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"Quantifying the Impact of Energy Prices on Financial Stability"

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All errors, policy recommendations and political expressions contained herein are mine and mine alone.

Abstract

Financial stability has always been at the forefront of research for both academics and practitioners alike. Given the current Russian invasion of Ukraine and the importance of energy commodities to the economic and strategic integrity of countries, understanding the importance of energy commodity price fluctuations on financial stability is of crucial importance. Current literature has fallen short of being able to quantify and explore such an issue through an all-inclusive approach. This has resulted in a split between the academic literature strands of Financial Stability and Energy Economics and Finance. This research, hence, aims to solve this issue by quantifying the risk posed to the European financial system from energy commodity price fluctuations through the implementation of an interdisciplinary approach. We propose a new methodology for doing so by building on Adrian and Brunnermeier's (2016) ΔCoVaR. This research is split into two sections: Section A pertains to quantifying said risk indirectly by calculating the ΔCoVaR of economic segments before employing panel regression analysis on said variable to deduce the impact of energy commodity prices on the total risk posed to the financial system. Section B pertains to measuring such an impact directly through modifying the definition of ΔCoVaR to be conditioned on the gain of an asset rather than a loss, before then employing time-series analysis on the newly created variable. Moreover, machine learning techniques are employed to ensure the robustness of our results. We find conflicting results from our two approaches in regard to prior academic literature findings. Overall, from the results of our study we can deduce that on average energy commodities are not as important to financial stability as originally thought and that central banks have many tools at their disposals to deal with the risk posed to the system by energy commodity price fluctuations. This all suggests that imposing sanctions on energy imports from Russia would not harm the financial integrity of the European continent if the correct actions are to be taken.

Keywords: Financial Stability; Energy Commodities; Financial Risk; Machine Learning; Energy Economics and Finance; Ukraine-Russia; ΔCoVaR; Bootstrapping; LASSO; Granger Causality; VAR; Impulse Analysis.

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Chapter 1: Introduction

Economies throughout history have always dealt with financial instability, each time arising from novel and unique sources with certain central features defining them. These features include but are not limited to political, such as the 1970’s oil crisis; behavioural such as the Dot-Com Bubble of the 2000s, financial, such as the 2008’s financial crisis; epidemiological, such as the Covid-19 pandemic. This has led to governments to try and limit the negative effects that arise from such events as hastily as possible. Consequently, such as during the Covid-19 pandemic, many measures governments aimed at utilizing to counteract the negative effects had never been tested at a large scale (e.g., lockdowns) prior to their employment. This in conjunction with the limited academic knowledge on the sources of financial instability, given the unorthodox nature of each new crisis, can cause the negative spillover effects to persist and even compound. Consequently, financial stability has thus always been a prominent research topic. The need for understanding financial stability can be argued to have culminated in the creation of central banking units, whose core end goal can be broadly defined as preserving price stability (European Central Bank (ECB), 2022a). Central banks, using macro and micro prudential policies aim to create a favourable financial climate (ECB, 2022a). Nonetheless, even if a “financial healthy” climate is perceived to subsist, crises have been shown to be able to break loose at any given moment. The epitome of which was the 2008 financial crisis from which the collapse of an individual firm had dragged the world into a global economic and financial debt crisis.

Once more the concern of a crisis starting has become prominent with the current outbreak of war in Ukraine and the enforcement of sanctions on Russia by the West. Given the EU’s strong dependence on energy commodities imported from Russia (see International Energy Agency, 2022) and the importance of energy commodities for economic activity (see Berk and Yetkiner, 2014), it is becoming increasingly more evident that understanding financial stability and the causes and effects of such a vital concern to individuals and society as a whole. In particularly with regard to the impact that energy commodities have on financial stability.

1.2 Addition to the Academic Knowledge and Structure.

Various attempts at quantifying financial stability have been developed over time. Each measure of which focuses on different aspects of financial stability. These can be split into:

1.2.1 Macro Risk Measuring

Given the large-scale impact of crises macro financial risk has always been at the forefront of academic research interest. Most attempts at quantifying macro financial risk comes in the form of financial stability indices, dynamic stochastic general equilibrium models (DGSE) and Vector Autoregressive (VAR) models. The most important of each strand being the "Composite Index of Systemic Stress" (see Hollo et al. 2012), DGSE with financial frictions (see Kolasa and Rubaszek, 2015) and VAR models with monetary aggregates (see Benk and Gillman, 2020).

1.2.2 Micro Risk Measuring

As financial instability tends to start from individual agents at a micro level, tools for understanding micro risk were also developed. The most popular of which were mainly linked with financial stability within the banking industry. These measures include Value-at-Risk (VaR) and Expected Shortfall (ES) (see Artzner et al., 1999; Tasche, 2002; Hull, 2018).

1.2.3 Mixed Methods

The largest issue with both micro risk and macro risk measurements is that they fail at considering both of each other's segment's perspectives i.e., looking at financial stability through both a macro and a micro lens. An attempt to try and salvage such an issue came mainly from Adrian and Brunnermeier (2016) with their ΔCoVaR, Acharya et al., (2017) with their Marginal Expected Shortfall (MES) and Brownlees and Engle (2017) with their SRISK measurement. Finally, as technological prowess evolved pure statistical attempts at understanding and predicting financial risk were also developed by employing a variety of different machine and deep learning techniques (see Chatzis et al., 2018). However, while a variety of different financial stability measurement tools were developed, the understanding of energy commodity prices on financial stability still remains limited.

1.2.4 Energy Economics and Finance

Energy Economics and Finance (EEF) academic literature mainly focuses on the impact of energy commodity prices on the macro-economy (See e.g. Hamilton, 1983, Du et al., 2010) While the EEF literature which focuses on financial stability either does so indirectly through looking at energy spillover effects (see Naeem et al., 2020), through focusing mainly on the stock market as a proxy for financial stability (e.g., Kim et al., 2019) or through employing unorthodox measures which have not seen popular use in the financial stability literature strand (e.g., Nasreen et al., 2017).

Nonetheless, this issue stems from the lack of interdisciplinary approaches from the two key academic literature strands that this research belongs to: The Financial Stability and the Energy Economics and Finance literature strand. Both literature strands offer invaluable insights to quantifying the risk that energy prices pose on financial stability.

1.3 Structure & Aim of Research

This research aims to quantify financial stability risk posed by energy commodity prices by combining the two academic literature strands' approaches into a new interdisciplinary approach. This is meant to add to the academic knowledge by employing established methods on novel data; reorganizing and improving upon established methods; looking at financial stability at the sectorial level; and finally employing unorthodox empirical methods such as machine learning.

More specifically, this research is split into two core parts. The first part looks at the risk posed to financial stability indirectly by measuring the impact of energy commodities (i.e. Oil, Gasoline, Natural Gas, & Carbon emission allowances) on systemic financial risk by employing a time-varying ΔCoVaR (as per Adrian and Brunnermeier, 2016) of the financial system conditioned on different economic segments before subsequently running an econometric analysis on the ΔCoVaR with energy related independent variables i.e., the price of oil, natural gas, gasoline and carbon emission allowances. This allows us to find the impact of different energy related variables on the systemic stress caused by economic segments, allowing for greater insight in regard to how energy shock transmissions occur.

The second part of this research looks at the direct risk that energy commodity prices pose on financial stability. This is done through changing the original definition of ΔCoVaR from being conditioned on a loss of a firm to being conditioned to a gain on a commodity price given the empirical tendency of energy prices (Berk and Yetkiner, 2014), before then running a time-series econometric analysis including impulse analysis. Finally, this research aims to add to the academic knowledge through employment of machine learning methods throughout the research for variable selection and robustness confirmation of our traditional econometric techniques.

The use of Adrian and Brunnermeier's (2016) ΔCoVaR is at the core of this paper given its ingenuity of the methodology employed but also given the limited use of using ΔCoVaR as a variable within academic literature which tends to opt for the easier alternative of basic percentage returns (e.g., Kim et al., 2019).

The rest of this paper is structured as follows: Chapter 2 contains an in-depth literature review on the literature stands of financial stability and energy economics and finance; Chapter 3 looks at the methodology and the methods employed by this research; Chapter 4 sets out the data that is used in the methodology and methods section and specifies the models used; Chapter 5 contains the empirical results and their implications; Chapter 6 presents a summary of the key results of Chapter 5; Chapter 7 contains policy recommendations; Chapter 8 contains the concluding thoughts and finally Chapter 9 showcases the delimitations of this research and the future research possibilities.

Chapter 2: Literature Review

2.1 Present Situation of the Ukraine-Russia Conflict[1]

On February 24th, 2022, Russia invaded Ukraine (Reuters, 2022), which immediately saw the organised condemnation from "Western countries" (see Nolsoe and Pop, 2022). These countries organised and immediately implemented a series of different sanctions. These include but are not limited to the banning of Russia from SWIFT (with the exception of the energy sector) (Blenkinsop, 2022), the sanctioning of the Central Bank of Russia (U.S. Department Of The Treasury), the sanctioning of politicians and key Russian figures, the sanctioning of Russian-linked companies within the UK, the EU, the US, Canada, Japan and Switzerland and the prohibition of exports of high-end and critical technical equipment to Russia (Nolsoe and Pop, 2022). While these measures have covered a wide array of economic and financial areas, the energy sector of Russia is still not directly sanctioned. Initially sanctions on the energy sector were not being considered by the US (Chiacu and Gardner, 2022) and Germany (Delfs, 2022). This was most likely due to the heavy reliance of the EU on Russian energy imports, e.g., on natural gas from Russia which accounts for around 45% of the whole of the EU's gas imports and close to 40% of its total gas consumption (International Energy Agency, 2022); Consequently, this overreliance has left the EU vulnerable to Russian energy commodity price fluctuations and energy commodity price fluctuations in general. However, as of the 15th of March 2022, the west and the E.U. in particular have been inching closer to directly strict sanctioning of the energy commodity sector of Russia, as the current sanctions imposed on Russia's energy sector are of a lenient nature. E.g., the current sanctions on the energy sector by the EU include the prohibition of new investments in the energy sector of Russia (excluding nuclear energy and transport of energy products) (European Commission, 2022). Nevertheless, current energy commodity fluctuations are most likely to derive now from the indirect costs to Russia's energy sector from the aforementioned sanctions or from either future potential sanctions. Thus, understanding the magnitude of the exposure of the EU to such energy

[1] Disclaimer: Given the rapid change of events of the current Ukraine-Russia conflict the information given in this text may be considered outdated. I have tried to ensure that the information used is as up to date and as accurate as possible. Last update: 15/03/2022

price fluctuations is of crucial importance to understanding the risk that energy price fluctuations pose to the financial stability and integrity of the EU.

This research paper quantifies this vulnerability of the EU's market's financial stability is in regard to overall energy commodity prices (gas, oil, etc.) as such this research paper is at its core related to two academic literature strands. The first strand pertains to financial stability, and the second strand is related to energy economics and finance. In the current chapter an in-depth look at these two literature strands is given.

2.2. Defining Financial Stability

A commonly used and clear definition of financial stability has always been a convoluted issue. Allen and Wood (2006) best exhibit this issue in their research paper. They argue that throughout time, over crises and over different academic and governmental institutions the definition of financial stability keeps changing. The following research paper employs the definition which the European Central Bank (2022b) uses. This is done in view of the comprehensive nature of such, i.e., it considers 1) Financial Intermediaries, 2) Markets and 3) Market Infrastructures. This is:

> "Financial stability can be defined as a condition in which the financial system – which comprises financial intermediaries, markets and market infrastructures – is capable of withstanding shocks and the unravelling of financial imbalances."
>
> European Central Bank, (2022b, para. 1)

2.2.1 Theory of Measuring Financial Stability

In order for us to be able to quantify the financial risk posed to the system by energy commodity prices it is of importance to understand the underlying theories of measuring and quantifying financial stability. Quantifying financial stability has changed across time as more data and computing power became gradually available to both academics and practitioners. More specifically, financial stability and risk literature has favoured the use of firm-level data over economic segments with a key focus on predicting the probability of bankruptcies (see e.g., Altman, 1968; Shumway, 2001; Merton, 1974; Tasche, 2002).

The literature pertaining to this strand can be categorized into three crucial strands: 1) Microprudential Risk Models, 2) Macroprudential Risk Models, 3) Mixed Models

2.2.2 Microprudential Risk Models

The microprudential risk academic strand focuses on the financial well-being of individual firms/agents/assets. Risk models pertaining to the microprudential literature strands are characterized by being of both theoretical and empirical in nature. These can be further split as:

Accounting Based Models

Accounting data has always been considered crucial to judging the financial standing and wellbeing of a firm. Accounting data has mainly been used within prediction models such as Altman's Z-score (Altman, 1968) and Ohlson (1980). Both of which are considered the seminal papers of this strand. Accounting based models, however, are known to be static and backward looking.

Hazard Models

To improve upon the accounting-based models and offer a solution to the limitations of these academic literature looked elsewhere. Eventually the so-called Hazard models were developed. These models are mainly based on Shumway (2001) who within their paper showcase that the probability of bankruptcy can be modelled as a function of more variables than only accounting data. In addition to this, the crucial improvement over accounting models by Shumway (2001) was the explicit consideration of time within their model. Improvements to Shumway (2001) later came in the form of Chava and Jarrow (2004) who considered idiosyncratic effects by including industry controls and by showcasing that the calculation and intuition behind hazard models is simpler than originally thought. Finally, the next improvement of hazard models came from Campbell et al, (2008) who included macroeconomic variables in an attempt to capture how the macro environment impacts firm survivability.

Contingent Claims Models

Contingent claims models are models known for their strong basis on financial economics theoretical frameworks rather than pure empirical analyses. They are characterized mainly by trying to evaluate the credit risk of a firm by assuming that equity is a call option on a firm's assets (e.g., Merton, 1974). This assumption allows for the use of option-pricing techniques to be used to quantify the probability that the value of a firm will fall below a predetermined level (usually proxied by debt) (see Charitou et al., 2013). One of the first attempts at modelling such a phenomenon comes from Merton (1974). In his model Merton (1974) showcased how equity can be seen as an option given the fact that shareholders have a right to any residual value of the firm once all other financial obligations of the firm are satisfied. Various attempts expanding on Merton's (1974) observations exist. The first area of expansion is the consideration of time when forecasting corporate defaults i.e., known as the Merton distance to default model (Bharath and Shumway, 2008). The second core area of expanding the Merton theory is by taking into account various asset classes and maturities of debt, with the KMV-Merton Model (Charitou et al., 2013) being a great example of such.

Value-at-Risk

While bankruptcy prediction is considered a crucial aspect of risk measurement, it falls short of being able to take into account market risk explicitly. Value-at-Risk (VaR) was one of the first proposed tools at solving such an issue (see Artzner et al., 1999; Tasche, 2002; Adrian and Brunnermeier, 2016; Hull, 2018). Value-at-Risk can be best defined as the maximum quantile loss that one can expect to experience over a pre-defined period given a constant fixed confidence level "a" (see Artzner et al., 1999; Tasche, 2002; Adrian and Brunnermeier, 2016; Hull, 2018). As per academic literature (see Artzner et al., 1999; Tasche, 2002; Adrian and Brunnermeier, 2016; Hull, 2018) VaR can summarize this by first defining VaR(X) of the 100(1-a)% confidence level as:

$$VaR(X) = up\{x \mid P[X \geq x] > a\} \tag{1}$$

Where formula (1) is expressed in terms of up{x|Z} being the upper limit of x given an event Z occurring and $up\{x \mid P[X \geq x] > a\}$ as the upper 100a percentile of a loss distribution (see Artzner et al., 1999; Tasche, 2002; Adrian and Brunnermeier, 2016; Hull, 2018). VaR, however, is limited by certain crucial aspects: VaR is not considered a coherent risk measure given the fact that it is not subadditive; VaR does not take into account tail losses, i.e., extreme losses (see Artzner et al., 1999; Tasche, 2002; Hull, 2018). An attempt to solve these issues was the development of the risk measurement tool known as CoVaR/Expected Short fall (ES) (see Tasche, 2002; Hull, 2018).

Conditional Value-at-Risk / Expected Shortfall

ES solves both of the first two key issues of VaR, i.e. it is both subadditive and takes into account tail events (see Tasche, 2002; Hull ,2018). This can be seen directly from the definition of ES, i.e.,

$$ES(X) = E[X|X \geq VaR(X)] \tag{2}$$

Where E is the expectation operator, i.e., ES is the average loss that one experiences beyond the predetermined VaR conditioned on an event X occurring (see Tasche, 2002; Hull, 2018).

2.2.3 Macroprudential Risk Models

The next important type of risk models come in the form of macroprudential risk models. These models are empirical in nature with strong theoretical economic frameworks. These models mainly are used to quantify financial stability and risk at a macro level, i.e., usually of an individual country or economic region. These models can be split further into:

Macroeconomic Models

Macroeconomic models come in a variety of different empirical forms however all these models are based on underlying macroeconomic theory. Pure theoretical models do exist with Foglia (2008) of the Bank of Italy showcasing that given the unique nature of each country's economic ecosystem a one-fits-all model does not exist and as such a variety of different internal models are currently being used. Furthermore, Foglia (2008) argues that theoretical models in nature are rigid and when unconventional events occur empirical models are preferred. Foglia (2008) suggests the use of Vector Autoregressive models (VAR).

Looking at macroeconomic models, one of the most favourite alternatives to VAR are dynamic stochastic general equilibrium (DSGE) models (see Christoffel et al., 2010). These models are known to be the current dominant models used by governmental institutions to assess the impact of economic policies and understand the sensitivity of such policies to various risk factors. Their favor over other models comes from their clearly defined and strong theoretical and empirical foundations (see Christoffel et al., 2010; Brooks, 2019). Within the DGSE models a variety of different models exist. E.g., de Bandt and Chahad (2016), used a DGSE model with a multi-period asset class framework to assess the impact of banking regulations on the financial sector and real economy, while Kolasa and Rubaszek (2015) instead employ a DGSE model with financial frictions in order to forecast market risk.

Macroprudential models at their core all remain the same regardless of the preferred empirical framework chosen. One of the best academic papers which captures such a phenomenon is by Vazquez et al., (2012), who showcases that macroprudential models that try to assess financial risk all follow three core steps. I.e., they first ensure that any relationships between macroeconomic variables and financial variables is captured, then these relationships are mapped and linked to loan performances of specific economic segments before finally employing a variety of different stress testing methodologies (see also Virolainen, 2004; Wong et al., 2006).

2.2.4 Mixed Models

Given the shortcomings of both micro and macro prudential models, mixed models were invented with the aim of combining the pros of both micro and macro prudential models.

Systemic Risk & Market Risk

Tools for quantifying market risk of an individual firm and/or portfolio conditioned on an event happening already exist in the form of VaR and ES. In spite of this, VaR and ES both fail at being able to capture the opposite relationship, i.e., the impact that an individual firm/or asset has on the whole financial system when that firm/asset is at its VaR a quantile level (see Adrian and Brunnermeier, 2016; Hull, 2018).

