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CAMA Working Paper 74/2021
August 2021

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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 generally, companies in the resource sector tend to have conditional capital shortfall before 2000 and conditional capital surplus after 2000 owing to the boom of the commodity sector stock and the moderate-to-careful capital structure management adopted by these companies. This finding is especially valid for resource firms from developed countries, whose observations dominate the dataset used in this study. Furthermore, the analysis using the panel vector autoregressive model indicates a positive influence of commodity price, geopolitical, and economic policy uncertainties on the conditional capital shortfall. These uncertainties have also been proven to increase the conditional failure probability of firms in the sample. Lastly, the performance analysis shows that potential capital shortfall is positively related to market return, 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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ISSN 2206-0332

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Conditional Capital Surplus and Shortfall across Renewable and Non-Renewable Resource Firms[†]

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[†]A part of this study is a result of the research project at Research Institute of Economy, Trade and Industry (RIETI) by the second author. The authors would like to thank David Stern, Renee Fry-McKibbin, the participants at IRMC 2020 conference and the seminar participants at RIETI and ANU for their valuable comments.

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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 possible factors of their dynamics. 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 the 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-year. 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 crucial for natural resource firms. In this study, $MSRISK$ to market asset ratio multiplied by negative 1 is termed as $CONCAP^M$, so is $CSRISK$

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

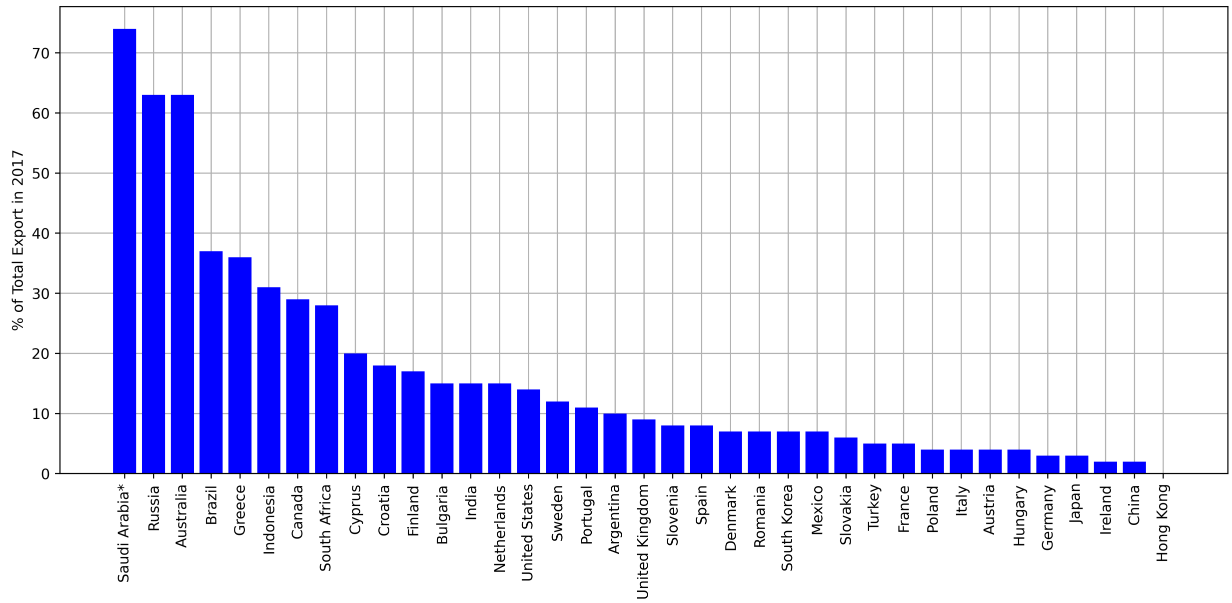

Figure 1: Natural Resource Export as a Percentage of Total Export by Country in 2017

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).

to market asset ratio, termed as $CONCAP^C$. Thus, positive value refers to capital surplus and 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.

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 3,337 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 the 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 firms' 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 from developed countries, which are the majority in the dataset used in this study, have relatively low leverage levels after 2000, indicating 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. Meanwhile, resource firms from emerging and frontier countries show relatively high leverage levels, and conditional capital is generally around zero for emerging countries or negative for frontier countries. The second analysis with the PVAR suggests procyclical capital shortfall responses toward shocks to commodity price, geopolitical, and economic policy uncertainties. 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. Finally, general results from country group analysis show a consistent pattern with the results from the sector-based analysis.

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 firms' 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 strand 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 fulfil 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 2008 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 and commodity markets 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% $CONCAP$ firms 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 phenomena 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 a 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 governments 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 an agency problem, outlining that the conflict of interest between managers and shareholders is the central tenet of the discussion. In the economic expansion periods, firms tend to have excess cash (free cash flow), which the managers will then decide what to do with. 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 impact firms' 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 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 1. It comprises unbalanced panel data of 3,337 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. Furthermore, to examine heterogeneity in the dataset, each analysis is also divided into three country groups: (1) developed, (2) emerging, and (3) frontier countries. Country classification follows the definition from MSCI. In addition, the second analysis includes a dummy for 2008 to control the 2008 global

[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 2008 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).

Table 1: Descriptive Statistics of Macro and Firm Variables

Variables		Description	Obs	Mean	Std. Dev.	Min	Max
(11)	$LIAB$	Liabilities to Market Assets Ratio	33,839	0.27	0.25	0.00	0.95
(12)	$PROFIT$	EBIT to Market Assets Ratio	31,251	-0.15	0.68	-45.30	27.22
(13)	$DEBT$	Total Debt to Market Assets Ratio	31,726	0.13	0.18	0.00	1.20
(14)	$CLTR$	Collateral to Market Assets Ratio	32,612	0.51	0.85	-0.03	37.12
(15)	$SIZE$	Logarithm of Market Assets	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 Assets 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 Snnual 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

financial crisis. All necessary data for these calculations are retrieved from Refinitiv Datastream. Data are trimmed one per cent each on top and bottom to exclude outliers.

In general, this section is divided into five sections. The first two sections explain "how" this study defines and constructs conditional capital surplus/shortfall. Specifically, 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. In other words, these two parts focus on "what" factors influencing conditional capital of sample firms. The last part explains the regression setting to outline the relationship between conditional capital surplus/shortfall and future firms' performance. This part focuses on "why" conditional capital matters for firms, specifically in the sense of how it affects their future 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's stock to the respective MSCI market index of which the company is listed. In addition, this study estimates the commodity beta (β^C) to measure the sensitivity of each company's 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:

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

[4]The GSCI index is based on a basket of futures 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.

