LUND UNIVERSITY
School of Economics and Management

Developments in Systemic Risk since the Global Financial Crisis

Assessment of Eurozone and US Systemically Important Banks based on Marginal Expected Shortfall

Master Essay

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Abstract

Present essay investigates if the systemic riskiness of Eurozone and US systemically important banks decreased subsequently to the Global Financial Crisis of 2007/2008. For each of these institutions, time series of the analytical systemic risk measure MES are estimated based on public information. This is done using a bivariate time series model and involves estimation of time varying conditional correlations via an asymmetric DCC GARCH model. The banks' MES series are compared to those of several indicators of systemic distress pre- and post-crisis. The indicators utilised here are the Early Warning Indicators of financial crises published by the Bank for International Settlements. The comparison is done by performing linear time series regressions of the banks' MES on the Early Warning Indicators and assessing changes in magnitude and their significance by examining the resulting parameters pre- and post-crisis. Supplementary, congeneric regressions of the US banks' MES series on a selection of bank specific indicators of potential systemic impact are performed as well. Ultimately, the obtained results are largely contradictory and lack validity so that no conclusive verdict can be achieved in this instance.

Keywords: Systemic Risk, Systemically Important Banks, Marginal Expected Shortfall, Dynamic Conditional Correlation, GARCH

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List of Abbreviations

ADCC	Asymmetric Dynamic Conditional Correlation
ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroscedasticity
AUC	Area Under the Curve
BIS	Bank for International Settlements
BLUE	Best Linear Unbiased Estimator
CCC	Constant Conditional Correlation
cdf	Cumulative distribution function
CoVaR	Conditional Value at Risk
cgdpg	Credit-to-GDP gap
DCC	Dynamic Conditional Correlation
dsrg	Debt service ratio gap
ES	Expected Shortfall
EWI	Early Warning Indicator
FSB	Financial Stability Board
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GJR	Glosten, Jagannathan and Runkle
HP	Hodrick-Prescott
KPSS	Kwaitkowski-Phillips-Schmidt-Shin
LLF	Log-Likelihood Function
ln	Natural logarithm
MES	Marginal Expected Shortfall
ML	Maximum Likelihood

OLS	Ordinary Least Squares
pdf	Probability density function
ppg	Property price gap
QML	Quasi Maximum Likelihood
ROC	Receiver Operating Characteristic
SES	Systemic Expected Shortfall
SIB	Systemically Important Bank
TGARCH	Threshold GARCH
VaR	Value at Risk

1 Introduction

Financial institutions take on a vital role within an economy. Banks in particular assist in the financing of business endeavours not only via provision of funds but also expertise. Thereby, they represent a major facilitator of entrepreneurship, economic development and progress. Moreover, in large parts of the world they constitute a government's main channel of implementing monetary policy (Peek & Rosengren, 2013), which further adds to their significance as integral elements of an economy. Besides the negligence and imprudent risk taking of financial institutions in the US subprime mortgage market, the Global Financial Crisis of 2007/2008 even more so highlighted their global reciprocal dependencies. These interdependencies combined with their immense economic importance lead to considerable systemic risk posed by the financial sector which is defined by the Bank for International Settlements (2009, p. 5) as the risk of "disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system; and (ii) has the potential to have serious negative consequences for the real economy". The endeavour to avoid such devastating consequences during the crisis led to the infamous bank bailouts, which saw reimbursements of approximately $444 billion in the US alone under the Troubled Asset Relief Program (Congressional Budget Office, 2018). The crisis left the banking industry with a stigma persistent to this day. Besides the extensive debate on principles, the most notable and only tangible consequence to the sector in the Eurozone and US was extensive reform and expansion of legislation based on the third Basel accord (Bank for International Settlements (2011), (2010a)). Ten years on, present essay pursues the question if the dreadful impressions of the Global Financial Crisis and the measures taken lead to a reduction in the degree of systemic risk, namely of the Eurozone and US Systemically Important Banks (SIBs).

Current research in the field of systemic risk mainly covers the design and evaluation of analytical measures. Most notable here are CoVaR developed in 2008 by Adrian and Brunnermeier (2016), MES and SES developed in 2010 by Acharya et al. (2017) and SRISK by Brownlees and Engle (2017). However, examinations of the development in banks' systemic riskiness are scarce, with only the works of Battaglia and Gallo (2013) and Engle, Jondeau and Rockinger (2015) providing insights along the same lines. This is although the topic arguably is of considerable relevance, where stagnation or even deterioration would indicate the need for increased efforts to contain systemic risk in order to prevent repetition of the drastic events experienced a decade ago.

Present essay therefore investigates if the systemic riskiness of Eurozone and US SIBs decreased subsequently to the Global Financial Crisis of 2007/2008. This is done by estimating time series of an acknowledged analytical systemic risk measure for these institutions and comparing their levels to those of several indicators of potential macroeconomic distress pre- and post-crisis. The analytical systemic risk measure utilised for this purpose is Marginal Expected Shortfall (MES), a concept pioneered by Acharya et al. (2017) and originally used as an input for their SES measure. As indicators of potential macroeconomic distress, the Early Warning Indicators (EWIs) of financial crises as published by the Bank for International Settlements (BIS) are utilised. After performing linear time series regressions of the banks' MES on the EWIs, changes in magnitude and their significance of the resulting parameters before and after the crisis are assessed. This allows for appraisal if the SIBs today would pose lower systemic risks under regimes of systemic distress. Supplementary, congeneric regressions of MES on a selection of bank specific indicators of potential systemic impact, namely market-to-book value ratio, total assets and leverage, are performed for the US banks.

2 Theory and Approach

2.1 Related Literature

The aftermath of the 2007/2008 Global Financial Crisis saw discussion of potential measures for addressing and containing systemic risk, as exemplified for instance by Corrigan et al. (2008), Caruana (2010) or the 2010 draft of Acharya et al. (2017). Ultimately, the implemented legislation based on Basel III (Bank for International Settlements (2011), (2010a)) mainly addresses risk on the institutional rather than systemic level (Acharya et al., 2017). The rationale here is to minimise the probability of future crises by strengthening the individual institutions' resilience (Bank for International Settlements, 2010b). The systemic aspect specifically is covered only for those banks deemed systemically important (SIBs) in form of a capital surcharge (Mesnard et al. (2017), Board of Governors of the Federal Reserve System (2015)). The banks subject to this surcharge are identified by the respective regional authorities compliant with the procedures laid out in Bank for International Settlements (2013). The Financial Stability Board (FSB) publishes a proprietary annual list of global SIBs according to this methodology, the 2017 edition of which is the basis for selection of the institutions examined in present essay (Financial Stability Board, 2017).

At the time of writing, research concerned with systemic risk is mainly focussed on design and evaluation of analytical measures based on publicly available data. These measures allow for a more continuous monitoring of institutions' conditions between assessments by the authorities (Acharya, Engle & Richardson, 2012), and the most notable instances are stated in the following. Adrian and Brunnermeier (2016) developed the systemic risk measure CoVaR in 2008, which indicates the loss of the financial system conditional on the distress of an individual institution. Acharya et al. (2017) developed Systemic Expected Shortfall (SES) in 2010, which is a measure for the loss of an individual institution conditional on the distress of the financial system. SRISK by Brownlees and Engle (2017) can be described as an extension of the SES concept and is published continuously on a designated website (Acharya, Engle & Richardson, 2012). Another notable instance and the measure of choice applied in present essay is MES. Originally merely a part of Acharya et al.'s (2017) SES, MES is now one of the most widely applied analytical measures for systemic risk in scientific research (Löffler & Raupach, 2018). Present essay employs Brownlees and Engle's (2012) methodology for determination of MES.

While no works explicitly pursuing present essay's objective could be identified, some of the studies utilising the above-mentioned analytical measures make observations along the same lines. Engle, Jondeau and Rockinger (2015) thus find that the aggregate potential loss of the European financial institutions in a systemic event seems to be significantly larger than that of the US institutions. And Battaglia and Gallo (2013) find that the systemic exposures of Italian banks seem to be still as high post-crisis as it did pre-crisis.

2.2 Research Approach

2.2.1 General Outline

Present essay examines if a favourable development in the systemic riskiness of the seven Eurozone and eight US banks on the Financial Stability Board's (2017) list of global SIBs took place since the 2007/2008 Global Financial Crisis. The examination is based on the acknowledged analytical systemic risk measure MES (Acharya et al., 2017), of which time series are calculated for each institute. The obtained MES values are juxtaposed to proxies of overall systemic distress in order to determine to what extent the banks' systemic riskiness change with this distress before and after the crisis. The degree of systemic distress is proxied by the Bank for International Settlements' three EWIs applicable to the respective region. The banks' change in exposure to systemic distress is examined by linearly regressing MES as dependent variable on the EWIs as independent variables over the whole sample period while including dummy terms that capture the change in parameters for the post-crisis period.

Beyond that, a supplementary regression is performed in which MES is regressed on bank specific variables as proxies of their individual potential impact in case of a systemic crisis. These are the market-to-book value ratio (mbv) as an indicator of a bank's business performance as evaluated by the stock market, the natural logarithm of total assets (lnta) as an indicator of firm size and with it size of potential impact, as well as leverage (lev) as a measure for a bank's risk taking. The underlying rationale here is identical to the first regression in that parameters of dummy terms capture the change in exposure post-crisis. Due to insufficient availability of data, this regression is performed for the US subsample of banks, only.

2.2.2 Marginal Expected Shortfall

The concept of Marginal Expected Shortfall was pioneered by Acharya et al. (2017) in 2010 as part of their SES measure. Being one of the most widely used analytical measures for systemic risk (Löffler & Raupach, 2018), it was found to be reliable in identifying SIBs (see for instance Idier, Lame & Mesonnier (2014), Banulescu & Dumitrescu (2015) and Lin, Sun & Yu (2018)) as well as predictive of their financial distress in crisis conditions (see for instance Kupiec & Güntay (2016) and Acharya et al. (2017)).

$$ES_\alpha = -E[y|y \leq -VaR_\alpha] \tag{2.1}$$

where

y: *return*

VaR_α: *Value-at-Risk at confidence level* α

While Value-at-Risk (VaR) can be described as the largest potential loss a bank is expected to incur at a certain confidence level α, Expected Shortfall (ES) is the expected loss conditional on the loss being greater than VaR_α (see (2.1)). Or put differently, ES is the average of returns on days when VaR_α is exceeded (Acharya et al., 2017).

$$ES_\alpha^m = -\sum\nolimits_i x_i E[y_i|y_m \leq -VaR_\alpha] \tag{2.2}$$

where

$y_m = \sum\nolimits_i x_i y_i\,; return\ of\ market\ portfolio$

y_i: *return of individual stock i*

x_i: *weight of individual stock i in market portfolio*

$$\frac{\partial ES_\alpha^m}{\partial x_i} = -E[y_i|y_m \leq -VaR_\alpha] \equiv MES_\alpha^i \tag{2.3}$$

The Expected Shortfall of the market portfolio can be decomposed into the weighted Expected Shortfalls of the individual stocks conditional on the market return breaching a pre-defined VaR_α as shown in (2.2). From this relationship, Marginal Expected Shortfall of stock i can be deduced as the market portfolio's sensitivity to exposure to stock i by taking the partial differential regarding stock i's weight as shown in (2.3) (Acharya et al., 2017). This is equivalent to determining the expected loss of stock i conditional on the market experiencing a crisis determined as breach of a certain VaR_α. Stock i's MES therefore measures how firm i's risk taking contributes to the overall risk of the market.

2.2.3 BIS Early Warning Indicators

Naturally, no such thing as a definitive indicator of systemic distress exists. Present essay here resorts to the EWIs routinely published by the BIS in their March and September Quarterly Reviews as well as Annual Reports since 2014. The rationale behind these indicators is that financial crises accrue from disruptive financial cycles (Aldasoro, Borio & Drehmann, 2018). This is since financial booms are thought to generate conditions for future banking distress such as increased risk appetite, inflated asset prices and surge in credit.

The three EWIs tracked by the BIS are the credit-to-GDP gap (cgdpg), the property price gap (ppg), and the debt service ratio gap (dsrg). This selection is based on the work of Drehmann and Juselius (2014), who identify these as the indicators with the highest unambiguity in signalling impending financial crises out of a range of suitable options. In their assessment they use the so-called receiver operating characteristic (ROC) approach on historical data. Here, a given EWI's breach of a predefined threshold is treated as a binary signal announcing a crisis. These announcements' type I and type II error rates are then plotted on a graph for a range of thresholds resulting in the so-called ROC curve. The signalling quality is measured by the area under the curve (AUC) which can be interpreted as the likelihood that the given EWI's distribution is stochastically larger ahead of a crisis than during normal times. The AUC's value is close to 1 for an indicator that is informative by taking on an increased value, while it is close to 0 for an indicator that is informative by taking on a decreased value. An AUC of 0.5 implies that an indicator is uninformative. Within the context of present essay, these three EWIs are therefore viewed as fairly reliable proxies for the prevalent level of systemic distress. This is due to their properties of general increase ahead of and high signalling quality regarding impending crises.