A solution to this was proposed by Adrian and Brunnermeier, (2016). They define their new market risk variable as ΔCoVaR. Their ΔCoVaR determines the change of a firm’s VaR by taking into account the transition of the firm’s conditioning event, i.e., from the average expected return of a firm to the firm’s return given an adverse event. This difference in-turn allows for a business’s inherent riskiness to be captured (Adrian and Brunnermeier, 2016). More specifically Adrian and Brunnermeier (2016) define their ΔCoVaR as:

$$\Delta \mathrm{CoVaR}_a^{s,i} = \left(CoVaR_a^s \middle| L_i = VaR_a^i\right) - \left(CoVaR_a^s \middle| L_i = VaR_{0.5}^i\right) \tag{3}$$

Where $\left(CoVaR_a^s \middle| L_i = VaR_a^i\right)$ is the VaR of the financial system at confidence level a conditioned-on firm i experiencing a loss equal to its VaR at confidence level a, while $\left(CoVaR_a^s \middle| L_i = VaR_{0.5}^i\right)$

represents the VaR of the financial system at the confidence level a given that the loss of firm i is equal to its VaR at confidence level of 0.5 (Adrian and Brunnermeier, 2016). Adrian and Brunnermeier (2016) select 0.5 as the conditioning event as a proxy for when firm i is not in distress and is in a normal operating condition. The difference of the two terms showcases the amount of systemic stress that is added to the financial system when firm i goes from normal operations to distressed (Adrian and Brunnermeier, 2016).

Another popular attempt at trying to quantify systemic risk is known as Marginal Expected Shortfall (MES) as per Acharya et al., (2017). Acharya et al.'s, (2017) MES focuses on capturing the marginal expected shortfall of a firm given the financial system has had a VaR violation. This measurement like ΔCoVaR allows for the computation of a firm's contribution to the total systemic risk (see Adrian and Brunnermeier, 2016; Acharya et al., 2017).

Finally, another important measurement to measuring market risk is the SRISK measure of Brownlees and Engle (2017). SRISK is a measure of systemic risk contribution of a financial firm, and it is calculated by finding the capital shortfall of a firm given that the firm is subject to severe systemic stress (Brownlees and Engle, 2017). SRISK is modeled by Brownlees and Engle, (2017) as a function of a firm's size, leverage and risk.

Composite Indicators of Systemic Stress

Another key and popular method for quantifying financial stability is the use of financial indexes. Arguably one of the most important ones being the Composite Indicator of Systemic Stress (CISS) (see Hollo et al., 2012). The CISS used by the European Systemic Risk Board (ESRB, 2021) amalgamated 15-market based financial stress indicators into five categories before mapping them based on their empirical distribution function and averaging them. Financial indexes allow for the capturing of a variety of risk factors at both a micro and macro level making them a useful tool in understanding the health of the financial system. See Table 1 for an overview of the literature regarding financial risk indexes.

Table 1: Financial Risk Index Literature Review

Author	Economic Region	Type
Bordo et al. (2002)	US	Financial Conditions Index
Hanschel and Monnin (2005)	Switzerland	Banking Stress Index
Illing and Liu (2006)	Canada	Financial Stress Index
Nelson and Perli (2007)	US	Financial Fragility Indicator
Cardarelli et al. (2009)	Various	Financial Stress Index
European Central Bank (2009)	Various	Global Index of Financial Turbulence
Hakkio and Keeton (2009	US	Monthly Kansas City Financial Stress Index
Brave and Butters (2010)	US	Financial Conditions Index
Duca and Pletonen (2011)	Various	Financial Stress Index
Grimaldi (2010)	Eurozone	Financial Stress Index
Hatzius et al. (2010)	US	Financial Stress Index
Morales and Estrada (2010)	Columbia	Financial Stress Index
Hollo et al. (2012)	EU	Composite Index of Systemic Stress
Louzis and Vouldis (2013)	Greece	Composite Index of Systemic Stress
Milwood (2013)	Jamaica	Composite Index of Systemic Stress
Cabrera et al. (2014)	Columbia	Composite Index of Systemic Stress
Wen (2015)	Norway	Composite Index of Systemic Stress
Chadwick and Ozturk (2019)	Turkey	Composite Index of Systemic Stress
Miyazaki (2021)	Japan	Composite Index of Systemic Stress

2.2.5 Artificial Intelligence in Quantifying Financial Stability

While most methods at quantifying and understanding financial stability are centered around strong theoretical frameworks and clearly defined econometric techniques, a variety of purely statistical methods are currently a popular topic within academic literature. At the forefront of such methods is artificial intelligence and more specifically machine and deep learning. Machine learning models can arguable be defined as a series of computational and algorithmic models which improve themselves with greater access to data (see Chatzis et al., 2018). Deep learning a subcategory of Machine learning are statistical methods which try and emulate the human mind through the creation of the so-called neural networks (Hayakin, 1998). Given the self-improvement quality of these models, the rise of big data has made such models not only appropriate but also the recommended approach to solving decades old questions.

Machine Learning

While a variety of different methods exist across a variety of different academic literature strands, the most recent academic papers employing such methods on financial stability include: Chatzis et al., (2018), Fouliard et al., (2021) and Duan et al. (2021). Chatzis et al., (2018) try and predict the out of sample probability of a financial stock crises from occurring by testing a variety of different machine learning methods and techniques. The machine and deep learning methods and techniques which they employ include Classification Trees, Support Vector Machines, Random Forests, Neural Networks Extreme Gradient Boosting and Feed Forward Neural Networks; LASSO, K-fold cross validation etc. Fouliard et al. (2021) too tries to predict out of sample financial crises. Their respective choice of statistical method is a non-parametric machine learning method known as online machine learning. Duan et al. (2021) instead opts to use for a more standard quantile regression forest to try and predict out of sample economic risk,

An attempt to combine machine learning techniques and microprudential models came in the form of Xu et al., (2016) and Li et al., (2021). The former used a quantile autoregression neural network to calculate VaR and the latter chose a Bayesian Long-Short-Term-Memory model for forecasting both VaR and ES.

Deep Learning

Deep learning while a subcategory of machine learning tends to not get the same usage within academic literature. While deep learning is known to have greater flexibility over machine learning, deep learning suffers from a "black box phenomenon" (see Qu et al., 2019; Buhrmester et al., 2021). This phenomenon makes it impractical and at times impossible to clearly understand the causal relations within a deep learning model while also hindering the accurate the interpretation of deep learning models' results. Nevertheless, deep learning has seen usage within academic literature, and in particularly within the bankruptcy prediction academic literature strand. Tsai and Wu (2008) where some of the first to employ deep learning methods to try and assess bankruptcy predictions. By employing a single and multi-neural network they were able to find that deep learning methods outperformed traditional econometric techniques. Zhao et al. (2015) on the other hand opts to use a multi-layer perceptron to try and assess credit risk.

Finally, other important and unique attempts at employing deep learning methods to try and predict bankruptcies comes from Hosaka (2019) and Mai et al., (2019). The former transforms firm financial ratios into a gradient grayscale image before using a convolution neural network to transform the gradient images into values to try and predict bankruptcies. The latter i.e., Mai et al. (2019) also employ unorthodox data by transforming text into array data and employing a variety of different methods to forecast out of sample bankruptcies.

2.3 Energy Economics & Finance

Financial Stability literature is vast with many subcategories within the strand, in contrast the Energy Economics & Finance (EEF) academic literature strand is more grounded within the topics that are explored. EEF academic literature mainly focuses on the impact of energy commodity prices and their impacts on the economy, financial stability and society (see Taghizadeh-Hesary et al., 2019). This means that this literature strand focuses less on the underlying empirical methods but instead focuses more on the underlying theories and results of energy price fluctuations (see Hamilton, 1983). It should also be stated that the EEF strand tends to focus mainly on macroeconomics, macrofinance and oil price fluctuations (see Hamilton 1983; Cunado and Perez de Gracia, 2003; Du et al., 2010). Finally, the EEF strand tends to follow certain key steps: firstly, EEF strand categorizes economies as either energy importers vs. energy exporters, followed by differentiating between developing and developed countries, before then defining the country's macro variables (usually GDP) as a function of some other key factors with energy prices being positive if it is a net energy exporter and negative if it is a net energy importer (see Du et al., 2010; Taghizadeh-Hesary et al., 2016)

2.3.1 Energy Commodity Price Movements and the Economy

Energy commodity movements have been one of the most popular research topics within the EEF strand, given the devastating effect that oil shocks can have on the overall economy of a country. One of the first papers in energy commodity price fluctuation was by Hamilton (1983) who investigated the causes of all the US's economic recessions from 1948-72. Hamilton (1983) found that all but one of these recessions was due to dramatic price increases of crude petroleum. In 2003 Cunado and Perez de Gracia (2003) instead focused on European countries from the 1960s up until 1999. They found that oil price fluctuations result in a permanent increase in inflation and a short-term decrease in GDP growth rates.

More recent findings include Du et al., (2010) who find that between 1995 to 2008 oil prices have impacted, albeit in a nonlinear way, the People's Republic of China's (PRC) growth rate and inflation. Further empirical evidence is given by Taghizadeh-Hesary et al. (2016), who assess the impact of crude oil price movements on the GDP growth rate and the consumer price index inflation rate of the US, Japan and the PRC; They find that developed countries i.e., the US, Japan, are more insensitive to oil shocks compared to the PRC, given that developed nations have more alternative sources of energy (mainly nuclear). Even more recent academic literature regarding energy price movements includes Taghizadeh-Hesary et al. (2019). Taghizadeh-Hesary et al. (2019) focuses on the impact that oil price movement volatility has on food security. They find that oil price movements have a significant impact on food prices and that an increase in oil prices is overall dangerous to the energy and food security of countries and the agricultural sector. Finally, regarding oil price movements, Mugaloglu et al., (2021) focuses on the recent impact of oil prices on energy stock returns during the Covid-19 pandemic. They find that oil prices are not informative in regard to their explanatory power during the pandemic.

2.3.2 Energy and Financial Stability

Energy and financial stability have always been a keen topic of interest to a wide array of different practitioners and academics. Nevertheless, most energy related academic literature tends to focus on financial stability indirectly by rather looking at stock market returns (See Huang et al., 1996; Ciner, 2001, Cong et al., 2008; Broadstock et al., 2012). A recent paper which focuses on stock return predictions using energy prices comes from Kim et al., (2019). They find that energy prices' predictive power varies across time, with negative effects being observed before 2008.

Academic literature which focuses directly on financial stability while does exist is rare. Nasreen et al., (2017) e.g., take a unique approach to measuring financial stability by looking at the relationships between financial market indicators (e.g., Interest Rate Spreads) and financial vulnerability indicators (e.g., fiscal deficit) with CO_2 emissions. Other research conducted in regard to financial stability and energy economics comes in the form of Safarzynska and van den Bergh (2017). They found that rapidly investing in renewable energy can cause a rise in financial vulnerability in mainly coal dependent economies. Saif-Alyousfi et al., (2018) instead opt to find the impact of oil and gas prices on bank deposits in Qatar. They find that oil and gas price fluctuations do in turn impact Qatari bank deposits.

Finally, academic literature which focuses on financial stability tends to do so through the studying of interconnectedness of energy commodity shocks and their spillover effects. Naeem et al., (2020) studies the interconnectedness of a variety of different energy commodities including: Oil; Carbon; Natural Gas; Coal; Electricity (Nord Pool electricity futures); and the S&P Clean Energy Index. They find that electricity futures can act as a hedging asset against oil shock prices, as electricity futures have the lowest interconnectedness with oil. While Green et al., (2018) focus on the spill over effects of shocks in the prices of gas, coal and carbon emission allowances in Germany. They find that gas and coal generate non-negligible spillovers during their sample period. However, they do find that carbon emission allowances generate significant spillover effects between the years of 2011 and 2014. Tiwari et al., (2019a) also try to find the impact of spillover effects albeit through a different approach. They model systemic risk as a dependence between oil prices and currency exchange rates finding that there are no contagion effects arising from the oil market to currency markets of the PRC, India and South Africa. Finally, in respect to financial stability and energy Tiwari et al., (2019b) uses a Non-parametric Granger CoVaR to test for granger causality among stock markets and oil prices.

Chapter 3 Methodology & Methods

The literature within both fields of financial stability and energy economics and finance covers a wide arrange of topics and at times even crosses into each other's segments. However, even when that is the case most papers do not follow a comprehensive interdisciplinary approach to answering the questions they pose but rather instead view the issue exclusively from their own specific segment's lens.

This research paper ensures that this is not an issue and adopts a neutral interdisciplinary approach by ensuring that both literature strands of Financial Stability and EEF are joint together. As a result of this, this research's methodology is split into two core areas.

The first section is related to measuring the impact of energy on systemic stress through the measuring of ΔCoVaR (as per Adrian and Brunnermeier, 2016) of the financial system, conditioned on different economic segments before subsequently running an econometric analysis on the ΔCoVaR with energy related independent variables i.e., the price of oil, gas, gasoline and carbon emission allowances. This allows us to find the impact of different energy related variables on the systemic stress caused by economic segments.

The second part of this research is related to finding the direct impact of energy commodity prices to the overall impact of systemic stress. This is done through changing the definition of ΔCoVaR and the conditioning event.

It should also be stated that the research methodology is also partially based on Asgharian et al., (2021). They too calculate a time-varying ΔCoVaR before conducting econometric analysis on their results. Albeit this is done in the context of how centrality of financial networks impacts systemic risk.

Section A: Indirect Measuring of Energy Commodity Price Impacts on Financial Stability

In order for us to be able to calculate the impact of energy prices to systemic stress we first need to calculate Adrian and Brunnermeier's (2016) ΔCoVaR. As aforementioned ΔCoVaR is the difference between CoVaR of the system given firm i is in distress minus the CoVaR of the system given the firm i is not in distress (Adrian and Brunnermeier, 2016). This means that we must first find the two CoVaRs.

3.1.1 Defining Losses

Before we can start defining CoVaR we must first define how we calculate losses. Losses are calculated as:

$$L_t^i = -\frac{\left(Price_t^i - Price_{t-1}^i\right)}{Price_{t-1}^i} \tag{4}$$

3.1.2 Defining CoVaR

To calculate the CoVaR it is first important to re-state the definition of what a firm's VaR is. VaR of a firm i can be defined as the expected maximum potential loss of firm i (L^i) with a confidence of a over a given holding period n (see Tasche, 2002; Adrian and Brunnermeier, 2016; Hull, 2018). Thus, as per Adrian and Brunnermeier (2016) we can start off by re-stating eq. (1) for ease:

$$\Pr\,(L^i \leq VaR_a^i) \tag{5}$$

From here we can then condition the VaR of the whole financial system s on an event which would make firm i be in distress i.e., EV(L^i) giving us CoVaR and:

$$\Pr\left(L^s \leq CoVaR_a^{s\,|\,EV(i)} \middle| EV\left(L^i\right)\right) = a \tag{6}$$

From eq. (6) we can then define the $CoVaR_q^{s\,|\,EV(i)}$ as the ath quantile of the loss distribution of the financial system conditional on some event EV happening and we can then define EV as the event which causes the firm i to reach its a%-VaR level i.e., $L^i = VaR_q^i$ (see Adrian and Brunnermeier, 2016). Finally, we can then define (as per Adrian and Brunnermeier, 2016) the amount of systemic stress caused by the firm i by calculating the CoVaR at a=50% and then taking the difference i.e.:

$$\Delta\mathrm{CoVaR}_a^{s,i} = \left(CoVaR_a^s \middle| L_i = VaR_a^i\right) - \left(CoVaR_a^s \middle| L_i = VaR_{0.5}^i\right) \tag{7}$$

With eq. 7 giving us Adrian and Brunnermeier's (2016) ΔCoVaR. Given that we are interested in finding the impact at the sectorial level we can easily change the definition of eq. (7) to

$$\Delta\mathrm{CoVaR}_a^{s,c} = (CoVaR_a^s | L_c = VaR_a^c) - (CoVaR_a^s | L_c = VaR_{0.5}^c) \tag{8}$$

Where c is the subscript representing the economic sector c instead of firm i. This means that all the other terms inherently change as well i.e., we calculate the losses for the whole economic sector rather than for an individual firm.

3.1.3 Estimating CoVaR, ΔCoVaR & €ΔCoVaR

While in the aforementioned subsection we defined Adrian and Brunnermeier's (2016) CoVaR and ΔCoVaR. Their estimation in practicality can be done easily through the use of quantile regressions as shown by Adrian and Brunnermeier (2016). This is because of how a quantile regression works. For example, if we were to run a quantile regression of the losses of sector c (L^c) on a constant X then we would get the sector's a%-VaR i.e., the ath quantile of L^c (see Adrian and Brunnermeier, 2016). Adrian and Brunnermeier (2016) explain this mathematically as:

$$L_a^c = X_a^c + \varepsilon_a^c \tag{9}$$

And from eq. (9) we get that:

$$VaR_q^c = \hat{X}_a^c \tag{10}$$

Thus from eq. (9) & (10) we can easily derive the CoVaR of the system s given that the economic sector c is in distress by running a quantile regression as:

$$L_a^s = X_a^c + \beta_a^c L^c + \varepsilon_a^c \tag{11}$$

and once again we get:

$$CoVaR_a^{s|L^c=VaR_a^c} = VaR_a^s|VaR_a^c = \hat{a}_a^c + \hat{\beta}_a^c VaR_a^c \tag{12}$$

Finally, we can now use the fitted values of L_a^s given that $L^c = VaR_a^c$ and derive the quantile regression ΔCoVaR. This is defined as:

$$CoVaR_a^{s|L^c=VaR_a^c} = \left(\hat{a}_a^c + \hat{\beta}_a^c VaR_a^c\right) - \left(\hat{a}_{0.5}^c + \hat{\beta}_{0.5}^c VaR_{o.5}^c\right) = \hat{\beta}_a^c (VaR_a^c - VaR_{o.5}^c) \tag{13}$$

(see Adrian and Brunneirmeier, 2016 for more information). In order however to quantify the actual impact in monetary terms of the systemic risk added to the economy we can multiply the ΔCoVaR by the market capitalization of the economic sector (see Adrian and Brunnermeier, 2016). Given our interest in the European region we can define this mathematically as follows:

$$€\Delta\text{CoVaR}_t^c = MarketCap_t^c * \Delta\text{CoVaR}_t^c \tag{14}$$

Where $€\Delta\text{CoVaR}_t^c$ is the Euro ΔCoVaR at time t and can be interpreted as the surplus number of euros that system's VaR experiences when economic sector c is in distress.

It is, however, important to note that this measure of CoVaR is an estimate of the average contribution of the economic sector c to the overall systemic risk for the chosen time period (Adrian and Brunnermeier, 2016). Given that is that this measure does not factor in the change of the CoVaR across time and as such as per Adrian and Brunnermeier (2016) we must also calculate a Time-Varying ΔCoVaR.

