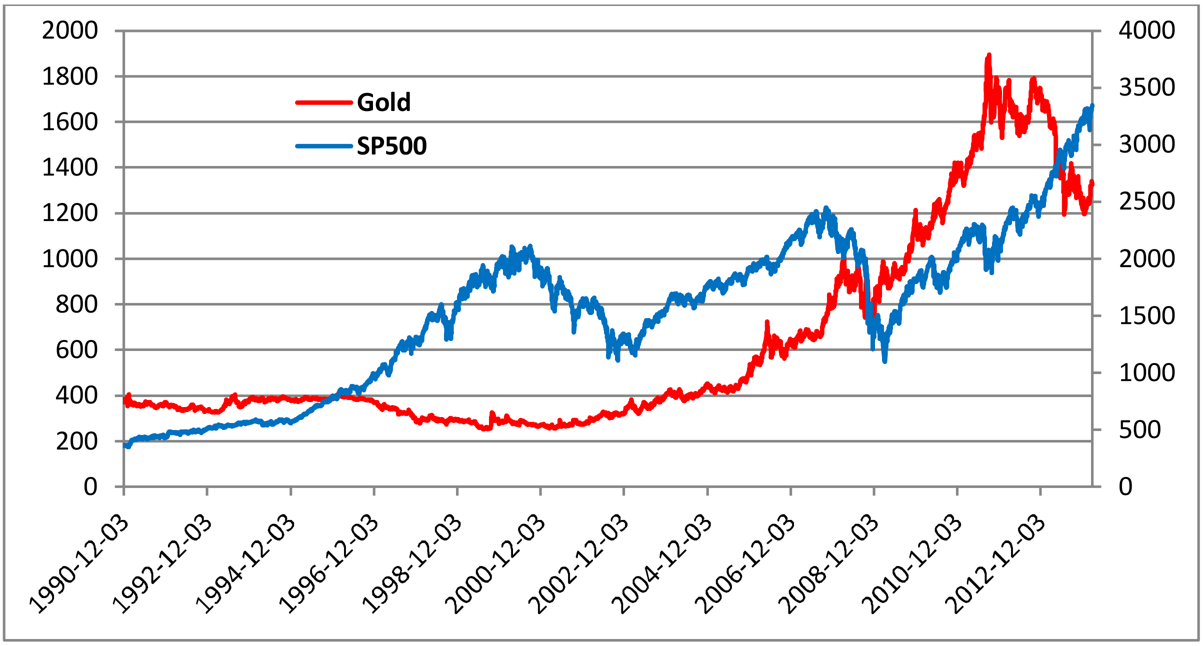


Fig. 1a.
Time series on the gold spot (left scale) and stock spot market (right scale) prices for the period of 3.12.1990–28.2.2014.

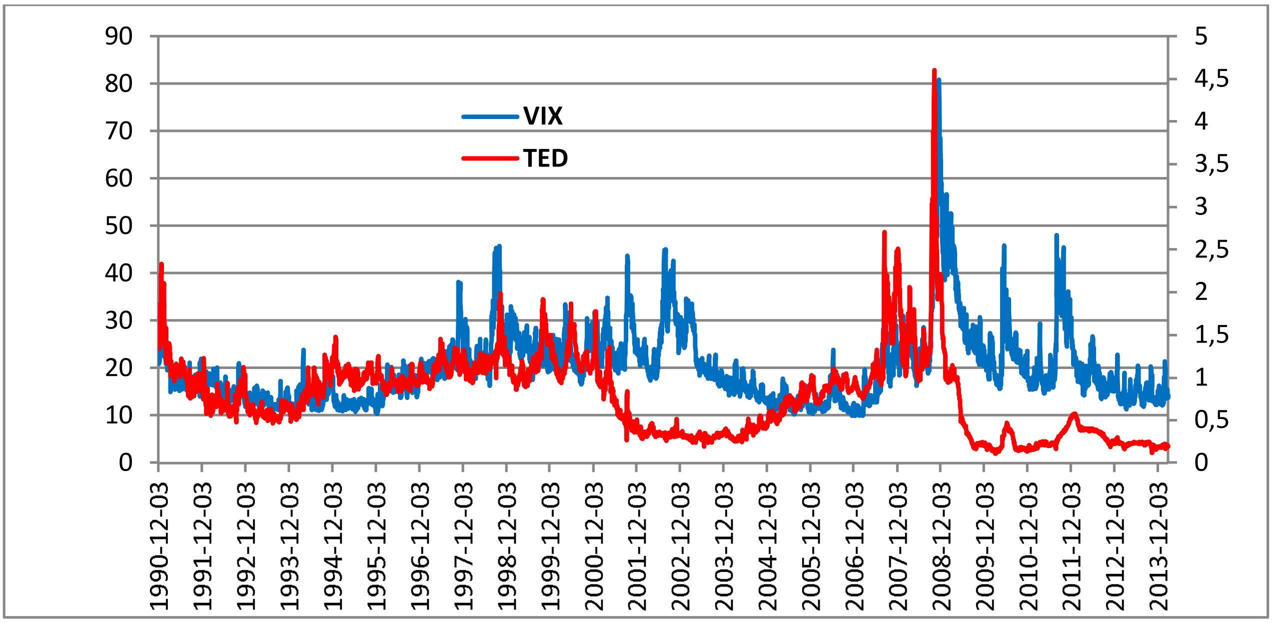


Fig. 1b.
Time series on the VIX Index (left scale) and the TED spread (right scale) for the period of 3.12.1990–28.2.2014.

Figure 1a shows that at the onset of the GFC the co-movement of the gold and stock market indices changed dramatically.[6] For example, during the dot-com bubble in the beginning of the 2000s the two markets did not seem to be strongly connected at all. Furthermore, the exogenous shocks, like the 9/11 events in 2001, seem to have had a short (positive) shock effect on the gold market, reflecting the possible hedging behavior of the market participants around the terrorist attacks. However, the overall trend in the gold market price process seems to have been negative for almost three years in the beginning of this millennium, whereas the overall tendency in the stock market was positive at the same time. These different patterns might well have been connected to the different reactions of these markets to the general conditions in the overall economy. Furthermore, after considering the differences in the sample means of the time series of these two price processes, since the beginning of 2008, the two markets seem to have been moving much more closely for two years, whereas after 2010, their trends have again been against each other. Basically, my first-stage, eyeballing of these time series gives clear insights that there is a strong time-varying relationship between the two markets, and the safe haven properties of the gold market regarding, for example, the hedging possibilities against the risks in the stock market should be analyzed actually taking into account their connection to some exogenous shocks, common or not to both of these markets.

Figure 1b reveals more interesting points from our data set. The well-known indicative properties of the VIX Index and the TED spread are somewhat evident already from simply viewing these two time series. For example, when looking at their behavior just before the GFC, their co-movement is strong, but the strong increase in

[6] Note that due to the strong positive correlation between the gold market spot and futures prices, I do not graph the time series of gold futures prices but will, nevertheless use the futures series, too, in the empirical analysis to enable the possibility that the two alternative forms of the gold markets might be differently connected to the other markets and variables scrutinized in our setting.

the correlation between these two indicator variables seems to have already occurred during the preceding year prior to the crisis period. The GFC seems to have caused a structural change in the relationship between these two highly important financial market indicator variables. However, in contrast to the pair of gold and stock market prices, the co-movement between the VIX and TED spread seems to have been clearly positive during and after the latest crisis period. All in all, when viewing the correlation of these two informative financial market time series, the analysis of their dependence on each other should clearly be conditioned perhaps on the behavior of the overall economy and exogenous shocks in the markets and the economy in general.

For the above-mentioned purpose, the next stage in my empirical strategy is to estimate a VAR-AGDCC-GARCH model revealing the systematic market behavior, analyze market reactions to different types of crisis events, including terrorist attacks, wars, market-specific shocks, and stock market crashes. For this purpose, I have collected a large number of events modelled as dummy variables and presented in more details in Appendix A.

The preliminary analysis of the time series was based on the familiar unit root tests, which were conducted for daily, weekly, and monthly return horizons of the data. According to my results the S&P500 Index, the gold price, and the gold futures price have unit roots in all three return horizons. Because of this, I use logarithmic returns for these series. In the case of the VIX Index and the TED spread the null hypothesis of unit root was rejected. However, based on both visual inspection and econometric analysis to be discussed later, these variables seem to have some properties typical to unit root processes, too. I interpret this as an indication of either a unit root with a structural change or fractionally integrated time series, and because of this, I also measure these two variables as logarithmic returns.

3.2 Model specification

Previous research on interactions between the stock and gold markets has given evidence of asymmetric behavior. First, it seems that economically good news is bad for the gold market and vice versa (Elder et al., 2012; Roache and Rossi, 2010). Second, while unexpected negative returns increase the stock market volatility (the so-called leverage effect), the gold return volatility decreases in the case of unexpected negative gold market returns and increases in the case of positive return surprises (Baur, 2012). In addition, correlations between the stock market returns and the precious metals decrease in periods of financial market turbulence (Demiralay and Ulusoy, 2014). All these findings point out to a covariance matrix formulation, which allows asymmetric behavior regarding positive and negative news, and behavior, which is distinctive for each of our market segments. I tackle this by the asymmetric generalized DCC (AGDCC) model by Cappiello et al. (2006):[7]

[7] For the estimation of the residual series to which the AGDCC model was applied we approximated the dynamic relationships between the analyzed variables with a VAR(1) model to restrict the number of parameters to a reasonable level. I also scrutinized other lag structures for my system of five variables, but the results seemed to

$$r_t^h = \pi' \bar{r}_{t-h}^h + e_t, \quad (1)$$

where $r_t^h = (Gold_t^h, GF_t^h, SP500_t^h, TED_t^h, VIX_t^h)'$,and h indicates the length of the forecasting return horizon measured in days. The notations $Gold_t^h$, GF_t^h, $SP500_t^h$, TED_t^h, and VIX_t^h denote the logarithmic returns for the gold spot market, the gold futures market, the Standard & Poor's 500 Composite Index, the three-month TED spread, and the VIX Volatility Index, respectively, all calculated for the period from the day *t-h* to the day *t* closing prices, $\bar{r}_t^h = (\iota', r_t^{h'})'$, where ι is a 5x1 vector of constants, π is a 5x6 matrix of coefficients and $e_t = \left(e_{Gold,t}, e_{GF,t}, \dots, e_{VIX,t}\right)'$ is a 5x1 vector of residuals.

The conditional covariance matrix H_t is modeled as the Cappiello et al. (2006) version of the Engle's (2002) dynamic conditional correlation (DCC) model. The 5x5 matrix of conditional covariances is decomposed to

$$H_t = D_t R_t D_t, \quad (2)$$

where D_t is a 5x5 diagonal matrix of conditional standard deviations $\sqrt{h_{i,t}}$, estimated from the univariate GJR-GARCH(1,1) models (Glosten et al.,1993):

$$h_{i,t} = \beta_{i,o} + \beta_{i,1} e_{i,t-h}^2 + \beta_{i,2} h_{i,t-h} + \beta_{i,3} I(e_{i,t-h} < 0) e_{i,t-h}^2, \quad (3)$$

where $\beta_{i,j}$ (i=Gold, GF, SP500, TED, VIX, j=0,1,2,3) are constant coefficients to be estimated, and $I\left(e_{i,t-h} < 0\right)$ is an indicator function, which is equal to 1, if the condition is met, and equal to zero otherwise.

R_t is the time-varying correlation matrix defined as

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \quad (4)$$

and $$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G\right) + A'\varepsilon_{t-h}\varepsilon_{t-h}' + B'Q_{t-h}B + G'n_{t-h}n_{t-h}'G, \quad (5)$$

where the elements of the 5x1 vector ε_t are the standardized residuals

be robust to using the VAR(1) specification. Furthermore, my results on the dynamic correlations seemed also to be robust regarding the order of variables in the VAR model, so the reporting of my results proceeds based on using the gold market returns (first, the spot market and second, the futures market) as the first two variables in the VAR representation of the variables.

$$\varepsilon_{i,t} = {e_{i,t}}\Big/{\sqrt{h_{i,t}}}\,, \tag{6}$$

and the elements of the 5x1 vector n_t are negative standardized residuals

$$n_{i,t} = I\left(\varepsilon_{i,t} < 0\right) \circ \varepsilon_{i,t}. \tag{7}$$

The matrices $\overline{Q}$ and $\overline{N}$ are sample unconditional correlation matrices

$$\overline{Q} = T^{-1} \textstyle\sum_{t-1}^{T} \varepsilon_t \varepsilon_t' \;\text{ and }\; \overline{N} = T^{-1} \sum_{t-1}^{T} n_t\, n_t'\,, \tag{8}$$

and elements of the diagonal matrix Q_t^* are square roots of the diagonal elements of the matrix Q:

$$q_{i,i,t}^* = \sqrt{q_{i,i,t}}\,. \tag{9}$$

Finally, A, B, and G are diagonal parameter matrices.

As mentioned, the model is estimated for three different return horizons - daily, weekly and monthly returns (h=1, 5, 22). Engle (2002), in the case of the DCC model and Cappiello et al. (2006), in the case of the AGDCC model, suggest a two-stage estimation procedure based on the separation of the likelihood function into a volatility part and a correlation part. I estimate the model by full information maximum likelihood based on the Bauwens and Laurent (2005) multivariate skewed t-density:

$$f(Z_t|\xi, \upsilon) = \left(\frac{2}{\sqrt{\pi}}\right)^5 \left(\prod_{i=1}^{5} \frac{\xi_i s_i}{1+\xi_i^2}\right) \frac{\Gamma\left(\frac{\upsilon+5}{2}\right)}{\Gamma\left(\frac{\upsilon}{2}\right)(\upsilon-2)^{\frac{5}{2}}} \left(1 + \frac{z_t^{*\prime} z_t^*}{\upsilon-2}\right)^{-\frac{5+\upsilon}{2}}, \tag{10}$$

$$Z_t = \left(z_{1,t}, z_{2,t}, \dots, z_{5,t}\right)' = S_t e_t. \tag{11}$$

Here S_t is the lower diagonal matrix of the Cholesky decomposition satisfying $S_t S_t' = H_t$,

$$z_t^* = \left(z_{1,t}^*, z_{2,t}^*, \dots, z_{5,t}^*\right)', \quad z_{i,t}^* = \left(s_i z_{i,t} + m_i\right)^{I_{i,t}}\,, \tag{12}$$

$$m_i = \frac{\Gamma\left(\frac{\upsilon-1}{2}\right)\sqrt{\upsilon-2}}{\sqrt{\pi}\,\Gamma\left(\frac{\upsilon}{2}\right)} \left(\xi_i - \frac{1}{\xi_i}\right), \tag{13}$$

$$s_i^2 = \left(\xi_i^2 + \frac{1}{\xi_i^2} - 1\right) - m_i^2, \tag{14}$$

$$I_{i,t} = \begin{cases} -1, \; if \;\; z_{i,t} \geq -\frac{m_i}{s_i} \\ +1, \; if \;\; z_{i,t} \geq -\frac{m_i}{s_i}, \end{cases} \tag{15}$$

where υ is the degree of freedom parameter, and $\xi = (\xi_1, \xi_2, \dots, \xi_5)'$ is a vector of the asymmetry parameters.

3.3 Parameter estimates

The first stage of my empirical analysis was the estimation of VAR-models, with AGDCC-GARCH errors for the set of five analyzed return variables. When I analyze the parameter estimates of the VAR system, I have to bear in mind the distinction between the immediate market reactions, which take place during a trading day, and the lagged systematic predictability, approximated by the estimated VAR system. Tables 1a – 1c reveal some interesting points from my first-stage estimation. First, in the case of a one-day horizon, the lagged value of an increase in the VIX return has a negative impact on all the other variables except the TED spread. Second, all the variables except the gold futures return have a large overshooting feature (mean reversion). The financial market variables have a lagged impact on the gold price, but not on the gold futures price. When the length of the horizon increases from one day to one week and one month, the return dynamics approximated by our VAR(1) model change. In the case of one-month returns the transmission from the financial markets to the gold markets is broken. On the other hand, there seems to be a direct and an indirect (via the VIX Index) transmission mechanism of shocks from the gold market to the stock market.

One novel finding from my analysis is that the impacts of a lagged change in the gold spot return and the gold futures return on the S&P 500 and on VIX Indices have different signs (Table 1 c). A lagged increase in the gold spot returns seems to be good news for the stock market, but a lagged increase in the gold futures return is bad news. The former result contradicts the seminal finding in Cohen and Qadan (2010), whereas the latter is in line with their results. Of course, both the gold spot and futures prices usually change by the same amount into the same direction, but not always. The reasons for this asymmetry in the VAR system may be based on differing liquidity of the markets, on the fact that gold is a physical commodity, and on the complex relationship between the LIBOR rates and the gold swap rates (i.e., GOFO rates; see LBMA (2011) for the definition).

Table 1a

Parameter estimates for the VAR-AGDCC-GARCH equations using daily returns.

	Gold	GF	SP500	TED	VIX
VAR(1) Equation (1)					
Constant			0.05705***	-0.32499***	-0.13727**
$Gold_{t-1}$	-0.39452***				
GF_{t-1}	0.57243***				
$SP500_{t-1}$	-0.02522***		-0.04969***		
TED_{t-1}				-0.10222***	
VIX_{t-1}	-0.00760***	-0.00623***	-0.00649***		-0.05544***
Univariate GJR-GARCH Equation (3)					
β_0	0.00304***	0.00323***	0.00835***	0.73545***	1.56131***
β_1	0.07158***	0.05422***	0.01555***	0.11716***	0.07872***
β_2	0.94517***	0.95791***	0.93709***	0.86601***	0.90098***
β_3	-0.03749***	-0.02995***	0.07674***	0.04976***	-0.05467***
AGDCC Correlation Equation (5)					
a	0.09680***	0.31504***	0.12733***		0.10165***
b	0.89589***	0.86267***	0.98765***	1.00505***	0.99536***
g	0.21608***	0.21226***			
Parameters of the t-distribution (10) – (15)					
υ			7.07727***		
ξ	-0.03047**		-0.08947***	-0.10146***	0.11901***

Notes: Table presents the parameter estimates from the VAR-AGDCC GARCH Model given in equations (1) – (15). 'Gold' refers to the gold spot market return equation, 'GF' to the gold futures market equation, 'SP500' to the stock market equation, TED to the Ted Spread equation, and VIX to the VIX volatility index equation. Parameters a, b and g are the elements of the matrices A, B, and G. *, ** and *** refer to the significance of the parameter estimates at 10, 5 and 1 % significance levels, respectively.

Table 1 b

Parameter estimates for the VAR-AGDCC-GARCH equations using weekly returns.

	Gold	GF	SP500	TED	VIX
VAR(1) Equation (1)					
Constant					-0.58456***
$Gold_{t-5}$	-0.00828*				
GF_{t-5}					0.13669***
$SP500_{t-5}$			-0.12513***	-0.36548**	0.91918***
TED_{t-5}			-0.00197*	-0.10619***	
VIX_{t-5}			-0.00887***		
Univariate GJR-GARCH Equation (3)					
β_0	0.10680***	0.10915***	0.17207***	2.24698***	18.25809***
β_1	0.13139***	0.13156***	0.03468***	0.05806***	0.08241***
β_2	0.88979***	0.89244***	0.88133***	0.92249***	0.82377***
β_3	-0.08101***	-0.08354***	0.13196***	0.03153**	-0.08172***
AGDCC Correlation Equation (5)					
a	0.28196***	0.46786***	0.05068***	0.07490***	0.08054***
b	0.27445***	0.20343***	0.99704***	0.96008***	0.99773***
g	-0.35001***	-0.27779***	-0.02674***		
Parameters of the t-distribution (10) – (15)					
υ			8.21452***		
ξ	-0.03694*		-0.30755***		0.08689***

Notes: See Table 1a for the notations.

Table 1 c

Parameter estimates for the VAR-AGDCC-GARCH equations using monthly returns.

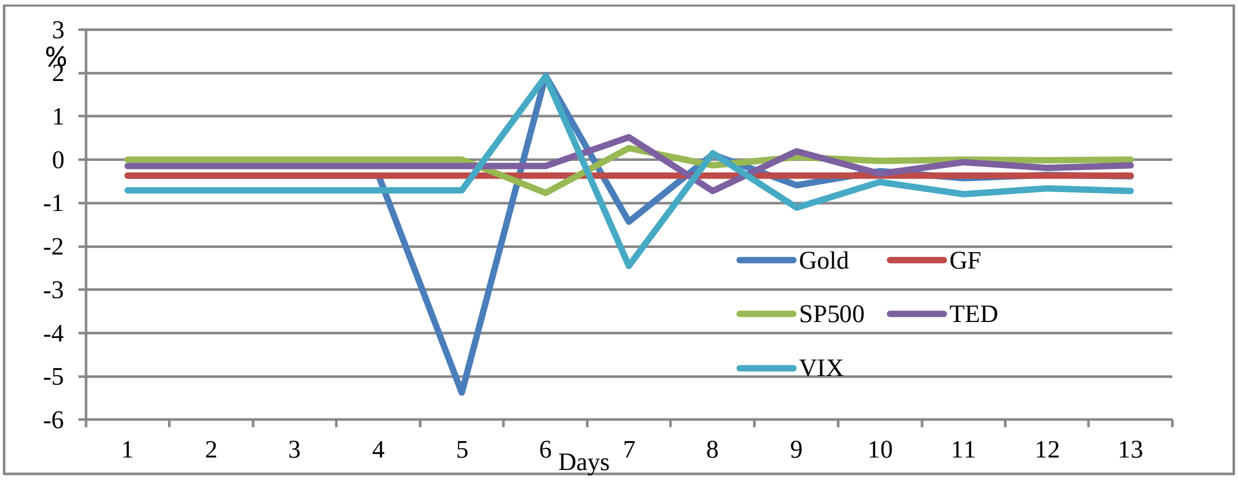
	Gold	GF	SP500	TED	VIX
VAR(1)					
Equation (1)					
Constant	-0.37599***	-0.39551***			-0.82323***
$Gold_{t-22}$	-0.46021***		0.15168***		-0.52676***
GF_{t-22}	0.37378***	-0.09272***	-0.15191***		0.48348**
$SP500_{t-22}$			0.10676***		0.18615****
TED_{t-22}		-0.00074***	0.00447**	-0.21103***	
VIX_{t-22}				0.24972***	-0.14586***
Univariate GJR-GARCH Equation (3)					
β_0	2.64092***	2.62170***	2.03785***	51.91964***	54.45411***
β_1	0.24419***	0.24058***	0.03930**	0.16204***	0.11857***
β_2	0.70124***	0.70711***	0.70754***	0.82861***	0.80270***
β_3	-0.14253***	-0.14202***	0.25702***	-0.06763**	-0.20040***
AGDCC Correlation Equation (5)					
a	0.26188***	0.24262***	0.14453***	0.07254***	0.17209***
b	0.63511***	0.65170***	0.97895***	0.97642***	0.98636***
g	0.23355***	0.27666***	-0.05975***	0.00534	-0.00403
Parameters of the t-distribution (10) – (15)					
υ			9.240421***		
ξ	0.14414***	-0.03215**	-0.31067***	0.12093***	0.19559***

Notes: See Table 1a for the notations.

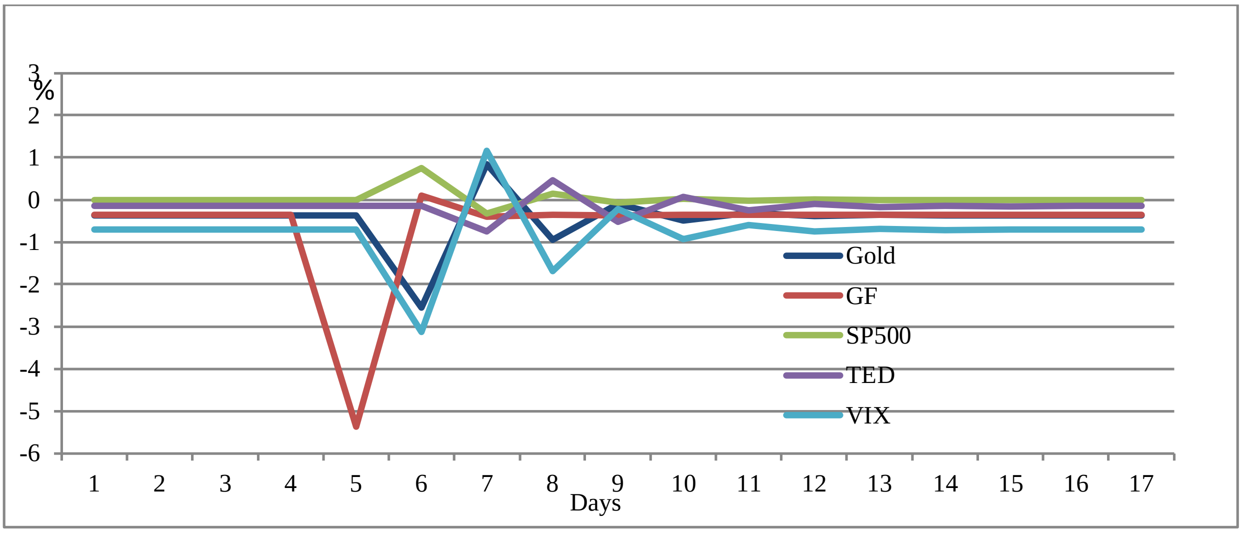
For the sake of brevity, in Figure 2, I present the impulse response functions based on the monthly parameter estimates (Table 1 c)[8] only. When I interpret the impacts, I have to bear in mind that these are not immediate reactions to shocks but instead the lagged responses. A simultaneous change by the same amount in the gold spot and gold futures returns does not have a significant impact on the stock market, but if either of these returns changes alone, the impact on asset markets and market volatility in general is significant. On the other hand, the lagged changes in the other asset market variables are not transmitted to the gold market.

[8] All the other empirical results for the other return horizons are available upon request.

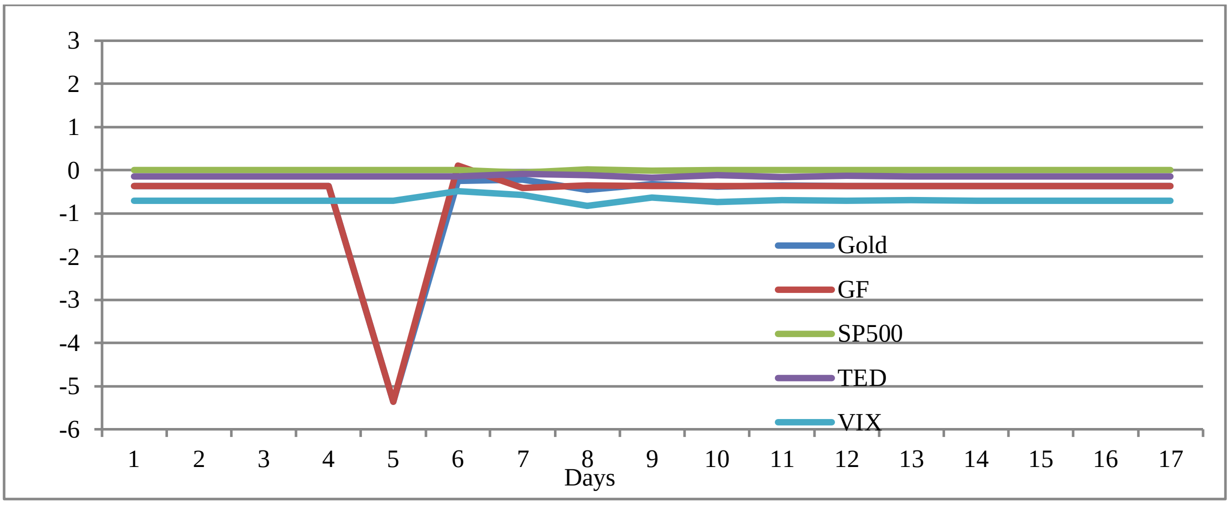
Panel A



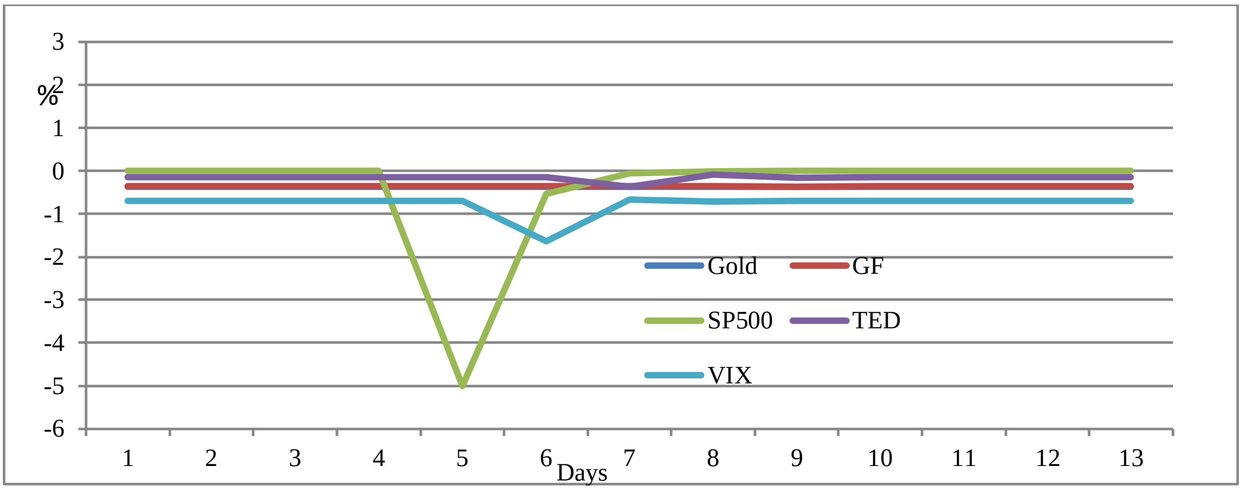
Panel B



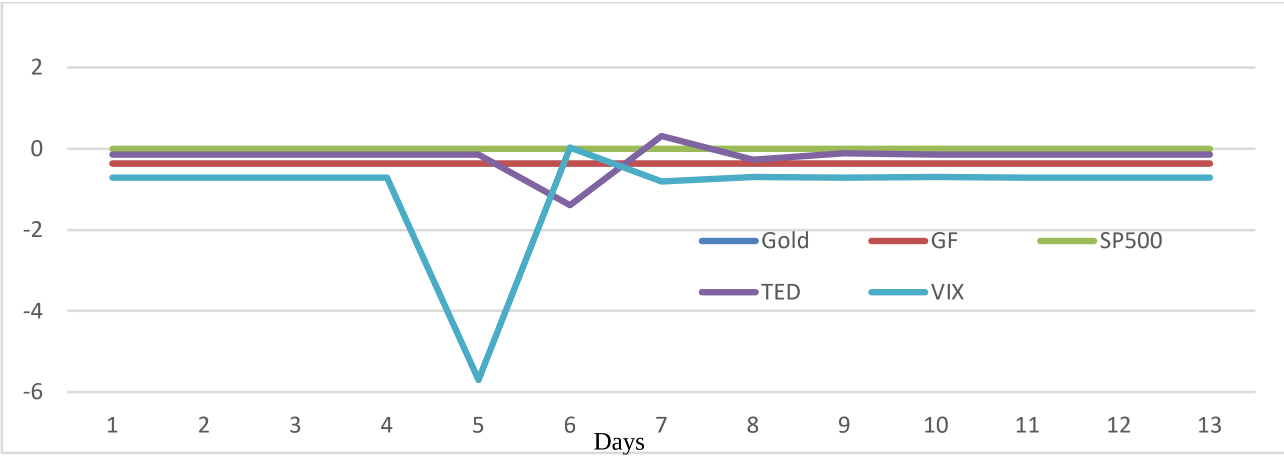
Panel C



Panel D



Panel E



Panel F

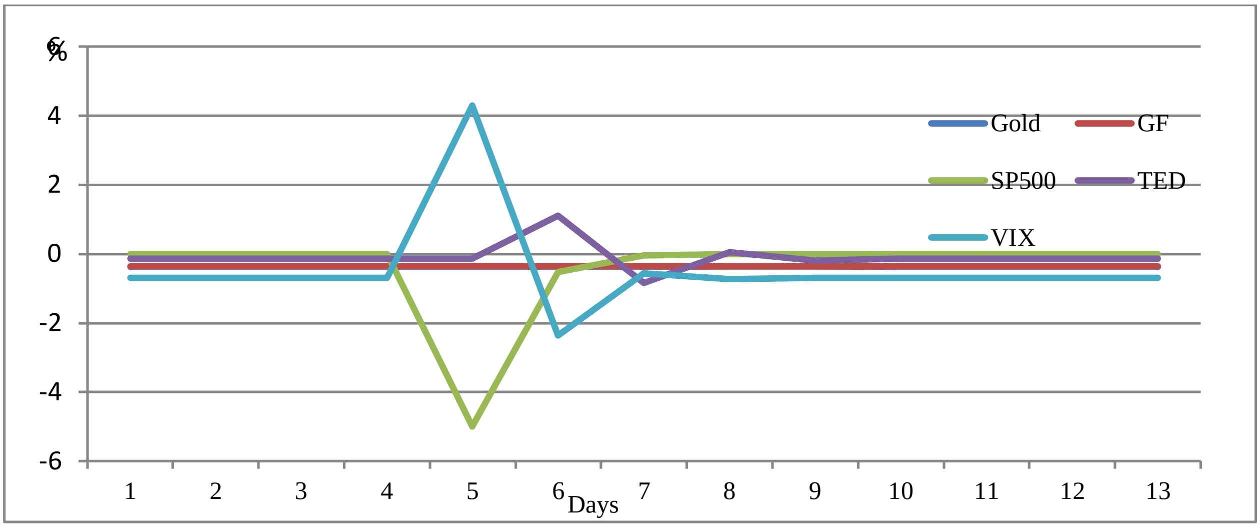


Fig. 2.
Impulse Response Functions. Panel A gives the impact of a 5 % decrease in the gold spot return (in %), Panel B the impact of a 5% decrease in the gold futures return, Panel C the impact of a simultaneous 5% decrease in the gold spot and futures returns, Panel D the impact of a 5% decrease in the S&P 500 return, Panel E the impact of a 5% decrease in the VIX return, and finally, Panel F the impact of a 5% increase in the VIX return and a simultaneous 5% drop in the S&P 500 return.

The AGDCC parameter estimates also reveal some interesting points. First, the asymmetry term in the univariate GJR-GARCH equations is positive in the case of stock returns but negative in the case of the gold market instruments. Baur (2012) and Demiralay and Ulusoy (2014) have made the same observation for precious metals as a group. There is also significant asymmetry in the correlation equations, and in most of the cases, the return distributions are skewed. In the case of the S&P500 returns, the skewness is always negative, while in the case of the gold market the sign of the skew depends on the length of the horizon. It is also worth noting that the AGDCC-GARCH equations are very close to being integrated of order one and in one case the stationarity conditions are not met. This is probably an indication of structural changes in the model parameters (Diebold, 1986; Hillebrand, 2005). However, considering the large number of parameters in our model, I cannot proceed in the direction of modelling further structural changes in my model parameters separately.

4. Impact of shocks

The impact of exogenous shocks on returns is explored by regressing the residuals of the above VAR(1) system on a large number of dummy variables describing the shocks. The results are given in Tables 2a–2c. The most striking finding is the strong and immediate transmission of the gold market specific shocks to the financial markets. In some of the cases, the price movements are in line with the "common wisdom" according to which good news for the stock market is bad news for the gold market and vice versa (see for example Elder et al., 2012; Christie-David et al., 2000). According to my results the reality is, however, much more complicated. For example, the first Central Bank Gold Agreement on September 27, 1999, (CBGA1) was good news for the gold market, because it was designed as a constraint for the future central bank sales. On the day the information was released, the stock markets also interpreted it as good news, probably because it increased the stability of the entire financial system. However, the impact of shocks on different markets seems to be highly case specific. An example of a gold market shock moving both the gold market and stock markets in the same direction, and simultaneously, pushing up both the TED spread and the VIX Index, was the rumor that the troika (the European Union, the European Central Bank, and IMF) forced the Central Bank of Cyprus to sell its gold reserves (Cyprus, 15.4.2013). The rumor was quickly refuted, but the short-lived market reaction was strong.

A general finding from the previous results regarding the financial market impacts of terrorist attacks is that they are bad news for the stock market (see also Barros and Gil-Alana, 2009; Charles and Darne, 2006; Karolyi and Martell, 2006; Kollias et al., 2011). Karolyi and Martell (2006) also showed that the impacts are case specific. According to the safe haven literature, one should expect that the gold market should be a safe haven and the decrease in stock returns and an increase in the risk should be accompanied by an increase in the gold spot and gold futures price. This behavioral pattern is also very clear in the 9/11 terrorist attack in my results, and the pattern becomes even clearer for longer horizons. However, even in the case of monthly returns, there are also examples of cases in which both the gold and stock prices move in the same direction.

Table 2 a

The impact of the shocks on residuals using daily returns

	Gold	GF	SP500	TED	VIX
Exogenous terrorist attacks					
WTC93	-0.70646***	-0.52048***	0.17282***	10.85331***	-4.80567***
Oklahoma	0.56043***	-0.11786***	-0.10224***	-1.62329***	1.30098***
WTC01	7.13208***	5.87880***	-4.47221***	77.19315***	30.29707***
Madrid	0.05582***	0.22526***	-1.54234***	-6.13454***	10.85467***
Russia2	-0.84408***	-0.08999***	-1.12548***	16.01278***	9.02688***
Egypt	0.13751***	-0.17274***	-1.03510***	6.95864***	8.54269***
London1	0.29302***	-0.06269***	0.20143***	8.20862***	2.07693***
London2	0.48568***	0.81328***	-0.69281***	-7.74003***	6.89262***
London3	0.29800***	0.07031***	-0.19862***	-6.31337***	4.37459***
London4	3.89701***	-0.74944***	-0.83422***	0.34434***	3.48403***
Events produced by political process					
DStorm1	-9.95953***	-0.58117***	-1.48860***	-18.62246***	4.88068***
DStorm2	1.30183***	1.04533***	0.75869***	5.03704***	-8.51988***
Dstorm3	-6.37431***	-7.80865***	3.60643***	-19.39083***	-19.46524***
SovUnion	-0.72500***	-1.37502***	1.33149***	-0.30481***	-1.77502***
Russia1	-1.04790***	-0.72937***	-0.02387***	-2.32812***	7.77853***
EURO	-0.56574***	0.07488***	-0.11181***	-1.37450***	7.19852***
Iraq	-0.06702***	-0.95675***	0.21629***	-4.74430***	-3.32466***
Gold market events					
UKGold1	-2.09682***	-2.40682***	0.92579***	-0.18365*	-7.38193***
UKGold2	-0.99872***	-1.95770***	-0.36618***	4.40413***	4.43855***
UKGold3	-2.12331***	-2.65972***	-0.25123***	3.00360***	10.24871***
GBGA1	4.32040***	5.07003***	0.41068***	-4.04655***	-5.11457***
GBGA2	5.63199***	8.83250***	-0.11323***	-3.99338***	-1.55411***
Cyprus	-8.01375***	-9.8523***	-2.38814***	0.54760***	35.85215***

Notes: Table presents the results from the analysis of the effects of various kinds of shocks measured by dummy variables (detailed descriptions given in Appendix A) on the estimated residuals from the VAR-AGDCC GARCH Model given in equations (1) – (15). 'Gold' refers to the gold spot market return equation, 'GF' to the gold futures market equation, 'SP500' to the stock market equation, 'TED' to the Ted Spread equation, and 'VIX' to the VIX Volatility Index equation. *, ** and *** refer to the significance of the parameter estimates on the shock dummy variables at 10, 5 and 1 % significance levels, respectively. Only the shock effects significant at least at 10 % level are reported.

Table 2 b

The impact of the shocks on residuals using weekly returns

	Gold	GF	SP500	TED	VIX
Exogenous terrorist attacks					
WTC93	-0.58143***	-0.19700***	1.72179***	1.70553	-10.1982***
Oklahoma	0.13916	-0.30035	0.21857	-6.91679*	-0.04008
WTC01	6.24786***	5.87856***	-10.84588***	113.51788***	45.69174***
Madrid	0.24417*	0.15732	-2.91708***	-2.35789	21.66504***
Russia2	-2.99150***	-2.97937***	-2.02584***	18.98729**	12.07183***
Egypt	0.23245	0.01837	-0.71676**	11.86953***	9.53574***
London1	-1.43834***	-1.24538***	1.27179***	4.15671***	-3.04852*
London2	0.68206***	0.83813***	0.13645*	-23.34514***	1.95402***
London3	0.47253***	0.81416***	1.03718***	-26.09337***	-4.82216***
London4	0.76445***	-0.01754	-0.52894***	-1.76263***	8.88229***
Events produced by political process					
DStorm1	-8.57859***	0.48092***	-2.66042***	-60.61868***	12.97624***
Dstorm3	-3.53341***	-5.45392***	4.72577***	-14.70933**	-28.87638***
SovUnion	-1.62031***	-1.62160***	5.70029***	-30.88672**	-0.20587
Russia1	-0.24579	0.43132**	-0.08700	11.87279*	1.85018***
EURO	0.31653***	0.82867***	2.25131***	-8.84515***	3.75282**
Iraq	-1.60852***	-2.31825***	2.96091***	-11.52865***	-10.28478***
Gold market events					
UKGold2	-2.67000***	-3.12750***	0.55653***	-2.45506**	2.65756***
UKGold3	-1.94067***	-2.18564***	2.37188***	11.18306***	-7.59367***
GBGA2	12.60765***	12.50168***	-1.58635***	29.98940***	0.11657
Cyprus	-11.77439***	-11.88668***	-1.70993***	4.76000***	23.57694***

Notes: See Table 2a for the notations.

Table 2 c
The impact of the shocks on residuals using monthly returns

	Gold	GF	SP500	TED	VIX
Exogenous terrorist attacks					
WTC93	-0.43328	-0.29459	0.78118*	-20.99299*	5.33782
Oklahoma	-0.59541	-0.19249	1.98458***	-12.81218	1.06532
WTC01	4.92084***	4.91131***	-8.48504***	62.48549***	42.22781***
Madrid	2.18825	2.37698	-3.63692***	-5.33147	14.80155***
Russia2	-3.91821**	-4.16393**	-3.18700***	12.45193*	7.96559**
Egypt	3.0054***	2.86172***	-1.18597**	15.04637	6.36405***
London1	-0.20537	-0.27066	0.46078	-18.75528***	-0.08344
London3	1.08534	1.06941	-1.33746**	-33.44148***	18.80499***
London4	-4.75889***	-4.76353***	-0.48286	0.93232	21.23729***
Events produced by political process					
SovUnion	-2.70871**	-2.81350***	7.21129***	-34.42954***	-3.26155*
Russia1	1.83926	2.17362**	-0.51840	34.92895***	-4.12816
EURO	-1.67264***	-1.48920***	3.81435***	-27.69518***	9.73864
Iraq	-6.77755***	-6.84154***	3.01032***	-8.73843*	-12.65447*
Gold market events					
UKGold2	-4.74983***	-4.86310***	-2.37686**	-19.22415**	7.75377***
UKGold3	-3.56219***	-3.55493***	1.36006	26.08949***	-5.34551
CBGA2	17.80019***	17.29750***	-4.34187***	51.64014***	3.82729
Cyprus	-10.50243***	-10.52219***	0.63661	12.50947***	6.40517

Notes: See Table 2a for the notations.

According to my results reported in Tables 2a – 2c and the descriptions of shocks listed in Appendix A, I can classify the shock effects in the following way. The first class would be the terrorist attacks, not seen before, and because of that, the market reactions can be confused. The WTC 1993 attack and the Oklahoma bombing are examples of this, as is probably also the killing of the president of Chechen Republic, Akhmad Karylov, on May 9, 2004. The next class comprises of the terrorist attacks resulting in typical market reactions. The 9/11 (WTC01), the Madrid attack, and the London2, London3, and London4 attacks belong to this class. Some of the attacks were bad news for the local stock market but, good news for the US market. The London1 attack is an example of this. However, it is obvious that all the terrorist attacks (except the WTC 93 attack) increase the risk measured by the VIX Index.

It is more difficult to classify the effects caused by political events. Wars are probably the most straightforward to interpret. The first day of the Desert Storm and the start of the second Iraq war have classical features: They were good news for the stock market and bad news for the gold market. The first day after the UN deadline for Iraq to withdraw its military forces from Kuwait expired (16.1.1991) and the first day the US military invaded Iraq (20.3.2003) are examples of an event increasing uncertainty but, nevertheless, having a positive effect on the stock market and a negative effect on the gold market. These results confirm the "war puzzle" hypothesis and the related results by Leigh et al. (2003), Rigobon and Sack (2005), Guidolin and La Ferrera (2010), and Brune et al. (2015) regarding the stock and gold markets.

