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Conditional Capital Surplus and Shortfall across Resource Firms*

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Abstract

This study examines the conditional capital surplus and shortfall dynamics of renewable and non-renewable resource firms. To this end, this study uses the systemic risk index by Brownlees and Engle (2017) and considers two conditional systemic events, namely, the stock market crash and the commodity price crash. The results indicate that companies in the resource sector tended to have conditional capital shortfalls before 2000 and conditional capital surpluses after 2000 owing to the boom of the commodity sector stock prices and the careful capital management adopted by these companies. The analysis using the panel vector autoregressive model indicates that commodity price, geopolitical, and economic policy uncertainties have a positive impact on the conditional capital shortfall. These uncertainties have also been proven to increase the conditional failure probability of firms in the sample. Lastly, the analysis of performance shows that conditional capital shortfall positively affects market returns, reflecting a high-risk, high-return trade-off for this sector.

Keywords: Systematic Risk Index, Commodity Prices, Macroeconomic Uncertainties, Panel Vector Autoregression

JEL classification: E32, G32

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1 Introduction

Measuring the potential capital shortfall for firms conditional on a systemic event is crucial for the economy. If a company experiences a capital shortfall during a systemic event, it will lead the company to insolvency and, likely, failure. In general, the capital shortfall is negatively related to a company's market value, suggesting that a lower market value implies a higher expected capital shortfall, particularly during a crisis period. When a crisis strikes, a company will lose its market value, but the leverage value of that company tends to remain. Furthermore, the market and its participants are in distress, making it more difficult than usual to raise capital. Thus, the capital shortfall potentially happens to many companies during a crisis, imposing severe problems for the economy.

On the other hand, if the company experiences capital excess during an extreme event, this might imply that the company is playing safely by minimising risk. This also suggests that companies might lose the opportunity to gain more profit or higher market returns. It could be argued that the ideal situation is when a company can maintain its conditional capital surplus and shortfall near zero.[1] Therefore, it is informative to examine the potential capital shortfall and surplus conditional on a systemic event and their possible factors. The current study tries to do so for resource firms.

Several previous studies consider a measure of capital shortfall conditional on a systemic event. For example, Acharya et al. (2012) develop a measure of capital shortfall for a financial firm conditional on a financial crisis based on publicly available information, but this measure is conceptually similar to the stress tests conducted by US and European regulators. Similarly, Brownlees and Engle (2017) introduce the systemic risk index (SRISK), defined as the expected capital shortfall of financial entities conditional on a prolonged market decline. The SRISK index can measure both capital surplus and shortfall of a firm, although Brownlees and Engle (2017) only focus on capital shortfall, tailoring the focus of their study on systemic risk aspects of the financial industry. Following their study, Wang et al. (2019) propose a measure of a financial institution's capital shortfall under the worst scenario, conditional on a substantial market decline.

Although the studies mentioned above focus on financial firms, the conditional capital shortfall is also critical for non-financial firms. Brownlees and Engle (2017) note that SRISK is general and can be applied to non-financial firms for conditional capital shortfall estimation. However, it is worth noting that the systemic characteristics of non-financial firms could differ from those of financial firms. Therefore, as a companion to the standard SRISK, it could be more informative to consider a different measure of conditional capital shortfall for non-financial firms. The current study addresses this issue for natural resource firms. To this end, this study modifies the SRISK proposed by Brownlees and Engle (2017) to measure the conditional capital shortfall induced by the dynamics of commodity prices. The original SRISK, referred to as the Market SRISK (MSRISK) in this paper, is based on the market long-run marginal expected shortfall (MLRMES). It is defined as the expected fractional loss of the firms' equity calculated using the market beta when a crisis strikes, as represented by the extraordinary decline in the benchmark stock index over the last six months. The modified Commodity SRISK (CSRISK) is based on the commodity long-run marginal expected shortfall (CLRMES) computed using the commodity price beta when commodity prices decline considerably over the last half years. In other words, CSRISK changes the basis of an extreme event from a capital market crash to a commodity price crash. This additional analysis is meaningful, as commodity prices are naturally important for natural resource firms. In this study, $MSRISK$ to market asset ratio multiplied by negative 1 is termed as $CONCAP^M$, so is $CSRISK$ to market asset ratio, termed as $CONCAP^C$. Thus, positive value refers to capital surplus and

[1] Throughout this paper, the conditional capital surplus and shortfall mean the capital surplus and shortfall conditional on a systemic event or crisis.

negative value refers to capital shortfall.

The natural resource sector plays a significant role in many large economies, primarily through export channels. In the G20 area, this sector contributes to more than 60% of the total exports of several large economies, including Saudi Arabia, Russia, and Australia (Figure 1). For some other countries such as Brazil, Greece, Indonesia, Canada, South Africa, and Cyprus, the sector contributes to more than 20% of the total exports. Even in the United States, the largest economy in the world, the resource sector contributes to approximately 14% of total exports. This condition puts the US as the second-largest natural resource exporter by value in 2017, after Russia. Considering its significant export contribution, the stability of these countries' macroeconomic conditions inevitably depends on the resource sector. These facts provide a solid reason for focusing on the resource sector.

[Figure 1].

Addressing the issue of the conditional capital shortfall among resource firms is crucial for at least three reasons. First, BIS (2016) outlines the imminent risk posed by the resource sector to the financial system through leverage default risk. Companies in the oil and gas sector accumulated total syndicated loans amounting to an estimated USD 1.6 trillion in 2016, with an average annual growth rate of 13% from USD 600 billion in 2006. Second, conditional capital shortfall provides forward-looking insight into the survival of resource firms, which play a significant role in the export of many big economies, as discussed above. Third, resource companies' overall financial health is vital to maintain their operational stability, which in aggregate determines the stability of global commodities supply.

Furthermore, some studies, such as Donders et al. (2018), find that corporate bonds of commodity-producing companies are less sensitive to commodity price dynamics than stock return dynamics. However, they also document that debt finance deteriorates with commodity bust. In addition, Donders et al. (2018) and Shiller (2008) discuss the influential role of hedging in minimising commodity price amplification in debt conditions. These studies also emphasise the importance of measuring the potential capital shortfall and surplus conditional on a significant commodity price decline in the resource sector and identifying their macroeconomic factors, which will be done by calculating and analysing $CONCAP^C$ in this study.

Moreover, many studies examine the transmission of commodity prices and other macroeconomic uncertainty shocks to the economy (e.g. countries or sectors), yet few studies analyse their effects on companies' capital conditions. This study also addresses this issue by analysing the transmissions of macroeconomic uncertainty and business cycle shocks to the dynamics of natural resource companies' capital conditions and possible failures conditional on a substantial stock price or commodity price decline. Finally, the study also examines the relationship between market returns and potential capital shortfalls and surplus. Specifically, this study has four aims. The first aim is to analyse the pattern of conditional capital surplus and shortfalls of natural resource companies. The second aim is to assess the effects of global and country-level uncertainties and business cycle dynamics on natural resource companies' conditional capital surplus and shortfall. Third, this study also aims to analyse the role of macroeconomic uncertainties in inducing capital depletion and, therefore, determines firms' possible failures in the sample. Lastly, this study examines how expected capital surplus and shortfall affect firm performance.

To this end, this study conducts the following four analyses using unbalanced panel data of 3,333 companies from 61 countries across the world in annual frequency during the 1981–2017 period in four resource sectors: (1) alternative energy, (2) forestry and paper, (3) mining, and (4) oil and gas producers. The first analysis focuses on the calculation and pattern of both $CONCAP^M$ and

$CONCAP^C$. The second analysis investigates how global and country-level macro uncertainties affect the dynamics of the conditional capital surplus and shortfall of resource firms. This analysis uses the panel vector autoregressive (PVAR) model comprising three levels of variables: the world (high), country, and firm (low) level. It is assumed that there is no feedback from lower- to higher-level variables, which is also crucial for identifying structural shocks in the PVAR analysis. The third analysis applies the $CONCAP$ index as a proxy for firms' failure. In this analysis, it is assumed that 11.4% of the firms with the worst $CONCAP$ will fail, based on data from the mining sector's exit rate in Australia as a benchmark, provided by Australian Productivity Commission (2015). The analysis then examines both firm- and macro-level determinants of firms' possible failures. Lastly, the fourth analysis focuses on how capital surplus and shortfall might influence a firm's future performance.

This study has several significant findings. The first results suggest that both $CONCAP^M$ and $CONCAP^C$ share a relatively similar pattern and magnitude, where both are determined significantly by the leverage level. Furthermore, the pattern shows that resource companies have relatively low leverage levels after 2000, which results in a noticeable conditional capital surplus for most companies in this sector. This pattern can be explained by real economic events: (1) the commodity boom after 2000, and (2) moderate capital structure management of resource companies. The second analysis with the PVAR suggests procyclical capital shortfall responses toward shocks to commodity price, geopolitical, and economic policy uncertainty. The third analysis indicates that macro uncertainties positively increase firms' failure probability. The last analysis shows that higher capital shortfall relates positively to higher market returns, indicating a high-risk high-return feature for the resource sector.

The remainder of this paper is organised as follows. Section 2 provides a literature review on how commodity price dynamics influence firms' value and economy. This section also reviews the recent development of measurement for systemic risk and capital shortfall, a literature block on firms' failure probability, and the relation between capital surplus/shortfall on performance. Section 3 explains the methodologies employed in the analysis, which covers (1) the calculation process of $LRMES$, $SRISK$, and $CONCAP$; (2) the outline of the PVAR model to investigate the sensitivity of $CONCAP$ toward shocks to global and country-level uncertainties and business cycle fluctuations; (3) the panel probit model used to estimate firms' failure probability; and (4) estimation of firm performance related to capital surplus/shortfall. Section 4 discusses the results of the estimation process. Finally, Section 5 concludes the paper.

2 Literature Review

There are four strands of literature that form the basis of the analyses conducted in this study. The first strand focuses on the literature that addresses how commodity price dynamics influence resource firms' values. The second concerns the recent development of systemic risk and capital shortfall measurements. The third block discusses firm failure and its determinants. Finally, the last block discusses the relationship between capital excess and shortfall with performance.

2.1 Commodity Price Dynamics, Firm Values, and Economy

Jin and Jorion (2006) examine the sensitivity of the US oil and gas producers' stock and market value toward the fluctuation of the oil and gas price. They exhibit a positive relationship between companies' stock towards the market index and commodity price. Moreover, they find that hedging activities reduce sensitivity. Buhl et al. (2011) investigate the effect of commodity price risk on commodity-producing firms' market value and find a negative relationship. Furthermore, they also show that hedging might reduce the negative effect of commodity price risk and increase profit, which translates to a better market value. Perez-Gonzales and Yun (2013) investigate how risk management might affect energy firms' value by introducing weather derivatives as a risk proxy. Their results suggest that weather derivatives benefit weather-sensitive firms and positively affect firms' value, investments, and leverage. Haque et al. (2014) measure how commodity price risk affects the valuation of a mining project using the real options valuation technique. Their results suggest that commodity price risk has a significant effect on the mining project value. Ntantamis and Zhou (2015) examine how different market phases (bull and bear) have a relation to the stock of commodity-producing firms and commodity prices. They find little evidence that commodity prices are related to stock market phases.

Many other studies document that commodity prices have a significant effect on companies' stock in various industries, including Tang (2015), Vandone et al. (2018), and Pal and Mitra (2019). For example, Tang (2015) analyses the restaurant industry's exposure to commodity price volatility and the determinants of risk exposure. They find that operating leverage and financial leverage are effective risk management tools, with financial leverage being more effective than operating leverage.

A number of studies examine the effects of commodity prices on the global economy. Classical examples investigating the macroeconomic effects of oil prices include Hamilton (1983) and Mork (1989), and comprehensive surveys can be found in Hamilton (2009), Kilian (2008), and Baumeister and Kilian (2016). For instance, Kilian (2009) identifies the underlying demand and supply shocks in the global crude oil market and demonstrate that, among other things, an oil price change driven by an unanticipated global aggregate demand shock will have a very different effect from an oil price change caused by an unanticipated increase in precautionary demand driven by fear about future oil supply shortfalls. Furthermore, Balashova and Serletis (2020) find that a positive shock in oil prices responds positively to economic activity, industrial production, and manufacturing in Russia. They argue that this procyclical behaviour indicates that oil prices lead the business cycle of the Russian economy.

2.2 Systemic Risk and Capital Shortfall

The phrase capital shortfall is often associated with default and insolvency, and mainly refers to the condition in which a firm's capital cannot service or meet its liability or commitment. Davydenko (2012) defines default in cash flow or payment as failures to fulfill cash flow commitment to creditors as stipulated in the debt contract. He also outlines two types of insolvency: economic and financial. Economic solvency and default refer to the market value of a firm's assets. This definition has roots in structural models, such as Merton (1974) and Black and Cox (1976). The assumption is that market value is the best representation of a firm's overall condition. The second definition, financial solvency, refers to the book value of a firm's assets. Following Brownlees and Engle (2017), the definition of capital shortfall in this study refers to economic rather than financial insolvency.