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

where t represents time. Terms r, $rMSCI$, and $rGSCI$ represent the daily returns of the company's stock and those 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 producers' 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 is initially developed for financial institutions, the value of k is assumed to be 8%. In this study, different levels of k are 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 2.

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

[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 2: 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)

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 contrary, this study employs 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 employs 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]

[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`.

The variables $WGDP$ and $HGDP$ represent the world and home country business cycles and are technically represented by the annual growth of the GDP of the world and each country, respectively. The variable $LIAB$ represents the liability level of companies and is defined by total liabilities divided by market assets. 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 $\sigma COMM$, GPR, $GEPU$, and $WGDP$. The country-level variable is $HGDP$. Meanwhile, $LIAB$ 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 $HGDP$, $LIAB$, 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 and country group, analyses are separately conducted with $CONCAP^M$ and $CONCAP^C$. The PVAR model represented by Equation (5) can be expressed as follows:

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

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 Cholesky decomposition ordering is based on two reasons: (1) level of the variables; and (2) the time responsiveness of each variable. The variables $\sigma COMM$, GPR, $GEPU$ and

$WGDP$ are world-level, $HGDP$ is country-level, and lastly $LIAB$ and $CONCAP$ ($CONCAP^M$ or $CONCAP^C$) are firm-level. Among world-level variables, $\sigma COMM$ is the most responsive and exogenous variable (the first in the ordering) because it is based on daily commodity futures price, which can be considered as a financial variable. The variables GPR and $GEPU$ are based on news-based indices and calculated as an annual average of monthly indices. They are the second and third in the ordering. Meanwhile, $WGDP$ is the least responsive (annual) among the four global-level variables, since macroeconomic variables move slowly in general.[8]

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% shortfalls are assigned a value of 1, and 0 otherwise. This treatment assumes that firms with the worst 11.4% capital shortfall of the total sample will turn to insolvency or failure. The value of 11.4% is chosen as a 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 basis for choosing the probit is 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 has depleted is not appropriate, which also means that right censoring is not an issue. Therefore, this study implements the panel probit model as follows:

$$Prob \ (CONCAP_{i,t}^{FAIL} = 1) = \Phi\Big(\alpha + \boldsymbol{\theta}_1 \boldsymbol{P}_{i,t} + \boldsymbol{\theta}_2 \boldsymbol{P}_{i,t-1} + \boldsymbol{\theta}_3 \boldsymbol{Q}_{i,t-1} + \boldsymbol{\theta}_4 \boldsymbol{R}_{i,t}\Big) \tag{9}$$

where $\boldsymbol{\theta}$ represents a vector of coefficients, $\boldsymbol{P}$ is a vector of macro variables ($\sigma COMM$, $GEPU$, GPR, $WGDP$, $HGDP$ and $INFL$), $\boldsymbol{Q}$ is a vector of firm-level variables ($PROFIT$, $DEBT$, $CLTR$, $SIZE$, and $SIZE^2$), and $\boldsymbol{R}$ comprises AGE and AGE^2. Subscript i denotes firm and t denotes the year. Macro variables are employed both in the current (t) and lagged one ($t-1$) to accommodate the dynamic aspect of the model, making it consistent with the structural equation of the PVAR model in the previous section. Firm-level variables are controls and lagged one to avoid endogeneity.

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 log-transformed of the global economic policy uncertainty from Davis (2016). Third, GPR, which is log-transformed of the GPR index by Caldara and Iacoviello (2019).

[8] As a robustness check, an alternative ordering is used to calculate the PVAR model with the following order: $WGDP$, GPR, $GEPU$, $\sigma COMM$, $HGDP$, $LIAB$, $CONCAP$. The results are qualitatively similar to those of the original ordering, showing the robustness of the results.

In addition, there are three 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 $INFL$ are retrieved from the World Bank.

Furthermore, five firm-level variables are 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 and extends the setting from Oler and Picconi (2014) as follows:

$$RTRN_{i,t} = \alpha + \beta_1 CONCAP^{+}_{i,t-1} + \beta_2 CONCAP^{-}_{i,t-1} + \boldsymbol{\theta}_1 \boldsymbol{V}_{i,t-1} + \boldsymbol{\theta}_2 \boldsymbol{W}_{i,t-1} + \mu_{i,t} \tag{10}$$

where i refers to the firm, and t is time. $RTRN$ is the annual market return of the firm.[9] $CONCAP$ 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. The term $\boldsymbol{\theta}$ represents a vector of coefficients, $\boldsymbol{V}$ is a vector of firm-level variables ($SALES$, $DEBT$, $SIZE$, and $RETURN$) and $\boldsymbol{W}$ is a vector of macro variables ($\sigma COMM$, $GEPU$, GPR, $WGDP$, $HGDP$ and $INFL$). $SALES$ 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. Definition of macro variables are the same with the previous subsection.

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 firms' future performance in the sample. Each analysis is conducted for all samples, renewable and non-renewable, each sector, and based on the country groups.

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

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 0.07 and 0.10, with the same standard deviation, 0.24, indicating that, on average, both indices share a resemblance, despite each index considering a different systemic event based on stock price and commodity price large declines.

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

To observe the pattern of conditional capital surplus and shortfall dynamics of resource companies in the sample, Figures 2–7 present $LIAB$, $CONCAP^M$, and $CONCAP^C$ for each sample set. Figure 2 presents the patterns for the full sample. It can be seen that $LIAB$ is relatively stable during the early 1980s to the late 1990s, with medians 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. $LIAB$ increased drastically during this year. After 2008, there were some cyclical fluctuations in the level of $LIAB$.

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 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 $LIAB$. 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. Figures for each sector analysis are provided in the appendix section.