One of my new findings is the fact that the start of the European Monetary Union had significant impacts on both the gold and stock markets. This has not been reported in previous studies. In other cases, the events classified into this category have highly case-specific impacts.

Impacts of the events classified as gold market specific shocks all have significant impacts on all markets, although the impacts on the stock market become weaker in longer horizons. The occasions in this category are shocks caused by the central banks. It is worth noting that in several cases (especially in the Cyprus case) the gold and stock markets move to the same direction. The results by Baur and McDermot (2010) confirm the "common wisdom" that gold is a safe haven for the stock market investors, while the results by Baur and Lucey (2010) suggest that if this feature exists it may be regime dependent. Cohen and Qadan (2010) also found an indication of a possible regime dependent relationship between the gold markets and the VIX Index. My results regarding the immediate shock reactions reveal a new point. In the case of large market shocks, in several cases, both the gold and stock prices may move in the same direction. In these cases, investing in the gold market does not offer a safe haven or a hedging possibility, but instead, increases the risk of a stock market investor.

5. Gold as a safe haven

I have estimated AGDCC-GARCH correlations also for returns, not for residuals of a VAR model as above but on pure logarithmic returns. Graph 3 shows that visually, the gold-stock correlation is low, and has tendency to be negative during bear markets and stock market crashes. I have tested the strong safe haven property of gold by estimating in daily and monthly data the proportion of negative correlation during days and months when the S&P 500 return has been i) negative, ii) the absolute value of the stock price decrease exceeding one standard deviation of stock returns, and iii) two standard deviations of stock returns. I have run this analysis for the whole sample and for subsamples around major stock market crashes. Results are presented in Table 3.

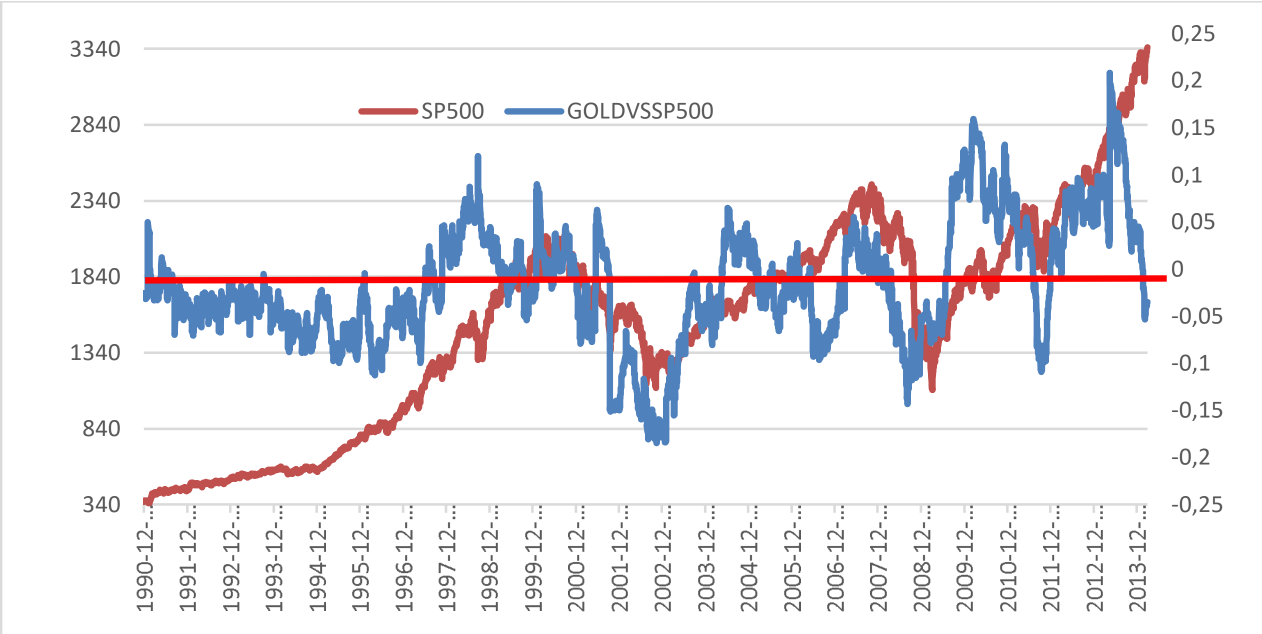


Fig. 3. S&P 500 Index (left axis) and dynamic correlation between S&P 500 daily return and daily gold price changes (right axis).

The results in Table 3 confirm the general result from the main line of research. Gold is a strong safe haven for equity investors in the US markets, but not all the time (for example, Baur and Lucey, 2010; Baur and McDermott, 2010; Hood and Malik, 2013; Flavin et al., 2014; Gürgün and Ünalmis, 2014; Areal et al., 2015; Baur and McDermott, 2016; Liu et al., 2016; Li and Lucey, 2017; Bredin et al., 2017; Shahzad et al., 2017). My results also show that the strength of the safe haven property differs across regimes and/or equity market crashes, which is in line with, for example, Baur and McDermott (2010). However, my results challenge the results of the main line of research with two points. First, the general conclusion is that the safe haven property lasts only for a short period of about 10–15 days (for example, Baur and McDermott, 2010; Bredin et al., 2017; Shahzad et al., 2017). Graphical inspections of the daily behavior of correlations[9] show that length of the safe haven period is significantly longer than 15 days. Results with monthly data (Table 3) confirm this. While my results regarding the length of the safe haven period are in conflict with the main line of research, they are more in line with Flavin et al. (2014), Bredin et al. (2015), and Dee et al. (2013).

[9] For space-saving purposes, I have not included these graphs in the articles. We will send the graphs to interested readers, when asked.

Table 3.
Proportion of observations, when correlation has been negative conditional that stock price decrease is larger than the threshold level.

Threshold	Whole sample	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 4
			Daily data		
Zero	64%	58%	66%	69%	29%
STDV	64%	46%	71%	77%	57%
2xSTDV	76%	36%	82%	90%	93%
			Monthly data		
Zero	59%	29%	57%	68%	54%
STDV	67%	21%	58%	74%	71%
2xSTDV	70%	-	70%	61%	94%

*Notes.*Theshold values: Zero – negative stock market return, STDV – stock price decrease larger that standard deviation of returns, 2xSTDV – stock price decrease larger than two times standard deviation of stock returns. Subperiod 1: 1.2.1996–31.12.1998, Subperiod 2: 4.1.1999–24.1.2003, Subperiod 3: 30.1.2007–1.4.2009, Subperiod 4: 26.10.2010–14.6.2012.

A generally accepted result is that under extreme equity market crash or very large stock price decrease, gold loses its safe haven property (Baur and McDermot, 2010; Hood and Malik, 2013; Areal et al., 2015; Choudhry et al., 2015; Drake, 2022; Iqbal, 2017; Shahzad et al., 2017; Tiwari et al., 2018; Liu, 2020; Balcilar et al., 2020). My results strongly challenge this result. Table 3 reveals that the strength of the (strong) safe haven property increases with the size of the stock price decrease. To my understanding, this is a new result.

6. Indicators of crisis periods

One of the key goals of my research were, first, to analyze the interaction between the gold market and the stock market, second, to test the impacts of the exogenous shocks on the market behavior, and, finally, based on my results, to construct simple indicators of at least stock market crashes, or even systemic crises. The above Model (1) - (15) serves well in the first two mentioned targets, but regarding the last, it is slightly problematic. The model estimation is extremely time consuming, and, due to the large number of parameters, convergence is often difficult to obtain. Because of this, I have constructed crash indicators by estimating pairwise asymmetric Dynamic Conditional Correlation (DCC) models based on the returns. These are based on estimating Equations (2) – (13) for the returns and restricting the diagonal elements of the matrices A, B, and G to be equal: ($a_{11} = a_{22}$, $b_{11} = b_{22}$ and $g_{11} = g_{22}$). I estimated the models for all the three return horizons. However, based on my empirical results it seems that only the daily horizon offers promising indicative power.

Financial market crises have several different definitions, most of which are more or less related to the banking sector. Our specific focus is narrower, namely that of the stock market crisis. Following the previous literature (for example, Patel and

Sarkar, 1998), I define a stock market crisis as a situation in which the stock market has dropped from its previous value by at least 20 %. The crisis period starts from the top and ends when the bottom is reached. Based on this classification, there are two crises in our sample period: the burst of the dot-com bubble (1.9.2000–25.7.2002) and the GFC (9.10.2007–9.3.2009). The periods of the Asian crisis around 1997–1998 and the 1998 Russian debt crisis and the related hedge fund crisis do not qualify to be labelled as stock market crashes in the US market data.

The best indicators of the market crashes in my data set are the correlation between the gold (spot) return and the S&P 500 return and the correlation between the TED spread return and the VIX return (see Figure 3). In the former case, the correlation increases before both of the crashes (and is positive) and decreases during the crises (and is negative). This implies that investors are buying gold as a hedge against the crisis and that at least some of them are already expecting. During the crisis the correlation is negative implying that gold offers an efficient hedge. The correlation between the return on the TED spread and the return on the VIX Index increases, especially before the Global Financial Crisis, implying that investors are already expecting an increase in the market risk and credit risk. This does not take place in the same way prior to the burst of the Dot-Com Bubble, because in this case, the banking crisis (credit risk) aspect seems not to have been as severe.

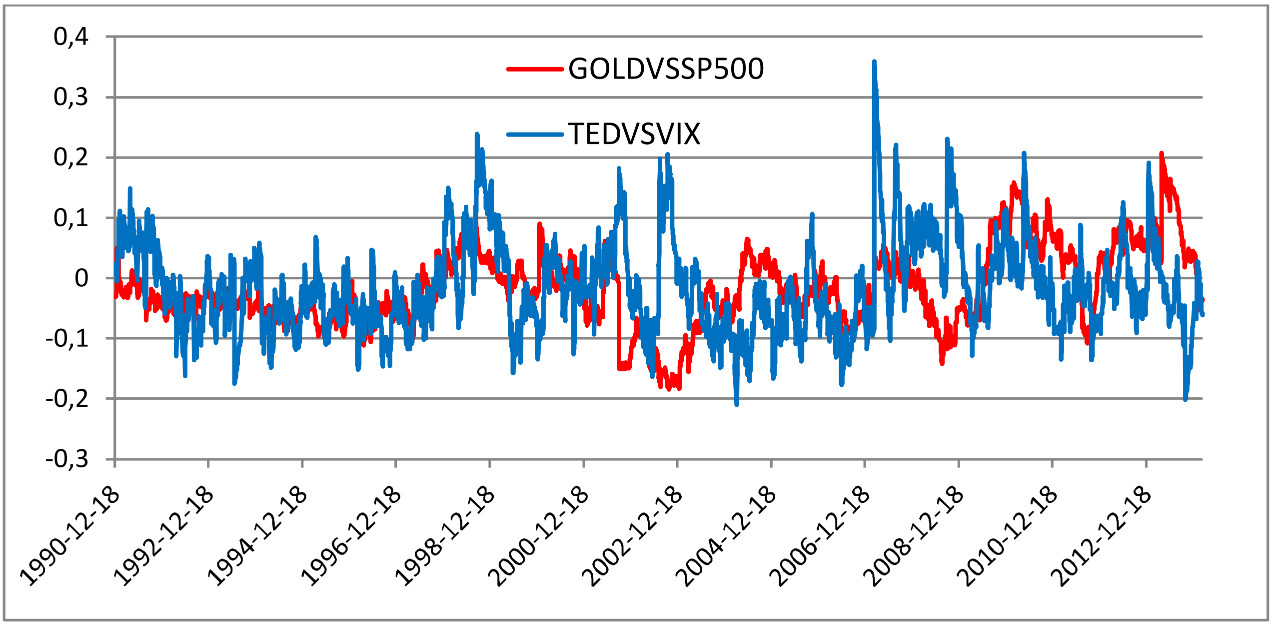


Fig. 4.

Estimated pairwise dynamic conditional correlations. GOLDVSSP500 gives the dynamic correlation between the gold spot and stock market returns, and TEDVSVIX the dynamic correlation between the TED spread logarithmic differences and the VIX return.

Finally, I tested whether the dynamic correlations between the different financial market sectors might be considered early warning indicators of the stock market crashes in the following way. I ran two regressions. In the first one, I regressed the correlations on their lagged values (only one lag), on the lagged cross terms between the standardized returns (Equation 5), and on the shock dummy variables discussed above. In the second case, I ran the same regression with the exception that I excluded the lagged correlation and the lagged cross terms from the regression equation. The set of dummy variables consists of the above-mentioned exogenous shocks, of the stock market crash dummies discussed above and dummies IT(k) and Sub(k), where the index k=1,2,…,22 indicates the time measured in days to the crash. My results reported in Appendix B (Table B1) indicate that the time-varying correlations may be termed as early warning indicators indeed. When the models are estimated excluding the dynamic terms, the dummies indicating the forthcoming crashes are all statistically significant, and they hold their signs. On the other hand, when I include the dynamic terms in the equations, even if several of the dummies indicating the future crash are still statistically significant, they are smaller in size, and they change their signs. This probably indicates possibilities for some kind of structural nonlinearity, which has not been modelled, and will be considered in our future studies.

7. Conclusions

In this paper, I tested whether gold is a safe haven and whether financial crises can be predicted by simple indicators based on investor behavior. My novel approach was to analyze the interactions between the stock market, and the ultimate safe haven, the gold market, and the investors' risk evaluations measured by two forward-looking variables: the VIX Volatility Index and the TED spread. Technically, at the first stage, the analysis was conducted by estimating a VAR-AGDCC-GARCH model for the data. The interactions of different markets were analyzed using daily, weekly, and monthly return observations from the spot and futures market for gold, the stock market (S&P500), TED spread, and quotations of the VIX Index for the period from the beginning of December 1990 to the end of February 2014. The interactions between these markets were scrutinized using a modification of the dynamic conditional correlation (DCC) model of Engle (2002). I specifically examined the dynamic reactions of these market dependencies on some exogenous shocks in the markets and overall economy. I classified these shocks into exogenous terrorist attacks, events produced by political process, and some specific gold market events. Because my ultimate target was to correctly model how the market pressure builds up before the financial crisis, I have to control for these exogenous structural shocks. This gave us an opportunity to analyze the impact of these types of shocks on financial markets, and at the same time, observe the transmission of shocks between the financial markets and the gold market.

My key findings are as follows. The interaction between the gold market and the stock market is much tighter than previously observed or even scrutinized. Particularly, some of the gold market specific shocks, such as the ones related to central bank money market sales, have a long-lasting impact also on the financial markets. In addition, some events which may have been misinterpreted as minor shocks regarding the financial markets have had significant impacts on both stock and gold markets. Furthermore, among my most important findings is the result that the events classified as gold market specific shocks all have significant impacts on all markets, although the impacts on the stock market become weaker for longer investment horizons. In addition, in many cases, the reactions of the gold and stock markets to these kinds of shocks move in the same direction.

Regarding my tests on whether gold is a safe haven for equity market investors, I confirmed the main line of result that gold is a strong safe haven for equity market investors in the US market, but not all the time, and the strength of the safe haven property is regime and crisis specific. My results suggest that the length of the safe haven period may be significantly longer than the main line of research has found. While the generally accepted result is that gold loses its safe haven property when the stock price decrease is extremely large, I challenged this result. According to my results the strength of the safe haven property increases with the size of the stock price decrease.

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Appendix A. Shock variables

DesertStorm1: 3.1.1991 a dramatic one day drop of the gold price probably based on speculation and rumors regarding the UN deadline (the Security Council passed Resolution 678) for Iraq until January 15, 1991, to withdraw from Kuwait. The gold market recovered on the next day. Excluded from monthly data.
DesertStorm2: A dummy for the first day after the UN deadline for Iraq to withdraw its military forces from Kuwait expired (16.1.1991). Excluded from weekly and monthly data.
DesertStorm3: A dummy for the first day of the Desert Storm 17.1.1991, when both the stock prices and the gold price made a drop and the SP500 index a mild jump. Excluded from monthly data.
SoVUnion: The final end of the Soviet Union occured on 25.12.1991, and the dummy is set for the first trading day after the event (26.12.1991).
WTC93: The bombing of the North Tower of the World Trade Center in New York on 26.2.1993.
Russia1: A dummy variable for the most aggressive phase of the Russian constitutional crisis on 4.10.1993.
Oklahoma: The bomb attack by Timothy McVeigh and Terry Nichols against the Alfred P. Murrah Federal Building in Oklahoma City on 19.4.1995.
Kenya: The simultaneous terrorist attacks on 7.8.1998 against the United States embassies in Daar es Salaam in Tanzania and in Nairobi, Kenya, which killed hundreds of people. However, this event took place at the same time as the Russian debt crisis, the 1998 market liquidity crisis, and the related collapse the Long-Term Capital Management. Because of this I am not using the Kenya terrorist attack as a dummy variable.
EURO: Dummy variable for the first day of the European Monetary Union: 4.1.1999
UKGold1: An exogenous gold market disruption on 7.5.1999, when the Bank of England announced its plan to sell most of its gold reserves. In the case of weekly and monthly returns UKGold1, this is merged into UKGold2.
UKGold2: An exogenous gold market disruption on 10.5.1999, the second business day after the Bank of England announcement to sell most of its gold reserves. There were exceptional gold price movement on 7.5.1999 and 10.5.1999.
UKGold3: The first Bank of England gold auction on 6.7.1999 after the announcement of a plan to sell most of its gold reserves.
CBGA1: 27.9.1999, a dummy variable for the first Central Bank Gold Agreement (CBGA). The background for the agreement was the announcement of the Bank of England to sell most of its gold reserves and the market disruptions which the announcement caused. The purpose of the agreement was to stabilize the gold market, and the agreement has been renewed several times after that. The agreement among other thing restricts the amount of gold that can be sold by the central banks. On 27.9.1999 and 28.9.1999, there were exceptional gold price movements, and the GOFO rates were heavily negative probably implying the dramatic change in expectations regarding the market equilibrium (especially the supply of reserve gold). In the case of weekly and monthly returns CBGA1 is merged into CBGA2.

CBGA2: 28.9.1999, a dummy variable for the first day after the first Central Bank Gold Agreement (CBGA).
WTC01: A dummy variable for 17.9.2001, when the stock exchanges were opened in the United States after the 9/11 terrorist attack. The attack took place on 11.9.2001 in the morning. The stock exchange was not opened before 17.9.2001, and only some early morning trades were executed on the New York Mercantile Exchange, and normal trading started on 17.9. Because of this, the period 11.9.2001–14.9.2001 was removed from the data.
Iraq: A dummy variable for the day the US military forces invaded Iraq on 20.3.2003.
Madrid: A dummy variable for the Madrid train bombings on 11.3.2004.
Russia2: A dummy for 10.5.2004, the first trading day after a bomb attack by Islamist terrorists which killed the president of Chechen Republic, Akhmad Karylov.
Egypt: The bomb attacks on 7.10.2004 by Palestinian terrorists against tourist hotels in the Sinai Peninsula in Egypt. The attacks killed 34 people and injured almost 200 people.
London1: A dummy variable for the 7/7 London bombings on 7.7.2005 (a series of coordinated suicide bombings in central London).
London2: A dummy variable for the London terrorist attack on 21.7.2005 (underground and a bus).
London3: A dummy variable for the incident of 29.6.2007 in London, when two unexploded car bombs were found.
Cyprus: 15.4.2013. An exceptional drop in gold price, probably based on the rumors that the EU would force the Central Bank of Cyprus to sell its gold reserves (382.5 tons of gold). The rumors were based on leaked EU documents. This is a huge, (more or less) permanent crash of the gold price.
London4: A dummy variable for the murder of a British soldier in London on 22.5.2013.

Appendix B:

Table B1

Results from the regression of the dynamic correlations on their lagged values and on the shock dummies.

	GoldvsSP500	GoldvsSP500	TEDvsVIX	TEDvsVIX
Constant	0.00003	-0.01082***	-0.00171***	-0.02238***
$GoldvsSP500_{t-1}$	0.99286***			
$TEDvsVIX_{t-1}$			0.97610***	
Exogenous terrorist attacks				
WTC93	-0.00278***	-0.01581***	-0.00863***	-0.03676***
Oklahoma	-0.00105***	-0.07776***	-0.00054	0.01309***
Madrid	0.00506***	-0.02184***	-0.01600***	-0.12885***
Egypt	0.00048***	0.048337***	0.02090***	-0.01214***
London1	0.00097***	-0.02945***	0.00439***	-0.03718***
London2	-0.00479***	-0.03959***	-0.02650***	-0.06498***
London3	-0.00092***	0.012240***	-0.00512**	-0.08094***
London4	-0.01593***	0.15336***	-0.000427	0.00281*
Events produced by political process and maybe partly expected				
DStorm1	0.06597***	0.06090***	-0.00841***	0.01714***
DStorm2	0.00184	0 .05459***	-0.00581***	0.02090***
DStorm3	0.00136	0.04970***	-0.006733***	0.05834***
Russia1	-0.00074***	-0.01962***	-0.00496***	0.04699***
Iraq	0.00035	-0.12299***	0.00460***	-0.05661***
Gold market events				
UKGold1	-0.01500***	-0.02654***	-0.00168**	0.03265***
UKGold2	-0.00381***	-0.02237***	0.00825***	0.04011***
UKGold3	-0.00526***	0.01195***	0.01200***	-0.08697***
CBGA1	0.01185**	-0.02937***	0.01110***	-0.02956***
CBGA2	0.00639	-0.02827***	0.00282***	-0.02722***
Cyprus	0.17427***	0.21780***	-0.05920*	0.02439***
Stock market crash				
IT Bubble	-0.00075*	-0.05191***	0.000482	0.01110**
Subprime	-0.00015	-0.04213***	0.00117	0.09128***
Dummies Prior to a stock market crash (in the parenthesis the number of days to the crash)				
IT(22)	0.00087***	0.02132***	0.00726***	-0.00752***
IT(21)	-0.00021	0.02106***	0.00012***	-0.00815***
IT(20)	-0.00587***	0.01509***	0.00020	-0.00891***
IT(19)	-0.00345***	0.01161***	0.00377***	-0.00442***
IT(18)	-0.00268***	0.00886***	-0.00742***	-0.01278***
IT(17)	-0.00030*	0.00860***	0.00576***	-0.00791***
IT(16)	0.00232***	0.01096***	0.00232***	-0.00633***
IT(15)	-0.00081***	0.01020***	0.00021	-0.00715***
IT(14)	0.00128***	0.01142***	0.03360***	0.02547***
IT(13)	0.01393***	0.02508***	-0.01320***	0.01099***
IT(12)	0.00197***	0.02699***	-0.00031	0.00925***
IT(11)	-0.00261***	0.02420***	-0.00053	0.00890***
IT(10)	0.00318***	0.02720***	-0.00001	0.00732***
IT(9)	0.00148***	0.02861***	0.00006	0.00625***
IT(8)	-0.00229***	0.02620***	0.00005	0.00514***
IT(7)	0.00021	0.02633**	-0.00103**	0.00282*
IT(6)	-0.00080***	0.02543***	0.00175***	0.00332**
IT(5)	-0.00063***	0.02470***	0.00605***	0.00823***
IT(4)	-0.00086***	0.02377***	0.01990***	0.02704***
IT(3)	0.00018	0.02386***	-0.00001	0.02519***

Table B1 continues

Table B1 continues

	GoldvsSP500	GoldvsSP500	TEDvsVIX	TEDvsVIX
IT(2)	-0.00053***	0.02326***	0.00045***	0.02815***
IT(1)	0.00159***	0.02479***	-0.01150***	0.01599***
Sub(22)	0.00296***	0.03740***	-0.00009	0.15768***
Sub(21)	-0.01872***	0.01797***	0.00636***	0.16292***
Sub(20)	-0.00040***	0.01752***	0.00151***	0.16021***
Sub(19)	0.00053**	0.01788***	0.00071***	0.16377***
Sub(18)	-0.00017	0.01768***	0.00018	0.15894***
Sub(17)	-0.00117***	0.01643***	0.00121	0.15517***
Sub(16)	0.00030	0.01634***	0.00084	0.15116***
Sub(15)	-0.00123***	0.01508***	-0.01450***	0.13295***
Sub(14)	-0.00914***	0.00525***	-0.06330***	0.08455***
Sub(13)	0.00532***	0.01032***	0.00915***	0.08931***
Sub(12)	-0.00470***	0.00543***	0.00347***	0.08976**
Sub(11)	0.00067***	0.00613***	-0.00058***	0.08185***
Sub(10)	0.00269***	0.00891***	-0.00030***	0.07559***
Sub(9)	-0.00019	0.00877***	-0.00395***	0.06906***
Sub(8)	0.00295***	0.01164***	-0.00580***	0.06110***
Sub(7)	-0.00128***	0.01038***	-0.00033***	0.05549***
Sub(6)	-0.00310***	0.00699***	-0.01240***	0.04159***
Sub(5)	-0.00064***	0.00626***	0.00349***	0.04267***
Sub(4)	0.00001	0.00641***	-0.00152***	0.03942***
Sub(3)	0.00010	0.00656***	0.00053***	0.03795***
Sub(2)	-0.00125***	0.00538***	-0.00011	0.03585***
Sub(1)	0.012134***	0.01716***	0.01260***	0.04810***
R^2	0.98	0.06	0.96	0.08
Durbin-Watson	2.0155	0.0188	1.9845	0.0494

Notes: The table reports the regression results for using the lagged values of the dependent variables, with constant and shock dummies (columns 1 and 3), and without the lagged values (columns 2 and 4) as the explanatory variables in the regression. The dependent variables are the obtained dynamic conditional correlations (i.e., pairwise DCC model-based correlations) between the returns from the gold and stock markets (columns 1 and 2) and the changes in the TED Spread and VIX return (columns 3 and 4). ***, **, and * denote significance at 1%, 5%, and 10% risk levels, respectively.

II

COMMODITY MARKET BASED HEDGING AGAINST STOCK MARKET RISK IN TIMES OF FINANCIAL CRISIS: THE CASE OF CRUDE OIL AND GOLD

by

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Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold

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Based on daily data from 1989 to 2016 we find that the correlations between gold and oil market futures and equity returns in the aggregate US market, and specifically in the energy sector stocks have changed strongly during the stock market crisis periods. The correlation between crude oil futures and aggregate US equities increases in crisis periods, whereas in case of gold futures the correlation becomes negative, which supports the safe haven hypothesis of gold. Also for the US energy sector equities our results support using gold futures for cross-hedging especially during the stock market crises.

1. Introduction

Commodity markets experienced a significant change during the beginning of this millennium when financial institutions introduced a variety of new commodity-linked investment products to provide investors a possibility to obtain more portfolio diversification benefits from commodities (see e.g. Gorton and Rouwenhorst, 2006). Nowadays commodities are considered as an alternative asset class, which many institutional investors, such as pension funds, hedge funds and insurance companies, hold in their portfolios. Based on the empirical results on the portfolio diversification benefits of commodities and low performance of stocks and bonds at the beginning of 2000's, institutional index-investors and hedge funds have emerged as one of the major players in commodity markets. At the same time, commodity prices have skyrocketed, peaking just before the outbreak of global financial crisis in 2008. The radical increase in commodity prices initiated speculation on whether the financial investors and speculation drive the commodity prices. For example, the Managing Member of Masters Capital Management, Masters (2008), expressed his concern in his testimony to the US senate that speculative trading of financial investors and hedge funds in commodity derivatives markets has caused a bubble in commodity prices and increased their price volatility. Thus, from a pricing perspective, the emergence of financial investors could imply that alongside with fundamentals, the financial motives have become one of the main determinants of commodity prices. The literature has named this phenomenon as the *financialization of commodity markets*.

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Understanding the evolution of co-movements between different asset classes is crucial in many portfolio and risk management assignments in financial markets. For example, when estimating the variance-covariance matrixes of returns for calculating optimal asset allocations, it is important to understand how correlations between asset class returns evolve over time. From a *hedging perspective*, it is crucial that the correlation between the asset classes remains low especially in periods of financial turmoil. Hence, it is essential to examine the time-varying co-movements between different asset returns especially during financial crises when the portfolio diversification benefits of asset classes are needed the most. In addition, the valuation of the most sophisticated structured products and exotic options, such as basket options, is based on the return correlations between the underlying assets, so analysing the time-varying correlations between different asset returns helps to understand the pricing of these products in periods of financial crises. The stronger role of institutional investors in commodity markets has introduced more intensive cross market linkages between commodities and equities. The empirical evidence has shown that after the outbreak of global financial crisis in late 2008 the correlations between commodity and equity returns increased drastically, whereas before the crisis these assets were typically uncorrelated (see e.g. Creti et al., 2013). In addition, recent empirical literature has provided evidence that the correlations across commodity prices and returns have increased actually starting from 2004 (see e.g., Tang and Xiong, 2012).

The purpose of this study is to analyze the co-movement of commodity futures and stock market returns in periods of financial turmoil by focusing especially on the crude oil and gold futures markets. Crude oil and gold are the main strategic commodities that investors and financial economists follow on a daily basis. The strategic importance of these commodities makes it interesting to analyze their dependence or correlation with respect to the equity markets. As commodities, the main difference between crude oil and gold is that crude oil can be regarded mainly as a consumption commodity, whose price depends on global demand and supply.[1] However, in addition to the industrial demand for jewelleries, speculative demand is one of the main factors affecting the price of gold. Moreover, recent empirical research has provided evidence that gold provides a safe haven against stock market crashes (see, e.g., Junttila and Raatikainen, 2017 and references therein). Based on this evidence, we will examine whether this safe haven effect is observable also in the time-varying correlations between the returns. As for crude oil, empirical literature has reported a jump in the price correlation with some assets after the global financial crisis in 2008. By extending the sample size to cover the period to 2016, we are able to study how these correlations have evolved in the zero-interest rate environment. The zero-interest rate period is particularly interesting, because low interest rates induce a decline in the *convenience yields* of physical commodities and makes commodity trading with financial assets more attractive than physical trading (see, e.g. Kolodziej et al., 2014). In addition, we hypothesize that the zero-interest rate environment makes alternative asset classes, such as commodities, more attractive for investors, because the traditional fixed income instruments, such as bonds, do not basically provide positive yields at all.

Our second contribution to the most recent literature is to extend the correlation analysis to include the energy sector equities. Theoretically there should be a positive dependence between the crude oil futures and energy sector stocks, since energy sector equities usually benefit from higher oil prices. For the gold futures, we will examine whether their safe haven effects can also be identified against the energy sector equities in terms of time-varying correlations. Finally, we will provide implications for cross-market hedging by examining how crude oil and gold futures can be used to hedge against stock market investment risks. It is especially important to scrutinize the hedge ratios in periods of stock market sell-offs, when hedging is needed the most. This analysis is carried out by calculating dynamic hedge ratios and optimal minimum variance portfolio shares for the assets considered, which show how investors should hedge their stock market positions using the analysed derivatives prior to and during periods of financial turmoil, and in other times.

Our results show that the time-varying correlations with the stock market returns, and hence, the dynamic hedge ratios and optimal portfolio shares, differ significantly for the crude oil and gold futures. In periods of stock-market sell-offs crude oil futures and S&P500 total returns become more positively dependent on each other, whereas in case of gold futures the correlation becomes negative, highlighting the safe haven properties of the gold futures. Hence, because of negative correlation in periods of financial turmoil, gold futures clearly seem to be much more attractive instruments in cross-market hedging compared to the crude oil futures. In addition, we also find that the correlation has stayed higher after the crisis, indicating that the 2008 crisis was a major break-point in these data. For the part of energy sector equities, already since 2004 the crude oil futures and energy sector equity prices have moved together more than they did previously. One possible explanation for this is that as a result of financialization of the commodity markets the cross-market linkage between crude oil and energy sector equities has become stronger. From a hedging perspective, the crude oil futures seem not to be so attractive instruments in minimizing the risk from the US energy sector equity investments. Quite contrary, our results actually indicate that for hedging purposes the share of gold futures should be even bigger for the energy sector portfolio in crashing times than it is for the portfolio containing the aggregate index, so gold clearly increases its role in hedging against energy sector risks in periods of financial distress, too.[2]

[1] Note that in reality the daily spot price of crude oil storages is based on the price of crude oil futures, so in the global markets crude oil is traded with futures contracts, whereas the spot price of crude oil is actually the *price for the extra oil* sold daily. Thus, in view of hedging purposes it is more relevant to use the prices of futures contracts in this study.

[2] It is worth to mention here that compared to many other previous studies, our finding of significantly higher shares (around 40% on average) of gold in optimal minimum variance portfolios is based on choosing a highly provocative set of assets (for the purposes of mainly analysing their hedging properties), i.e., we only consider portfolios that do not contain any forms of e.g. interest yielding assets.

The remainder of this paper is organized as follows. Section 2 briefly discusses the previous literature on our theme and relates the contribution of our paper to that. Section 3 presents the econometric methods and data for our analysis, and Section 4 details the empirical results. Finally, Section 5 gives concluding remarks and suggestions for further research.

2. Previous literature

2.1. The role of gold market in hedging for stock market risks

Gold has been used in trade for many millennia and it is still considered as an important precious metal in modern economies. In consumer market the demand for gold arises in the form of jewelleries, whereas for industrial purposes gold is used in technology and dentistry. In addition, central banks, investors and speculators demand gold for *asset management purposes and as a store of value*. In early days, gold was used as a basis for monetary system for a long time, which means that currencies were linked to the value of gold at a fixed price. The largest share of the physical gold demand is in the form of jewelleries, but following the financialization of commodity markets the demand for gold-linked exchange traded products has increased significantly. Today the investment demand for gold accounts for the second largest share of total demand for gold (O'Connor et al., 2015). The supply of gold is based on mining and recycled gold. According to the estimates of the World Gold Council (2016) the supply from mining accounts for two thirds of the total gold supply, whereas recycled gold accounts for the remaining third.

Fig. 1 below shows the evolution of gold spot price in the US from 1989 to 2016. We see that there has been a steep increase in the gold price since the beginning of 2000s. For example, between 2003 and 2013 the price of gold increased 382%. According to Baur and McDermott (2010) one of the main reasons for a steep increase in the price of gold has been the increased investment activity in gold. As already mentioned in the introduction, the number of commodity-linked investment products increased significantly during the beginning of this millennium, and recent empirical research has studied whether the exponential growth in the price of gold between 2002 and 2012 was due to financial speculation based on financialization of commodity markets in general. For example, the evidence of Baur and Glover (2015) suggests that the price development in this period can partly be explained by speculative trading in gold markets. In addition, Fig. 1 reveals that after 2010 the price of gold continued to increase reaching its highest level in its history despite the global financial and European debt crises.

Traditionally the attraction of gold as a financial asset has been based on its observed ability to provide a hedge against inflation and the fluctuations in the value of the US dollar (see for example Ghosh et al., 2004; Capie et al., 2005). For the relationship between gold and equities, it has been argued that gold retains its value especially during periods of political or economic uncertainty. Based on this attribute, investors and speculators have usually referred to gold as a safe haven asset. Baur and Lucey (2010) investigated whether gold is a hedge or safe haven asset against stock and bond market risks. They defined a hedge asset as a security, which is *uncorrelated* with stocks and bonds on average, whereas safe haven assets are securities, which are *uncorrelated or negatively correlated* with stocks and bonds in extreme stock or bond market conditions. For example, in times of declining stock prices, the price of safe haven asset would go up, but during bullish market conditions, the correlation between safe haven asset and stock market might be positive. Their dataset covered a 10-year period from November 30, 1995 until November 30, 2005, focusing on three financial markets with different currencies: United States, the United Kingdom and Germany. According to their results gold was a safe haven asset for stocks in all three markets used in the analysis, but it only functioned for a short period of time.[3] For the bond market they did not find any evidence for gold serving as a safe haven asset.

The analysis of Baur and Lucey (2010) did not take the global financial crisis into account, whereas Baur and McDermott (2010) used a 30-year data set covering the time period from 1979 to 2009 to examine the role of gold in the global financial system. Their main idea was to analyze the safe haven properties of gold against developed and emerging markets' equity risks. In addition, they distinguished between *weak and strong forms of safe haven and hedge assets*. A strong hedge asset is negatively correlated with stock markets on average, whereas weak hedge asset has zero correlation with stocks on average. A strong safe haven is defined as an asset that is negatively correlated with equities during periods of extreme negative returns, whereas a weak safe haven asset is uncorrelated with equities during corresponding periods. Their results gave evidence on safe haven and hedge asset effects for most developed countries' stock markets, such as for major European stock markets and the US. Furthermore, for the European and US stock markets gold was observed to be a strong safe haven. In contrast, Baur and McDermott observed that gold is neither a safe haven nor a hedge asset for Australia, Canada, Japan and BRIC countries. For emerging markets gold was, at best, observed to be a weak safe haven. This indicates that the significance of safe haven assets in emerging market is not as evident as it is in developed markets, which might be due to investors' portfolio allocation behaviour. The results also suggested that investors use gold as a safe haven when the global economic uncertainty rises, but in extreme cases of global uncertainty the gold market moves in the same direction as do the global stock markets, limiting the safe haven role of gold under global uncertainty. Interestingly, the results also indicated that the safe haven role of gold is *currency dependent*. The common currency denomination of gold and stock indices seems to

[3] Gold performed as a safe haven asset for around 15 trading days after an extreme negative shock to stock returns. Their portfolio analysis indicated that an investor, who holds gold longer than 15 days may suffer losses from holding a position in gold too long.

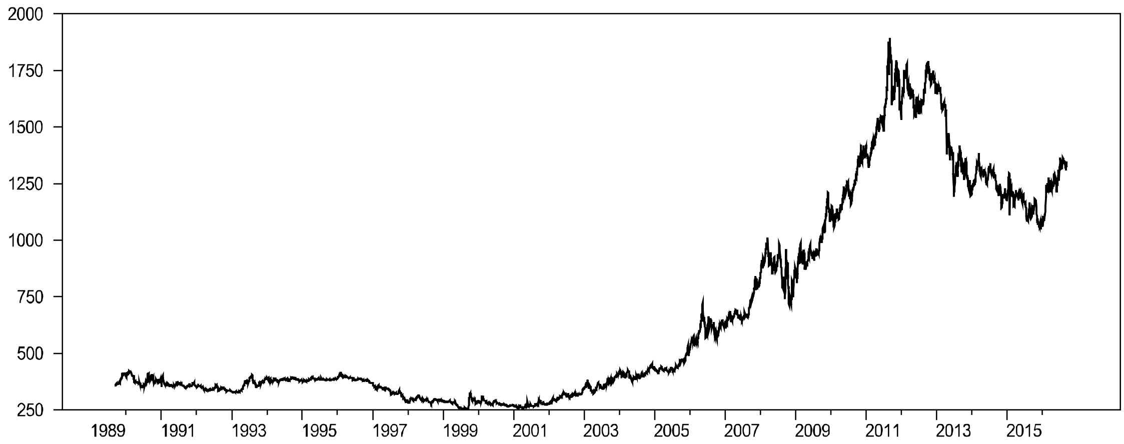

Fig. 1. Handy & Harman gold bullion spot price ($/Troy Oz). *Source:* Datastream.

induce generally higher co-movement even in extreme market conditions, which in turn reduces the usability of gold as safe haven asset during periods of uncertainty.

Previous research has also studied whether financial speculation could explain the safe haven property of gold. Baur and Glover (2012) argued theoretically that significant speculative investments in gold can undermine the safe haven property of gold in the long run, whereas in the short run the safe haven properties still exist. They proposed that the more investors hold gold in their portfolios against the stock market shocks, the more the safe haven properties of gold are likely to suffer in periods of financial turmoil, because of different contagion mechanisms between these markets.

Uncertainty in the financial markets is usually related to high volatility of asset returns. Empirical research has shown that stock market return volatility is inversely related to the level of stock returns, which implies that volatility is expected to be higher during periods of declining stock prices. Evidence of the asymmetric volatility in equity markets is, for example, provided by Bekaert and Wu (2000). Based on this, Hood and Malik (2013) studied the safe haven effects of gold under changing stock market volatility. Using data from 1995 to 2009 they showed that gold represents hedging and weak safe haven properties against the US stocks. However, they also showed that in periods of extremely low and high volatility, gold market does not display negative correlation with the US stock market. This evidence suggests that the safe haven role of gold is not evident during periods of extreme uncertainty, such as during the global financial crisis in 2008. On the contrary, Hood and Malik found that the VIX index has negative correlation with stock markets even during the periods of extremely high volatility, which suggests that the VIX index-related investment products, such as VIX futures, could be a superior hedging tool against stock market risks compared to gold.

2.2. Connections between crude oil and stock markets

Crude oil is one of the most important commodities traded in the global markets and its price plays a significant role in affecting macroeconomic variables such as inflation, exchange rates and economic growth. The most frequently used benchmarks for crude oil prices are the WTI Cushing Crude Oil Spot Price, traded at the New York Mercantile Exchange (NYMEX) and the North Sea Brent, traded at the Intercontinental Exchange (ICE). The fundamental spot price of crude oil is based on the equilibrium of demand and supply. Basically, as described e.g. in Behmiri and Pires Manso (2013), crude oil prices react to economic, political, meteorological, financial and technological factors. In addition, Behmiri and Manso note that information about oil reserves has an impact on crude oil prices. A special feature of crude oil is that it is an exhaustible resource, and hence, according to e.g. Hamilton (2008), scarcity and speculation are relevant pricing factors in the market for crude oil.

Fig. 2 below describes the WTI crude oil price (in dollars) from September 1989 to September 2016. Evidently, the price of crude oil increased continuously from 1999 to 2008. It is also worth to note that the oil price movements show some steep increases, which are followed by abrupt drops. For example, in July 2008 before the outbreak of the global financial crisis, the price of WTI crude oil peaked at 145.31 dollars per barrel and by the late December 2008 the crude oil price had dropped 79% to 30.28 dollars per barrel. Another significant drop was experienced between 2014 and 2016, when the excess oil supply and decreasing global demand pressed down the oil prices by 75%. All in all, Fig. 2 reveals that the price of crude oil price has fluctuated a lot, showing rapid increases and decreases over the sample period.

A theoretical motivation for the co-movements between crude oil and stock market prices can be found from asset pricing theory. Traditional asset pricing theory suggests that asset prices are determined based on expected cash-flows. Thus, an increase in oil price should induce higher costs for companies, which use oil as an input in production. Higher costs, in turn, decrease expected cash-flows, which should lead to a decrease in stock prices. On the other hand, for oil exporting economies higher oil prices imply higher revenues, which should be accompanied by an increase in the stock prices. From another perspective, an increase in oil price should have positive impacts on the whole economy of oil exporting countries because of

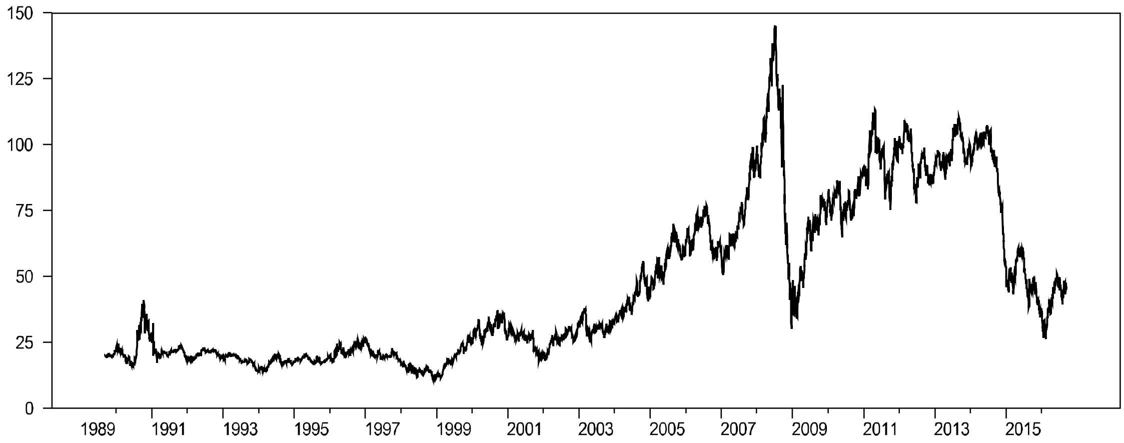

Fig. 2. Crude oil-WTI spot price. *Source:* Datastream.

increased income in oil exporting industry. An increase in income should, in turn, enhance country's economic conditions, which should be reflected positively in the stock markets (see, e.g. Jimenez-Rodriguez and Sanchez, 2005).