3.1.4 Estimating Time-Varying ΔCoVaR

Calculating a Time-Varying ΔCoVaR will allow us to model the joint distributions over time and allows us to have a clearer picture of the impact of energy prices on systemic stress (see Adrian and Brunnermeier, 2016). Adrian and Brunnermeier (2016), also present a methodology for calculating a Time-Varying ΔCoVaR through assuming that ΔCoVaR is a function of key lagged state variables defined as $\boldsymbol{M_{t-1}}$. These variables are explained in detail in the following chapter. The process for calculating them as per Adrian and Brunnermeier (2016) is presented below:

Firstly, as with eq. (11) we find

$$L_t^c = X_a^c + \gamma_a^c \boldsymbol{M_{t-1}} + \varepsilon_{a,t}^c \tag{15}$$

We then find the new quantile regression based off eq. (10) as:

$$L_t^{s|c} = X_a^{s|c} + \gamma_a^{s|c} \boldsymbol{M_{t-1}} + \beta_a^{s|c} L_t^c + \varepsilon_{a,t}^{s|c} \tag{16}$$

We can then use the predicted values from eq. (15) and (16) to find the following regressions:

$$VaR_{a,t}^c = \hat{a}_a^c + \hat{\gamma}_a^c \boldsymbol{M_{t-1}}$$

$$CoVaR_{a,t}^c = \hat{X}_a^{s|c} + \hat{\gamma}_a^{s|c} \boldsymbol{M_{t-1}} + \hat{\beta}_a^{s|c} VaR_{a,t}^c \tag{17}$$

Finally, the Time-Varying ΔCoVaR can be computed for each economic sector:

$$\Delta CoVaR_{a,t}^c = CoVaR_{a,t}^C - CoVaR_{50,t}^c = \hat{\beta}_a^c \left(VaR_{a,t}^c - VaR_{50,t}^c\right) \tag{18}$$

3.1.5 Estimating a Time-Varying VaR

In order for use to calculate the time-varying ΔCoVaR it is first important as seen from eq. 17 to calculate the VaR. Adrian and Brunnermeier (2016) do not specify their approach in calculating the VaR, however, given that the aim of a time-varying CoVaR is to truly capture the change over time we thus employ a time-varying VaR rather than using a static one. To do this we employ the popular Basic-Historical-Simulation (BHS) with a time-span of 250 days (as per van den Goorbergh and Vlaar, 1999). A BHS was selected over other types of simulations based on two core reasons. Firstly, given the fact that BHS is the simplest method. The quantile regressions of Adrian and Brunneirmeier (2016) contain the macro variables whose role is to capture the change of the statistical moments of the ΔCoVaR. This means that if we calculate the VaR using a more complicated method e.g. volatility or age-weighted, we may end up artificially changing the true movement of the VaR across time or double-counting them. Furthermore, the simplicity of BHS allows for easy comparison among other academic literature and easy interpretation. The second core reasoning BHS is used is its non-parametric approach (see van den Goorbergh and Vlaar, 1999). A non-parametric approach ensures that we do not have to impose any form of assumptions on the loss distribution. This is of critical importance given the fact that this is the role of the macro variables initially employed as per Adrian and Brunnermeier (2016).

3.1.6 Econometric Analysis

ΔCoVaR allows for good understanding of the sources of financial instability, however it lacks the ability to find the root causes of such. I.e., we can find the amount of financial instability caused by the conditioning agent, however we cannot find what causes said agent to become distressed in the first place (see Adrian and Brunnermeier, 2016). A solution to such a problem can be overcome by simply employing an econometric analysis on the ΔCoVaR. This research paper opts to employ panel regression analysis.

Panel regressions have been a staple in the financial literature and especially in the EEF literature strand (see Dauvin, 2014; Ge and Tang, 2020; Zhang et al., 2021). While panel regression has its negative features (e.g., such as losing the ability to analyse time-variability), the core reasoning for its employment in this research is its flexibility (see Brooks, 2019). Given that panel regressions take into account both time-series and cross-sectional data, one can increase the number of available observations they have and get a stronger understanding of how variables impact each-other (see Brooks, 2019).

Furthermore, panel regressions are employed given the nature of ΔCoVaR. ΔCoVaR needs a conditioning agent by definition (see Adrian and Brunnermeier, 2016). If there is no conditioning agent ΔCoVaR is merely the change of the VaR of the financial system from a normal state to a distressed state (see Adrian and Brunnermeier, 2016). Thus, by employing panel regressions we are able to not only increase our observations but also amalgamate all the different ΔCoVaRs across the different economic sectors. Finally, panel regressions are employed in order to avoid a large number of regressions (See Chapter 8 Delimitations).

3.1.7 Panel Model

We thus employ the following general panel data econometric model:

$$\Delta CoVaR_{a,t}^{c} = a_t + \boldsymbol{\beta_t X_t^c} + \boldsymbol{\gamma_t EC_t^c} + \boldsymbol{SFE_t^c} + \varepsilon_t^c \tag{19}$$

Where $\boldsymbol{X_t^c}$ are the control variables for the specific sectors c at time t, $\boldsymbol{EC_t^c}$ are the energy commodities at time t for sector c, $\boldsymbol{SFE_t^c}$ are the sectorial fixed effects and ε_t^c is the error term. We employ two different methods of panel estimation: In Asgharian et al. (2021) they argue that given that CoVaR is approximately equal to beta*VaR and given the fact that the median CoVaR is indifferent from zero (see eq. 18), beta only varies cross-sectionally. As such they argue that when employing a FE panel model, one should either only include either VaR or FE in their model as including both should cancel out the effect of beta. Given this, we thus employ the following models:

$$With\ Fixed\ Effects: \Delta CoVaR_{a,t}^{c} = a_t + \boldsymbol{\beta_t X_t^c} + \boldsymbol{\gamma_t EC_t^c} + \boldsymbol{FE_t^c} + \varepsilon_t^c \tag{20}$$

$$With\ VaR: \Delta CoVaR_{a,t}^{c} = a_t + \boldsymbol{\beta_t X_t^c} + \boldsymbol{\gamma_t EC_t^c} + \boldsymbol{VaR_t^c} + \varepsilon_t^c \tag{21}$$

The control variables are selected based on academic literature. We only focus on the importance of micro variables given the fact that the time varying ΔCoVaRs are calculated with macro variables as explained in the prior part of this research and as such including macro variables in a linear regression model may in turn result in spurious results. The areas identified from the literature for which control variables are required are as follows: Leverage, Size, Market Risk, Liquidity, Profitability, Purchasing Power. These areas and their relationship with financial markets has always been examined and linked (see e.g., Fama and French, 1993; Amihud and Mendelson, 1986). More specifically we define and explain their significance as follows:

Leverage: Leverage refers to the indebtedness of the economic sector. It measures how much that said sector owes in payments and coupons. Leverage as seen from the 2008 financial debt crisis is arguably one of the largest and most important areas needed to be included.

Size: Size is a measure of how "big" the economic sector is. Size is a crucial aspect of understanding the importance of an economic sector and the riskiness it poses. For example, if two economic sectors have the same ΔCoVaRs, then the larger economic sector would have a larger €ΔCoVaR and thus can be argued to be more overall risky to the financial system.

Market Risk: Market Risk measures the idiosyncratic micro-economic riskiness of an economic sector. As such one would inherently assume that the larger the idiosyncratic risk the larger risk it poses to the overall financial system.

Liquidity: Liquidity refers to the ability of an economic sector to meet unexpected obligations and its ability to quickly generate cash flows if required. Liquidity is also usually seen as the flexibility of an economic sector in being able to withstand unexpected detrimental events.

Profitability: Profitability refers to the ability for an individual firm to be able to generate profits. Profitability is a crucial area to look at as a highly profitable sector should cause more financial instability if it is in distress rather than a non-profitable sector.

Purchasing Power: Purchasing power is an area which the academic literature does not usually split on its own but rather incorporates it under other names. In the context of this research purchasing power refers to the ease of an economic sector to be able to make purchases of the energy product it requires.

3.1.8 Model Selection for Econometric Analysis

In order for us to select the best control variables which represent each of the aforementioned areas for our econometric analysis we follow a reduced Chatzis et al. (2018) model selection methodology i.e., a form of mixture of Best Subset and LASSO regression. Initially we employ a LASSO (Least Absolute Shrinkage and Selection Operator) regression as originally envisioned Tibshirani (1996). A LASSO regression is a regularized linear regression used for model selection which accomplishes this by minimizing the model's bias and variance (James et al., 2013). This is achieved by setting a penalty term to all predictor variables which are then adjusted to the value which optimizes the model (James et al., 2013). LASSO's importance in model selection is based on its tendency to set most of the predictor variables equal to zero (which is why Ridge Regression as per Hoerl and Kennard (1970) is not preferred), allowing for the possibility of employing a variety and a large amount of different predictor variables without fears of multicollinearity and other statistical issues (James et al., 2013). Tibshirani's (1996) LASSO is usually defined mathematically as follows:

$$\beta_{\lambda}^{L} = \arg\min \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \left|\beta_j\right|^2 \qquad (22)$$

Where β_{λ}^{L} is the regularized predictor variable coefficient. The LASSO regression is run once for the Time-Varying ΔCoVaR of the financial system (i.e., the difference of the system's VaR at 99% and at a 95% confidence interval) with a set of predictor variables $\boldsymbol{X_t^s}$. This is mainly done due to the large number of regressions that have to be run in total throughout this paper and the limited time frame. Thus, in order to avoid having a variety of different predictor variables and limited cross-comparability among models we instead opt to try and see which variables best predict the average systemic risk of the system. To increase the robustness of the LASSO result we also employ the re-sampling K-Fold cross-validation technique and run the LASSO regression a total of $1e^5$ times (see James et al., 2013).

Given the pure statistical nature of the LASSO regression we thus also employ a qualitative variable selection methodology on top of this (as per Chatzis et al., 2018). Once the LASSO regression results are outputted, we first select the variables with a non-zero value regularization and include the most important variables for prediction of each of the identified control variable categories. This is done until all areas are represented by the variables found. If an area is not represented, we then identify the variable in the said category which is last to be regularized to zero. Once the selected models are found we then test the standard issues in regression analysis: Normality; Multicollinearity; Heteroskedasticity; Autocorrelation.

It should be stated that this methodology for defining the areas of interest i.e., the control variable categories and then using a purely statistical optimization approach to finding such variables helps overcome the issue of omitted-variable bias. In particularly due to the large amount of predictor variables that are used in our LASSO regression.

3.1.9 Normality

Normality while not a necessary attribute for the OLS to be considered the most efficient estimator, is required in the residuals of the regression for inference analysis to be conducted (see Brooks, 2019). The greatest issue is that financial data is rarely normal, however, Brooks (2019) basing themselves on the central limit theorem have shown that if the number of observations are large enough then the issue of non-normality is considered miniscule and correct inferences can still be drawn from such an analysis. Nevertheless, there are methods for increasing the normality of data. We test each variable with the Jarque-Bera (Jarque and Bera, 1987) test of normality and then test following two methods for fixing non-normal data: We firstly transform any data into its logarithmic version of itself and then we windsorize any predictor variable to control for outliers. We then test if the transformed variables do in fact help with the normality of the data. If this is not the case, we keep the raw forms for the following reasons: The less transformations a variable undergoes the easier its interpretation; There is a fine line between windsorizing and transforming a variable and data manipulation.

In order however to ensure that our model is further robust, we also employ the popular resampling method of Bootstrapping. Bootstrapping is a form of random sampling with replacement, which allows for the calculation of confidence intervals and thus allows for inference without making the assumption that the data is normally distributed (see Efron and Tibshirani 1993; Davidson and Monticini, 2014).

3.1.10 Multicollinearity

Multicollinearity is the econometric concept in which multiple independent variables in a regression analysis are correlated (see Brooks, 2019). Multicollinearity results in inference testing to be difficult and at times impossible (see Brooks, 2019). The presence of multicollinearity is tested with the Variance Inflation Factor (VIF) (see Brooks, 2019).

3.1.11 Heteroskedasticity

Heteroskedasticity refers to a lack of equal variances within a random distribution (see Brooks, 2019). The presence of which results in the Gauss-Markov theorem not upholding any longer and as such resulting in our OLS not being considered the Best Linear Unbiased Estimators (Blue) (see Brooks, 2019). The presence of Heteroskedasticity is tested with the Breusch and Pagan (1979) test.

3.1.12 Autocorrelation

Autocorrelation can be broadly defined as a process which is a function of a delayed copy of itself (see Brooks, 2019). The presence of autocorrelation can result in spurious regressions and type-II errors (see Brooks, 2019). Autocorrelation is tested with the Durbin-Watson test (Durbin and Watson, 1950, 1951).

3.1.13 Estimating Robust Models

Given the chaotic nature of financial data is easy to assume that financial data will not be well behaved. That is, it will be heteroskedastic, autocorrelated and also suffer from multicollinearity. To ensure that our inferences remain robust we ensure that if they are present, they are dealt accordingly. See Chapter 4 for more information regarding this.

Section B: Direct Measuring of Energy Impact on Financial Stability

3.2.1 Modifying & Re-stating ΔCoVaR

In order for us to be able to understand the impact of energy commodity prices directly, one might suggest to calculate the ΔCoVaR conditioned on energy commodity prices. However, given the fact that empirical evidence tends to suggest that a rise in energy prices results in a decrease in GDP of a country (see Berk and Yetkiner, 2014), measuring the ΔCoVaR of the financial system, conditioned on energy commodity price losses, would not be fruitful. This is because a loss in energy prices should not empirically cause any systemic stress. As such by slightly adjusting the original definition of ΔCoVaR of Adrian and Brunnermeier (2016) i.e.

$$\Delta\text{CoVaR}_{a}^{s,i} = \left(CoVaR_{a}^{s} \middle| L_{i} = VaR_{a}^{i}\right) - \left(CoVaR_{a}^{s} \middle| L_{i} = VaR_{0.5}^{i}\right) \tag{23}$$

To

$$\Delta\text{CoVaR}_{a}^{s,i} = \left(CoVaR_{a}^{s} \middle| G_{i} = VaR_{a}^{i}\right) - \left(CoVaR_{a}^{s} \middle| G_{i} = VaR_{0.5}^{i}\right) \tag{24}$$

Where G is the gain in energy prices, we can find the systemic stress caused to the financial system given the gains in energy prices.

Please note this is not the "opposite" of VaR i.e., this is not a form of "Value-at-Increase" as in an a-quantile gain but rather a VaR conditioned on the gain of an asset. In other words, how much would a firm lose given x commodity increases in value given a confidence of "a".

3.2.2 Econometric Analysis

The econometric analysis for Section B is inherently different due to the change of the definition of the Time-Varying ΔCoVaR i.e., being conditioned on energy commodity prices. This means that selecting appropriate predictor variables is inherently limited if we were to base ourselves entirely on the financial stability literature strand. Thus, by turning to the EEF strand we can see that in most cases macro-variables are used in large time-varying datasets. As such we too follow suit. We thus employ a standard Vector-Auto-Regression model (VAR) (see Foglia, 2008; Brooks, 2019) with key explanatory variables being macro variables which central banks can immediately impact and a Time-Varying ΔCoVaR.

3.2.3 Vector Autoregressive Model

A Vector-Autoregressive model has seen popular use within governmental and academic settings given its flexibility (see Foglia, 2008). In a VAR system there is no need to specify which variables are considered endogenous and which ones are explanatory (see Brooks, 2019). The reason for this is that within a VAR system all variables are treated as endogenous, i.e., each variable within the VAR system depends on past lags of the other variables (Brooks, 2019).

A standard VAR of p lags is broadly defined as:

$$\boldsymbol{y_t} = c + \sum_{t=1}^{p} \varphi_i \boldsymbol{y_{t-1}} + \varepsilon_t \tag{25}$$

Where y_t can be defined as a vector of endogenous variables (n x 1), c is a n x 1 intercept vector of the VAR and φ_i is the ith (n x n) matrix of autoregressive coefficients for i=1, 2, … N. and ε_t is a n x 1 white noise process (see Brooks, 2019).

Like with panel regressions a VAR model requires certain steps to be executed for its implementation and its analysis to be both robust and stable. As such the following are examined in order:

3.2.4 Stationarity and Unit Root Testing

Stationarity as a concept has many different definitions (see Brooks, 2019). The following research employs the concept of weak stationarity. Weak stationarity can be defined as a series which has a constant mean, constant variance and constant autocovariances (Brooks, 2019). Stationarity within a model is important as a system which is not stationary can lead to spurious regressions as well as hinder inference analysis (Brooks, 2019). Moreover, in a non-stationary series a shock to the system does not die out but can even compound (Brooks, 2019). Brooks (2019) even argues that given a non-stationary series, t-tests will not be possible as the standard assumptions for asymptotic analysis will not hold true anymore.

In order for us to ensure that our series are all stationary we employ the popular Augmented-Dickey-Fuller (Dickey and Fuller, 1979) (ADF) test and the Phillips-Perron (Phillips and Perron, 1988) test covering a total of 12 lags prior (see Brooks, 2019). If a unit root is detected (i.e., the series is not stationary) we integrate the series until the series becomes stationary.

3.2.5 Selecting an Optimal Lag Length

As seen from equation X in a VAR the lagged values of different variables are required to specify a VAR. The importance of selecting the correct lag length Brooks (2019) argues is due to the fact that a mis-specified VAR could not only be inefficient but can also lead to wrong inferences. As different strategies exist for determining the correct lag length, we employ a combined information criteria selection process. Since Brooks, (2019) argues that different information criteria have different setbacks, we opt to calculate the following three information criteria and a measure for final prediction error according to Pfaff (2008) before selecting the suggested average lag length. The information criteria and final prediction error employed are calculated as per Pfaff's (2008) R Package 'vars', these are:

Akaike Information Criterion (see Akaike, 1974; Pfaff, 2008):

$$AIC\ (n) = \ln(det)\left(\tilde{\Sigma}_u(n)\right) + \frac{2}{T}nK^2 \tag{26}$$

Hannan-Quinn (see Hannan and Quinn, 1979; Pfaff, 2008):

$$HQ\ (n) = \ln(det)\left(\tilde{\Sigma}_u(n)\right) + \frac{2\ln(\ln(T))}{T}nK^2 \tag{27}$$

Schwarz's Criterion (see Schwarz, 1978; Pfaff, 2008):

$$SC\ (n) = \ln(det)\left(\tilde{\Sigma}_u(n)\right) + \frac{\ln\ (T)}{T}nK^2 \tag{28}$$

Akaike's Final Prediction Error (Akaike, 1969; Pfaff, 2008):

$$FPE\ (n) = (\frac{T + n*}{T - n*})^K \det\left(\tilde{\Sigma}_u(n)\right) \tag{29}$$

For more information on Information Criteria see Brooks, (2019) and Pfaff (2008)

3.2.6 Cointegration

Cointegration by Engle and Granger (1987) is usually defined as the circumstance in which if a set of variables are linearly combined their combination is stationary. The importance, however, of cointegration is not from the mathematical aspect of the definition but the underlying consequences of such. If two variables are cointegrated it suggests that those two variables share a long-term relationship i.e., while such variables may deviate from each other in the short-term in the long-term they will return to their equilibrium (Brooks, 2019). Thus, if we were to use a standard VAR model and our variables are cointegrated, this would mean that we would not be able to capture any of the long-term relationships (Brooks, 2019). Given the possibility of many cointegrating relationships existing we aim to employ the Johansen Procedure (Johansen, 1988) using both the Trace and Eigenvalue approach assuming that our variables are all of I(1) level of integration. (see also Johansen, 1991, Johansen and Juselius, 1990, Brooks, 2019). In the case that cointegrating relationships are observed, we instead opt to use a Vector Error Correction Model (VECM) (see Brooks, 2019).