Comparing Figures 3 and 4 show differences in patterns between the renewable and non-renewable sectors. In general, the median of $LIAB$ for the renewable fluctuates around 0.4-0.6 during the sample period. Meanwhile, $LIAB$ for non-renewable is approximately between 0.0-0.4, with a lower level of $LIAB$ 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 gener-

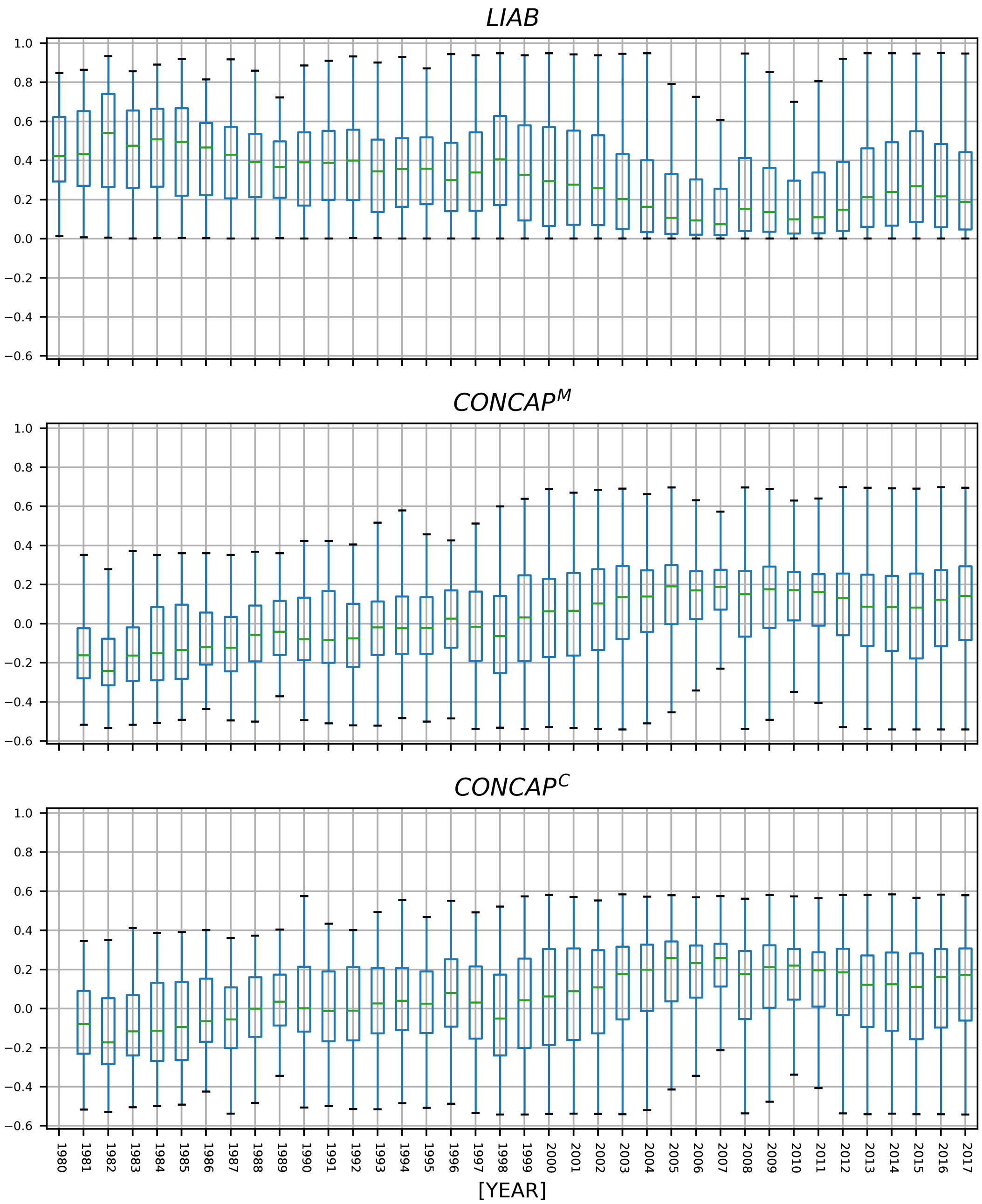

Figure 2: Distribution of LIAB, CSRISK, and MSRISK by Year - Full Sample

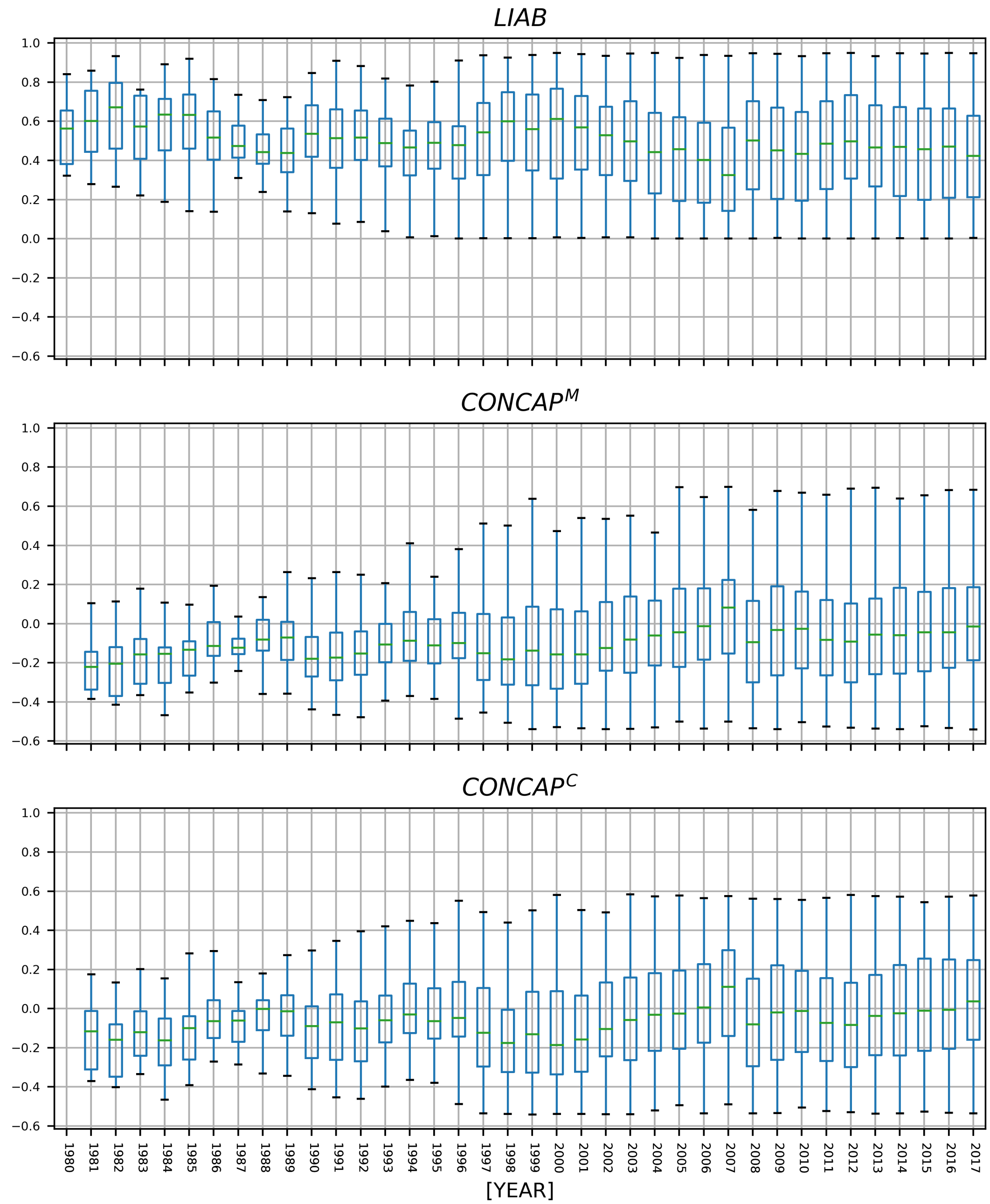

Figure 3: Distribution of LIAB, CSRISK, and MSRISK by Year - Renewable

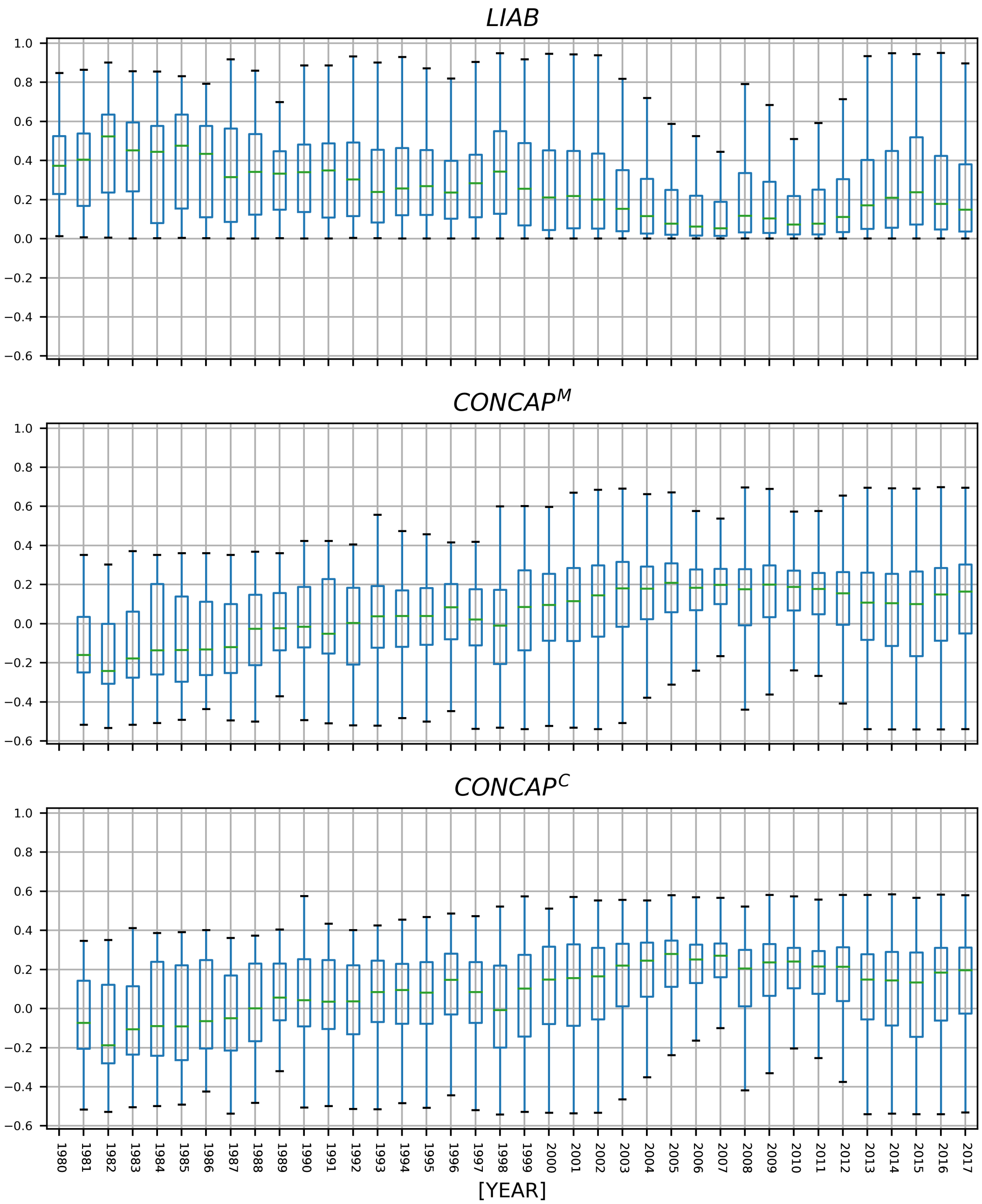

Figure 4: Distribution of LIAB, CSRISK, and MSRISK by Year - Non-Renewable

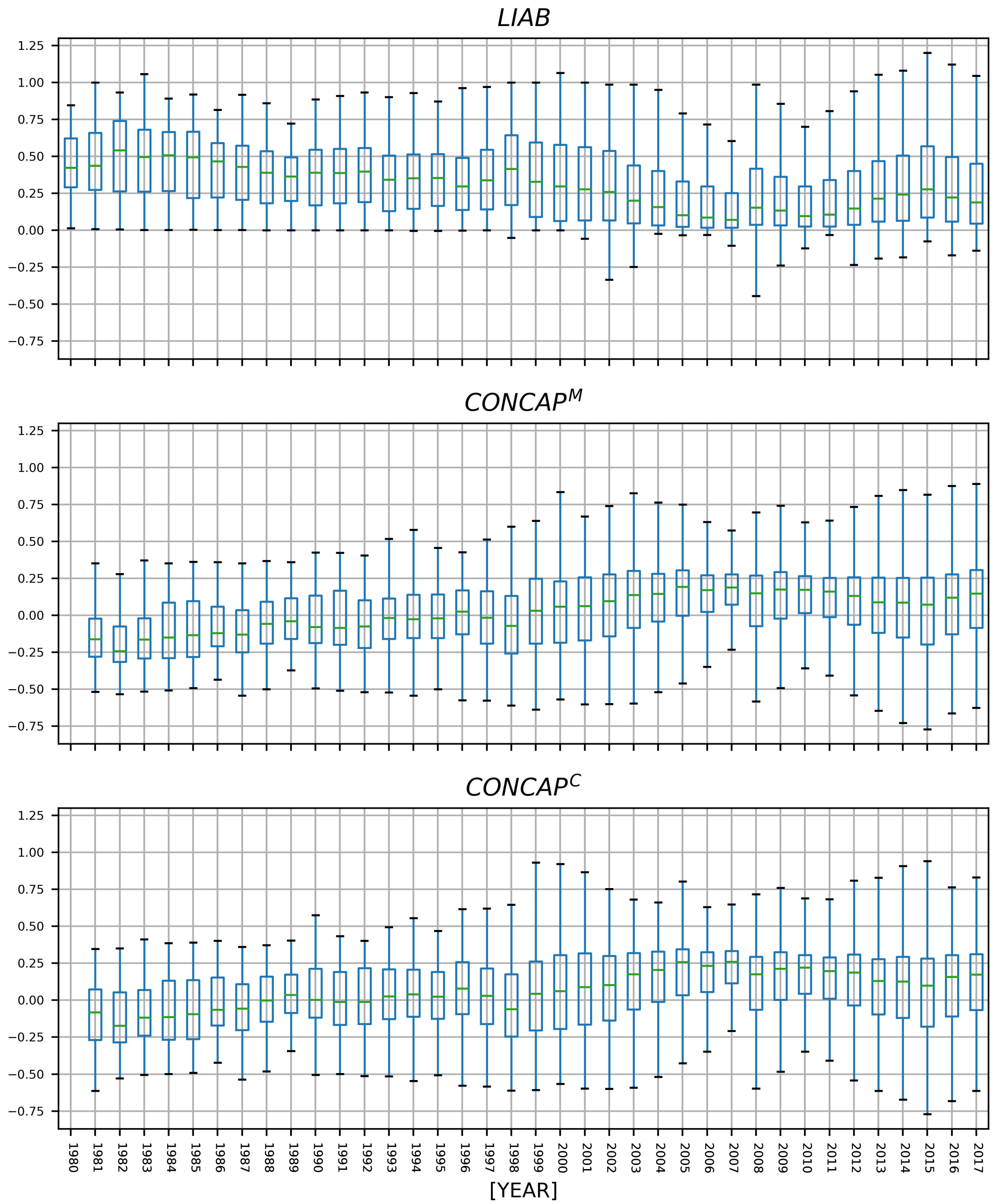

Figure 5: Distribution of LIAB, CSRISK, and MSRISK by Year - Developed Countries

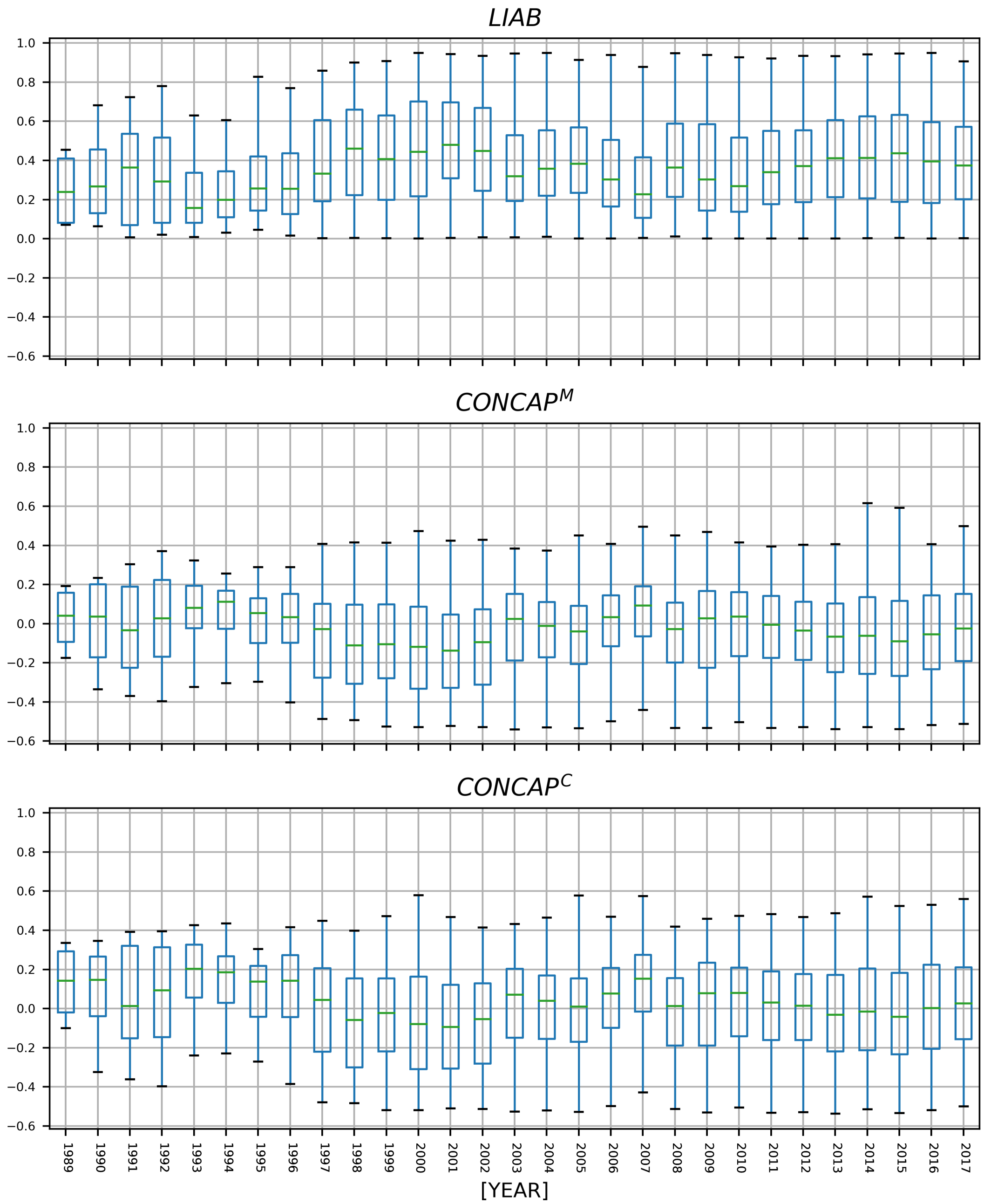

Figure 6: Distribution of LIAB, CSRISK, and MSRISK by Year - Emerging Countries