Jones and Kaul (1996) were among the first to investigate how stock markets react to oil price shocks. Using a standard cash-flow dividend valuation model they provided evidence on the negative relationship between crude oil price changes and aggregate stock market returns. Their results also implied that for the US and Canadian stock markets, the reactions on the changes in oil price can be explained by the impact of oil price changes on cash flows, which is consistent with the theoretical link between crude oil and stock market prices. However, in case of Japan and the United Kingdom the impact of oil price changes on stock prices could not be only justified by changes in cash flows or by changes in expected returns. In these countries, the reaction was larger than changes in the cash flows would have predicted. In addition, numerous other studies have confirmed this negative relationship. For example, Park and Ratti (2008) used a multivariate VAR analysis to investigate the impacts of oil price shocks on real stock returns over the period from January 1986 to December 2005. Based on a sample of real stock returns from the US and 13 European countries, they showed that oil price shocks have a statistically significant impact on real stock market returns. Furthermore, oil price shocks had a negative effect on the stock market returns for the US and 12 European countries. However, the causality was positive for the Norwegian stock markets, which is justifiable, because Norway is an oil-exporting country. These results gave further support for the asymmetric impacts of oil price shocks. Miller and Ratti (2009) used a vector autoregressive model (including cointegration) to study the long-run relationship between the crude oil prices and international stock markets over the period from January 1971 to March 2008 and found a negative long-run relationship between the world price of crude oil and stock market returns for six OECD countries. Kilian and Park (2009), in turn, showed that unanticipated changes in the crude oil prices, driven by demand and supply shocks, explain about 20% of the long-run changes in US returns.

Empirical literature has also provided evidence on a positive relationship between crude oil and stock market returns. The positive impacts are usually reported for oil-exporting economies. For example, Arouri and Rault (2012) studied the links between oil prices and stock markets in countries belonging to the Gulf Cooperation Council (GCC)[4] using bootstrap panel cointegration and SUR methods. Their cointegration analysis suggested that there is a long-run relationship between oil prices and stock markets. Moreover, the results of SUR analysis indicated a positive impact of higher oil prices on stock market returns, except in Saudi Arabia, which is theoretically justifiable, because GCC countries are major oil exporters in global oil markets, and hence, benefit from high oil prices.

Earlier studies have also examined how financial distress affects the correlation between crude oil and equities. Based on the earlier evidence on the relationship between crude oil and equities Filis et al. (2011) used a DCC-GARCH-GJR approach to analyze the time-varying correlation between oil and stock market prices to identify how correlations vary in periods of economic uncertainty. In order to take the asymmetric effects of oil price shocks into consideration, they analysed the correlations separately for oil-exporting and oil-importing economies. The sample consisted of monthly data from 1987 to 2009 of three oil-exporting countries (Canada, Mexico and Brazil) and three oil-importing countries (the US, Germany and Netherlands). Their results showed that the correlations between stock and oil prices do not show different patterns for oil-exporting and oil-importing countries. However, Filis et al. found that oil price shocks, originated from precautionary demand shocks, such as terrorist attacks and wars, and other aggregate demand side shocks like the Asian crisis at the end of 1990's, the housing market boom, and the Chinese economic growth and global financial crisis in 2008, seem to have a significant effect on the relationship between oil and stock prices. The effects were observed to be similar for oil-exporting and oil-importing countries. The results also suggest that the aggregate demand-side oil price shocks cause a positive correlation between oil prices and stock market prices, whereas precautionary demand shocks cause the correlations to be neg-

[4] GCC countries include Bahrain, Oman, Kuwait, Qatar, Saudi Arabia and the United Arab Emirates.

ative. On the other hand, supply shocks such as the OPEC production cuts and hurricanes do not seem to have a significant effect on the correlation between oil and stock markets. To sum up, based on previous findings, because aggregate demand shocks induce a positive correlation between crude oil and equity returns, one might conclude that oil does not provide a safe haven against losses in stock markets in periods of economic turbulence.

Previous empirical research also has also reported that the global financial crisis has imposed a structural break in the time-varying correlation between crude oil and US equity returns. The evidence suggests that the cross-market linkages got significantly stronger as a result of the global financial turmoil, which is reflected in a higher correlation between crude oil and stock market returns than before the crisis period. Many empirical studies have also reported a significant jump from negative to positive values in the correlation between crude oil prices and US stock market prices during the global financial crisis in 2008 (see e.g. Filis et al., 2011; Kolodziej et al., 2014; Creti et al., 2013).

2.3. Oil and gold market together in hedging against stock market risks

In view of our research questions on the role of oil vs. gold as hedging tools for stock market risks, empirical research has also examined the relationship between the prominent hedging assets, i.e., the oil and gold prices. The theoretical motivation for the co-movement between gold and oil prices comes from the relationship between inflation and gold prices. As discussed earlier, investors have traditionally used gold to hedge against inflation. The increase in oil price induces an increase in the general price level, which implies higher inflation. As inflation increases, the demand for gold increases, which pushes gold prices up. Thus, the inflation channel suggests that there is a positive relationship between oil and gold prices. Based on this theoretical motivation, Narayan et al. (2010) studied the long-run relationship between gold and crude oil futures prices at different levels of maturity using cointegration analysis. Their results suggested that gold and oil spot and futures market returns are cointegrated up to the maturity of 10 months. According to Narayan et al. the results indicate that investors have used gold as a hedge against inflation (or oil price movements) and oil prices can predict the gold market prices. Similarly, Zhang and Wei (2010) showed using daily data from 2000 to 2008 that the crude oil and gold prices are cointegrated, which supports the earlier evidence that crude oil and gold prices share a similar long-run price trend. However, the evidence from their Granger causality tests indicated that there was linear Granger-causality from crude oil to gold prices but not vice versa. This evidence supports the theoretical hypothesis, that an increase in oil price causes an increase in the gold price.

More recently, Reboredo (2013) has examined whether gold provides a hedge or safe haven against oil price movements. Using copula analysis and data from January 2000 to September 2011 he obtained evidence of a positive dependence between gold and oil markets, so gold cannot be used as a hedge asset against oil price fluctuations. However, copula analysis revealed that there is tail independence between oil and gold prices, which indicates that the gold market provides a safe haven against negative oil market shocks.

The safe haven property of gold against equity and oil markets implies that there is a negative correlation between gold and equity markets on one hand, and on the other and, between equity and oil markets, in periods of market stress. Moreover, the financialization of commodity markets has induced not only an increase in correlations across equities, but also an increase in correlations between commodities and equities. Nevertheless, for example the empirical evidence of Creti et al. (2013) reveals that the correlation between gold and S&P 500 index decreased significantly during the global financial crisis in 2008, whereas other commodities became more correlated with the stock market during the crisis. This evidence gives a further a priori support, from a correlation analysis perspective, that gold provides a safe haven against stock market crashes.

The main novelty of our paper is to introduce the stock, gold and oil markets to the same setting when analyzing the hedging possibilities between these assets, and furthermore, specifically to pay also attention to the connections of energy sector equity returns to the gold and oil market returns. In the previous studies, perhaps closest to our data set, e.g. Mensi et al. (2013) used a VAR-GARCH model of Ling and McAleer (2003) for the analysis of connections between returns and volatilities of the S&P500 and commodity prices for energy, food, gold and beverages during the period of 2000–2011. Their main finding was that there was a significant transmission mechanism between the S&P500 and commodity markets. The highest conditional correlations were found between the S&P500 and gold index, and the S&P500 and the WTI index. The most recent of all our reference papers, i.e., the paper by Mensi et al. (2017) analysed time-varying equicorrelations and risk spillovers between crude oil, gold and the Dow Jones conventional, sustainability and Islamic stock index aggregates and 10 associated disaggregated Islamic sector stock indexes (basic materials, consumer services, consumer goods, energy, financials, health care, technology, industrials, telecommunications and utilities), using the multivariate DECO-FIAPARCH model and the spillover index of Diebold and Yilmaz (2012) for the period of 9/11/1998–5/3/2015. Their results showed strong evidence of time-varying risk spillovers between these markets. Moreover, they found increasing dynamic correlations among the markets around the 2008–2009 global financial crisis, and provided evidence that gold offers better portfolio diversification benefits and downside risk reductions than oil.

Other emerging markets have been analysed by e.g. Arouri et al. (2015), who used again the VAR-GARCH approach, but now for the first time on Chinese data and found strong return and volatility cross effects between gold and stock prices. Their results implied that adding gold to the Chinese aggregate stock portfolio improves its risk-adjusted return and helps to effectively hedge against stock risk exposure over time, and for the most recent global crisis period, gold serves as a safe haven for stocks in the Chinese markets.

From a methodological point of view, Chkili et al. (2014) is perhaps the closest to our approach, because they applied a multivariate dynamic conditional correlations model with fractionally integrated asymmetric power GARCH specification

(DCC-FIAPARCH) to the analysis of time-varying properties of returns and volatilities of crude oil and US stock markets over the period 1988–2013. Their fundamental finding was that investors in the US markets should have more stocks than crude oil as assets in their portfolio to be able to reduce the overall portfolio risk.

Our paper adds three new dimensions to the analysis of Chkili et al. (2014) and many other previous studies mentioned above. First, we introduce gold as a highly prominent hedging asset when analyzing the combinations of oil as an asset, and stocks in the US aggregate market portfolio. Second, due to the dual role of oil prices in affecting the valuation of stocks in general (depending on whether the aggregate stock market is an oil-importing or oil-exporting country market), we also analyze specifically the return connections of US energy sector equities to the gold and oil markets, because the United States is both importing and exporting oil and petroleum products.[5] Third, compared to e.g. Chkili et al. (2014) and especially Mensi et al. (2017), as an empirical approach we introduce parametrically perhaps a more straightforward, but equally efficient way to take into account the role of asymmetries in the return generating processes for the analyses of return connections and hedging possibilities, based on the asymmetric generalized dynamic conditional correlation model (AG-DCC) VAR model of Cappiello et al. (2006).

3. Econometric methods and data

3.1. Dynamic conditional correlation model

In modelling the risk correlations in financial markets, unlike the constant conditional correlation model for the family of generalized autoregressive conditional heteroscedasticity (GARCH) models proposed by Bollerslev (1990), the dynamic conditional correlation (DCC-GARCH) model enables the investigation of time-varying conditional correlations. The standard version of DCC-GARCH model of Engle (2002) is built on the following ideas. Let us assume r_t to be a $k \times 1$ vector of conditional returns. DCC GARCH-model is based on the assumption that the conditional returns are normally distributed with zero mean and time-varying variance-covariance matrix $H_{t,}$ i.e., $r_t|\xi_{t-1} \sim N(0, H_t)$, where ξ_{t-1} denotes the information set at time $t - 1$. DCC GARCH model relies on the assumption that the time-varying variance/covariance matrix can be decomposed as

$$H_t = D_t P_t D_t, \tag{1}$$

where $\mathrm{P_t}$ is a time-varying correlation matrix containing the conditional correlations and $D_t = diag\left[\sqrt{h_{i,t}^2}\right]$ is $k \times k$ diagonal matrix of time-varying conditional standard deviations. The diagonal matrix of time-varying standard deviations can be generated, for example, as a result of estimating a univariate GARCH (p, q) model proposed by Bollerslev (1986) for the individual asset returns, giving

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

where h_t^2 denotes time-varying conditional variance of the return in question. After the estimation of univariate volatility models for each return series, the standardized residuals, defined as $\varepsilon_{it} = \frac{r_{it}}{\sqrt{h_{it}}}$ are used to estimate the evolution of the correlation, given by equation

$$Q_t = (1 - \alpha - \beta)\bar{P} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1}, \tag{3}$$

where $\bar{P} = E[\varepsilon_{t-1} \varepsilon'_{t-1}]$ is the unconditional correlation matrix of the standardized residuals. In order to ensure the mean reversion of the model, the condition $\alpha + \beta < 1$ must hold. Now the time-varying correlation matrix $\mathrm{P_t}$ can be decomposed to

$$P_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \tag{4}$$

where $diag\{Q_t\}^{-1}$ is an inverted diagonal matrix containing the square root of diagonal elements of $\mathrm{Q_t}$, i.e.,

$$diag\{Q_t\}^{-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\sqrt{q_{nnt}} \end{bmatrix}. \tag{5}$$

Because of the normality assumption, the parameters of the model can now be estimated using maximum likelihood estimation based on the likelihood function

$$\begin{aligned} L &= -\frac{1}{2} \sum_{t=1}^{T} (nlog(2\pi) + log|H_t| + r'_t H_t^{-1} r_t) \\ &= -\frac{1}{2} \sum_{t=1}^{T} (nlog(2\pi) + 2\log|D_t| + r'_t D_t^{-1} D_t^{-1} r_t - \varepsilon'_t \varepsilon_t + log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t). \end{aligned} \tag{6}$$

[5] In 2016, the United States imported approximately 10.1 million barrels per day (MMb/d) of petroleum from about 70 countries, and exported about 5.2 MMb/d of petroleum to 101 countries, see https://www.eia.gov/tools/faqs/faq.php?id=727&t=6.

Finally, the time-varying conditional correlations are calculated using the equation

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, \tag{7}$$

where $q_{i,j,t}$ is the covariance between asset returns i and j at time t, and $q_{ii,t}$ and $q_{jj,t}$ are the diagonal elements in the variance-covariance matrix Q_t, that is, they are the conditional variance estimates of i and j at time t.

Cappiello et al. (2006) note that time varying risk premia may induce asymmetric response in correlations between returns of different assets. According to their idea, the theoretical justification behind the conditional asymmetries in correlations relies on the principle that a negative shock in returns of any pair of stocks will increase the variances of these stocks. In the CAPM world, if betas of these stocks do not change, then the covariance between this pair of stocks will increase. Correspondingly, if idiosyncratic variances do change, then more likely after the negative shocks than after positive shocks, correlation will increase. Thus, the correlations are expected to be higher after negative shocks than after positive shocks.

To introduce conditional asymmetries in correlations when modelling the dynamic conditional correlations, Cappiello et al. proposed an *asymmetric generalized* DCC GARCH (AG-DCC) model that captures the asymmetric news impacts on correlations. In case of AG-DCC GARCH model, the evolution of dynamic correlation is estimated using a process

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B. \tag{8}$$

In Eq. (8) A, B and G denote $k \times k$ parameter matrices. The effect of negative shocks on correlations is captured by the variable n_t, which can be written as a Hadamard product of an indicator function and standardized residuals ε_t, that is $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$, where $I[\varepsilon_t < 0]$ denotes a $k \times 1$ indicator function, which takes a value of 1 if $\varepsilon_t < 0$, and 0 otherwise. Finally, $\bar{N}$ denotes the unconditional correlation matrix of standardized residuals.

Cappiello et al. (2006) also show how the special cases of AG-DCC GARCH model can be obtained by restricting the parameter values in the model. In case of asymmetric DCC (i.e., A-DCC) model, the parameter matrices A, B and G are replaced by scalars, which reduces the evolution of dynamic correlations to

$$Q_t = (\bar{P} - a^2\bar{P} - b^2\bar{P} - g^2\bar{N}) + a^2\varepsilon_{t-1}\varepsilon'_{t-1} + g^2n_{t-1}n'_{t-1} + b^2Q_{t-1}. \tag{9}$$

Correspondingly, the conditional asymmetries in correlations can be erased from the model by setting G = 0. In this case, the generalized DCC model can be expressed as

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'Q_{t-1}B. \tag{10}$$

The last modification of AG-DCC model restricts the parameter matrices to be diagonal matrices. In this case, the dynamic correlation process can be written as

$$Q_t = \bar{P}(ii' - aa' - bb') - \bar{N} \circ gg' + aa' \circ \varepsilon_{t-1}\varepsilon_{t-1} + gg' \circ n_{t-1}n_{t-1} + bb' \circ Q_{t-1}. \tag{11}$$

In Eq. (11), i denotes the vector of ones and a, b and g denote the vectors containing the diagonal elements of matrices A, B and G.

In our empirical application of the family of DCC models the time-varying conditional correlations will be estimated using the Generalized Diagonal DCC GARCH model of Cappiello et al. (2006). In our case the estimation is carried out in three steps. In the first step, a vector autoregressive (VAR) model is estimated for the variables of interest (i.e., the returns), from which the residuals are obtained for the dynamic conditional correlation model. The VAR representation of the data is

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{pmatrix} + \begin{pmatrix} \pi_{1,1} & \pi_{1,2} & \pi_{1,3} \\ \pi_{2,1} & \pi_{2,2} & \pi_{2,3} \\ \pi_{3,1} & \pi_{3,2} & \pi_{3,3} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix}, \tag{12}$$

where y_{1t} denotes the WTI crude oil futures return, y_{2t} is the CMX gold futures return, and y_{3t} the S&P 500 index return, or alternatively, the S&P 500 Energy IG index return series. Using the 3×1 vector of residuals obtained from the VAR model above, the 3×3 conditional covariance matrix H_t is decomposed as

$$H_t = D_tP_tD_t, \tag{13}$$

where D_t is 3×3 diagonal matrix of conditional standard deviations and P_t denotes the time-varying correlation matrix. In order to capture the potential leverage, i.e., asymmetric effects of innovations on conditional variances and volatility clustering in the conditional variances, conditional standard deviations are estimated by using univariate GJR (1, 1) GARCH model proposed by Glosten et al. (1993), that is,

$$h^2_{i,t} = \alpha_{0,i} + \alpha_{1,i}u^2_{i,t-1} + \beta_i h_{i,t-1} + \gamma_i u^2_{i,t-1}I_{i,t-1}, \tag{14}$$

where $I_{i,t-1} = \begin{cases} 1 \ \textit{if} \ u_{i,t-1} < 0 \\ 0 \ \textit{otherwise} \end{cases}$ and $i = 1, 2, 3$.

The constant coefficient $\alpha_{0,i}$ is the estimate for constant volatility, whereas $\alpha_{1,i}$ measures the impact of lagged return shocks of asset i on its conditional variance and β_i gives the influence of the conditional variance in the previous period on the conditional variance in the current period. Possible asymmetries in the conditional variance are captured by the coefficient γ_i.

Once the conditional standard deviations are estimated from the univariate processes, the residuals, obtained from the VAR model estimated in the first step, are standardized based on conditional standard deviations. Formally, the standardized residuals are defined as

$$\varepsilon_{i,t} = \frac{e_{i,t}}{\sqrt{h_{i,t}^2}}. \tag{15}$$

Using the 3×1 vector of standardized residuals, the evolution of conditional correlation matrix P_t is given by

$$P_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \tag{16}$$

where $diag\{Q_t\}^{-1}$ is an inverted 3×3 matrix containing the square root of diagonal elements of Q_t, and Q_t denotes a 3×3 time-varying conditional correlation matrix for the returns. Using the generalized diagonal DCC model, proposed by Cappiello et al. (2006), the evolution of conditional correlation matrix is given by[6]

$$Q_t = \bar{P}(ii' - aa' - bb') + aa' \circ \varepsilon_{t-1}\varepsilon_{t-1} + bb' \circ Q_{t-1}. \tag{17}$$

The coefficients are estimated by maximum likelihood as described above (Eq. (6)). Once the model is estimated, the time-varying conditional correlation series are given by

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}}. \tag{18}$$

Next, after the dynamic conditional correlations are estimated, we will calculate the risk-minimizing optimal dynamic hedge ratios in order to examine whether the gold and crude oil futures can be used to hedge against the risks in the spot positions of the S&P 500 Total Return Index, or alternatively, in the S&P 500 Energy IG Price index. The risk minimizing dynamic hedge ratios are calculated following the specification of Kroner and Sultan (1993), which is given by

$$\beta_t = \frac{h_{sf,t}}{h_{ff,t}}, \tag{19}$$

where $h_{sf,t}$ denotes time-varying conditional covariance between spot and futures returns and $h_{ff,t}$ is the time-varying conditional variance of the returns of futures contracts, both measured at time t. The time-varying variances and covariances are obtained from the time-varying variance-covariance matrix, estimated with the Generalized Diagonal DCC-GARCH model.

Finally, because we have a three-dimensional model for asset returns, we do not have to limit our focus only to bi-variate hedging, as has been the usual case in the previous literature, but we can instead explore the portfolio and risk management strategies beyond that. Minimum variance portfolio weights in our 3-asset portfolio are the solution for investor's minimization problem

$$\min_{\omega_t} \omega_t' H_t \omega_t \text{ st. } \sum_{i=1}^{3} \omega_i = 1, \tag{20}$$

in which $\omega_t = \begin{pmatrix} \omega_{1,t} \\ \omega_{2,t} \\ \omega_{3,t} \end{pmatrix}$ is a vector of minimum variance portfolio weights. The Lagrangian of the problem is given as

$$\mathcal{L}_t = \omega_t' H_t \omega_t + \lambda\left(\sum_{i=1}^{3} \omega_i - 1\right), \tag{21}$$

where λ is the Lagrange coefficient. The first order conditions for the solution are

$$2\omega_t' H_t + \Upsilon = 0 \tag{22}$$

$$\omega_{1,t} + \omega_{2,t} + \omega_{3,t} = 1,$$

where $\Upsilon = \begin{pmatrix} \lambda \\ \lambda \\ \lambda \end{pmatrix}$, and in a more compact way we may write

$$\Omega_t \omega_t = z, \tag{23}$$

[6] The correlation equation selection was based on choosing between the Generalized Diagonal DCC-GARCH model and an Asymmetric Generalized Diagonal DCC-GARCH model, both proposed as the possibilities by Cappiello et al. (2006). Stability conditions indicated that the AGD-DCC model does not fit our data, whereas the Generalized Diagonal DCC model fulfilled the stability conditions.

where $\Omega_t = \begin{pmatrix} 2h_{1,1,t} & 2h_{1,2,t} & 2h_{1,3,t} & 1 \\ 2h_{2,1,t} & 2h_{2,2,t} & 2h_{2,3,t} & 1 \\ 2h_{3,1,t} & 2h_{3,2,t} & 2h_{3,3,t} & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$, $\omega_t = \begin{pmatrix} \omega_{1,t} \\ \omega_{2,t} \\ \omega_{3,t} \\ \lambda \end{pmatrix}$, and $z = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$ and $h_{i,j,t}$ (i = 1, 2, 3, j = 1, 2, 3) are the elements of the conditional variance-covariance matrix H_t based on DCC estimations. Finally, the minimum variance portfolio weights for the assets are given by

$$\omega_t = \Omega_t^{-1} z. \tag{24}$$

In terms of the implications of our DCC results for the portfolio management and hedging decisions, our analysis at the final stage will be based on discussions regarding the optimal minimum variance portfolio shares for the two interesting cases, i.e., where the stock market asset is either the general S&P500 portfolio, or the portfolio of energy sector equities, and the other assets are always the gold and oil market futures.

3.2. The data

Our dataset consists of daily observations for the COMEX Gold Futures continuous settlement prices and West Texas Intermediate (WTI) crude oil futures near month settlement prices, which are denominated in US dollars per barrel. For the equity market prices, the analysis relies on S&P500 Composite Total Return Index, which is one of the most relevant stock market indexes in the US. Since our focus is also in the ability of oil market derivatives' hedging possibilities, it is natural to extend the analysis to the energy sector equities, too, so we will also use the S&P500 Energy IG Price Index in our analysis. This index also comprises of companies included in the S&P500 index, but classified as the GICS energy sector equities. All the data are collected from Thomson Reuters EIKON/Datastream and cover the period from September 11, 1989 to September 13, 2016. The equity prices are also denominated in US dollars.

For a preliminary co-movement analysis, in Figs. 3a–3d the time series on crude oil and gold futures price observations are plotted together with the S&P500 Index and S&P500 Energy IG Price index observations. Fig. 3a illustrates the development of S&P500 Total Return index and Crude oil-WTI futures near month settlement price. From the figure we can see that the crude oil futures prices and S&P500 index movements were more or less unrelated from 1989 to the early 2000s. However, during the IT bubble in the beginning of 2000s the S&P500 prices and crude oil futures showed similar price trends. Furthermore, before the onset of the most recent global financial crisis we see that the settlement price of crude oil futures skyrocketed, but when the global financial crisis finally erupted, initiated by the bankruptcy of Lehman Brothers in September 2008, this triggered a significant drop in the crude oil futures and equity prices. In addition, especially after the global financial crisis, the crude oil futures and the US aggregate equity market prices showed similar price trends until 2013, when the settlement prices of crude oil futures dropped dramatically, reflecting the excess global supply of crude oil during the global economic downturn.

Fig. 3b plots the evolution of the COMEX gold futures continuous settlement price and the S&P500 Total Return index. Unlike in case of crude oil prices, the gold futures and equity prices show unrelated or even adverse price trends throughout the sample period. As for the periods of financial crises, e.g. during the IT bubble the gold futures market showed positive price development, whereas the equity prices dropped at the same time. Similarly, during the outbreak of the global financial crisis, gold futures showed adverse price movement compared to the equity prices, which is consistent with some previous empirical evidence that gold provides a safe haven against the US equity market price changes.

Figs. 3c and 3d plot the time series of crude oil and gold futures prices against the S&P500 Energy IG Price index. Fig. 3c shows a clear co-movement of the crude oil and energy sector stock prices. The similar price movements are justifiable, because obviously, the revenues of energy sector firms are dependent on the price level of crude oil. However, a more careful look at the figure reveals that the co-movement between these price series intensified starting from 2003, when the index investors appeared in the commodity markets. On the other hand, for the gold futures a preliminary analysis based on Fig. 3d reveals that starting from 2003 the gold futures and energy sector stock prices have started to experience similar price trends, and this reflects the extensive financialization of the commodity markets from around 2003.

Before our dynamic conditional correlation analyses we performed the unit root tests to check for the stationarity of the asset price series. We used the standard Augmented Dickey-Fuller and Phillips-Perron tests with the null of unit root, and in addition, the stationarity test of Kwiatkowski, Phillips, Schmidt and Shin to test the robustness of the unit root test results. The results in Table 1 show that all the prices are I(1), i.e., non-stationary time series processes. As a result of the unit root test results, all our empirical analyses in the remaining parts of the paper will focus on the co-movements between the commodity futures and equity markets using *daily logarithmic return series*, defined as

$$r_t = 100 \times [\ln(P_t) - \ln(P_{t-1})], \tag{25}$$

where $\ln(P_t)$ and $\ln(P_{t-1})$ denote the log transformation of the daily price series in periods t and $t-1$.

Table 2 reports the descriptive statistics for all the *return* series. The full sample consists of 7046 observations for each variable. From September 11, 1989 to September 13, 2016, the mean daily total rate of return on Crude-oil WTI futures was 0.01%, with a minimum daily return of −41.55% and a maximum of 22.92%. An abnormally low daily drop in the Crude-oil WTI futures price was due to the oil price shock in 1990, which occurred in response to Iraq invasion of Kuwait. We can see that the daily average return on gold futures is slightly higher than that of crude oil. Interestingly, the standard

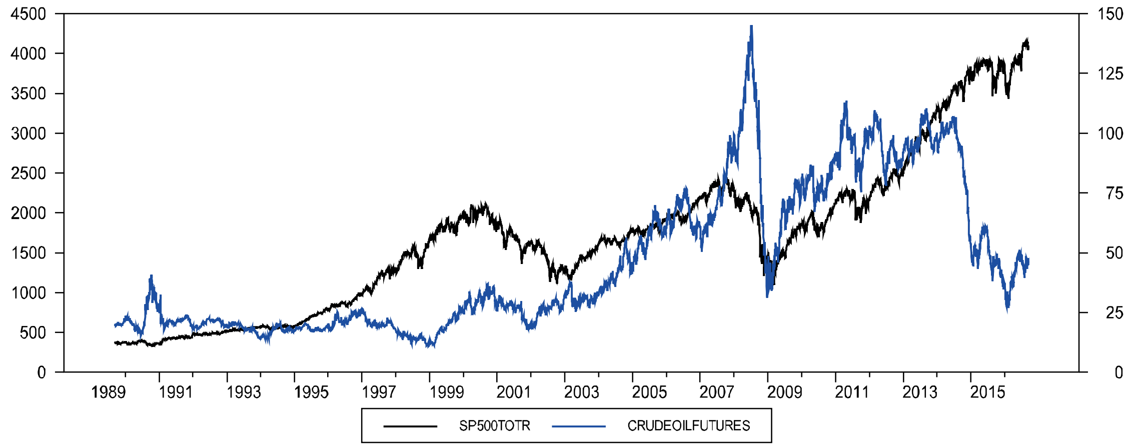

Fig. 3a. S&P500 Total Return Index and Crude oil-WTI futures near month settlement price. *Source:* Datastream.

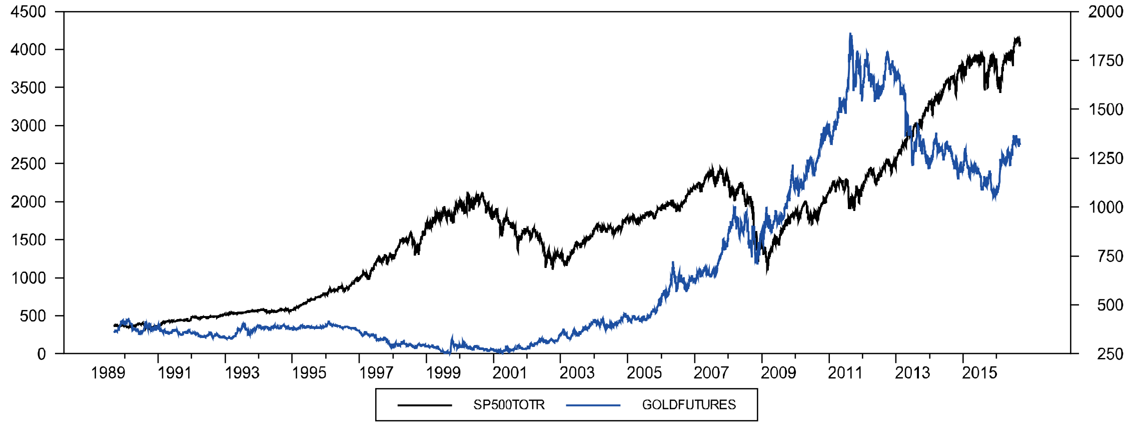

Fig. 3b. S&P500 Total Return Index and COMEX Gold futures continuous settlement price. *Source:* Datastream.

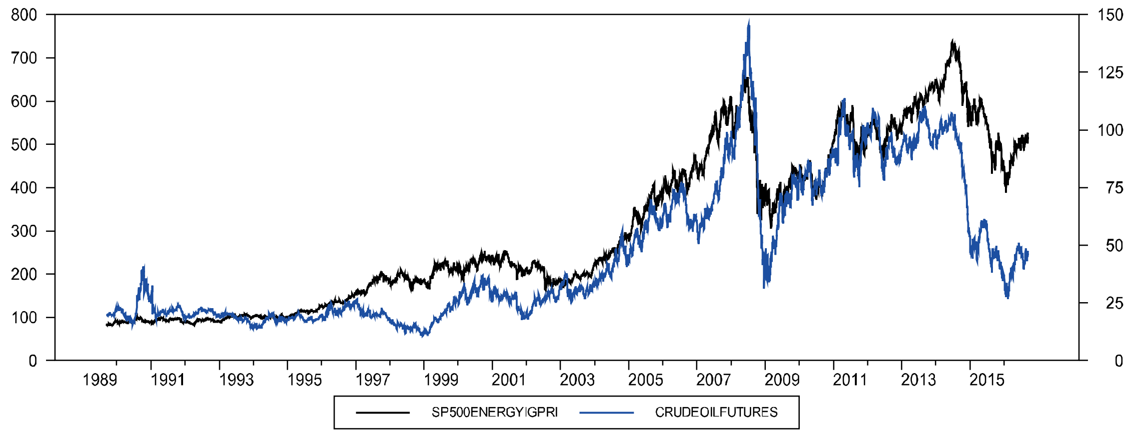

Fig. 3c. S&P500 Energy IG Price index and Crude oil-WTI futures near month settlement price. *Source:* Datastream.

deviation of gold futures return is also remarkably lower than the standard deviation of the WTI crude oil futures return indicating higher risk-adjusted returns for the gold futures. In case of equities, the average daily returns of S&P500 and S&P500 Energy IG Price indexes were higher than for the crude oil and gold futures. The standard deviations of the stock market index returns indicate lower volatility of stock returns compared to the WTI crude oil futures, but higher volatility than for the gold futures returns. As one might intuitively expect, the S&P500 Energy sector index returns have higher volatility than the returns from S&P500 Total Return Index.

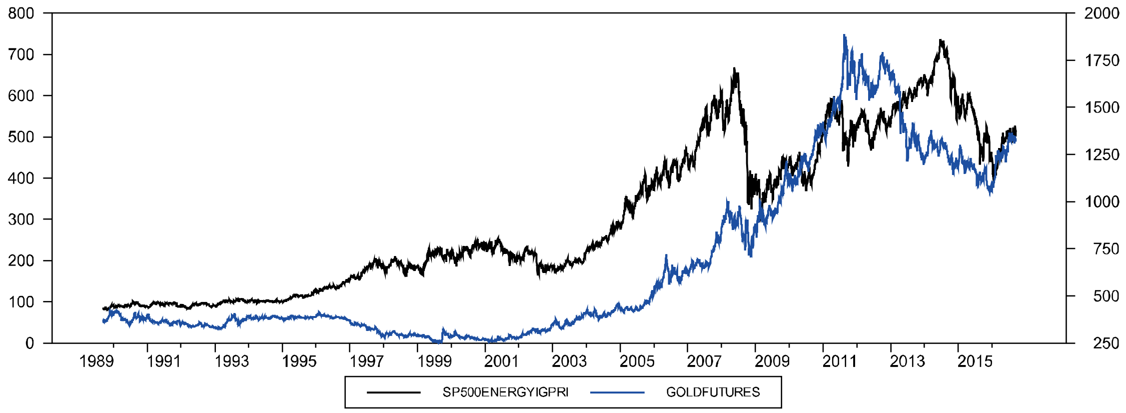

Fig. 3d. S&P500 Energy IG Price index and COMEX gold futures continuous settlement price. *Source:* Datastream.

Table 1
Unit root test results.

Test statistics	ADF	PP	KPSS
Price series			
Crude-oil WTI	−1.682	−1.637	99.501***
COMEX Gold	−0.396	−0.368	106.436***
S&P500 Total Return Index	0.425	0.462	112.278***
S&P500 Energy IG Price Index	−1.181	−1.220	126.866***
Return series			
Crude-oil WTI	−85.974***	−86.059***	0.077
COMEX Gold	−84.467***	−84.489***	0.216
S&P500 Total Return	−88.899***	−89.109***	0.121
S&P500 Energy return	−65.178***	−89.620***	0.069

Notes: ADF refers to the Augmented Dickey-Fuller test, PP to the Phillips-Perron test and KPSS to the Kwiatkovski, Phillips. Schmidt, Shin-test, where the first two tests have the null hypothesis of non-stationarity and the KPSS has the null of stationarity of the analysed time series. *, **, and *** refer to the significance of the test statistics at 10, 5 and 1% risk levels. Percentage returns are calculated as log differences of daily price observations, multiplied by 100.

Table 2
Descriptive statistics of the daily returns.

	Crude-oil WTI	COMEX Gold	S&P500 Total	S&P500 Energy
Observations	7046	7046	7046	7046
Mean	0.01%	0.01%	0.03%	0.03%
Standard deviation	2.37	1.02	1.11	1.47
Minimum	−41.55%	−9.81%	−9.46%	−16.88%
Maximum	22.92%	8.87%	10.96%	16.96%
Kurtosis (excess)	18.27***	8.19***	9.07***	11.30***
Skewness	−0.71***	−0.24***	−0.27***	−0.28***
Jargue Bera stat.	98553.56***	19737.39***	24257.94***	37551.01***
ARCH test	239.76***	261.82***	1384.44***	1780.07***

Notes: *, **, and *** indicate the significance of reported statistics at 10, 5, and 1% risk levels, respectively.

The shape of the probability distributions of daily returns is described using excess kurtosis and skewness statistics in Table 2. The reported kurtosis statistics indicate that each variable shows statistically significant positive excess kurtosis, which implies that their probability distributions have fat tails. Moreover, negative skewness figures indicate that the probability distributions are negatively skewed in each case. From a probability perspective, this implies that all these assets have higher probability of extremely negative than extremely positive returns. Also the Jarque-Bera test statistics imply that the null hypothesis of normally distributed asset returns is rejected in every case at 1% significance level.

The time series on daily returns are plotted in Appendix A. The plots reveal an interesting feature of the commodity futures market returns. First, the crude oil futures show extreme returns more intensively than the aggregate US and energy sector equities. In the case of gold futures, the extreme daily returns are lower than in the case of equities and crude oil, but the gold futures show extreme returns more frequently than the equities and crude oil futures. One reason for this might be the centralized trading in gold markets. Central banks form a group of key investors in the gold market, so their actions may also induce extreme returns for the gold positions. For example, in 1999 the HM Treasury announced to sell approximately

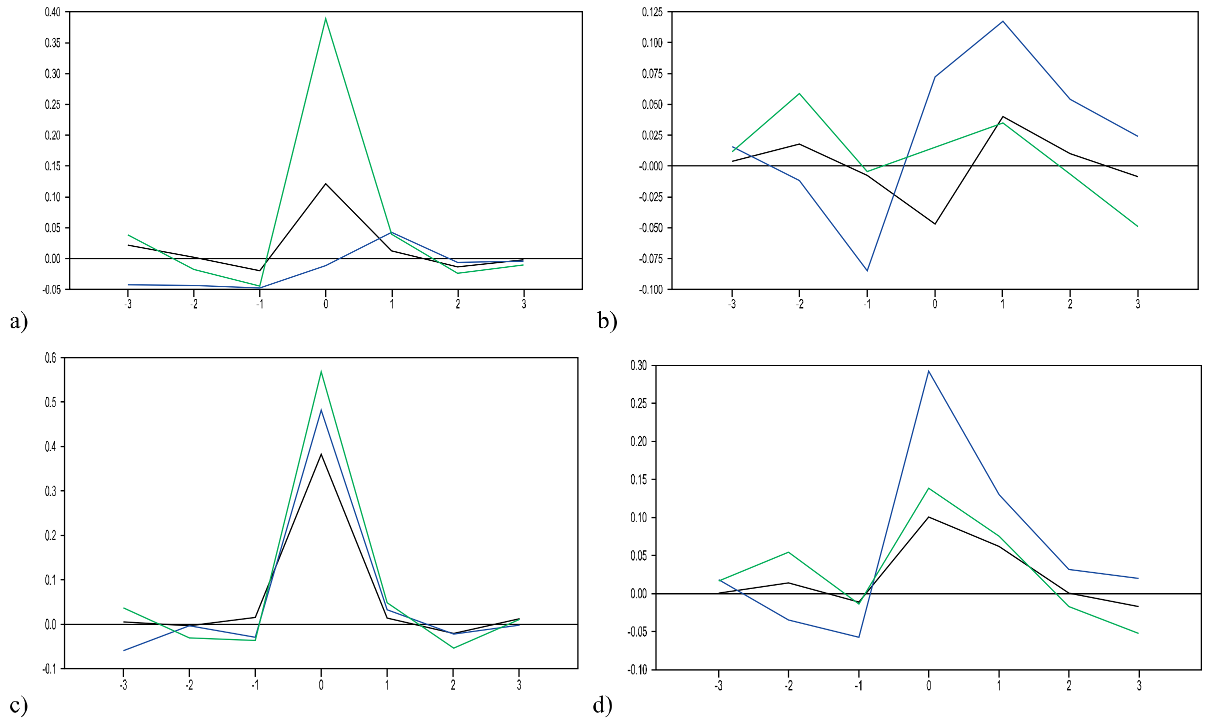

Fig. 4. Cross correlations.*Notes:* In Figure a (upper left, for the crude oil futures and aggregate S&P500 returns), b (upper right, for the gold futures and aggregate S&P500 returns), c (lower left, for the crude oil futures and energy sector equity returns) and d (lower right, for the gold futures and energy sector equity returns), the black line shows cross-correlation calculated using the sample from September 11, 1989 to September 13, 2016, the blue line using the sample from January 2004 to September 2008 and the green line using the sample from October 2008 to September 2016.

half of the UK gold reserves, which resulted to an extended period of bear market in gold price (see e.g. O'Connor et al., 2015; Junttila and Raatikainen, 2017). As a result of these actions the price of physical gold decreased to its lowest levels in 20 years. In addition, the safe haven role and speculative demand for gold futures may induce frequent extreme returns.

For our further modelling purposes, it is useful to test whether non-linear models are appropriate to capture the time series behaviour of the data used in our analysis. Hence, we start from the results for the standard ARCH effects proposed by Engle (1982). The test statistics reported in Table 2 indicate that the null hypothesis is rejected for each variable, suggesting the presence of non-linear ARCH effects in crude oil, gold, S&P500 TOTR and S&P500 Energy sector index returns. Hence, using more advanced non-linear models in the analysis of our data seems also to be justified a priori.

As a preliminary simple tool for giving an idea on whether the somewhat technically oriented dynamic conditional correlation modelling might be appropriate for our data, Fig. 4a–d plots the cross-correlations between commodity and equity returns used in our analysis. In the cross-correlation analysis we used three lead and lag values of each return series and the graphs plot the correlations of each of them against the contemporaneous values of the return series in question. Using different subsamples, the figures clearly indicate variation in the cross-correlations between a set of different sample periods for the individual return series. Hence, variation in the cross-correlations gives further support that perhaps also the co-movements between the analysed return series should be modelled with time-varying conditional correlation models.

4. Empirical results

4.1. Dynamic relationships

Our modelling strategy was to estimate first the simplest model, and then, stepwise a more general version of the model, and select the best model based on the likelihood ratio statistics regarding the conditions for the stationarity of the variance process and positive definiteness of the covariance matrix. According to this specification strategy the best model was a VAR model with generalized dynamic conditional correlations and a Glosten-Jagannathan-Runkle GARCH representation for the error terms, i.e. a VAR with G-DCC-GJR-GARCH errors. The asymmetric version of this specification did not satisfy the sufficient conditions for positive definiteness.[7]

Tables 3a and 3b report the parameter estimates of the VAR model (Eq. 12), the univariate GJR-GARCH model (Eq. (14)) and the Generalized Diagonal DCC GARCH correlation Eq. (16) given in Section 3. Table 3a provides the parameter estimates for the model using crude oil futures, gold futures and S&P500 Total Return Index returns as the variables. The parameter

[7] Because the necessary conditions are not known, we rejected all the models not satisfying the sufficient conditions.

Table 3a
Parameter estimates of the conditional correlation model for the commodity futures and S&P500 Total returns.

Equation for	Crude oil-WTI$_t$	COMEX Gold$_t$	S&P500 Total$_t$
Parameter	**VAR(1) Equation (Eq. (12))**		
Constant	0.011	0.017	0.036***
Crude oil WTI$_{t-1}$	−0.025**	0.010*	−0.005
COMEX Gold$_{t-1}$	−0.014	−0.009	−0.009
S&P500 Total$_{t-1}$	0.031	0.034***	−0.057***
	GJR-GARCH(1, 1) Equation (Eq. (14))		
α_0	0.032***	0.002**	0.016***
α_1	0.065***	0.055***	−0.001
β	0.926***	0.961***	0.921***
γ	0.012	−0.031***	0.126***
Sationarity condition:	0.998	1.000	0.982
	Generalized Diagonal DCC Equation (Eq. (16))		
A	0.160***	0.110***	0.127***
B	0.985***	0.989***	0.990***

Notes: Reported parameter values refer to the parameterization of our model based in Eqs. (12), (15), (17) and (19) given in Section 3. Notations *, ** and *** refer to the statistical significance of the reported parameter estimate at 10, 5, and 1% risk levels, respectively.

Table 3b
Parameter estimates of the conditional correlation model for the commodity futures and S&P500 Energy returns.