3.2.7 Impulse Response Analysis

In order for us to then understand our results we will employ a Granger and instantaneous causality test as originally seen in Granger, (1969) as per Pfaff (2008) using their R package ‘vars’. While causality tests allow us to observe causality patterns fully understanding the implications of such patterns still remains limited. To overcome this, impulse analysis as per Pfaff (2008) are carried out (through their R package ‘vars’).

3.2.8 Stability and Robustness

In order for us to ensure that our analysis is robust we employ the following two robustness measures. Firstly, we ensure that the model is stable by calculating the cumulative sum control chart (CUSUM) (see Pfaff, 2008; Han et al., 2010) and we then also employ a simple non-parametric bootstrap on our results as seen in Pfaff (2008). Both of these are done through Pfaff’s (2008) R package ‘vars’.

Chapter 4 Data, Variable & Model Specifications Definitions

In the following chapter the variables, the proxies used for each variable, as well as the databases from which data is derived is analysed and given.

Section A: Variable Definitions and Specifications

4.1.1 Defining the Macro Variables Included in calculating the Time-Varying ΔCoVaR

As aforementioned Adrian and Brunnermeier (2016) employ certain lagged-macroeconomic variables to their quantile regression of the time varying ΔCoVaR. These are as follows:

i. The Federal Reserve Board's change of the three-month yield
ii. The change in the slop of the yield curve i.e., the change between the 10-year and the 3-month treasury bills
iii. The TED spread i.e., the 3-month LIBOR minus the three-month secondary-market treasury bill rate
iv. The change of the credit spread between Moody's Baa-rated bonds and the 10-year treasury rate
v. The S&P 500 weekly returns
vi. The real estate sector return in excess of the market financial sector return (i.e., with real estate firms with SIC code 65-66)
vii. A 22-day rolling standard deviation of the daily CRSP equity market returns i.e., the Equity volatility

Since the macroeconomic variables are not inherently considered risk factors but rather are used to capture the statistical moments of the change of the systemic risk climate it is only natural that this too be adapted to the applicable economic area (Adrian and Brunnermeier, 2016). Thus, since we are interested in creating a European version of the ΔCoVaR it is important to change these macro variables to their European counterpart were applicable. This thus means that the macro variables used are:

i. The European Central Banks All Government Triple A bond change of the three-month yield (ECB Statistical Data Warehouse (ECBSDW))

ii. The change in the slope of the yield curve i.e., the change between the 10-year and 3-month ECB All Government Triple A bond yields (ECBSDW)
iii. The 3 Month Libor Rate minus the 3-month ECB All Government Triple A Bond three-month yield (Bloomberg, ECBSDW)
iv. The change of the credit spread between Moody's Baa-rated bonds and the 10-year ECB All Government Triple A Bond rate (Bloomberg, ECBSDW)
v. The EURO STOXX 600 daily returns (Bloomberg)
vi. The EURO STOXX 600 real estate sector returns in excess of the EURO STOXX 600 banking sector return (Bloomberg)
vii. A 30-day rolling standard deviation of the equity market of the EURO STOXX 600 (Bloomberg).

In accordance with Adrian and Brunnermeier (2016) variables (i), (iii) and (vii) are meant to capture future economic growth and inflation. More specifically (as per Adrian and Brunnermeier, 2016) variable (i) captures inflation, variable (iii) captures short-term liquidity risk, variable (vii) captures future market sentiment. Moreover, variables (ii) and (iv) are considered to represent time variation in the return tails and variables (v) and (vi) are used as control variables for equity market returns (Adrian and Brunnermeier, 2016).

To calculate sectorial returns, we employ the sectorial version of the EURO STOXX 600. These are split into 19 different sectors given below in Table 2:

Table 2: EURO STOXX SECTORES

No:	Index Name	Economic Sector	Ticker
1	STOXX Europe 600	Health Care	(SXDP)
2	STOXX Europe 600	Industrial Goods & Services	(SXNP)
3	STOXX Europe 600	Food & Beverage	(SX3P)
4	STOXX Europe 600	Banks	(SX7P)
5	STOXX Europe 600	Technology	(SX8P)
6	STOXX Europe 600	Personal & Household Goods	(SXQP)
7	STOXX Europe 600	Insurance	(SXIP)
8	STOXX Europe 600	Oil & Gas	(SXEP)
9	STOXX Europe 600	Chemicals	(SX4P)
10	STOXX Europe 600	Utilities	(SX6P)
11	STOXX Europe 600	Retail	(SXRP)
12	STOXX Europe 600	Telecommunications	(SXKP)
13	STOXX Europe 600	Construction & Materials	(SXOP)
14	STOXX Europe 600	Financial Services	(SXFP)
15	STOXX Europe 600	Real Estate	(SX86P)
16	STOXX Europe 600	Automobiles & Parts	(SXAP)
17	STOXX Europe 600	Basic Resources	(SXPP)
18	STOXX Europe 600	Media	(SXMP)
19	STOXX Europe 600	Travel & Leisure	(SXTP)

Most of the macro variables used are not directly available from databases and are thus inherently calculated as one would assume. The databases used are given here and more specifically in each name above as: Bloomberg, ECB Statistical Data Warehouse (ECBSDW).

4.1.2 Defining the Variables that make up the Macro Variables

The STOXX Europe 600 index is used as the basis of the financial system given its broad coverage of companies across a variety of countries in Europe. It has a constituent list of exactly 600 firms from a variety of different sectors, as well as market capitalization across 17 countries in Europe. These countries are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the U.K (Qontigo, 2022a). This makes STOXX Europe 600 one of the broadest stock market indexes covering the European region as a whole, e.g., compared to the likes of EURO STOXX 50 (Qontigo, 2022b) and the S&P Europe 350 (S&P Dow Jones Indices, 2022), and thus makes it an appropriate proxy of the financial system of the region.

Variables regarding the yield curve i.e., the 3-month and the 10-month yield from the European Central Bank's statistical data warehouse, are made up of all Euro area nominal government bonds whose rating is considered triple A (ECB, 2022c). The calculation of the yield rates is based on the Svensson (1994) methodology (ECB, 2022d).

4.1.3 Sample Size

The sample size was determined differently for the static ΔCoVaR and for the time varying ΔCoVaR. Each respective ΔCoVaR was calculated with the largest available historical time-series dataset. To ensure consistency among the different sectors when calculating both the static and time-varying ΔCoVaR the datasets were synchronized in respect to time. From there any date which had a missing observation for any of the variables used was removed. As a result of this for the static ΔCoVaR a total number of 5454 observations over the timerange of 02-Jan-2001 up until the 31-Mar-2022 are available.

Given the use of a BHS for the calculation of the VaR and the limited data of the Euro Area triple A yield, we end up with a total of 4049 different ΔCoVaRs spanning a range of 14-Sep-2005 up until 29-Mar-2022.

4.1.4 Econometric Analysis Variable Definition

Basing ourselves on the literature review, we initially selected a series of different micro as well as macro variables to act as independent and predictor variables. Initially we start off with Section A's panel regression followed by Section B's VAR model.

4.1.5 Panel Regression Predictor Variables

Note that all the data relating to predictor variables (excluding the Value-at-Risk which we calculated prior with data from Bloomberg) was taken directly from Eikon Refinitive database.

Initially the following variables were considered:

Market Risk: Value-at-Risk (99%); As aforementioned VaR is a common metric used by a variety of different academic as well as professional institutions to gauge the risk of an individual firm. By including VaR at the (99%) we aim to capture the micro market risk the economic sector has.

Size: Size is proxied from the following three variables.

1. Market Capitalization: Market Capitalization is one of the most popular methods for measuring the size of a firm, economic sector etc.
2. Enterprise Value: Enterprise Value like Market Capitalization is a metric for the size of an individual firm, however unlike Market Capitalization Enterprise Value is considered a more comprehensive version of market capitalization. The reason this is the case is given that enterprise value considers the market capitalization of a company, the long-term, the short-term debt as well as any cash alternatives (see Koller et al., 2020).

Leverage: Leverage is captured by the following ratio.

1. Net Debt to Enterprise Value: As mentioned above the all-inclusive nature of Enterprise Value makes it a great substitute for any other form of firm value; thus makes this ratio one of the best options for proxying the value of leverage within a firm.
2. Total Debt to Equity Ratio: This ratio acts as a proxy for the leverage of the firm and can be considered the raw version of the Net Debt to Enterprise Value.
3. Interest Coverage Ratio: This ratio captures the ability of a company to be able to repay back interest payment obligations.

Liquidity: Liquidity is proxied by:

1. Enterprise Value to Operating Cash Flow. This ratio captures the liquidity of the firm by measuring the total value of a firm with its ability to generate cashflows.
2. Current Ratio: The current ratio measures the economic sector's ability to overcome short-term obligations.
3. Quick Ratio: Like the Current Ratio this ratio aims to capture the firm's ability to pay back short-term obligations however it measures this ability by only looking at liquid assets.

Profitability:

1. Enterprise Value to Sales: Enterprise Value to Sales is a more comprehensive price-to-sales ratio (see Koller et al., 2020). It showcases the value that investors are willing to pay for each monetary unit of a firm's revenue.

2. Price-to-Earnings: The PE ratio measures the ratio of the share price of the economic sector to its earnings.
3. Earnings-per-Share: The EPS ratio is the inverse of the PE ratio.
4. Operating Margin: Measures the profit made from one euro of sales after taking into account costs of production.

Purchasing Power:

1. Foreign-Exchange: The ability for European firms to purchase energy products relies heavily on the current exchange rate. This is mainly because Europe as a region is an energy importer (Eurostat, 2022). Furthermore, the de facto preference for oil producing firms to settle energy exchanges in USD (i.e., the so called pretrodollar system) means that the access of firms to USD is an issue of purchasing power. This is proxied from the following exchange rates:
    a. The Euro effective exchange rate (EER) against 19 currencies,
    b. The Euro EER against 42 currencies
    c. USD-EUR Spot Rate.
    d. USD-EUR % Change Spot Rate

Energy Commodities: The energy variables which are examined here are based on the crucial role they are playing in the current crisis unfolding in the European region. These are identified as: Oil, Natural Gas and Gasoline. We also look at carbon emission allowances. Emission allowances are included due to their indirect ability to measure demand for energy related commodities and thus allows for unique inferences to be drawn. Energy Commodities are proxied through the following percentage change in price of generic 1st futures. Given that we are using percentage changes of the generic 1st futures, the nominal values of such futures are not important themselves. Using percentage changes still allows us to capture the effect of price increases in energy commodities while increasing comparability among the different energy commodities. Generic 1st futures are also preferred over the actual price of the individual energy commodities as direct energy commodities suffer from being heterogeneous (e.g., oil grades) and this thus makes comparability, analysis and interpretation to be convoluted. Using generic futures bypasses these issues.

The variables are thus:

1. Oil Price % change: CO1 Comdty
2. Gasoline Price % change: XB1 Comdty
3. Natural Gas % change: NG1 Comdty
4. Emission Rights: M01 Comdty

Section A: Model Specifications and Statistical Testing

4.1.6 LASSO Selected Variables

The variables selected from LASSO regression and the qualitative selection process is as follows:

- **Market Risk:** 99% VaR
- **Size:** Market Capitalization
- **Leverage:** Net Debt to Enterprise Value
- **Liquidity:** Quick Ratio
- **Profitability:** Enterprise Value to Sales
- **Purchasing Powers:** Change of the USD-EUR exchange rate

4.1.7 Panel Regression Models

After testing for multicollinearity, we can be confident that there is no presence of multicollinearity within the variables (See Appendix 1) and as such we firstly run the following within panel models:

Model 1-Oil:

$$\Delta CoVaR = Intercept + \beta_1 NetDebtToEV + \beta_2 Oil + \beta_3 FXC + \beta_4 QuickRatio + \beta_5 EVToSales + \beta_6 MKTCAP + FE + \varepsilon \qquad (30)$$

Model 2-Gasoline:

$$\Delta CoVaR = Intercep + \beta_1 NetDebtToEV + \beta_2 Gasoline + \beta_3 FXC + \beta_4 QuickRatio + \beta_5 EVToSales + \beta_6 MKTCAP + FE + \varepsilon \qquad (31)$$

Model 3-Natural Gas:

$$\Delta CoVaR = Intercept + \beta_1 NetDebtToEV + \beta_2 NaturalGas + \beta_3 FXC + \beta_4 QuickRatio + \beta_5 EVToSales + \beta_6 MKTCAP + FE + \varepsilon \qquad (32)$$

Model 4-Emission Rights:

$$\Delta CoVaR = Intercept + \beta_1 NetDebtToEV + \beta_2 EmissionRights + \beta_3 FXC + \beta_4 QuickRatio + \beta_5 EVToSales + \beta_6 MKTCAP + FE + \varepsilon \qquad (33)$$

Where: *Intercept* is the intercept, *NetDebtToEV* is the Net Debt to Enterprise Value, *FXC* is the percentage change of the USD-EUR exchange rate, *QuickRatio* is the Quick Ratio, *EVtoSales* is the Enterprise Value to Sales and *MKTCap* is the Market Capitalisation, *FE* are the fixed effects, and ε is the error term.

After running the FE models, we then run the following models where we replace FE for the individual VaR of each economic sector:

Model 1-Oil:

$$\Delta CoVaR = Intercept + \beta_1 VaR + \beta_2 NetDebtToEV + \beta_3 Oil + \beta_4 FXC + \beta_5 QuickRatio + \beta_6 EVToSales + \beta_7 MKTCAP + \varepsilon \qquad (34)$$

Model 2-Gasoline:

$$\Delta CoVaR = Intercept + \beta_1 VaR + \beta_2 NetDebtToEV + \beta_3 Gasoline + \beta_4 FXC + \beta_5 QuickRatio + \beta_6 EVToSales + \beta_7 MKTCAP + \varepsilon \qquad (35)$$

Model 3-Natural Gas:

$$\Delta CoVaR = Intercept + \beta\_1\ VaR + \beta\_2\ NetDebtToEV + 〖\beta\_3\ NaturalGas + \beta\_4\ FXC + \beta\_5\ QuickRatio + \beta\_6\ EVToSales + \beta\_7\ MKTCAP + \varepsilon \qquad (36)$$

Model 4-Emission Rights:

$$\Delta CoVaR = Intercept + \beta\_1\ VaR + \beta\_2\ NetDebtToEV + 〖\beta\_3\ EmissionRights + \beta\_4\ FXC + \beta\_5\ QuickRatio + \beta\_6\ EVToSales + \beta\_7\ MKTCAP + \varepsilon \qquad (37)$$

4.1.8 Heteroscedasticity and Autocorrelation

All eight models suffer from both heteroscedasticity and autocorrelation (See Appendix 2 and Appendix 3 respectively). For us to get robust standard errors and to ensure that our inference is correct we calculate the Arellano (1987) robust standard errors for within panel models.

4.1.9 Normality, Sample Size and Bootstrapping[2]

As aforementioned financial data is rarely normal, however given the large number of observations we have this is not an issue. The sample size for each model is 54,252 unique observations spanning from 22-Sep-2008 up until the 29-03-2022.

The key issue, however, is the presence of heteroscedasticity and autocorrelation within our model. As such we must select the correct bootstrapping technique. Davidson and Monticini (2014) showcase that standard non-parametric bootstrapping techniques, while can handle heteroscedasticity, seem to fail in dealing with autocorrelation. The solution to the issue of heteroscedasticity can be dealt with the so-called Wild Bootstraps (as originally proposed by Freedman, 1981). Wild Bootstraps are known for being the best bootstrapping technique with dealing with heteroscedasticity (see Davidson and Monticini, 2014) with a variety of different approaches existing (see Wu 1986; Liu 1988; Mammen 1993). The issue of autocorrelation however is far greater with many bootstrapping models failing to present favourable results. The most common type of bootstrapping technique for dealing with autocorrelation are known as Block Bootstrapping (see e.g., Lahiri, 1999; Paparoditis and Politis, 2001; Paparoditis and Politis, 2002). However, other approaches for dealing with autocorrelation come in the form of cluster-robust bootstrapping (see Esarey and Menger, 2019; Cameron et al., 2008). Thus, a combination of wild bootstrapping and either block or clustered bootstrapping methods is preferred as also suggested by Davidson and Monticini (2014).

Our chosen joint-bootstrapping technique for dealing with heteroscedasticity and autocorrelation is thus based on Cameron et al., (2008) and is run through the R (the programming language) package known as 'ClusterSEs' from Esarey (2021); this method is also selected given its focus specifically on dealing with fixed effect within panel models.

Please note that Section A's data analysis is independent of Section B and as such for the interest of the reader, one can immediately skip to Chapter 6 for the results and analysis if they so please to do so.

[2] The banking sector is not included in the panel regressions since banks do not have a current ratio.

Section B

In the latter part of this research, the macro variables used to calculate the time-varying ΔCoVaRs as well as the energy commodity proxies used to capture the changes are the same as in section A.

4.2.1 Sample Size

The sample size for the ΔCoVaRs is also found through the same methedology as in Section A. This thus leaves the static ΔCoVaR with a total number of 4235 observations across the time span of 04-Oct-2005 to 31-Mar-2022 and the Time-varying-ΔCoVaR with 3785 observations ranging from the 06-Oct-2006 up untill 29-Mar-2022.

4.2.2 Macro Variables for VAR

The macro variables selected to examine the impact mainly based on the theoretical framework for the EEF academic literature strand as well as considering transmission channels of monetary policies set by central banking units. We thus, identify a set of key finance and economic macro variables. All the following data is taken from the ECB Statistical Data Warehouse:

1. Inflation Rate: Inflation rate is proxied through money aggregate M3 (the broadest definition of money aggregate).
2. Exchange Rate: The Euro EER against 42 currencies, the broadest currency basket available.
3. Interest Rates: The Bank interest rate (i.e., the interest rate charged to banks)
4. Financial Risk: ΔCoVaR of the system conditoined on oil, gasoline, natural gas, and emission allowances.