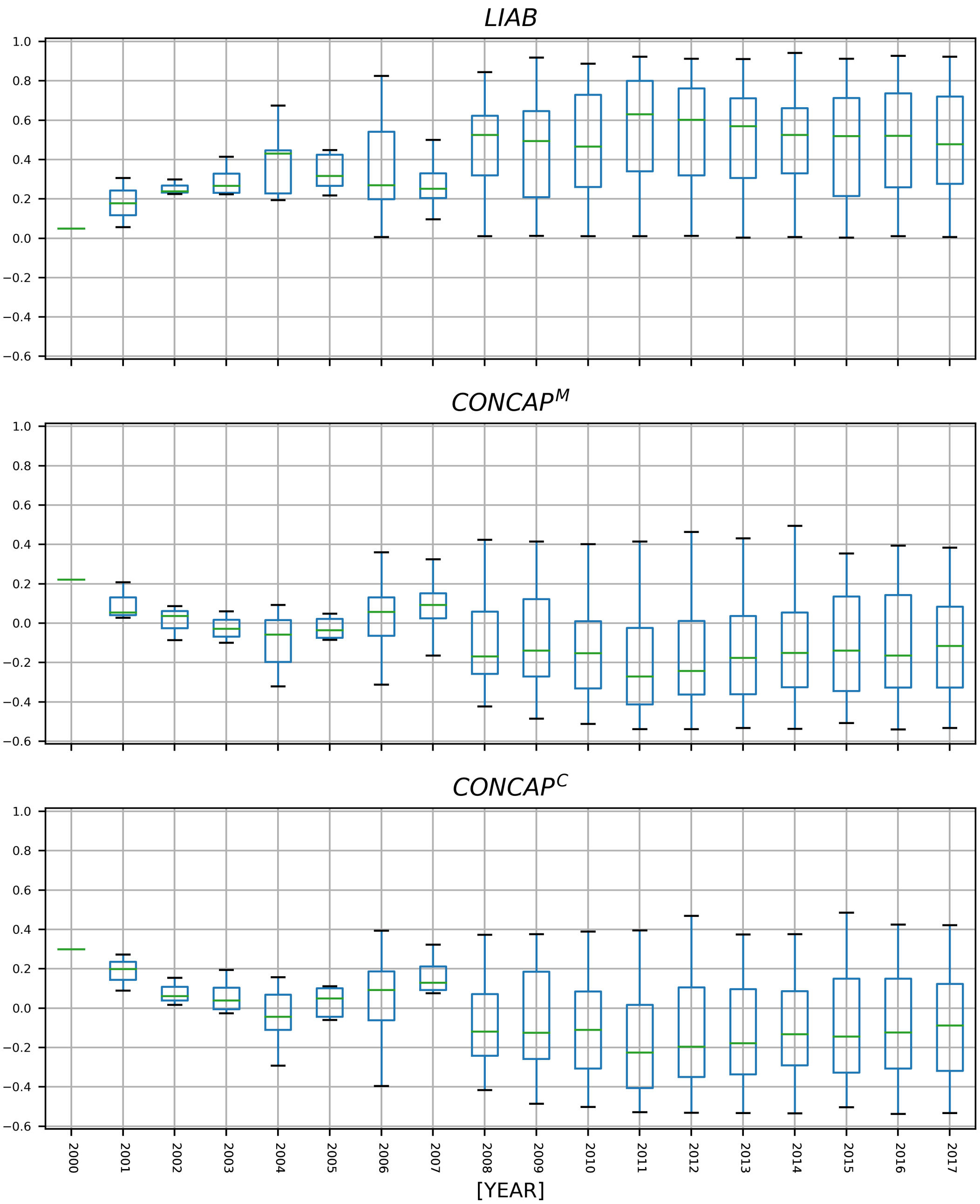

Figure 7: Distribution of LIAB, CSRISK, and MSRISK by Year - Frontier Countries

ally negative in the early period of the sample, and then become positive after 2000, indicating a change from a shortfall to a surplus trend.

Figures 5-7 provide results for country group analysis, which show variation of patterns across the three groups. Given observations from developed countries dominate the dataset in this study, it is not unexpected that the results for developed countries (Figure 5) share resemblance with the full sample (Figure 2). $LIAB$ are generally lower for sample firms from developed countries, especially after 2000, and this pattern determines the patterns of $CONCAP^M$ and $CONCAP^C$. Patterns for emerging and frontier countries (Figure 6 and 7) are noticeably different from developed countries. For the emerging group, observations start from 1989, and $LIAB$ remains relatively high starting from 1997 until 2017, with the median