Equation for	Crude oil-WTI$_t$	COMEX Gold$_t$	S&P500 Energy$_t$
Parameter	**VAR(1) Equation (Eq. (12))**		
Constant	0.011	0.018	0.027
Crude oil WTI$_{t-1}$	−0.033**	0.002	0.030***
COMEX Gold$_{t-1}$	−0.018	−0.014	−0.018
S&P500 Energy$_{t-1}$	0.044**	0.042***	−0.079***
	GJR-GARCH(1, 1) Equation (Eq. (14))		
α_0	0.032***	0.002**	0.015***
α_1	0.066***	0.054***	0.028***
β	0.926***	0.961***	0.939***
γ	0.012	−0.031***	0.049***
Sationarity condition:	0.997	1.000	0.992
	Generalized Diagonal DCC Equation (Eq. (16))		
A	0.123***	0.116***	0.110***
B	0.991***	0.987***	0.994***

Notes: See Table 3a.

estimates of the VAR model for the crude oil futures return equation show that only the lagged crude oil futures returns seem to Granger cause the crude oil futures returns at 5% significance level. The negative sign on the lagged returns suggests a mean reverting behaviour of the returns. In the equation for the gold futures returns, the parameter estimates imply that lagged crude oil futures returns Granger cause the present gold futures returns at 10% significance level. The positive sign on the coefficient is consistent with the evidence of Reboredo (2013), who found a positive dependence between the crude oil and gold markets. However, the statistically significant positive parameter estimate on the lagged S&P500 returns is inconsistent with earlier evidence of the safe haven role of gold futures.[8] One explanation for the positive parameter estimate is that it may imply a positive dependence between gold futures and US equities at the aggregate level in the long-run. As previous research has indicated, gold provides a safe haven against extreme negative returns in the US equity market. Moreover, for example the results of Baur and Lucey (2010) indicate that the safe haven effect applies only for a short period of time and the effect is observed for extreme returns. The last column reports the parameter estimates of the VAR model for the S&P500 returns. The negative parameter estimate on the lagged S&P500 return observations indicates again a mean reverting behaviour of the S&P500 index returns. Interestingly, lagged crude oil returns do not have a statistically significant impact on the S&P500 total returns. Previous empirical research has reported a negative relationship between crude oil and stock markets in the US. Hence, the sign of the coefficient estimate does not support earlier empirical evidence of the relationship between crude oil prices and stock market returns.

The parameter estimates of the conditional variance equation for the crude oil and gold futures returns show that the lagged shocks in returns and lagged conditional variance have a statistically significant effect on the conditional variance in the current period. However, the lagged return shocks do not have a statistically significant effect on the conditional variances of the S&P500 returns in our sample. On the other hand, consistent with the earlier evidence (see e.g., Bekaert and Wu,

[8] Theoretically, the safe haven role of gold would imply that the lagged S&P500 TOTR index returns Granger cause gold futures returns with a negative sign.

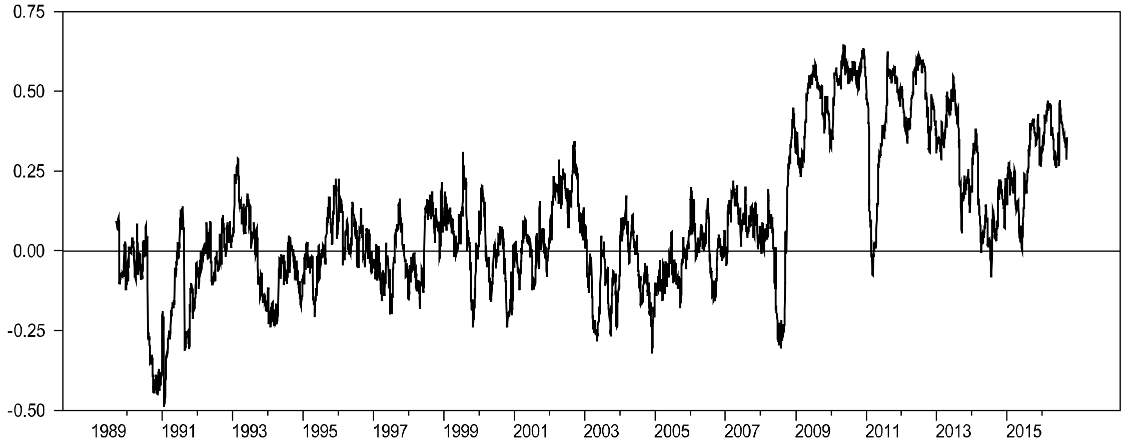

Fig. 5a. Dynamic correlation between crude oil futures and S&P500 TOTR index returns.

2000), the conditional variance of S&P500 returns exhibits a leverage effect implying higher volatility in response to negative vs. positive return shocks, but the volatility of the crude oil futures returns does not show asymmetric reactions to negative and positive shocks. Interestingly, the parameter estimate for gold futures returns indicates that positive return shocks increase volatility more than negative return shocks which contradicts the leverage effect in volatility reported from the equity markets. According to Baur (2012) this asymmetric volatility is due to safe haven role of gold. Baur hypothesizes that the increase in the price of gold can be interpreted as an increase of safe haven purchases from investors. In turn, these safe haven purchases can be interpreted as a signal of higher uncertainty and risk in financial markets and macroeconomic conditions, which leads to higher volatility in the gold markets. On the other hand, negative returns in the gold markets can be interpreted to be connected to lower volatility of gold futures returns. Stationarity conditions[9] of the conditional variance equation hold for each variable, which implies that conditional variances are stationary processes. However, in case of gold, the univariate volatility process seems to be an integrated process (the stationarity condition equals one), which means that shocks to the gold futures returns have permanent effects on future volatilities. The parameter estimates in the correlation equation are statistically significant at 1% significance level, which indicates that a Generalized Diagonal DCC GARCH model is an appropriate parameterization of the dynamic co-movements in this dataset.

Table 3b reports the coefficients for the model including the S&P500 Energy sector index as an alternative stock market investment asset. In this case the coefficients of the VAR(1) -system indicate that the crude oil futures returns, and the S&P500 Energy sector index returns show bi-directional causality, which is justifiable because the energy sector index includes oil companies, which benefit from higher oil prices. In addition, the S&P500 Energy sector return series shows mean reverting behaviour. Like in case of the aggregate S&P500 returns, the lagged returns of S&P500 Energy sector index have a positive impact on gold futures returns at 1% significance level, which is again against the evidence of the safe haven role of gold in the financial markets. The univariate conditional variance equation reveals that like S&P500 TOTR index, the energy sector index also shows a leverage effect in its conditional variance. The parameter estimates of the Generalized Diagonal DCC correlation equation are statistically significant at 1% significance level, which implies that the correlation model fits well the dataset.

Fig. 5a plots the dynamic conditional correlations between the crude oil futures and S&P500 Total Return index returns. Consistent with earlier evidence, before the global financial crisis the correlation shows mean reverting behaviour around zero. Moreover, it is worth noticing that the correlation is highly volatile. The sample used in this analysis incorporates two major financial crises, namely the IT bubble in 2001 and the global financial crisis since 2008. During the IT bubble the correlation between the crude oil futures and US equity returns did not increase significantly. However, as previous research has also reported, the correlation jumped significantly after the collapse of the Lehman Brothers in 2008. As Fig. 5a shows the global financial crisis imposed a structural break in the correlation. Notably, after the global financial crisis, the correlation between crude oil futures and aggregate US equity market returns *has stayed at higher* level until the end of sample period, which is against the theoretical relationship between crude oil prices and stock market returns. This result has already been confirmed in some previous studies, too (see e.g. Filis et al., 2011; Kolodziej et al., 2014; Creti et al., 2013) However, in our data, Fig. 5a reveals that the correlation dropped significantly in 2013, but started to increase again in late 2014.

Compared to previous studies, the longer time series used in our analysis reveal that the correlation has stayed exceptionally high after the global financial crisis. As discussed in the previous section, the zero-interest rate environment might partly explain the higher correlation between crude oil futures and aggregate US equity market returns. One possible explanation for higher correlation might be the low *convenience yields* due to the zero lower bound interest rate regime. Low convenience

[9] Stationarity condition for the parameters in the variance equation is $\alpha_1 + \beta + \frac{1}{2}\gamma \leqslant 1$.

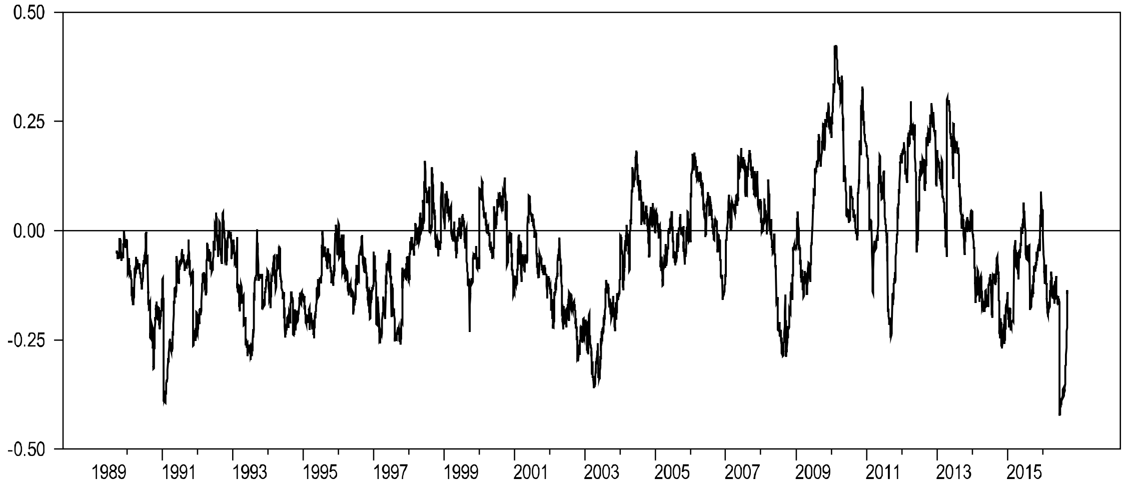

Fig. 5b. Dynamic correlation between gold futures and S&P500 TOTR index returns.

yields make trading in futures contracts more attractive than trading the physical crude oil. On the other hand, the low interest rate environment also makes interest yielding assets less attractive because of their low yield. According to our observations it seems that the low interest rate environment and low convenience yields have increased the investment activity in crude oil futures markets as they have become more attractive part of investment portfolios of especially the institutional investors.

In view of the shape of the WTI crude oil futures curve (see Appendix B),[10] the market seems to have been in backwardation until 2005. After 2005, a contango market has become the normal condition in the crude oil futures market, and the market switched from backwardation to contango more permanently after the outbreak of global financial crisis, which was associated with an increase in the correlation between the crude oil futures and US equity returns. Kolodziej et al. (2014) proposed that in the contango market it is more beneficial to trade crude oil as a financial asset, since capital gains dominate the convenience yields, especially in a low interest rate environment. However, the crude oil futures forward curve inverted from contango to backwardation in late 2012. As Fig. 5a shows, this seems to have been associated with a decline in the correlation between the crude oil futures and S&P500 total returns in 2014. Since late 2014, the crude oil futures market switched again from backwardation to contango market due to the global excess supply of crude oil. Previous literature has shown that there is a negative relationship between the convenience yields and crude oil inventories (see, e.g. Alquist et al., 2014), and our results also support the finding that the convenience yields decreased in 2014 due to the global excess supply of crude oil, which again pushed the futures market to contango. Fig. 5a shows that in 2014 the correlation between crude oil futures and S&P500 aggregate index returns started to increase again. Based on earlier discussion, it seems that in contango market, when crude oil futures are more attractive to hold as financial assets, the correlation with S&P500 total return index has been higher than in periods of backwardation market.

Relying on the evidence of Büyüksahin and Robe (2014), especially the activity of traders who trade both equities and crude oil increases the cross-market linkage in the rates of returns of aggregate US equities and crude oil futures. Hence, in contango market, these traders are more likely to increase their positions in crude oil. However, because of the limited availability of the data on actual positions this hypothesis remains to be tested empirically in our future research.

Fig. 5b illustrates the time-varying correlation between gold futures and S&P500 aggregate index returns. The time series plot shows that the correlation is experiencing high volatility and it is fluctuating around the value of zero. During the IT bubble at the beginning of the millennium, the correlation declined significantly showing also negative values. In addition, during the global financial crisis in 2008 and the European debt crisis in 2010 the correlation between gold and US aggregate equity market returns has been negative, which gives further support to the hypothesis that gold futures provide a safe haven against US equity market risk as earlier research has shown. However, high volatility of the correlation shows that the safe haven effect might be only temporary, especially during the global financial crisis, which is consistent with the evidence of Baur and Lucey (2010), who also showed that gold provides a safe haven only for a short time period. Interestingly, the correlation has been highly volatile and obtained positive values in the aftermath of the global financial crisis, which could indicate higher economic uncertainty in the global economy. From 2014 onwards the correlation has stayed clearly below zero, suggesting that gold has provided a hedge against the aggregate S&P500 index return risk especially in recent years.

Fig. 5c plots the time-varying conditional correlations between crude oil futures and S&P500 Energy IG Price index returns. Unlike in case of the aggregate S&P500 index, the correlation between crude oil futures and energy sector index returns shows fluctuations around a positive value. As discussed earlier, the positive average correlation is justifiable, as

[10] The shape of crude oil futures price curve is defined as 30-day moving average of the continuous settlement price difference (USD/bbl) between near month contract and the 6th listed contract on the price curve in WTI crude oil futures. Positive values indicate that the WTI crude oil futures market is in normal backwardation, whereas negative values imply that the futures market is in contango.

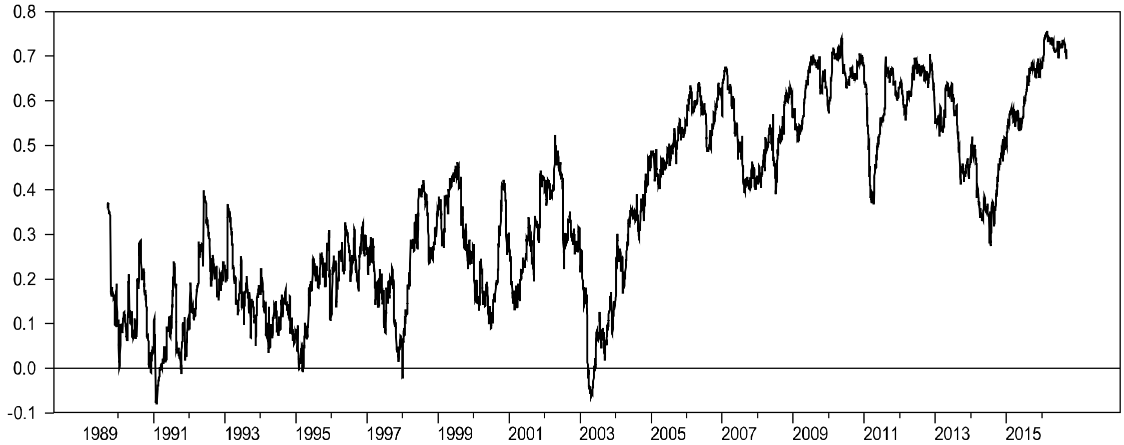

Fig. 5c. Dynamic correlation between crude oil futures and S&P500 Energy IG Price index returns.

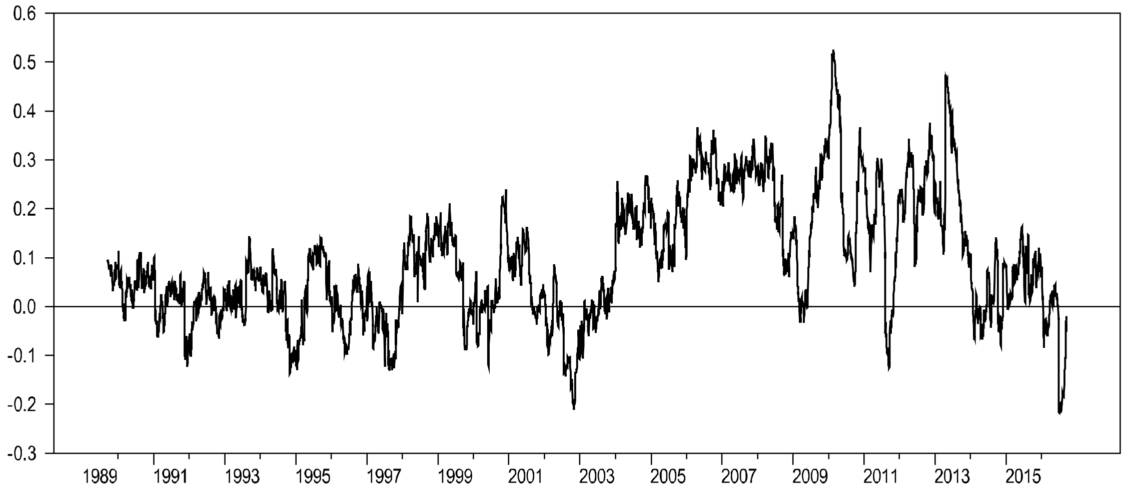

Fig. 5d. Dynamic correlation between gold futures S&P500 Energy IG Price index returns.

the revenues of energy sector firms depend partly on the price of crude oil. However, Fig. 5c also reveals that the correlation increased significantly starting from 2003 shifting the average level of correlation upwards. The shift in the correlation could indicate that the financialization of commodity markets intensified the cross-market linkages between the crude oil futures and US energy sector equities. Investors can speculate on the crude oil price movements by investing in energy sector firms or directly in the crude oil linked financial products. Hence, because of the increased supply of commodity-linked investment products, it seems that the crude oil futures and energy sector equity returns have become more related after 2004. However, unlike in the case of S&P500 index, the correlation did not increase significantly during the global financial crisis.

Fig. 5d plots the dynamic conditional correlations between gold futures and S&P500 Energy IG Price index returns. Previous literature has not studied the safe haven effect of gold against energy sector equities at all. The evolution of the correlation shows that as in the case of crude oil futures, the financialization of commodity markets imposed a structural break in this correlation as well. Before 2004, the correlation between gold futures and US energy sector equities fluctuated around zero. After 2004, the average level of correlation increased and remained higher until the outbreak of the global financial crisis. Unlike in case of gold and S&P500 index, the correlation does not show negative values during the stock market crash in 2008, which suggests that gold might not have provided a safe haven against the US energy sector equity risks during that period. Similarly, as in the case of S&P500 Total index and gold futures, in the aftermath of the global financial crisis the correlation between gold futures and energy sector equities also shows volatile behaviour reflecting the uncertainty in the global economy. However, as in case of the S&P500 Total index returns, the correlation has also in this case decreased significantly and remained lower in recent years, stressing the possibility that after all, in the most recent time period gold might actually have served as a hedge against the S&P500 energy sector stock market risks, too.

4.2. Dynamic optimal hedge ratios

Fig. 6a plots the risk-minimizing hedge ratio of crude oil futures against the S&P500 Total Return index risk. When scrutinizing the periods of stock market crises, the hedge ratio shows abrupt increases during those periods. Interestingly, the

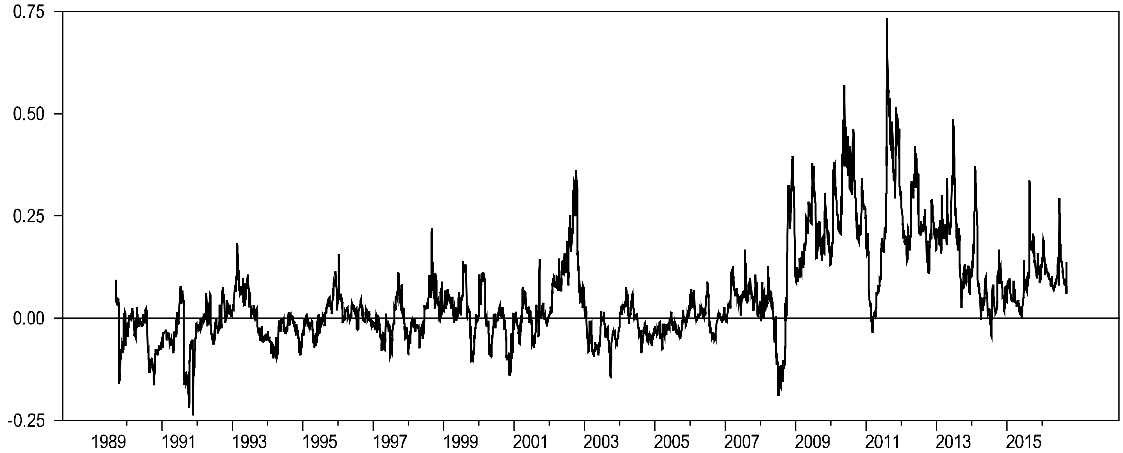

Fig. 6a. Dynamic optimal hedge ratio between S&P500 TOTR index and WTI crude oil futures.

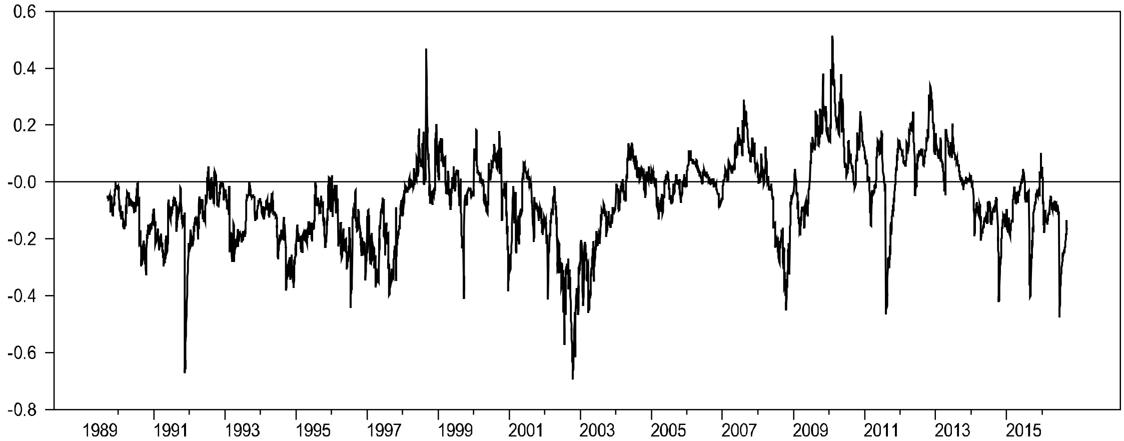

Fig. 6b. Dynamic optimal hedge ratio between S&P500 TOTR index and COMEX gold futures.

hedge ratio peaks nearly as high in the aftermath of IT bubble as after the outbreak of the global financial crisis. The structural change in the correlation between crude oil futures and aggregate S&P500 Total index returns after the global financial crisis has also been reflected in higher hedge ratios for the crude oil futures. The higher hedge ratio makes crude oil futures attractive hedging instruments for the US equity market risk, because investors should hold bigger short positions to minimize the risk in the aggregate US equity investments. Moreover, the hedge ratio has recently been more volatile than it was before the global financial crisis. This implies that in order to maintain a risk minimizing hedge against positions in the S&P500 Total index, investors have to rebalance strongly and frequently their positions in crude oil futures. Hence, taking into account the transaction costs, the high volatility of hedge ratio implies higher costs of hedging, too.

As discussed in the context of correlation analysis, the correlation between crude oil futures and aggregate stock market returns seems to have been higher in the contango market especially during recent years, whereas in the high backwardation market the correlation seems to be lower. From a hedging perspective, backwardation market seems to be less attractive, because low correlation makes hedging inefficient. Fig. 6a confirms this, since the hedge ratio has been significantly lower, when the crude oil futures market was in backwardation especially before the outbreak of global financial crisis and during 2014. However, the hedge ratio has started to increase and become more volatile, as the forward curve inverted to contango at the end of 2014.

As we see from Fig. 6b, in the case of gold futures the hedge ratio turned negative in the beginning of 2000's in the aftermath of the IT bubble, when the US stock market performed poorly. In addition, during the global financial crisis in 2008, the hedge ratio becomes negative, indicating that *holding a long position in gold futures minimizes the risk of long position in S&P500 Total return index*. This evidence supports the safe haven hypothesis of gold in periods of financial crises. However, after the global financial crisis, the hedge ratio becomes quickly positive, which implies that investors should short gold futures. Hence, a long position in gold futures has only a temporary risk minimizing impact against aggregate S&P 500 return risk. As in case of crude oil futures, the high volatility of dynamic hedge ratio and the switches between negative and positive values suggest that in normal times hedging with gold futures might be expensive.

Fig. 6c reveals that the shift in the correlation between crude oil futures and energy sector equities after 2004 also implies a higher optimal hedge ratio. The plot shows that there is a significant structural break in the hedge ratio, which indicates

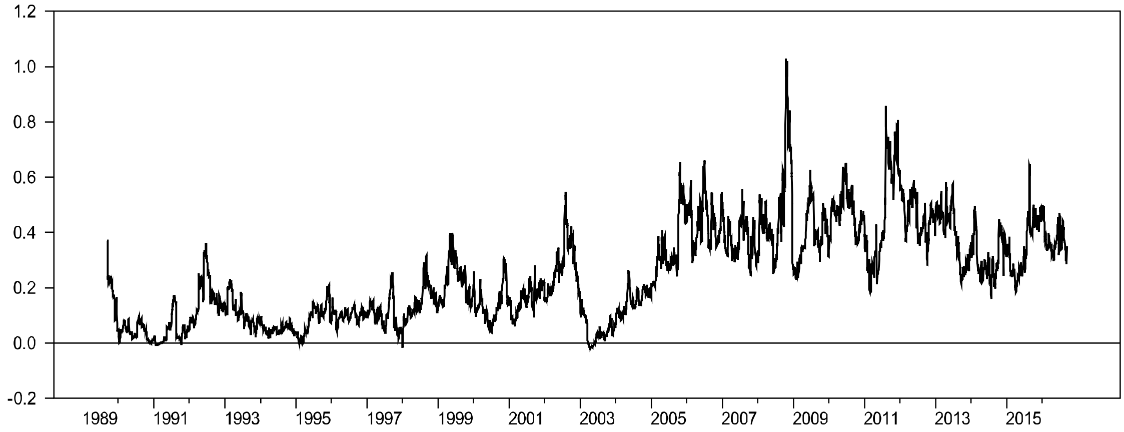

Fig. 6c. Dynamic optimal hedge ratio between S&P500 Energy IG Price index and WTI crude oil futures.

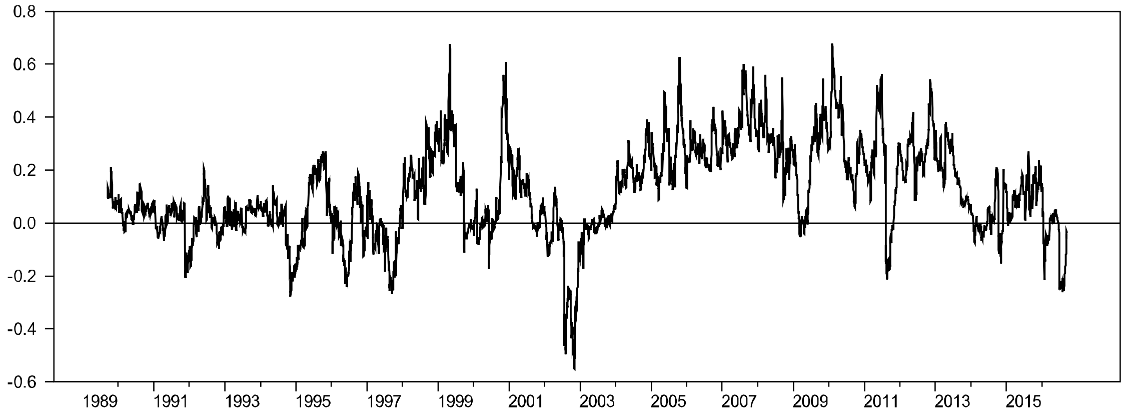

Fig. 6d. Dynamic optimal hedge ratio between S&P500 Energy IG Price index and COMEX gold futures.

that as a result of closer integration of these markets, investors are required to have higher short positions in crude oil to minimize the risk in energy sector equity investments. Hence, based on *only viewing the optimal hedge ratios*, the closer integration of crude oil futures and energy sector equity market could have increased the attractiveness of crude oil futures as a hedging instrument against the energy sector equity risks. In addition, as in previous cases, the high volatility of optimal hedge ratio restricts the usefulness of crude oil futures as hedging instruments in normal times.

During the bear market after the IT bubble the hedge ratios did not increase significantly compared to earlier fluctuations. However, during the stock market crash in 2008, the hedge ratio peaked close to one, implying that risk-minimizing hedging against stock market crash in energy sector with crude oil futures would have required a corresponding position in crude oil futures than in energy sector equities. As we saw from Fig. 3c above, the crude oil market prices decreased steeply during the outbreak of the global financial crisis, which was also reflected in declining S&P500 Energy IG Price index due to the negative outlooks for the energy sector firms. A high hedge ratio during periods of financial turmoil naturally supports using crude oil futures as a risk minimizing hedging instrument against the energy sector equity risks.

Fig. 6d plots the dynamic hedge ratio of gold futures against the risks in energy sector equities. In contrast to the S&P500 Total index case, the safe haven effects might not be as evident based on viewing this figure. During the bear market after the IT bubble the hedge ratio becomes negative, which supports the safe haven hypothesis of gold futures. However, during the stock market sell-off in 2008, the hedge ratio shows positive values. This means that investors in energy sector equities should have shorted gold futures to minimize the risk during the stock market crash, which is actually against the safe haven hypothesis.

As we saw from Fig. 5d, there has been a structural break in the gold market and energy sector return correlations after 2004, which lasted until 2014. From Fig. 6d we see that during this period the average level of optimal hedge ratio increased, making hedging with gold futures more attractive. Moreover, as in previous cases, the high volatility of hedge ratio does not favor gold futures as a risk-minimizing hedging instrument in long horizon here, too. To sum up our results, the dynamic optimal hedge ratios seem to be highly volatile, which suggests that hedging with crude oil and gold futures against the aggregate US equity and energy sector market risk might be expensive in 'normal' times of the markets. However, it is more important to scrutinize the hedge ratios in periods of stock market sell-offs, because during these periods the hedging instruments are needed the most. Based on our results from this stage, compared to gold market, crude oil futures would not seem

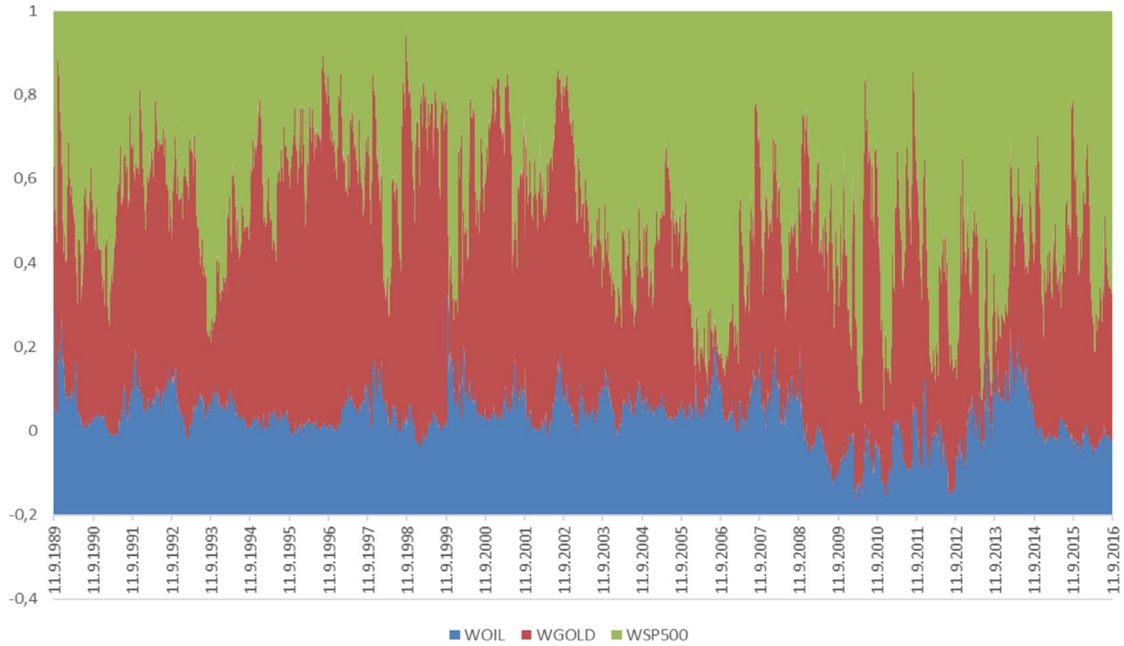

Fig. 7a. Minimum variance weights of the stock market asset (WSP500), COMEX gold futures (WGOLD) and WTI crude oil futures (WOIL) in a portfolio containing the S&P500 Total return index.

to be so attractive risk-minimizing hedging instrument neither against the US aggregate nor the energy sector equity market risks in periods of financial turmoil, as are the gold futures. A long position in gold futures seems to minimize the risk in aggregate US equities during stock market sell offs, but not quite similar conclusions can be drawn for the case of energy sector equities based on only viewing the optimal hedge ratios. For a clearer picture about the role of time-varying dynamic conditional correlations and optimal hedge ratios in hedging behaviour, we next examine the time-varying minimum variance portfolio weights, that resembles somewhat the analysis performed also in a very recent study of Mensi et al. (2017).

4.3. Minimum variance portfolio weights

Optimal hedge ratios reveal the size of the short positions in oil and gold futures giving the best hedge against a given long position in stock markets. However, an even more interesting question is how the evolution of risks change the portfolio structure over time. As the final step for our hedging analysis, we now explore the minimum variance portfolio weights in a portfolio consisting first of investments in the S&P500 index, gold futures and oil futures. Secondly, we do the same analysis for the portfolio consisting of the energy sector equities, and again, gold and oil futures.

From Fig. 7a we see that the minimum variance portfolio weight of S&P500 stocks varies between 2% and 100%, while the weights of oil and gold futures vary between −17% to 33% and 5–93%, respectively. As is expected, during and just prior to the financial crises, the weight of stocks decreases and the weight of gold increases. However, even during the crisis the weights change sharply, reflecting the changing risk environment and short-lived moments of recovery. One of the clearly new findings from our results is that based on the minimum variance portfolio approach the share of gold should be much higher than previously thought, i.e., *even under normal market conditions over 40% of the minimum variance portfolio should consist of gold*.[11] An interesting finding is also that between the years 2000 and 2006 the share of gold has a declining trend, which turns around only during the subprime crisis. A third general finding is that even though the portfolio weights clearly react to the subprime crisis, they are very volatile even under normal market conditions. The only exception in this respect is the share of oil, which makes a drastic change after the year 2007.

Our results show now that oil does seem to play some role in a low risk portfolio. In general, the minimum variance weight of oil is low, most of the time below 10%, but in some instances, its weight clearly increases. For example, just prior to the burst of the IT-bubble, over a third of the minimum variance portfolio consisted of oil for a short period around October 1999. On the other hand, during the subprime crisis and during the European debt crisis a low risk investor should have taken almost a 20% short position in oil futures and almost an exactly opposite position in gold futures. Our findings indicate that the *role of oil – and probably also the role of many other cyclical commodities – may be much more important in investment strategies than previously observed.*

[11] Obviously, the extremely high share of gold compared to most of the other previous studies on actual optimal portfolio shares is partly based on the fact that we do not have for example any kind of interest yielding assets included into our portfolios.

Table 4
Average minimum variance portfolio weights (in %) for specific periods in the sample.

	Portfolio with S&P500			Portfolio with energy sector equities		
Period|/Weight on	S&P500	Oil Fut.	Gold Fut.	S&P500 Energy IG	Oil Fut.	Gold Fut.
I	41.7	5.1	53.2	30.0	4.3	65.7
II	39.1	3.5	57.4	22.9	3.1	74.0
III	33.8	5.3	60.9	25.7	2.7	71.6
IV	58.3	6.2	35.5	38.7	3.9	57.4
V	47.9	11.8	40.3	23.9	13.7	62.4
VI	47.2	5.2	47.6	29.2	2.1	68.7
VII	59.6	−1.1	41.5	42.9	−1.4	58.5

Notes: The analysed time periods are I: 11/9/1989–31/7/2000; II: 1/8/2000–30/8/2000; III: 1/9/2000–23/8/2002; IV: 24/8/2002–8/9/2007; V: 9/9/2007–8/10/2007; VI: 9/10/2007–9/3/2009; VII: 9/10/2007–13/9/2016.

It is worth to note that the weight of oil in an optimal minimum variance portfolio during the period of September 2007–June 2014 is clearly different compared to its historical weight. For some reason, an optimal risk minimizing portfolio strategy during the subprime and the European debt crises should have been clearly different compared to the 2000–2002 IT crash highlighting especially the role of oil futures. On the other hand, after the 2008 crisis, the weight of oil has been mostly clearly negative until mid-2013, and from the end of 2014 this seems to have been the optimal situation again.

As observed from the hedge ratio analyses, the volatility of all the minimum variance portfolio weights is high reflecting the need for very active rebalancing in portfolio management, too. However, this makes the interpretation of Fig. 7a somewhat demanding. To clarify a bit longer-term evolution, we have calculated the average weights for specific periods in Table 4. We have defined the periods in terms of the situation in the aggregate US stock markets as follows. Period I captures a bull stock market period, period II is the last month prior to the IT crash, III is the IT crash period, IV is a bull market period again, V is the last month prior to the subprime crash, VI is the 2008–2009 crisis period, and finally, VII is the whole period after the subprime crisis, including the European debt crisis. The results in Table 4 show a clear trade-off between the stock and gold weights regarding the crisis periods. During the crisis, the *share of gold always increases* and the share of stocks decreases. Note that this seems to take place already during the last month prior to the crisis. As already discussed above, the weight of oil doesn't have this kind of behavioural pattern, and its role is different especially prior to and during the IT crash at the beginning of millennium compared to the time of subprime crash. Furthermore, the estimated optimal portfolio weights in Table 4 exhibit an interesting long-term trend as the share of stocks in a minimum variance portfolio has increased from the average of 42% in period I to 60% in period VII, while the share of gold has decreased. This raises an interesting research question for further studies of why the role of gold as a low risk asset has decreased over time in general.

When we replace the aggregate S&P500 stocks by the energy sector stocks (S&P500 IG) in our portfolio, the optimal weights of stocks, gold and oil vary momentarily between 1–86%, 12–96%, and −19% to 45%, respectively (see Fig. 7b). The time series pattern of weights is similar to the one with well-diversified stock portfolio (S&P500 index) with two major exceptions. First, as expected, the share of stocks in this portfolio is smaller and the share of gold higher, because of higher correlation between the return of oil futures and energy stocks. Second, the share of gold does not have a declining trend during the years 2000–2006, as is the case, when the stock holdings are well-diversified. Finally, we actually see a very strong change (rise) in the share of oil futures just prior to the subprime crisis, but not before the IT crisis, for both the general and energy sector stock portfolio cases. However, during the crisis period the gold market takes the leading role as the hedging vehicle, as it seems to have done also during the IT crisis.

The average values for the optimal portfolio weights in different time periods are approximately comparable in magnitude to the values obtained e.g. in Mensi et al. (2017) for the case of Islamic stock markets,[12] but from Table 4 we can see that gold seems to play even stronger role now in a minimum variance portfolio containing the S&P500 energy sector equities. On average, and especially around the time of IT bubble, the optimal weight of gold in the energy sector portfolio is very high, i.e., 74% in the last month (August 2000) prior to the bubble burst. Furthermore, also during the worst years of the global financial crisis, between October 2007 and March 2009, the weight of gold in the optimal portfolio is relatively much higher than it was in the portfolio containing the aggregate S&P500 stocks. Obviously, one reason for this is that by definition, the aggregate index portfolio is much more well diversified than the single sector index portfolio. As noted before, the role of gold in the optimal minimum variance portfolio seems to have decreased over time in general for the aggregate index, but for the energy sector stocks, the decline is not nearly so big. During bull markets, both the oil and gold assets have clearly the lowest weights in the optimal portfolios for both the general S&P500 index and the energy sector equities.

Among our main policy implications is first of all, that the role of gold seems to have decreased over time (in long-term) when hedging against the general stock market risks, but in an industry-specific stock market hedging the decrease is not so

[12] In Mensi et al. (2017) the average values for the optimal weights of gold in different Islamic industry and aggregate index portfolios range from 2.8% to 60.8%, and the range for the average values in our case is from 35.5% to 74.0%, so the scales are comparable. However, there are many differences in the individual observations based on using completely different data sets and a somewhat different method for the calculation of dynamic conditional correlations, and hence, optimal hedge ratios and portfolio weights, too.

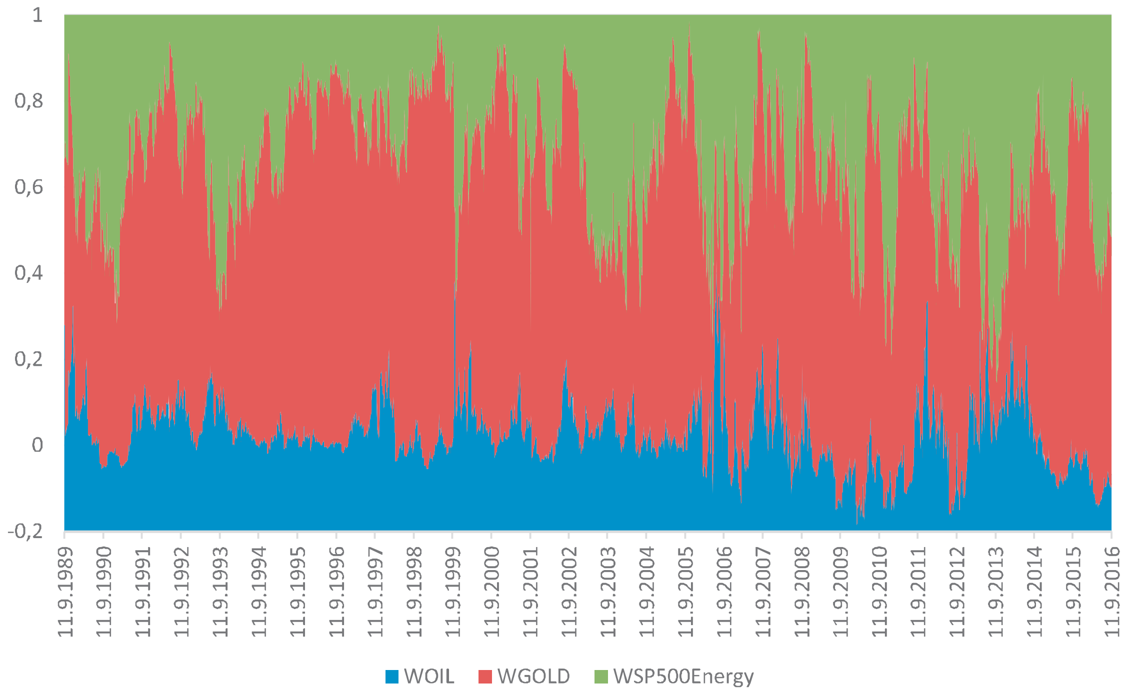

Fig. 7b. Minimum variance weights of the stock market asset (WSP500Energy), COMEX gold futures (WGOLD) and WTI crude oil futures (WOIL) in a portfolio containing the S&P500 Energy sector IG index.

evident. This naturally calls for extensions of the sector-specific analyses in the future regarding the US stock market, too, to be able to reveal for the policy makers the relevant industry sectors that seem to be most sensitive to first of all, the simple stock market, and even more importantly, to systemic level crashes. In addition, it is also essential for the policy makers to know what might be the role of commodity derivatives markets in general for hedging against these risks also in the future. For the part of energy sector, according to our results it seems that the gold market has kept its strong role as a prominent hedging tool also during the global financial crisis, and not just during the short-term crisis periods, like the IT bubble at the beginning of millennium.

Our second main policy implication is related to the role of oil futures in optimal hedging strategies, and the implication regarding its connection to the zero-interest rate era, where the situation in the oil futures market (contango or normal backwardation) seems to have something to do, too. During the IT bubble the correlation between the crude oil futures and US equity returns did not increase significantly, and the shape of the futures price curve (see Appendix B) in WTI crude oil futures indicated mostly a period of normal backwardation. As argued also e.g. in Kolodziej et al. (2014), in times of normal backwardation the convenience yield of oil futures exceeds the capital gain, so for investors it is not so beneficial to trade crude oil as a financial asset. Moreover, as we have already pointed out, the financialization of the oil markets might clearly have affected our result that the oil market futures might have increased their importance in hedging strategies, too, and this seems to be especially connected to the ongoing period of zero (and negative) market interest rates after the 2008 crisis. As we can see from Appendix B, the oil futures market was mostly (and strongly) in contango from the beginning of 2005 until approximately the end of 2012. During this time, and especially during the strongest wave of extreme monetary policy actions (QEs) in 2008–2009, the oil futures market was in strong contango, which means that capital gains from investing in this market clearly outperformed the convenience yield. However, we find that this phenomenon seems to also be clearly connected to the rising optimal share of oil futures in a portfolio containing the stock market assets just prior to the collapse of the markets during 2007, because at that time, the oil market experienced its *strongest change from the situation of contango to the normal backwardation*. Hence, our results seem to indicate that actually the shape of the futures price curve in WTI oil futures might have some *indicative power* in terms of hedging against future stock market risks, because at the time of change from contango to normal backwardation of almost equal size (during 2007), the optimal weight of oil futures doubled in the S&P500 aggregate portfolio and more than tripled in the energy sector portfolio, compared to the preceding 5 years of bull or normal markets (see Table 4). Hence, extreme monetary policy actions seem to have had strong effects also on the commodity market hedging possibilities, and this obviously should be taken into account when designing the future policy actions, too.