The VAR system is thus made up of seven variables. These variables are assumed a priori to be endogenous, in particularly regarding the different ΔCoVaRs conditioned on the different energy commodity prices. Given however that our model is made up of seven different variables in order however to avoid having 42 different impulse analysis we will limit ourselves only to the impact of monetary variable shocks' impact on the energy ΔCoVaRs. This would thus give us a total of 12 different impulse analysis to look at.

4.2.3 Model Specification.

The first step of our model specification is to test the stationarity of our model. Table 3 showcases the order of Integration (see Appendix 4 for Test Results):

Table 3: Order of Integration

Variables	Order of Integration
Oil ΔCoVaR	I(0)
Gasoline ΔCoVaR	I(0)
Natural Gas ΔCoVaR	I(0)
Emission Allowances ΔCoVaR	I(0)
M3	I(1)
Bank Interest Rate	I(1)
Effective Exchange Rate	I(1)

We then integrate all the I(1) variables to ensure that they are stationary.

The next stage of the model specification is to test for the optimal number of lags. We start of by setting the maximum number of lags to be included as 12 (i.e., a time period of 1 year) and then as per the optimal lag length selection criteria methodology find the correct number of lags to include. The results of the different test are shown below in table.

Table 4: Optimal Lag Length Test Results

Test	AIC(n)	HQ(n)	SC(n)	FPE(n)
Lag Length	12	1	1	3

From Table 4 given that the most popular lag is 1 we opt to use 1 lag. In addition, the reasoning for this is the assumption that effects should occur immediately and with a slight delay. We then proceed with testing for cointegration.

Given that Table 3 has shown that we have various degrees of integrated variables according to Brooks, (2019) we cannot test for cointegration and as such we cannot implement a VECM model accordingly. As such we continue with using a basic VAR model. While a VAR model may lose information regarding long-term relationships, we can still deduce the short-term relationships of the different variables in question (see Brooks, 2019).

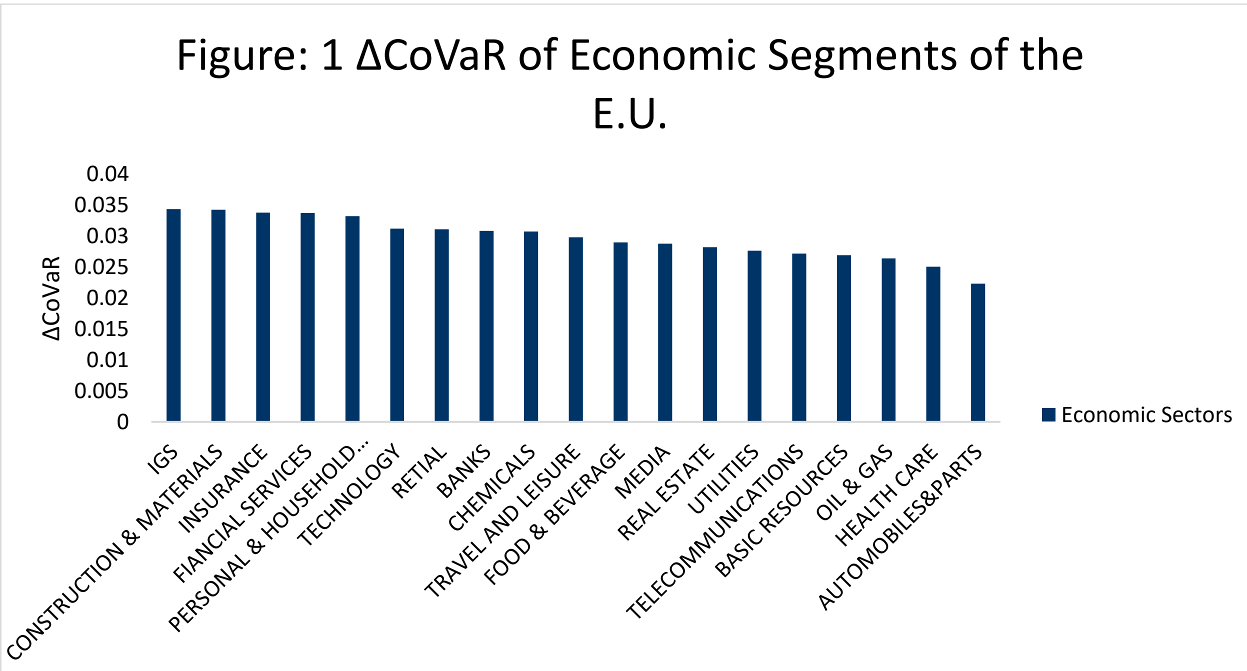
Chapter 5 Data Analysis and Empirical Results

In the following chapter an analysis of the data results calculated using the aforementioned methodology and data is given. This section is split up respectively in Section A and Section B. For both of these sections a general overview of the static and time-varying ΔCoVaR and €ΔCoVaR are given, this is then followed by their respective econometric analysis.

Section A1

5.1.1 Non-Time Varying ΔCoVaR & General Observations

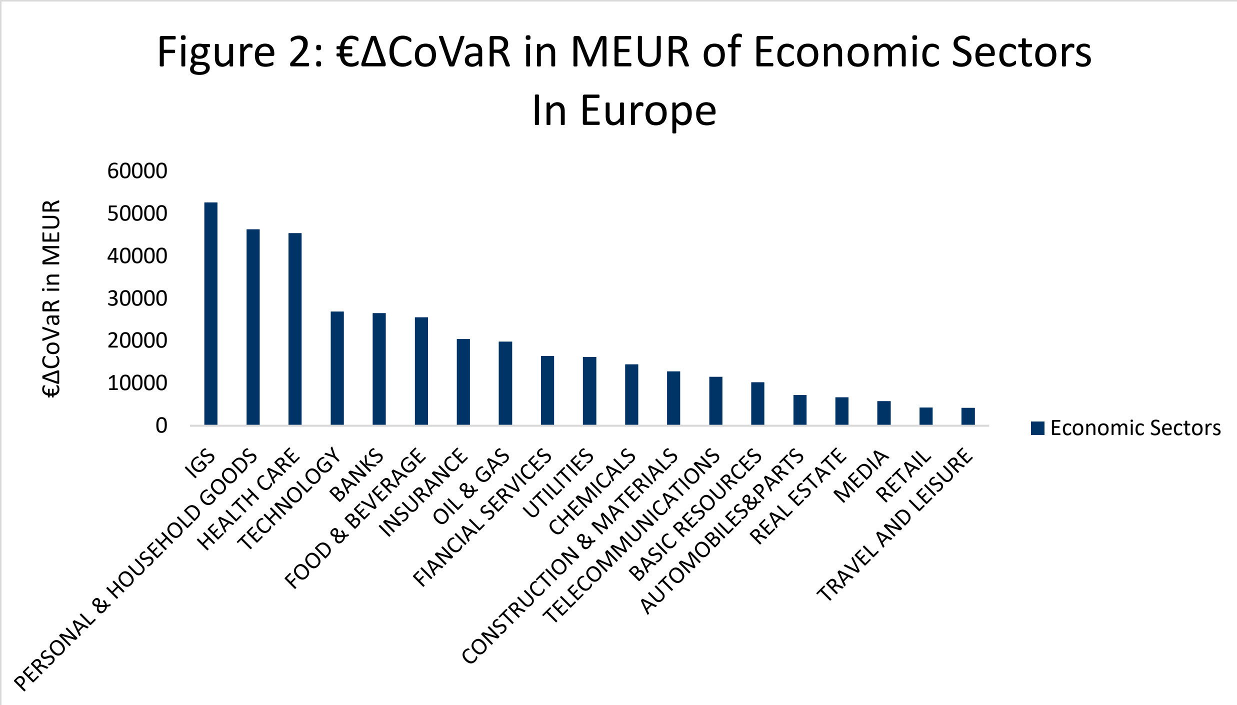
The results for the non-time varying ΔCoVaR are presented graphically in Figure 1 below.



From Figure 1 we can see that on average for the past 20 years economic sectors relating to heavy industries and finance are dominating the systemic stress added to the economic region. Industrial Goods & Services sector comes in first followed by the Construction & Materials sector and the Insurance and Financial sector respectively. Of interest here is first the fact that the Real Estate economic sector is 13^{th} in ranking of how much it adds to the systemic risk of the economic region. The Real Estate sector is usually used as a proxy for the "real economy" of a region and used by Adrian and Brunnermeier (2016) in their macro variables. However, it might be more beneficial for academic literature to instead investigate the use of the IGS and the Construction and Materials sector instead, as both of these sectors are linked to the "out-put" of the economy but also are found to have higher impacts to the overall systemic stress of the economy. Nonetheless to maintain some consistency with Adrian and Brunnermeier (2016) we continue to use the Real Estate sector in macro variable vi. Furthermore, interestingly the Banking sector does not contribute as much risk to the system as its other "financial" counterparts even though the banking sector's losses are closely correlated (a Pearson R of 0.89 with the Insurance sector, and 0.85 with the Financial Services sector). This could be due to the stringent measures that the banking industry must follow over the other financial sectors e.g., due to Basel iii (see Basel Committee on Banking Supervision, 2022).

Finally, looking at the sectors which are directly related to energy commodities i.e., the Utilities and the Oil & Gas sector respectively, we can see that these sectors are shown to pose some of the lowest financial instability risk. A variety of reasons could be explaining such a result, including the timeframe looked at, e.g., not covering any large energy crises pre-2001 or the fact that energy commodity prices can easily be manipulated by artificially decreasing supply to maintain commodity prices e.g., by OPEC (see Simpson, 2008**)**. However, this is most likely linked to the empirical view of the EEF literature strand regarding energy prices and GDP. It is arguable to assume that energy prices are demand inelastic given their importance in economic growth, and as such regardless of crises the losses in the Utilities and the Oil & Gas sector are limited. It should also be noted that in the event of energy commodity crises the Utilities and the Oil & Gas sector could stand to gain from such an event given the rise of their product and service prices and their inelastic demand. This most likely also explains the large systemic stress from the heavy industry sectors, which are known to make extensive use of energy commodities and thus are expected to suffer the most from energy commodity crises.

5.1.2 Non-Time Varying €ΔCoVaR & General Observations



When we take into account the market capitalization of each economic sector, the true riskiness of each economic sector is revealed. Compared to Figure 1, only the IGS sector remains consistent at the top (as seen from Figure 2). This further confirms the importance of the IGS sector in the financial stress it adds. Furthermore, when we look at the “financial” sectors i.e., the Banking, Financial Services and Insurance, the large amount of market capitalization of the Banking sector showcases why banking crises are more severe and as to why they are heavily regulated compared to the other financial sectors. Looking at the rest of the sectors, the large market capitalization of the Personal & Household Goods and the Healthcare sectors have risen to second and third place respectively in regard to their contribution of systemic risk. Finally, regarding the energy related economic sectors (i.e., Oil & Gas and Utilities), both are riskier than originally found in Figure 1. This showcases the damage that an energy crisis can have on the financial stability of an economic region, as if the sectors are in distress this could spillover to the rest of the other sectors, with a spill over to the IGS sector being the most damaging.

5.1.3 Time Varying ΔCoVaR Descriptive Statistics

Descriptive statistics of all the Sectorial Time Varying ΔCoVaR of are given in Table 5. All the descriptive statistics are based on the raw daily data of the Sectorial Time Varying ΔCoVaR without any adjustments.

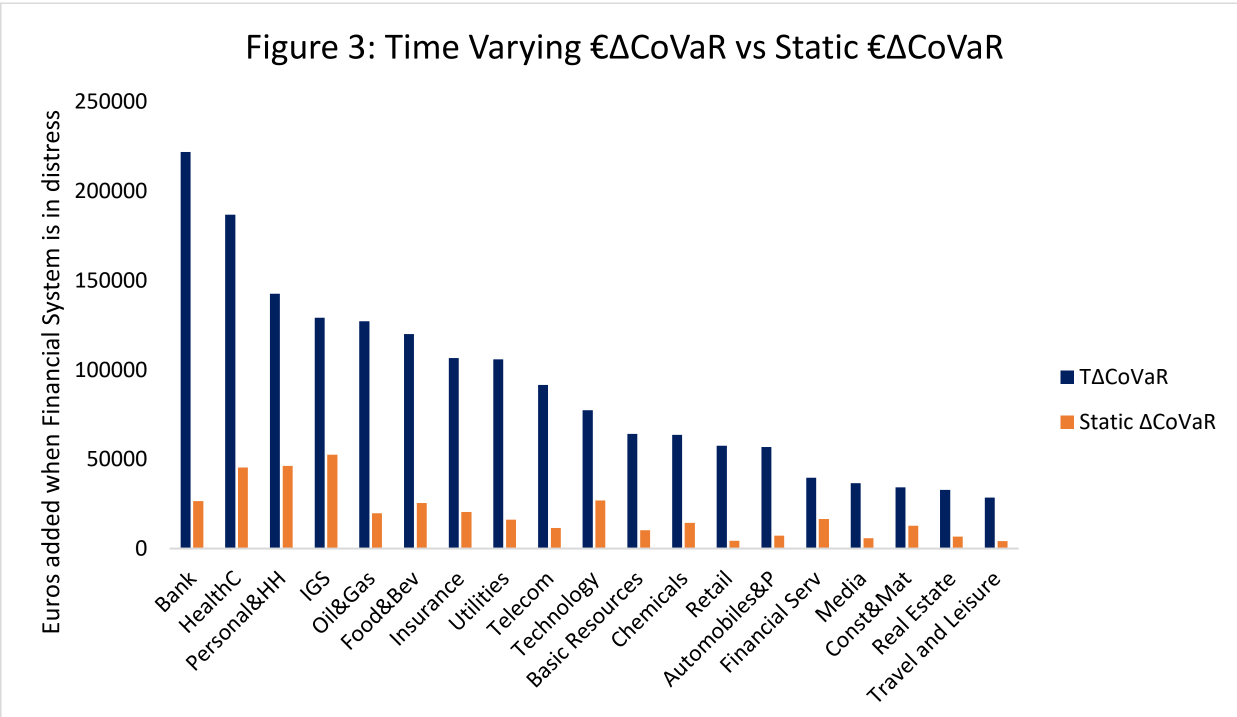
Table 5:Descriptive Statistics for Daily Time-Varying ΔCoVaR

	Standard Deviation	Mean	Skewness	Kurtosis	Min	Max
Healthcare	2.435	0.207	2.275	12.4746	-6.342	21.035
IGS	2.328	0.149	2.351	13.9287	-6.624	20.837
Food & Beverages	2.394	0.191	2.278	12.3684	-6.377	21.654
Bank	2.432	0.209	2.382	13.5121	-6.946	19.850
Technology	2.463	0.217	2.377	13.6954	-6.317	20.488
Personal & Household	2.488	0.217	2.353	13.3036	-7.484	22.235
Insurance	2.407	0.230	2.204	12.4008	-6.488	23.331
Oil & Gas	2.411	0.210	2.271	12.2354	-6.981	17.753
Chemicals	2.378	0.200	2.195	11.8717	-6.583	17.802
Utilities	2.391	0.215	2.061	11.0942	-7.020	18.145
Retail	2.422	0.198	2.121	11.1679	-7.690	17.169
Telecom	2.433	0.219	2.312	12.6526	-6.885	19.680
Construction &Materials	2.330	0.149	2.321	12.8273	-7.086	17.907
Financial Services	2.388	0.198	2.351	13.1905	-6.929	19.625
Real Estate	2.454	0.232	2.513	14.3432	-6.559	21.141
Automobiles & Parts	2.426	0.233	2.456	14.1938	-7.278	22.164
Basic Resources	2.437	0.206	2.449	14.7575	-6.868	23.334
Media	2.413	0.192	2.295	13.2911	-7.135	25.232
Travel and Leisure	2.432	0.222	2.461	15.067	-6.996	26.018

Most sectors behave the same across the descriptive statistics with most sectors having a mean close to the range of 0.150 and 0.200. This form of uniformity is seen in the skewness of the sectors. All sectors are rightly skewed which is suggestive of more risk added to the system rather than taken away. This suggests that there is no single “hedge” or risk-free sector to the overall financial system. Furthermore, the kurtosis of each sector does not stray far away from each other either. All the sectors showcase a high kurtosis suggesting a heavy tailed distribution and more specifically a large amount of non-homogenous tail events.

Figure 3 below showcases the €ΔCoVaR against the static €ΔCoVaR. It seems that overall, the time-varying €ΔCoVaR showcases that in reality the financial risk economic sectors pose is greater than what the static version captures.

5.1.4 Time Varying €ΔCoVaR General Observations



It is important to note that these are of daily Time Varying ΔCoVaR which are more likely to be sensitive to any form of changes in the market including prone to the market's misjudgement. Adrian and Brunnermeier (2016) argue that averaging the Time Varying ΔCoVaRs to a weekly or quarterly basis smooths out their statistical moments and allows for better interpretation of the results. We believe, however, that the benefit of using a Time Varying ΔCoVaR is in its market approach. Given that the Time Varying ΔCoVaR is in it of itself a market model, it allows us to capture market sentiment throughout every day, something that would be lost if smoothed out. This difference is also most likely due to the time spans looked at, with the static €ΔCoVaR taking into account approximately 4 more years of data than the Time Varying €ΔCoVaR. Specifically, those four years of data could most likely result in the dampening of the true €ΔCoVaR of each economic sector and suggestive of the fact that it seems that our financial systems are inherently getting riskier. Furthermore, given the methodology we employed in calculating the Time Varying

ΔCoVaR i.e., the use of a basic historical simulation (as compared to using a static VaR) might have in turn captured the true riskiness of each observation. This thus means that each observation could vary to greater extents than it could if we used a static VaR. In addition, when we look at the skewness of the Time Varying ΔCoVaR the lack of normality would mean that when we average such observations the losses would outweigh the gains leading to overall more riskiness compared to using a static ΔCoVaR. Finally, given that it is not at the core of this research to find the systemic stress added to the financial system of the sectors but rather how energy commodity prices impact this, this thus means that having more observations we can get a better data centric picture from our econometric analysis.