Brownlees and Engle (2017) outline that capital shortfall is negatively related to the market value of a company, suggesting that higher market value means a lower expected capital shortfall, particularly in a crisis period. When a crisis strikes, a company will lose its market value, while the leverage value of that company remains. Moreover, in the crisis, the market and all of its participants are in distress, making it more difficult to raise funding from the market compared with a normal period. Therefore, many companies potentially suffer from capital shortfalls during the crisis, which can be considered a systemic risk.

After the 2007/8 financial crisis, many studies have focused on developing indices to measure systemic risk, especially in the financial sector. For example, Acharya et al. (2012) develop a measure of capital shortfall for a financial firm conditional on a financial crisis that is based on publicly available information but is conceptually similar to the stress tests conducted by US and European regulators. Similarly, Brownlees and Engle (2017) introduce the MSRISK, defined as the expected capital shortfall a company experiences when a crisis strikes. This index has the advantage of calculating the nominal amount of capital shortfall that a company will experience. Thus, this value can be aggregated to measure the overall system capital shortfall. The capital shortfall contribution of a firm to the total system is defined as the systemic risk. Following their study, Wang et al. (2019) propose a measure of a financial institution's capital shortfall under the worst scenario, conditional on a substantial market decline.

As an application of these measures, Matousek et al. (2020) employ MSRISK to analyse the capital shortfall sensitivity of global financial firms as induced by global policy uncertainty. They find a positive relationship between expected capital shortfalls and economic policy uncertainty. Furthermore, they find that well-capitalised firms are less affected. Thus, the capital structure of a firm controls its expected capital shortfall.

This study adopts MSRISK by Brownlees and Engle (2017) to measure the capital shortfall and surplus for non-financial firms conditional on stock market crashes. It is worth noting that the systemic characteristics of non-financial firms are undoubtedly different from those of financial firms. In particular, for resource firms, commodity prices significantly affect firm value and performance, as discussed in the previous subsection. Therefore, MSRISK is modified by replacing the market index with commodity prices to accommodate the dynamics of the commodity price cycle as the main driver of the capital shortfall.

2.3 Determinants of Firm Survival and Failure

This study employs $CONCAP$ as a proxy for firm survival and failure. As explained in the previous section, $CONCAP$ provides an estimate of the conditional capital surplus and shortfall of a firm when a crisis strikes. Based on this characteristic, it is assumed that the worst 11.4% $CONCAP$ firm will turn to insolvency or failure when a crisis strikes, based on the exit rate of the mining sector in Australia as a benchmark, as in Australian Productivity Commission (2015). Then, this study examines how macroeconomic uncertainties and global variables might induce the failure of firms in the sample.

Many studies have analysed firm-specific factors that can explain the phenomenon of survival and failure. For example, Zingales (1998) investigates whether capital market imperfections and leverage levels determine firm survival in the US trucking industry and finds that highly leveraged firms have lower survival after deregulation. The crucial role of leverage as a tool for risk mitigation is also examined by Adrian and Shin (2014). They provide a theoretical framework along with empirical exercises that support the argument that the probability of default of a firm is positively related to the leverage ratio and negatively related to the business cycle. Thus, their research demonstrates that as economic conditions improve in the boom phase, the probability of default is lower. This argument could be consistent with the other view, which argues that the probability of default risk builds up during the booming period and thus will be realised when the economy is in recession.

Moreover, Chung et al. (2013) investigate how capital structure policy affects firm survival using data from the oil industry and find no significant evidence between the two phenomena. On the other hand, Calvo (2006) finds that innovation positively increases firm survival. Sharif and Huang (2012) also analyse how innovation strategy determines firm survival and relocation from Guangdong province, China. They find that firms that engage in R&D or collaborative innovation activities are more likely to survive and stay in the business. Similarly, Zhang et al.

(2018) investigate how innovation might determine the survival of Chinese high-tech firms and find that innovation efficiency increases firms' survival rates.

Furthermore, Tsoukas (2011) tests whether the financial development of a country in which firms operate affects survival. They find that financial development significantly affects firm survival. A more liquid financial market will improve firms' chances of survival. Carr et al. (2010) investigate whether firm age when deciding to do internationalisation has an effect on survival and short-term growth. They find that internationalisation timing has important implications for the survival and short-term growth of firms. Musso and Schiavo (2008) analyse the role of financial constraint on firm survival and find that financially constrained firms have a lower probability of surviving. Brogaard et al. (2017) examine how stock liquidity affects firm bankruptcy risk and find that enhanced liquidity decreases bankruptcy risk. Zorn et al. (2017) test whether downsizing increases the likelihood of firm bankruptcy and find the positive relationship between both phenomena.

Many studies investigate firm survival and develop models to analyse the bankruptcy phenomenon. A model by Cox (1972), the proportional hazard model (PHM), is believed to be one of the most prominent. This model is argued by Zhang et al. (2018) to model firm survival better based on three reasons. First, it relies on conditional probability instead of unconditional probability, such as analysis with an ordinary least square or probit model. Second, PHM relaxes the assumption of a constant survival rate during the sample period because it focuses on firm survival duration instead of exit event timing. Third, PHM accommodates right-censoring issues. Consequently, for conventional survival analysis, PHM is one of the most widely used models. However, in this study, the event which becomes the focus is capital depletion instead of a conventional exit event, such as bankruptcy. Therefore, right censoring is not an issue, because, in many cases, the government (either fiscal or monetary authority) would normally help these companies survive.[2] Thus, it is not necessary to assume that they will exit once their capital is depleted. Therefore, this study implements probit analysis. In addition, the probit model is also among the most popular for survival analysis, as implemented in many studies.[3] The assumption that the government of countries will assist firms with depleted capital will also influence the design of the third analysis.

2.4 Capital Surplus/Shortfall and Performance

Many studies outline the notion of optimal cash or, in a broader sense, capital holding. How much cash or capital should a company hold at a given time? Jensen (1986) discusses this problem as agency problem, outlining that the conflict of interest between managers and shareholders as the central tenet of the discussion. In the economic expansion period, firms tend to have excess cash (free cash flow), which then the managers will decide what to do with the cash. Harford et al. (2008) outline that it is not theoretically clear as to why managers would decide to spend the free cash flow or hold it. However, empirically, it could be argued that their decision will have an effect on firm performance, as many studies outline.

Harford et al. (2008) find limited evidence of the relationship between excess cash and profitability. They document that the accumulation of excess cash negatively relates to future profitability and offers two explanations for this relationship. First, it reflects the long-run mean reversion between them, and second, the cash excess accumulation might indicate a decline in the firms' growth prospects. Oler and Picconi (2014) examine the effect of both insufficient and excess cash on future

[2] One of the most popular examples is the Large Scale Assets Purchase (LSAP) programs launched by many central banks in advanced economies during or after the 2007/8 global financial crisis.

[3] Almost all studies discussed in this section implement probit for survival analysis, including Zhang et al. (2018), Brogaard et al. (2017), Zorn et al. (2017), Chung et al. (2013), Sharif and Huang (2012), Tsoukas (2011), Carr et al. (2010), Musso and Schiavo (2008), Calvo (2006), and Zingales (1998).

performance in the form of profitability and market return. They document a negative relationship between both insufficient and excess cash to future performance, outlining the notion of optimality of cash holdings.

3 Methodology

This section explains the methodology used to achieve the aims of this study. The first analysis focuses on the pattern of conditional capital shortfall and surplus of resource companies in the sample, as induced by both market and commodity price downfalls. The second focuses on explaining the effect of commodity price and business cycle uncertainties on companies' conditional capital shortfall and surplus. The third analysis discusses how macroeconomic uncertainties might increase firms' capital depletion or failure. Lastly, the fourth analysis examines the relationship between conditional capital surplus/shortfall and firms' market performance.

The complete dataset for these analyses is summarised in Table 2 and comprises unbalanced panel data of 3,333 companies in four resource sectors: (1) alternative energy, (2) forestry and paper, (3) mining, and (4) oil and gas producers in 61 countries across the world from 1981 to 2017. The first two sectors are renewable, and the other two are non-renewable. For this reason, each analysis is divided into seven separate sample sets: (1) full sample, (2) renewable, (3) non-renewable, (4) alternative energy, (5) forestry and paper, (6) mining, and (7) oil and gas producers. In addition, the second analysis includes a dummy for 2008 to control the 2007/8 global financial crisis. All necessary data for these calculations were retrieved from Refinitiv Datastream.

In general, this section is divided into five sections. The first part explains the calculation steps for both the market and commodity beta. In addition to the standard market beta, the commodity beta is employed to measure the sensitivity of each company stock against fluctuations in commodity prices. The second part explains the detailed calculation steps of the $LRMES$, $SRISK$, and $CONCAP$ indices. As is clear, $SRISK$ (and then later $CONCAP$) measures the conditional capital surplus and shortfall which each company will experience if a crisis strikes. The third part explains the PVAR model employed in this study to measure the sensitivity of each company's $CONCAP$ to fluctuations in macroeconomic uncertainties and business cycles. The fourth part discusses the probit model estimation of firms' capital depletion or failure. The last part explains the regression setting to outline the relationship between conditional capital surplus/shortfall and future firms' performance.

3.1 Commodity Beta

Two beta (β) coefficients are implemented in this study. The first is the standard market beta (β^M), which measures the sensitivity of each company stock to the respective MSCI market index of which the company is listed. In addition, this study also estimates the commodity beta (β^C) to measure the sensitivity of each company stock towards fluctuations in commodity prices. This beta takes the form resembling the standard market beta, except that the factor employed is the commodity price return, which is represented in this study by the S&P Goldman Sachs Commodity Index (GSCI).[4] Specifically, the estimation of the market and commodity beta take the forms as represented by the following equations:

[4]The GSCI index is based on a basket of future price of about 30 commodities and available from 1970 in real-time. The GSCI is chosen as the proxy of commodity price owing to its popularity and forward-looking characteristics to calculate the commodity beta of the firms in the sample. Furthermore, it is also employed in the PVAR model to analyse the sensitivity of CONCAP and as an explanatory variable for survival analysis.

$$r_t = \alpha + \beta^M (rMSCI_t) + v_t, \tag{1}$$

$$r_t = \alpha + \beta^C (rGSCI_t) + v_t, \tag{2}$$

where t represents time. Terms r, $rMSCI$, and $rGSCI$ represent the daily returns of the company's stock and that of the MSCI and GSCI, respectively. The estimation of both annual market and commodity beta is based on the one-year daily returns of companies' stock, MSCI and GSCI, meaning that each beta is typically based on approximately 260 observations. These two β values are then employed as the basis of the LRMES and SRISK calculations.

Previously, Talbot et al. (2013) test the sensitivity of commodity price beta for oil producer stocks. They find that the commodity beta is driven by oil price (+), bond rate (+), volatility of oil returns (−), and cost of carry (+). In addition, Hong and Sarkar (2008) explore the determinants of commodity beta for gold mining firms. They find that commodity beta is affected by the speed of reversion of gold price (−), volatility of gold price (−), tax rate (−), interest rate (−), and firm size (+).

3.2 LRMES, SRISK, and CONCAP

To measure the potential capital shortfall of the companies in the sample, the LRMES and SRISK indices based on Brownlees and Engle (2017) are calculated. Brownlees and Engle (2017) define the LRMES as expected fractional loss of the firms' equity when a crisis strikes as represented by the six-month decline of the benchmark stock price index. Following the documentation from NYU Volatility Lab (2021), Anginer et al. (2018), and Chu et al. (2020), the LRMES is calculated using the following equation:

$$LRMES = 1 - e^{log(1-d)*\beta} \tag{3}$$

MLRMES and CLRMES are further used to calculate MSRISK and CSRISK. Specifically, Brownlees and Engle (2017) define SRISK as the expected capital shortfall of a firm when a crisis strikes, and it is calculated as follows: where d represents the six-month market index decline. The assumed value of d is 40%, following Brownlees and Engle (2017), meaning that the value of the benchmark index declines by 40% or worse in the six months. The LRMES is calculated for each company for each year using Equation (3). In addition to the Market LRMES (MLRMES), which uses market beta, β^M, defined in Equation (1), the commodity LRMES (CLRMES) based on the commodity beta, β^C, defined in Equation (2), and the six-month commodity price decline is also calculated.

$$SRISK = k \cdot LIAB - (1-k) \cdot EQUITY \cdot (1 - LRMES) \tag{4}$$

$SRISK$ is calculated as in (4), where the term k represents the minimum capital requirement as mandated by regulators, $LIAB$ represents the total liabilities of each company, and $EQUITY$ represents the market value of equity. Because SRISK was initially developed for financial institutions, the value of k was assumed to be 8%. In this study, different levels of k were applied for each sector in the analysis. The level of k uses the benchmark of the book equity to capital ratio provided by Damodaran (2021).[5] The data used are at the global level, dated 5 January 2018 which refers to the end of the 2017 position, following the last period used in this study. Specifically, the book equity-to-capital ratio used as a benchmark of k for each sector is summarised in Table 1.