5. Conclusions

We have analysed the return correlations and optimal hedging strategies based on the dynamic connections of two types of commodities, i.e., the gold and crude oil futures markets with respect to the US aggregate and energy sector equities, focusing specifically on the periods of financial distress. For this purpose we have used the Generalized Diagonal Dynamic Conditional Correlation GARCH model proposed by Cappiello et al. (2006). We have especially examined whether the crude oil and gold futures could serve as efficient hedging instruments against the aggregate US and energy sector equity risks by calculating first the optimal dynamic hedge ratios, and then, using the obtained time-varying return correlations to calculate the optimal minimum variance weights in portfolios consisting of these assets.

Our main findings can be summarized as follows. The correlation between crude oil futures and aggregate US equity returns increases strongly in periods of financial distress. After the outbreak of the recent global financial crisis the correlation between crude oil and US equity returns has been continuously higher than it was before the crisis. In addition, the results suggest that the correlation may at least partly depend on the shape of the crude oil futures forward curve. Analogously to Kolodziej et al. (2014), we also argue that crude oil might be more attractive to trade as a financial asset when the market is in contango. Especially during the low interest rate era the convenience yields for crude oil futures tend to be lower, which pushes the futures market to contango, causing capital gains of crude oil futures to dominate the convenience yields. Thus, during these periods the cross-market linkages increase because traders, who also trade equities, increase their positions in crude oil futures and thus intensify the cross-market linkage between the crude oil futures and aggregate US equities. However, this hypothesis remains to be tested in the future research. According to our results the co-movements between crude oil futures and energy sector equity returns, in view of the average level of correlation, increased significantly after 2004. One possible explanation is that as a result of financialization of commodity markets the cross-market linkage between the crude oil futures and energy sector equities has become stronger. For the gold futures, our evidence clearly supports the safe haven hypothesis of gold in periods of financial turmoil for the aggregate US equity market risks, because the return correlation between these two markets becomes negative during major stock market crashes in our sample. Furthermore, based on our optimal minimum variance portfolio analysis, the safe haven properties of gold as an asset are even more evident for the energy sector equities. However, the optimal weight of the gold asset especially in a portfolio containing the aggregate S&P500 index and oil futures has actually declined towards the end of our sample period, and gold seems to have been even more important hedging asset during the IT crash period than during the subprime crisis.

From the cross-market hedging perspective, compared to gold markets, the near month crude oil futures do not seem to be an attractive long-term hedging instrument in periods of major stock market sell-offs, because investors require significantly bigger short positions on them during these periods. However, during the more systemic type crisis of 2008, at the onset of the zero-interest rate period, for a short period of time during 2007–2008, the oil market derivatives have actually performed better as a hedge against the stock market risks than they did during the time of IT bubble. Nevertheless, based on our results we argue in general that hedging with crude oil futures might be less attractive during a period of backwardation in the oil markets, because the correlation with the aggregate S&P500 index has been lower during those periods. On the other hand, hedge ratios against the energy sector equity risks are higher over the sample period compared to the case of aggregate US index. Moreover, during stock market crises the hedge ratio seems to be significantly higher than in normal times. Furthermore, in accordance with the behaviour of time-varying correlations, also the risk-minimizing dynamic hedge ratio is highly volatile in both cases. This makes crude oil futures an expensive hedging instrument against the aggregate US equity market and energy sector risks in normal times, because the hedging position would require frequent adjustments.

For the future research our analysis raises many important topics. First, all dynamic correlations seem to react in a similar way during the period 2001–2003. Based on visual inspection this may point to a possibility of structural change at that time, which can be observed also in the optimal hedge ratios related to oil. The timing is consistent with the findings of for example Fan and Xu (2011) and Chen et al. (2014). However, if there has been a structural break, there probably have also been other structural breaks caused by e.g. the subprime crisis and by the zero-interest rate quantitative easing regime. It remains an open question how these impact the model structure and parameters. The second important research topic is why the optimal hedge ratios, and hence, also the minimum variance portfolio weights of the assets analysed here, are so volatile, and how risk management actions should be conducted under these conditions. In addition, it would be interesting to scrutinize whether the shape of the commodity market futures forward curve and the behaviour of convenience yields, along with the zero-interest rate era, could explain the obviously strongly time-varying commodity-equity market return correlations. Finally, a natural extension to all our analyses is to consider many other forms of commodity markets, like other precious metals, agricultural products, raw materials, etc. for hedging purposes around the times of heavy and possibly long-lasting financial market crises that have also strong effects on the real economies in general.

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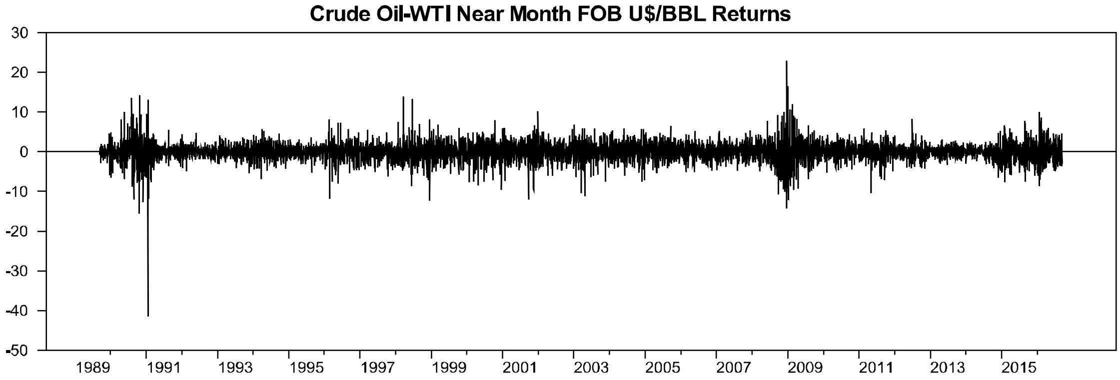
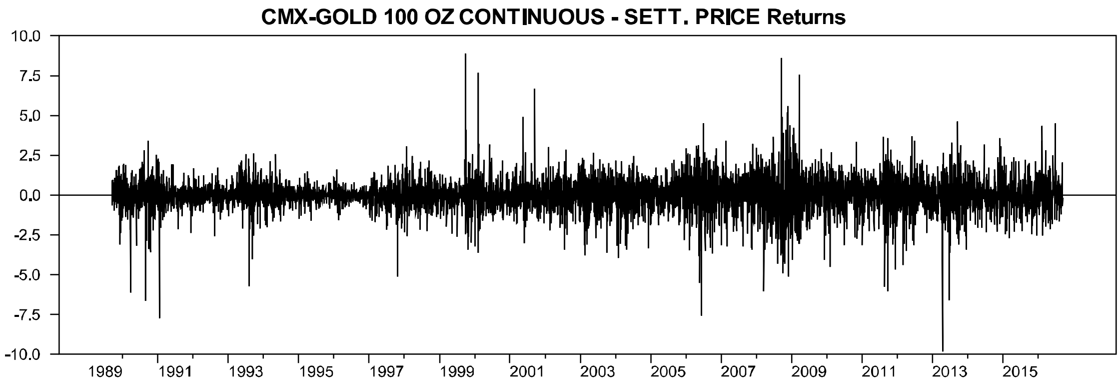
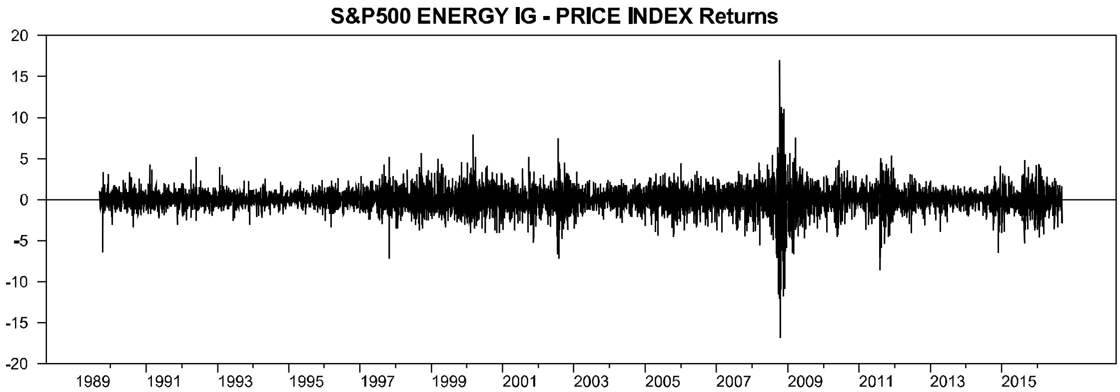
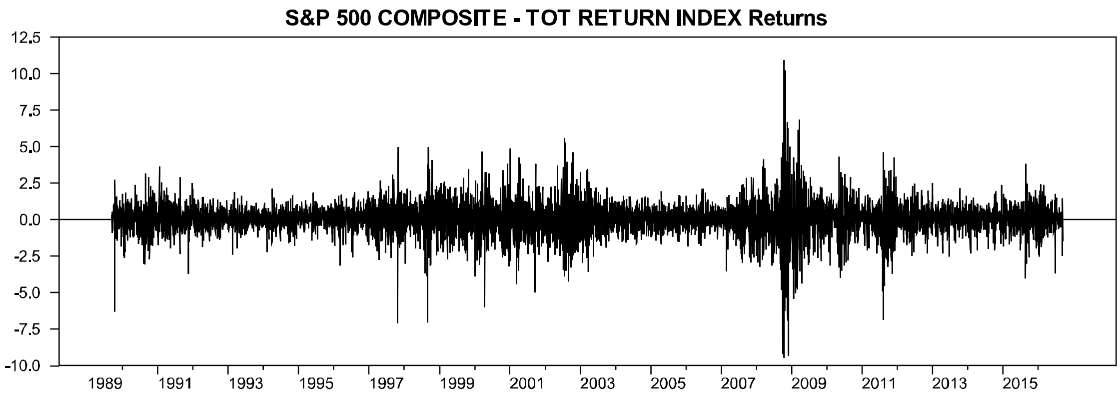
Appendix A. Daily returns

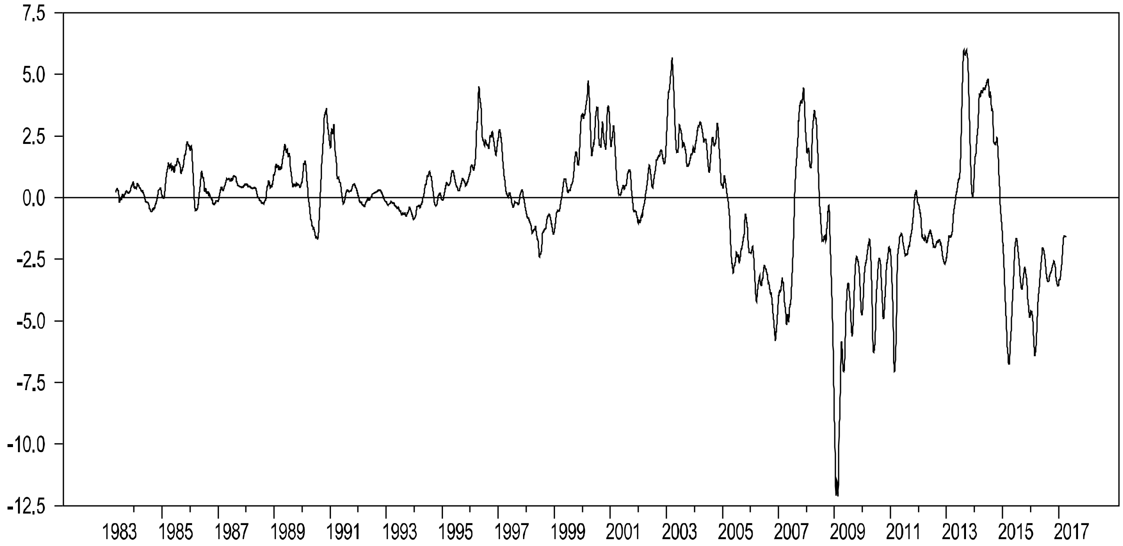








Appendix B. The shape of futures price curve in WTI crude oil futures



Note. The shape of futures price curve in WTI crude oil futures is defined as 30 day moving average of the continuous settlement price difference (USD/bbl) between near month contract and 6th listed contract on the price curve in WTI crude oil futures. Positive values indicate that WTI crude oil futures market is in *normal backwardation*, whereas negative values imply that the futures market is in *contango*. (*Source:* Datastream.)

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III

KEEP THE FAITH IN BANKING: NEW EVIDENCE FOR THE EFFECTS OF NEGATIVE INTEREST RATES BASED ON THE CASE OF FINNISH COOPERATIVE BANKS

by

Juha Junttila, Jukka Perttunen & Juhani Raatikainen

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Keep the faith in banking: New evidence for the effects of negative interest rates based on the case of Finnish cooperative banks[☆]

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ABSTRACT

This paper analyses the profitability of Finnish cooperative banks during the period of negative nominal interest rates. Contrary to expectations, the continuous decline in money market interest rates between 2009 and 2014, and the following negative rate era, did not have adverse effects on the profitability of banks at the beginning of negative interest rate period. Based on especially using a risk-adjusted measure for bank profitability, these results contrast with previous findings. In our findings, the increasing wholesale funding (WSF) ratio seems to be an important factor. However, after 2017 the banks have not been able to improve especially their risk-adjusted profitability so strongly anymore, because the WSF and the development of other than net interest margin returns have been in negative connection to it. In addition, the unconventional monetary policy actions seem not to improve profitability in the most recent observations of our data. These results raise serious concerns for the future of bank profitability during the prolonged period of negative interest rates.

1. Introduction

Most European countries and their aggregate economies have witnessed a period of negative short-term money market interest rates for over six years at the time of writing. For example, after the main European Central Bank (ECB) steering rates broke the zero-floor limit in the summer of 2014, initiating the era of negative money market interest rates, the Euro Overnight Index Average (EONIA) rate fell below zero in November 2014 and has been there ever since that. After that, the Euribor interest rates followed the path, first at three months' maturity in April 2015 and then at 12 months' maturity in February 2016.[1] Especially due to the extremely severe COVID-19 crisis, there is still an alarmingly strong need for expansive (unconventional) monetary policy actions in the near future. Hence, the conclusion of the negative interest rates era has yet to appear probably far on the future horizon.

This extraordinary, textbook contrarian phenomenon in financial markets has been found to be harmful for the profitability of banking sector in most of the earlier studies. This is due to the obviously declining profits based on the sector's main source of returns, the net interest margin (NIM). However, the most recent literature on bank profitability has suggested that the effects of negative reference rates on banks' profitability might actually be dependent on banks' respective business models.[2] Moreover, since the era of negative interest rates clearly appears to be lasting longer than originally planned by the ECB

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[1] See Heider et al. (2019) for a more detailed description of the events in the interbank markets and central bank funding at the European level since the first decrease in the ECB deposit facility rate (DFR) to below zero on June 11, 2014.

[2] See e.g. Roengpitya, Trashev and Tsatsaronis (2014) for the classification of banks based on their business models, particularly with regard to sources of funding. The key factor in the division of banks based on their different business models is each bank's dependence on funding sources, i.e., is the funding deposit- or wholesale-based, and how are the banks diversified geographically and by business line (see also Chen et al., 2018)

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policy makers right after the global financial crisis,[3] banks that were previously largely retail-based (deposit-funded) might have had an incentive to move towards a more wholesale-based funding model, since *borrowing from interbank markets with a negative interest rate actually improves the NIM*. In practice, this is due to the negative interest payments on new interbank loans obtained from the market, and the previously observed general unwillingness of banks to pay negative interest rates on their customers' deposits.[4] For the special case of Finnish cooperative (OP, where the abbreviation comes from the Finnish word *osuuspankki*) banks, it is worth emphasizing here, at the beginning of our analysis, that none of the individual banks alone would have been able to materialize the prominent positive effects of the extremely low costs of wholesale funding. This is because, in terms of their sizes and other conditions, they would have been unable to access the market as individual, independent entities. Hence, the benefits of low funding costs have only been available to them through the central cooperative's access to the European interbank markets.[5] Another important component related to interbank activities in general is that, in the special case of Finnish OP banks, the balances for liquidity reserves (and their requirements) have always been managed centrally (i.e. by the central cooperative), so the individual member banks have not been required to meet these obligations. This has clearly also had a direct impact on the profitability of the member banks, as all costs related to these activities have been centralized.[6]

The main purpose of this study is to analyse the connections between a set of four highly relevant measures of bank profitability before and during the negative money market interest rate era. The key profitability measures are the risk-adjusted measure for the return on economic capital (ROEC)[7]; the standard, most frequently used measures of return on assets (ROA) and return on equity (ROE); and, above all, the main component of bank's profitability, particularly during periods of normal market conditions with positive reference rates, i.e. the NIM. Our study will focus on carefully revealing, first, the effects of changes in nominal money market interest rate (EONIA mid-rate) on each of the individual profitability measures. Second, we also aim to reveal the specific effects of negative market interest rates on this relationship. Third, we are interested in whether the introduction of negative money market interest rates has induced a change in the banks' business models, i.e. from deposit-based funding to more wholesale-based funding, that has been based on negative loan interest rates for the banks. For all these purposes, we will use a unique, strictly confidential bank-level balance sheet and financial statement data from all the banks belonging to the Finnish group of cooperative banks, the OP Group. Within the OP Group, the prominent structural change in the individual banks' business models may have been partly caused by the introduction of negative interest rates. This is because soon after the quotation of the negative money market interest rates began, the central cooperative of the Group began to grant loans to member banks with negative interest rates, particularly at the shorter end of the maturity spectrum. This was mainly based on the principle of joint and several liability (see Appendix A), which particularly stresses the idea of common benefits and liabilities among all banks in the Group. Hence, when the central cooperative is able to obtain funding from the market with a negative interest rate, it passes this funding possibility, with a slightly higher (but still negative, depending on the maturity of the loan) interest rate through to the individual member banks also in need of funding. We are particularly interested in ascertaining whether this has occurred in the OP Group on a larger scale, and what are its effects on average bank profitability of the OP banks of different sizes within the Group.

The original data used in this study are monthly observations from the period 1/2009–12/2018 on each member bank of the OP Group. For example, the top managers and boards of directors in all the individual banks follow these data carefully in the form of monthly reports produced by the headquarters of the OP Group. Following a reasonably large number of mergers during the period under analysis, at the end of our sample (in December 2018), the final number of banks in our data set was 151. In our empirical analyses, we will use the average values for the profitability measures calculated based on classifying the banks into largest (denoted R1; $n = 23$), medium-sized (R2; $n = 39$), and smallest (R3; $n = 89$) banks.[8]

In addition to using various profitability measures, one of our main targets is to analyse the differences between the three bank size categories to determine whether the extraordinary period of negative interest rates has affected them differently. In the empirical analysis, we will focus particularly on the dynamic relationships between the analysed average profitability measures, paying less attention to the actual factors affecting the profitability of individual banks in different operating environments. In other words, we aim particularly to adopt a

[3] Based on a thorough analysis of the potential role of negative paper currency interest rate (PCIR), in particular, within the entire banking system in modern, digitalized economies, Agarwal and Kimball (2019) argue that *deeply negative interest rates*, (i.e. nominal rates below – 1%), at least for a short time period, might even be an effective monetary policy tool in the future. They propose that central banks should actually adapt to using them more permanently in their fight against recessions, because similar mechanisms in the transmission of monetary policy actions to the real economy might still be valid under the episodes of negative interest rates, as there are during positive rate eras.

[4] In relation to the strong need for unconventional actions to continue, already before the onset of the current Corona crisis, there were numerous discussions about the possibility that banks will also pay negative interest rates on customer deposits. For example, in August 2019, the Danish Jyske Bank launched the world's first negative interest rate mortgage – handing out loans to homeowners with charges of minus 0.5% a year. Furthermore, the Nordea Bank informed approximately at same time that it will begin offering 20-year fixed-rate deals at 0% and a 30-year mortgage at 0.5%, that are extremely low levels for longer term interest rates applied by banks (see,https://www.theguardian.com/money/2019/aug/13/danish-bank-launches-worlds-first-negative-interest-rate-mortgage). In addition, Altavilla, Burlon, Giannetti, and Holton (2019) actually have shown, based on their confidential euro area data, that *sound* banks within the ECB system had actually begun to charge negative interest rates on corporate deposits already quite soon after the DFR became negative in June 2014, and the corporate deposit rate was even lowered below the DFR in some banks.

[5] At the end of 2017, the entire Finnish OP Group was only the fiftieth largest of all European banks based on the size of its balance sheet. Hence, although it currently holds a 40% market share in many of the main customer business activities in the Finnish banking markets, even the whole OP Group does not belong to the major systemically important banks (SIB) at the European level.

[6] This is one example of the principle of joint and several liability to which the OP Group adheres (see Appendix A).

[7] In some earlier studies on bank profitability, a corresponding term has been the return on risk-adjusted capital (RORAC). The main principle in the calculation of ROEC is the same, i.e. the risk-adjustment of the *denominator* in the profitability measure. However, in the special case of Finnish cooperative banks, we wish to stress the connection of ROEC in particular to the actual measurement of economic capital, that is, the economic profit in euros that accounts for all return and cost items and the costs in relation to their risk in the form of actual capital requirement.

[8] See section 3 on empirical strategy and data for further details about the classification of the individual OP banks to R1, R2 and R3 banks.

stance on whether the risk-adjusted measure of profitability (ROEC) used by the OP Group behaves very differently compared to the standard, non-risk-adjusted measures (ROE and ROA), and what the role of negative money market interest rates is in terms of the difference between these measures of bank profitability. Furthermore, we also wish to reveal whether the NIM, as the main component affecting all the fundamental profitability measures, behaves differently in terms of its connections to them during the negative interest rates, compared to more 'normal' times.

Our study makes four main new contributions to the extant literature on the effects of negative interest rates on bank profitability. First, we are not aware of any other study that has used such an extensive risk-adjusted profitability measure (ROEC) in comparison to more standard profitability measures, such as ROE and ROA. Second, this is the first study to analyse the dynamic connections of NIM to both risk-adjusted and non-risk-adjusted profitability. Third, we use a practically oriented, monthly data set that enables us to use modern time-series techniques due to the reasonable number of observations. Finally, our study focuses particularly on the differences in the results between the banks of various sizes, i.e. small, medium-size, and large banks (in the Finnish scale). Hence, from a policy and practically oriented point of view, our results will also give some completely new background information for the discussions about the role of negative interest rate era on the profitability of banks of different sizes, and for the ongoing discussions on e.g. the need for structural changes (i.e., number of banks) within the Finnish OP Group.

Based on our thorough time-series analysis, we obtained the following results for the relationships between the average values of the different profitability measures in the three bank size categories and the chosen money market interest rate, the EONIA overnight mid-rate. First, we find that, in contrast to most earlier studies on this theme, the introduction of negative money market interest rates in European interbank markets since 2014 did have a positive effect in general on the profitability of Finland's OP banks during the first couple of years. However, this conclusion is considerably dependent on the measure of profitability used in the analysis. The results are strongest with respect to the profitability of the largest cooperative banks and when using the risk-adjusted measure (ROEC) as the measure of profitability. The second key finding from our research is that the increasing wholesale funding ratio during the era of negative interest rates has played an extremely important role.

Additionally, our results reveal that it is methodologically vital to control for the almost-zero volatility of the money market interest rates and NIMs when executing the profitability analysis of banks during the negative interest rate era. Our dynamic time series modelling approach reveals that also the risk-adjusted profitability might have started to suffer from the beginning of 2017, because even the biggest (R1) banks have not been able to improve their profitability anymore. Reason for this might be that the benefits of using more WSF with negative central bank loan rates have been exploited fully, and accordingly, the development of returns also e.g. from other income components has been very modest or even in negative connection to the profitability after that. Hence, our results raise extremely serious concerns for the near-term profitability of banks due to the obvious continuation of negative interest rates in Europe at least during the real economic survival period from the COVID-19 crisis. Our results serve as a primer for more detailed analysis of all the components affecting bank profitability during the negative interest rate era that appears likely to persist long into the future now. Furthermore, at least in the case of Finnish OP Group, the profitability dependence on especially the negative market interest rates of smaller, R2- and R3-size banks is somewhat different compared to the R1-size profitability. Hence, it also seems that if we assume that the negative interest rate period continues, merger discussions and plans involving only small sets of banks belonging to the intermediate (R2) and small (R3) banks are not very relevant for the purposes of improving the overall profitability of the merger banks. Another very much policy relevant finding from our results is that even though it seems to be the case that the unconventional monetary policy actions (QE) have had a lowering effect on the bank profitability risk premium, defined here as the difference between the risk-adjusted (ROEC) and non-risk-adjusted (ROE) profitability, the last two years of data also witness a decreasing effect on overall profitability of banks as the market interest rates and also the shadow interest rate have remained in the negative era, and even still lowered from time to time. According to our results, already from a risk balancing point of view, the optimal new, merger-based conglomerates within the group should always also include (at least) one bank from the group of biggest (R1) banks. This result also introduces a strong need to conduct all these profitability analyses using a much larger, international panel dataset on banks of different sizes, and importantly, also with different ownership structures.

Our study is structured as follows. In the next section, we describe the most relevant extracts from the previous literature on our theme. Section 3 describes the data and empirical strategy in details. Section 4 reports the empirical results. Finally, Section 5 discusses the implications of our results for the current mainstream literature on bank profitability, presents conclusions, and offers suggestions for future research.

2. Related literature

An early study emphasizing the role of banks' funding strategies (before the 2008 financial crisis and the current era of negative money market interest rates) is the one by Demirgüç-Kunt and Huizinga (2010). They examined the implications of bank activity and short-term funding strategies for bank risk and returns using an international sample of 1334 banks in 101 countries before the subprime mortgage crisis. One of their main findings was that the expansion of bank activities into non-interest income-generating items, such as trading, increased the rate of ROA and that it could offer some risk diversification benefits at very low levels. However, an interesting finding that is particularly relevant to our study is that, prior to the global financial crisis, the non-deposit, wholesale-based funding lowered the rate of ROA, while it could have offered some risk reduction at commonly observed low levels of non-deposit funding. Demirgüç-Kunt and Huizinga (2010) also pointed out that a sizeable proportion of banks attract most of their short-term funding in the form of non-deposits at a cost of enhanced bank fragility. Overall, their results clearly suggested that before the period of negative money market interest rates, banking strategies that relied prominently on generating non-interest income or attracting non-deposit funding were deemed to be very risky, consistent with the demise of the US investment banking sector.

More recently, Köhler (2015) analysed the impact of banks' business models on bank stability in 15 EU countries between 2002 and 2011. He proxied the banks' business models by the share of non-interest income in total operating income and the share of non-deposit funding in total liabilities. In contrast to most earlier studies, he also included numerous unlisted banks in the sample, which even now represent majority of banks in the EU. He found that banks would be significantly more stable and profitable if they were willing to increase their share of non-interest income, so income diversification plays a major role in bank profitability and riskiness. He also found that such benefits are particularly large for savings and cooperative banks, whereas investment banks become significantly more precarious due to income diversification. Furthermore, according to Kohler's results, diversification into non-deposit funding will also have a different impact. While retail-oriented banks will be significantly less stable if they increase their share of non-deposit funding, investment banks will be significantly more stable. Hence, he calls for further analyses on data sets that would distinguish clearly between banks following different kinds of business models.

From a slightly different perspective, Berger and Bouwman (2013), for example, focused particularly on the role of bank capital in enhancing the bank's performance. Their study analysed how capital affects a bank's performance (survival and market share) and how this effect varies across banking crises, market crises, and periods of normality that have occurred in the US over the last quarter-century. They found that increasing the amount of bank capital particularly helps small banks to increase their probability of survival and market share in all times. Furthermore, capital also seems to have enhanced the performance of medium and large banks, primarily during banking crises.

With greater emphasis on the role of the general situation in the interest-yielding asset markets, the effects of the so-called slope of the yield curve on bank profitability were scrutinized in Alessandri and Nelson (2015). They presented a model of a monopolistically competitive bank subject to repricing frictions and tested the model's predictions on UK banks, using a unique panel data set. Their analyses yield evidence that large banks retain a residual exposure to interest rates, even after accounting for hedging activity operating through the trading book. Furthermore, in the long run, both the level and slope of the yield curve contribute positively to profitability, which follows the standard way of thinking about the effects of changes in the market reference rates on bank profitability through the NIM. In the short term, however, they found that increases in market rates compress interest margins, consistent with the presence of non-negligible loan pricing frictions.

Although the period of negative interest rates has prevailed for clearly over six years now at the European level, literature analysing its actual effects on bank profitability and/or riskiness remains surprisingly limited. Focusing particularly on Nordic countries, Turk-Ariss (2016) used bank-level data from large Danish and Swedish banks to demonstrate that the bank margins of loans to customers have remained broadly stable during the era of negative interest rates. Hence, reductions in wholesale funding costs and higher fee income have offset the lower interest income, and bank profitability has not suffered much due to negative reference rates in Sweden and Denmark. However, Turk-Ariss also warns that this situation may affect the banking sector's overall health, and so negative interest rates and their effects on the banking sector should be closely monitored in the future.

Bikker and Vervliet (2017) focused specifically on the US banking sector data from 2001 to 2015 and used the standard profitability measures, i.e. the NIM, ROA, ROE, and profit as reported in the bank's balance sheet (as a ratio of total assets). For risk measurement, they used the total capital ratio (TCR, the ratio of total risk-based capital over risk-weighted assets), and the loan loss provisions to total loans ratio. These risk measures were used as explanatory variables in one setting and as dependent variables in another. The vectors of explanatory variables in the panel regressions were a set of bank-specific variables and two macro variables (real GDP growth and CPI inflation), and as the short-term interest rate, they used the three-month money market interest rate. Their main finding was that the low interest environment indeed impairs banks' performance and compresses NIMs. However, US banks have been able to maintain their overall profit levels due to lower provisions (for loan losses etc.), but this induces greater risk for financial stability. Furthermore, US banks do not appear to have compensated their lower interest income by expanding operations to include trading activities with higher risk exposure.

Recently, Chaudron (2018) has also highlighted the special role of interest rate risk in bank profitability. He analysed the size and development of interest rate risk in the banking book positions of Dutch banks between 2008 and 2015. According to his results, due to hedging, interest rate risk has been minor, and the income from maturity transformation has actually formed a small share of the NIM and the ROA. However, in his data set, interest rate risk positions vary significantly between banks and over time, and he suggests that banks lower their interest rate risk significantly when the yield curve flattens. Furthermore, he suggests that interest rate risk is negatively related to on-balance sheet leverage and has a U-shaped relation with solvability for banks that do not use derivatives. Additionally, banks that had received government assistance during the financial crisis had higher interest rate risk than banks that had not received assistance.

In the most recent studies focusing specifically on the period just before or during negative interest rates, Claessens, Coleman, Donnelly, and M. (2018) used data from 3385 banks and 47 countries over the period 2005–2013 and found that a one percentage point drop in the reference rates during this time resulted in, on average, NIM of 8 basis points lower for banks.[9] However, the effect has been 20 basis points at low interest rate levels, i.e., non-linear. Hence, extremely low interest rates do affect bank profitability negatively, but with significant variation. According to their results, for each additional year of 'low-for-long' interest rates, margins, and profitability fall by another 9 and 6 basis points, respectively. Detragiache, Tressel, and Turk-Ariss (2018) analysed the profitability of banks at the EU level and found that banks whose profits have not decreased significantly during the zero-lower bound (ZLB) and negative interest rates period have experienced less deterioration in loan quality and considerable improvement in cost efficiency. These banks also downsized their assets more aggressively in response to the crisis and reduced their reliance on wholesale funding after the crisis. They also found that the NIM remained stable throughout the whole sample period they analysed, and the results showed no evidence that the reliance on fees and commissions would have improved profitability after the crisis.

Discussions of changes in the bank business models enhanced by the negative interest rate era were also the focus of Chen, Katagiri, and Surti (2018), who argue that if the scenario of very low and negative interest rates continues very long, it also implies low values for the longer-term, natural real interest rate. This may induce more consolidation waves in the banking industry in the long run. Furthermore, based on their theoretical model, and especially empirical data from Japan (and other industrial countries), they also argue that demographic factors, low productivity growth, and advances in financial technology will likely cause significant shifts in banks' business lines under low and/or negative interest rates. Furthermore, in a scenario of low rates and advances in financial technologies, banks may lose their market share in the debt financing of larger companies, when the non-banking sector is better able to price the corporate credit risk, and large firms seek more for bond market funding with low interest rates.

Also focusing particularly on NIM behaviour, Angori, Aristei, and Gallo (2019) analysed its determinants during the period 2008–2014 in the euro area. The starting point for their analysis was the premise that this standard measure of bank profitability should still be the main gauge of financial institutions' health and stability. Besides considering the main bank-level drivers affecting the NIM, such as market power, capitalization, interest risk, and the level of efficiency, they also accounted for the effects of regulatory and institutional settings. Their results reveal a persistence in the vulnerability of the banks' sustainable profitability, although this negative trend has been partially mitigated by the ECB's recent monetary policies. The increase in non-traditional activities seems to have contributed significantly to the slowdown in bank margins from traditional activity. Furthermore, the differences in the regulatory environment have effects on NIM, which has remained lower in countries with higher capital requirements and greater supervisory power.

Bottero et al. (2019) have studied the negative interest rate policy (NIRP) exploiting the ECB's introduction of NIRP and administrative data from Italy, whose real economy and banking sector were severely hit by the eurozone crisis. According to their results, the NIRP has expansionary effects on credit supply and, hence, the real economy, through a portfolio-rebalancing channel, and it affects banks with higher ex-ante net short-term interbank positions or, more broadly, more liquid balance sheets, but not those with higher retail deposits. NIRP-affected banks rebalance their portfolios from liquid assets to

[9] Other very recent papers focusing especially on the determinants of NIM profitability and comparison between different bank sizes are e.g. Kusi et al. (2020) and Asongu and Odhiambo (2019).

credit—especially to riskier and smaller firms—and cut loan rates, inducing sizeable real effects. Hence, by shifting the entire yield curve downwards, NIRP differs from rate cuts just above the ZLB.

In one of the most recent studies Lopez, Rose, and Spiegel (2020) performed an explicit analysis on the effects of negative nominal interest rates on bank profitability using annual data from 5200 banks in 27 countries from the period 2010–2017. They used proxies for the country-level local conditions as instruments for the negative interest rates and other explanatory variables and split the data set based on the bank size (amount of assets) and reliance on deposit, i.e., retail funding. One of their main findings is that the effects of negative interest rates are clearly heterogeneous. Banks from regimes with floating exchange rates, small banks, and banks with low deposit ratios drive most of the results. It appears that low-deposit banks have enjoyed particularly striking gains in non-interest income. Additionally, banks responded to negative interest rates with increased lending activity and by raising the share of deposit funding. In sum, the effects of negative interest rates on bank profitability seem to have been relatively benign in their data set. In another very recent paper, Heider, Saidi, and Schepens (2019) used a differences-in-differences method and compared the lending behaviour of eurozone banks with different deposit ratios around the ECB's introduction of negative policy rates in June 2014. Hence, they also focus particularly on the role of retail- vs wholesale-based funding of banks' lending activities. They find that the introduction of negative interest rates in funding leads to increased risk taking among banks as a whole and less lending on the part of banks that are more dependent on deposit funding. Hence, they suggest that negative interest rates are less accommodative and could pose a risk to financial stability if lending activities are concentrated in high-deposit banks.

Finally, among the few theoretical papers that have investigated the explicit role of negative interest rates on bank profitability are studies by Eggertsson, Juelsrud, Summers, and Wold (2019) and Xu, Hu, and Das (2019). In the former paper, an essential finding from their empirical analyses is that, as deposit rates stopped responding to policy rates at the ZLB, bank lending rates in some cases actually began to increase rather than decrease in response to the policy rate cuts. Hence, the increase in lending margins has improved banks' profitability. In the study by Xu et al. (2019), one of the main findings, which also derives from the theoretical argumentations based on a profit maximization model of a bank, is that the movement from retail-based funding to wholesale-based funding might actually pose a serious threat to the systemic stability of the entire banking sector. Their main finding is that a bank's profitability is negatively correlated with its contribution to systemic risk and its idiosyncratic risk. Additionally, over-reliance on non-interest income, wholesale funding, and leverage is associated with higher risks. Moreover, reduced competition between banks also induces greater contribution to systemic risk. Hence, their main policy suggestion is that policy makers should aim for an improved understanding of bank profitability, particularly in conditions of negative interest rates and banks' increased share of wholesale funding.

As can be seen from our brief literature review, the effects of negative money market interest rates in the banking sector are currently under considerable scrutiny, but a definitive finding or conclusion with respect to whether the effects on bank profitability, risk-adjusted or not, are positive or negative, has yet to be reached. Some of the most recent (also theoretical) studies seem to indicate that, for some banks, negative interest rates might even improve their profitability. However, a key factor influencing the outcome is the bank business model, i.e., whether the bank in question is more dependent on retail (deposit) or wholesale funding. Next, based on our unique, highly confidential data set from all banks belonging to the Finnish OP Group, we will shed new empirical light on this issue.

3. Data and empirical strategy

We will apply several modern time-series econometric techniques in our analyses of the key bank profitability measures. First, we will carefully examine the time series under analysis using descriptive statistics and informative graphs. Thus, we will form an idea of the statistically most appropriate forms (i.e., levels or differences) of the variables for further analyses. Second, we will utilize multivariate time-series analytical techniques to reveal the dynamic connections between the analysed bank profitability measures and the money market interest rate. Finally, we will also test for the presence of conditional heteroscedasticity in the estimated multivariate models, which will also provide indications as to the need for more advanced, GARCH-type time-series modelling approaches, that will be utilized to draw the very final conclusions of our analyses. In interpreting all parts of our results, we will focus particularly on the negative money market interest rate regime with respect to its effects on the various bank profitability measures.

3.1. Data description

Our empirical analysis uses monthly observations from all banks belonging to Finland's OP Financial Group for the period 1/2009–12/2018. The original, strictly confidential data were collected from the income statements, balance sheets, and financial statements of all banks included. Many of the variables in the original data set are being regularly (in approximately monthly meetings) followed by the boards of directors of the individual OP banks. However, instead of focusing on individual bank-specific data,[10] we will here concentrate on *average values* of the main interesting profitability measures, calculated based on the size reference categories R1, R2, and R3.[11] The classification of the individual OP banks to R1, R2 and R3 banks made by the central co-operative refers to their reference classes in terms of the volume of customer business activities. The group of biggest (R1) banks includes all the 19 regional banks plus 4 other largest banks comparable in size to the regional banks, decided by the Supervisory Board for the entire OP Group. By definition, the next 40 banks in terms of their size belong to the reference group R2. Finally, rest of the banks form the biggest group of banks in terms of the number of individual banks, but they contribute only to a small part of the whole OP Group customer business activities volume.

At the end of our data sample in December 2018, the number of banks was 151 in our filtered data set (156 according to the Group-level statistics referred to in Appendix A). Because some current OP Group member banks had joined the Group from the local cooperative banks'

[10] Due to limitations of space, we will analyse the original bank-level panel data set using panel-econometric methods in a separate study.

[11] Note that the monthly reporting of the data based on these three size groups is based on the ready-made classification of the banks to these size groups by the central co-operative of the OP Group. Hence, we use this readily given classification through-out the whole sample, and hence, for example the effects of mergers and acquisitions of individual banks have already been accounted for in the actual data reported in the original database. However, because we spotted some outliers and accounting irregularities in the data, a detailed description of some additional stages in the cleaning and construction of the final data set utilized in this study's empirical analyses is given in Appendix C. We are extremely grateful to Ari Saarinen and Arto Kuhmonen from the OP Group Business Control department for providing the original confidential data set on all the OP Group banks, and for the preliminary cleaning of the data on accounting and financial statement figures.

(so-called PoP) group during the latter years of our sample period (e.g. in the third quarter of 2016), owing to their lack of historical observations, particularly from the period before the negative interest rates, they were not included into our data set. However, analogously to the merger-type structural changes that occurred throughout the entire sample period, also in the most recent data, some banks in the OP Group had dropped from the R2 group to R3, while others had moved from R3 to R2.[12] Hence, in our empirical analyses based on the average values of the R1, R2, and R3 banks, the number of banks belonging to size category R1 is 23. The R2 category includes 39 banks, and finally, all remaining 89 banks belong to the R3 category, bringing the total number of banks in our data set to 151 at the end of 2018.

3.1.1. The development of market interest rate and bank profitability measures

From a set of various possible reference rates in banking activities (see for example Heider et al., 2019), we will use the EONIA overnight mid-rate as representative of the short-term money market interest rates. It began to obtain negative values since November 2014, following the negative path of the main ECB reference rates in the summer, and was followed by negative values for the main bank reference rates in credit activities, i.e., the 3-month (negative since April 2015) and 12-month (negative since February 2016) Euribor rates. Hence, we treat the EONIA as a 'median indicator' of when the eurozone money market interest rates began to turn (and stay) negative.

The most frequently used standard measure for bank profitability in previous studies is the Return on Assets (ROA), defined as

$$ROA = \frac{Net\ income\ (after\ taxes)}{Assets} \times 100. \tag{1}$$

The amount of assets in ROA calculations is based on the average of the values at the beginning and end of fiscal year, and the tax effects are included as net of appropriations. Alternatively, in some of the previous studies mentioned also in the literature review, profitability has been measured based on the Return on Equity (ROE), that is,[13]

$$ROE = \frac{Net\ income\ (after\ taxes)}{Equity} \times 100 \tag{2}$$

Although we will start our analysis by also examining the behaviour of ROE values in our data set, we will see that it is strongly correlated with at least two other profitability measures, i.e. the ROA and Net Interest Margin (NIM) values in all cooperative banks, irrespective of their size. This correlation should be borne in mind in the more thorough analyses.[14]

Our third profitability measure is the NIM, defined as

$$NIM = \left(\frac{Interest\ income - Interest\ Expenses}{Assets}\right) \times 100. \tag{3}$$

Evidently, when we specifically analyse the dynamics of the other, broader profitability measures, for example, for this main profitability measure of banks we have

$$\Delta NIM \cong \frac{\Delta Interest\ income - \Delta Interest\ expenses}{Assets}, \tag{4}$$

so changes in both the interest income and expenses have an effect on the overall change in NIM. Furthermore, the ROA and NIM values are also connected to one another by definition, because

$$\Delta ROA \cong \Delta NIM + \frac{\Delta Non\ interest\ income}{Assets} - \frac{\Delta Non\ interest\ expenses}{Assets} - \frac{\Delta Loan\ Loss\ Provisions}{Assets} + \frac{\Delta Net\ other\ income}{Assets}, \tag{5}$$

[12] See Appendix A for further details on the entire OP Group and its member banks at the end of 2018. Note also that at the beginning of our empirical analyses we detected one individual bank in the R2 group whose accounting and financial statement numbers differed so significantly from all other banks in its reference group that we decided to treat that bank as an outlier, and excluded it from our data set.

[13] The amount of equity includes the minority shares and movable cumulative items at the closing of accounts minus tax effects net of appropriations.

[14] We would like to point out also that the definition of equity, and hence, its use in analysing the profitability of banks is somewhat ambiguous in the special case of Finnish cooperative banks. This is due to the key role of the member banks in owning the OP cooperative (i.e., central cooperative) through an amalgamation (see Appendix A for more details) and the specific role of customer ownership and profit shares in all the Finnish cooperative banks. By definition, the equity capital of the entire OP Financial Group includes cooperative shares paid by the Group's cooperative bank members, and the bank has an absolute right to refuse to pay interest on them and refund the capital. Cooperative contributions and the ensuing customer ownership entitle the customer to participate in the bank's administration and decision-making. Furthermore, the equity capital of OP Group also includes investments in profit shares made by members of the Group member cooperative bank members, and the bank has an absolute right to refuse to pay interest on them and refund the capital. For example, for 2018–2019, the OP Financial Group sought an interest rate of 3.25% and will confirm the interest payable annually after the financial year has ended. The return target may change on an annual basis. No customer-owner rights are involved in profit shares, and they do not confer any voting rights. If a member cooperative bank has not refused a refund, the cooperative contribution and the profit share contribution may be refunded within 12 months after the end of the financial year when membership is terminated, or the profit share has been cancelled by its holder. If the refund cannot be made in full in any given year, the balance will be refunded from disposable equity capital based on subsequent financial statements. However, this entitlement to the refund for the balance will terminate after the fifth financial statements. No interest will be paid on the balance. Due to the strong role of especially these cooperative profit shares in the calculation of equity capital (see the OP Financial Group Report by the Executive Board and Financial Statements 2018, and Appendix A), in deeper analyses of the Finnish OP banks' profitability the results on ROE must be scrutinized while bearing these special features in mind.

where changes in NIM are given by eq. (4) and

$$\Delta Non\ interest\ income = \Delta Trading\ volume + \Delta Fees\&commissions\ incl.insurance\ income + \Delta Other\ operating\ income. \quad (6)$$

Hence, it is obvious that other income components besides changes in the NIM might play a significant role in the determination of bank profitability when measured, for example, based simply on the changes in ROA. In calculating the changes in ROA, net other income items usually include non-customer loan impairment charges, net recurring income not related to the core business, extraordinary net income, tax expenses, and profit/loss from discontinued operations (see also Detragiache et al., 2018).[15]

One of the most significant innovations of our study is the use of Return on Economic Capital (ROEC) in analysing the profitability of Finnish cooperative banks.[16] The main idea in the calculation of ROEC is that it gives a bank-specific measure for the riskiness of bank performance, based on assigning risk values (weights) to the main components of the bank's balance sheet. The fundamental purpose of the requirement for economic capital (EC, the denominator in the calculation of ROEC) is that it is designed to cover for all the risks, particularly in the customer business activities of the OP banks.