around 0.4. The median of $CONCAP^M$ and $CONCAP^C$ for emerging group moves not far from zero during the same period. This pattern may indicate that firms in emerging countries can maintain their conditional capital level around zero, which can be perceived as optimal, neither too high nor too low. Meanwhile, for frontier countries, observations start from 2000, and the median of $LIAB$ remains relatively high (0.5-0.6) since 2008. Meanwhile, the medians of $CONCAP^M$ and $CONCAP^C$ for the frontier group are significantly negative after 2008 compared to the developed and emerging groups.

Based on country group analysis, several patterns could be inferred. First, resource firms from developed countries are more well-capitalized than emerging and frontier groups, as seen from their $LIAB$ level. However, this impacts their conditional capital, where firms from developed countries experience surplus after 2000. This pattern is not unexpected since developed countries have a bigger economic size and a more efficient capital market, and therefore firms are well-capitalized. Second, there is a noticeable different pattern between groups. For the developed group, the year 2000 is a crucial flipping point in their $LIAB$ and $CONCAP$ patterns. For emerging and frontier groups, they are the year 1997 and year 2008, respectively. One explanation for this is different business cycle phases for each group. Business cycles for countries in one group tend to move together with their group peer and thus create noticeable differences between groups.

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. Figures 8–9 present the impulse responses of $CONCAP^M$ and $CONCAP^C$ for all sample sets, while Figure 10 presents results for country group estimation. As can be seen, the results show that the responses of both $CONCAP^M$ and $CONCAP^C$ are somewhat mixed depending on the sector and country group, although some strong patterns are observed.