[5] The book equity to capital ratio is calculated as $100\% - DTC$, where DTC is book debt to capital ratio for each sector provided by Damodaran (2021).

[Table 1].

Conditional capital surplus (shortfall) increases as the market capitalisation of the companies increases (decreases). The result of the SRISK calculation based on Equation (4) represents the expected capital shortfall with a positive value. The negative value of this calculation refers to the expected capital surplus. In their study, Brownlees and Engle (2017) only focus on capital shortfalls and ignore capital surplus by replacing them with a value of zero. On the other hand, this study uses and analyses both the conditional capital surplus and shortfall from the SRISK calculation.

Specifically, in this study, conditional capital is termed as $CONCAP$, which is defined as $SRISK$ divided by market assets calculated as the sum of market equity and book liabilities. It is then multiplied by negative 1 so that a positive value refers to capital surplus and a negative value refers to capital shortfall. In addition, dividing by market assets allows to control both firm size and currency, making $CONCAP$ comparable across firms and countries. $CONCAP^M$ and $CONCAP^C$ refer to market-based conditional capital and commodity-based conditional capital, respectively.

3.3 PVAR model

This study implements the PVAR model to analyse the influence of both global- and country-level macro variables on the $CONCAP$ ($CONCAP^M$ and $CONCAP^C$) of firms in the sample. Because the analysis is based on annual data, this study implements one lag for the PVAR model.

The PVAR analysis is based on the seven variables PVAR model given as follows:

$$\boldsymbol{Y}_{i,t} = \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1 \boldsymbol{Y}_{i,t-1} + \boldsymbol{\Gamma}_2 \boldsymbol{X}_{i,t} + \boldsymbol{u}_{i,t}, \tag{5}$$

where i represents firms and t represents time. Term $\boldsymbol{Y}$ is a vector of the seven endogenous variables in the system, $\boldsymbol{X}$ represents exogenous dummies for the crisis, $\boldsymbol{\Gamma}$ represents a vector or matrix of coefficients, and $\boldsymbol{u}$ is a vector of residuals.

The seven variables in the PVAR model are $\sigma COMM$, GPR, $GEPU$, $WGDP$, $HGDP$, $LIAB$, and $CONCAP$. The variable $\sigma COMM$ represents the log-transformed annual standard deviation of the GSCI index, which represents the commodity price cycle uncertainty in this study. The variable GPR represents the geopolitical risk (GPR) index by Caldara and Iacoviello (2019), which measures global geopolitical tensions based on major newspapers tally from across the world. The index is provided and updated monthly by the authors on their website.[6] The global economic policy uncertainty is represented by the $GEPU$ index provided by Davis (2016).[7]

The variables $WGDP$ and $HGDP$ represent the world and home country business cycles, respectively, and represent the annual growth of the GDP of world and each country, respectively. The variable $LIAB$ represents the liability level of companies and is defined by the log-transformed total liabilities. Seven variables are chosen to adopt and extend the theoretical model by Adrian and Shin (2014). Their framework argues that a firm's default probability, which can be proxied by conditional capital shortfall, is affected positively by the leverage level and negatively by the business cycle. It is believed that as the business cycle or overall economic condition improves, the probability of default will be lower.

Specifically, the variables employed in the analysis comprise seven variables from three different levels: (1) world level, (2) country level, and (3) firm level. The world-level variables are $\sigma COMM$,

[6] The GPR index is provided and updated monthly by Caldara and Iacoviello (2019) on https://www.matteoiacoviello.com/gpr.htm.

[7] The GEPU index is provided and updated monthly by Davis (2016) on https://www.policyuncertainty.com/global_monthly.html.

GPR, $GEPU$, and $WGDP$. The country-level variable is $HGDP$. Meanwhile, $LIAB^{MA}$ and $CONCAP$ are at the firm level. Higher-level variables are assumed to be free from the influence of lower-level variables. For instance, $\sigma COMM$, GPR, $GEPU$, and $WGDP$ are only influenced by the lags of these four variables and not by lags of $HGDP$, $LIAB^{MA}$, and $CONCAP$. Therefore, block exogeneity is implemented to avoid a feedback loop from lower-level variables to a higher level. Exogeneity is imposed by putting zero restrictions for parameter matrix estimation. For each subsample, analyses are separately conducted with $CONCAP^M$ and $CONCAP^C$. The PVAR model represented by Equation (5) can be expressed as follows:

$$\begin{bmatrix} \sigma COMM_{i,t} \\ GPR_{i,t} \\ GEPU_{i,t} \\ WGDP_{i,t} \\ HGDP_{i,t} \\ LIAB_{i,t} \\ CONCAP_{i,t} \end{bmatrix} = \begin{bmatrix} \mu^{\sigma COMM} \\ \mu^{GPR} \\ \mu^{GEPU} \\ \mu^{WGDP} \\ \mu^{HGDP} \\ \mu^{LIAB} \\ \mu^{CONCAP} \end{bmatrix} + \begin{bmatrix} \phi_{1,1} & \phi_{1,2} & \phi_{1,3} & 0 & 0 & 0 \\ \phi_{2,1} & \phi_{2,2} & \phi_{2,3} & 0 & 0 & 0 \\ \phi_{3,1} & \phi_{3,2} & \phi_{3,3} & 0 & 0 & 0 \\ \phi_{4,1} & \phi_{4,2} & \phi_{4,3} & 0 & 0 & 0 \\ \phi_{5,1} & \phi_{5,2} & \phi_{5,3} & \phi_{5,4} & 0 & 0 \\ \phi_{6,1} & \phi_{6,2} & \phi_{6,3} & \phi_{6,4} & \phi_{6,5} & \phi_{6,6} \\ \phi_{7,1} & \phi_{7,2} & \phi_{7,3} & \phi_{7,4} & \phi_{7,5} & \phi_{7,6} \end{bmatrix} \begin{bmatrix} \sigma COMM_{i,t-1} \\ GPR_{i,t-1} \\ GEPU_{i,t-1} \\ WGDP_{i,t-1} \\ HGDP_{i,t-1} \\ LIAB_{i,t-1} \\ CONCAP_{i,t-1} \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \end{bmatrix} [CRISIS_{i,t}] + \begin{bmatrix} u_{i,t}^{\sigma COMM} \\ u_{i,t}^{GPR} \\ u_{i,t}^{GEPU} \\ u_{i,t}^{WGDP} \\ u_{i,t}^{HGDP} \\ u_{i,t}^{LIAB} \\ u_{i,t}^{CONCAP} \end{bmatrix} \tag{6}$$

Furthermore, the Cholesky decomposition is implemented to identify contemporaneous relationships and structural shocks in the PVAR model. Specifically, the error terms of the PVAR model (6), u, are assumed to be decomposed into structural shocks as follows:

$$\begin{bmatrix} u_{i,t}^{\sigma COMM} \\ u_{i,t}^{GPR} \\ u_{i,t}^{GEPU} \\ u_{i,t}^{WGDP} \\ u_{i,t}^{HGDP} \\ u_{i,t}^{LIAB} \\ u_{i,t}^{CONCAP} \end{bmatrix} = \begin{bmatrix} t_{1,1} & 0 & 0 & 0 & 0 & 0 & 0 \\ t_{2,1} & t_{2,2} & 0 & 0 & 0 & 0 & 0 \\ t_{3,1} & t_{3,2} & t_{3,3} & 0 & 0 & 0 & 0 \\ t_{4,1} & t_{4,2} & t_{4,3} & t_{4,4} & 0 & 0 & 0 \\ t_{5,1} & t_{5,2} & t_{5,3} & t_{5,4} & t_{5,5} & 0 & 0 \\ t_{6,1} & t_{6,2} & t_{6,3} & t_{6,4} & t_{6,5} & t_{6,6} & 0 \\ t_{7,1} & t_{7,2} & t_{7,3} & t_{7,4} & t_{7,5} & t_{7,6} & t_{7,7} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t}^{\sigma COMM} \\ \varepsilon_{i,t}^{GPR} \\ \varepsilon_{i,t}^{GEPU} \\ \varepsilon_{i,t}^{WGDP} \\ \varepsilon_{i,t}^{HGDP} \\ \varepsilon_{i,t}^{LIAB} \\ \varepsilon_{i,t}^{CONCAP} \end{bmatrix} \tag{7}$$

This structural decomposition implies that variables GPR and $\sigma COMM$ are assumed to be the most exogenous in the system, followed by $WGDP$, $HGDP$, $LIAB$, and then $CONCAP$ ($CONCAP^M$ or $CONCAP^C$).

3.4 Failure Analysis

This analysis employs $CONCAP^M$ and $CONCAP^C$ as proxies for firm survival, and the aim is to examine how macroeconomic uncertainties and global variables induce failure of firms in the sample. For this analysis, $CONCAP^M$ and $CONCAP^C$ are ranked based on the worst shortfall, and then converted to a dummy, where the worst 11.4% shortfall is assigned a value of 1, and 0 otherwise. This treatment assumes that firms with the worst 11.4% capital shortfall of total sample will turn to insolvency or failure. The value of 11.4% is chosen as the benchmark following the exit rate data of the mining sector in Australia provided by Australian Productivity Commission (2015). Thus, in this study, it is assumed that 11.4% of the observations will fail if a crisis occurs. Technically, this threshold is represented by the following equation:

$$CONCAP_{i,t}^{MFAIL} \ or \ CONCAP_{i,t}^{CFAIL} = \begin{cases} 1 & if \quad CONCAP_{i,t} <= 11.4 \text{ percentile} \\ 0 & if \quad CONCAP_{i,t} > 11.4 \text{ percentile} \end{cases} \tag{8}$$

Furthermore, $CONCAP_{i,t}^{MFAIL}$ and $CONCAP_{i,t}^{CFAIL}$ are employed as dependent variables in the failure analysis. The analysis is conducted using a panel probit, with clustered residuals at the firm level. The grounds for choosing the probit are mainly because the proxy of failure in the analysis is capital depletion, and not actual failure events such as bankruptcy, given that in many cases, the government (either fiscal or monetary authority) would normally assist in helping these companies to survive. Thus, assuming that they will exit once their capital is depleted is not appropriate, which also means that right censoring is not an issue. Therefore, this study implements the panel probit model as follows.

$$\begin{aligned} Prob\ (CONCAP_{i,t}^{FAIL} = 1) = \Phi\Big(&\alpha + \beta_1 \sigma COMM_{i,t-1} + \beta_2 GEPU_{i,t-1} + \beta_3 GPR_{i,t-1} \\ &+ \beta_4 WGDP_{i,t-1} + \beta_5 HGDP_{i,t-1} + \beta_6 INFL_{i,t-1} \\ &+ \beta_7 PROFIT_{i,t-1} + \beta_8 DEBT_{i,t-1} + \beta_9 CLTR_{i,t-1} \\ &+ \beta_{10} SIZE_{i,t-1} + \beta_{11} SIZE_{i,t-1}^2 + \beta_{12} AGE_{i,t} + \beta_{13} AGE_{i,t}^2\Big) \end{aligned} \tag{9}$$

where subscript i denotes firm and t denotes the year. In this model, three variables represent macroeconomic uncertainties. First, the global commodity price uncertainty, $\sigma COMM$, represents the log-transformed annual standard deviation of the daily GSCI index. Second, $GEPU$ represents the global economic policy uncertainty from Davis (2016). Third, GPR, which is the GPR index by Caldara and Iacoviello (2019).

Furthermore, there are four macro variables in the estimation outside the macro-uncertainties. First, $WGDP$, which is the world's annual GDP growth, represents the global business cycle. Second, $HGDP$ represents the home country's annual GDP growth. Third, $INFL$ is the annual inflation rate of the home country. Data for $WGDP$, $HGDP$, and $INFL$ were retrieved from the World Bank.

Furthermore, four firm-level variables were employed in the estimation. These variables are selected according to previous related literature, such as Tsoukas (2011). First, $PROFIT$, represents firm performance, proxied by the ratio of earnings before interest and tax (EBIT) divided by market assets. Second, $DEBT$ represents the leverage of the firm, specifically the ratio of total debt divided by market assets. Third, $CLTR$ is collateral, proxied as firms' property, plant, and equipment divided by market assets. Fourth, $SIZE$ represents firms' total size, specifically log-transformed market assets. Lastly, the term AGE represents firm age, proxied by the current year minus the firm's first-year data available.