The suitability of the credit-to-GDP gap as an indicator of impending financial crises was first documented by Borio and Lowe (2002). Based on this property, the Bank for

International Settlements (2010c) even applies it as key input in the setting of countercyclical capital buffers in context of the Basel III framework. The intuition behind this measure is that an increase of the credit-to-GDP ratio of the private non-financial sector in general may be attributed to the financial deepening of an economy. A widening gap between this ratio and its long-term trend, however, indicates that credit supply and demand grow in excess of the economy (Drehmann et al., 2010). The resulting excess in credit is likely to contain problem loans due to a natural limit in banks' ability to screen borrowers (Bank for International Settlements, 2014). Drehmann and Juselius (2014) identify this EWI as a highly reliable harbinger of impending crises in the long run already via its elevated level.

The qualities of the debt service ratio as an EWI were first examined by Drehmann and Juselius (2012). It is a measure of the extent to which borrowers are burdened by their debt and calculated as the aggregate proportion of interest payments and principal repayments relative to income for the private non-financial sector. A relatively high ratio indicates households and firms are overextended so that income shortfalls will result in investment restraints or even defaults, ultimately contributing to the emergence of a financial crisis (Drehmann & Juselius, 2014). Furthermore, debt service ratios are observed to revert around stable historical means. This is since high costs of servicing debt relative to income will result in less taking as well as granting of loans, which will ultimately lead to lower costs of servicing debt. Lower such costs in turn release borrowers' capacities to take on new debt, again inducing an increase of debt servicing costs (Bank for International Settlements, 2014). To highlight deviations from their stable mean and to enable comparability between countries, among which these means tend to differ considerably, debt service ratios are demeaned by deducting their long-run average (Drehmann & Juselius, 2014). The BIS does typically not use different terms for the original and demeaned series. In the context of present essay, the demeaned series are utilised and referred to as debt service ratio gap (dsrg). Drehmann and Juselius (2014) consistently find this EWI to be sharply rising in the run-up to a financial crisis. However, this is observed only within rather short time horizons compared to the credit-to-GDP ratio gap.

The property price gap (ppg), first examined for its EWI qualities by Drehmann, Borio and Tsatsaronis (2011), highlights excessive changes in real residential property prices based on their long-run trend. Variations in house prices strongly influence households' net wealth and overall spending. Furthermore, the mortgage market is highly affected by such variations as well. Therefore, property price increases that considerably outpace the long-run trend are likely to indicate asset price bubbles of systemic scope (Bank for International Settlements, 2018). Drehmann and Juselius (2014) find this EWI to be highly informative in the run-up to a crisis, although its signalling quality starts to cease again quite close to one. This is since it does not consistently peak during the same phases but rather randomly shortly before, during or shortly after a crisis.

3 Methodology

3.1 Estimation of MES

3.1.1 Bivariate Dynamic Time Series Model

Present essay draws on the MES estimation methodology conceived by Brownlees and Engle (2012), which intrinsically provides forecasts of MES. In the context of present essay, a basic historical simulation as suggested by Acharya et al. (2017), would be an equally sufficient choice. However, modelling MES as subsequently elucidated is considered advantageous since it takes current market conditions into account. Thereby, the obtained MES data better matches the conditions around the reference dates of the EWI- and firm-specific data, which are collected end of period, instead of echoing the events of the whole period.

$$y_{m,t} = \sigma_{m,t}\varepsilon_{m,t} \tag{3.1}$$

where

$y_{m,t}$: *daily market return*

$\sigma_{m,t}$: *conditional standard deviation of daily market returns*

$\varepsilon_{m,t}$: *stochastic shock to market return*

$$y_{i,t} = \sigma_{i,t}\rho_{im,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{im,t}^2}\xi_{i,t} \tag{3.2}$$

where

$y_{i,t}$: *daily stock return*

$\sigma_{i,t}$: *conditional standard deviation of daily stock returns*

$\rho_{im,t}$: *conditional correlation of stock and market returns*

$\xi_{i,t}$: *idiosyncratic stochastic shock to stock return*

Brownlees and Engle's (2012) bivariate process for the daily stock and market returns is shown in (3.1) and (3.2). As can be seen in (3.1), it assumes returns to be zero-mean processes, while it is also noteworthy that this particular representation already anticipates the use of standardised residuals (see Section 3.1.3.1). With henceforth no specified applicable distribution (see Section 3.1.2), the shocks $\varepsilon_{i,t}$ and $\xi_{i,t}$ are assumed to have mean zero and unit variance as well as to be independent and identically distributed over time. Furthermore, they are assumed to have zero covariance but not to be independent of each other. This is an important requirement based on the underlying assumption that for systemically important banks these disturbances are likely to be even further in the tail when the market disturbances are in the tail of the distribution. (3.2) is used to ensure correlated market and firm returns from a likewise unspecified bivariate distribution (Hull, 2015).

$$MES_{t-1}^{i}(C) = -E_{t-1}[y_{i,t}|y_{m,t} < C] \tag{3.3}$$

$$= -\left[\sigma_{i,t}E_{t-1}\left[\rho_{im,t}\varepsilon_{m,t} + \sqrt{1-\rho_{im,t}^{2}}\xi_{i,t}\middle|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right]\right]$$

$$= -\left[\sigma_{i,t}\rho_{im,t}E_{t-1}\left[\varepsilon_{m,t}\middle|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right] + \sigma_{i,t}\sqrt{1-\rho_{im,t}^{2}}E_{t-1}\left[\xi_{i,t}\middle|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right]\right]$$

where

$$C = -VaR_{\alpha}$$

Based on (2.3) as well as the bivariate process in (3.1) and (3.2), a bivariate dynamic time series model for MES can be established as shown in (3.3). C here is a threshold loss seen as a systemically critical event. That is, the value-at-risk for a pre-defined suitable confidence level. Due to $\varepsilon_{i,t}$ and $\xi_{i,t}$ not being independent, $E_{t-1}[\xi_{i,t}|\varepsilon_{m,t} \leq C/\sigma_{m,t}] \neq 0$ so that the obtained model allows for time varying moments as well as tail dependence of the shocks. Implementation of the model requires estimation of

- the time varying conditional return volatilities $\sigma_{i,t}$ and $\sigma_{m,t}$
- the time varying conditional correlation $\rho_{im,t}$
- the time varying tail expectations $E_{t-1}[\varepsilon_{m,t}|\varepsilon_{m,t}<C/\sigma_{m,t}]$ and $E_{t-1}[\xi_{i,t}|\varepsilon_{m,t}<C/\sigma_{m,t}]$

3.1.2 Conditional Return Volatilities

The conditional return volatilities are modelled with a version of Bollerslev's (1986) and Taylor's (1987) Generalised Autoregressive Conditionally Heteroscedastic (GARCH) model, which in turn builds on Engle's (1982) ARCH model. GARCH estimators are in wide-spread use to model the heteroscedasticity in stock returns and provide time varying forecasts of their conditional variance dependent on prior return observations and variance estimations. Incorporating prior data allows this family of models to account for the so-called volatility clustering first discussed by Mandelbrot (1963). This denotes the stylised fact that, notwithstanding the sign, small returns tend to ensue small returns while large returns tend to ensue large returns. One explanation offered for this observation is that the information driving stock price changes tends to emerge in bursts rather than evenly distributed over time (Brooks, 2014).

Present essay follows Brownlees and Engle's (2012) approach in that a GJR GARCH (Glosten, Jagannathan & Runkle, 1993), also referred to as TGARCH (Zoikan, 1994), is employed to model the time varying conditional correlations. This is a GARCH specification enabling capture of the so-called leverage effect. The term addresses the stylised fact that volatility tends to respond asymmetrically to returns, that is, it increases more subsequent to negative than to positive returns. This observation was first discussed by Black (1976) who theorises that the volatility of overall firm value should stay constant. Increases in a firm's debt-to-equity ratio due to a loss in value of its equity will therefore be met by a compensating increase in volatility of the equity. Hence the term "leverage effect". The theory of time varying risk premia is an additional explanation proposed by French, Schwert and Stambaugh (1987). According to this proposition, an unexpected increase in volatility leads to an increase in the expected rate of return (risk premia) and thereby lowers current prices, resulting in a negative current return. An elaboration of this is the volatility feedback theory (Campbell & Hentschel, 1992), according to which news induce volatility, which in turn leads to higher expected returns, decreases in current prices and negative current returns. So as a result of good news, prices will increase but the increase will be dampened by the induced volatility. In case of bad news, however, an already news induced decrease in prices is amplified by the news induced volatility.

$$\sigma^2_{i,t} = \omega_i + \alpha_i y^2_{i,t-1} + \gamma_i e^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \tag{3.4}$$

where

$e_{i,t-1} = min[y_{i,t-1}, 0]$

parameter restrictions

$\omega_i > 0; \alpha_i > 0; \alpha_i + \gamma_i \geq 0; \beta_i \geq 0$

$(\alpha_i + 0.5\gamma_i + \beta_i) < 1$

The GJR GARCH model employed in present essay is specified in (3.4). The conditional variance $\sigma_{i,t}^2$ is required to be strictly positive, which is ensued by the stated parameter restrictions (Brooks, 2014). The term including $e_{i,t}$ induces an increased value for $\sigma_{i,t}^2$ for prior observations of negative returns. The restriction $(\alpha_i+0.5\gamma_i+\beta_i)<1$ ensures stationarity of the estimated series of conditional variances under the assumption that the probability of a negative shock is 0.5 (Brownlees & Engle, 2012).

The non-linear form of GARCH models precludes parameter estimation with the use of Ordinary Least Squares (OLS), which is why Maximum Likelihood (ML) estimation is the method of choice for this type of model. In ML, the parameters are determined in a way that the product of the probability densities in each of the sample's observations, their joint density also referred to as likelihood function L, is maximised. The particular probability density function (pdf) applied in this process is dependent on the assumed distribution of the data. By taking the natural logarithms of the individual pdfs, turning the product into a sum, the process can be simplified and entails maximisation of the so-called log-likelihood function lnL. Since the natural logarithm function is continuous and strictly increasing, the sought-after maximising parameter values are the same for both cases. (Brooks, 2014)

$$\max_{\omega_i,\alpha_i,\gamma_i,\beta_i} \ln L(\omega_i,\alpha_i,\gamma_i,\beta_i) = -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + \ln(\sigma_t^2) + \frac{y_t^2}{\sigma_t^2} \tag{3.5}$$

where

$$\sigma_{i,t}^2 = \omega_i + \alpha_i y_{i,t-1}^2 + \gamma_i e_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

Present essay follows Brownlees and Engle (2012) in that the estimation method is regarded as quasi maximum likelihood (QML) based on the Gaussian pdf as shown in (3.5). The concept of QML is used to express that consistent parameter estimations are obtained without stipulating an assumed distribution for the examined data. Building on White (1982), Gourieroux, Monfort and Trognon (1984) show that if the true distribution of the data can be described by a density function from the linear exponential family, any ML estimation that is based on a pdf from this family will yield consistent alas not efficient parameter estimates, assuming the model itself is correctly specified. All $\sigma_{i,t}$ and $\sigma_{m,t}$ for the MES calculation according to (3.3) are calculated as in-sample one day ahead forecasts.

3.1.3 Dynamic Conditional Correlations

Present essay follows Brownlees and Engle (2012), in estimating the time varying correlations as part of applying Engle's (2002) Dynamic Conditional Correlation (DCC) GARCH methodology. The DCC GARCH (Engle (2002), Engle & Sheppard (2001)) belongs to the multivariate category of GARCH estimators, the purpose of which is to model conditional covariances of assets in addition to their conditional variances. It is based on the principle of decomposing the conditional covariance matrix into conditional variances and correlations (see (3.6), (3.7)), first utilised by Bollerslev (1990) in the Constant Conditional Correlation (CCC) GARCH. The DCC model, however, makes use of a time varying conditional correlation matrix R_t whereas a time-invariant conditional correlation matrix R is utilised in the CCC model.

$$\sigma_{ip,t} = \sigma_{i,t}\rho_{im,t}\sigma_{m,t} \tag{3.6}$$

$$H_t = D_t R_t D_t \tag{3.7}$$

where

$$H_t = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{im,t} \\ \sigma_{im,t} & \sigma_{m,t}^2 \end{bmatrix}$$

$$D_t = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{m,t} \end{bmatrix} = diag(\sqrt{H_t})$$

$$R_t = \begin{bmatrix} 1 & \rho_{im,t} \\ \rho_{im,t} & 1 \end{bmatrix}$$

H_t for N assets is an N×N matrix with the individual assets' time varying conditional variances on the main diagonal and their respective time varying conditional covariances above and below the main diagonal. D_t is a diagonal N×N matrix with the time varying conditional standard deviations of the examined assets on the main diagonal. R_t is thus an N×N matrix with ones on the main diagonal and time varying correlations of the assets elsewhere. As the applications in this essay are confined to bivariate cases of a stock i and the market portfolio m, which is here treated as second asset, equations are expressed in the less general, bivariate case. Furthermore, all stated equations are applicable to the case m=i, too, where individual stocks' variances or correlations with themselves are determined. Present essay by and large follows a comprehensive and comprehensible description of the three main procedures inherent to DCC GARCH estimation provided by Engle (2009). This description is recapitulated in the following while highlighting any deviations.