According to the information available from the OP Financial Group Intranet,[17] the EC requirement is the OP Group's own proxy for the amount of capital required to cover all the risks associated with losses from business activities during a single year at the level of 99.97% probability. This means that if an individual bank has its own funds of the precise amount corresponding to the total EC requirement, the bank runs out of funds once in 3333 years on average. Hence, the EC requirement gives the bank a hedge against extremely rare and unexpectedly large losses. The reason for using the 99.97% probability level is that it corresponds to the entire OP Group's external credit rating target (level AA). This definition also enables a more direct comparison to the main competitors (e.g. Nordea and Danske Bank) that are using conceptually similar measures for the EC requirement. By definition, in the OP Group, the EC requirement covers the risk categories for credit risk, interest rate risk, equity risk, real estate risk, measurable risks, operational risks, and other measurable risks. As such, the exchange rate risk, for example, is not included.[18] Indicators based on EC requirement are used within the Group to measure individual banks' general performance. Furthermore, they are used to measure bank-specific limits and Group-level supervision limits in many more detailed performance measures, in rewarding the personnel, pricing the loans and insurance products, and in capital budgeting for the purpose of defining the amounts of capital buffers.

Fig. 1 shows that, after the introduction of negative money market interest rates, the role of equity risk in banking in the EC requirement would seem to have strongly diminished to below half of the situation immediately following the 2008–2009 crisis.[19] At the same time, the EC requirement coming from the credit risk appears to have increased by around 13 percentage points. Furthermore, an interesting point that may already be clearly observed from this figure is that both these changes seem to have emerged even more prominently after the introduction of negative money market interest rates around 2014–2015. In addition, the EC requirement emanating from the interest rate risk also clearly seems to have increased permanently after the introduction of negative money market interest rates. Hence, everything that is related to the main, traditional functions of banks (i.e., acquiring deposits and giving loans to customers), seems to have been treated as riskier during the latest 4–5 years, because the EC requirements based on both the credit risk and interest rate risks have clearly increased.

Further details on the actual numerical values and procedures for the calculation of individual components in the EC requirement are available only with the permission from the OP Group Control personnel. For the purposes of our study, we will describe in greater detail only the procedure for calculating the EC requirement for the interest rate risk, because it actually includes currently the scenario of extremely low negative money market interest rates (of the level of even −2% in annual terms). Furthermore, as observed from Fig. 1, its role has more than doubled in the EC requirement since the introduction of negative money market reference rates.

The EC requirement for the OP banks' interest rate risk is based on the use of a so-called interest income risk method, which gives a value for the most negative effect on the bank's NIM during the next 12 months (assumed holding period) from a change of four percentage units (positive or negative) in the level of interest rate. The model accounts for the changes in legislation and other conditions in the agreements that allow banks to charge interest from the credit customer corresponding at least to the amount of the customer-specific margin. The calculation of interest income risk also takes into account the effects of negative

[15] Note that particularly with respect to the NIM calculations, and for all other profitability components, at least two important additional characteristics emerge from our data. First, the loan interest rate floors have been an important factor in the balance sheet management for retail banks because, due to those, the deposit interest rates have also remained approximately at the zero level or just above it. In addition, balance sheet growth plays a role here. In the OP group, based on our data, the NIM has remained approximately constant over the last six years, but the size of the balance sheet has increased by almost one third. During the ten years of our sample, the balance sheet has doubled and the NIM has increased by a third. In the set of profitability measures, ROE and risk-adjusted profitability do not capture all these effects, but the ROA, as the measure for capital profitability should also account for these developments.

[16] Note that the actual calculation process of ROEC is a highly classified procedure, available in detail only for the bank managers and e.g. the chairpersons of the boards of directors of individual banks in the OP group through the Group's intranet. However, due to the novelty of its application in this paper, the main ideas in the calculation of the ROEC values are described in Appendix B, based on the information obtained from the Group intranet, at the accuracy level accepted by the OP Group business control personnel.

[17] Permission to publish this short, very general description of the principles of both the EC requirement and ROEC (in Appendix B) calculations has been obtained from the Group control personnel on 11th December 2019 (e-mail from Esa Vilhonen).

[18] During the sample period, the individual OP banks gave no foreign currency denominated loans to their customers at all. All the currency risks have been centred to the Group level, because the member bank-level currency risks emanating from e.g. the foreign currency-denominated customer deposits have been transferred to the Central cooperative level with counter deposits. The Central cooperative also provides many other types of currency market-related products to all customers, but all the currency market risks are centrally managed and hedged. Hence, the individual member banks do not bear currency risks in their activities at all, other than through the principle of joint and several liability at the group level, again.

[19] Based on discussions with the Group control personnel, the OP banks' equity investments have been reduced to avoid the additional need to acquire market-based funding for these purposes. Hence, the reduction in the equity risk is, for the most part, based on active Group-level guidance.

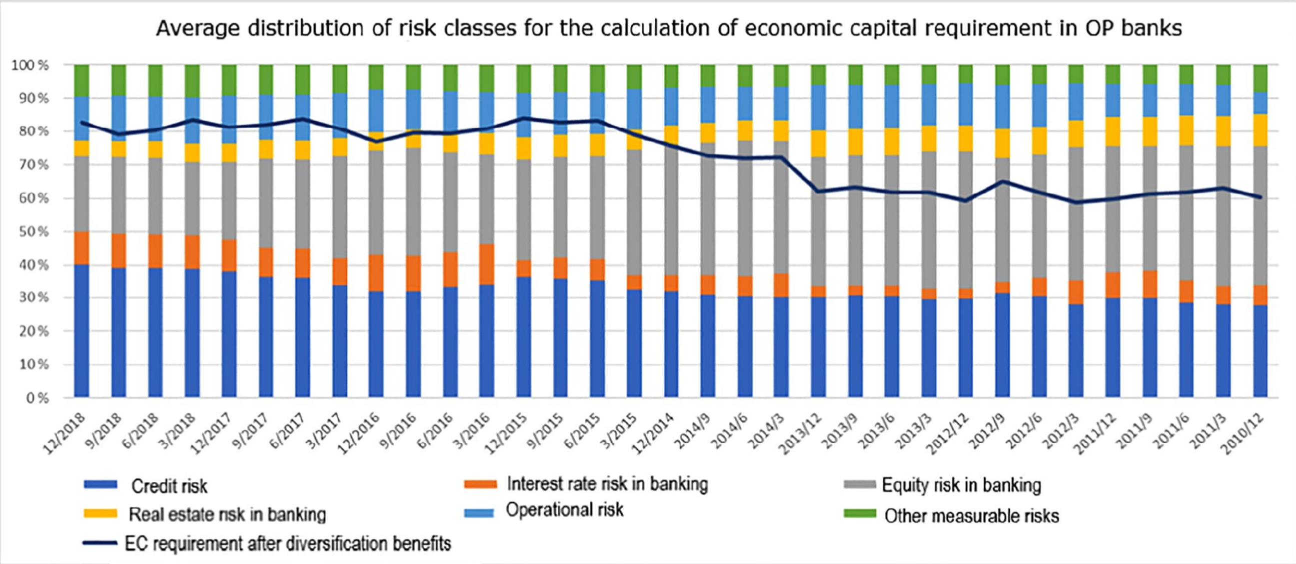


Fig. 1. Composition of the risk component weights in the economic capital (EC) requirement over time (source OP Group Control). NOTE: Reverse time axis starting from the most recent observations.

interest rates using the floor of −2%.[20] In addition, debt assets valued at market values are allocated the most negative discounted present value interest rate risk reflected to the bank's own assets for a 4-percentage-unit interest rate change during the entire maturity. In this calculation, the floor of −2% is also applied. The 4% change in the calculation is intended to cover both changes in interest rate and credit risk margins.

If an individual bank deposits a special OP-deposit (to the central cooperative), the EC requirement on interest rate risk is based on summing up the interest income risk and a requirement of 2.9% that is based on a specialist evaluation. The OP-deposit is based on seniority terms, but normally it cannot be withdrawn before maturity. In a specific bank stress situation, an early withdrawal induces costs to the issuer of the deposit agreement. Taken together, the interest income risk and the present value risk of investments are combined in absolute terms. The EC requirement of OP banks is the sum of EC requirement on interest risk and a separate OP-deposit EC requirement. However, the EC requirement for the interest rate risk of an individual OP is always at least 0.25% of the total value of the balance sheet, due to the model risk and one-year holding period. This is to ensure that the risk associated with the main income component (NIM) is reflected in all the OP banks. It should also be noted that the interest income risk is not calculated at all for the central cooperative capital and the cooperative capital, additional cooperative capital, or the profit share units of the individual OP banks.

Evidently, both the ROEC and EC calculation procedures have been carefully designed to yield a fundamental picture of the risks involved in all the business activities of the individual cooperative banks. Due to the detailed decompositions of both, the analysis and comparison of ROEC-based performance against the most standard ROA- or ROE-based performances may also give a somewhat different perspective on the profitability effects of the negative interest rate era. Furthermore, as we have already observed from Fig. 1, the role of different risk classes also seems to have changed after the introduction of negative money market reference rates. However, here it is worth pointing out that many changes in the weights of the risk classes are likely to have been administered by the central cooperative, but the actual decisional data pertaining to these changes are beyond our reach due to their confidentiality. Nevertheless, it is clear, that these decisions probably also reflect the general developments in the interest-yielding asset markets.

In our empirical analyses, the ROEC values are calculated as follows:

$$ROEC = \frac{(\text{Operating income} + \text{customer bonuses}) \times (1 - \text{tax rate})}{\text{Economic Capital Requirement on Customer Business Activities (cum.)}} \times 100\%. \quad (7)$$

Finally, details regarding how we obtain the monthly (average) observations for each bank size class from the original lower frequency data (used for the calculation of some composites of the main interesting variables) for the three profitability measures utilized in the regression analyses are provided in Appendix C. Figs. 2a–2c show the development of the analysed profitability measures compared to the values of the EONIA overnight mid-rate during our sample period.

From Figs. 2a–2c we see that the standard textbook hypothesis stating that decreasing general market interest rates have a negative effect on the NIM seems to clearly hold in our data, and for all bank size groups. More specifically, when the EONIA turned negative in November 2014, the average NIM profitability in all the OP bank size categories began to decrease, and it has continued to do so up to the most recent observations. However, an interesting new eye-ball finding is that when we measure the profitability by a wider measure, i.e., ROA, the negative effect of below-zero interest rates might not be so clear at all in the data on Finnish cooperative banks. Only after the beginning of 2017 can we clearly say that ROA-based profitability has consistently decreased across all bank size groups in average terms. Furthermore, as

[20] See also https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp137.pdf.

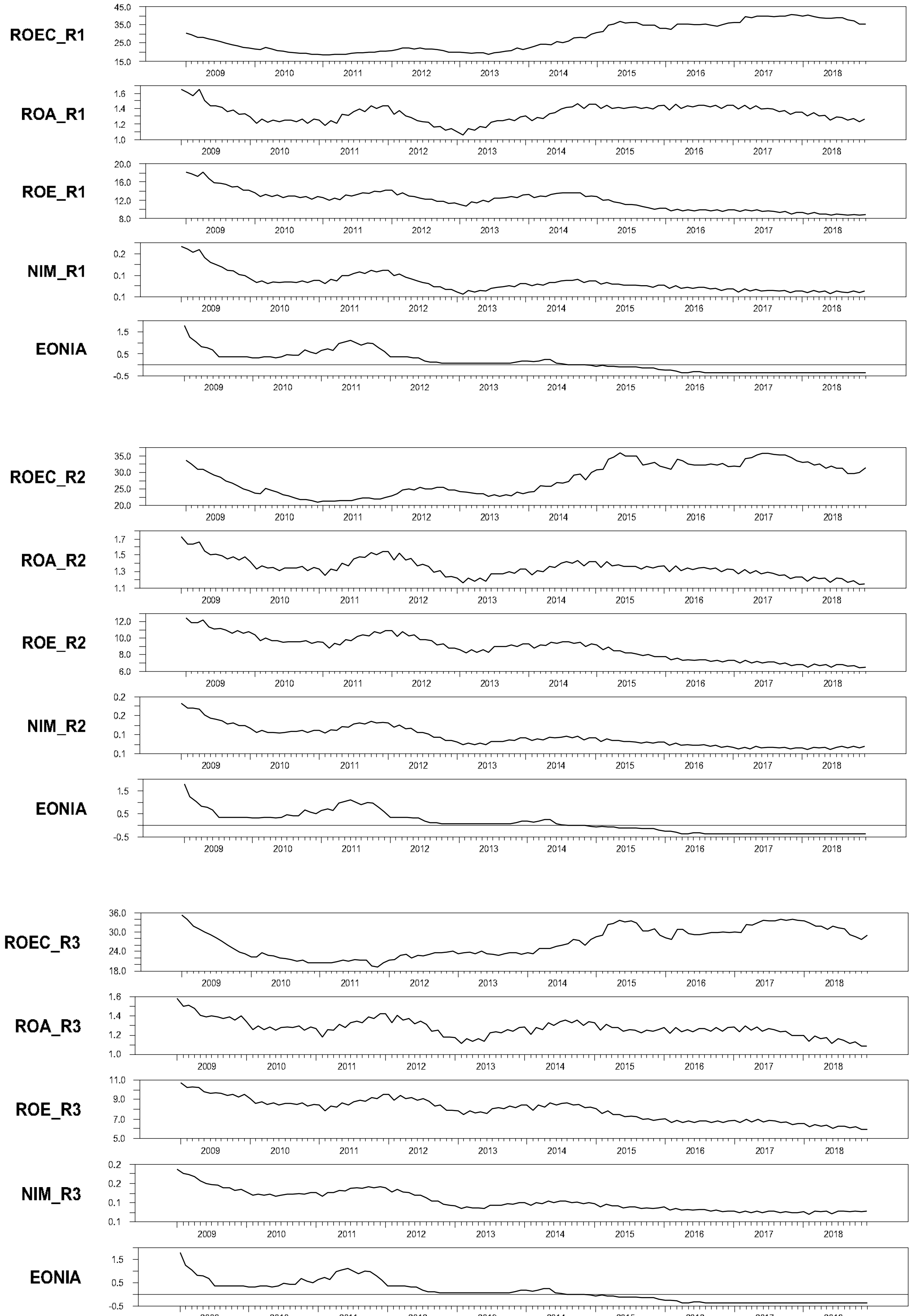


Fig. 2. a. Alternative average profitability measures for R1 banks compared to EONIA mid-rate. b. Alternative average profitability measures for R2 banks compared to EONIA mid-rate. c. Alternative average profitability measures for R3 banks compared to EONIA mid-rate. a*. Differenced values of profitability measures for R1 banks and EONIA b*. Differenced values of profitability measures for R2 banks and EONIA. c*. Differenced values of profitability measures for R3 banks and EONIA

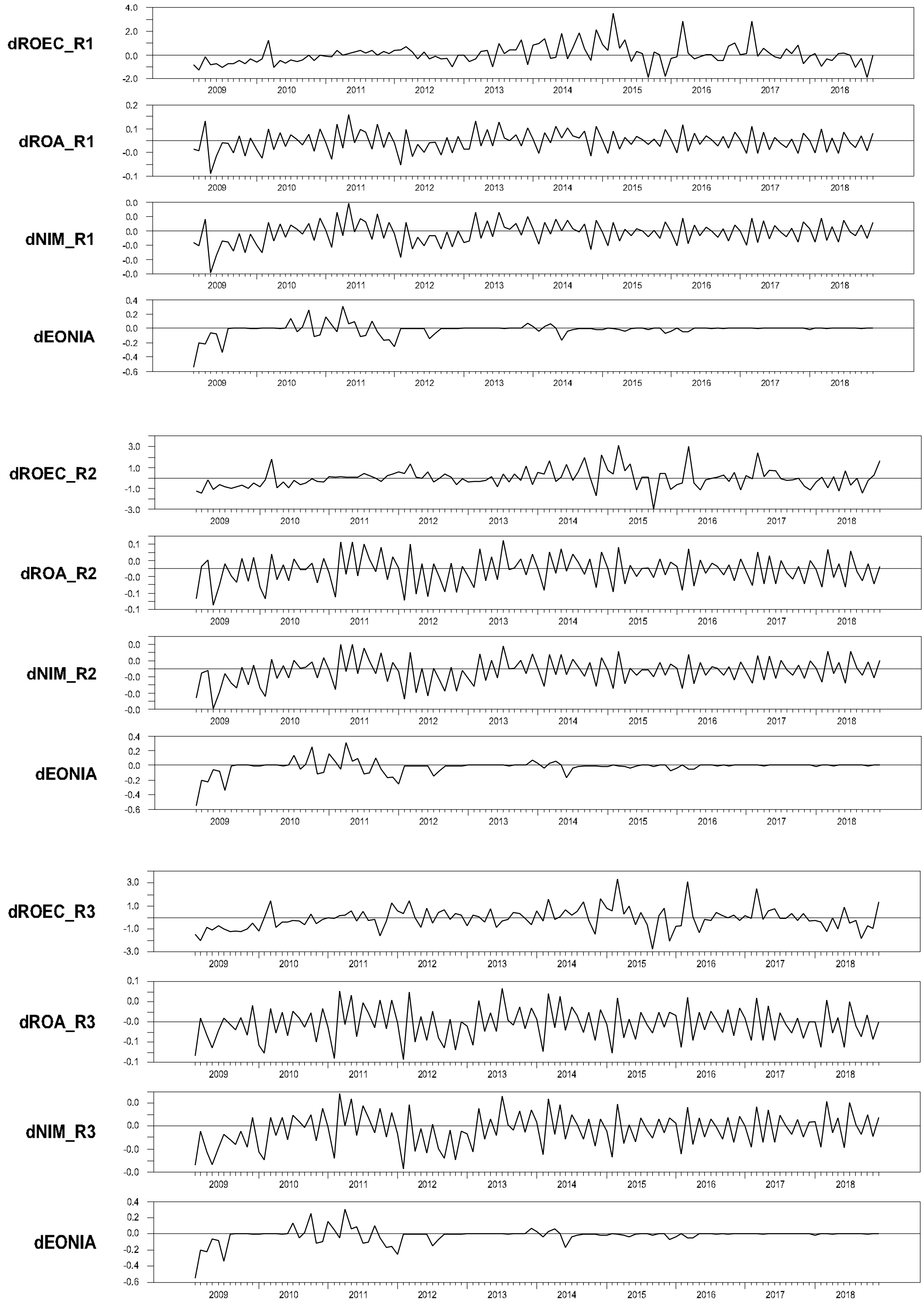


Fig. 2. (*continued*).

Table 1
Descriptive statistics, unit root test results, and correlations for the bank profitability measures and the EONIA mid-rate, all measured in %.

Variable / Descr. stat.	*ROEC_R1*	*ROE_R1*	*ROA_R1*	*NIM_R1*	*ROEC_R2*	*ROE_R2*	*ROA_R2*	*NIM_R2*	*ROEC_R3*	*ROE_R3*	*ROA_R3*	*NIM_R3*	*EONIA*
Mean	27.95	11.94	1.34	0.11	28.20	8.84	1.36	0.12	26.77	7.94	1.28	0.12	0.13
Std Dev	7.76	2.16	0.11	0.02	5.01	1.47	0.11	0.02	4.51	1.14	0.09	0.02	0.45
Min	18.32	8.62	1.07	0.09	20.84	6.49	1.16	0.09	19.24	5.95	1.09	0.10	−0.37
Max	40.86	18.10	1.65	0.17	36.71	12.55	1.72	0.19	35.32	10.78	1.58	0.19	1.81
# of banks in the size group	23				39				89				
Unit root tests													
ADF	−0.96	−2.92**	−3.52***	−4.46***	−1.12	−1.94	−3.04**	−2.89**	−1.88	−1.37	−2.30	−2.24	−4.35***
KPSS	1.94***	1.94***	0.27	1.47***	1.64***	2.18***	0.98***	2.02***	1.40***	2.18***	1.08***	2.14**	2.11**
Z-A	−5.07**	−5.27***	−5.34***	−6.03***	−4.66*	−4.68*	−4.31*	−5.39***	−5.21**	−4.02	−3.71	−4.76*	−3.23
Break point in Z-A test	2014:5	2013:2	2014:3	2012:1	2014:2	2011:3	2014:3	2012:5	2014:2	2011:3	2014:2	2012:5	2011:11
	Correlations of the profitability measures within the bank size groups and with the EONIA Midrate												
	ROEC_R1	*ROE_R1*	*ROA_R1*	*NIM_R1*	*ROEC_R2*	*ROE_R2*	*ROA_R2*	*NIM_R2*	*ROEC_R3*	*ROE_R3*	*ROA_R3*	*NIM_R3*	*EONIA*
ROEC_R1	1.00												
ROE_R1	−0.64	1.00											
ROA_R1	0.48	0.25	1.00										
NIM_R1	−0.37	0.90	0.52	1.00									
EONIA	−0.72	0.84	0.06	0.81									
ROEC_R2					1.00								
ROE_R2					−0.61	1.00							
ROA_R2					−0.11	0.80	1.00						
NIM_R2					−0.49	0.95	0.85	1.00					
EONIA					−0.65	0.87	0.68	0.91					
ROEC_R3									1.00				
ROE_R3									−0.53	1.00			
ROA_R3									−0.11	0.82	1.00		
NIM_R3									−0.45	0.94	0.81	1.00	
EONIA									−0.55	0.85	0.64	0.92	1.00

NOTE: We report first the descriptive statistics, i.e. the mean, standard deviation, and minimum and maximum values for the analysed bank profitability measures and the EONIA mid-rate for the entire sample of monthly observations for 2009/1–2018/12 for the banks in different size groups. The total number of all OP banks at the end of the sample period was 151. In the middle panels, we report the results from three different unit root tests. ADF refers to the standard Augmented Dickey and Fuller (1979) test statistics, with the null of non-stationarity. KPSS denotes the Kwiatkowski, Phillips, Schmidt, and Shin (1992) test, with the null of stationarity, and finally, Z-A refers to the test by Zivot et al. (1992), with the null of non-stationarity, but allowing the presence of structural breaks in the data-generating process of the analysed time series. Notations ***, ** and * refer to the statistical significance of the test statistics at the 1, 5, and 10% risk levels. In the lowest panels, we report the correlation coefficients among the profitability measures themselves within the bank size groups, and with the EONIA mid-rate. *ROEC_R#* denotes the average values for the return on economic capital, *ROA_R#* the return on assets, and *NIM_R#* the net interest margin (relative to the size of balance sheet) in the bank groups, where # = 1, 2 or 3. R1 refers to the group of largest banks, R2 to the medium-sized banks, and R3 to the group of smallest banks. *EONIA* refers to the EONIA mid-rate.

pointed out earlier, the ROE and NIM series appear to be strongly correlated, and this is also observed in the reported high correlation coefficients in Table 1.[21]

However, it is also clear from a glance at the behaviour of the risk-adjusted profitability measure (ROEC) in all bank size groups that it behaves clearly differently to the other standard profitability measures, such as ROA and NIM. The trend in the average ROEC values of each size group has been robustly positive until the beginning of 2018, when the OP Group Control changed some risk weights in the calculation of the EC requirement. Hence, from viewing the size group-based time series of the three average profitability measures it is clear, that the empirical results regarding their dynamic connections to the negative money market reference rates may also vary considerably.

The results on descriptive statistics, unit root tests, and contemporaneous correlation coefficients reported in Table 1 confirm our earlier eye—ball findings that the data-generating processes of the analysed average profitability measures indeed behave quite differently, even though by definition, based on the calculation procedures given in eqs. (1)–(7), they are also interconnected in many ways. The descriptive statistics for the NIM reveal practically no differences between the three different size groups, because the mean, standard deviation, and extreme values (min and max) are approximately the same for all groups. The same conclusion applies to the interpretation of the ROA values. The strongest differences in the descriptive statistics are observed for the ROE values, whereby the largest (R1) banks seem to have been the most profitable, but their ROE values also varied the most during the sample period. The same applies to the risk-adjusted profitability measure (ROEC), in which the variation has been the strongest for the largest banks. When interpreting the test results from the unit root analyses, we see that for the smallest banks, all four profitability measures seem to behave similarly to non-stationary processes, but this conclusion may be biased in light of the observed break in the data series, either around the beginning of 2014, or around the eurozone sovereign crisis period in 2011–2012. Even though the introduction of the endogenous structural break procedure to the unit root testing

[21] In Figs 2a*–2c*, we also give the time-series graphs of the differenced values for all the profitability measures (excluding ROE, due to its strong correlation e.g. with NIM) and EONIA. All these series proved to be stationary in terms of differences, although, based on the various reported unit root test results, some of the analysed time series might have behaved similarly to nonstationary processes in levels. However, as we proceed with our analyses, we will use the levels of all variables because, as observed from Figs 2a*–2c*, for example, the series on NIM and EONIA obtained a continuum of zero observations for their differenced values after 2014. This would be problematic in our analyses, because at the final stages we will be using highly advanced versions from the GARCH model family (see section 3.2), where zero observations for the analysed variables impose serious computational problems in the maximum likelihood estimations of the conditional variances and covariances.

framework seems to result stationarity of the analysed profitability measures in many cases, it is obvious that we also have to do some analyses using the differenced values of all the variables. Finally, the preliminary (static) correlation analyses reveal that the ROE values are very strongly correlated with especially the NIM values in every size group, even more than NIM is correlated with EONIA. Hence, as already mentioned, for example, in the VAR-type analyses involving all the discussed profitability measures, we will in some cases omit the ROE from the vector of analysed variables. However, as discussed in the introduction, one of our main hypotheses is that the introduction of negative money market interest rates may have induced changes in the OP banks' business models. Hence, during the negative interest rate era, they might have increased their reliance on wholesale funding, i.e., loans from the central cooperative, and for this part of our empirical analysis, we will also introduce ROE to the set of profitability measures. Furthermore, in the final, pairwise dynamic conditional correlation analysis we will use the ROE values, too, to give a full picture of the interrelationships between the variables.

3.2. *Empirical strategy*

Based on the unit root test results reported in the previous subsection, we opted to use all the analysed time series in levels in the first stage because after taking into account the possibility of structural breaks in the form of Zivot and Andrews (1992) test, almost all the series seem to be stationary at least at 10% risk level.[22] Put it more precisely, in all cases for the ROEC and ROA series in all bank size groups, the break point seemed to be in connection to the extremely low, and ultimately negative money market reference rates. Furthermore, the dramatic decrease of EONIA in November 2011 and of the Euribor rates at varying maturities within a few months subsequently might have caused a structural break to the average NIM of all bank size groups between January 2012 and May 2012. As already mentioned, our final modelling procedure, i.e., the application of one form of asymmetric, regime-dependent dynamic conditional correlation (DCC- GARCH) models, requires that the analysed time series do not contain an excess of zero observations, which would basically wipe out all dynamics in the variances and particularly in covariances of the analysed series. Hence, after the standard VAR and Granger causality analyses, we will seek the statistically best possible parametric representation of the dynamic relationships between the analysed variables based on the following empirical idea.

Our methodology in modelling DCC-GARCH connections between the various bank profitability measures and the other relevant variables assumed to have affected them (i.e., the money market (EONIA) interest rate and the wholesale funding (WSF) ratio) was as follows. We estimate the time-varying covariance structures using the asymmetric generalized DCC-(AGDCC) model by Cappiello, Engle, and Sheppard (2006). To keep the number of parameters tractable, instead of using e.g. VAR-specifications for the mean equations, we estimate pairwise models between a set of all four profitability measures (ROEC, ROA, ROE, and NIM) and the EONIA mid-rate or wholesale funding ratio (WSF). Because we use pairwise analyses at this final stage, our results are not biased for example by the high correlation of ROE series with the other profitability measures. The mean values of the analysed time series are modelled as.

$$r_{i,t} = \alpha_i + e_{i,t}, i = 1, 2 \tag{8}$$

where $r_{1,\ t}$ is always alternatively ROEC_R1, ROEC_R2, ROEC_R3, ROE_R1, ROE_R2, ROE_R3, ROA_R1, ROA_R2, ROA_R3, NIM_R1, NIM_R2, or NIM_R3, and $r_{2,\ t}$ is always either the EONIA Mid-rate or WSF. Parameter α_i denotes the constant term in the mean equation, and the vector of residuals follows an N(0, H_t) distribution, where the conditional covariance matrix is decomposed based on.

$$H_t = D_t R_t D_t, \tag{9}$$

and D_t is a 2 × 2 diagonal matrix of conditional standard deviations

$$\varepsilon_{i,t} = e_{i,t} \Big/ \sqrt{h_{i,t}}. \tag{10}$$

We estimate $h_{i,\ t}$ from univariate GJR-GARCH(1,1) model (see Glosten, Jagannathan, & Runkle, 1993) as

$$h_{i,t} = \beta_{i,o} + \beta_{i,1} e^2_{i,t-1} + \beta_{i,2} h_{i,t-1} + \beta_{i,3} I\left(e_{i,t-1} > 0\right) e^2_{i,t-1}, \tag{11}$$

where $\beta_{i,\ j}$ are the constant coefficients to be estimated and $I(e_{i,\ t-h} > 0)$ is an indicator function, which is equal to 1 if the condition is met and zero otherwise. R_t is the time-varying correlation matrix defined as.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{12}$$

where

$$Q_t = \left(\overline{Q} - a\overline{Q} - b\overline{Q}B - c\overline{N}\right) + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} + cn_{t-1}n'_{t-1}, \tag{13}$$

and $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals based on eq. (10), and *a*, *b*, and *c* are scalar parameters. $\overline{N}$ refers to the unconditional covariance matrix of the standardized residuals, satisfying condition.

$$n_{i,t} = \begin{cases} \varepsilon_{i,t} \ if \ \varepsilon_{i,t} < 0 \\ 0, if \ \varepsilon_{i,t} \geq 0 \end{cases} \tag{14}$$

for all variables expect the risk-adjusted profitability measures of ROEC_R1, ROEC_R2, and ROEC_R3, for which the conditions are

$$n_{i,t} = \begin{cases} \varepsilon_{i,t} \ if \ \varepsilon_{i,t} > 0 \\ 0, if \ \varepsilon_{i,t} \leq 0. \end{cases} \tag{15}$$

This ensures that $\beta_{i,\ 3} \geq 0$ in the conditional covariance matrix (11), which is unnecessary but makes the interpretation of stationarity conditions for the conditional covariances more straightforward. Finally, we estimate the models in three stages, as suggested by Cappiello et al. (2006), and force the GARCH parameters to satisfy the conventional stationarity and non-negativity conditions.

$$\beta_{i,j} \geq 0\ (\mathrm{j} = 0, 2), \beta_{i,1} + \beta_{i,2} + \frac{\beta_{i,3}}{2} \leq 1 \tag{16}$$

4. Results

4.1. *Dynamic relationships between the profitability measures and EONIA*

Tables 2a and 2b report the results from the standard linear Granger causality tests for the levels (Table 2a) and differences (Table 2b) of alternative bank profitability measures. In adopting a special focus on the money market interest rate's effects on profitability, we see that the levels of EONIA mid-rate seem to affect (Granger cause) NIM in all banks of different sizes, but that in all other respects the results vary between the different size groups. It seems that EONIA affects the risk-adjusted ROEC profitability only in the smallest R3 banks, and not at all in the larger banks, and this holds particularly during the negative interest rate period. Although EONIA clearly has a very strong causal relationship

[22] Based on the ADF and KPSS-tests, the EONIA midrate is actually already stationary before any structural break tests have been applied, so as observed from Table 1, the Z-A test is unable even to detect a statistically significant break point for it. However, for R3 banks, the ROA and ROE series seemed to behave as unit root processes, even when taking into account the structural breaks, so we will conduct our first stage analyses for the multivariate models also using differenced time series for all group sizes and variables (see Figs 2a*–2c* for the time series of differenced values).

Table 2a
Results from Granger causality tests for the levels of alternative bank profitability measures.

	Sample								
	Whole sample			Sub-sample 2009:1–2014:10			Sub-sample 2014:11–2018:12		
Dependent (Y) / Independent (X)	$ROEC_t$	ROA_t	NIM_t	$ROEC_t$	ROA_t	NIM_t	$ROEC_t$	ROA_t	NIM_t
R1 Banks									
No GC from ROEC	–	0.39	0.22	–	3.50**	2.76*	–	0.90	0.54
No GC from ROA	17.08***	–	7.05***	19.13***	–	7.00***	3.23**	–	2.47*
No GC from NIM	10.35***	15.02***	–	14.89***	13.31***	–	2.82*	8.16***	–
No GC from EONIA	0.04	7.24***	7.97***	0.09	6.82***	6.31***	2.02	3.75**	3.92***
MVARCH	181.79***			212.85***			281.61		
R2 Banks									
No GC from ROEC	–	0.38	0.11	–	0.22	0.08	–	0.33	0.21
No GC from ROA	10.27***	–	1.41	11.03***	–	0.96	2.99*	–	0.53
No GC from NIM	8.56***	10.65***	–	9.78***	3.54**	–	2.36	7.04***	–
No GC from EONIA	0.19	13.12***	11.75***	1.12	6.57***	5.67***	2.53*	4.60**	4.79**
MVARCH	145.92***			168.07***			221.27***		
R3 Banks									
No GC from ROEC	–	0.59	0.30	–	0.07	0.01	–	1.95	1.71
No GC from ROA	7.33***	–	2.55*	4.85**	–	1.75	3.71**	–	0.07
No GC from NIM	7.23***	7.62***	–	5.37***	2.24	–	3.41**	13.76***	–
No GC from EONIA	0.32***	8.68***	7.38***	0.91	2.91*	2.32	3.69**	6.57***	6.62***
MVARCH	111.49			126.00**			100.00***		

NOTES: We report the Granger causality test statistics based on a VAR(2) model for the bank profitability measures and the EONIA mid-rate. The *EONIA* was introduced as a prominently endogenous variable to the VAR system in this case. The optimal lag length (2) was chosen based on the multivariate Bayesian Schwarz criterion. The subsamples were based on dividing the total sample by two, where the critical change point was the month in which the EONIA mid-rate went negative, i.e. November 2014. Notations ***, ** and * refer to the statistical significance of the F-tests at the 1, 5, and 10% risk levels, where the null hypothesis is that the independent variable (*X*) in question does not Granger cause (denoted *GC*) the dependent variable (*Y*) observed at time point *t*. For the sake of clarity of the results, we do not report the F-test statistics for the effects of own lags of each of the independent variables, because we are more interested in the dynamic connections between the various profitability measures and *EONIA*. *ROEC* denotes the return on economic capital, *ROA* the return on assets, and *NIM* refers to the net interest margin (relative to the size of balance sheet). We also report the multivariate (MVARCH)-test of Hacker and Hatemi-J (2005) indicating the possible presence of at least some form of (general) autoregressive conditional heteroscedasticity (i.e., of (G)ARCH-type) in the residuals of the dynamic relationships between the analysed variables based on the estimated VAR-model. Here, ***, ** and * also refer to the statistical significance of the test-statistics at the 1, 5, and 10% risk levels, for the null of no ARCH-effects in the residuals.

Table 2b
Results from VAR-estimation for the differenced values of alternative bank profitability measures.

	Sample								
	Whole sample			Sub-sample 2009:1–2014:10			Sub-sample 2014:11–2018:12		
Dependent/ Independent variables	$DROEC_t$	$DROA_t$	$DNIM_t$	$DROEC_t$	$DROA_t$	$DNIM_t$	$DROEC_t$	$DROA_t$	$DNIM_t$
R1 Banks									
$DROEC_{t-1}$	0.17*	0.00	0.00	0.06	−0.00	0.00	0.10	−0.00	−0.00
$DROA_{t-1}$	−11.82	−1.72***	−0.22***	−22.10***	−2.22***	−0.26***	36.97	0.41	−0.04
$DNIM_{t-1}$	109.42	14.64***	2.16***	261.71***	21.19***	2.72***	−581.03*	−13.98*	−0.21
Exogenous									
Constant	0.09	0.01	0.00	0.34**	0.01	0.00	0.03	−0.01	−0.00
$EONIA_{t-1}$	−0.11	0.01	0.00	−0.45*	−0.01	−0.00	0.10	−0.02	−0.00
# of obs.	118	118	118	68	68	68	50	50	50
R2 Banks									
$DROEC_{t-1}$	0.07	0.00	0.00	0.16	0.00	0.00	−0.04	−0.00	−0.00
$DROA_{t-1}$	−9.80	−1.65***	−0.22***	−16.57**	−1.86***	−0.23***	22.51	0.07	−0.07
$DNIM_{t-1}$	81.74	13.51***	2.06***	177.18**	16.67***	2.33***	−361.64	−9.66	0.13
Exogenous									
Constant	0.03	−0.00	−0.00	0.19	0.00	0.00	0.17	−0.01	−0.00
$EONIA_{t-1}$	−0.07	0.02**	0.01*	−0.28	0.02	0.00	0.64	−0.01	−0.00
# of obs.	118	118	118	68	68	68	50	50	50
R3 Banks									
$DROEC_{t-1}$	0.15	0.00	0.00	0.18	0.00	0.00	0.03	−0.00	−0.00
$DROA_{t-1}$	−8.43	−1.21***	−0.18***	−18.96**	−1.56***	−0.21***	27.26	0.48	−0.04
$DNIM_{t-1}$	51.88	8.22**	1.63***	193.04**	13.09***	2.03***	−427.12	−14.55**	−0.20
Exogenous									
Constant	−0.00	−0.00	−0.00	0.28*	0.00	0.00	0.01	−0.02**	−0.00
$EONIA_{t-1}$	−0.22	0.01	0.00	−0.58**	0.00	−0.00	0.07	−0.04	−0.00
# of obs.	118	118	118	68	68	68	50	50	50

NOTES: We report the VAR-parameter estimates from OLS regressions for the alternative bank profitability measures using differenced values. For all the other notations, see Table 2a, but now *DROEC* denotes the difference in the return on economic capital, *DROA* the difference in the return on assets, and *DNIM* refers to the difference in net interest margin (relative to the size of balance sheet). The EONIA overnight mid-rate was now used as an exogenous variable in the regressions, because according to various unit root test results (see Table 1) it might be a stationary time series in levels. The optimal lag length (1) was again chosen based on the multivariate Bayesian Schwarz criterion. Due to the relatively large number of zero observations in *NIM*, the testing for (G)ARCH-effects was not possible for the VAR-systems for the differenced values.

with NIM in all banks, its changes also affect the ROEC unanimously, because NIM Granger causes the ROEC in all banks, at least for the first sub-period before the negative interest rate period. However, there is no feedback from the ROEC to NIM, and even the causality from NIM to ROEC appears to vanish for the R1 and R2 banks during the negative interest rate period (at 10% risk level). Hence, it is clear, that the relationships between the various profitability measures and the money market interest rates have changed considerably since the introduction of negative interest rates.

Regarding the most standard overall profitability measure, ROA, it seems that NIM affects ROA in all banks and in both periods but, as already mentioned, the results in terms of ROEC being affected by NIM are clearly different. For our further analyses, it is also worth noting that, based on the Hacker and Hatemi-J (2005) multivariate GARCH-tests, in 7/9 cases the variables systems would seem to contain (conditionally) heteroscedastic error terms. Clearly, these results call for deeper analyses of the dynamic relationships between the analysed profitability measures and the money market interest rate, and highlights further reasons to apply the asymmetric DCC-GARCH models in the final stage.

The results reported in Table 2b follow a somewhat different modelling principle compared to the standard Granger causality results reported in Table 2a. In Table 2b, we report the actual parameter estimates from VAR models estimated for the systems of profitability variables using differenced values. Based on Schwarz's Bayesian information criteria, the optimal lag length of the VAR models was 1 for each case. We report the parameter estimates for the first lag of the independent variables in each VAR-equation, and we always included the lagged values of the EONIA mid-rate (in levels[23]) and the constant term as additional exogenous regressors[24] to each of the VAR systems. Hence, here we wish to particularly emphasize the role of money market interest rate in affecting each of the analysed profitability measures.

The results reported in Table 2b have significantly different implications for the dynamic relationships between the bank profitability measures and the money market interest rate. The main message seems to be that the introduction of negative interest rates has wiped out all dynamic connections between the main relevant profitability measures, when we analyse the variables in differences, i.e., monthly changes in the observations. Only in the data from before the negative interest rate period do we find a statistically significant (positive) connection between the NIM and the other profitability measures, ROEC, and ROA. However, this holds for all banks' sizes and, based on the parameter estimates, the most significant results are for the largest banks, where a one basis point positive change in the NIM in the previous period appears to cause a 2.61% (0.21%) improvement in the ROEC (ROA) in the next period. Furthermore, past changes in the money market interest rate do not seem to play any role in changes to profitability, either before the negative interest rate period or during it, when we use a monthly frequency. In general terms, the negative interest rate era clearly seems to have affected the dynamic relationships between the main profitability measures, and their connection to money market interest rates and, to reveal the time-varying nature of these changes at the final stage, we report the results based on the dynamic conditional correlation analyses of these variables. At first, we will examine the results with respect to the role of changes in the business model, measured based on the ratio of WSF in the banks.

4.2. *Results on the dependence between the profitability measures and the business model measure*

In Table 3 we report the results from the Granger causality analysis focusing on the relationship between bank profitability measures and the WSF ratio, i.e. from the perspective of whether the banks might have changed their business models in response to the introduction of negative interest rates. At this stage, we executed the estimations using all three profitability measures (ROEC, ROE and ROA) separately, but always including the NIM, due to its major role as the standard 'profit-making machine' of a bank, which is also most significantly affected by the market interest rates. Furthermore, to highlight the prominent role of the bank's business model, we also always include the WSF ratio to the VAR-model. Additionally, as in Table 2b, the EONIA is always treated as an exogenous variable. We conduct all analysis for the variables in levels and separately for the periods before and after the introduction of negative interest rates.

From the results in Table 3, we see that first, the role of rising values of EONIA in positively affecting the NIM in all banks is clear during the 'normal' period of positive money market interest rates. When the EONIA increases, the contemporaneous NIMs also increase in a way that is statistically significant (and by the same amount) in all banks. However, even this result is valid for all bank size groups only when the risk-adjusted profitability ROEC is used as the profitability measure. When any of the non-risk-adjusted measures are used, the positive dynamic effect from past EONIA values is observed only for R2 banks and only when ROA is used as the profitability indicator before the negative interest rate period. This highlights one of our new findings that it is essential to analyse bank profitability using both risk-adjusted and standard profitability measures.

Furthermore, an extremely interesting finding to emerge from these results is that, during the negative interest rate period, in the smaller banks (R2 and R3), the NIM has a much stronger (positive) connection to the EONIA, and this finding is not at all dependent on the measure of profitability. The effects of changes in EONIA on NIM have been approximately three times higher in R2 and R3 banks during the era of negative interest rates. Hence, when the market interest rates have risen (fallen), the NIM in R2 and R3 banks has improved (worsened) approximately three times more than during the positive interest rate era, and this finding is statistically significant at the 1% risk level. Additionally, the effect of EONIA on all profitability measures is also evident in smaller banks during the NIRP, but not during 'normal' times. However, in the big (R1) banks, EONIA has statistically significant effects only on the NIM and only during the 'normal' times, and not on any of the profitability measures (ROEC, ROE or ROA) at any time. This is also remarkably different compared to the smaller banks.