3.5 Performance Analysis

Last, but not least, this study attempts to test the relationship between conditional capital surplus/shortfall and future performance. To this end, this analysis adopts the setting from Oler and Picconi (2014) as follows:

$$\begin{aligned} RTRN_{i,t} = \alpha &+ \beta_1 CONCAP_{i,t-1}^{+} + \beta_2 CONCAP_{i,t-1}^{-} + \beta_3 SALES_{i,t-1} \\ &+ \beta_4 DEBT_{i,t-1} + \beta_5 SIZE_{i,t-1} + \beta_6 RTRN_{i,t-1} + \mu_{i,t}. \end{aligned} \tag{10}$$

where i refers to the firm, and t is time. $RTRN$ is the annual market return of the firm.[8] $CONCAP$ refers to either $CONCAP^M$ or $CONCAP^C$. Furthermore, superscript "+" refers to a surplus, meaning $CONCAP^+ = max(CONCAP, 0)$. Similarly, "−" refers to a shortfall, or $CONCAP^- = -min(CONCAP, 0)$. Note that, for ease of analysis, $CONCAP^-$ is multiplied by a negative value. Thus, both $CONCAP^+$ and $CONCAP^-$ have positive values. $SALES$ is net sales or revenue divided by market assets. $DEBT$ is the ratio of total debt to market assets. $SIZE$ is log-transformed market assets, while μ denotes the residual.

4 Empirical Results

This study makes four main contributions to the literature. The first is the pattern analysis of the conditional capital surplus and shortfall dynamics of the resource companies of the sample. The second contribution focuses on the analysis of the effect of macroeconomic dynamics and uncertainties on the amplification of the conditional capital surplus and shortfall using the PVAR framework. In addition, the role of leverage in inducing the conditional capital shortfall is examined. The third contribution focuses on the influence of macroeconomic uncertainties on firm failure. The last analysis focuses on how the conditional capital surplus and shortfall might affect the future performance of firms in the sample. Each analysis is conducted for all samples, renewable and non-renewable, and each sector.

4.1 Conditional Capital Surplus and Shortfall Dynamics

This subsection presents a pattern analysis of the conditional capital surplus and shortfall dynamics of the resource companies of the sample. First, Table 3 reports the summary statistics of $CONCAP$ and its related variables. As can be seen, the average of $CONCAP^M$ and $CONCAP^C$ are 0.7 and 0.10, with the same standard deviation, 0.24, indicating that, on average, both indices share resemblance, despite each index considering a different systemic event based on stock price and commodity price large declines.

[Table 3].

To observe the pattern of conditional capital surplus and shortfall dynamics of resource companies in the sample, Figures 2–8 present $LIAB^{MA}$, $CONCAP^M$, and $CONCAP^C$ for each sample set. Figure 2 presents the patterns for the full sample. It can be seen that $LIAB^{MA}$ is relatively stable during the early 1980s to the late 1990s, with a median of approximately 0.4. However, it decreased significantly during the 2001–2007 period. This pattern is reasonable since this period was a booming period, where the market value of firms in the sample increased significantly. Thus, the ratio of liabilities to market assets decreases significantly during this period. This period coincided with the global economic bubble. Then, the bubble burst in 2008, as indicated by a significant decline in both market capitalisation of firms and commodity prices. $LIAB^{MA}$ increased drastically during this year. After 2008, there were some cyclical fluctuations in the level of $LIAB^{MA}$.

[Figure 2-8]

Furthermore, Figure 2 shows that both $CONCAP^M$ and $CONCAP^C$ share the same pattern. It is important to note that negative CONCAP refers to conditional capital shortfall, and positive

[8] $RTRN$ is calculated as $RTRN_t = (MKTCAP_t - MKTCAP_{i,t-1})/MKTCAP_{i,t-1}$, where $MKTCAP$ is market capitalisation.

CONCAP refers to conditional capital surplus. As can be seen, during the early 1980s to the late 1990s, the median values of both $CONCAP^M$ and $CONCAP^C$ are generally below zero. These patterns are not unexpected, as can be explained by the pattern of $LIAB^{MA}$. Then, after 2000, the median values of $CONCAP^M$ and $CONCAP^C$ are positive, with some fluctuations between 0.1 and 0.2. Similar results are also documented for other sub-samples, except for alternative energy and forestry and paper. For the alternative energy sample set, the data started in 1991, and throughout the entire period, the median values of $CONCAP^M$ and $CONCAP^C$ are generally positive. In contrast, for the forestry and paper sample sets, the median values of $CONCAP^M$ and $CONCAP^C$ are negative throughout the entire period.

Comparing Figures 3 and 4 show differences in patterns between the renewable and non-renewable sectors. The median of $LIAB^{MA}$ for the renewable fluctuates during the sample period, although in general it is around 0.4-0.6. Meanwhile, $LIAB^{MA}$ for non-renewable is approximately between 0.0-0.4, with a lower level of $LIAB^{MA}$ observed in recent years. Consequently, this pattern is followed by conditional capital for both sectors. The medians of $CONCAP^M$ and $CONCAP^C$ for the renewable sector are generally negative, around -0.2 to 0.0, indicating capital shortfall during the sample period. Meanwhile, the median of $CONCAP^M$ and $CONCAP^C$ for the non-renewable are generally negative in the early period of the sample, and then become positive after 2000, indicating a change from a shortfall to a surplus trend.

4.2 Macro Uncertainties and Conditional Capital Surplus/Shortfall

The second analysis investigates how global and country-level macro uncertainties affect the dynamics of conditional capital surplus and shortfall of resource firms based on the PVAR model. More specifically, this study estimates the PVAR model and calculates the impulse responses of the conditional capital surplus and shortfalls to the shock of each variable. Figure 9–10 presents the impulse responses of $CONCAP^M$ and $CONCAP^C$ for all sample sets. As can be seen, the results show that the responses of both $CONCAP^M$ and $CONCAP^C$ are somewhat mixed depending on the sector, although some strong patterns are observed.

[Figure 9]

[Figure 10]

The results show that both $CONCAP^M$ and $CONCAP^C$ respond negatively to shocks in $\sigma COMM$, except for the mining sector. In general, this indicates that higher commodity price uncertainty increases the potential capital shortfall of firms in the sample when a crisis occurs. The results are similar for all subsamples, except for the mining sector. Thus, it can be argued that the relationship between $\sigma COMM$ and $CONCAP$ is generally robust and negative. A higher commodity price uncertainty induces a higher conditional capital shortfall. As for the mining sector, the negative relationship between commodity price uncertainty and conditional capital shortfall is documented. One explanation for this result is that higher commodity price uncertainty influences the firms in this sector to maintain their leverage cautiously, thus lowering the conditional capital shortfall of the sector. Relating to the literature, this result supports many previous studies which find a negative effect of commodity risk to financial performance and/or firm value, such as Jin and Jorion (2006), Buhl et al. (2011), Perez-Gonzales and Yun (2013), Haque et al. (2014), Tang (2015), Vandone et al. (2018), and Pal and Mitra (2019). The current study contributes to this block of literature by expanding the analysis to include not only commodity price uncertainty, but also other forms of macro uncertainties (both economic and non-economic), as discussed below.

Furthermore, $CONCAP^M$ and $CONCAP^C$, in general, respond negatively to shocks in GPR, except for the mining and forestry and paper sectors. The negative responses imply that a higher GPR increases firms' conditional capital shortfall if a crisis strikes. Meanwhile, for firms in the mining and forestry and paper sectors, it could be argued that higher risk reduces their risk-taking activities, and thus higher GPR could reduce their potential capital shortfall.

As for $GEPU$, $CONCAP^M$ and $CONCAP^C$ show relatively similar response patterns to the shock of GPR. In general, $CONCAP^M$ and $CONCAP^C$ respond negatively to the positive shock of $GEPU$, indicating that a higher economic policy uncertainty increases the conditional capital shortfall. Meanwhile, for the mining and forestry and paper sectors, the positive responses are believed to be because firms change their behaviour when $GEPU$ becomes higher, thus indicating the risk-averse strategy of firms in these two sectors.

$CONCAP^M$ and $CONCAP^C$ generally have negative responses towards the positive shock of the world business cycle, $WGDP$. These responses outline the risk built-up process, where the booming economy increases firms' aggressive investments. The results imply a countercyclicality of conditional capital surplus in the world business cycle. One noticeable difference is the responses of the forestry and paper sector, which are positive in both the $CONCAP^M$ and $CONCAP^C$ estimations. Thus, specific to this sector, the responses of capital surplus are procyclical toward the world business cycle.

$CONCAP^M$ and $CONCAP^C$ generally respond positively to shock in $HGDP$. This pattern contradicts the response to $WGDP$. Thus, it can be inferred that for the home country business cycles, the conditional capital surplus responses are procyclical.

Lastly, $CONCAP^M$ and $CONCAP^C$ respond negatively to the shock of $LIAB^{MA}$, indicating a strong positive relationship between leverage level and conditional capital shortfall. The results for $LIAB^{MA}$ are very reasonable and align with those of Brownlees and Engle (2017) and Adrian and Shin (2014), where higher leverage increases the probability of default, or in this analysis, the conditional capital shortfall.

Based on the results presented in this section, several patterns can be inferred. First, conditional capital responds negatively to the shock of uncertainties ($\sigma COMM$, $GEPU$, and GPR). This outlines the role of macro uncertainties in inducing capital shortfalls. Second, the response of conditional capital is mixed towards the shock of business cycles, which are negative to the world business cycle, but positive to the home country business cycle.

4.3 Macro Uncertainties and Firm Failure

Adrian and Shin (2014) argue that there are two prominent factors determine the probability of default of a firm. The first is leverage, since higher leverage might induce the risk of default of a firm. Thus, it can be inferred that the relationship between leverage level and the probability of default is positive. The second factor is the business cycle, which represents the overall condition of the economy. Adrian and Shin (2014) discuss that the boom phase would lower the probability of default, suggesting that the business cycle is negatively related to the probability of default. The third analysis empirically assesses these hypotheses using the conditional capital shortfall in this study as a proxy for firm failure. In addition, this study examines the role of macroeconomic uncertainty in firm failure. More specifically, the analysis employs $CONCAP^{MFAIL}$ and $CONCAP^{CFAIL}$ from (8) as dependent variables. The estimated model is a panel probit model (9), with clustered residuals with firm as the cluster.

Table 4 presents results for analysis with $CONCAP^{MFAIL}$ as dependent variable. As can be seen, $\sigma COMM$ is significant for the full sample, renewable, non-renewable, forestry and paper and oil and gas panels, with positive signs. The results imply that commodity price uncertainty increase firm failure probability, and in general aligned with results of Jin and Jorion (2006) and Buhl et al. (2011). Aligned with $\sigma COMM$, $GEPU$ has also a significantly positive effect for the full sample, renewable, non-renewable, forestry and paper and oil and gas panels, indicating higher economic policy uncertainty contribute positively to firms' failure. Meanwhile, results for GPR are mixed. GPR shows a significantly positive effect for the full sample, non-renewable, mining, and oil and gas panels, indicating positive relationship between geopolitical risk and firms' failure. In contrast, GPR is significant for the renewable and forestry and paper panels, with negative signs, implying the anomaly responses for the renewable sector. One explanation that can be offered is that the renewable sector is a substitute for the conventional resource sector (mining and oil and gas). Thus, once geopolitical risk deteriorates, the renewable sector will instead thrive.

[Table 4]

The proxy for the world business cycle, $WGDP$, is significant only for the mining sector, with a negative sign (Table 4), indicating that a better world business cycle lowers default risk, as argued by Adrian and Shin (2014). Meanwhile, the proxy for the home country business cycle, $HGDP$, has a significantly negative effect on almost all panels, except for alternative energy, oil, and gas. In the same sense as $WGDP$, these results strongly show that better business cycle conditions lower the failure risk. Considering these results, it could be inferred that the influence of business cycles, particularly of the home country, on firms' failure tends to be negative. The variable $INFL$, which represents the home country inflation rate, is positively significant for many panels (Table 4). This suggests that higher inflation induces more firms' failures.

For firm-level variables, $PROFIT$ is a proxy of firms' performance and has a significantly negative effect on the full sample, non-renewable, alternative energy, and mining panels. This indicates that a better performance will lower the failure probability (Table 4). $DEBT$ is significant with positive signs for all panels, implying that highly leveraged firms have a higher failure probability. $SIZE$ and AGE are controls and, in general, not significant.

The results of the analysis with $CONCAP^{CFAIL}$ as the dependent variable in Table 5 generally show patterns similar to those of the analysis with $CONCAP^{MFAIL}$. $\sigma COMM$ has a significantly positive effect on the full sample, renewable, non-renewable, forestry, paper, and oil and gas panels. $GEPU$ is significant for almost all panels, with positive signs. GPR is significant for most panels with mixed signs. $WGDP$ is not statistically significant. Meanwhile, $HGDP$ is significantly negative for the full sample, non-renewable, and mining panels. Furthermore, $DEBT$ is significant for all panels, all of which have positive signs. $PROFIT$ is significant, with negative signs for the majority of panels.