3.1.3.1 DE-GARCHING

The DCC model builds on the principle that the correlation of the returns y_t is equal to the covariance of the volatility adjusted returns ε_t, also referred to as standardised residuals, as shown in (3.8).

$$Cov_{t-1}[\varepsilon_{i,t}, \varepsilon_{m,t}] = Cov_{t-1}\left[\frac{y_{i,t}}{\sigma_{i,t}}, \frac{y_{m,t}}{\sigma_{m,t}}\right] = \frac{Cov_{t-1}[y_{i,t}, y_{m,t}]}{\sigma_{i,t}\sigma_{m,t}} = \frac{\sigma_{im,t}}{\sigma_{i,t}\sigma_{m,t}} = \rho_{im,t} \tag{3.8}$$

The first procedure of Engle's (2009) estimation routine is the DE-GARCHING of asset returns. Here, the conditional standard deviations σ_t of the returns are estimated for each asset separately, which is equivalent to estimating D_t or the square root of the diagonal elements of H_t, respectively. These time series of conditional variances are then used to obtain time series of standardised (i.e., DE-GARCHED) residuals $\varepsilon_t = y_t/\sigma_t$ for each of the assets. These in turn are used to estimate the conditional correlations of the demeaned returns in the subsequent second procedure. While there are multiple potential ways to determine the conditional standard deviations, the method propounded by Engle (2009) is to use an asymmetric GARCH model such as the one described in Section 3.1.2 and take the square root of the obtained conditional variances. In fact, there is no reason to use different GARCH models in the estimation of the return volatilities for Brownlees and Engle's (2012) MES determination and the DE-GARCHING in the DCC model determination. Therefore, the conditional variances σ_t obtained from the GJR GARCH model described in Section 3.1.2 are reutilised here.

3.1.3.2 Quasi-Correlations

In the second procedure, a stochastic process is used to model the time varying conditional variances and covariances of the standardised residuals $\varepsilon_{i,t}$, which corresponds to modelling the conditional correlations of the returns $y_{i,t}$ as seen above. This approach in itself does not ensure a proper correlation matrix R_t, however, where all the diagonal elements, which concern the correlations of assets with themselves, are equal to 1. For this reason, a further rescaling of the modelled conditional correlations is required, which is performed in the third procedure. The conditional correlations obtained in the second procedure are therefore referred to as the quasi-correlations $q_{im,t}$ of the demeaned returns, which form the elements of the quasi-correlation matrix Q_t. Engle (2009) suggests using one of three GARCH-type models to obtain the conditional quasi-correlations. These are the integrated and mean-reverting models introduced in Engle's (2002) original article, as well as the asymmetric DCC (ADCC) model introduced by Cappiello, Engle and Sheppard (2006).

Contrary to Brownlees and Engle (2012), where a symmetric specification is chosen, present essay deploys an asymmetric DCC GARCH. This specification recognises the stylised fact that, similar to variances, correlations increase more in response to negative than to positive market developments. An observation made by Cappiello, Engle and Sheppard (2006) or Sandoval Jr. and De Paula (2012), among others. One explanation for this observation proffered by Cappiello, Engle and Sheppard (2006) relies on the volatility feedback theory in that negative systemic shocks will depress current returns and increase volatility for any pair of stocks. In a CAPM world, assuming their betas do not change, their covariance increases together with their idiosyncratic variances. Given their individual variances do not increase proportionally this will lead to higher correlations.

$$q_{im,t} = w_i + a\varepsilon_{i,t-1}\varepsilon_{m,t-1} + c\eta_{i,t-1}\eta_{m,t-1} + bq_{im,t-1} \tag{3.9}$$

where

$$\varepsilon_{t-1} = \frac{y_{t-1}}{\sigma_{t-1}}$$

$$\eta_{i,t-1} = min[\varepsilon_{i,t-1}, 0]$$

$$Q_t = W + a\varepsilon_{t-1}\varepsilon'_{t-1} + c\eta_{t-1}\eta'_{t-1} + bQ_{t-1} \tag{3.10}$$

where

$$\varepsilon_{t-1} = \begin{pmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{m,t-1} \end{pmatrix}$$

$$\eta_{t-1} = \begin{pmatrix} \eta_{i,t-1} \\ \eta_{m,t-1} \end{pmatrix}$$

parameter restrictions

$$W > 0; a > 0; a + c \geq 0; b \geq 0$$

$$(a + 0.5c + b) < 1$$

The basic form of the estimator for the quasi-correlations deployed in present essay is stated in (3.9) and (3.10) in its element and matrix forms, respectively. As can be seen, this specification yields the plausible results of higher correlations during periods when stock and market returns move in the same direction, notwithstanding which direction that is. Furthermore, the elements in η_{t-1} are non-zero only when stock and market returns are simultaneously negative, which entails the desired property of yielding correlations that increase more in response to negative than to positive market- and stock return developments. The stated parameter restrictions ensure stationarity of the estimator as well as a positive definite quasi-correlation matrix Q_t, which is required for a positive definite R_t and in turn H_t. The estimator in (3.10) is analogous in form to a scalar diagonal vector GARCH, which means a, c and b are scalars and each requires only one parameter estimate for any number of assets. The intercept matrix, however, requires N/2*(N-1) parameter estimates, where N is the number of assets involved. In DCC GARCH estimations involving a large number of assets, this can constitute a considerable computational burden. For this reason, Engle (2009) suggests to estimate a preliminary form $\hat{W}$ of the intercept in an intermediate step. A method that is emulated in Brownlees and Engle (2012).

$$\widehat{W} = (1 - a - b)\overline{R} - c\bar{N} \tag{3.11}$$

where

$$\overline{R} \equiv \frac{1}{T}\sum\nolimits_{t=1}^{T} \varepsilon_t \varepsilon_t'$$

$$\bar{N} \equiv \frac{1}{T}\sum\nolimits_{t=1}^{T} \eta_t \eta_t'$$

parameter restrictions

$$(1 - a - b - c) > 0$$

Under the assumption of stationarity, the estimator's unconditional variance can be proxied by the sample variance. For the asymmetric case at hand, this leads to the relationship expressed in (3.11), where the estimate for the intercept is expressed dependent on the unconditional covariance matrices of $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$ as well as $\eta_{i,t}$ and $\eta_{m,t}$. The stated parameter restrictions are the requirement for $\hat{W}$, and with it Q_t, to result positive definite. Substituting $\hat{W}$ for W in (3.10) provides (3.12), which is the final form of the estimator for the quasi-correlation matrix applied in present essay.

$$Q_t = \overline{R} + a(\varepsilon_{t-1}\varepsilon_{t-1}' - \overline{R}) + c(\eta_{t-1}\eta_{t-1}' - \bar{N}) + b(Q_{t-1} - \overline{R}) \tag{3.12}$$

Due to the parameter restrictions inherent in (3.11), the unconditional variance for (3.12) results equal to the sample variance, which is why this approach is referred to as variance targeting or in this case correlation targeting, respectively. This substitution leaves only the parameters a, c and b to be estimated but, while still consistent, comes with a loss of efficiency since it is built an approximation of the intercept. That said, Brownlees and Engle (2012) do not provide a rationale for implementing correlation targeting in this bivariate case where estimation of only one intercept parameter is required as is. Nonetheless, present essay follows their standard in this regard.

3.1.3.3 Rescaling

As stated above, the process for Q_t does not ensure a proper conditional correlation matrix R_t where all the diagonal elements, which concern the correlations of assets with themselves, are equal to 1. These elements are in fact the conditional variances of the standardised residuals and, since these are volatility adjusted, their unconditional variance results equal to 1. However, while this means their time average is 1, the same cannot be realised for the individual estimates at each point in time.

$$\rho_{im,t} = \frac{q_{im,t}}{\sqrt{q_{ii,t}q_{mm,t}}} \tag{3.13}$$

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{3.14}$$

Equations (3.13) and (3.14) show the rescaling process suggested by Engle (2009) and applied by Brownlees and Engle (2012) in its element and matrix forms. Here, diag(Q_t) is a diagonal matrix that carries only the elements of the main diagonal of Q_t.

3.1.3.4 Estimation

In general, the parameter estimates for a DCC or ADCC GARCH can be obtained by maximising the log-likelihood function lnL in (3.15). Given knowledge of the adequate distribution and a correctly specified model, maximising the function as a whole and estimating each parameter simultaneously is referred to as full ML estimation. This is a demanding task from a computational standpoint, however. In practice, as in present essay, the so-called two-step or three-step estimations are therefore commonly applied.

$$\max_{\theta,\varphi} \ln L(\theta,\varphi) = -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + \ln(|H_t|) + y_t' H_t^{-1} y_t \tag{3.15}$$

$$= -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + \ln(|D_t R_t D_t|) + y_t' D_t^{-1} R_t^{-1} D_t^{-1} y_t$$

$$= -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + 2\ln(|D_t|) + \ln(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t$$

$$= -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + 2\ln(|D_t|) + y_t' D_t^{-2} y_t - \varepsilon_t'\varepsilon_t + \ln(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t$$

As shown in the bottom line of (3.15), lnL can be partitioned in two segments. Here, the first three terms contain the conditional variance parameters and the original data while the last three terms contain the conditional correlation parameters and the volatility-adjusted data. Both parts are displayed individually in equations (3.16) and (3.17).

$$\max_{\theta} \ln L_v(\theta) = -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(2\pi) + 2\ln(|D_t|) + y_t' D_t^{-2} y_t \tag{3.16}$$

where

$\theta = (\omega_i, \alpha_i, \gamma_i, \beta_i)$

The first step of a two-step estimation entails maximisation of (3.16), which corresponds to estimating GARCH models (see (3.4)) for each asset independently, and retrieving estimates for the conditional return volatilities ensued by the calculation of the standardised residuals. In the second step, these standardised residuals are employed in maximisation of (3.17), which is equivalent to modelling and rescaling the conditional quasi-correlations (see (3.12) as well as (3.13) or (3.14), respectively). Besides that, the three-step estimation, which is employed in present essay, includes an interim step consisting in above-mentioned calculation of the unconditional correlation matrices of the standardised residuals in order to substitute the intercept matrix W.

$$\max_{\varphi} \ln L_c\left(\hat{\theta},\varphi\right) = -\frac{1}{2}\sum\nolimits_{t=1}^{T} \ln(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t'\varepsilon_t \tag{3.17}$$

where

$\varphi = (W, a, c, b)$

Maximising lnL in two parts, although still yielding consistent parameter estimates, leads to a loss in efficiency. This makes this the method a QML estimation by construction, as does using a likelihood function based on the Gaussian pdf while not making assumptions about the actual distribution. The time varying correlations $\rho_{im,t}$ for application in (3.3) are calculated as in-sample one day ahead forecasts.