As observed in Fig. 2, NIM volatility has almost reached zero during the negative interest rate period. However, it still appears to have played a significant role in particularly affecting the smaller banks' profitability, at least in terms of ROE and ROA during the negative interest rate era. A somewhat confusing result that might have something to do with the close-to-zero volatility of the NIM during the negative interest rate period is that the dynamic effect of increasing NIM values in the most recent (two months) past has been negative, i.e., when the NIM has previously increased, the profitability of R2 and R3 banks, in particular, has subsequently decreased. Clearly, this result merits further scrutiny through the discussion of the effects and role of WSF ratio because it has increased during the negative interest rate era, particularly in R1 banks. As can be seen from Fig. 3 below, the WSF ratio actually began to increase significantly from mid-2012 in all the three bank size groups, but in R2 and R3 banks it has remained more or less stable since 2016, even though it continued its rapid growth in the biggest (R1) banks.

Obviously, the previous results and the strong dependence of NIM on the development of EONIA requires the analysis of the role of banks' business model, i.e., the effects of WSF ratio. From the Granger causality test results reported in Table 3, we see that first, for the largest R1 banks

[23] As was pointed out in the results reported in Table 1, the EONIA midrate seems to have behaved as a stationary variable already in levels, so it was also included in levels of the analyses reported in Table 2b.

[24] Clearly, the EONIA midrate should be considered exogenously determined in all our analyses, because it is highly unlikely that any of the eurozone-level money market interest rates would react to the profitability of Finnish OP banks by any means.

Table 3
Results from Granger causality tests for the alternative bank profitability measures (ROEC, ROE and ROA), including net interest margin (NIM) and wholesale funding (WSF) ratio as endogenous variables to the systems, and EONIA midrate and constant as exogenous variables. Each profitability measure is analysed individually so, for example, the system for ROEC does not include ROE or ROA at all.

	Sub-sample 2009:1–2014:10					*Sub-sample 2014:11–2018:12*				
Dependent (Y) / Independent (X)	$ROEC_t$	ROE_t	ROA_t	NIM_t	WSF_t	$ROEC_t$	ROE_t	ROA_t	NIM_t	WSF_t
R1 Banks										
No GC from ROEC	97.29***	–	–	0.120	0.65	37.73***	–	–	0.59	4.23**
No GC from NIM	0.99	–	–	64.91***	4.10** (−)	6.02*** (−)	–	–	8.66***	2.73* (−)
No GC from WSF	5.65*** (+)	–	–	2.93* (+)	86.27**	3.33** (−)	–	–	0.14	2.96*
Constant	−0.94	–	–	0.01	1.06	19.88	–	–	0.05	27.83***
EONIA	−0.56	–	–	0.01***	−1.17**	0.96	–	–	0.01	0.56
No GC from ROE	–	1.82	–	4.39** (−)	7.96*** (+)	–	70.71**	–	0.31	0.56
No GC from NIM	–	1.19	–	20.00***	7.70*** (−)	–	1.69	–	19.04***	0.19
No GC from WSF	–	1.62	–	2.56* (+)	10.89***	–	0.01	–	0.07	9.36***
Constant	–	0.77	–	0.78	0.41	–	1.07	–	0.02	8.61
EONIA	–	0.13	–	0.13	−0.88*	–	0.04	–	0.01	0.57
No GC from ROA	–	–	20.64***	3.64** (+)	0.23	–	–	32.84***	1.85	1.91
No GC from NIM	–	–	2.06	15.18***	0.06	–	–	5.17*** (−)	11.62***	0.73
No GC from WSF	–	–	1.00	1.06	78.25***	–	–	0.11	0.14	3.57**
Constant	–	–	−0.06	−0.00	0.95	–	–	0.53**	0.05**	6.57
EONIA	–	–	0.07*	0.01*	−1.11*	–	–	0.15	0.01	−5.48
R2 Banks										
No GC from ROEC	176.84***	–	–	0.22	1.20	47.80***	–	–	1.31	0.20
No GC from NIM	1.08	–	–	178.92***	1.25	3.20* (−)	–	–	8.40***	1.60
No GC from WSF	1.44	–	–	5.00*** (+)	23.74***	1.78	–	–	1.74	1.02
Constant	0.73	–	–	0.01	1.76	13.81	–	–	0.05***	1.86
EONIA	−0.22	–	–	0.01***	−0.10	9.23*	–	–	0.03***	−3.36*
No GC from ROE	–	1.43	–	2.24	0.67	–	41.03***	–	0.44	0.63
No GC from NIM	–	1.51	–	18.08***	0.75	–	3.37** (−)	–	6.62***	1.87
No GC from WSF	–	5.02*** (+)	–	5.41*** (+)	18.31***	–	1.93	–	1.22	0.64
Constant	–	1.12	–	0.01	0.59	–	1.69	–	0.04*	4.48
EONIA	–	0.38	–	0.01	−0.18	–	1.64**	–	0.03**	−2.08
No GC from ROA	–	–	14.26***	0.27	1.01	–	–	32.59***	3.36** (−)	1.40
No GC from NIM	–	–	0.88	29.96***	0.96	–	–	3.56** (−)	12.41***	0.46
No GC from WSF	–	–	3.90** (+)	3.93** (+)	18.31***	–	–	3.05* (+)	2.82* (+)	0.06
Constant	–	–	0.01	0.00	0.79	–	–	0.41	0.04*	5.80
EONIA	–	–	0.13***	0.10***	−0.19	–	–	0.30***	0.03***	−2.94*

	Sub-sample 2009:1–2014:10					*Sub-sample 2014:11–2018:12*				
Dependent (Y) / Independent (X)	$ROEC_t$	ROE_t	ROA_t	NIM_t	WSF_t	$ROEC_t$	ROE_t	ROA_t	NIM_t	WSF_t
R3 Banks										
No GC from ROEC	332.07***	–	–	1.07	1.21	31.61***	–	–	1.90	1.50
No GC from NIM	2.34	–	–	204.39***	1.30	4.27** (−)	–	–	4.57**	0.95
No GC from WSF	2.20	–	–	4.93** (+)	37.70***	0.35	–	–	2.97* (+)	9.67***
Constant	0.90	–	–	0.00	2.65*	34.81**	–	–	0.09***	−2.36
EONIA	−0.33	–	–	0.01***	−0.11	11.61*	–	–	0.04***	−3.16
No GC from ROE	–	1.63	–	6.16*** (−)	1.19	–	71.58***	–	0.88	3.19* (−)
No GC from NIM	–	4.11** (+)	–	36.98***	1.42	–	4.71** (−)	–	4.34**	3.88** (+)
No GC from WSF	–	7.34*** (+)	–	7.40*** (+)	23.11***	–	4.34** (+)	–	3.34** (+)	3.95** (+)
Constant	–	1.14	–	0.02*	0.73	–	2.66*	–	0.05**	3.07
EONIA	–	−0.07	–	−0.00	0.35	–	1.89***	–	0.03***	−2.07
No GC from ROA	–	–	2.60*	4.86**	2.53*	–	–	64.85***	2.76*	1.65
No GC from NIM	–	–	2.30	44.83***	2.93*	–	–	6.62***(−)	5.91*** (+)	2.46* (+)

(*continued on next page*)

Table 3 (*continued*)

	Sub-sample 2009:1–2014:10					*Sub-sample 2014:11–2018:12*				
Dependent (Y) / Independent (X)	*ROEC$_t$*	*ROE$_t$*	*ROA$_t$*	*NIM$_t$*	*WSF$_t$*	*ROEC$_t$*	*ROE$_t$*	*ROA$_t$*	*NIM$_t$*	*WSF$_t$*
No GC from WSF	–	–	7.23*** (+)	7.14***	11.06***	–	–	3.36** (+)	3.45** (+)	3.73** (+)
Constant	–	–	0.05	0.06	1.16	–	–	0.71***	0.06***	4.59
EONIA	–	–	0.03	0.00	0.31	–	–	0.35***	0.03***	−3.72*

NOTES: We report first the Granger causality test statistics based on a VAR(2)-model for each of the three bank profitability measures (ROEC, ROE and ROA) separately. The net interest margin (NIM) and wholesale funding (WSF) ratio are always included as endogenous variables, and EONIA mid-rate as an exogenous variable to the systems involving each individual profitability measure. The optimal lag length (2) was chosen based on the multivariate Bayesian Schwarz criterion. In addition to the F-statistics for the Granger causality analysis, when we find statistically significant (at least at the 5% level) causality, we also report in parenthesis the sign of the sum of lagged VAR(2) regression parameters of the endogenous variables to indicate the direction of dynamic effects from the variable in question. In addition, we also report the parameter estimates on exogenous variables in each case. The subsamples are based on dividing the total sample into two sub-samples, whereby the critical change point was the month when the *EONIA* mid-rate went negative, i.e. November 2014. ***, ** and * refer to the statistical significance of the F-tests and individual regression parameters on the exogenous variables at the 1, 5, and 10% risk levels, respectively. In the Granger causality analysis, the null hypothesis is that the independent variable (*X*) in question does not Granger cause (denoted *GC*) the dependent variable (*Y*) observed at time point *t*.

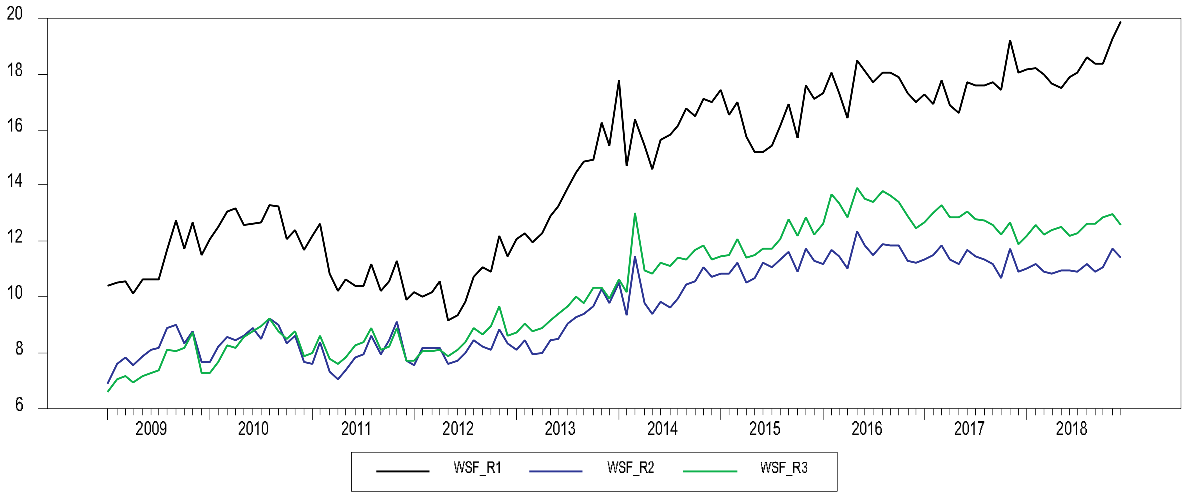


Fig. 3. Time series of wholesale funding (WSF) ratio for the banks in different bank size groups.

during the first sub-period, the increasing values of the WSF ratio in the previous two months have had a positive effect on the current, risk-adjusted ROEC profitability. However, this is not the case for the other profitability measures. Furthermore, before the negative interest rate period, past increases in WSF have also improved both the ROE and ROA profitability of R2 banks, but not the risk-adjusted ROEC profitability. The same may be stated for the smallest R3 banks, i.e., their ROE and ROA profitability has improved when WSF has increased.

Some of these results change when we move to the period of negative interest rates. Namely, the positive risk-adjusted profitability reaction of R1 banks to positive changes in WSF becomes a negative reaction during the negative interest rate period, although none of the other profitability measures appear to react in any way. Furthermore, for the smaller R2 and R3 banks, non-risk-adjusted (ROE and ROA) profitability appears to have been in positive connection to previous increases in WSF, and this result appears to hold during the negative interest rate era, at least for the smaller R3 banks. Hence, at least based on these results, the smallest banks benefitted the most from the positive effects of increasing WSF on NIM, based on the negative interest rates that the central cooperative has charged on central bank loans taken by the smallest member banks. In general terms, this conclusion does not apply to the data from R1 banks, because the increasing WSF values do not appear to be significantly connected to the average profitability of the 23 largest banks, expect when he ROEC measure is used during the first sub-sample.

Clearly, there may be several empirical caveats in our previous analyses. The first is that we have chosen the introduction of negative money market (EONIA) interest rates in November 2014 as the break point in our data. As we have seen from the figures above, the EONIA mid-rate also experienced strong changes (lowering) in 2011–2012 around the eurozone sovereign debt crisis, so choosing the November 2014 observation as the 'main' and only structural break point might be questionable. Additionally, after the introduction of negative interest rates, the volatilities of banks' NIMs and the EONIA mid-rate have decreased significantly, so it is clear that these, and due to their interconnections to the analysed profitability measures, all the analysed time series contain volatility clustering in their data-generating processes. Furthermore, several asymmetries may be evident in the behaviour of volatilities of the analysed time series, so both the correlations and variances may have changed abruptly during our sample period. Hence, at the final stage of our empirical analysis, we use the asymmetric DCC-GARCH modelling procedure described in Section 3.2, which allows for the time-variation in the dynamic correlations (and covariances) between the variables. In this procedure, the break points in the data-generating processes of the time series are also determined endogenously.

4.3. Results from the asymmetric DCC-GARCH analysis

In Tables 4a and 4b we report the results from estimating the asymmetric DCC-GARCH models given by eqs. (8), (11) and (13) in

Table 4a
Parameter Estimates of the pairwise Asymmetric DCC-GARCH models.

Variable\Parameter	α_i	$\beta_{i,0}$	$\beta_{i,1}$	$\beta_{i,2}$	$\beta_{i,3}$	a	b	c	$a^{\#}$	$b^{\#}$	$c^{\#}$
Profitability Measures											
ROEC R1	27.93***	1.12	0.96***	0.0000	0.07	0.67***	0.29*	−0.02	0.52***	0.45***	−0.01
ROEC R2	27.93***	1.42***	0.93***	0.00	0.05	0.84***	0.00	0.05	0.48***	0.49***	−0.03*
ROEC R3	26.69***	1.94*	0.88***	0.0000	0.02	0.81***	0.03	0.04	0.57***	0.40***	−0.02*
ROE R1	11.89***	0.18***	0.65***	0.18***	0.17***	0.51***	0.56***	−0.16**	0.92***	0.30	−0.43***
ROE R2	8.79***	0.06***	0.64***	0.24***	0.15**	0.48***	0.59***	−0.13	0.94***	0.27*	−0.44***
ROE R3	7.92***	0.05***	0.59***	0.28***	0.14**	0.56***	0.34	0.03	0.69***	0.36***	−0.15
ROA R1	1.34***	0.02***	0.52***	0.24***	0.13	0.61***	0.36***	−0.03	0.82***	0.13	−0.08
ROA R2	1.35***	0.01*	0.51***	0.35***	0.12	0.47***	0.52***	−0.04	0.48***	0.53***	−0.09
ROA R3	1.27***	0.01**	0.51***	0.33***	0.04	0.34***	0.51***	0.11	0.47***	0.44***	0.04
NIM R1	0.11***	0.01***	0.65***	0.14**	0.18	0.47***	0.40****	0.11*	1.10***	0.03	−0.52
NIM R2	0.12***	0.0000	0.64***	0.27*	0.08	0.51***	0.39***	0.07	0.86**	0.19	−0.33
NIM R3	0.12***	0.0000	0.61***	0.30***	0.09*	0.35***	0.54***	0.12*	0.48***	0.48***	0.02
Business Model Measure											
WSF R1	14.52***	0.80**	0.59***	0.29***	0.08	0.57***	0.30***	0.12***	–	–	–
WSF R2	9.72***	0.27*	0.47***	0.41***	0.03	0.61***	0.22***	0.16***	–	–	–
WSF R3	10.42***	0.59***	0.54***	0.29***	0.03	0.53***	0.39***	0.07	–	–	–
Market Interest Rate											
EONIA	0.12***	0.01**	0.98***	0.01	0.02	–	–	–	–	–	–

NOTES: ***, **, and * refer to the significance levels of the parameter at 1, 5, and 10% risk levels, respectively. DCC-parameters a, b, and c refer to pairwise asymmetric DCC-GARCH-models described in Section 3.2, where EONIA mid-rate is always the second variable, whereas # refers to the case where the wholesale funding (WSF) Ratio is the second variable. R1, R2, and R3 refer to the bank size groups of the largest, medium-sized, and smallest banks, respectively. ROEC = return on economic capital, ROE = return on equity, ROA = return on assets, NIM = net interest margin (relative to the size of balance sheet), WSF = wholesale Funding Ratio, and EONIA = EONIA mid-rate.

Table 4b
Results from two-sided *t*-tests for the equality of asymmetric dynamic conditional covariances between the bank size groups in sub-samples 2009/5–2014/10 and 2014/11–2018/12.

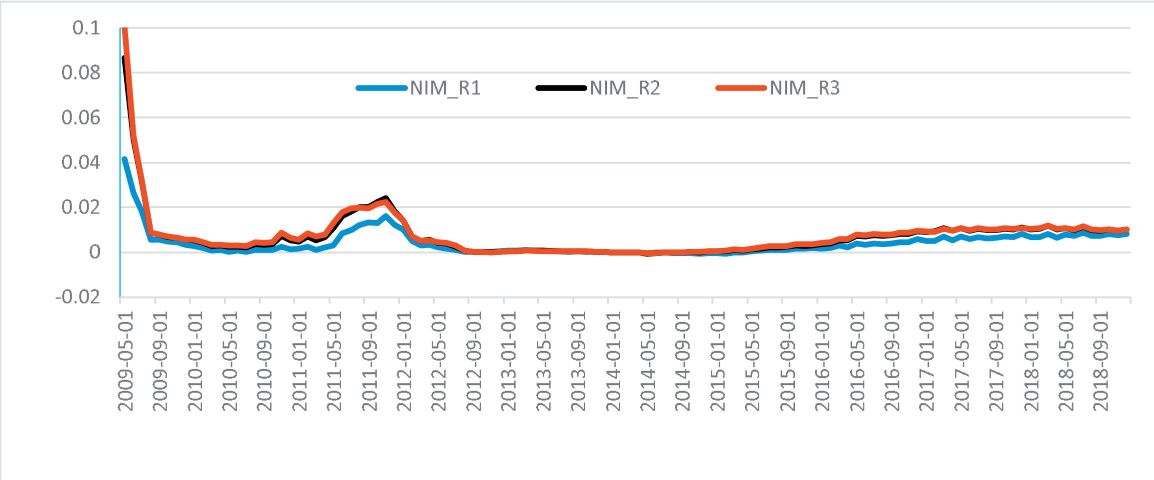
Covariances with EONIA mid-rate											
Sub-sample 2009/5–2014/10											
	ROEC_R1	ROEC_R2		ROE_R1	ROE_R2		ROA_R1	ROA_R2		NIM_R1	NIM_R2
ROEC_R2	−1.71*		ROE_R2	0.80		ROA_R2	−3.29***		NIM_R2	−1.81*	
ROEC_R3	−2.00**	−0.30	ROE_R3	2.05**	1.45	ROA_R3	−2.70***	1.27	NIM_R3	−1.92*	−0.19
Sub-sample 2014:11–2018:12											
	ROEC_R1	ROEC_R2		ROE_R1	ROE_R2		ROA_R1	ROA_R2		NIM_R1	NIM_R2
ROEC_R2	−5.72***		ROE_R2	2.44**		ROA_R2	−7.28***		NIM_R2	−3.79***	
ROEC_R3	2.08**	−1.19	ROE_R3	−4.62***	2.32**	ROA_R3	−3.73***	1.17	NIM_R3	−10.69***	−0.40
Covariances with wholesale funding (WSF) ratio											
Sub-sample 2009/5–2014/10											
	ROEC_R1	ROEC_R2		ROE_R1	ROE_R2		ROA_R1	ROA_R2		NIM_R1	NIM_R2
ROEC_R2	6.07***		ROE_R2	−2.70***		ROA_R2	3.16***		NIM_R2	−0.54	
ROEC_R3	5.38***	−0.82	ROE_R3	−2.28**	0.87	ROA_R3	3.55**	0.73	NIM_R3	0.78	1.55
Sub-sample 2014/11–2018/12											
	ROEC_R1	ROEC_R2		ROE_R1	ROE_R2		ROA_R1	ROA_R2		NIM_R1	NIM_R2
ROEC_R2	9.15***		ROE_R2	−6.17***		ROA_R2	5.93***		NIM_R2	−1.70*	
ROEC_R3	20.78***	−0.99	ROE_R3	−2.03**	1.10	ROA_R3	2.75***	1.12	NIM_R3	9.60***	4.37***

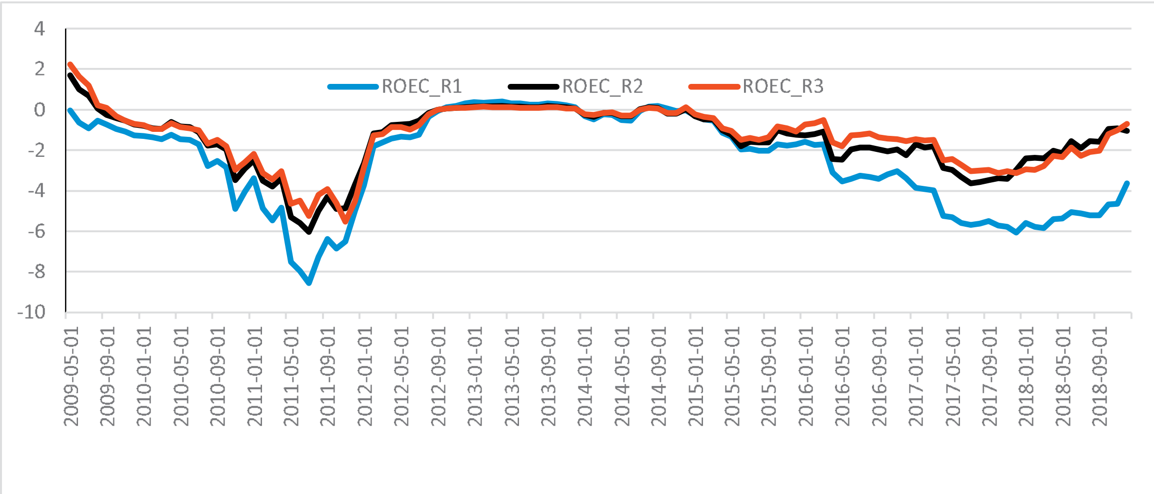
Notes: ***, **, and * refer to the significance levels of the parameter at the 1, 5, and 10% risk levels, respectively. ROEC = return on economic capital, ROE = return on equity, ROA = return on assets, NIM = net interest margin (relative to the size of balance sheet), R# refers to the bank size group (R1 = largest banks, R2 = medium-sized, and R3 = small banks).

Section 3.2. The parameter estimates and the estimated covariances are presented in Table 4a. In addition, in Table 4b we report the *t*-test results from tests to determine whether the estimated dynamic conditional covariances differ among the different bank size groups, particularly during the period of negative money market interest rates compared to the previous sub-sample. Finally, the development of the time-varying pairwise covariances is given in Figs. 4a–4e and Figs. 5a–5d.

Based on our results, all the DCC parameters satisfy the stationarity conditions presented in Cappiello et al. (2006). From Table 4a we see that the parameter estimates obtained from the modelling procedure applied are valid and that the entire approach yields statistically relevant results. First, the GARCH equation has robustly significant parameter estimates, both for the effects of error terms (ARCH-part) and for the effects of variance terms (the generalized (G)ARCH-part) in all cases.[25] Additionally, the asymmetric effects on the conditional variance coming from the sign of the error term in the GARCH equation (parameter $\beta_{i,3}$) are statistically significant for the ROE profitability analysis, i.e. when the errors are positive, they increase the conditional

[25] The conditional variance equations for the ROEC measures seem to be simple ARCH processes in each case, i.e., for all the bank size categories, and so seems to be the variance of the EONIA midrate process, too. However, for each ROEC and EONIA pair, the asymmetric effects are still evident in the covariances coming from the error terms, because the a parameters are also statistically significant at the 1% risk level for the ROEC equations.





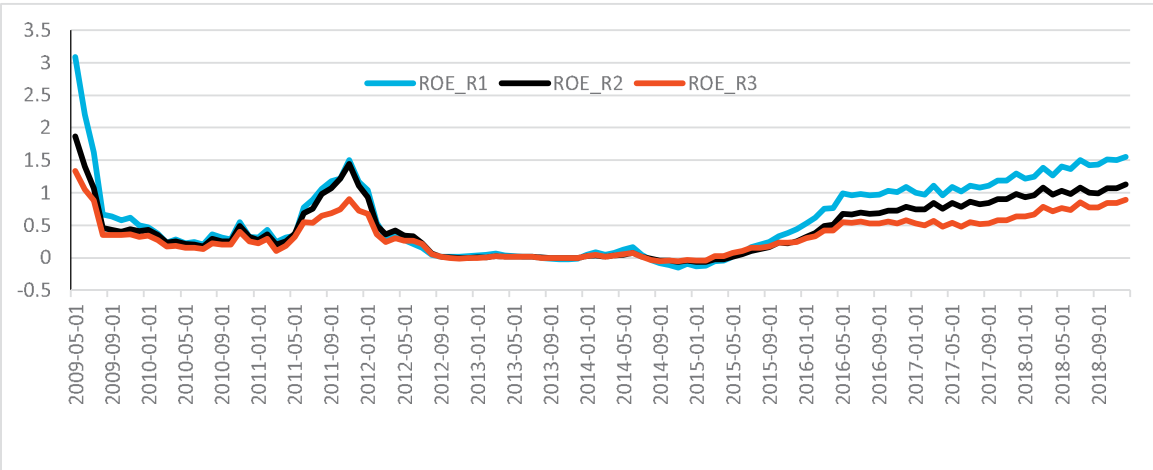
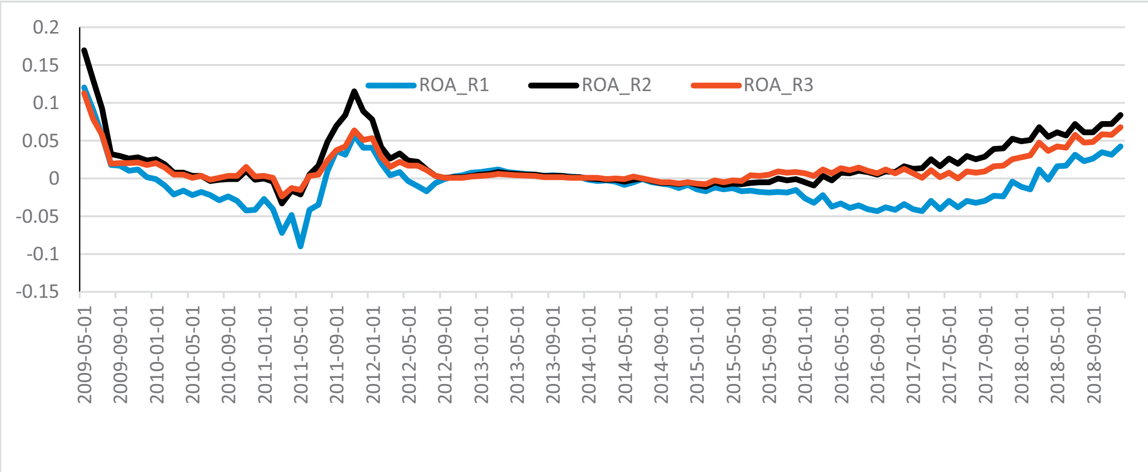


Fig. 4. a. Asymmetric DCC-GARCH covariance between net interest margin (NIM) and EONIA mid-rate in the three bank size groups. b. Asymmetric DCC-GARCH covariance between return on economic capital (ROEC) and EONIA mid-rate in the three bank size groups. c. Asymmetric DCC-GARCH covariance between return on equity (ROE) and EONIA mid-rate in the three bank size groups. d. Asymmetric DCC-GARCH covariance between return on assets (ROA) and EONIA mid-rate in the three bank size groups. e. Asymmetric DCC-GARCH covariance between wholesale funding (WSF) ratio and EONIA mid-rate in the three bank size groups.



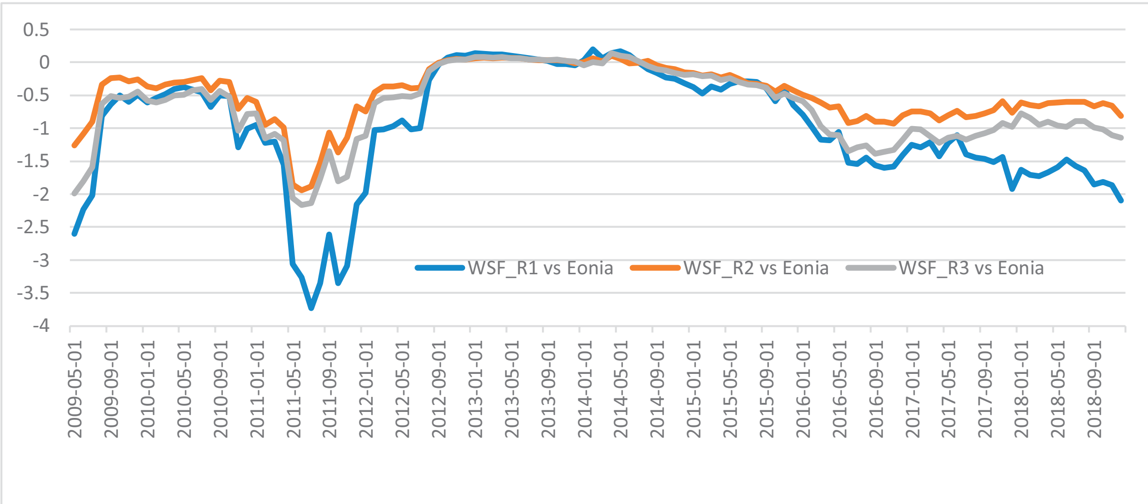
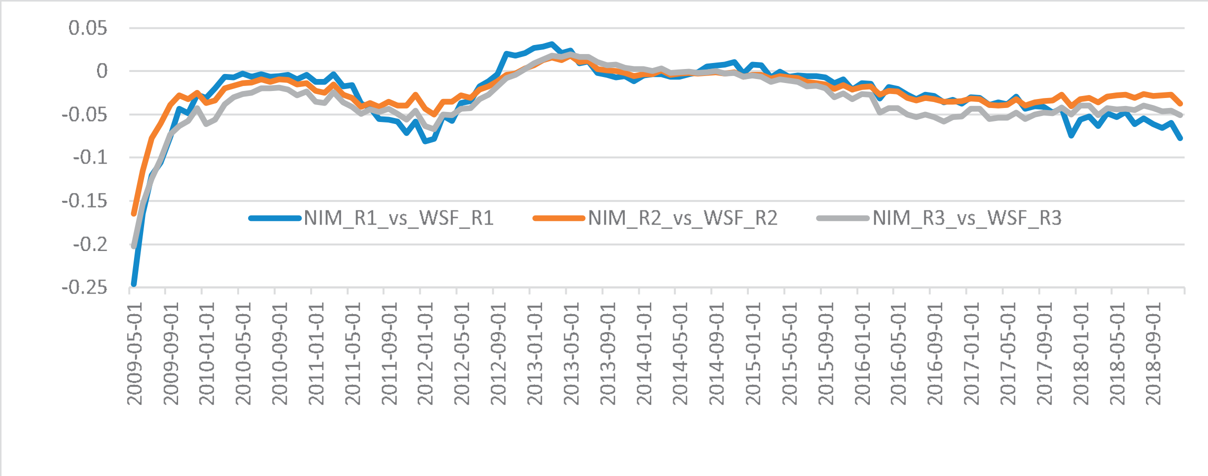
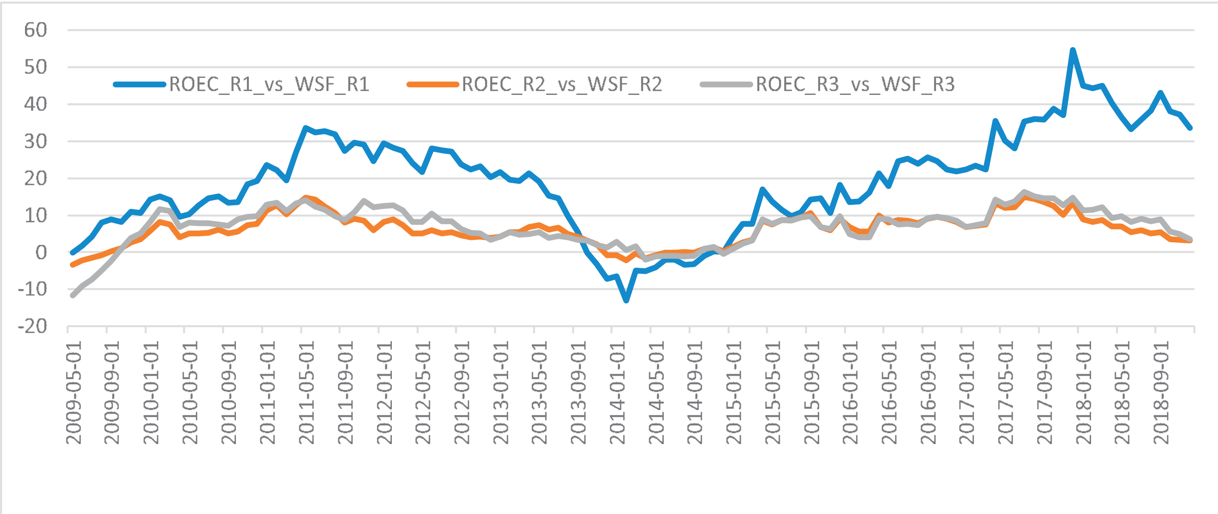


Fig. 4. (*continued*).

variance of profitability measured by the ROE more than when the errors are negative. In all other cases, when we analyse the dynamic time-varying correlation/covariance of the EONIA mid-rate with the profitability measures, we see that the asymmetric effects derive from asymmetry in both the error terms (reflected by the significance of a parameters) and the conditional pairwise covariances (captured by the significance of b parameter). However, no effects are caused by the asymmetry of correlations because the c parameters are only rarely statistically significant. Additionally, it seems that when analysing the dynamic conditional covariance between EONIA and the risk-adjusted measure of profitability (ROEC), it is essential to consider the asymmetry in the GARCH error terms.

In comparing the results of the DCC analysis when using the EONIA vs. the WSF ratio in the pairwise correlation analysis, a striking difference becomes evident in the latter case. When WSF is the correlating variable, we find that the risk-adjusted profitability (ROEC) is also dynamically correlated with the WSF, when the asymmetry in conditional pairwise covariances is taken into account (cf. significance and magnitude of parameter $b^{\#}$ compared to b). In addition, when measuring the profitability by ROE, the asymmetry derived from the dynamic correlations also seems to be relevant. However, when using WSF, the asymmetry that derives from conditional pairwise covariances vanishes in the data for the R1 and R2 banks, when the NIM is the profitability measure. Hence, based on all the results reported in Table 4a, it is vital to account for major asymmetries, particularly at the level of variances between the analysed pairs of variables, and they clearly also affect the dynamic conditional covariances. Furthermore, the dynamic, time-varying dependence of various profitability measures seems to differ somewhat with respect to the EONIA mid-rate and the WSF ratio. Here, in economic terms, it is important to note that the latter variable is clearly a decisive variable upon which individual banks can decide, while the EONIA mid-rate is purely an exogenous, informative variable that must simply be taken as a given indicator of the level of market interest rates. The importance of EONIA with respect to bank profitability and WSF comes from the fact that it is strongly correlated, for example, with the main loan and deposit reference (i.e., Euribor) rates. Indeed, based on our results, the dynamic connection between probability and WSF seems to differ somewhat to its connection of EONIA. Intuitively, and in economic terms, this is clearly related to the fact that when the EONIA has entered the negative zone, the individual banks





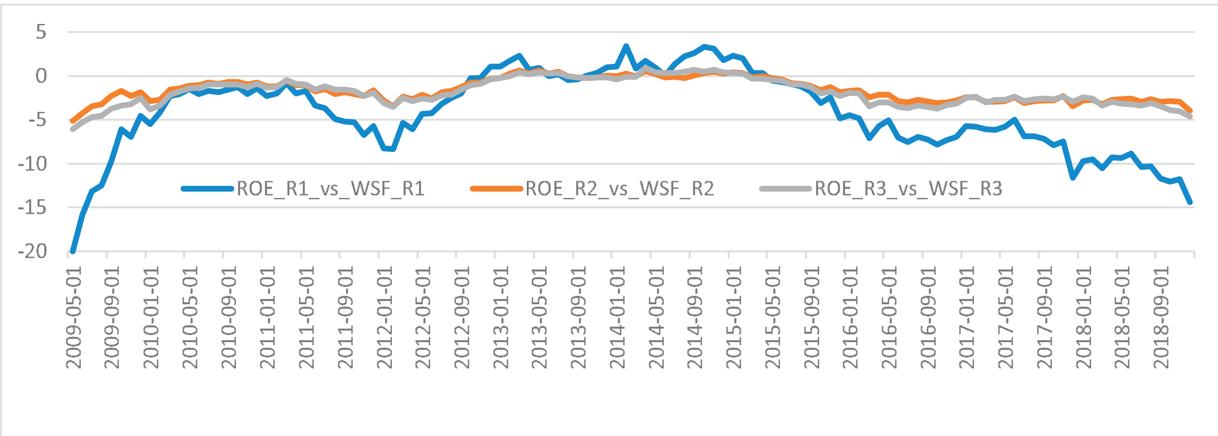
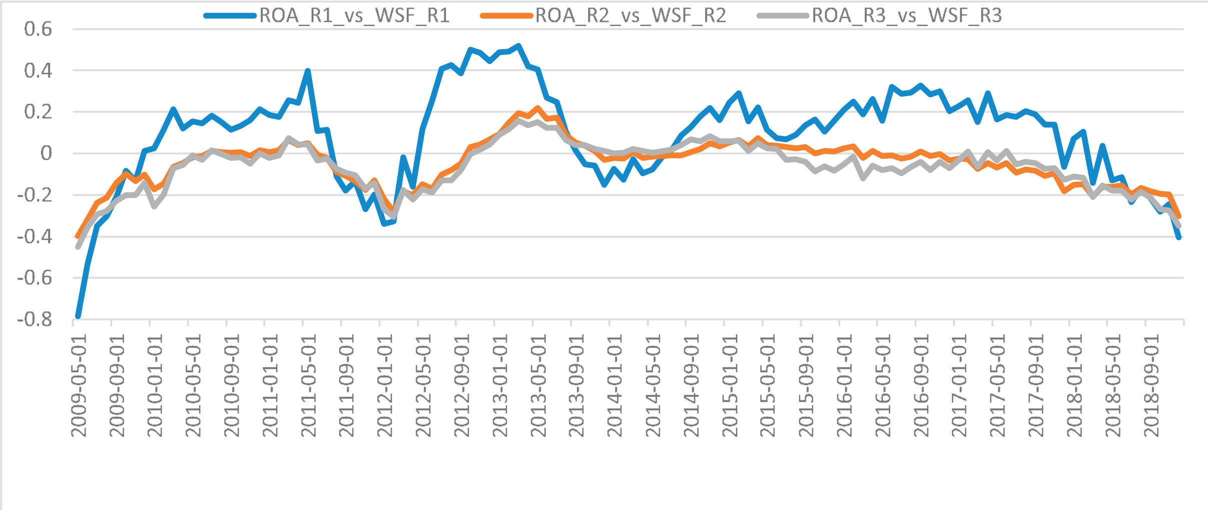
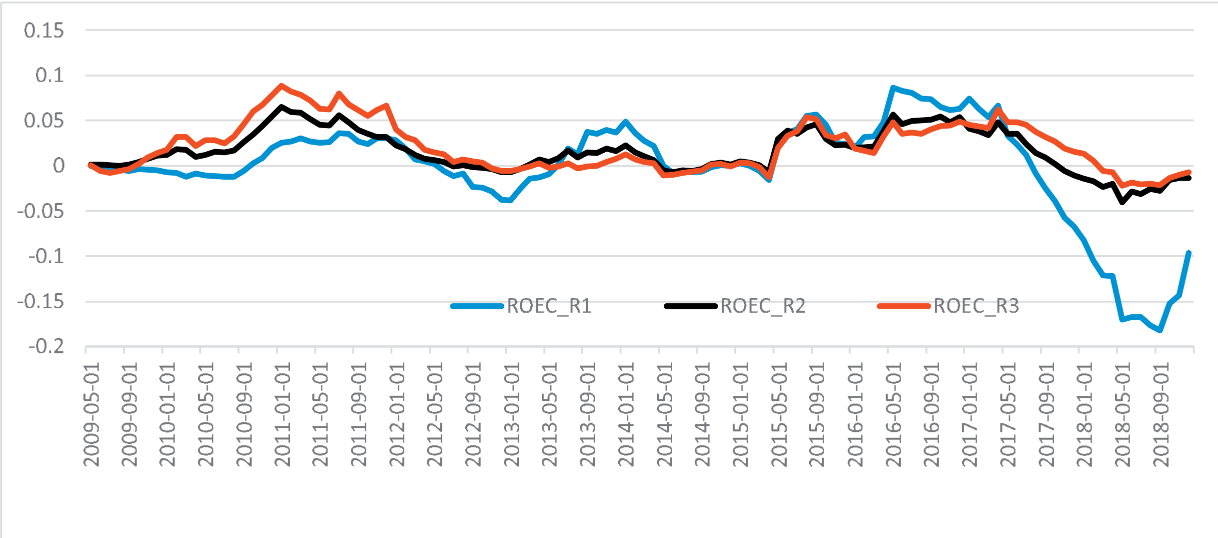


Fig. 5. a. Asymmetric DCC-GARCH covariance between net interest margin (NIM) and wholesale funding (WSF) ratio in the three bank size groups b. Asymmetric DCC-GARCH covariance between return on economic capital (ROEC) and wholesale funding (WSF) ratio in the three bank size groups. c. Asymmetric DCC-GARCH covariance between return on equity (ROE) and wholesale funding (WSF) ratio in the three bank size groups. d. Asymmetric DCC-GARCH covariance between return on assets (ROA) and wholesale funding (WSF) ratio in the three bank size groups. e. Asymmetric DCC-GARCH covariance between return on economic capital (ROEC) and return on other income components (ROIC) ratio in the three bank size groups. f. Asymmetric DCC-GARCH covariance between return on other income components (ROIC) ratio and wholesale funding ratio (WSF) in the three bank size groups.





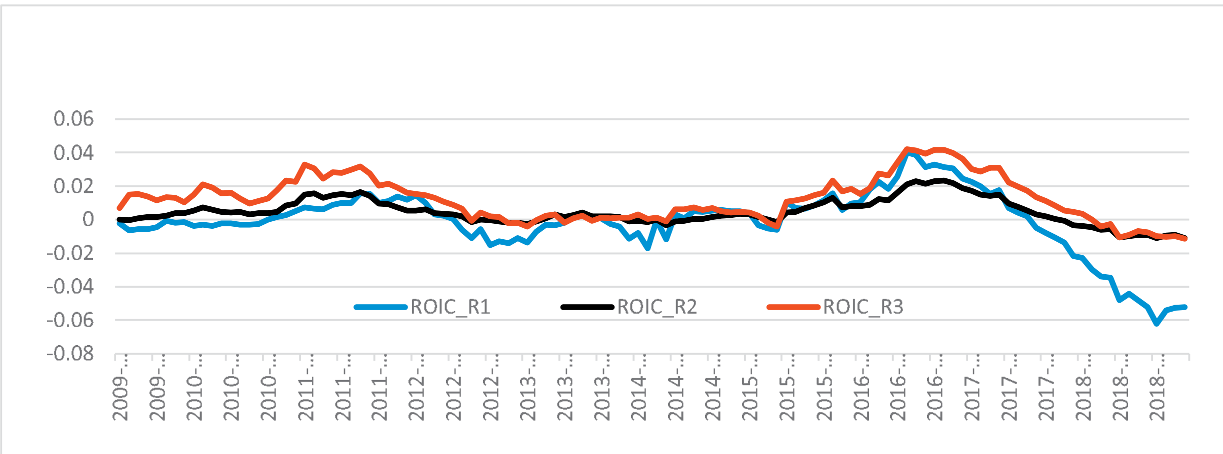


Fig. 5. (*continued*).

might have increased their loans from the central cooperative, because ceteris paribus, this action has improved their NIMs.[26] If this hypothesis were to hold, it would imply that WSF and EONIA should have been negatively correlated, particularly during the era of negative money market interest rates, i.e., since November 2014 in our data set.