[Table 5]

From the results in Tables 4 and 5, some general patterns can be inferred. $\sigma COMM$ and $GEPU$ have strong positive effects on firms' failure, emphasising the strong positive relationship between global macroeconomic uncertainties and firm failure. The effect of GPR is, in general, significantly positive for the non-renewable sector, and thus strengthens the general stream that global macro uncertainty has a positive influence on firm failure. Meanwhile, for business cycles, $WGDP$ and $HGDP$ generally negatively influence firms' failure, supporting the theoretical model by Adrian and Shin (2014) which outlines the negative relationship between the business cycle and default probability. Meanwhile, for firm-level variables, $DEBT$ has a strongly positive role in increasing firms' failure probability, whereas $PROFIT$ shows a strongly negative effect on failure probability. The current study contributes to the literature which explains how macro (both economic and non-economic) uncertainties explain firm failure, including Zingales (1998), Adrian and Shin (2014), and Tsoukas (2011). Furthermore, this study also contributes to the literature on how firm-level factors affect firm survival, such as Chung et al. (2013), Carr et al. (2010), Musso and Schiavo (2008), Brogaard et al. (2017), and Zorn et al. (2017).

4.4 Performance and Conditional Capital Surplus and Shortfall

This analysis focuses on the optimal notion of capital and how it may affect future performance. An earlier discussion can be traced back to Jensen (1986) and early studies such as Harford et al. (2008) and Oler and Picconi (2014). Adopting the estimation from Oler and Picconi (2014), this study develops an estimation to see how conditional capital surplus and shortfall may affect future performance. The estimation results from Equation (10) are presented in Tables 6–7.

[Tables 6–7].

Table 6 presents results with $CONCAP^{M+}$ and $CONCAP^{M-}$ among independent variables. The dependent variable is $RTRN$, which is annual growth of market capitalisation of each firm. The results show that $CONCAP^{M+}$ is significant for the full sample, non-renewable, and mining panels, with negative signs. Although not unanimous, the results suggest that higher conditional capital surplus relates to lower future market performance. Meanwhile, $CONCAP^{M-}$ is significant for all panels, all with positive signs, strongly suggest that higher conditional capital shortfall is strongly related to higher future market performance. In other words, if firms behave aggressively with higher conditional capital shortfall, the future market performance tends to be better. The results confirm the existence of the high-risk high-return trade-off. The higher risk (conditional capital shortfall) the company takes, the higher potential market return it can have. Furthermore, $SALES$ is significant for the full sample, non-renewable, and mining panels, with negative signs. $DEBT$ is significantly negative only for the mining panel, indicating that leveraged firms have lower market performance. Size is significant for all panels, with negative signs, implying that smaller firms have higher market return.

The estimation results for $CONCAP^{C+}$ and $CONCAP^{C-}$ are listed in Table 7. In general, the results resemble Table 6. $CONCAP^{C+}$ is significantly negative for the full sample, non-renewable, and mining panels. $CONCAP^{C+}$ is significant for all panels with positive signs. $SALES$ is significant for the full sample, non-renewable, and mining panels, with negative signs. $DEBT$ is significant for the full sample, non-renewable, and mining panels, with negative signs. $SIZE$ is significant for all the panels with negative signs.

The estimation results from this analysis provide two important insights. First, a risk–return trade-off exists, as proven by the positive relationship between conditional capital shortfall and future market performance. Second, as related to the previous point, the axiom of optimal (near to zero) conditional capital only applies to capital surplus, as proven by the negative relationship between expected capital surplus and future market performance. These results partially diverge from the findings of Harford et al. (2008) and Oler and Picconi (2014), who find that both cash excess and shortfall are negatively related to future performance.

5 Conclusion

This study analyses the dynamics of the conditional capital surplus and shortfall of natural resource companies when a systemic event occurs. This study also explains their sensitivity to commodity prices, business cycle fluctuations, and their role in firms' performance. To measure capital surplus and shortfall, this study employs the standard market SRISK (MSRISK) from (Brownlees and

Engle, 2017) and its modified version to accommodate commodity beta, becoming CSRISK. In other words, this study considers two important systemic events for resource firms: stock market crash and commodity market crash. MSRISK and CSRISK are used to calculate $CONCAP$ as the ratio of conditional capital surplus/shortfall to market assets. Four analyses are conducted in this study, each focusing on (1) market and commodity $CONCAP$ patterns, (2) responses of market and commodity $CONCAP$ toward global uncertainties and business cycles, (3) the role of macroeconomic uncertainties in inducing firms' failure, and (4) the relationship between conditional capital surplus and shortfall to firms' performance, respectively. The analyses were conducted using an unbalanced dataset of natural resource firms across 61 countries. The firms included in the dataset are from four resource sectors: (1) alternative energy, (2) forestry and paper, (3) mining, and (4) oil and gas producers.

The first analysis shows that, in general, $CONCAP^M$ and $CONCAP^C$ share the same pattern during the analysis period, demonstrating that stock and commodity price shocks have similar effects on resource firms. One important insight is that during the early 1980s to the late 1990s, the median values of both $CONCAP^M$ and $CONCAP^C$ are generally below zero, meaning that the sectors experience conditional capital shortfall. These patterns are not unexpected, as can be explained by the pattern of $LIAB^{MA}$ during this period. Then, after 2000, the median values of $CONCAP^M$ and $CONCAP^C$ are positive (conditional capital surplus) with some fluctuations. This pattern can be explained by the commodity boom after 2000 and the moderate to careful capital structure management of resource companies.

The second analysis employs the PVAR approach to analyse how $CONCAP^M$ and $CONCAP^C$ respond to the shock to the global business cycle and uncertainties. The results document a general pattern in which macro uncertainties contribute positively to conditional capital shortfalls. The results also show strong procyclical (countercyclical) responses of $CONCAP^M$ and $CONCAP^C$ toward the world (home country) business cycle.

The third analysis uses $CONCAP^M$ and $CONCAP^C$ as proxies of firm failure and how macro uncertainties influence firms' failure. The results suggest that global macro uncertainties have a positive influence on firms' failure, implying that higher uncertainty induces firms' failure. Meanwhile, for business cycles, $WGDP$ and $HGDP$ generally negatively influence firms' failure, supporting the theoretical model by Adrian and Shin (2014) which outline the negative relationship between the business cycle and default probability.

The last analysis focuses on the relationship between future performance and conditional capital surplus/shortfalls. The results show that the risk-return trade-off exists, as proven by the positive relationship between conditional capital shortfall and future market performance. In addition, as related to the previous point, the axiom of optimal (near to zero) conditional capital only applies to capital surplus, as proven by the negative relationship between conditional capital surplus and future market performance.

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6 Tables

Table 1: Book Equity to Capital for Each Sector

	Sector	Book Equity to Capital
(1)	Alternative Energy	44.48%
(2)	Forestry and Paper	56.94%
(3)	Mining	61.22%
(4)	Oil and Gas Producers	61.41%

The book equity to capital ratio in this table is used as the benchmark value of k for SRISK calculation for each firm in the sample based on the respective sector of the firm. *Source*: Damodaran (2021)

Table 2: Descriptive Statistics of Macro and Firm Variables

	Variables	Description	Obs	Mean	Std. Dev.	Min	Max
(11)	$LIAB$	Liabilities to Market Asset Ratio	33,839	0.27	0.25	0.00	0.95
(12)	$PROFIT$	EBITDA to Market Asset Ratio	31,251	-0.15	0.68	-45.30	27.22
(13)	$DEBT$	Total Debt to Market Asset Ratio	31,726	0.13	0.18	0.00	1.20
(14)	$CLTR$	Collateral to Market Asset Ratio	32,612	0.51	0.85	-0.03	37.12
(15)	$SIZE$	Logarithm of Book Asset	33,839	11.91	3.63	3.87	25.59
(16)	AGE	Year Since Go Public	33,839	12.15	8.93	-2.00	53.00
(17)	$SALES$	Sales to Market Asset Ratio	33,809	0.32	1.11	-3.70	162.64
(18)	$RETURN$	Annual Growth of Market Capitalization	33,839	0.50	1.80	-0.91	18.10
(19)	$\sigma COMM$	Log of annual std. dev. of GSCI	33,839	5.66	0.74	2.85	7.58
(20)	GPR	Log of annual GPR Index	33,696	4.43	0.37	3.50	5.32
(21)	$GEPU$	Log of Annual GEPU Index	32,368	4.77	0.31	4.14	5.24
(22)	$WGDP$	Annual World GDP Growth	33,839	2.78	1.36	-1.69	4.62
(23)	$HGDP$	Annual Home Country GDP Growth	33,596	2.79	2.48	-14.81	25.12
(24)	$INFL$	Annual Home Country Inflation Rate	33,516	2.68	12.86	-4.48	2075.89
(25)	$CRISIS$	Dummy of 2008 Financial Crisis	33,839	0.05	0.23	0.00	1.00

Table 3: Descriptive Statistics of LRMES and SRISK

	Variables	Description	Obs	Mean	Std. Dev.	Min	Max
(1)	$MLRMES$	Market LRMES	33,839	0.20	0.34	-19.14	1.00
(2)	$CLRMES$	Commodity LRMES	33,839	0.09	0.24	-10.62	1.00
(3)	$CONCAP^{M}$	Market SRISK to Market Asset Ratio	33,839	0.07	0.24	-0.54	0.70
(4)	$CONCAP^{C}$	Commodity SRISK to Market Asset Ratio	33,839	0.10	0.24	-0.54	0.58
(5)	$CONCAP^{MFAIL}$	Dummy of MSRISK Failure	33,839	0.11	0.31	0.00	1.00
(6)	$CONCAP^{CFAIL}$	Dummy of CSRISK Failure	33,839	0.10	0.31	0.00	1.00
(7)	$CONCAP^{M+}$	Positive MSRISK	33,839	0.14	0.15	0.00	0.70
(8)	$CONCAP^{C+}$	Positive CSRISK	33,839	0.17	0.15	0.00	0.58
(9)	$CONCAP^{M-}$	Negative MSRISK	33,839	0.07	0.13	0.00	0.54
(10)	$CONCAP^{C-}$	Negative CSRISK	33,839	0.06	0.12	0.00	0.54

Table 4: Failure Analysis - $CONCAP^M$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$\sigma COMM_{i,t}$	0.1955***	0.2670***	0.1788***	0.1214	0.3070***	0.0597	0.3489***
$GEPU_{i,t}$	0.3140***	0.3065**	0.3457***	0.4665	0.4376***	0.0591	0.7984***
$GPR_{i,t}$	0.1932***	-0.2787***	0.3781***	-0.3361	-0.2492**	0.3351***	0.4489***
$WGDP_{i,t}$	-0.01	-0.0003	-0.0108	0.0518	0.0035	-0.0315*	0.0184
$HGDP_{i,t}$	-0.0273***	-0.0467***	-0.0265**	-0.0765	-0.0538***	-0.0302**	-0.0129
$INFL_{i,t}$	0.0248***	0.0758***	0.0158***	0.0533	0.0702***	0.0131	0.0169***
$PROFIT_{i,t-1}$	-0.0887***	-0.2218	-0.0822***	-0.3621*	-0.3575	-0.0931***	-0.0432
$DEBT_{i,t-1}$	4.3979***	5.1228***	4.1712***	4.3328***	5.3930***	4.0959***	4.2461***
$CLTR_{i,t-1}$	0.0398	0.2468	0.0284	-0.5523	0.2511	0.0452*	-0.0025
$SIZE_{i,t-1}$	-0.0776*	0.0441	-0.0757*	-0.2845	0.0617	-0.1159**	-0.0823
$SIZE^2_{i,t-1}$	0.0042***	0.0002	0.0041**	0.0125	-0.001	0.0059***	0.0034
$AGE_{i,t}$	0.0129*	0.0084	0.011	0.0751	-0.0228	0.0213**	-0.0025
$AGE^2_{i,t}$	-0.0001	0.0001	-0.0001	-0.0029	0.0006	-0.0002	0.0002
$CONS$	-5.8715***	-5.5439***	-6.6386***	-3.2979	-6.0783***	-4.3146***	-9.6920***
OBS	28,364	4,765	23,599	1,624	3,141	16,463	7,136
$Pseudo\ R^2$	0.3386	0.3744	0.3308	0.2323	0.4039	0.3422	0.3137
LL	-5860	-1320	-4490	-299.2758	-995.4851	-2710	-1750