3.1.4 Tail Expectations

The basic way to estimate the conditional tail expectations in (3.3) would be to take the average of the observed $\varepsilon_{m,t}$ and $\xi_{i,t}$ in the cases that satisfy $\varepsilon_{m,t}<C/\sigma_{m,t}$. Given the expectedly low quantity of the sought after large values for $|C/\sigma_{m,t}|$, changes to the underlying sample of such an estimator may lead to heavy fluctuations in the obtained results. Brownlees and Engle (2012) for this reason resort to a nonparametric estimator based on kernel smoothing, which is more stable.

$$\hat{p}_T(u) = \frac{1}{Th}\sum\nolimits_{t=1}^{T} k\left(\frac{u-\varepsilon_{m,t}}{h}\right) \tag{3.18}$$

where

T: *sample size*

h: *bandwidth*

$k(.)$: *kernel function*

In kernel smoothing, an estimate of the probability density function $\hat{p}_T(u)$ of a sample with unknown distribution is constructed based on a kernel function as shown in (3.18). The size of the bandwidth h determines the intensity of smoothing, with a larger h resulting in smoother, more obscured functions of the underlying data. A smaller h in turn leads to less smoothened densities closely resembling the original sample's empirical density.

$$E_{t-1}[\varepsilon_{m,t}|\varepsilon_{m,t} < c] = \int_{-\infty}^{c} \varepsilon_{m,t} f(u|u<c)du \tag{3.19}$$

where

$c = \dfrac{C}{\sigma_{m,t}}$

$C = VaR_\alpha$

$f(u|u<c)$: *conditional density function*

The initial concept for Brownlees and Engle's (2012) estimation approach was first discussed in Scaillet (2005) and is explicated quite comprehensively in Banulescu and Dumitrescu (2015). The tail expectation for the standardised residual of the market $\varepsilon_{m,t}$ conditional on $\varepsilon_{m,t}<c$ is expressed in (3.19).

$$f(u|u<c) = \frac{f(u)}{\Pr(u<c)} = \frac{f(u)}{F(c)} \tag{3.20}$$

where

$f(u)$: *probability density function*

$\Pr(u<c)$: *cumulative distribution function in point* c, *i.e.* $F(c)$

The conditional density function $f(u|u<c)$ in turn can be restated as in (3.20).

$$E_{t-1}[\varepsilon_{m,t}|\varepsilon_{m,t}<c] = \frac{\int_{-\infty}^{c} \varepsilon_{m,t} f(u)du}{F(c)} = \frac{\int_{-\infty}^{c} \varepsilon_{m,t} f(u)du}{\int_{-\infty}^{c} f(u)du} \tag{3.21}$$

Restating (3.19) with the expression shown in (3.20) gives (3.21).

$$\hat{E}_{t-1}[\varepsilon_{m,t}|\varepsilon_{m,t}<c] = \frac{\sum_{t=1}^{T} \varepsilon_{m,t} K\left(\frac{c-\varepsilon_{m,t}}{h}\right)}{\sum_{t=1}^{T} K\left(\frac{c-\varepsilon_{m,t}}{h}\right)} \tag{3.22}$$

$$\hat{E}_{t-1}[\xi_{i,t}|\varepsilon_{m,t}<c] = \frac{\sum_{t=1}^{T} \xi_{i,t} K\left(\frac{c-\varepsilon_{m,t}}{h}\right)}{\sum_{t=1}^{T} K\left(\frac{c-\varepsilon_{m,t}}{h}\right)} \tag{3.23}$$

where

$K(.)$: *cumulative distribution function*

Proxying the probability density function $f(u)$ with $\hat{p}_T(u)$ from (3.18) while integrating numerator and denominator gives the final estimators for the conditional tail expectations as shown in (3.22) and (3.23). In accordance with Brownlees and Engle's (2012) procedure, the Gaussian cdf is applied for $K(.)$ in present essay.

$$h = 0.9\sigma_m T^{-0.2} \tag{3.24}$$

The bandwidth h is determined as shown in (3.24) which is the optimal approach for the Gaussian cdf according to Silverman (1986). All tail expectations are calculated backwards looking on a daily basis with an initial sample of 100 trading days prior to 1st January 2004. The critical market loss threshold C is set to $VaR_{0.95}$ of the respective underlying sample in accordance with Brownlees and Engle's (2012) approach.

3.2 Determination of BIS Early Warning Indicators

3.2.1 Credit-to-GDP Gap

The credit-to-GDP gap (cgdpg) as measured by the BIS is the difference between the credit-to-GDP ratio and its long-term trend. The ratio itself, in turn, is the proportion of aggregate credit to the private non-financial sector to GDP (Drehmann & Juselius, 2014).

$$\min_{\{z_t\}_{t=1}^{T}} \left\{ \sum\nolimits_{t=1}^{T} (d_t - z_t)^2 + \lambda \sum\nolimits_{t=1}^{T} [(z_t - z_{t-1}) - (z_{t-1} - z_{t-2})]^2 \right\} \tag{3.25}$$

where

d_t: *quarterly data series*

z_t: *quarterly trend series*

The detrending is necessary to account for benign and instead highlight excessive increases of the ratio. The applicable trend series is determined via a one-sided Hodrick-Prescott (HP) filter (Hodrick & Prescott, 1997). With their filter, the trend series is obtained by minimising a loss function, the general form of which is shown in (3.25). According to their approach, a data series d_t can be segmented into two components, the trend z_t and the cyclical part (d_t-z_t). The depicted loss function penalises the variance of the cyclical part in its first term as well as the lack of the trend's smoothness in its second term, where the smoothness is controlled by the parameter λ. This results in a trade-off between the trend's smoothness and its fit to the original data series. Hodrick and Prescott (1997) suggest λ=1,600 for quarterly data, which corresponds to an underlying business cycle length of approximately 7.5 years. Present essay, however, follows Drehmann et al.'s (2010) approach in using λ=400,000, which corresponds to their assumption of the length of the credit cycle being approximately four times longer. One-sided in this context means that the filter is applied backward-looking so that the gap is calculated at each point in time based on a trend that only takes into account the observations up to that point. This is done by Drehmann & Juselius (2014) in order to evaluate the predictive capabilities of the credit-to-GDP gaps. Although in present essay this indicator could as well be calculated based on information exceeding a given point in time, benefitting from extended information for calculation of the trend, the backward-looking approach is applied as well. This is since MES is a market-based indicator that relies on the information available to market participants at a given point in time. Calculating it for past points in time based on information unavailable to market participants back then is therefore not representative. Granting this information advantage in the calculation of the EWIs would therefore be inconsistent.

In the context of present essay, the credit-to-GDP gap series for the US, determined in above-mentioned fashion and starting Q1 1962, is retrieved directly from the BIS' statistics database as quarterly data series, stated in percent. However, since the gap series are available only from the point in time when at least ten years of prior credit-to-GDP ratio data is available as a basis for the first trend estimate, the gap series for the Eurozone only starts in Q1 2009. For the purposes of present essay, therefore, this particular gap series is recalculated manually based on the existing credit-to-GDP ratio data, starting with a data basis for the first trend estimate of only five years. This results in a credit-to-GDP gap series for the Eurozone starting with the first quarter of 2004.

3.2.2 Debt Service Ratio Gap

The debt service ratio gap (dsrg) as measured by the BIS is the difference between the debt service ratio and its 15-year rolling average (Drehmann & Juselius, 2012). The ratio itself is calculated as the aggregate credit to the private non-financial sector divided by its aggregate income (Drehmann & Juselius, 2014). The demeaning is performed to identify deviations from the debt service ratio's long-run stable mean and to allow for cross-country comparisons. It is realised in reference to the online appendix of Aldasoro, Borio & Drehmann (2018) in such a way that the average of all the first 60 observations of the respective data series is used in the gap calculation for these first 60 observations. Only afterwards, an actually moving window of observations is used for the mean calculation.

In the context of present essay, the debt service ratio for the US is retrieved directly from the BIS' statistics database as quarterly data series, stated in percent. Since this database does not include a debt service ratio series for the Eurozone, a proxy is created that contains the weighted average of individual debt service ratios for all available member states of the Eurozone. These are Belgium, Finland, France, Germany, Italy, the Netherlands, Portugal and Spain. The weighting is performed according to quarterly GDP data retrieved from the database of the Federal Reserve Bank of St. Louis. The calculation of the debt service ratio gaps, that is, the demeaning of these series, is performed as described above.

3.2.3 Property Price Gap

The property price gap (ppg) as measured by the BIS is the difference between the real residential property price and its long-run trend (Drehmann & Juselius, 2014). The detrending is performed in order to highlight price increases that considerably outpace the long-run trend and likely indicate asset price bubbles of systemic scope. The applicable trend series is determined via a one-sided HP filter with a smoothing parameter λ=400,000, analogous to the procedure described in Section 3.2.1.

Here, no trend or gap series are provided directly in the BIS' statistics database. Therefore, real residential property prices, stated in percent based on the 2010 absolute value, are retrieved and the calculation of the gap series is performed manually as described in Section 3.2.1. Each trend series used in determination of the ppg series is based on at least ten years of prior data.

3.3 Regression Analysis

3.3.1 Data Properties

The daily stock returns used in calculation of the MES time series for each bank are calculated based on stock price data obtained from Datastream. Namely the proprietary data series F:BNP(P), D:DBK(P), F:CRDA(P), H:INGA(P), E:SAN(P), F:SGE(P) and I:UCG(P) for the Eurozone banks as well as U:BAC(P), U:BK(P), U:C(P), U:GS(P), U:JPM(P), U:MS(P), U:STT(P) and U:WFC(P) for the US banks. The market returns required for the MES calculations are proxied based on the STOXX Europe 600 index for the Eurozone banks and the S&P 500 Composite index for the US banks, with the corresponding Datastream series being DJSTOXX(PI) and S&PCOMP(PI), respectively. As described above, the MES series are calculated in daily frequency at first (see Appendix A for plots of these series). For application in the subsequent regressions, these series are then translated into quarterly frequency by retaining only the last observation of each quarter. This is done, contrary to for instance taking an average of each quarter, in order to match the collection mechanism of the EWI data, which is declared to be end-of-period in the data carrying spreadsheet files available for download on the BIS website.

The EWI data or the base data for their calculation, respectively, is retrieved from the BIS website (see Appendix A for plots of each series). The data series are set up by the BIS in quarterly frequency, which is why the remaining data series for the regressions are either translated to or collected in quarterly frequency as well. As described in Section 3.2.1, the Eurozone credit-to-GDP gap series can only be initiated in Q1 2004, since otherwise the amount of base data for the trend estimation is insufficient. Furthermore, at the time of writing, the data available on the BIS website ranges until Q3 2017 the latest, which is why these two points in time define the sample period examined in the regressions. Data for the bank specific variables is retrieved from Datastream as well, where the proprietary series MTBV, WC02999A and WC08231A provide quarterly values for the banks' market-to-book value ratio, total assets and leverage, respectively.

Appendix B provides descriptive statistics of each data series except the Eurozone bank specific variables. Furthermore, it provides the results of their stationarity assessments via confirmatory data analysis, that is, a combination of Augmented Dickey-Fuller (ADF) and Kwaitkowski-Phillips-Schmidt-Shin (KPSS) (1992) stationarity tests, using the EViews default settings. As can be seen, the combined tests predominantly imply stationarity for the MES series and their first differences with only very few ambiguous cases. For the EWI and bank specific variables series, the combined tests mainly imply non-stationarity. Regarding the EWI series, first differencing largely yields ambiguous but no outright non-stationary series. In terms of the bank specific variables, first differencing largely yields stationary series with only few ambiguous and no outright non-stationary cases left. Thus, for both, the EWI and bank specific variable series, a distinct shift away from distinct non-stationarity can be observed, with no outright non-stationary series resulting from the differencing. Henceforth, it is therefore assumed that the ambiguous first difference series are in fact stationary and the ambiguousness is owed to the small amount of underlying base data (Brooks, 2014). The subsequent regressions are performed on the first difference series. Unfortunately, the Eurozone bank specific variable series are rather incomplete compared to those of the US banks, with their first differencing of course yielding even more incomplete series. These are unfit for utilisation in the corresponding regression, which is therefore performed only on the US data. Furthermore, Appendix B provides correlation matrices for the first differences of the independent variable series used in the subsequent regressions, where in two cases the absolute value of correlation is slightly greater than 0.8. Due to the only minor exceedance, however, multicollinearity, which impairs significance testing of the regression parameter estimates, is not considered an issue here.

3.3.2 Regression Designs

Applicability of OLS as Best Linear Unbiased Estimator (BLUE) for the performed linear regressions requires the error terms u_i to conform to five particular assumptions. The first is for them to have zero mean, since otherwise biased slope parameters will be estimated. This is realised by including a constant term α_i in the regression specifications (Brooks, 2014). The second and third assumptions are for the u_i to have constant variance and not to be autocorrelated, respectively, which otherwise leads to inefficient parameter estimates and unreliable significance tests. The necessity of compliance with these assumptions is avoided by using Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors (Brooks, 2014). The fourth assumption is for the independent variables and the u_i to be uncorrelated, since otherwise the parameter estimates will result inconsistent. One way to ensure conformity with this requirement is to perform an instrumental variable based Two-Stage Least Squares regression. In the context of present essay, however, the independent variables are considered to be exogenous so that this is not deemed necessary. The fifth assumption is for the u_i to be normally distributed, a cornerstone the parameter significance tests are built upon and a requirement for them to produce reliable results. Here it is referred to the central limit theorem in that the sample size is considered sufficient for the test statistics to asymptotically follow the appropriate distributions (Brooks, 2014).