Section A2

Table 6: Multivariate Regression Analysis Fixed Effects Only

Dependent Variable: ΔCoVaR Variables	**Model 1** Oil	**Model 2** Gasoline	**Model 3** Natural Gas	**Model 4** Emission Rights
Net Debt To EV	4.4609e-02***(***) (5.5728e-03)	4.4574e-02***(***) (5.5575e-03)	4.4741e-02***(***) (5.5955e-03)	4.4652e-02***(***) (5.5886e-03)
Energy Commodity Price	-2.8237***(***) (3.1109e-01)	-3.1965***(***) (3.6437e-01)	-3.5135e-01.(.) (2.0121e-01)	-7.3112e-01***(***) (1.8480e-01)
Percentage Change Exchange Rate	-2.4360***(***) (2.3790e-01)	-2.4395***(***) (2.3736e-01)	-2.4387***(***) (2.3883e-01)	-2.4399***(***) (2.3817e-01)
Quick Ratio	2.9976e-02() (2.7085e-02)	2.9958e-02 (2.6910e-02)	3.0059e-02 (2.7352e-02)	3.0174e-02 (2.7258e-02)
EV To Sales	-1.8173e-02 (1.9410e-02)	-1.8099e-02 (1.9330e-02)	-1.8354e-02 (1.9526e-02)	-1.8333e-02 (1.9500e-02)
Market Capitalisation	-5.4771e-07 ***(***) (1.4032e-07)	-5.4519e-07***(***) (1.3993e-07)	-5.5426e-07***(***) (1.4122e-07)	-5.5248e-07***(***) (1.4108e-07)
Observations	54,252	54,252	54,252	54,252

Note: This table represents the different "within panel" regression results for each of the identified energy commodities. Arellano (1987) standard errors are given in the parenthesis below the estimates. ***/**/*/. indicate statistical significance to the 0.1/1/5/10 percent level. Statistical significance from the wild-clustered bootstrapping is given in the parenthesis next to the Arellano (1987) statistical significance results.

Table 7: Multivariate Regression Analysis

Dependent Variable: ΔCoVaR	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Variables	Oil	Gasoline	Natural Gas	Emission Rights
Intercept	2.1895***(***) (1.2532e-01)	2.1971***(***) (1.2484e-01)	2.1863***(***) (1.2603e-01)	2.1915***(***) (1.2576e-01)
VaR	-1.4905e-02***(***) (4.2717e-03)	-1.5036e-02***(***) (4.2830e-03)	-1.4076e-02***(***) (4.2423e-03)	-1.3959e-02***(***) (4.2113e-03)
Net Debt To EV	9.7965e-03**(**) (3.0840e-03)	9.7890e-03**(***) (3.0796e-03)	9.8272e-03**(**) (3.0951e-03)	9.8019e-03**(**) (3.0879e-03)
Energy Commodity Price	-3.0222***(***) (2.9943e-01)	-3.3686e+00***(***) (3.6450e-01)	-4.1636e-01*(**) (1.8653e-01)	-8.9095e-01***(***) (1.6098e-01)
Percentage Change Exchange Rate	-1.6542***(***) (9.2737e-02)	-1.6596***(***) (9.2569e-02)	-1.6525***(***) (9.3075e-02)	-1.6563***(***) (9.2879e-02)
Quick Ratio	9.9323e-03() (2.3786e-02)	9.8410e-03 (2.3635e-02)	1.0171e-02 (2.4069e-02)	1.0277e-02 (2.3990e-02)
EV To Sales	-1.9578e-02*() (8.2607e-03)	-1.9502e-02*() (8.1994e-03)	-1.9790e-02*() (8.3702e-03)	-1.9761e-02* (8.3507e-03)
Market Capitalisation	-1.5745e-07*(.) (6.9677e-08)	-1.5674e-07*(.) (6.9589e-08)	-1.5938e-07*(.) (7.0042e-08)	-1.5877e-07*(.) (6.9957e-08)

Observations	54,252	54,252	54,252	54,252

Note: This table represents the different panel regression results (which contain VaR) for each of the identified energy commodities. Arellano (1987) standard errors are given in the parenthesis below the estimates. ***/**/*/. indicate statistical significance to the 0.1/1/5/10 percent level. Statistical significance from the wild-clustered bootstrapping is given in the parenthesis next to the Arellano (1987) statistical significance results.

5.2.1 Econometric Analysis & Discussion

Given Table 6 and 7 we can immediately see that across all our models, across both different methodologies as well as across the results from the bootstrapping employed, the results are consistent with the partial exception of the results of EV to Sales. All the models find that all predictor variables and the Quick Ratio to be statistically significant and insignificant respectively, while EV to Sales is found to be statistically significant only in the non-bootstrapped model including VaR. However, when we bootstrap, we find that EV to Sales is once again considered statistically insignificant. Thus, assuming ceteris paribus for inference purposes we can confidently assume that EV to Sales is statistically insignificant.

Assuming ceteris paribus for the following analysis we can firstly see that the VaR of each economic sector is considered statistically significant across all models at the same significance level (p-value <0.001). This result bolsters the assumption that systemic risk is closely linked to the idiosyncratic risk and the importance of surveilling idiosyncratic risks posed by individual economic sectors and firms (as seen in the 2008 financial crisis). Furthermore, this is suggestive of the assumption that VaR is still relevant as a tool for capturing idiosyncratic risk and should not be forgotten about over other risk capturing methods. Looking at the estimates of VaR we can see that all estimates have a negative coefficient. This thus means that as the idiosyncratic risk of a firm increases the amount of risk posed to the financial system decreases (albeit at a very minimal amount). This is however contentious. Looking at the results found by Asgharian et al. (2021) we can see that that the larger the individual bank's VaR the higher the ΔCoVaR. However, they find that the higher the centrality of a firm the larger the risk posed to the financial system. Thus, while the results may seem initially paradoxical, if VaR is interpreted as idiosyncratic risk posed by an individual economic sector then our results are in fact aligned with Asgharian et al. (2021).

Looking at Net Debt to EV, we initially can see the importance of leverage within each economic sector. As aforementioned a debt crisis stemming from an individual firm can still cause a large economic and financial crisis let alone a whole economic sector. For all models this proxy has a positive coefficient and thus as expected: the larger the leverage within the economic sector the larger the risk posed to the financial system as a whole. This result is consistent with most academic literature regarding the impact of debt on financial stability (See Bratis et al., 2020; Keddad and Schalk, 2020).

Market Capitalisation for all models is shown to also be statistically significant as well as being negative. This suggests that as the market capitalization increases then the less the actual systemic risk added to the system is. Such an outcome was unexpected especially when considering the change of the actual €ΔCoVaR vs the ΔCoVaR in Figure 3. However, it should be noted that these models do not take into account the underlying riskiness of an economic sector but rather see the impact of market capitalisation on ΔCoVaR. Thus, this is suggestive of the fact that the larger an economic sector is the less likely the economic sector is to actually become distressed in the first place. Furthermore, this could also be due to the confidence of the market in the too-big-to-fail phenomenon that has been observed in the past.

Interestingly the lack of statistical significance in the Quick Ratio as well as the general statistical insignificance of EV to Sales is unexpected. Liquidity and profitability not being able to explain the risk added to the financial system can be addressed to a variety of reasons. The most likely cause however is due to the structure of the models used (i.e., panel regressions) which find the "average" effect across time. This is suggestive of the fact that maybe liquidity and profitability on average might not have an impact but rather only in specific scenarios could prove to be important.

Looking at the purchasing power i.e., the percentage change in the exchange rate, we can deduce the following. Firstly, the exchange rate is statistically significant in all models making it an important predictor variable to include within models as well as the concept of purchasing power for individual economic sectors rather than looking at individual agents through the use of a proxy for inflation rate. Furthermore, the percentage change in the exchange rate has a negative coefficient. Given that this is proxied through the USD-EUR spot rate, i.e., how many euros can a USD buy, this suggests that as the USD appreciates the risk posed to the financial system decreases. Understanding as to why this might occur can be convoluted. However, this is most likely attributed to the following reasons: either this occurs due to the large amount of USD reserves that economic sectors in the EU have pre-allocated; either that a weak EU currency means that products and services are now more competitive globally allowing for a net gain in profits; either that the petrodollar is not in reality as important as originally suspected and thus purchases can still be made directly using euros.

Finally, the results of energy commodity prices offer a unique insight. Across all energy commodities selected we can see once more a common pattern. All energy commodity prices are seen to have negative coefficients once more. This thus suggests that as energy prices increase then the overall risk posed to the financial system decreases.

In relation to academic literature the results are both supportive and at the same time in contrast. Looking at Cunado et al., (2003) they found that as oil prices increase then industrial production growth rates decrease, however they also found that the opposite effect does not occur. Taghizadeh-Hesary et al. (2019) also find that as oil price shocks occur affect the economy in a negative manner. However, looking at Du et al. (2010) they found a positive relationship between oil prices and GDP and CPI. Their results are of even further interest when considering that they focused on China an oil-importing country and still observe the same abnormal effect. They argue that this is most likely due to China's exports being highly related to the US and EU countries' economic activities. That being said Du et al. (2010) contend that this is an abnormal phenomenon which requires further theoretical research.

Empirical evidence regarding energy commodities gets even more intricate when looking at Tiwari et al., (2019a) who found that when looking at the upper quantiles between oil prices and stock returns of BRIC countries there is no link. They argue that this is due to the extremities of such events. Tiwari et al., (2019b) found further evidence of abnormal energy commodity movements and returns. Specifically, they found that granger causality does not only vary in significance among the different countries studied but also in regard to the direction. Thus, trying to interpret the results from our regressions with concrete answers remains limited. These results are just further evidence of the uniqueness of energy commodity prices and their impacts.

5.2.2 Robustness of Results and Econometric Implications

Understanding the robustness of our results is important in order to make correct inferences, especially in the presence of non-normality, heteroskedasticity, and autocorrelation. The results from our bootstrapping merely showcase that from a statistical and econometric standpoint our regressions are robust. However, how does one explain the unique results obtained from such regressions?

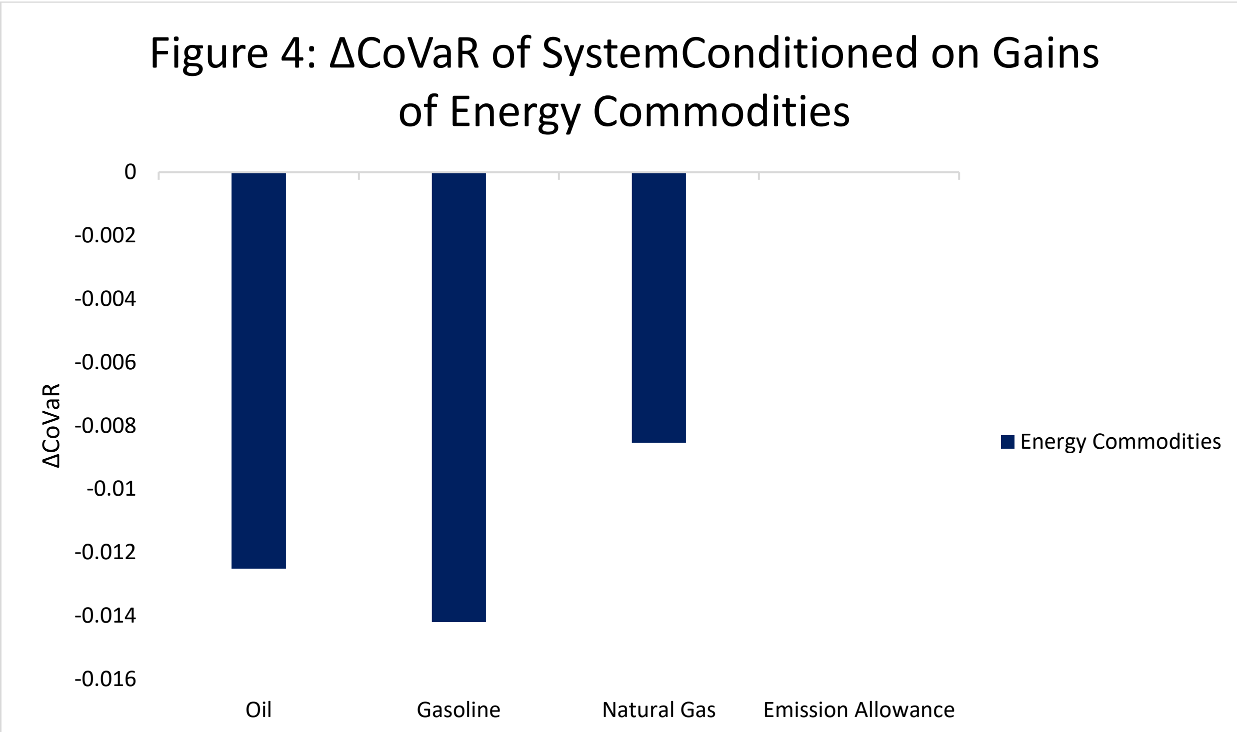
The most important and first-most cause that must be addressed is the time-period. Given the limited access to data that we had, we looked at the longest time span for which we had available data. This meant that we overlooked major energy commodity crises all of which (excluding the Ukraine-Russia war of 2022 which is still currently unfolding) happened prior to the 2000s.

The second crucial aspect of our results is the use of a pan-European index rather than looking at individual countries. The use of a pan-European index could result in many countries' true impact to oil crises being averaged and even ratioed out. While this might not initially be seen as an issue given the broad nature of the index we used, the reality is that no current pan-European index can capture the intricacies of each individual European country.

The same issue with using a pan-European index could also be argued for using sectorial data rather than firm-level data. While firms may belong to the same sector, in reality their operations may vary a great extent, thus, causing our results to be more difficult to interpret. Nevertheless, the reason for examining the causes to systemic risk through a direct and indirect approach is to get more concrete explanations for the phenomena we observe.

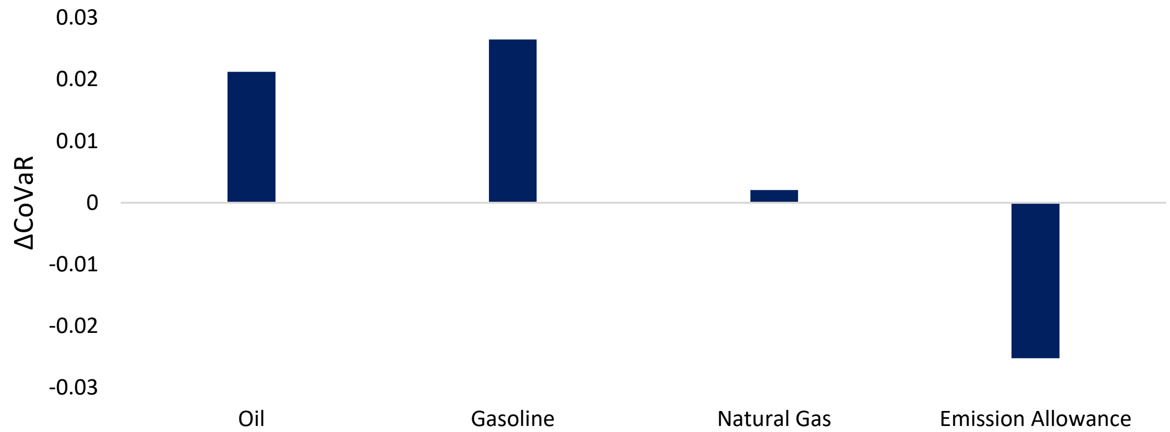
Section B1

5.3.1 Non-Time Varying ΔCoVaR & General Observations



From Figure 4 the first important aspect to note is the negative ΔCoVaR and the fact that this is conditioned on gains of energy commodity items. A negative ΔCoVaR suggests that when these items see a rise in their value the monetary financial risk actually decreases. This might seem like a contradiction to the original idea that a rise in energy commodity prices should result in an increase in the amount of financial risk, but in reality, this is most likely due to the creation of the static ΔCoVaR. The static ΔCoVaR suffers from "averaging" out the impact of energy prices which might result in information being lost. Given that GDP and Oil prices have been shown to have a negative correlation (Hamilton, 1983), one would expect that oil prices too should increase the risk posed to financial stability, however, it might be the case that a rise in oil prices is merely indicative of strong economic production capability of the region and thus a high demand for such items. Nevertheless, Figure 5 below showcases the static ΔCoVaR for the time range of the start of the Ukrainian conflict i.e., 24-03-2022 up until the 31-03-2022. Uniquely the ΔCoVaR for all energy commodities excluding emission allowances is shown to be positive, something which is now in support of most academic literature findings (see Hamilton, 1983, Sadorsky 1999, Berk and Yetkiner, 2014). This suggests that positive gains in energy commodities result in a burden on financial stability.

Figure 5:ΔCoVaR of SystemConditioned on Gains of Energy Commodities during the Ukrainian War



Furthermore, this change in ΔCoVaR across time is the key reason as to why a Time-varying ΔCoVaR is required.

5.3.2 Time-Varying ΔCoVaR

Table 8: Descriptive Statistics for Daily Time-Varying ΔCoVaR

	Standard Deviation	Mean	Skewness	Kurtosis	Min	Max
Oil	1.512	0.098	0.016	5.438	-7.181	7.702
Gasoline	1.553	0.130	-0.077	5.837	-8.816	7.759
Natural Gas	1.541	0.101	-0.311	6.341	-10.004	7.133
Emission Rights	1.520	0.077	-0.155	5.743	-8.393	7.324

Table 8 presents the descriptive statistics for daily Time-Varying ΔCoVaR conditioned on different energy products. Most descriptive statistics are uniform across all energy commodities. Standard deviations, as well as kurotsis seems to be uniform across all energy commodity prices. All energy commodities have a kurtosis excess of what a normal distribution would have, suggesting heavy tailed distributions and large amount of outlier events.

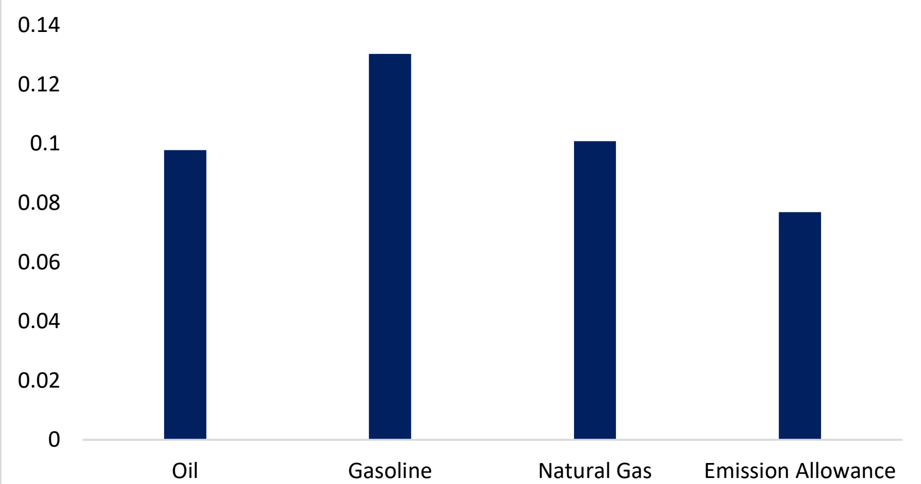
Of interest is the fact that only Oil has a positive skewness compared to that of the other energy products. However, most skewness in the energy conditioned time-varying ΔCoVaRs are close to zero, suggesting almost no skewness and a more equal amount of the spread of risk across time.