Table 5: Failure Analysis - $CONCAP^C$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$\sigma COMM_{i,t}$	0.1923***	0.3166***	0.1713***	0.1004	0.3649***	0.0599	0.3312***
$GEPU_{i,t}$	0.3496***	0.4781***	0.3636***	0.9308**	0.5370***	0.0646	0.8383***
$GPR_{i,t}$	0.2109***	-0.3724***	0.4211***	-0.5999**	-0.2975**	0.4036***	0.4583***
$WGDP_{i,t}$	-0.0096	-0.0055	-0.0077	0.0717	-0.0093	-0.0271	0.0181
$HGDP_{i,t}$	-0.0260***	-0.0203	-0.0331***	-0.075	-0.0242	-0.0346**	-0.0221
$INFL_{i,t}$	0.0243***	0.0425	0.0181***	0.0511	0.0353	0.0166*	0.0191***
$PROFIT_{i,t-1}$	-0.0939***	-0.2323	-0.0874***	-0.4807**	-0.1751	-0.0873***	-0.0915
$DEBT_{i,t-1}$	4.3759***	5.1274***	4.1551***	4.5733***	5.3058***	4.0470***	4.2945***
$CLTR_{i,t-1}$	0.0435	0.3582**	0.0306	-0.5783	0.3458*	0.0605***	-0.032
$SIZE_{i,t-1}$	-0.1107***	-0.0478	-0.1095**	-0.2044	-0.0672	-0.1677***	-0.0716
$SIZE^2_{i,t-1}$	0.0047***	0.002	0.0048***	0.0077	0.0021	0.0072***	0.0024
$AGE_{i,t}$	0.0159**	0.0181	0.0130*	0.0896*	-0.0171	0.0231**	0.001
$AGE^2_{i,t}$	-0.0002	-0.0003	-0.0001	-0.0032	0.0004	-0.0004	0.0001
$CONS$	-5.8043***	-5.4880***	-6.5820***	-4.8066*	-5.5954***	-4.2422***	-9.8227***
OBS	28,364	4,765	23,599	1,624	3,141	16,463	7,136
$Pseudo\ R^2$	0.3318	0.3596	0.3278	0.2632	0.3833	0.3398	0.3133
LL	-5820	-1300	-4470	-274.0029	-992.8336	-2720	-1710

Table 6: Performance Analysis - $CONCAP^M$

Dep. Variable = $RETURN_{i,t}$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$CONCAP^{M+}_{i,t-1}$	-0.2752**	-0.0554	-0.2824*	0.0299	0.3762	-0.2732*	-0.2332
$CONCAP^{M-}_{i,t-1}$	2.9256***	2.5643***	2.9757***	4.6992***	1.7627***	3.4597***	2.0021***
$SALES_{i,t-1}$	-0.1014***	-0.0095	-0.1033**	-0.0836	0.0958	-0.1703**	0.0319
$DEBT_{i,t-1}$	-0.3198	-0.2635	-0.3097	-0.7729	0.1962	-0.4980*	0.1577
$SIZE_{i,t-1}$	-0.5920***	-0.4761***	-0.6019***	-0.6121***	-0.3691***	-0.6630***	-0.4751***
$RETURN_{i,t-1}$	0.0014**	-0.0012	0.0016**	-0.0021	0	0.0027*	0.0005
$CONS$	7.5126***	6.7916***	7.4158***	8.0545***	5.2949***	7.8506***	6.3100***
OBS	29,122	5,137	23,985	1,602	3,535	16,571	7,414
R^2	0.1307	0.1031	0.1339	0.1258	0.0963	0.1424	0.1202
LL	-53400	-7760	-45100	-2810	-4710	-31900	-13000

Table 7: Performance Analysis - $CONCAP^C$

Dep. Variable = $RETURN_{i,t}$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$CONCAP^{C+}_{i,t-1}$	-0.3079*	-0.027	-0.6934***	-0.0265	0.1987	-0.7363***	-0.3126
$CONCAP^{C-}_{i,t-1}$	3.1791***	2.4796***	3.2241***	4.8474***	1.6935***	3.6417***	2.3932***
$SALES_{i,t-1}$	-0.1036***	0.0016	-0.1148***	-0.0718	0.0998	-0.1836**	0.0272
$DEBT_{i,t-1}$	-0.4460**	-0.1547	-0.6022**	-0.6483	0.2498	-0.7684**	-0.0956
$SIZE_{i,t-1}$	-0.5853***	-0.4755***	-0.5937***	-0.6051***	-0.3700***	-0.6532***	-0.4697***
$RETURN_{i,t-1}$	0.0014**	-0.0012	0.0016**	-0.002	0	0.0028*	0.0005
$CONS$	7.4673***	6.7966***	7.4384***	7.9902***	5.3358***	7.8770***	6.2791***
OBS	29,135	5,142	23,993	1,602	3,540	16,577	7,416
R^2	0.1328	0.1034	0.1374	0.1277	0.0963	0.1459	0.1233
LL	-53300	-7770	-45100	-2810	-4720	-31900	-12900

7 Figures

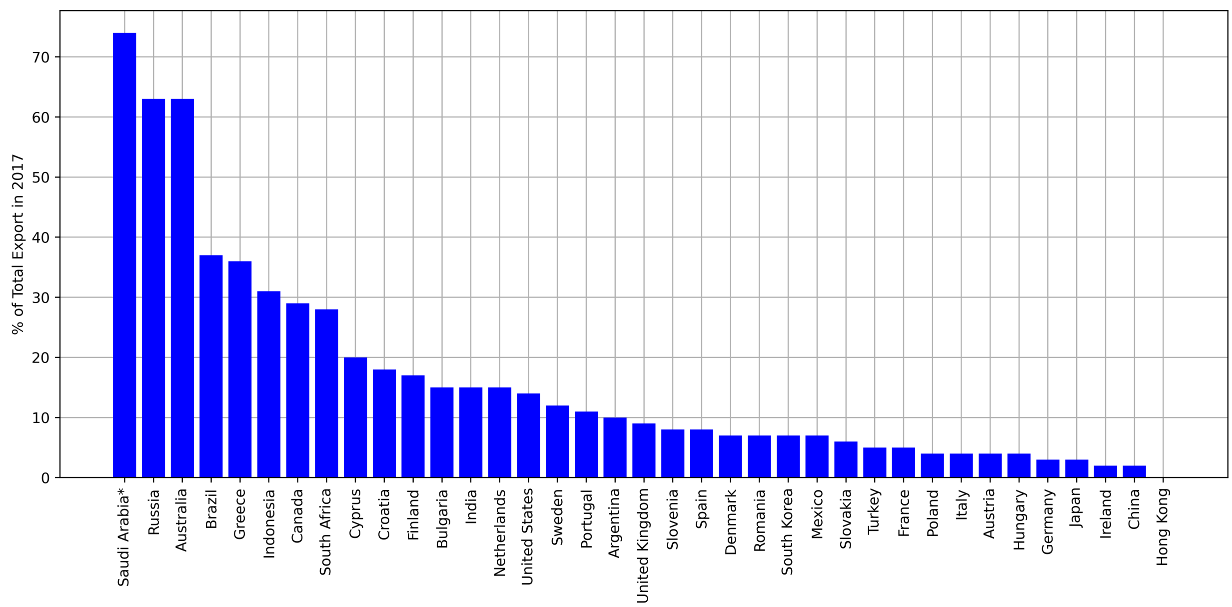

Figure 1: Natural Resource Export as a Percentage of Total Export by Country in 2017

Source: UN COMTRADE

Note: Data from 2016 for Saudi Arabia. The calculation is based on exports of Crude Materials and Fuels (SITC 2 and 3)