Furthermore, as was noted in the previous section, the EWI and bank specific variable series seem to be non-stationary data, which demands further consideration. Since the dependent MES variable series seem to be stationary per se, regressing them on the non-stationary series should not result in spurious regressions (Brooks, 2014). However, the parameter significance tests' reliability might still be impaired (Brooks, 2014). Therefore, the independent variables' first differences are employed in the regressions, which are considered to be stationary (see Section 3.3.1). To aid interpretability, the first differences of the MES series are used likewise, so that changes in the independent variables explain changes in MES, as opposed to magnitude of MES.

$$\begin{aligned}\Delta MES_{i,t} = \alpha_i &+ \beta_{cgdpg,i}\Delta cgdpg_{j,t} + \beta_{dsrg,i}\Delta dsrg_{j,t} + \beta_{ppg,i}\Delta ppg_{j,t} \\ &+ \beta_{cgdpg\_d,i} I_t \Delta cgdpg_{j,t} + \beta_{dsrg\_d,i} I_t \Delta dsrg_{j,t} \\ &+ \beta_{ppg\_d,i} I_t \Delta ppg_{j,t} + u_{i,t}\end{aligned} \tag{3.26}$$

$$\begin{aligned}\Delta MES_{i,t} = \alpha_i &+ \beta_{mbv,i}\Delta mbv_{i,t} + \beta_{lnta,i}\Delta lnta_{i,t} + \beta_{lev,i}\Delta lev_{i,t} \\ &+ \beta_{mbv\_d,i} I_t \Delta mbv_{i,t} + \beta_{lnta\_d,i} I_t \Delta lnta_{i,t} + \beta_{lev\_d,i} I_t \Delta lev_{i,t} \\ &+ u_{i,t}\end{aligned} \tag{3.27}$$

$where$

Δ: $indicates\ first\ difference, i.e.\ variable_t - variable_{t-1}$

$j = EU, US$

$$I_t = \begin{cases} 0 & prior\ to\ Q1\ 2013 \\ 1 & starting\ Q1\ 2013 \end{cases}$$

(3.26) and (3.27) show the specifications for the regressions of the banks' MES first differences on the regional EWI first differences and the bank specific variable first differences, respectively. While (3.26) is performed for Eurozone and US banks, (3.27) is performed for US banks only, due to insufficient data for the Eurozone banks. The dummy terms that include the indicator function I_t are designed to capture the change in parameters that took place subsequent to the crisis. Here, the parameters $\beta_{variable}$ of the original terms provide information about the relation and sensitivity of MES to the independent variables before and during the crisis. The sums of these parameters and their counterparts from the dummy terms $\beta_{variable}+\beta_{variable\_d}$ provide information about the relation of MES to the independent variables after the crisis. Given an unfavourable, that is, amplifying, effect of an independent variable on a bank's systemic riskiness, $\beta_{variable}$ results positive. In case of a bank's systemic riskiness having improved post-crisis, the dummy parameter $\beta_{variable\_d}$ should therefore result significant and with negative sign. That is, for all EWIs and bank specific variables except mbv, where a higher value is considered tantamount to less systemic riskiness. The point in time used in the indicator function I_t that signifies the beginning of the post-crisis period is determined via optical evaluation of the MES plots provided in Appendix A. Especially the Eurozone banks' MES stay noticeably tumultuous during the years following the 2007/2008 Global Financial Crisis due to the beginning European Debt Crisis. Ultimately, Q1 2013 is seen as a point in time when things had calmed enough for potential improvements to subsequently be reflected in the data.

4 Findings

4.1 Presentation and Interpretation

Table 1: Results of regression (3.26) with Eurozone bank data.

EU	intercept	cgdpg	cgdpg_d	dsrg	dsrg_d	ppg	ppg_d
BNP Paribas (bnp)	-0,0008	-0,0022	0,0069	0,0561 ***	-0,1788 **	0,0029	-0,0143
	(0,7637)	(0,4422)	(0,3308)	(0,0076)	(0,0475)	(0,4118)	(0,1081)
Deutsche Bank (dbk)	-0,0021	-0,0031	0,0047	0,0531 ***	-0,1113 ***	0,0015	-0,0023
	(0,2843)	(0,1929)	(0,2132)	(0,0061)	(0,0096)	(0,5677)	(0,5459)
Credit Agricole (gca)	0,0005	0,0003	0,0027	0,0558 **	-0,1215 *	0,0048	-0,0120 *
	(0,8652)	(0,9163)	(0,6267)	(0,0183)	(0,0701)	(0,1938)	(0,0799)
ING (ing)	0,0004	-0,0003	0,0058	0,0679 *	-0,1800 *	0,0076	-0,0186
	(0,9292)	(0,9496)	(0,5052)	(0,0505)	(0,0861)	(0,2570)	(0,1109)
Banco Santander (san)	-0,0009	-0,0002	0,0055	0,0364 **	-0,1981 *	0,0018	-0,0168 *
	(0,6976)	(0,9415)	(0,4943)	(0,0121)	(0,0681)	(0,5604)	(0,0833)
Societe Generale (sge)	0,0002	-0,0023	0,0074	0,0631 **	-0,1807	0,0061	-0,0176
	(0,9536)	(0,5629)	(0,4007)	(0,0321)	(0,1048)	(0,1448)	(0,1043)
Unicredit (uni)	0,0003	-0,0003	0,0051	0,0574 **	-0,1892 *	0,0042	-0,0190 *
	(0,9068)	(0,9332)	(0,5520)	(0,0125)	(0,0899)	(0,1290)	(0,0799)

p-values in parentheses *** significant at 1% level ** significant at 5% level * significant at 10% level

The results of the regressions specified in (3.26), involving EWIs, for the Eurozone banks are compiled in Table 1. First, it can be seen that the estimated intercept terms are insignificant throughout at quite high p-values. The parameter estimates for the credit-to-GDP ratio gap are predominantly negative with only one exception. This implies negative changes in systemic riskiness in response to positive changes in systemic distress for most of the examined banks before and during the crisis. The corresponding dummy term parameter estimates are positive throughout, indicating increased exposure to accumulating systemic distress post-crisis. The sums of the estimated parameters for original and dummy term are positive, which implies a shift from favourable to unfavourable reaction to increases in systemic distress post-crisis for these banks. However, these estimates are insignificant at quite high p-values for both, the original and the dummy term. The parameter estimates for the debt service ratio gap are positive throughout, implying increases of systemic riskiness with increases of systemic distress for the examined banks before and during the crisis. The corresponding dummy term parameter estimates are negative throughout, indicating reduced exposure to accumulating systemic distress post-crisis. Their sums, however, result negative throughout, implying a shift from unfavourable to favourable reaction to increases in systemic distress post-crisis. What is more, the estimates are significant at the 10% level or below for both, the original and the dummy term, with only one exception where the p-value is only slightly above the 10% mark. The parameter estimates for the property price gap and the corresponding dummy term result confirmative of the implications in context of the debt service ratio gap, implying exactly the same behaviours. However, only a few of the dummy term parameter estimates are statistically significant in this case.

Table 2: Results of regression (3.26) with US bank data.

US	intercept	cgdpg	cgdpg_d	dsrg	dsrg_d	ppg	ppg_d
Bank of America (boa)	-0,0001	0,0054	-0,0085	-0,0415	0,0623	-0,0024 *	0,0015
	(0,9857)	(0,5341)	(0,4932)	(0,4034)	(0,1583)	(0,0544)	(0,6081)
Bank of N.Y.M. (bny)	0,0050	0,0149	-0,0170	-0,0598	0,0480	-0,0023	-0,0010
	(0,4534)	(0,3671)	(0,4057)	(0,4030)	(0,4455)	(0,1569)	(0,7310)
Citigroup (ctg)	-0,0001	0,0040	-0,0050	-0,0308	0,0269	-0,0021 **	0,0014
	(0,9819)	(0,5364)	(0,6331)	(0,3952)	(0,4413)	(0,0357)	(0,6599)
Goldman Sachs (gms)	0,0009	0,0036	-0,0068	-0,0136	0,0217	-0,0010	0,0004
	(0,7784)	(0,4860)	(0,3264)	(0,6051)	(0,3502)	(0,1176)	(0,7903)
J.P. Morgan (jpm)	0,0012	0,0076	-0,0087	-0,0427	0,0404	-0,0021 *	0,0008
	(0,8119)	(0,4013)	(0,4659)	(0,3432)	(0,3419)	(0,0521)	(0,7351)
Morgan Stanley (mgs)	0,0013	0,0059	-0,0094	-0,0268	0,0336	-0,0018 *	0,0006
	(0,7829)	(0,5024)	(0,4321)	(0,5062)	(0,3879)	(0,0672)	(0,8307)
State Street (sts)	0,0014	0,0081	-0,0098	-0,0413	0,0363	-0,0020 *	0,0012
	(0,7884)	(0,4331)	(0,4643)	(0,4277)	(0,4291)	(0,0797)	(0,6248)
Wells Fargo (wfg)	-0,0009	0,0027	-0,0024	-0,0252	0,0324	-0,0019 **	0,0015
	(0,8521)	(0,6264)	(0,7528)	(0,4421)	(0,2905)	(0,0290)	(0,5517)

p-values in parentheses *** significant at 1% level ** significant at 5% level * significant at 10% level

The results of the regressions specified in (3.26), involving EWIs, for the US banks are compiled in Table 2. Here, again, the estimated intercept terms are insignificant throughout at quite high p-values. The parameter estimates for the credit-to-GDP ratio gap and corresponding dummy term imply increasing systemic risk with increasing systemic distress before and during the crisis as well as a reduction of this exposure after the crisis. Combined, however, they also imply a shift from unfavourable to favourable exposure post-crisis in all but one case. That said, exhibiting rather high p-values these estimates are not significant. The parameter estimates for the debt service ratio gap and corresponding dummy term imply decreasing systemic risk with increasing systemic distress before and during the crisis as well as increased exposure to systemic distress after the crisis. Here, only for some of the banks a shift from favourable to unfavourable exposure is implied post-crisis. Again, however, these estimates are not significant. The parameter estimates for the property price gap and corresponding dummy term, too, imply decreasing systemic risk with increasing systemic distress before and during the crisis as well as increased exposure to systemic distress after the crisis in all but one case. Here, for no bank a shift from favourable to unfavourable exposure is implied post-crisis. While the original term parameters are mostly significant or at least close to significance, the dummy term parameters, that is, the changes in exposure, are not.

Table 3: Results of regression (3.27) with US bank data.

US	intercept	mbv	mbv_d	lnta	lnta_d	lev	lev_d
Bank of America (boa)	-0,0041	-0,0321 *	0,0576 **	0,2109 ***	-0,0187	0,0002 *	-0,0004
	(0,2407)	(0,0568)	(0,0170)	(0,0004)	(0,9031)	(0,0993)	(0,3694)
Bank of N.Y.M. (bny)	-0,0052 *	-0,0182	0,0788 **	0,1768 **	-0,2179 **	0,0009 *	-0,0015 *
	(0,0751)	(0,2847)	(0,0316)	(0,0199)	(0,0333)	(0,0580)	(0,0803)
Citigroup (ctg)	0,0009	0,0124	0,0217	-0,1737 **	0,4116 **	0,0001 **	-0,0008
	(0,7538)	(0,4049)	(0,4884)	(0,0434)	(0,0188)	(0,0451)	(0,1338)
Goldman Sachs (gms)	-0,0024	-0,0199 **	0,0292 **	0,1194 ***	0,0650	0,0000	0,0000
	(0,1339)	(0,0402)	(0,0200)	(0,0060)	(0,4813)	(0,4644)	(0,1045)
J.P. Morgan (jpm)	-0,0060 **	-0,1019 ***	0,1631 ***	0,2564 ***	-0,1617	0,0001	-0,0002
	(0,0408)	(0,0021)	(0,0003)	(0,0043)	(0,1725)	(0,6142)	(0,1456)
Morgan Stanley (mgs)	-0,0019	-0,0100	0,0174	0,0842	0,2616	0,0000	-0,0002
	(0,5182)	(0,4098)	(0,3455)	(0,1293)	(0,2387)	(0,2560)	(0,1744)
State Street (sts)	-0,0012	-0,0249	0,0208	0,0667 **	-0,0782 *	0,0001 **	0,0003
	(0,6024)	(0,1789)	(0,3938)	(0,0154)	(0,0882)	(0,0137)	(0,2405)
Wells Fargo (wfg)	0,0009	-0,0595 **	0,0802 ***	-0,0736 ***	0,0759	0,0002	-0,0004 **
	(0,6259)	(0,0306)	(0,0089)	(0,0023)	(0,3976)	(0,1043)	(0,0177)

p-values in parentheses *** significant at 1% level ** significant at 5% level * significant at 10% level

The results of the regressions specified in (3.27), involving bank specific variables, for the US banks are compiled in Table 3. The intercept estimates are mostly insignificant with only two achieving significance at the 10% level or lower. Except for one bank, the parameter estimates for the market-to-book value ratio are negative, indicating decrease in systemic riskiness for increases in business performance before and during the crisis. The parameter estimates of the corresponding dummy term are positive throughout, implying that the favourable effect of higher performance on systemic riskiness deteriorated after the crisis. The market-to-book value ratio related parameters are significant for half of the banks while for one bank only the post-crisis change is significant. Looking at the sum of original and dummy term parameters, the influence of increased performance on systemic riskiness is implied to reverse post-crisis for all of the banks with significant parameter estimates. The parameter estimates for the ln of total assets are significant for all but one bank, with five banks implying increased systemic riskiness with increased impact due to size while two imply the opposite before and during the crisis. The corresponding dummy term's parameter estimates imply reduced sensitivity within the respective relation post-crisis in each case, as well as reversal of the relation in several cases. These estimates are only significant for three banks. The parameter estimates for leverage imply increasing systemic riskiness with increasing individual riskiness for each bank before and during the crisis, while only being significant in four cases. The parameter estimates for the corresponding dummy term imply an easing as well as reversal of this relation for all but one bank, with only two estimates being significant.