Table 9:Average Descriptive Statistics for Time-Varying ΔCoVaR

	Standard Deviation	Mean	Skewness	Kurtosis	Min	Max
Economic Sectors	2.414	0.205	2.317	13.072	-6.873	20.811
Energy Commodities	1.5315	0.1015	-0.13175	5.83975	-8.5985	7.4795

Looking at Table 9 we can see that when we take the average of the statistical moments of the different economic sectors and the energy commodities in question, the results vary greatly. Firstly, one can see that economic sectors on average are more heterogenous than energy commodities i.e., from looking at the high standard deviation and kurtosis. Furthermore, we can see that on average economic sectors are positively skewed compared to the energy commodities which are negatively skewed. This is important given the results from the panel regressions. A negative skewness here suggests that during "tail events" on average energy commodities do not add to the financial risk of the system but rather take away from it compared to the economic sectors.

Figure 6: Average Time-Varying ΔCoVaR



Moving on to the Time-varying ΔCoVaR, we can see from Figure 6 that all energy commodity prices do infact result in a burden to the financial stability of an economic region, when their prices increase. Interestingly unlike the Time-varying ΔCoVaR's of economic sectors, there is a clear distinction in the energy commodities of the most "risky" energy commodity product i.e. gasoline.

Given that gasoline is a product derived from crude oil and other petroleum liquids (i.e., is in the later stage of the production line) and is in a more accessible form than other energy commodities (U.S. Energy Information Administration, 2021) it is expected that it would have a greater risk posed to the financial system. Emission allowances on the other hand have the lowest risk posed to the financial system. This is expected as unlike the other energy commodities, energy allowances are not inherently an energy commodity that an economy "imports" in the same manner. That is under acute conditions (such as a direct threat to the survival of an economic region) emission allowances could be relaxed or even unilaterally cancelled if countries choose to do so. Finally, oil and natural gas seems to behave equally with similar risk levels posed to the financial system.

Section B2

5.4.1 Econometric Analysis

The following table showcases the results of the Granger causality relationships. Granger's (1969) causality can be loosely described as: knowing the present and past variables of a predictor variable x helps forecast variable y.

Table 10: Granger Causality Test Results

Variables	P-Value	Granger Causality to the Model
Oil ΔCoVaR	0.3865	No
Gasoline ΔCoVaR	0.01666	Yes
Natural Gas ΔCoVaR	0.977	No
Emission Allowances ΔCoVaR	0.9362	No
M3	0.06572	Yes
Bank Interest Rate	0.2624	No
Effective Exchange Rate	0.5533	No

Note: H0: No Causality

From Table 10 we can see that the only variable which Granger causes the other variables in the model is the systemic risk posed to the system by Gasoline (ΔCoVaR Gasoline) and the money supply of the system M3. Looking back at the analysis of Figure 6 we can see that as explained it seems that gasoline is the most important energy commodity and as an extension then crude oil (if countries produce gasoline directly within their country).

Looking now towards the money supply we can see that overall, as the amount of money within the system granger causes the other variables. The other monetary units i.e., the effective exchange rate and the bank interest rate show no signs of Granger causality. This is suggestive that the actual responses a central bank can take could be limited.

Focusing on recent academic literature we can see that Benk and Gillman (2020), who too employed a VAR model, found that in the US, money supply did not Granger predict oil prices after 2008. This is in direct contrast to our results, from which we can see that M3 is in fact one of the few variables that granger causes the model. However, our results confirm their results when central bank swaps are subtracted from money. This could be attributed to the inherently different economic structure of a region suggesting that different regions have different demands for different types of monies, as originally supported by Ratti and Vespignani, (2016). They found that different monetary variables have different impacts across the world. They argue that this is due mainly to the heterogenous financial structures in place across countries in particularly regarding exchange rates, monetary policies and interest rate policies.

It is worth noting as well that the lack of strong granger causality could also be associated with the results that Taghizadeh-Hesary et al., (2016) found. They found that developed countries such as the US and Japan are more insensitive to oil price shocks given the fact that alternative sources of energy (mainly nuclear) are an option.

Table 11: Instant Causality Test Results

Variables	P-Value	Instant Causality Present
Oil ΔCoVaR	2.22E-16	Yes
Gasoline ΔCoVaR	2.20E-16	Yes
Natural Gas ΔCoVaR	2.22E-16	Yes
Emission Allowances ΔCoVaR	4.44E-16	Yes
M3	0.0647	Yes
Bank Interest Rate	0.501	No
Effective Exchange Rate	0.6013	No

Note: H0: No Instant Causality

Table 11 showcases the instantaneous causality between the predictor variable and the system. Granger’s (1969) definition for instantaneous causality can be summarized as: knowing the future past and present values of x help predict and forecast variable y.

Looking at table 12, we can see that all variables except Bank Interest Rate and the Effective Exchange Rate cause an instant causality. Overall, it seems that there seems to be a more prominent instantaneous causality compared to the standard Granger causality. Furthermore, it seems that all ΔCoVaR are important in forecasting the system, showcasing the interconnectedness of the overall system. Our results still remain consistent with our prior observations and with Benk and Gillman (2020) and with Ratti and Vespignani (2016).

5.4.2 Impulse Analysis

The following figures showcases the impulse responses of the Energy ΔCoVaRs to the different monetary variables:

Figure 7: M3's Shock to Energy ΔCoVaRs

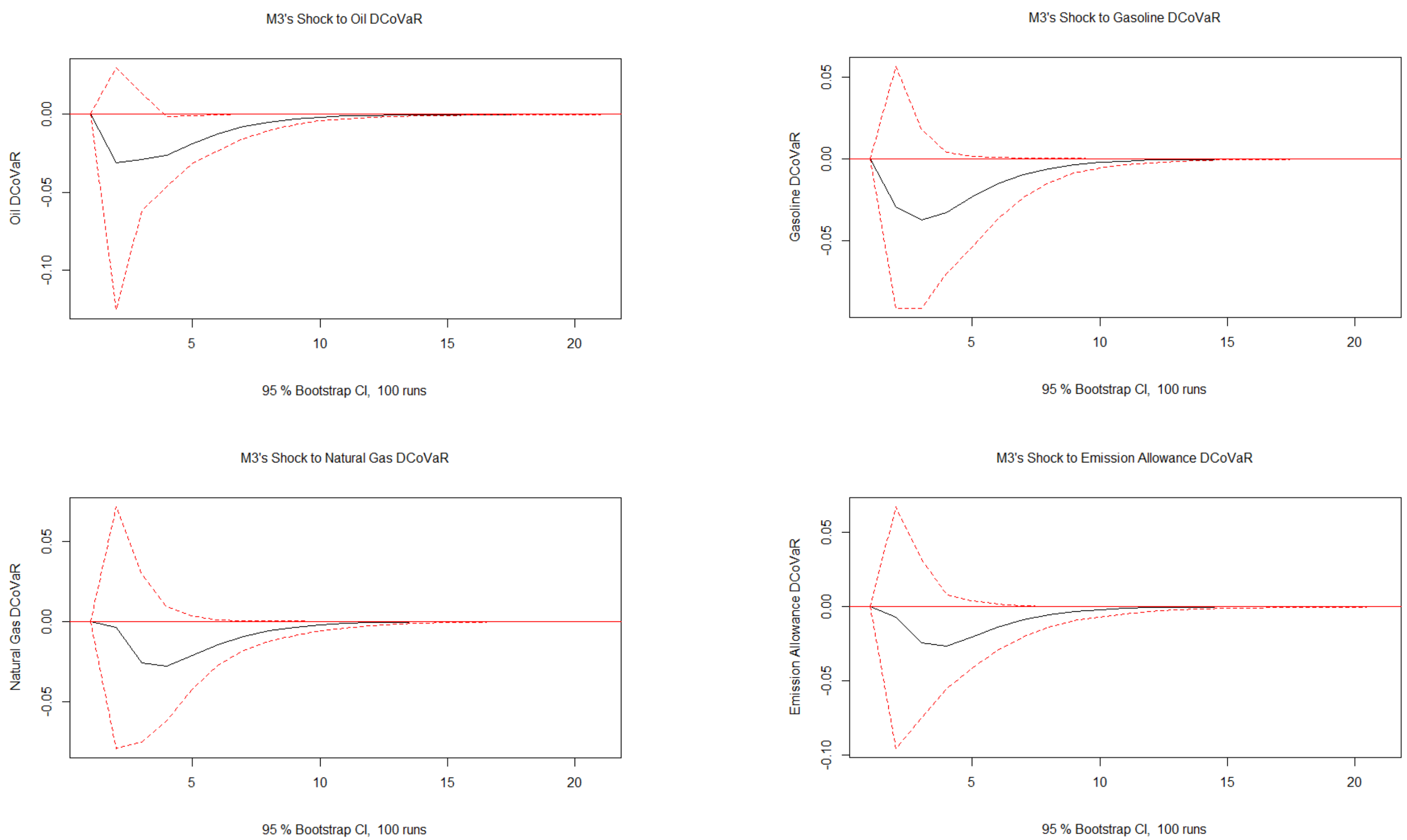
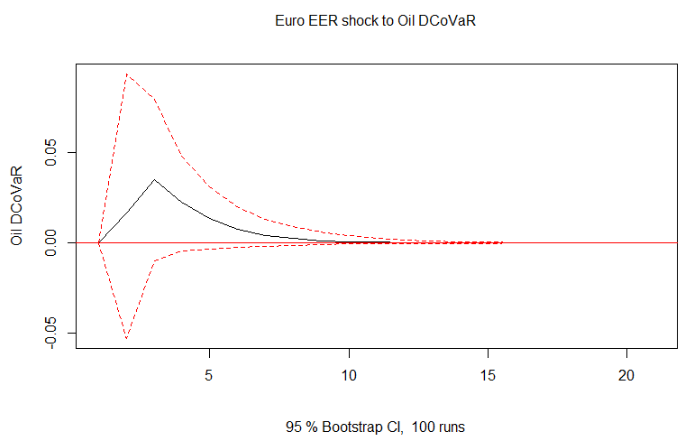
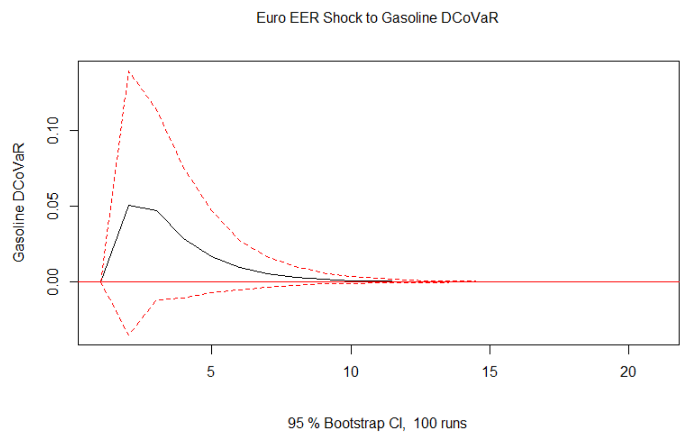
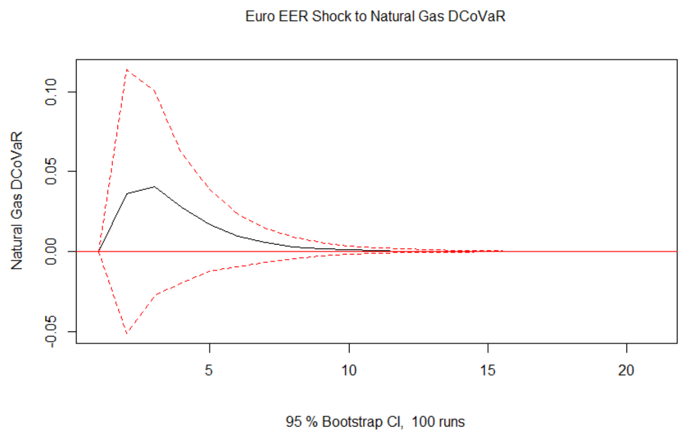


Figure 8: Effective Exchange Rate' Shock to Energy ΔCoVaRs







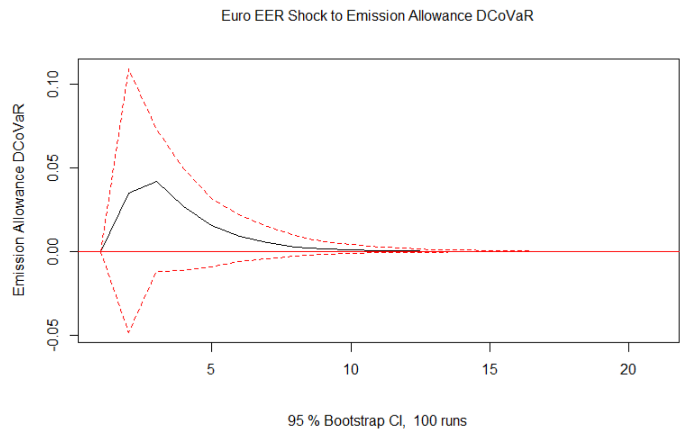
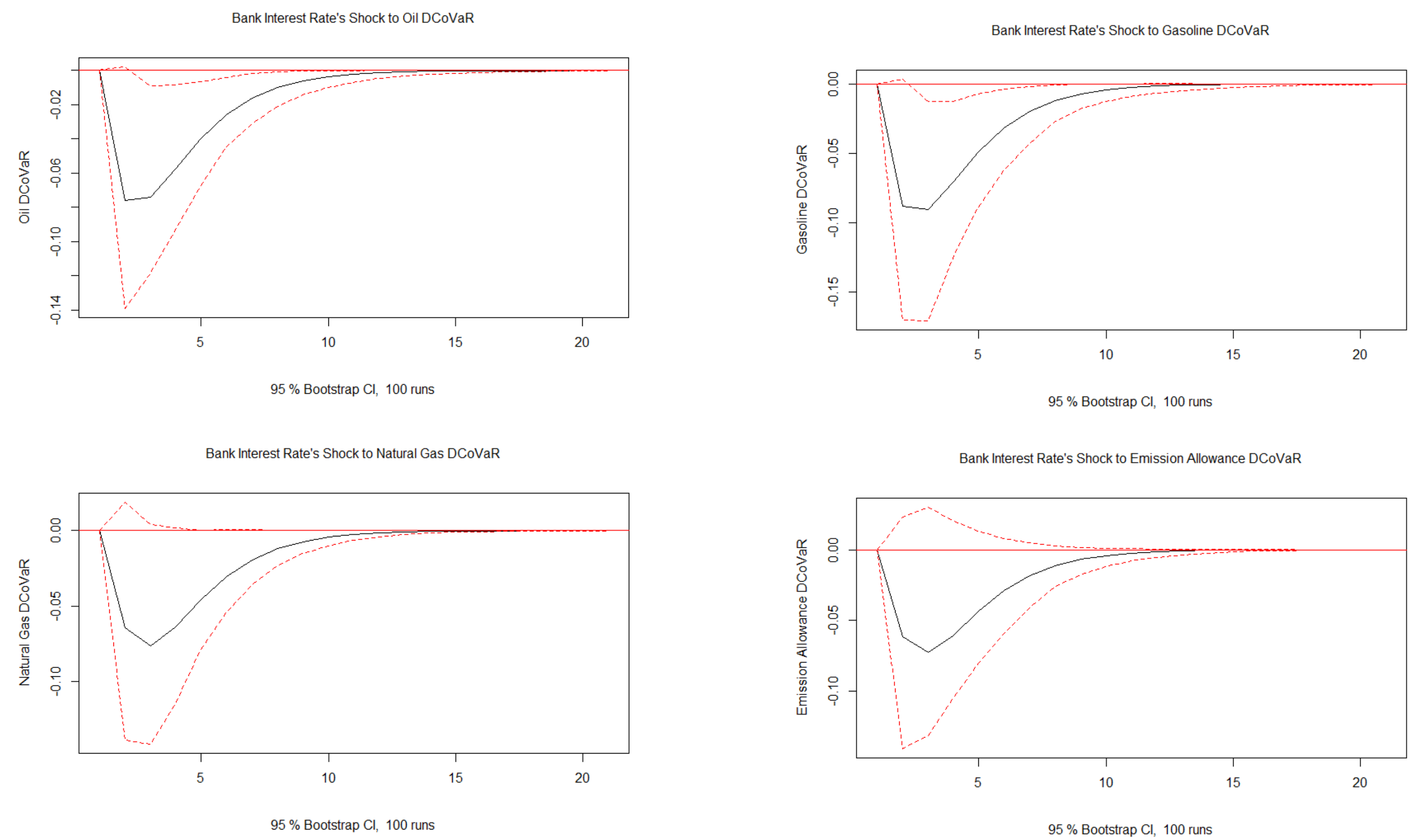


Figure 9: Bank Interest Rate' Shock to Energy ΔCoVaRs



Before looking at each individual Figure, we can see that across all energy commodities and across all shocks the reaction and response time seems to be uniform. This constitutes further evidence that energy commodities follow uniform trends as well as showcases that academic literature focusing only on oil can be applicable to other energy commodities.

When M3 is shocked, from Figure 7, we can see that the ΔCoVaRs of each energy commodity initially drastically decreases before gradually returning to zero (as the series is stationary). An increase in M3 could be attributed to the greater flexibility that firms will have. With greater access to funding firms can more easily overcome the short-term oil price rises.

The same can be seen from Figure 9 regarding the Bank Interest Rate. A larger interest rate charged to banks from central banks forces corporate banks to actively invest their money as such increasing the amount of money in circulation leading to a similar effect as in M3.

However, looking at the Effective Exchange Rate (EER), when the EER is shocked we note that overall, the amount of financial risk posed to the system increases. This is consistent with Chapter A's regression outputs in regard to the USD-EUR % change variable. We see that a weak Euro is preferred than a strong Euro, which could be further confirmation of the originally observation in Section A.

In regard to academic literature, given that as far as the author knows this is the first research to employ a ΔCoVaRs conditioned on energy prices within a VAR model, and as such direct comparability remains limited. Academic literature regarding monetary variables in regard to energy price shocks tends to prefer looking at how oil price shocks to the system impact monetary aggregates and from there indirectly deduce how monetary policy would react. This seems to happen as first oil shocks would occur and then monetary policy would react. However, given the current situation, the European region knows it is heading towards an energy crisis and as such beneficial analysis would come from seeing how the European governments can pre-emptively act to the oncoming crisis. Nonetheless, academic literature regarding energy commodities is once more divisive regarding the implications of an oil crisis mainly due to the different idiosyncratic nature of each country (see Lee et al., 2001; Rahman and Serletis, 2010; Carlstrom and Fuerst, 2006). Looking once more towards Ratti and Vespigani, (2016), they try and address the issue of heterogeneity within countries by creating global macro variables. They found that when oil prices get shocked monetary policy tends to tighten, and when M2 gets shocked then oil prices rise. These results are in contrast to ours. However, when we look at Wen et al., (2018) who focused on China, they found that when monetary supply increase it can dampen the increase of oil prices. Such results are in support of ours. This becomes further interesting when we re-look at Du et al. (2010) (as mentioned in Section A) who found a positive link between economic growth and oil price increases. Such results are either suggesting that the European region's economic structure is slowly becoming more similar to the Chinese economic structure.