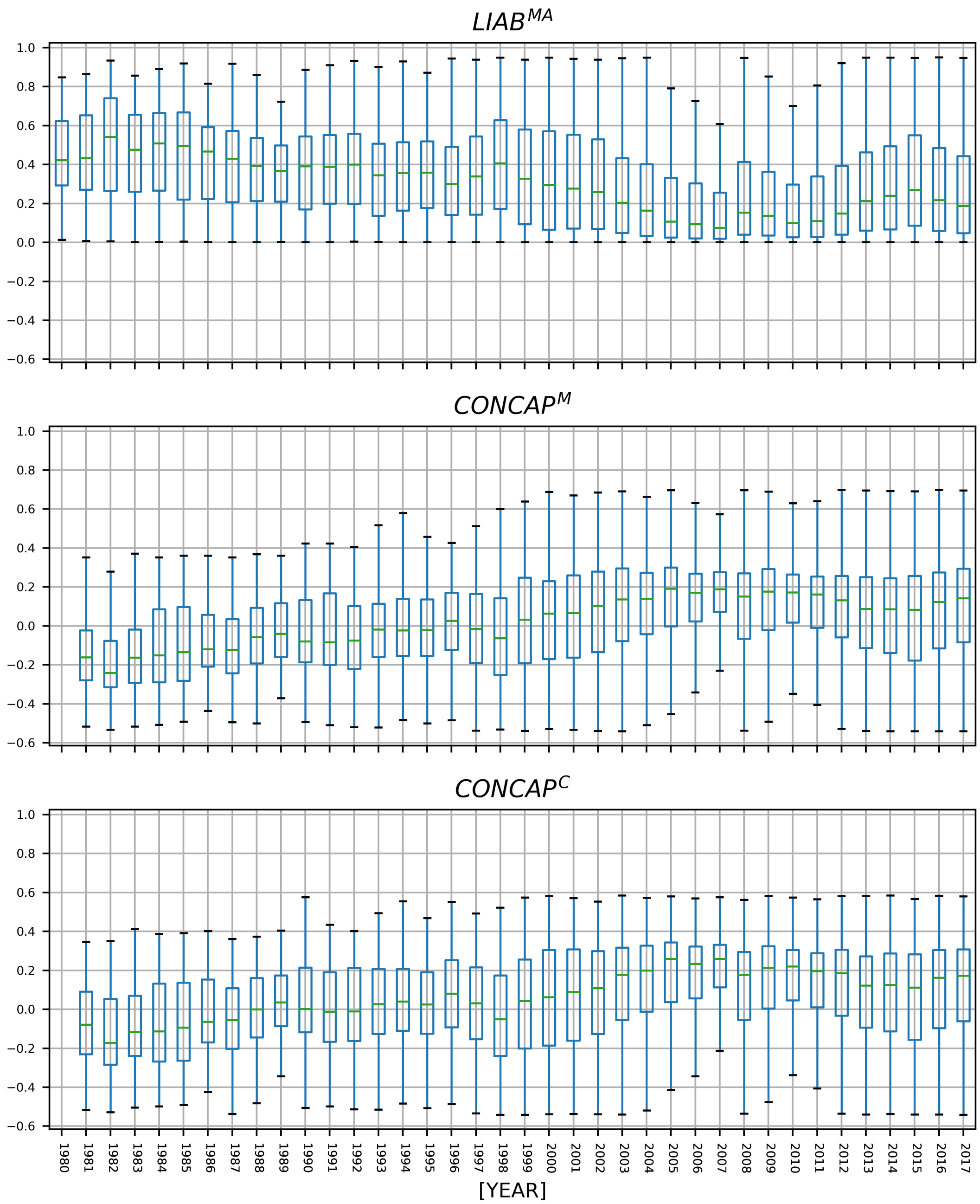

Figure 2: Distribution of LIAB, CSRISK, and MSRISK by Year - Full Sample

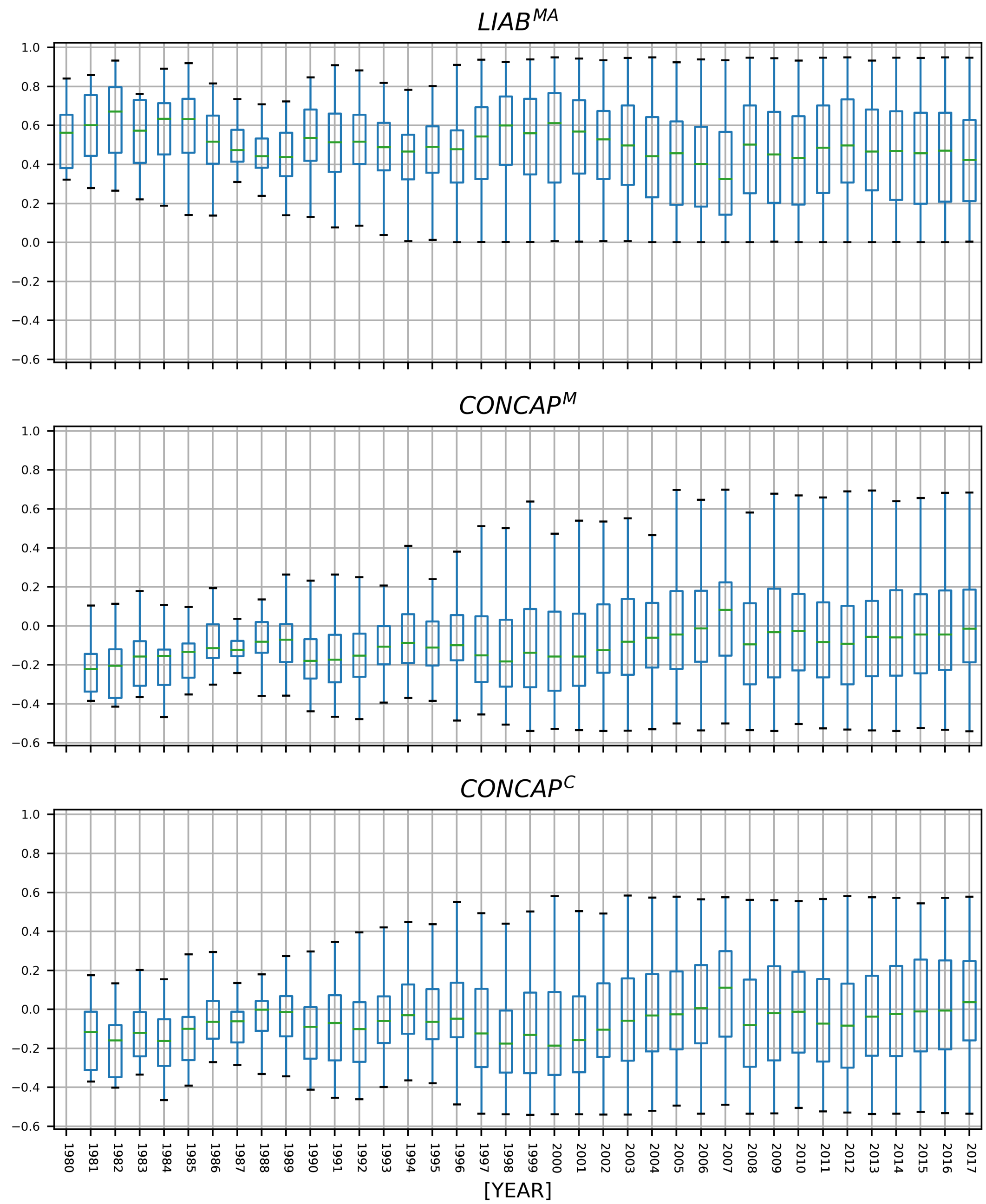

Figure 3: Distribution of LIAB, CSRISK, and MSRISK by Year - Renewable

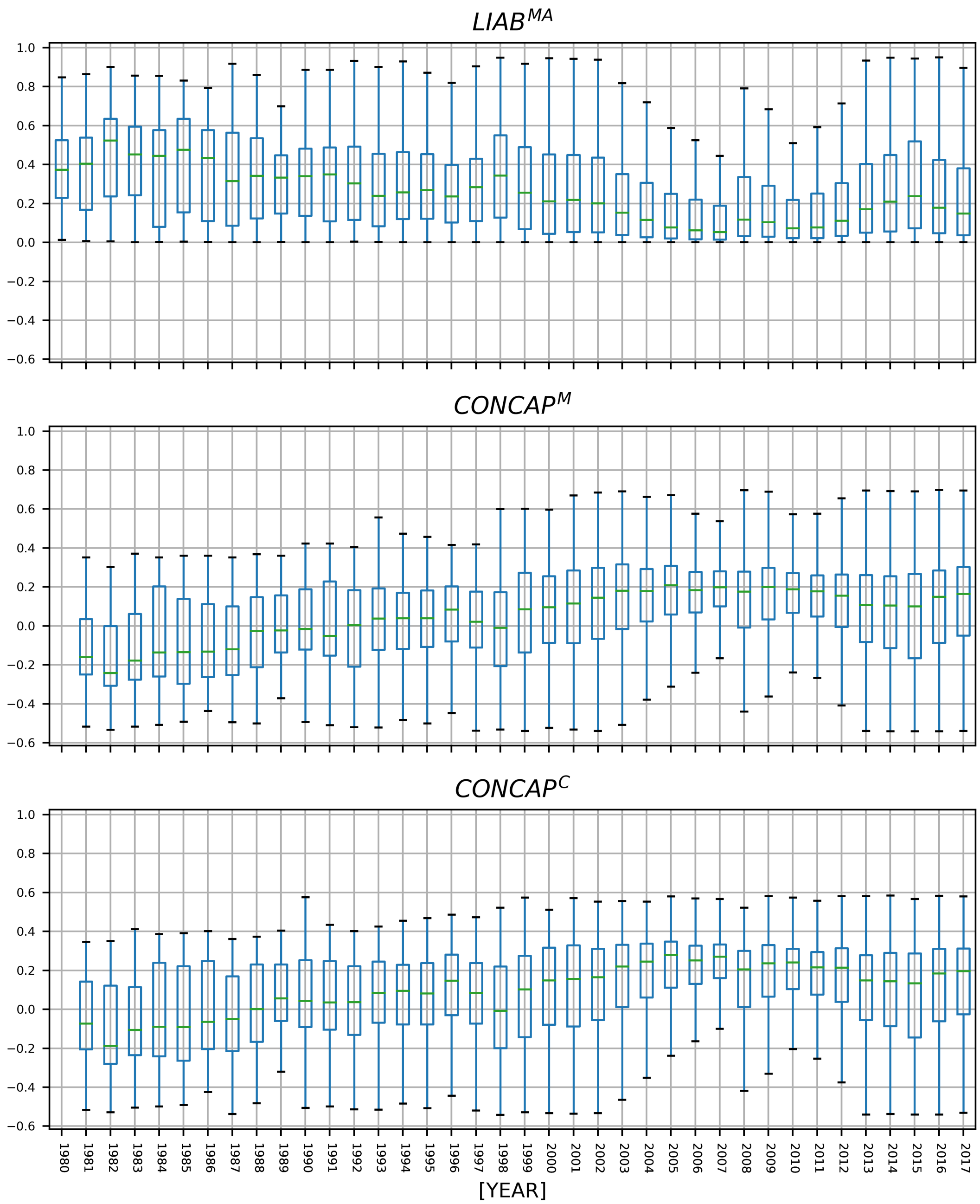

Figure 4: Distribution of LIAB, CSRISK, and MSRISK by Year - Non-Renewable

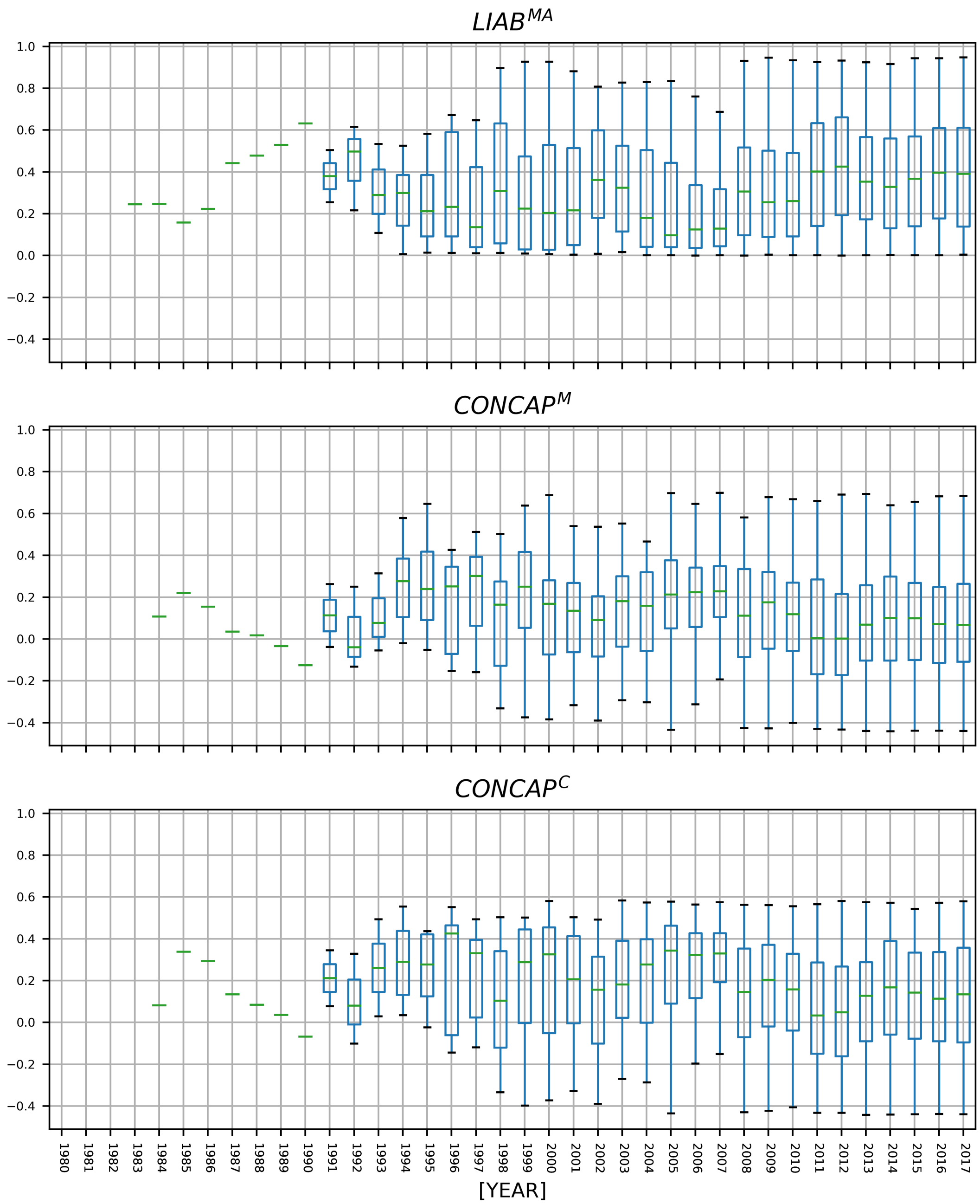

Figure 5: Distribution of LIAB, CSRISK, and MSRISK by Year - Alternative Energy

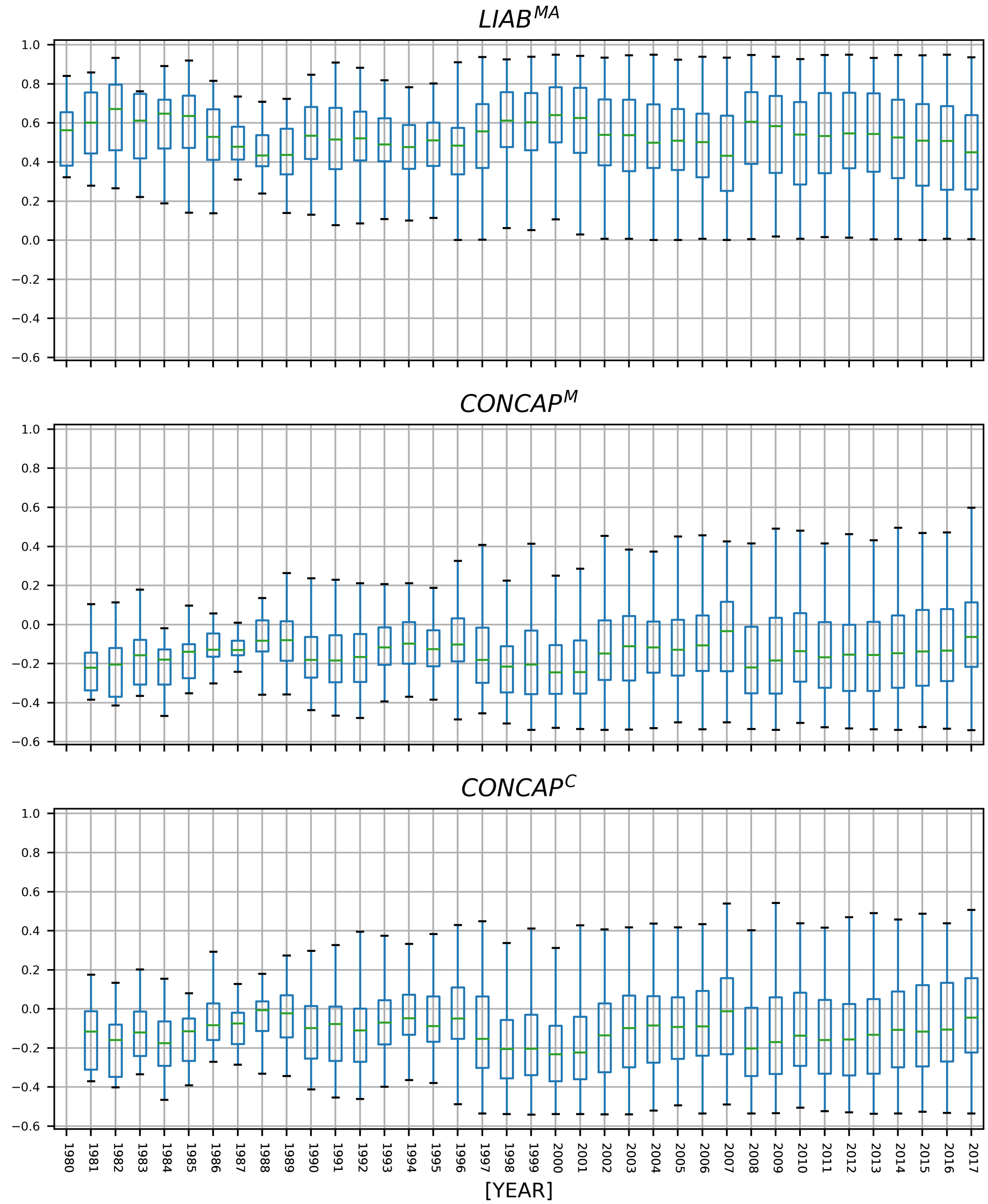