4.2 Discussion

With increasing systemic distress, as measured by the credit-to-GDP ratio gap, the parameter estimations for the Eurozone banks imply alleviation before and during while increasing severity of systemic riskiness after the crisis. Although not significant, the estimates' consistency among the banks is noteworthy nonetheless. A possible explanation is that a higher credit-to-GDP ratio implies increased business for banks. This was reflected positively in the banks' stock prices, and with it MES, at first, until the peril of bad debt received more attention as a consequence of the crisis. Oddly, the results for the US banks, while equally insignificant but consistent among each other, imply the exact opposite behaviour. That is, a shift from adverse to beneficial relation between increases in credit-to-GDP ratio and systemic risk of the banks. A possible explanation would be that the peril of accumulating bad debt was adequately reflected in stock prices pre-crisis but this peril was assessed to be quite low compared to the increase in business activity due to low interest rates for most of the time since the crisis.

The Eurozone banks' parameter estimates for the debt service ratio gap consistently result implying an increase of banks' systemic risk with an increase of the indicator pre-crisis, while the sensitivity to systemic distress is implied to have decreased afterwards. However, the results also imply that the relation between the banks' systemic risk and systemic distress changed fundamentally from unfavourable to favourable. This is a rather counterintuitive implication, since increasing debt service ratios lead to less borrowing or even defaults, that is, they should be reflected negatively in stock prices and in turn MES. These observations are supported, however, by the estimates being nearly invariably significant. The results for the US banks imply a favourable reaction to systemic distress as measured by the debt service ratio gap before and during the crisis, while the crisis-induced change in exposure is implied to be unfavourable. This leads to a reversal of the initially observed relation for some of the banks. Overall, these equally counterintuitive estimates for the US banks, while largely consistent among the banks, are not significant.

The parameter estimates for the property price gap for the Eurozone banks provide exactly the same implications as those for the debt service ratio gap. That is, an unfavourable relation between the banks' systemic risk and the indicator before and during the crisis with this exposure decreasing post-crisis to a point where the relation reverses and becomes favourable. Considering the integral role, the US real estate market played in triggering the Global Financial Crisis, this seems rather counterintuitive an outcome of the crisis, even for a different region. In this case, however, except for a few of the dummy term parameter estimates, the results are largely insignificant. The implications for the US banks are a favourable influence of increasing systemic distress, as measured by this indicator, before during and after the crisis. While the change in exposure indicated by the dummy term parameter estimates implies a less favourable relation, it is also insignificant. The original term's parameter estimates, however, are almost entirely significant. As was reasoned above, this is a quite counterintuitive result, especially for the US region.

The implied relation of systemic riskiness and market-to-book value ratio before and during the crisis is quite consistent among the US banks, suggesting lower riskiness at a higher ratio. This is to be expected since a high ratio results from a high stock price, which in turn reflects the satisfaction of stockholders with the respective bank's performance. The dummy term parameter estimates imply not only a deterioration of this relation but a reversal. This observation holds for all of the significant estimates as well as most of the insignificant ones and seems rather counterintuitive with no compatible explanation. The largely significant parameter estimates for the ln of total assets indicate an inconsistent relation among banks before and during the crisis, where the systemic riskiness of some benefits from size, while it suffers for others. This could be explained by some banks being sized too big to fail and enjoying a size advantage reflected in their stock price. However, considering the examined banks are SIBs and therefore considered too big to fail anyway, they should exhibit kindred relations of size and systemic riskiness throughout. The dummy term parameter estimates imply reversals of these relationships in most of the cases, which only adds ambiguity. The implied relation of leverage and systemic riskiness is implied to be unfavourable before and during the crisis. The dummy term estimates imply not only a reduction of exposure but a complete reversal of this relation for most of the banks. This again is counterintuitive and lacks a potential economic explanation.

5 Conclusion

Present essay investigates the systemic riskiness of the Eurozone and US SIBs by reference to the analytical systemic risk measure MES. Time series of MES are estimated with a bivariate time series model and compared to the EWIs of financial crises published by the BIS as measures of systemic distress pre- and post-crisis. The comparison is done by performing linear time series regressions of MES on the EWIs and assessing changes in significance and magnitude of the resulting parameters pre- and post-crisis. The change in parameters is captured with dummy terms that indicate the post-crisis period. Supplementary, congeneric regressions of the US banks' MES series on a selection of bank specific indicators of potential systemic impact are performed as well.

Looking at the EWIs, the implications derived from the parameter estimates are largely quite consistent among the banks of the respective regions, that is, in terms of sign and with it the implied relationship. Among the EWIs, however, the estimates provide quite contradictory implications, where some indicators suggest favourable and some unfavourable responses of the banks' systemic riskiness to increases in systemic distress. When comparing the two regions, the same EWI usually indicates opposite responses in each of them. While the consistency of the implications among the banks indicates a certain validity of the results, most of the estimates are statistically insignificant and therefore ineligible for conclusions anyhow. Focussing hereafter on the results for the debt service ratio gap in the Eurozone and the property price gap in the US, which are the sole largely significant series of results, remains inconclusive as well. While the first implies increasing systemic riskiness with increasing systemic distress and a reduction of this exposure following the crisis, it also implies a favourable relation of systemic riskiness and systemic distress post-crisis in the Eurozone. The latter implies a favourable relation of systemic riskiness and systemic distress to begin with in the US, with no significant change in this relation after the crisis. Looking at the bank specific variables of the US banks, the implications are quite ambiguous as well. Among the banks, the significant parameter estimates consistently imply increased exposure to systemic distress via the market-to-book value ratio while alleviated exposure via the leverage ratio post-crisis. In both cases they additionally imply a fundamental reversal of the relation, voiding interpretability. Regarding the ln of total assets, implications are inconsistent among the banks, while the post-crisis change in relation again not only indicates a change but total reversal for all of the significant estimates, voiding interpretability. Given these partly void and partly contradictory results, no confident answer to the question if the Eurozone and US SIBs' systemic riskiness has improved subsequent to the Global Financial Crisis of 2007/2008 can be provided by present essay.

Naturally, present essay is subject to considerable limitations. Most notably that the applied proxy for systemic risk, MES, is based on stock prices and therefore highly exposed to irrational evaluations that are especially common during high systemic distress. This most certainly affects its ability to precisely measure a bank's systemic riskiness to some extent. Furthermore, the EWIs, while indicative of systemic distress overall, might be less suited to derive a precise level of distress at a given time. Ultimately these are factors that certainly play into the ambiguousness of the obtained results. For future research with the same objective and similar approach, it is therefore advised to try different variables. Suggestions would be SES or SRISK for systemic riskiness and asset quality, liquidity or size of capital cushions as individual proxies for exposure to systemic distress. Another observation deemed to deserve further attention is the distinct difference of Eurozone and US banks in reaction to the EWIs. It would be worthwhile to further examine the difference in exposure to systemic distress for the banks of both regions as well as the underlying reasons, such as approach to capitalisation during the crisis and regulation.

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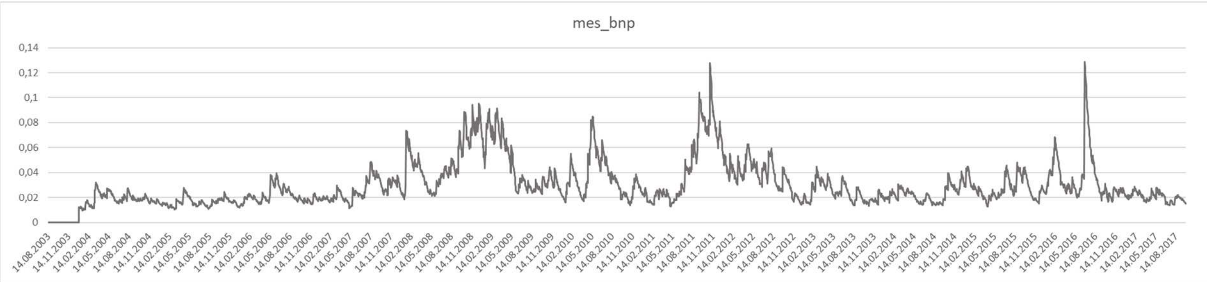
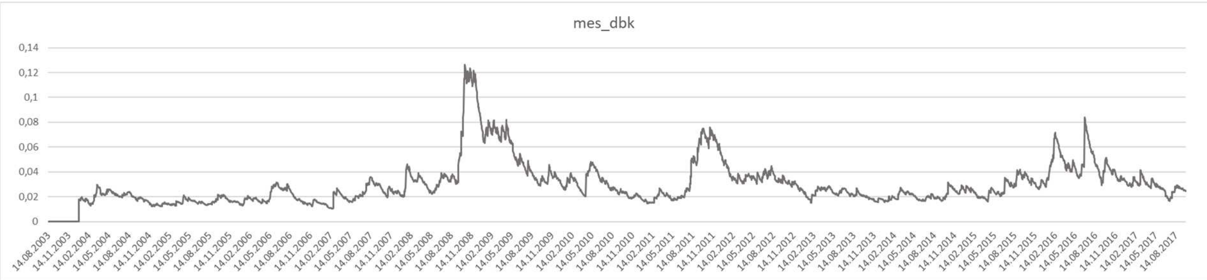
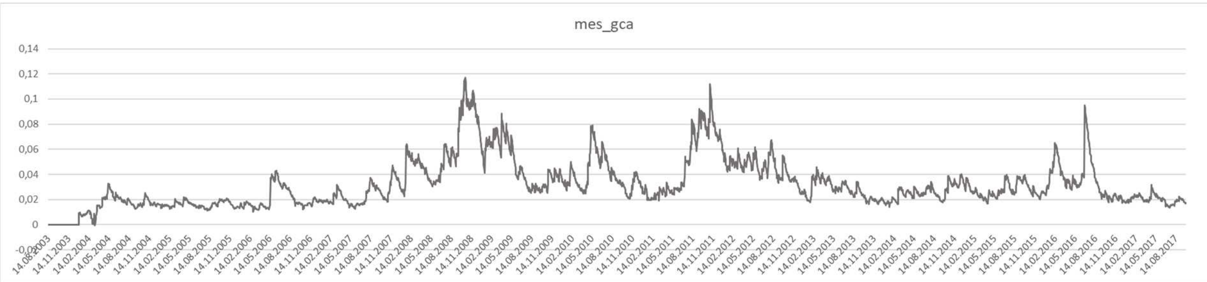
Appendix

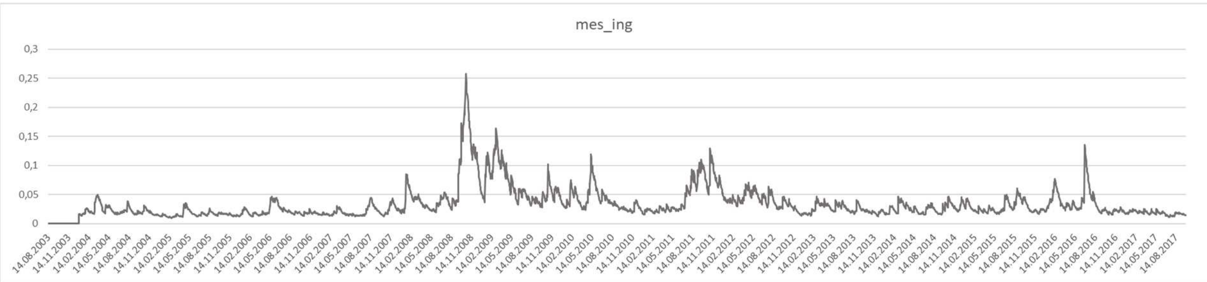
Appendix A

Plots of daily MES series:







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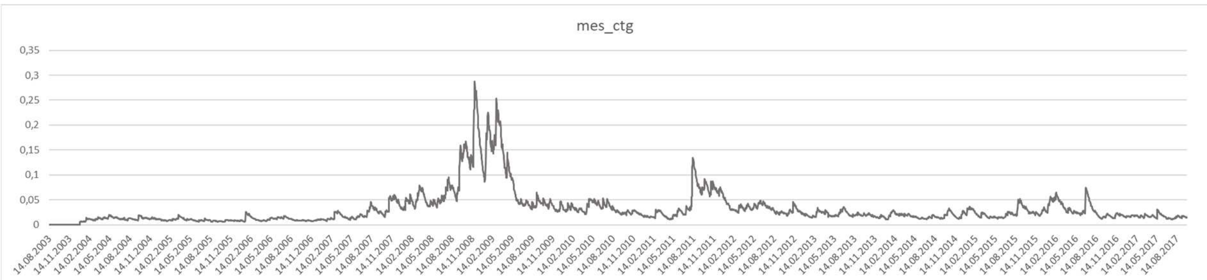
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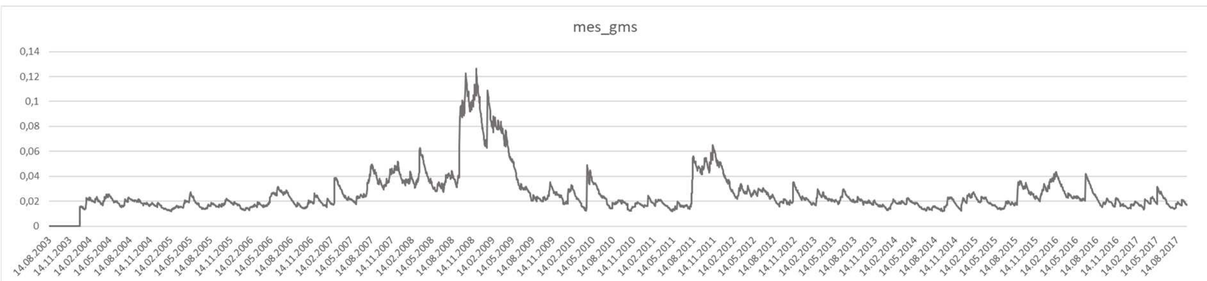
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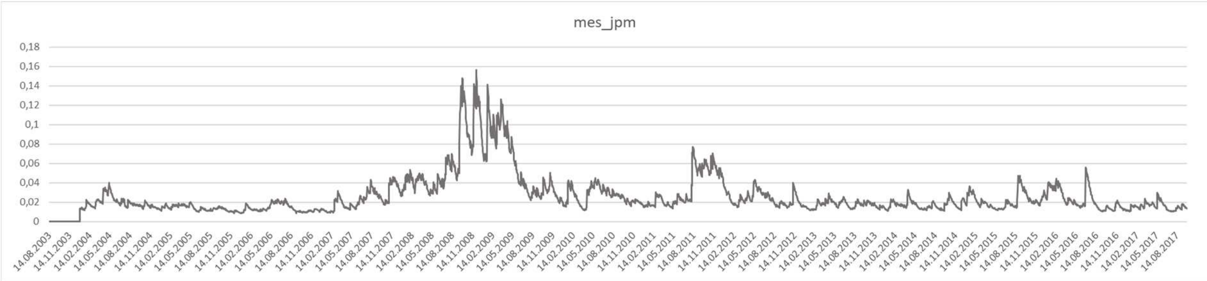
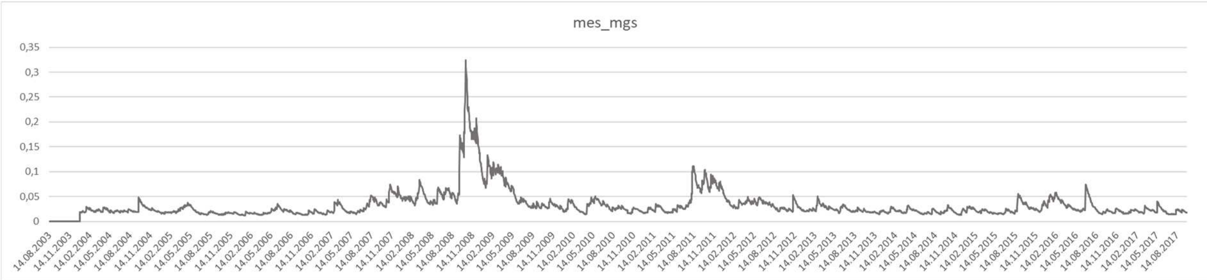
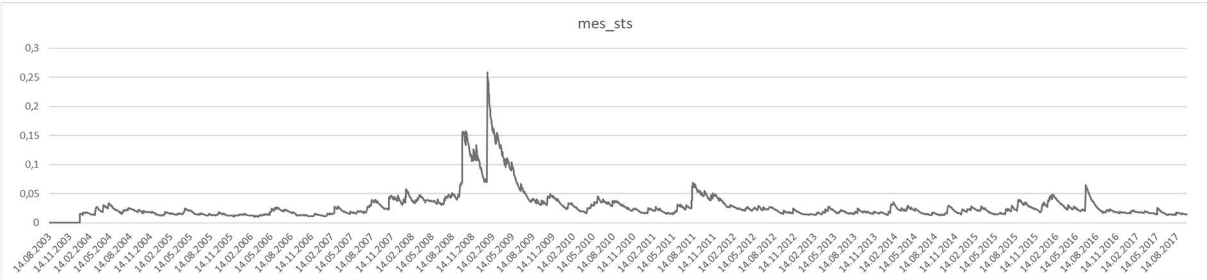
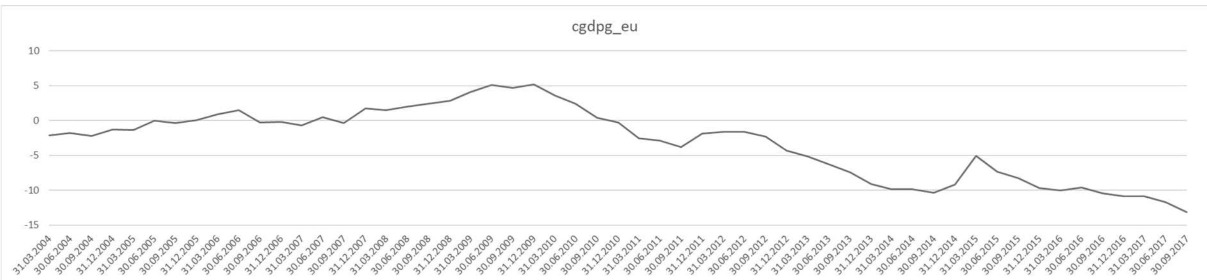
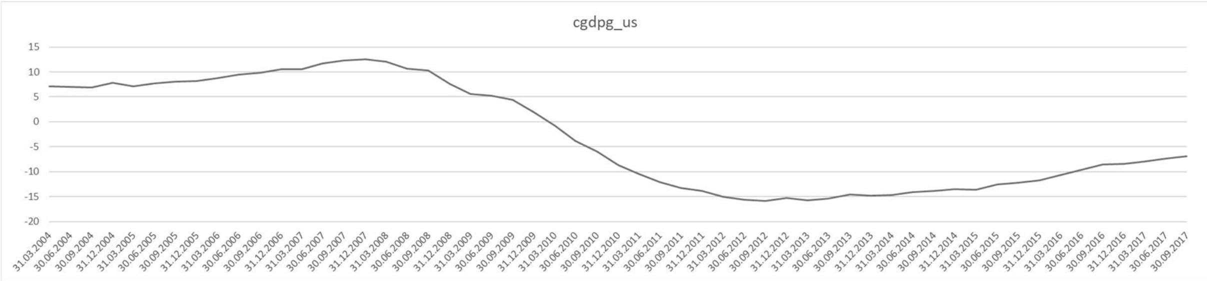






Plots of quarterly EWI series:

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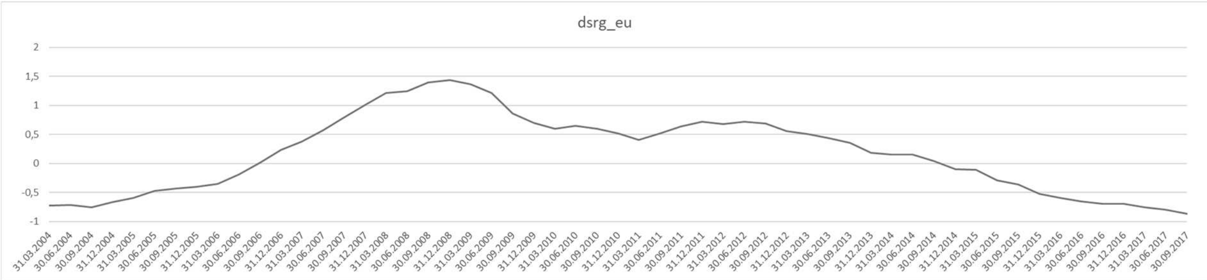
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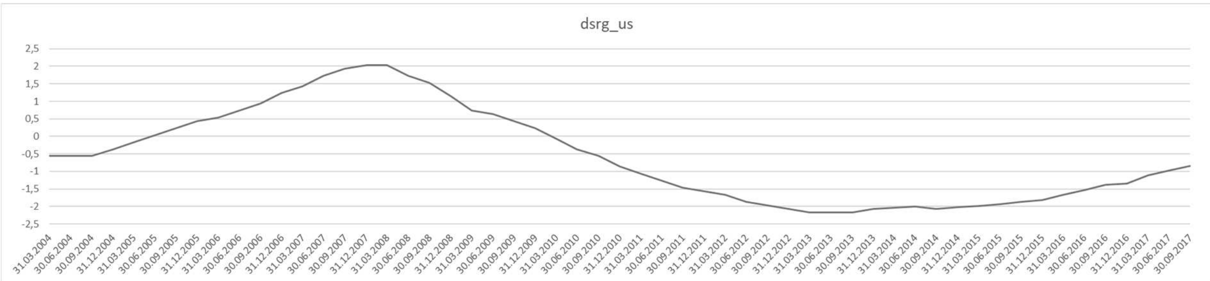
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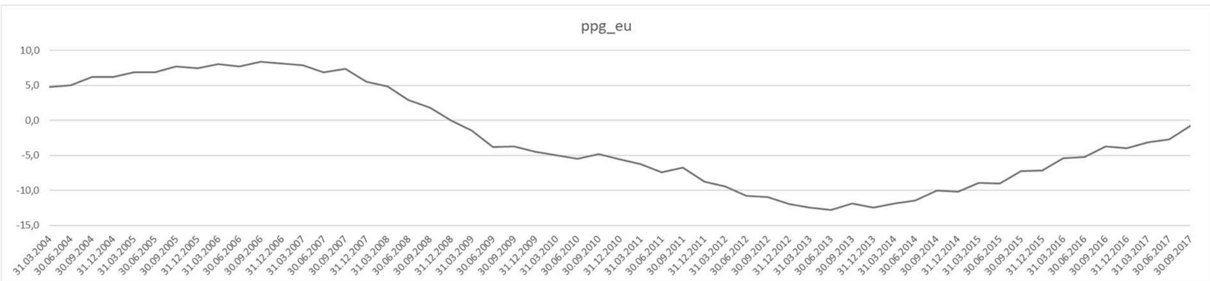
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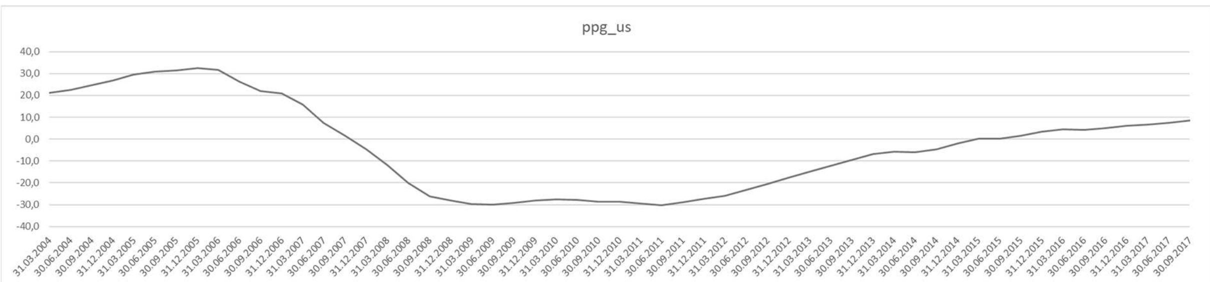
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Appendix B

Descriptive statistics and stationarity test results of the quarterly Eurozone and US MES, and EWI series, as well as their first differences:

Original Series	mes_bnp	mes_dbk	mes_gca	mes_ing	mes_san	mes_sge	mes_uni	mes_boa	mes_bny	mes_ctg	mes_gms	mes_jpm	mes_mgs	mes_sts	mes_wfg	cgdpg_eu	cgdpg_us	dsrg_eu	dsrg_us	ppg_eu	ppg_us
Descriptive Statistics																					
minimum	0,012	0,013	0,013	0,012	0,010	0,012	0,008	0,007	0,009	0,007	0,014	0,008	0,013	0,013	0,006	-13,138	-15,900	-0,868	-2,165	-12,834	-30,177
maximum	0,119	0,079	0,099	0,173	0,136	0,142	0,154	0,166	0,218	0,162	0,101	0,148	0,158	0,155	0,148	5,207	12,500	1,431	2,035	8,382	32,513
mean	0,031	0,031	0,033	0,035	0,029	0,035	0,033	0,031	0,028	0,032	0,027	0,027	0,034	0,029	0,025	-3,043	-2,793	0,178	-0,553	-2,485	-3,511
median	0,024	0,025	0,026	0,025	0,025	0,028	0,026	0,021	0,019	0,022	0,020	0,019	0,026	0,021	0,017	-1,792	-6,900	0,237	-0,850	-3,952	-4,568
standard deviation	0,021	0,017	0,020	0,030	0,020	0,024	0,025	0,031	0,030	0,031	0,017	0,025	0,026	0,025	0,025	5,068	10,542	0,673	1,338	7,194	20,725
excsss kurtosis	6,044	2,203	2,689	9,620	15,169	7,565	9,839	9,851	29,500	8,047	8,174	13,533	10,221	13,644	13,052	-1,054	-1,751	-1,134	-1,047	-1,412	-1,207
skewness	2,287	1,668	1,747	2,922	3,323	2,462	2,679	3,004	4,965	2,719	2,732	3,463	2,859	3,477	3,340	-0,339	0,148	0,077	0,485	0,228	0,236
Stationarity Test Results																					
ADF t-statistic*	-5,229	-3,300	-4,554	-5,614	-5,924	-5,408	-5,137	-3,306	-2,982	-3,409	-3,385	-2,402	-3,893	-2,345	-3,346	0,315	-1,651	-1,373	-2,332	-2,658	-3,715
KPSS LM-statistic**	0,176	0,153	0,179	0,118	0,203	0,179	0,277	0,120	0,112	0,123	0,122	0,134	0,126	0,120	0,126	0,659	0,673	0,233	0,542	0,627	0,279
combined implication	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	ambig.	stat.	ambig.	stat.	non-stat.	non-stat.	ambig.	non-stat.	non-stat.	stat.