To gain further insight into the dynamic, time-varying connections between the profitability measures and EONIA and our measure for the bank business model (WSF), first in Figs. 4a–4d we examine the time-varying covariances between EONIA and profitability measures. In the next step, in Fig. 4e, we plot the dynamic conditional covariances between EONIA and WSF. Finally, in Figs. 5a–5d we plot the time series of dynamic conditional covariances between the profitability measures and WSF. This should give us the final answer to the question of whether the observed higher rate of WSF, reflecting a change in the bank business model, has affected bank profitability, and what the role of 'right' measure of profitability is in this conclusion.

Based on the time-series plots of the asymmetric dynamic conditional covariances, we obtain several interesting new results pertaining to the effects of negative interest rates on bank profitability. First, the standard textbook idea of the positive dependence of the main profitability origin of banks, the NIM, on money market interest rate also holds in our data for all three bank size categories. Hence, during the era of negative interest rates also, even though the volatilities of both the NIM in all banks and the EONIA mid-rate have been very close to zero, the dynamic conditional covariances have consistently remained positive, implying that the correlation has been positive (or very close to zero), as the standard, textbook banking theories imply, too. However, our results emphasize the importance of examining bank profitability through a much larger set of profitability measures, since the conclusions obtained are highly sensitive to the chosen profitability measures.

In focusing on the risk-adjusted (ROEC) profitability, it is clear that the significant decrease in the money market interest rates in mid-2009 has changed the relationship between ROEC and market interest rates so that the correlation between ROEC and EONIA became profoundly negative when the decline of EONIA stabilized during 2010. However, since mid-2012, the covariance was almost zero until the quotation of negative EONIA midrates began in November 2014. Subsequently, the dynamic conditional covariance path between ROEC and EONIA for the largest R1 banks has deviated significantly from the development of the smaller banks. This deviation is also statistically significant, as can be seen from the two-sided *t*-test statistics for the difference between the covariance series in the different bank size groups in Table 4b. According to these statistics, the covariance between ROEC and EONIA has been approximately equal in R2 and R3 banks for both sub-periods, but the development of the R1 group has deviated from the others, particularly since the introduction of negative money market interest rates. Hence, based on our results, the largest R1 banks, in particular, have actually improved their risk-adjusted profitability during the negative interest rate era, as the deeper in the negative zone the EONIA rate has been, the higher the ROEC profitability of the R1 banks in particular has been. *However, it is worth observing that this strong negative dependence started to weaken already in the mid of 2017 in the banks of all sizes, so the continuum of extremely low and negative interest rates does not seem to benefit the banks especially in terms of the risk-adjusted profitability anymore.* It is also worth noting that when the OP Group changed the weight of the interest risk component in the calculation of the requirement for EC at the beginning of 2018, it seems to have at least partly affected the change in the slope of the dynamic covariance between the ROEC and EONIA in all banks.

With respect to the more standard profitability measures (ROE and ROA), we see that analogously to the NIM covariance with EONIA, the ROE dynamic conditional covariance with EONIA remains positive throughout the whole sample but, again, the behaviour begins to differ significantly in different bank size groups after the quotation of negative market rates. As may also be seen from the results presented in Table 4b, the difference between the various bank size groups is statistically significant (at least at 5% level) for all cases after 2014/11, but only for the pair of R1 and R3 banks before that. It seems that the ROE profitability has the strongest positive correlation with the development of EONIA in R1 banks, and the smallest in R3 banks. Hence, when the EONIA has gone deeper into the negative zone, the ROE profitability has suffered the most in R1 banks, because the dynamic asymmetric covariance is highest for them as a group. Regarding the ROA covariances with the EONIA, the result differs somewhat. Analogously to the ROEC analysis, in this case we also see a deep dive into the negative zone in covariances around 2010–2011, particularly for the R1 banks, but afterwards the covariances were approximately zero for all bank size groups until the quotation of negative money market interest rates began in 2014/11. Immediately after that, the dynamic dependence of ROA profitability on EONIA development began to deviate in R1 banks from that in both the R2 and R3 banks. More importantly, until the beginning of 2018, the covariance between ROA and EONIA for the R1 banks remained negative, but it has remained positive (and increased) towards the end of the sample for the R2 and R3 banks. This implies that were we to focus solely on the ROA profitability measure, the effect of increasingly negative money market interest rates on profitability has been improving for R1 banks (but note that only until 2018), but deteriorating for the smaller banks. Again, the differences in these dependencies are statistically significant, particularly in the comparison of R1 to both the R2 and R3 banks. In other words, when also focusing on the most standard profitability measure (ROA), especially the R1 banks have benefitted from the introduction of negative money market interest rates at the onset.

The most important aspect of the economic narrative behind our analyses relies considerably on the hypothesis that the introduction of negative money market interest rates has induced a change in banks' business models, i.e., shifted the emphasis in their sources of funding further towards wholesale-based rather than traditional retail (deposit)-based funding. This is because the individual banks within the OP Group have been able to enjoy the benefits from the negative overall (European) money market interest rates because the central cooperative has been willing to almost completely pass the negative interest rates through its central bank loan rates to the Group's individual member banks. Hence, it is clearly important to also investigate the dynamic dependence between the average values of WSF and EONIA mid-rate in the different bank size groups. From Fig. 4e, it is again clear that the introduction of negative rates in 2014/11 has also more or less permanently changed the dynamic conditional covariance structure between these variables. The obvious main interpretation of Fig. 4e's covariance series is that after the quotation of negative money market interest rates, the degree of WSF has increased as the interest rates have dropped deeper into the negative zone, which strongly supports our main hypothesis about the effects of negative interest rates on bank business models. In banks of all sizes, in average terms, the dependence on WSF has increased when the money market interest rates have become more negative. Additionally, when comparing the results shown in Fig. 4e (WSF against EONIA) with those in Fig. 4b (ROEC against EONIA), it is also clear that these two dynamic covariance series resemble one another remarkably closely in all bank size groups, except for the scale of covariances. Hence, the banks also continued to increase WSF during 2018, when the money market interest rates remained fairly deep, but stable (EONIA mid-rate exactly at −0.36 almost throughout the year), in the negative zone.

At the final stage of our analysis, we performed the asymmetric DCC-

[26] See also Fig 3, from which we can clearly observe that the largest (R1-banks) in particular have increased their dependence on wholesale funding throughout all the years of decreasing money market interest rates, i.e., since mid-2012 already. Although, in average terms, the smaller banks generally seem to have placed a hold on this development in recent years, the largest banks have continued along the same path during the period of negative interest rates.

GARCH modelling for the dependence of the various profitability measures on the bank business model variable, i.e., the WSF ratio. These results also strongly support our earlier findings regarding the prominent effects of negative interest rates on the change in the business model and, hence, bank profitability. From Figs. 5a–5d, it is clear, that the improving profitability effect of increasing the ratio of wholesale funding might not have come through simply the effects on NIM, because the covariance between NIM and WSF has also been quite close to zero in the negative interest rate era (Fig. 5a). The covariance has become steadily more negative in recent years so, as the WSF has increased, the NIM has decreased or remained more or less the same. This is in connection with the fact that, as we already learned from Figs. 1a–1c, the NIM has almost not varied at all since the beginning of 2016 (because the market rates have not varied), so its mild (and even negative) reaction to the WSF may actually be quite reasonable. This interpretation is also valid for the years 2010–2011 during which, after the money market interest rates had suddenly dropped in mid-2009 but remained stable for about a year after that, the increases in WSF ratio were actually negative in relation to NIM.

When we extend our analyses from NIM to wider profitability measures, we find strikingly different results, supporting our earlier implications. First, the risk-adjusted, ROEC profitability of the largest banks appears to have been positively connected to the increases in WSF. This connection has begun to be valid exactly at the time of the launch of negative money market interest rates.[27] For the smaller banks, the results are not so robust, although the dynamic conditional covariance relationship between WSF and ROEC is also positive throughout almost the entire sample. However, since 2017, this dependence has weakened and has almost vanished at the end of the sample period for the smaller banks, but for the R1 banks, it has remained strong until the end of the entire sample period.

The results for the non-risk-adjusted, more standard profitability measures again differ somewhat. Using the ROE as the profitability measure, when the WSF ratio has increased, the profitability has decreased especially for the R1 banks after the introduction of negative interest rates. Hence, when focusing on this measure, neither the largest nor the smaller banks have benefitted from increasing the WSF ratio during the negative interest rates period. Nevertheless, this conclusion seems once again to be highly sensitive to the selected profitability measure. If we focus on the most standard profitability measure used in previous studies, i.e. ROA, we see once again that throughout most of the negative money market interest rates era, the largest (R1) banks have been able to improve their ROA profitability by increasing the WSF ratio up until the beginning of Cappiello et al., 2006, after which the conditional covariance has started to decrease also for the R1 banks and in the most recent observations, the relationship between ROA and WSF appears to have become negative for the largest banks. In other words, increasing the WSF ratio no longer seems to improve the ROA so, in the most recent observations, both the ROE and ROA measures indicate similar conclusions with respect to the negative profitability effects of increases in the WSF ratio.

Our main findings until now, based on the analysis of dynamic connections between the various profitability measures with respect to the negative interest rates and to the role of banks' business models in the form of WSF ratio, are as follows. The standard textbook view that as the market interest rates increase (decrease) the NIM increases (decreases), is also valid for our data set, irrespective of the bank size category. However, for all other profitability measures, we obtained somewhat varying and completely new results between the banks of different sizes. Our results reveal that it is essential to use several indicators for bank profitability, and among the most important ones is some kind of risk-adjusted measure of profitability. When using the OP Group specific risk-adjusted measure of Return on Economic Capital (ROEC), we find that, first, the introduction of negative money market interest rates has particularly improved the risk-adjusted profitability of the largest R1 banks on average. However, according to the most recent data this relationship has changed, because the *slope* of the dynamic conditional covariance between EONIA and ROEC has changed from negative to positive (although the actual covariance remains clearly negative) since the beginning of 2018. Furthermore, this improving profitability effect of negative rates at the start of their quotation is much more difficult to reveal if we use more traditional measures like ROE and ROA. Again, an exception here is the category of biggest banks, where also the ROA profitability seems to have improved since the beginning of the negative interest rate era due to the utilization of more WSF with a negative interest rate on central cooperative loans. However, none of these clear, new bank profitability implications of the era of negative interest rates would have been possible to reveal had the asymmetries in the variances of the analysed time series and their effects on the dynamic correlations (covariances) not been accounted for.

Because some of the most recent previous studies focusing on the period of negative nominal interest rates (especially Lopez et al., 2020, and Xu et al., 2019) specifically stress the role of other than the net interest margin income items in having effects on the bank profitability during this era, in the final part of our empirical analyses we applied the asymmetric DCC-GARCH modelling approach to analyse this point of view, too. Here we discuss these results only for the analysis regarding the role of other income items in having effects on the dynamic development of the risk-adjusted (ROEC) profitability, and on the other hand, for the connections between the business model measure (WSF) and the share of other income components in relation to bank assets.[28]

Figs. 5e and 5f support strongly our previous results and justify again the need for doing dynamic analysis in these data. The conditional covariance of the other income component with respect to the ROEC started to increase and was fairly unanimous between the different bank size categories from the quotation of negative interest rates up until the beginning of 2017, but after that, the covariance started a deep dive into the negative values especially in the data for the biggest R1 banks. Hence, especially in the biggest OP banks a prominently positive development of other income items based on strong extension of the balance sheet has not affected positively the risk-adjusted profitability of the banks in the most recent data anymore. A similar implication can be obtained also from Fig. 5f that shows a clear positive trend in the conditional covariance between the wholesale funding ratio and returns from other income components at the onset of the quotation of negative interest rates, between late 2014 and 2016. However, from the beginning of 2017 this trend has been strongly negative. Hence, in the most recent observations of the OP group data the increasing rate of wholesale funding ratio is not enabling profitability improvement stemming from further returns from other income items, but more likely, the effect on ROEC is negative. Hence, analogously to some of the recent studies mentioned above, we also find that in the longer run, the negative era of nominal money market interest rates is not beneficial for the (risk-adjusted) bank profitability, because the development of all the main income items (both the net interest margin and other than income components) seem to be suffering from it.

[27] Around 2010–2011, after the significant drop in money market interest rates in mid-2009, the increasing WSF ratio has been positively connected in particular to the risk-adjusted profitability of R1 banks, but this relationship also began to weaken from 2012 onwards, when the level of money market interest rates began to stabilize. However, since the end of 2014, the positive relationship has strengthened throughout the rest of the sample for R1 but not for the smaller banks.

[28] Results for the analysis of all the other profitability measures' covariance with the other income component. and for the covariance between EONIA and other income component are available upon request.

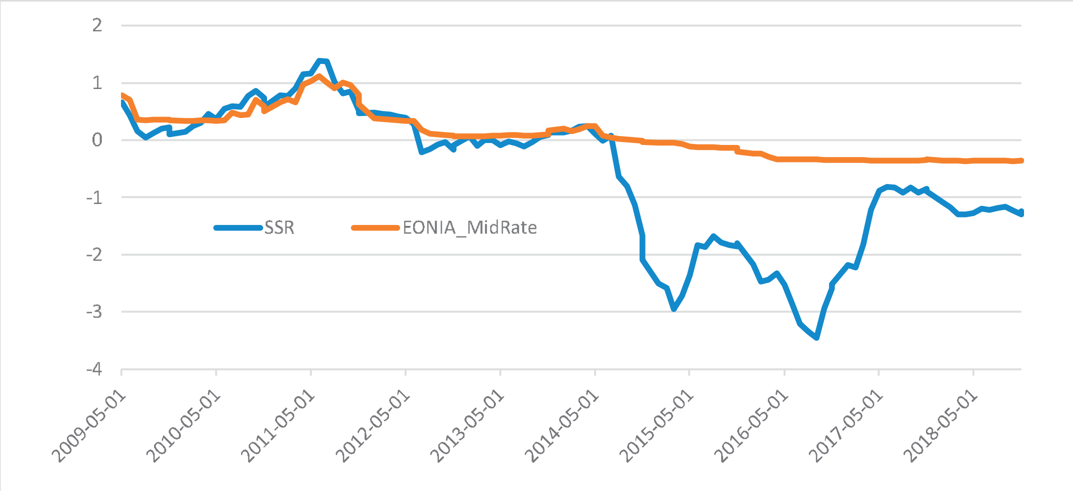


Fig. 6. Development of EONIA Midrate and the ECB shadow interest rate (SSR) (both in %) during the sample period from 1/2009 to 12/2018. The data on shadow interest rate obtained from Tomi Kortela at the OP Group.

4.4. Robustness check: The role of quantitative easing period

Our empirical analyses have so far utilized the EONIA Midrate as the main money market interest rate to characterize also the changes in the main reference rates for example in customer loan pricing activities of the banks. Even though in view of the standard ideas in the term structure theories of interest rates, it is a relevant indicator, since it was the first that dipped into the negative era in the euro area money markets, and the Euribor interest rates with increasing maturities followed the path within couple of months in 2014–2015, other relevant interest rate information might be nowadays obtained from the so-called shadow interest rate observations. Put it simply, the shadow interest rate can be viewed as an implicit, factor-analysis based indicator of the *efficient monetary policy steering rate* that is not bounded by the zero lower bound, so it can also go deep in the negative territory in practise.[29]

We will use the shadow interest rate data based on Kortela (2016), updated to the observations covering our whole sample period until the end of 2018, to proxy the role of unconventional monetary policy actions in the form of quantitative easing (QE) in the euro area. First of all, we acknowledge that the shadow rate data used here to help us to define the periods or the 'deepness' of QE are in fact capturing a large set of conditioning information (on macro variables and term structure of interest rate factor components), and hence, its usage as a direct indicator of 'effective' money market reference rate in every-day bank business activities is perhaps a bit questionable. However, since we also are well aware of its potential as a general measure for the efficient short-term implicit *monetary policy steering rate*, and as can be seen from Fig. 6, it is much more time-varying than e.g. the official central bank steering rates (like the deposit facility rate, DFR), we use it in our analysis based on the following idea.

First, when remembering that the ROE profitability was found to be strongly correlated with some other measures, like the NIM and ROA, we will use it as a measure of non-risk-adjusted profitability. Furthermore, because the dependence of risk-adjusted profitability, ROEC, on the market development, and also on the wholesale funding ratio, was clearly the one with biggest differences between the banks of different size categories, we will focus on that, too. Hence, the dependent variable in our final robustness checks for the role of QE effects is the *difference between the risk-adjusted and non-risk-adjusted profitability*, and we define it as to be representing the *risk premium* of bank profitability. The main argument for this is that as seen from the definitions for the analysed profitability measures given in section 3 and Appendix B, the return on economic capital (ROEC) adjusts for the riskiness of activities only by adjusting the required amount of economic capital assumed to be covering for the expected losses in extreme conditions. However, it is obvious that in this kind of risk adjustment, it is not actually the numerator (return or profits) of the profitability measure that is being adjusted, but only the denominator, the capital. Hence, when we analyse the difference between ROEC and ROE (in levels),[30] we are giving now also a prominent role for the required risk premium, based on a set of relevant conditioning information that might be affecting on it, i.e., the difference between the risk-adjusted and non-risk-adjusted returns.

Since in our previous analyses the relevant horizon for the dynamic dependencies between the analysed variables was revealed to be one month, we are essentially using here now a forecasting equation for the risk premium (RP), i.e., the difference between ROEC and ROE. The conditioning information set in this forecasting exercise comes, first of all, from the lagged value of risk premium and the EONIA Midrate, as it was found to be relevant for all the profitability measures. However, to control for the QE effects at the first stage, we also add now the past difference between the shadow interest rate and EONIA Midrate (denoted QE), as the variable that indicates the effects of unconventional monetary policy actions on the difference between the risk-adjusted and non-risk-adjusted profitability. We also have to take into account that in all our earlier regression analyses there was a possibility for unit roots in the data generating processes of the variables, and especially the months around the break point related to the start of negative nominal rate era seemed to be relevant in this. Hence, we do the regression analyses once again for the whole sample, but also for the two subsamples, where the break point was in October 2014, when the EONIA midrate went negative permanently.

[29] A set of research papers introducing the main ideas in the calculation of shadow interest rates includes Krippner (2015), Wu and Xia (2016), Christensen and Rudebusch (2016), and Bauer and Rudebusch (2016) for the US data. For euro area, the papers like Lemke and Vladu (2014), Pericoli and Taboga (2015), and for the UK, Andreasen and Meldrum (2015) have also analysed shadow interest rates. Our empirical analysis is based on the shadow interest rate data obtained directly from Tomi Kortela at the OP Group, where the original reference is Kortela (2016). The very first shadow rate models were presented by Black (1995) and Bomfim (2003).

[30] We are very grateful to an anonymous referee for suggesting us to take a closer look at the prominent importance of the relationship between ROEC and ROE, and also to discuss the role of shadow interest rates in our analyses.

Table 5
Role of EONIA Midrate vs. quantitative easing (*QE*) in affecting the risk premium (*RP*), defined as the difference between risk-adjusted (ROEC) and non-risk-adjusted profitability (ROE).

				Whole sample			Sub-sample 2009:1–2014:10			Sub-sample 2014:11–2018:12		
Dependent/ Independent variables	RP_t	RP_t	RP_t	RP_t	dRP_t	dRP_t	RP_t	dRP_t	dRP_t	RP_t	dRP_t	dRP_t
R1 Banks												
Constant	0.59***	0.28	0.47	0.61***	0.11	–	0.66	0.04	–	3.18**	0.17	–
RP_{t-1}	0.96***	0.99***	0.97***	0.96***	–	–	0.94***	–	–	0.87**	–	–
$EONIA_{t-1}$	−0.47**	–	–	–	–	–	−0.42**	–	–	−0.87	–	–
QE_{t-1}	−0.38***	–	–	–	–	–	−0.30	–	–	−0.06	–	–
dRP_{t-1}	–	–	–	–	0.16**	0.18**	–	−0.02	−0.02	–	0.26***	0.30***
dQE_{t-1}	–	–	–	–	−0.53	−0.53	–	−0.32	−0.32	–	−0.69	−0.68
$EONIAPlus_{t-1}$	–	−0.57***	−0.46***	−0.49**	–	–	–	–	–	–	–	–
$EONIAMinus_{t-1}$	–	−1.29	−0.91	–	–	–	–	–	–	–	–	–
$QEMinus_{t-1}$	–	–	−0.36**	−0.36***	–	–	–	–	–	–	–	–
DW	1.80	1.76	1.84	1.80	2.08	2.08	2.00	2.02	2.012	1.65	2.08	2.11
R^2	0.99	0.99	0.99	0.99	0.03	0.02	0.88	0.03	0.00	0.94	0.06	0.05
R2 Banks												
Constant	1.44***	0.88*	1.38***	1.39***	0.04	–	1.77***	−0.00	–	3.43	0.13	–
RP_{t-1}	0.92***	0.96***	0.92***	0.92***	–	–	0.89***	–	–	0.86***	–	–
$EONIA_{t-1}$	−0.61***	–	–	–	–	–	−0.55***	–	–	−0.20	–	–
QE_{t-1}	−0.38***	–	–	–	–	–	−0.60	–	–	−0.20	–	–
dRP_{t-1}	–	–	–	–	0.08	0.08	–	0.13	0.13	–	0.05	0.06
dQE_{t-1}	–	–	–	–	−0.83*	−0.84*	–	−0.44	−0.44	–	−1.14**	−1.14**
$EONIAPlus_{t-1}$	–	−0.71***	−0.57***	−0.57***	–	–	–	–	–	–	–	–
$EONIAMinus_{t-1}$	–	−0.19	−0.03	–	–	–	–	–	–	–	–	–
$QEMinus_{t-1}$	–	–	−0.37***	−0.37***	–	–	–	–	–	–	–	–
DW	1.90	1.84	1.89	1.89	2.00	2.00	1.78	2.03	2.03	1.89	1.88	1.87
R^2	0.98	0.98	0.98	0.98	0.02	0.03	0.92	0.00	0.01	0.78	0.03	0.04
			Whole sample				Subsample 2009:1–2014:10			Sub-sample 2014:11–2018:12		
	RP_t	RP_t	RP_t	RP_t	dRP_t	dRP_t	RP_t	dRP_t	dRP_t	RP_t	dRP_t	dRP_t
R3 Banks												
Constant	1.65***	1.34***	1.55***	1.51***	−0.00	–	1.88***	−0.05	–	3.11	0.10	–
RP_{t-1}	0.90***	0.93***	0.91***	0.92***	–	–	0.88***	–	–	0.86***	–	–
$EONIA_{t-1}$	−0.71***	–	–	–	–	–	−0.62**	–	–	−0.07	–	–
QE_{t-1}	−0.33**	–	–	–	–	–	−0.44	–	–	−0.15	–	–
dRP_{t-1}	–	–	–	–	0.18**	0.18**	–	0.26**	0.26**	–	0.12	0.12
dQE_{t-1}	–	–	–	–	−0.69	−0.69	–	−0.22	−0.21	–	−1.00**	−1.00*
$EONIAPlus_{t-1}$	–	−0.89***	−0.70***	−0.71***	–	–	–	–	–	–	–	–
$EONIAMinus_{t-1}$	–	−0.77***	−0.19	–	–	–	–	–	–	–	–	–
$QEMinus_{t-1}$		–	−0.31***	−0.32***	–	–	–	–	–	–	–	–
DW	1.78	1.74	1.79	1.78	2.02	2.02	1.77	2.03	2.04	1.74	1.95	1.95
R^2	0.97	0.97	0.97	0.97	0.04	0.05	0.94	0.05	0.06	0.77	0.04	0.04

NOTES: We report the estimation results from an OLS-regression (with HAC-consistent standard errors) from regressing the risk premium on lagged values of EONIA midrate, and/or quantitative easing measure (*QE*), defined in the basic form as the difference between the ECB shadow interest rate (based on Kortela, 2016) and the EONIA Midrate. The dependent variable, risk premium (*RP* or *dRP*) is defined as the difference between the ROEC and ROE (= *RP*) or change in *RP* (= *dRP*). In the non-linear control experiments using only the whole sample observations, EONIAPlus is defined as EONIA Midrate, when Eonia is positive and otherwise zero, and EONIAMinus as EONIA Midrate, when Eonia is negative, otherwise zero. On the other hand, QEMinus is defined *directly as the ECB Shadow rate*, when EONIA is negative, otherwise zero. *dRP* and *dQE* refer to the changes in risk premium and *QE*, respectively, used to capture the implications of possible unit rotos in the data generating processes of the relevant variables. ***, ** and * refer to the statistical significance of the parameter estimates at 1, 5, and 10% risk levels. In addition to the coefficient of determination (R^2) values, we report the Durbin-Watson (DW) test values as the goodness of fit statistics.

For the part of differenced values of the variables (RP and QE) we do the analysis for subsamples,[31] too, but especially in the whole sample data we wanted to put even more emphasis to the periods when the EONIA Midrate obtained negative values. Hence, we control also for these switching, i.e., nonlinear effects by setting up indicator (dummy) variables to reflect the periods, when the EONIA Midrate was either in the positive or negative era, and whether the effect of shadow interest rate on the risk premium is different when the EONIA Midrate is negative, too. Hence, in the last experiment for the whole sample levels observations, we define the QE measure to be directly given by the shadow interest rate (denoted as QEMinus), when the EONIA Midrate is below zero.

The results in Table 5 reveal once again the essential role of the negative values of the EONIA Midrate. In the whole sample results we see that there seems to be a statistically significant drift term in the risk premium series for all the bank size categories. Furthermore, since the constant term in the regressions reflects this average value of the risk premium and it increases when the bank size group gets smaller, the smallest, R2 and R3 banks have the highest risk premia, and they are always more than double the average premium for the R1 banks. Even more interestingly, the average risk premium is not even statistically different from zero for the biggest (R1) banks, when we control separately for the effects of positive EONIA midrate observations and use the shadow interest rate as the reference rate, when EONIA midrate goes below zero (see column 3 results in Table 5). However, the average risk premium is still very high for both the R2 and R3 banks in this case, too.

[31] Using the differenced values for RP and QE did not reveal statistically significant new results compared to the whole sample results for the levels of variables, so we will not discuss those in further details, even though they are also reported in Table 5.

Furthermore, irrespective of whether we define the QE variable as the difference between the shadow rate and EONIA, or directly as the shadow rate, when EONIA is negative, the QE effect is quite similar in all banks. In other words, when the QE efforts accelerate, i.e., when the shadow rate goes deeper in the negative zone, it has a lowering effect on the risk premium, and the scale of this effect is around 31–38 basis points in all banks, so this really is a large effect. Put it in other words, in terms of lowering the overall riskiness of banking activities, our results speak in favour of using the QE, but it is worth to note that the effects on bank profitability directly, and especially over time, cannot be observed from these results, because they are based on the whole sample parameter estimates, and hence, e.g. the time-variation in the dependencies between the variables is not captured here parametrically. This will be done based on DCC-GARCH analyses.

Finally, we can also see from the results reported in the first four columns of Table 5 that for the smallest (R3) banks both the negative and positive values of EONIA have a lowering effect on the risk premium, whereas for the bigger (R2 and R1) banks only the positive values of EONIA lower the risk premium, and also this effect is milder. These additional results for the effects of negative interest rate era once again emphasize the clear differences between the three size categories of Finnish OP Group banks. Hence, from the policy recommendations point of view, also these results actually imply that the biggest (R1) banks are probably very different in terms of their scales and diversity of customer business activities, because also their risk premium development and its dependence on the market situation and reference rates is different from the smaller banks. These implications are also clear when we look at the time-varying development of DCC covariances of the various profitability measures against the shadow interest rate, reported in an online Appendix AI. These results confirm that the introduction of negative money market interest rates, and the accompanying deep dive of shadow interest rate around 2014–2016, when the negate money market interest rates stayed fairly constant, has a very different effect on R1 banks compared to the other two size reference groups. A general message from e.g. Fig. A1 is that when the shadow rate went very deep into the negative side around 2015–2016, the risk adjusted profitability of especially the R1 banks improved at the same time. However, also from the DCC covariance figures based on the shadow rate we see the previously observed similar implications for the last two years in our data, that the negative conditional covariance has started to diminish and has moved towards even positive dependence. This once again raises serious concerns for the future profitability of all banks when the negative interest rate period seems to be lasting clearly longer than was perhaps originally planned by the central bank policy makers.

5. Conclusions

Based on careful application of a set of various time-series analytical tools, we obtain somewhat revolutionary results regarding the average profitability of the Finnish OP banks in the three size reference categories during the period of negative interest rates. One of our study's main innovations was to use a risk-adjusted profitability measure, and it appears to result in completely new implications. One clear result is that the largest (R1) banks have been able to reap the greatest advantages from the period of negative money market interest rates during the first couple of years of the quotation of negative money market interest rates. This is based on the fact, that although all the individual OP banks have had the chance to shift their business models towards more wholesale funding profitably based on the negative central cooperative loan interest rates, the largest banks seem to have had the greatest interest in doing so. However, in the face of the long period of prevailing negative rates after the Corona crisis, we also find very alarming results based on the most recent OP data, because it seems that from the beginning of 2017 the advantageous connection between (risk-adjusted) profitability and more negative interest rates, along with increasing rate of wholesale funding has started to vanish. In other words, even though banks still get their funding with negative interest rate from the central co-operative, they have not been able to improve their profitability anymore based on that. More specifically, even though the standard ROA- and ROE-based profitability measures are also in the most recent data improving in connection to the other than interest income items, especially the risk-adjusted (ROEC) profitability has been decreasing along with the rising return from other income items. This alarming development has been especially strong in the biggest banks during the last two years of our data.

As noted above in our literature review, the number of studies on bank profitability utilizing actual negative (nominal) interest rate data remains limited. However, the results of some earlier studies resemble ours at least partially. For example, Turk-Ariss (2016) found from the data on Swedish and Danish banks that reductions in WSF costs based on the negative interest rates have offset the lower interest income and that bank profitability has not suffered from negative interest rates in Sweden and Denmark too much. In fact, our Finnish cooperative bank data indicate that profitability has improved as a result of the utilization of central cooperative loans with negative interest rates during the first 2–3 years of negative market rates, but not in the most recent data, particularly in the largest R1 banks. Furthermore, for example Eggertsson et al. (2019) found that at extremely low (and negative) interest rate levels, banks might actually have been able to increase their lending margins, and this has improved bank profitability. However, our results imply that also this might not be valid in the most recent data on Finnish OP banks, at least when we consider their risk-adjusted profitability measures.

Our results are in favour of some earlier studies that have actually advocated the possibility that *over-reliance on WSF during the negative interest rate era might increase the systemic risk to the banking sector*. We also strongly question the profitability of too long over-reliance on WSF, even with negative nominal reference rates. Since the OP Group currently holds almost a 40% share of most banking business segments (e.g. housing loans) in Finland, this is a significant concern in the Finnish context. Nevertheless, due to the relatively small proportional role of the entire OP Group in the European banking markets, this may not induce further systemic risk stemming solely from Finland's OP banks. However, if similar time-varying behaviour with respect to the reaction of profitability to market interest rates were to be revealed from the data on the largest European banks, this may also clearly raise some serious systemic risk concerns. Compared to previous studies, from a somewhat different perspective, our results indicate these same concerns, because the largest banks appear to have increased the volume of customer lending based on WSF to the greatest extent. The alarming aspect of this development can be most clearly seen from the time-series behaviour of the various dynamic conditional covariances between the profitability measures and EONIA or WSF ratio, because the volatility and the range between minimum and maximum values of the dynamic covariances is also the greatest for the data on R1 banks across all our analyses. Hence, when the money market reference rates and, as a follow-up, the WSF ratio change, particularly in the negative interest rate zone, the effects are the strongest for the biggest (R1) OP banks, which constitute the major part of all customer activity volumes in all business areas of the OP Group.

Another very relevant finding from our results is that even though it seems to be the case that the unconventional monetary policy actions (QE) have had a lowering effect on the risk premium, defined here as the difference between the risk-adjusted (ROEC) and non-risk-adjusted (ROE) profitability, the last two years of data also witness a decreasing effect on overall profitability of banks as the market interest rates and also the shadow interest rate have remained in the negative era, and even still lowered from time to time. For example, the biggest banks' non-risk-adjusted return on assets (ROA) profitability has also started to lower along with the lowering of nominal reference rates (because the conditional DCC covariance has turned positive, see Fig. AI.3 in Appendix AI), so the overall profitability development of the whole OP group might be in danger if the negative interest rate era continues far into the future, and starts to be the new norm.

Our results obviously require in the future a much more detailed, panel data methodological analysis, and furthermore, also utilization of more recent observations, and of also an international data set, where the role of ownership structures and many other relevant variables affecting the bank profitability are controlled much more carefully. However, our current findings already serve as a good starting point, and we have uncovered some interesting, completely new findings already from this Finnish OP Group data set and observations based on the average values of the data within the size reference categories of the analysed banks.

Appendix A

Structure and selected details of the OP Financial Group (as of December 2018)

(see also https://www.op.fi/op-financial-group/about-us/corporate-governance/group-structure and the 2018 financial statement and annual report, from which the selected details are extracted exactly as reported in the statement and report)

OP Financial Group was established in 1902 as a cooperative financial services group formed by independent cooperative banks and the Group's central cooperative with its subsidiaries operating under the principle of joint and several liability. At the end of 2018, OP Financial Group consisted of 156 member cooperative banks and their central cooperative, OP Cooperative, with its subsidiaries and affiliates. The Group's operations are based on the cooperative principle, which aims to create sustainable prosperity, security, and well-being for its owner-customers and in its operating region by means of its strong capital base and efficiency.

OP Financial Group's business was divided into three segments that were valid until the end of 2018: banking, non-life insurance, and wealth management. However, a new business segments structure took effect on 1st January 2019. These new business segments are banking for private and SME customers, banking for corporate and institutional customers, and banking for insurance customers. OP Financial Group consists of the following amalgamation of OP Financial Group cooperative banks and other entities and organizations of OP Financial Group.

The amalgamation is formed by OP Cooperative (the central cooperative), companies belonging to its consolidation group, the central cooperative's member credit institutions and companies belonging to their consolidation groups, and credit institutions, financial institutions and service companies, in which the abovementioned institutions jointly hold more than half of the voting rights. OP Financial Group is comprised of the amalgamation and those non-amalgamation entities of which entities belonging to the amalgamation hold more than half of the total votes. The extent of OP Financial Group differs from that of the amalgamation, in that OP Financial Group subsumes companies other than credit and financial institutions or service companies. The most important of these are the insurance companies with which the amalgamation forms a financial and insurance conglomerate. Additionally, Pohjola Health Ltd., a hospital, belongs to OP Financial Group.

OP cooperative banks are independent, local deposit banks engaged in retail banking. They provide modern and competitive banking services to households, SMEs, agricultural and forestry customers, and public-sector entities. Helsinki Area Cooperative Bank, which belongs to the central cooperative consolidated and whose governance model and structure differs from that of other OP cooperative banks, engages in corresponding retail banking in the Helsinki Metropolitan Area. In terms of the type of their business organization, the member cooperative banks are cooperatives whose basic values underlying their decision-making include the one member, one vote principle. Within the OP cooperative banks, the owner-customers' decision-making power is exercised by the Representative Assembly, comprising owner-customers, or the cooperative meeting, which elects a supervisory board for the bank. The Supervisory Board in turn elects a board of directors for the bank.

The central cooperative of OP Financial Group is OP Cooperative in English and OP Andelslag in Swedish and is domiciled in Helsinki. Within the central cooperative, the decision-making powers of member cooperative banks rest with the Cooperative Meeting and the Supervisory Board elected by it, and operational decision-making powers are exercised by the Executive Board acting as the board of directors, elected by the Supervisory Board and composed of management executives. The central cooperative's member banks own OP Cooperative. The central cooperative's members may include credit institutions, as referred to in the Act on the Amalgamation of Deposit Banks, whose Bylaws or Articles of Association have been approved by the central cooperative. The Supervisory Board takes decisions on admitting new members.

Based on the financial statements of the OP Financial Group at the end of 2018,[32] the OP Financial Group-level earnings before tax amounted to EUR 1017 million (1031 in 2017). Income from customer business activities improved, because net interest income increased by 7% to EUR 1175 million and net commissions and fees by 1% to EUR 887 million. Net insurance income increased by 19% to EUR 566 million – comparable change was −2%. Investment income fell by 46% to EUR 280 million and other operating income by 26% to EUR 61 million. Investment income was affected by a year-on-year decrease of EUR 227 million in capital gains. Expenses decreased by 5% to EUR 1681 million.

Concentrating particularly on the profitability and scale of the banking business, earnings before tax amounted to EUR 795 million (619). Total income increased by 4.8%, and net interest income increased by 4.2% year on year, but net commissions and fees decreased by 6.3%. Total expenses decreased by 9.5% to EUR 878 million. The transfer of the earnings-related pension liability decreased personnel costs by EUR 172 million. Other operating expenses increased by 18.1% due to the stability contribution, development costs and higher volumes.

In actual banking business, the loan portfolio increased by 5.9% to EUR 87.1 billion and the deposit portfolio by 5.8% to EUR 61 billion. Hence, a significant aspect of the loan portfolio at the entire group level is funding based on the acquisition of wholesale funding from the interbank markets. The loan portfolio showed the fastest growth in corporate loans as well as housing company loans and other loans. Impairment losses amounted to EUR 45 million (47). Non-performing receivables accounted for 1.0% (1.2) of the loan and guarantee portfolio. The most significant banking development investments involved the upgrades of payment and finance systems, for example, those concerning the development of the digital home loan service. OP Financial Group's banking comprises banking for private and SME corporate customers as well as that for corporate and institutional customers. OP cooperative banks are mainly responsible for banking for private and SME corporate customers. The corporate and institutional customer business is almost entirely centralized in OP Corporate Bank, which accounts for 26% of the loan portfolio and 19% of the deposit portfolio.

Home loan borrowers have historically enjoyed low interest rates for an exceptionally long time, and customers have demonstrated greater interest

[32] For more details, see https://www.op.fi/documents/209474/31336404/OP+Financial+Group+Report+by+the+Executive+Board+and+Financial+Statements+2018/47db0917-a4c0-8768-9d41-796039598ca0

in protecting their home loans and housing company loans against higher interest rates. At the end of the financial year, 19.7% (11.5) of private customer home loans were covered by the interest rate protection. The number of banking customers totalled 3.6 million (3.7) at the end of December 2018.

Appendix B

Components in the calculation of the Return on Economic Capital (ROEC)

(original source: *OP Group Intranet*, permission to publish obtained from the Group Control by Esa Vilhonen)

Partly due to the requirements induced by the Basel Accords (I to III, and the forthcoming IV), the calculation procedure for ROEC in the OP Group has evolved throughout the years since its adoption around 2007–2008. In the most recent version, the bank-specific final income after taxes, balance sheet items and economic capital (EC) requirement are divided into two parts: the first is connected to the customer business activities and the other to ownership. The exact term for the new profitability measure is the 'return on economic capital based on customer business activities' (ROECCBA) but, in our study we will use the shorter acronym, i.e. the 'return on economic capital' (ROEC). In the most recent version of ROECCBA calculation (= ROEC in our study), the values are based on.

$ROEC = \frac{(\text{Operating income}+\text{customer bonuses})\times(1-\text{tax rate})}{\text{Economic Capital Requirement on Customer Business Activities (cum.)}} \times 100\%.$

More specifically, the role of individual items in the *ROEC* calculation is roughly based on the following decompositions:

1. **Decomposition of income into its components**

The financial result (operating income) is divided into income statement items as:

Customer business activity (income items (+) and expenses (−))

\+ Net Interest Margin (NIM) excluding the NIM from ownership
\+ Net income from fees and commissions
\- Expenses
\- Impairment of assets
\- Bonuses
= **Operating income**

Ownership

\+ Part of NIM
\+ Returns from income based on own capital (equity) and items alike
\+ Net income from trading in asset markets and currency market activities
\+ Sales profits from financial assets available for sale
\+ Net returns from investments in real estate
\+ Impairment of other financial assets
= **Operating income**

2. **Decomposition of balance sheet and net interest income**

To decompose the NIM into customer business activities and ownership, the balance sheet is also decomposed into two corresponding parts. In practice, this is based on extracting the ownership items from the bank balance sheet, and the remaining part constitutes the share of balance sheet items connected to the customer business activities. The decomposition of balance sheet is based on the following principles:

- Equity, fund, and bond market investments are allocated to ownership.
- Structured investments are allocated to customer business activities.
- Own capital (equity) is decomposed so that part of it is allocated to customer business activities with a constant multiplier of 3 (i.e. 3× the EC requirement amount of customer business activities) and the rest is allocated to ownership.
- After these allocations, the new balance sheets are levelled with a levels item, for which an interest expense (if the levels item is in liabilities) or an interest return (if the levels item is in assets) is calculated using the 12-month Euribor rate.

Investments allocated to the balance sheet based on ownership

\+ Debt securities
\+ Other domestic bonds
\+ Equity and shares
\+ Real estate investments

Amount of own capital (equity) due to ownership

\+ Own capital (equity)
\+ Appropriations after tax deductions based on 20% tax liability
\- 3× the EC requirement amount of customer business activities

Interest income items due to NIM from ownership

Interest returns from investments on ownership are allocated to NIM based on:

+ Interest returns from debt securities
+ Interest returns from other domestic bonds

3. **Decomposition of the requirement for economic capital (EC)**

The EC requirement is decomposed between the customer business activities (CBA) and ownership, as follows:

- Items of EC requirement allocated completely to CBA:
- Interest rate risk
- Other measurable risks
- Items of EC requirement allocated completely to ownership:
- Equity risk
- The following ROEC items are allocated to ownership and CBA, as follows:
- Credit risk
  - credit risk from debt securities is allocated to ownership, other credit risks to CBA
- Real estate risk
  - investments in real estate are allocated to ownership
  - the share of real estate in own use is allocated to CBA
- Operational risk
  - allocated based on the relative shares of returns from the forms of operational activities

The share of ownership in the EC requirement on operational risk is calculated based on the value of previous year's income from ownership in relation to total income, as

Income from ownership /Total income × EC requirement for operational risk,

where

Income from ownership = Interest returns from ownership + net income from asset market trading + net income from financial assets available for sale + net income from investments in real estate

Total income = Income from ownership + NIM from CBA + Net income from fees and commissions + Other income from business activities

Appendix C

The original, confidential individual bank-level database reports the return on assets (ROA) of each bank on a monthly basis. However, the monthly ROA values are calculated in terms of the ratio of cumulative earnings (from the beginning of the calendar year) to the corresponding average value of assets. Clearly, in this case, the ratio does not actually measure the month-specific profitability appropriately. Furthermore, the time-series observations of the ratio appear to be noisy and contain obvious outlier observations. As the database reports the monthly revenues and expenses item by item, we decided to recalculate for example the monthly earnings and the ROA values in the following way, to get a more appropriate measure for the monthly values of this standard profitability indicator

First, we detected the outlier observations in the interest revenues and interest expenses. An observation (in a few cases, a pair of adjacent observations) in a time series was identified as an outlier if it deviated (in terms of the percentage change) by more than two standard deviations from both the previous and the next observation in the time series. The standard deviation of the percentage changes was calculated separately for each bank and also separately for the interest revenues and expenses. The filtered value of the observation was adjusted to have a change of one standard deviation instead. The final time series of the net interest margin (NIM) is then calculated based on the adjusted values for the interest revenues and interest expenses.

The other revenue and expense items (13 variables altogether in the original data set) are treated using a similar kind of procedure. In these cases, the standard deviations of the time-series variables were also calculated separately for each bank, and an observation was identified as an outlier, if it was further than three standard deviations from both the previous and the next observations in the time series. Here, the value of the observation was adjusted according to the time-series mean of the variable. The variables also appeared to contain relatively strong seasonality (primarily due to accounting practices) so, for the purpose of smoothing the seasonal components from the monthly observations, we used 12-month moving averages of the time-series observations on all variables.

In the case of the variable 'revenues from equity investments', there were a few abnormal observations, which are common to (almost) all banks in the data. The observations typically represent revenues from block trades by the OP Financial Group. An example of these regular items is the return on ownership of the central cooperative, which is credited to the member banks in March every year. These observations were also cleaned from the data.

Finally, we re-calculated the monthly earnings using the adjusted variables, and calculated the adjusted monthly return on assets (ROA) and return on equity (ROE) observations, using the previous month Total Asset and Equity values as the denominators in the two ratios.

The time series for the risk-adjusted measure of profitability, i.e. the Return on Economic Capital (ROEC) do not seem to contain similar kinds of seasonal components as did the ROA and ROE values. Hence, we use the original raw data from each individual bank for ROEC, after cleaning some obvious outliers, probably due to data entry errors or sudden, abrupt (monthly level) changes in the calculation process, which can also be treated as recording errors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2021.101724.

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