Figure 6: Distribution of LIAB, CSRISK, and MSRISK by Year - Forestry and Paper

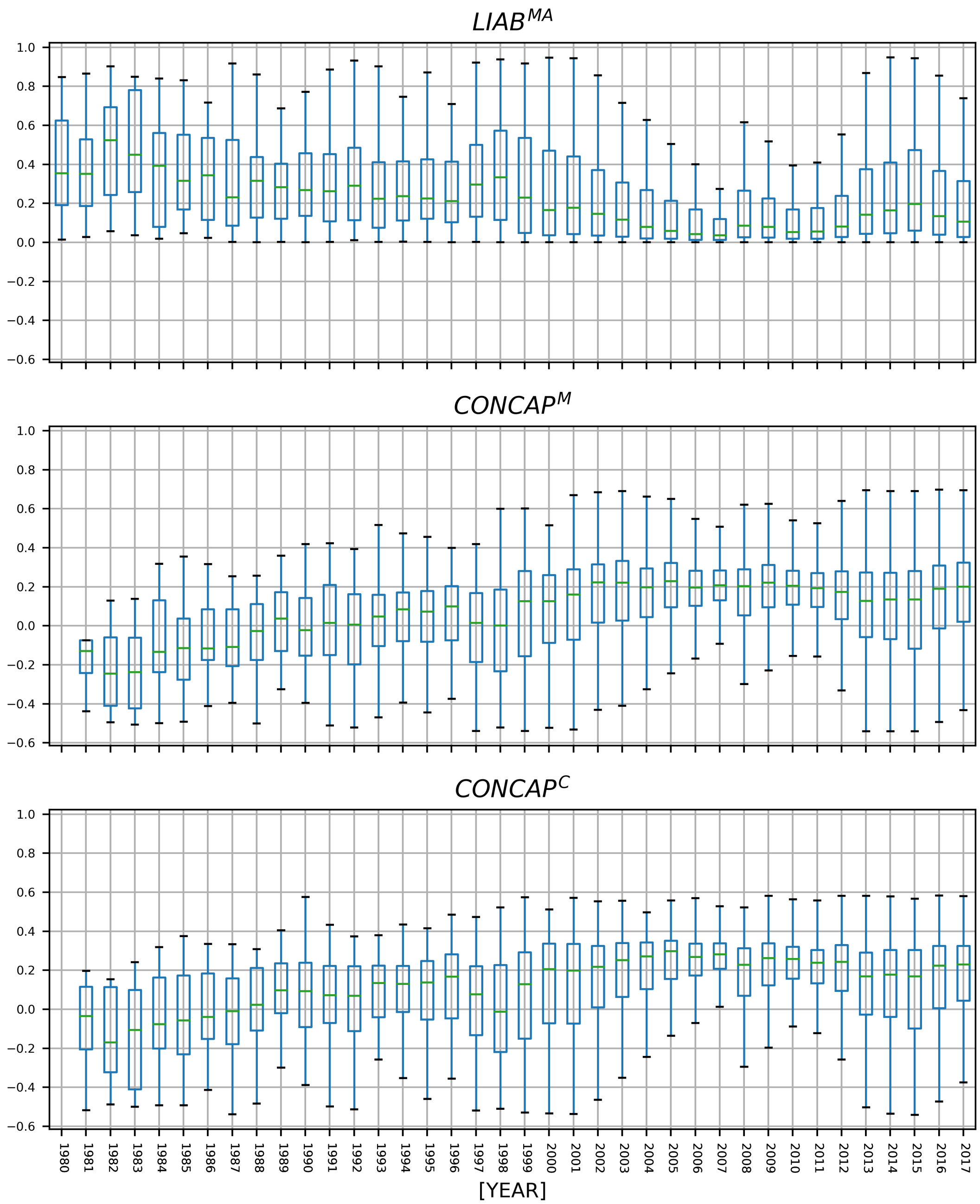

Figure 7: Distribution of LIAB, CSRISK, and MSRISK by Year - Mining

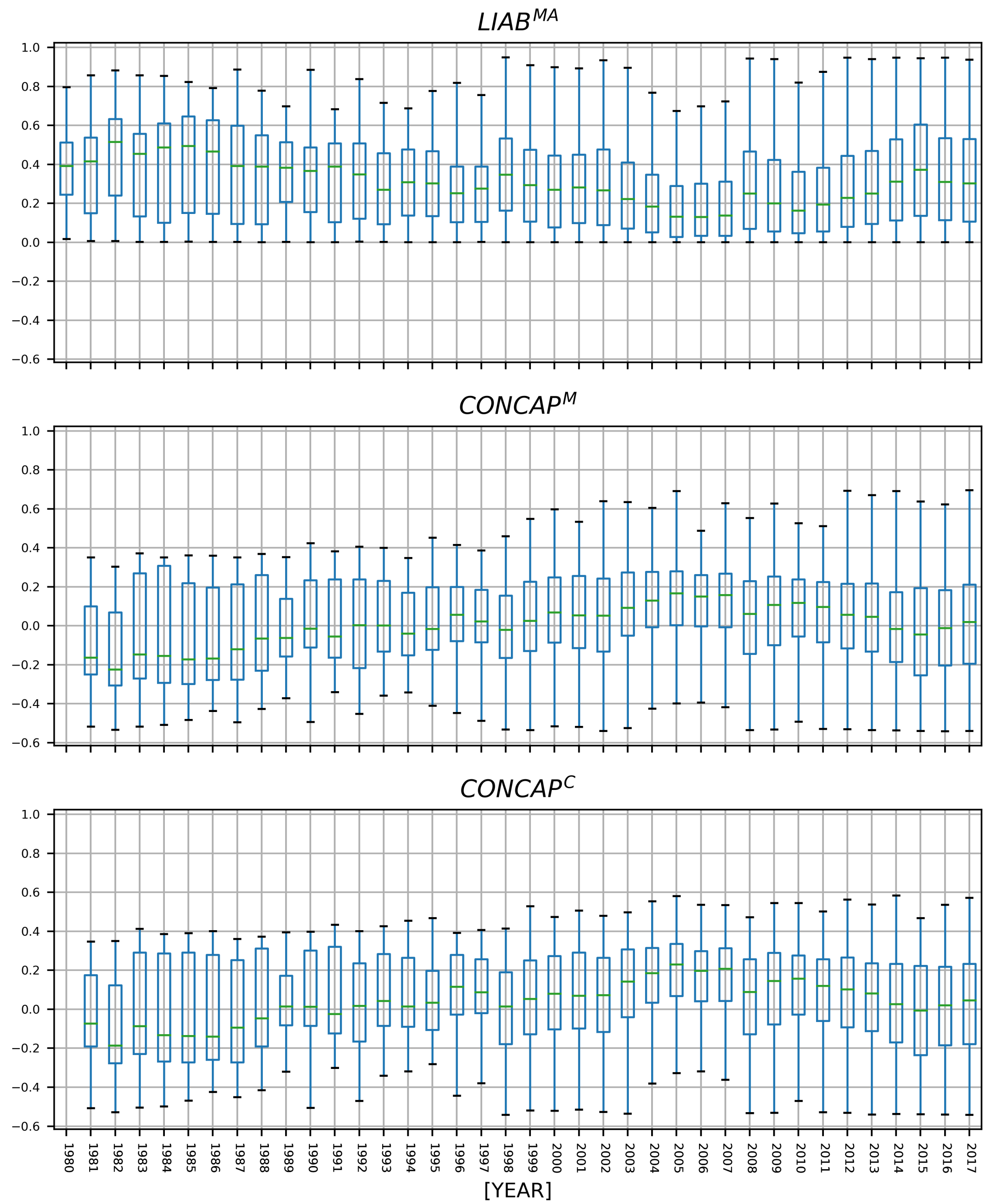

Figure 8: Distribution of LIAB, CSRISK, and MSRISK by Year - Oil and Gas Producers

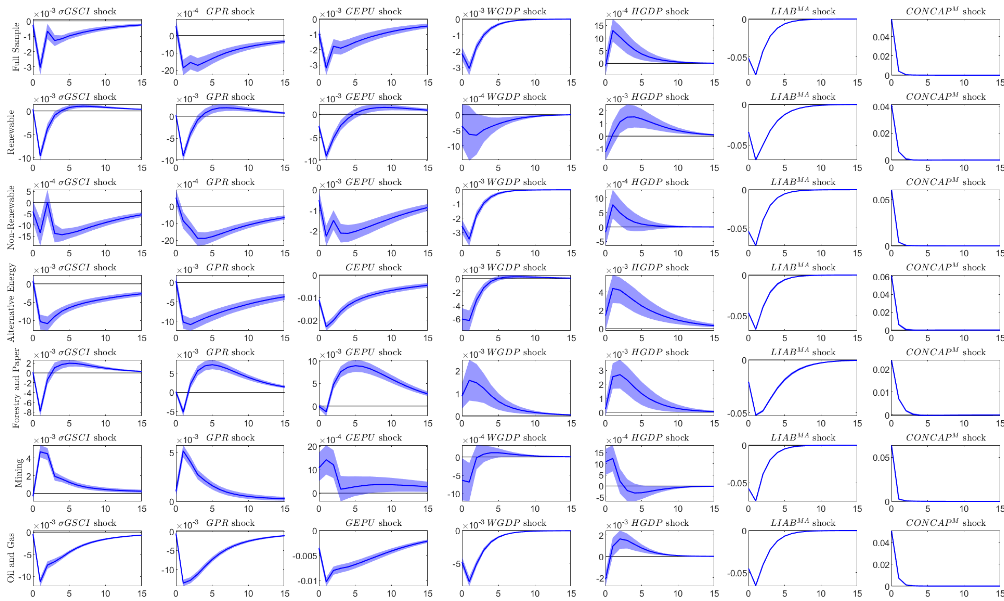

Figure 9: Responses of MSRISK - All Panels

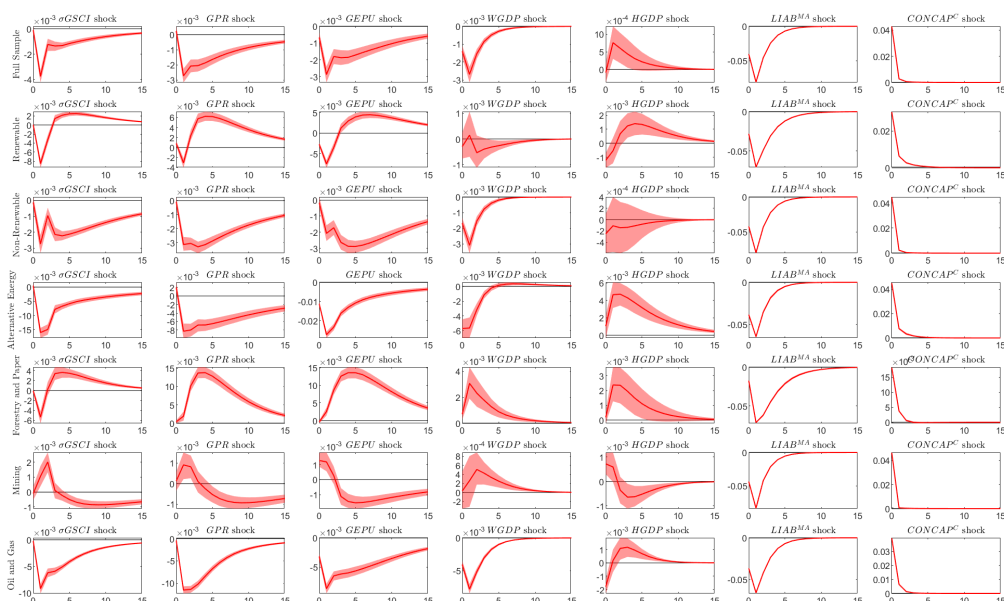

Figure 10: Responses of CSRISK - All Panels