*implies stationarity at 5% significance level if < -2,919 **implies stationarity at 5% significance level if ≤ 0,463

First Differences	mes_bnp	mes_dbk	mes_gca	mes_ing	mes_san	mes_sge	mes_uni	mes_boa	mes_bny	mes_ctg	mes_gms	mes_jpm	mes_mgs	mes_sts	mes_wfg	cgdpg_eu	cgdpg_us	dsrg_eu	dsrg_us	ppg_eu	ppg_us
Descriptive Statistics																					
minimum	-0,091	-0,028	-0,064	-0,121	-0,107	-0,112	-0,114	-0,100	-0,152	-0,121	-0,048	-0,081	-0,069	-0,073	-0,099	-2,285	-3,000	-0,360	-0,400	-2,383	-8,437
maximum	0,091	0,053	0,057	0,126	0,106	0,104	0,121	0,104	0,182	0,082	0,067	0,104	0,105	0,122	0,068	4,149	1,200	0,230	0,300	1,973	2,887
mean	0,000	0,000	0,000	-0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	-0,204	-0,259	-0,003	-0,005	-0,103	-0,235
median	0,001	-0,002	0,000	0,000	0,000	-0,002	-0,001	0,000	-0,001	0,000	-0,001	0,000	-0,001	0,000	0,000	-0,358	0,100	-0,031	0,030	-0,178	0,782
standard deviation	0,024	0,014	0,022	0,037	0,026	0,029	0,029	0,026	0,036	0,026	0,015	0,024	0,025	0,025	0,021	1,195	1,134	0,123	0,184	1,024	3,032
excsss kurtosis	6,671	3,744	2,192	4,792	9,991	6,632	8,559	8,323	17,749	9,280	9,496	8,653	6,931	12,425	11,467	2,136	0,080	0,158	-0,796	-0,339	1,023
skewness	0,076	1,233	0,174	0,164	0,013	0,141	0,329	0,359	1,002	-1,138	1,270	0,478	0,946	1,596	-0,964	0,854	-1,008	0,012	-0,380	-0,085	-1,390
Stationarity Test Results																					
ADF t-statistic*	-10,480	-7,961	-11,237	-13,193	-11,522	-11,185	-11,849	-9,978	-13,366	-10,605	-10,090	-12,315	-11,590	-12,400	-10,592	-6,314	-2,759	-2,970	-1,977	-0,668	-2,288
KPSS LM-statistic**	0,229	0,059	0,242	0,127	0,304	0,308	0,500	0,075	0,193	0,095	0,103	0,099	0,106	0,089	0,102	0,327	0,221	0,475	0,201	0,350	0,328
combined implication	stat.	stat.	stat.	stat.	stat.	stat.	ambig.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	stat.	ambig.	ambig.	ambig.	ambig.	ambig.

*implies stationarity at 5% significance level if < -2,918 **implies stationarity at 5% significance level if ≤ 0,463

Descriptive statistics and stationarity test results of the quarterly US bank specific variable series, as well as their first differences:

Original Series	mbv_boa	lnta_boa	lev_boa	mbv_bny	lnta_bny	lev_bny	mbv_ctg	lnta_ctg	lev_ctg	mbv_gms	lnta_gms	lev_gms	mbv_jpm	lnta_jpm	lev_jpm	mbv_mgs	lnta_mgs	lev_mgs	mbv_sts	lnta_sts	lev_sts	mbv_wfg	lnta_wfg	lev_wfg
Descriptive Statistics																								
minimum	0,180	20,520	170,130	0,640	18,344	66,830	0,090	20,999	179,800	0,650	19,910	427,660	0,550	20,501	215,790	0,420	20,255	327,870	0,810	18,347	86,360	0,590	19,800	121,510
maximum	1,890	21,584	536,270	2,760	19,809	130,240	2,400	21,581	951,580	2,630	20,893	1613,930	1,430	21,670	542,000	2,940	20,906	2402,240	3,060	19,500	798,220	2,810	21,392	553,830
mean	0,968	21,342	326,891	1,442	19,246	92,652	1,126	21,324	415,955	1,341	20,556	850,227	1,049	21,370	326,833	1,252	20,551	876,945	1,791	18,963	240,253	1,695	20,741	223,565
median	0,770	21,486	323,070	1,240	19,401	90,640	0,790	21,346	368,360	1,170	20,597	734,930	1,060	21,511	307,760	1,050	20,524	760,020	1,600	18,972	181,690	1,470	20,973	207,830
standard deviation	0,511	0,259	103,224	0,600	0,525	15,735	0,710	0,118	209,804	0,505	0,200	368,899	0,220	0,317	88,439	0,653	0,144	479,088	0,652	0,368	158,567	0,589	0,558	89,737
excsss kurtosis	-0,968	0,874	-1,224	-0,553	-1,124	-0,022	-1,159	0,792	-0,029	-0,531	3,278	-0,782	-0,500	0,171	-0,329	-0,345	0,753	0,303	-0,990	-1,289	1,111	-0,976	-1,412	2,995
skewness	0,611	-1,322	0,036	0,851	-0,660	0,584	0,663	-0,760	0,903	0,724	-1,750	0,743	-0,091	-1,104	0,759	0,816	0,814	0,803	0,482	-0,294	1,118	0,609	-0,537	1,532
Stationarity Test Results																								
ADF t-statistic*	-1,330	-4,687	-1,955	-2,421	-1,571	-4,726	-1,848	-3,369	-1,037	-2,029	-3,902	-1,888	-2,343	-3,472	-2,606	-1,872	-2,317	-0,764	-2,214	-1,759	-1,849	-1,705	-1,257	-1,896
KPSS LM-statistic**	0,547	0,771	0,751	0,656	0,804	0,154	0,588	0,264	0,657	0,683	0,388	0,629	0,199	0,915	0,441	0,621	0,159	0,732	0,625	0,824	0,918	0,488	0,824	0,442
combined implication	non-stat.	ambig.	non-stat.	non-stat.	non-stat.	stat.	non-stat.	stat.	non-stat.	non-stat.	stat.	non-stat.	ambig.	ambig.	ambig.	non-stat.	ambig.	non-stat.	non-stat.	non-stat.	non-stat.	non-stat.	non-stat.	ambig.

*implies stationarity at 5% significance level if < -2,919 **implies stationarity at 5% significance level if ≤ 0,463

First Differences	mbv_boa	lnta_boa	lev_boa	mbv_bny	lnta_bny	lev_bny	mbv_ctg	lnta_ctg	lev_ctg	mbv_gms	lnta_gms	lev_gms	mbv_jpm	lnta_jpm	lev_jpm	mbv_mgs	lnta_mgs	lev_mgs	mbv_sts	lnta_sts	lev_sts	mbv_wfg	lnta_wfg	lev_wfg
Descriptive Statistics																								
minimum	-0,470	-0,057	-235,660	-1,230	-0,155	-52,770	-0,830	-0,075	-354,440	-0,600	-0,206	-303,290	-0,300	-0,059	-264,850	-0,860	-0,405	-980,170	-1,000	-0,498	-483,720	-0,820	-0,048	-125,790
maximum	0,470	0,245	88,350	0,600	0,376	61,750	0,440	0,094	184,880	0,650	0,116	523,960	0,600	0,331	81,700	0,340	0,128	1012,910	0,680	0,669	616,530	0,580	0,733	138,270
mean	-0,005	0,019	-6,591	-0,024	0,025	0,541	-0,025	0,007	-3,975	-0,015	0,014	-3,835	0,011	0,022	-5,288	-0,020	0,005	-11,756	-0,020	0,017	-6,978	-0,021	0,029	-1,548
median	0,020	0,004	-5,050	0,015	0,012	0,080	0,020	0,008	-5,620	0,005	0,013	-1,915	-0,010	0,016	-2,475	0,020	0,015	-5,055	0,030	0,019	-2,760	0,025	0,016	-1,215
standard deviation	0,180	0,053	43,631	0,253	0,087	17,728	0,218	0,043	71,440	0,236	0,050	114,671	0,142	0,060	48,738	0,228	0,072	238,655	0,307	0,135	114,503	0,208	0,100	34,642
excsss kurtosis	1,215	10,659	14,611	9,198	5,787	3,885	5,398	-0,668	11,119	1,136	5,970	8,690	4,636	16,023	14,760	3,654	19,192	10,513	2,659	13,416	21,825	4,846	47,908	7,692
skewness	-0,132	2,901	-2,796	-1,879	1,725	-0,045	-1,774	-0,014	-1,855	-0,169	-1,415	1,349	1,326	3,528	-2,739	-1,539	-3,474	0,135	-1,006	1,035	1,730	-1,249	6,737	0,239
Stationarity Test Results																								
ADF t-statistic*	-7,590	-8,868	-12,722	-7,522	-6,093	-8,204	-6,691	-2,171	-5,803	-8,676	-2,633	-3,375	-7,593	-6,900	-8,600	-5,790	-5,963	-3,499	-7,117	-9,969	-8,447	-8,349	-7,394	-5,452
KPSS LM-statistic**	0,125	0,779	0,092	0,384	0,239	0,131	0,227	0,291	0,149	0,221	0,430	0,265	0,128	0,550	0,089	0,178	0,124	0,154	0,244	0,500	0,098	0,160	0,133	0,079
combined implication	stat.	ambig.	stat.	stat.	stat.	stat.	stat.	ambig.	stat.	stat.	ambig.	stat.	stat.	ambig.	stat.	stat.	stat.	stat.	stat.	ambig.	stat.	stat.	stat.	stat.

*implies stationarity at 5% significance level if < -2,918 **implies stationarity at 5% significance level if ≤ 0,463

Correlation matrices for the first differences of the independent variable series:

corr()	cgdpg_eu	dsrg_eu	ppg_eu
cgdpg_eu	1		
dsrg_eu	0,309	1	
ppg_eu	-0,252	-0,145	1

corr()	lev_gms	lnta_gms	mbv_gms
lev_gms	1		
lnta_gms	0,670	1	
mbv_gms	-0,046	0,077	1

corr()	cgdpg_us	dsrg_us	ppg_us
cgdpg_us	1		
dsrg_us	0,834	1	
ppg_us	0,023	-0,059	1

corr()	lev_jpm	lnta_jpm	mbv_jpm
lev_jpm	1		
lnta_jpm	-0,263	1	
mbv_jpm	-0,470	0,320	1

corr()	lev_boa	lnta_boa	mbv_boa
lev_boa	1		
lnta_boa	-0,098	1	
mbv_boa	-0,319	-0,018	1

corr()	lev_mgs	lnta_mgs	mbv_mgs
lev_mgs	1		
lnta_mgs	0,222	1	
mbv_mgs	0,085	0,580	1

corr()	lev_bny	lnta_bny	mbv_bny
lev_bny	1		
lnta_bny	0,162	1	
mbv_bny	-0,284	0,169	1

corr()	lev_sts	lnta_sts	mbv_sts
lev_sts	1		
lnta_sts	0,827	1	
mbv_sts	0,293	0,361	1

corr()	lev_ctg	lnta_ctg	mbv_ctg
lev_ctg	1		
lnta_ctg	0,222	1	
mbv_ctg	-0,260	0,286	1

corr()	lev_wfg	lnta_wfg	mbv_wfg
lev_wfg	1		
lnta_wfg	0,650	1	
mbv_wfg	-0,106	0,002	1