5.4.3 Robustness of Our Results

Our results are tested with the cumulative sum control chart (CUSUM) (see Appendix 5 for results). All our results are stable across time. Furthermore, we also employ a basic non-parametric bootstrap as per Pfaff (2008), which is based on Efron and Tibshirani (1993). Although our results were integrated of different order and as such cointegration tests could not be run as per Brooks (2019) depriving us of the ability to see long-term relationships between our variables, we are still confident in the robustness of our results.

Chapter 6: Section A and B Analysis Key Insights Summary

Section A and B aimed to tackle the issue of quantifying the risk posed to the financial stability of the system by energy commodities. Each methodology has its own advantages and shortcomings but nonetheless both are of complementary nature. Given the length of this research, for the ease of the reader, a short summary of each section's key insights is presented below:

6.1 Section A1:

1. Economic Sectors seem to pose the same risk to the financial system when looking at the static ΔCoVaR.

2. When taking into account market capitalisation, the monetary risk posed to the system changes greatly. The Industrial Goods and Services seem to be the most important sector in regard to the "real" economy of a region and consistently the highest threat to the financial stability of a region.

3. When taking into account a Time-Varying ΔCoVaR the actual risk posed to the system increases greatly. This showcases that in actuality the banking system is the greatest risk to financial stability. The IGS sector still remains a high contributor to financial risk albeit not the riskiest.

6.2 Section A2:

1. A rise in energy commodity prices does not in fact cause any rise in the financial risk posed to the system but in reality, decreases it.

2. High amounts of debt are the single most important factor when looking at risk posed to the financial stability.

3. A weak Euro is preferred than a strong Euro.

4. A large market capitalisation decreases the amount of risk posed to the system, suggesting the view that "larger" sectors can more easily adapt. This is not in contrast with the euro ΔCoVaR, as Euro ΔCoVaR assumes that the whole system is in distress while the results from the panel regressions suggest that the chances of a high market capitalisation sector to go in distress, in the first place, is low.

5. The higher the idiosyncratic risk the lower the total amount of risk posed to the financial system.

6.3 Section B1:

1. Static ΔCoVaR once again underestimates actual risk posed to the financial system.
2. All energy commodities examined showcase that a rise in their price results in an increase to the financial system.
3. Gasoline is the contender for the greatest risk posed to the financial system.

6.4 Section B2:

1. Regarding causality it seems that only gasoline and M3 granger causes the VAR system; all variables instant granger causes the system excluding for the Bank Interest Rate and the Effective Exchange Rate.
2. All energy commodities behave identically in regard to impulse responses from the monetary aggregates.
3. M3 and the Bank Interest Rate result in the ΔCoVaR to decrease.
4. A rise in the EER causes the ΔCoVaR to increase supporting the preference for a weak Euro.

6.5 General Observations:

1. The impact of energy commodity prices may change across time and across region, but all energy commodities examined seem on average to follow similar trends.
2. Energy commodities may not have as much of a negative impact on financial stability as originally thought.
3. High amounts of debt seem to be the greatest risk posed to the stability of the financial system.
4. An increase in the Euro exchange rate has negative effects for the financial stability of the region.

5. Central Banks monetary policy transmission channels can alleviate the risk posed to the financial system.
6. The European economic region seems to be transforming to a more output oriented one as seen in China.
7. Energy commodities play both a direct and indirect role in the in financial stability of a region.

Chapter 7 Policy Recommendations

The European continent has found itself once more in a new politico-economic crisis. Taking the correct actions and understanding the trade-offs that European politicians must consider in order to ensure the security and protection of the economy of their countries is of crucial importance. Based on the empirical results of this study, its analysis and discussion the following actions are recommended:

1. Given that debt is the most prominent aspect in regard to increasing the financial risk posed to the system, governments must take steps to limit the amount of debt within the economy and try to limit any possibility of the energy crisis leading to another debt crisis. Since the banking industry is seen to be at the forefront of the threat posed to the financial stability, governments can tackle both issues at once by e.g., by increasing the amount of reserves banks must maintain, decreasing the amount of debt banks can issue or own.
2. It is suggested that Central Banks start gradually loosening their monetary policies and should be ready to increase the money supply, increase interest rates charged to banks and decrease the euro's effective exchange rate when required. Quantitative easing is a method that seems to be a pertinent solution as it increases money supply, decreases debt in the system and also tends to decrease the exchange rate of a country (see. Dedola et al., 2021).
3. Based on the energy commodities examined in this research. Governmental institutions need not worry that different energy commodities will act differently and therefore can apply blanket policies across the energy commodities in question.
4. A primary concern for governments in such an energy crisis would be to support the industrial goods and services sector and ensure that supply disruptions are minimized by setting up different commodity supply channels and exploiting alternative energy sources. Measures such as the U.S.'s release of stock from its emergency energy commodity stockpile (Somasekhar and Kelly, 2022) should dampen the negative effects, at least in the short-term.

Finally, the answer to the key question that has been at the core of the EU's response to Russia's aggression against the sovereign country of Ukraine: "Could the EU impose a complete ban on all energy commodities from Russia". Assuming ceteris paribus and in regard to the risk posed to the financial system by energy prices the answer to such a question would be "Yes".

While there will be risk posed to the financial system for the foreseeable future, this does not seem to be as much as governments might have originally thought. Moreover, while there will be temporary negative impacts on the overall economies of various countries, this is not only a financial issue but rather one of strategic and humanitarian importance; With the correct response from central banking and governmental institutions the short-term negative effects could be overcome as European governments adapt and either secure other sources of imports or transition to renewable energy allowing for European governments to gain their own strategic energy independence. This thus begs a final question within this research: "Should governments transition to renewable energy?". The answer to this proves to also be a positive one, as one could theoretically eliminate a large percentage of risk posed to the financial system if the system did not depend on imported non-renewable energy. However, how this is to be done is complicated, as Safarzynska and van den Bergh (2017) warn, countries that invest too quickly in renewable energy can result in decreasing their country's financial stability. The process of how a country can transition to renewable energy is beyond the scope of this research.

Given this information, before any action is to be taken it is important for the EU to first strive to eliminate (or minimize as much as possible) dependence on energy commodity imports from Russia as soon as possible in order to avoid inflicting irreversible damage to their economies and society. While such a suggestion might be an ethically difficult one to undertake (over immediately banning all energy imports from Russia) it is important for the European region to safeguard itself in order to be in a position to be able to continue to aid Ukraine.

Chapter 8: Concluding Thoughts

As Russia invaded Ukraine, a lot of different political and economic worries and questions within the European continent have resurfaced. Given the European continent's over-reliance on Russian energy imports (International Energy Agency, 2022), European countries have found themselves in a position of having to choose between their own economic prosperity by avoiding a forthcoming energy crisis or their morals. This research aims to understand the importance that energy commodity prices have on the financial stability of an economic region with the goal of assisting institutional bodies to adjust to an energy commodity crisis and select the correct measures to deal with one, if one is to occur.

To be able to do this, this research employs a variety of innovative empirical and theoretical methods. This is done by looking at how energy commodity prices impact financial stability from both a direct and indirect manner as well as by taking into account both key academic literature strands (i.e., Financial Stability and EEF). The first innovation of this research starts off by calculating Adrian and Brunneirmeier's (2016) ΔCoVaR conditioned on different economic segments. This is then followed by calculating Adrian and Brunneirmeier's (2016) ΔCoVaR for the European continent by adapting the methodology to include European macro variables as well as using a BHS for calculating a time varying VaR when calculating the time varying ΔCoVaR. The next key theoretical advancement within this research is the transformation of the ΔCoVaR definition to be conditioned on the gain of an asset rather than its loss, allowing for the measuring of the risk posed to the financial system by energy commodities. After the calculation of the different time varying ΔCoVaR are calculated, standard econometric analysis is conducted. While the econometric analysis conducted might be considered standard, this is one of the only papers that considers using ΔCoVaR as a variable in an econometric analysis. That being said the econometric analysis conducted also includes certain strategies which while are uncommon are important in ensuring the robustness of our results, i.e., mainly using machine learning techniques for finding predictor variables and bootstrapping. Finally, in regard to the methodology section this research also considers time series analysis to be able to try and fully cover all aspects of standard econometric analyses.

Our results suggest that overall, energy commodity prices do not pose as great a risk to the financial stability of a region as originally thought, clearing the way for European governments to implement energy related sanctions against Russia sooner rather than later. Furthermore, we find that central banks are well equipped with dealing with the risk that energy commodities pose to the financial system, further increasing the confidence in our policy recommendations such as implementing sanctions. This research also further adds to the academic evidence that energy commodities' impacts on financial stability across countries varies and there is no standard and common trend in proper reaction to such. E.g., looking at the time varying ΔCoVaR conditioned on energy prices it showcases that as prices increase the risk to the financial system increases, however this is not the case when we look at the indirect method. Moreover, this research has also uncovered other useful insights on causes to financial instability, by looking at how each sector impacts financial instability and by looking at how micro and macro variables impact financial instability.

In conclusion, this research has been able to quantify the risk posed to the financial system by energy commodities, set-out a methodology that can be easily applied across a variety of different commodities and variables and answer the key question that European governments are currently lamenting over while also adding to the academic literature and creating a new path for interdisciplinary research.

Chapter 9: Delimitations and Future Research Capabilities

This research like most research papers suffers from a variety of delimitations. The first and foremost is data related. As mentioned in Section A, the lack of an in-depth and inclusive pan-European stock index that truly represents each European country is lacking. The need for the creation of a new pan-European index is important to both practitioners as well as academics. The second limitation is in regard to time. More in-depth results could have been extracted if we chose to run econometric regressions for each individual country, for each individual economic sector, for each energy commodity. However, given the restricted time and resources this is not a possibility. That being said, given the vast preparatory work needed to create the ΔCoVaR and the data for analysis, future researchers can focus on fully analysing a single country and thus closing the current literature gap that exists. Furthermore, future research capabilities can be seen in Adrian and Brunneirmeier's (2016) ΔCoVaR which for the most part seems to have been underused in academic literature. Such a measure is ingenious and allows a lot of flexibility in understanding the risks posed to the financial system. Future research capabilities can be seen in the underlying methodology of this research, by implementing more machine learning and deep learning optimization techniques for variable selection, prediction and forecasting.

ΔCoVaR is a flexible variable that is underused in financial literature that has the capability of unlocking a lot of future insights and as such for the foundation for future research capabilities, we suggest three new ideas of ΔCoVaR which might prove beneficial. The first is conditioning ΔCoVaR on each country's stock market losses, i.e., selecting (or creating a new) pan-European index conditioned on the stock market of a country. This can showcase the financial risk posed to the system by an individual country and allow for better understanding of how financial risk is spread across the European continent. The second proposition is the creation of a ΔCoVaR for an individual agent/firm. I.e., by conditioning for e.g., the stock return of a firm on revenue, debt, etc. one can see how each factor impacts a firm's own financial risk. Finally, the third proposition is the "opposite" of VaR, i.e., Value-at-Increase (VaI). By finding the VaI and from there as with the standard ΔCoVaR one could calculate a ΔCoVaI to find how much money is added to the system when firm i is in a prosperous situation. This can allow countries and investors to examine which firms, economic sectors and countries contribute the most to the prosperity of the region.

Appendix

A.1

Variance-Inflation Factor For Panel Models

	Oil	Gasoline	Natural Gas	Emission Rights
Variables				
VaR	1.0017	1.0015	1.0007	1.0008
Net Debt To Enterprise Value	1.1322	1.1322	1.1322	1.1323
Energy Commodity	1.0013	1.0013	1.0003	1.0011
Change of the USD-EUR Exchange Rate	1.1223	1.1224	1.1224	1.1227
Quick Ratio	1.1731	1.1731	1.1731	1.1731
Enterprise Value to Sales	1.7629	1.7629	1.7629	1.7629
Market Capitalisation	1.7546	1.7546	1.7546	1.7546
Average VIF	1.2783	1.2783	1.2780	1.2782
Presence of Multicollinearity	Low	Low	Low	Low

A.2

Breusch-Pagan Test Results for FE Regressions

Model	BP Value	DF	P-Value	Presence of Heteroscedasticity
1 Oil	2629.7	7	< 2.2e-16	Yes
2 Gasoline	2649.3	7	< 2.2e-16	Yes
3 Natural Gas	2733.2	7	< 2.2e-16	Yes
4 Emission Allowances	2632	7	< 2.2e-16	Yes

Breusch-Pagan Test Results for VaR Regressions

Model	BP Value	DF	P-Value	Presence of Heteroscedasticity
1 Oil	2629.7	7	< 2.2e-16	Yes
2 Gasoline	2649.3	7	< 2.2e-16	Yes
3 Natural Gas	2733.2	7	< 2.2e-16	Yes
4 Emission Allowances	2632	7	< 2.2e-16	Yes

A.3

Durbin-Watson Test Results For FE Regressions

Model	DW Value	P-Value	Presence of Autocorrelation
1 Oil	1.4058	< 2.2e-16	Yes
2 Gasoline	1.4068	< 2.2e-16	Yes
3 Natural Gas	1.4023	< 2.2e-16	Yes
4 Emission Rights	1.4031	< 2.2e-16	Yes

Durbin-Watson Test Results for VaR Regressions

Model	DW Value	P-Value	Presence of Autocorrelation
1 Oil	1.4058	< 2.2e-16	Yes
2 Gasoline	1.4068	< 2.2e-16	Yes
3 Natural Gas	1.4023	< 2.2e-16	Yes
4 Emission Rights	1.4031	< 2.2e-16	Yes

A.4

Unit Root Tests on Level Data

Augmented Dickey-Fuller test

Variables	T-Stat	P-Value	Stationary
Oil ΔCoVaR	-4.6623	0.01	Yes
Gasoline ΔCoVaR	-4.4064	0.01	Yes
Natural Gas ΔCoVaR	-4.3076	0.01	Yes
Emission Allowances ΔCoVaR	-4.2819	0.01	Yes
M3	-2.6717	0.2953	No
Bank Interest Rate	-1.9569	0.5942	No
Effective Exchange Rate	-2.0151	0.5699	No

Phillips-Perron Unit Root Test

Variables	T-Stat	P-Value	Stationary
Oil ΔCoVaR	-8.9142	0.01	Yes
Gasoline ΔCoVaR	-7.4864	0.01	Yes
Natural Gas ΔCoVaR	-7.6464	0.01	Yes
Emission Allowances ΔCoVaR	-7.6464	0.01	Yes
M3	-1.8785	0.627	No
Bank Interest Rate	-2.0753	0.5447	No
Effective Exchange Rate	-2.4456	0.3899	No

Unit Root Tests on Differenced Data

Augmented Dickey-Fuller test

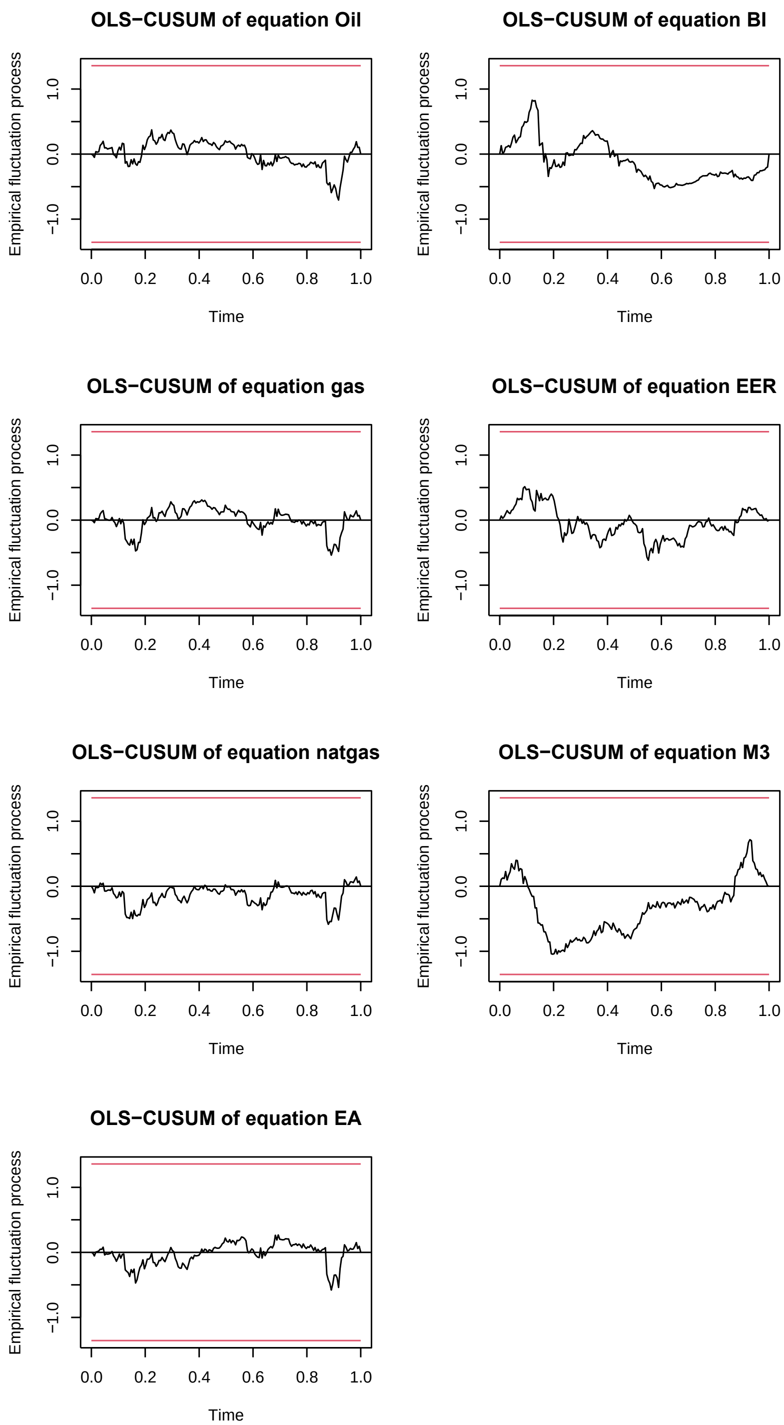
Variables	T-Stat	P-Value	Stationary
M3	-5.3887	0.01	Yes
Bank Interest Rate	-3.6617	0.02929	Yes
Effective Exchange Rate	-4.7946	0.01	Yes

Phillips-Perron Unit Root Test

Variables	T-Stat	P-Value	Stationary
M3	-12.486	0.01	Yes
Bank Interest Rate	-8.5978	0.01	Yes
Effective Exchange Rate	-11.066	0.01	Yes

A.5

CUSUM Stability Plots



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