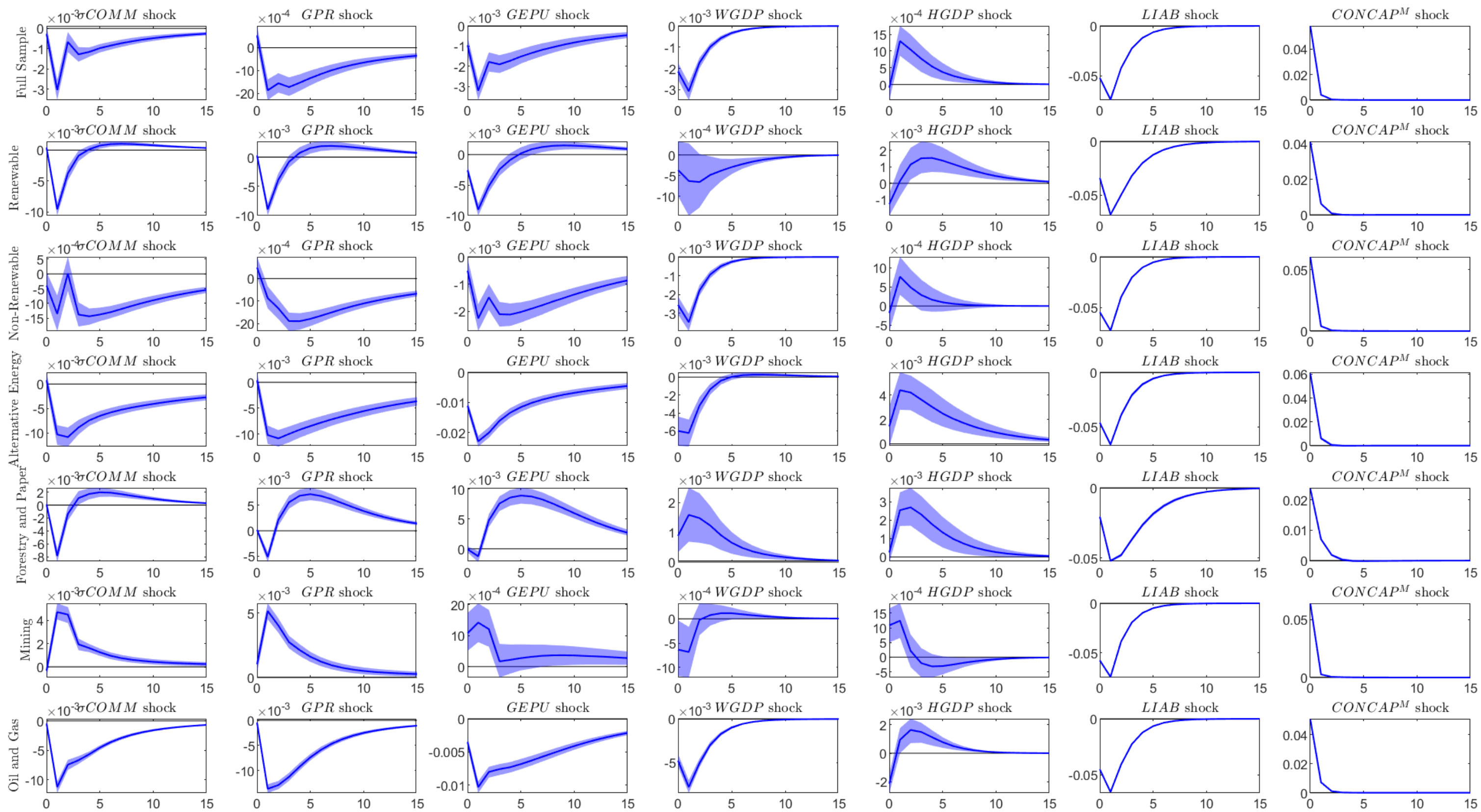

Figure 8: Responses of $CONCAP^M$ - All Panels

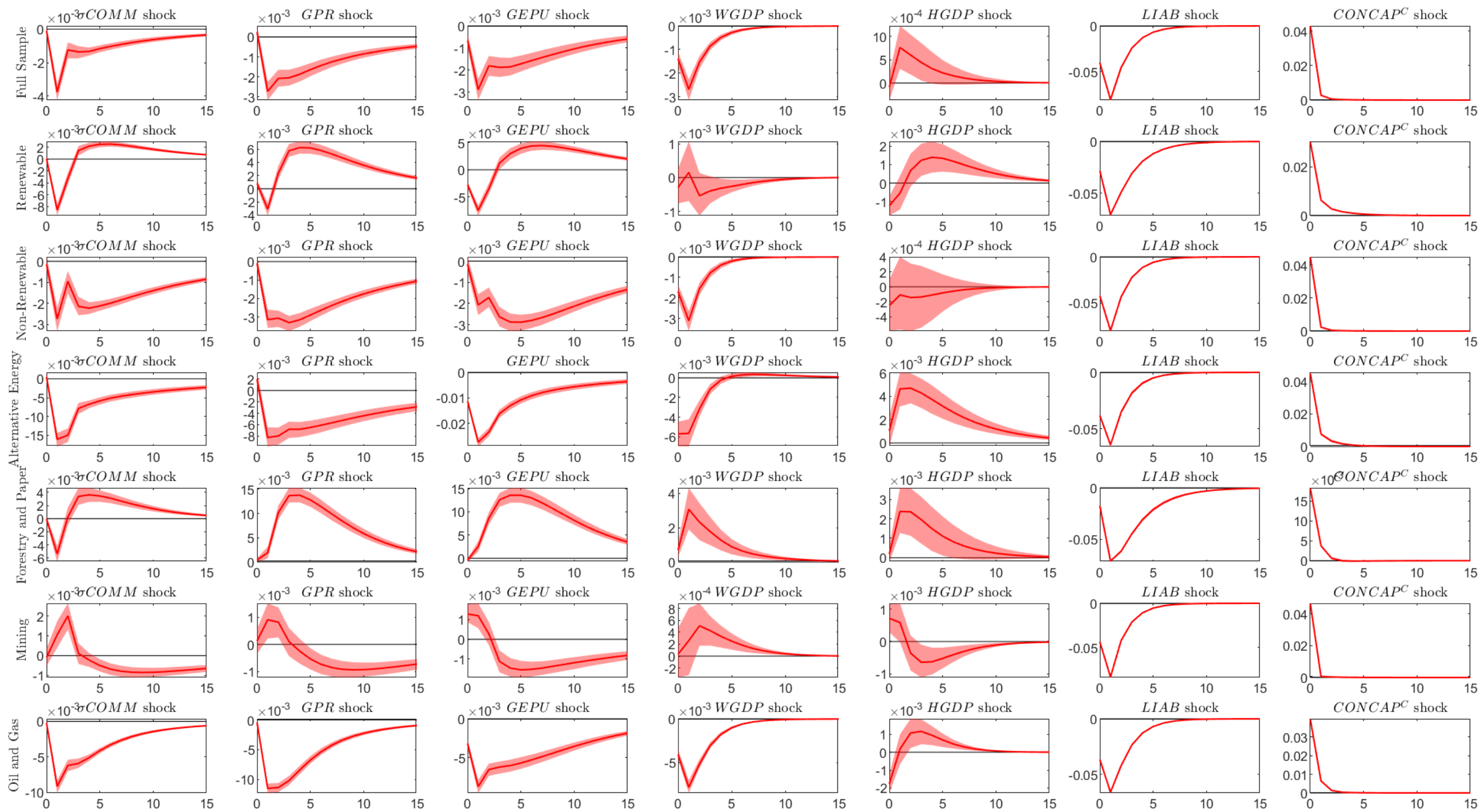

Figure 9: Responses of $CONCAP^C$ - All Panels

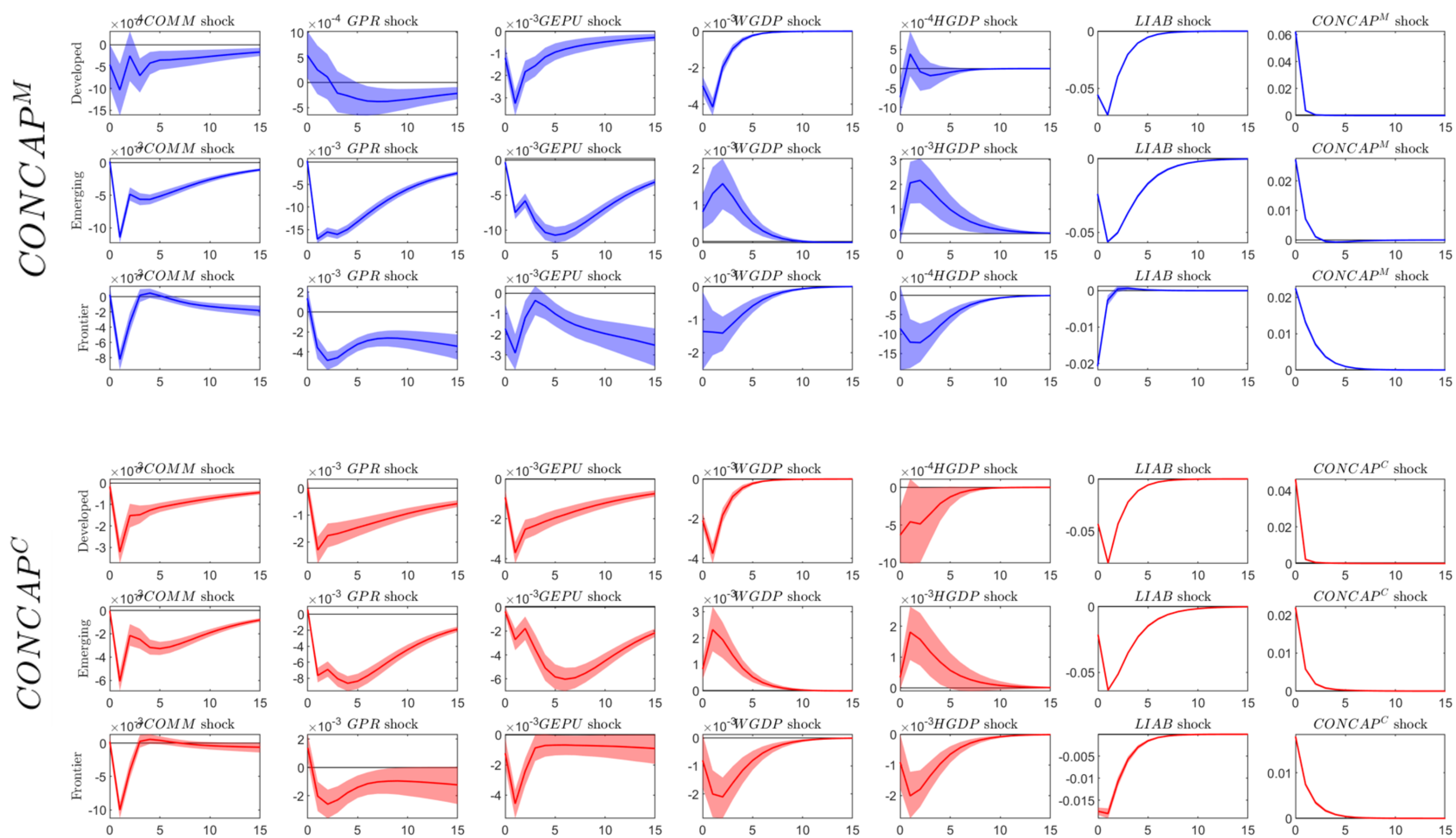

Figure 10: Responses of $CONCAP^M$ and $CONCAP^C$ by Country Group

The results show that both $CONCAP^M$ and $CONCAP^C$ respond negatively to shocks in $\sigma COMM$. 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 and country groups, 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 to the world business cycle. One noticeable difference is the responses of the forestry and paper sector and emerging group, which are positive in both the $CONCAP^M$ and $CONCAP^C$ estimations. Thus, specific to these groups, 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 differs from the response to $WGDP$. Thus, it can be inferred that for the home country business cycles, the conditional capital surplus responses are procyclical. Some exceptions can be observed for developed and frontier groups, which show countercyclical responses.

Lastly, $CONCAP^M$ and $CONCAP^C$ respond negatively to the shock of $LIAB$, indicating a strong positive relationship between leverage level and conditional capital shortfall. The results for $LIAB$ 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 generally 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 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 inducing 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 the firm as the cluster.

Table 4 presents results for analysis with $CONCAP^{MFAIL}$ as dependent variable. As can be seen, $\sigma COMM$ is contemporaneously significant for almost all panels except alternative energy, with positive signs. The results for lagged $\sigma COMM$ are generally not significant. The results imply that commodity price uncertainty contemporaneously increases firm failure probability, and in general aligned with the results of Jin and Jorion (2006) and Buhl et al. (2011). Aligned with $\sigma COMM$, $GEPU$ generally has a significant positive effect both contemporaneously and lagged, indicating that higher economic policy uncertainty contributes positively to firms' failure. Meanwhile, results for GPR are mixed. GPR shows a significantly positive effect contemporaneously for non-renewable related panels, indicating a positive relationship between geopolitical risk and firms' failure, but a negative lagged effect. In contrast, GPR is contemporaneously significant and negative for the alternative energy, implying the anomaly responses for this sector. One explanation that can be offered is that the alternative energy sector substitutes the conventional resource sectors (mining and oil and gas). Thus, once geopolitical risk deteriorates, the alternative energy sector will instead thrive.

The proxy for the world business cycle, $WGDP$, is contemporaneously generally not significant (Table 4), but considerably significant and positive in a delayed setting. These results indicate that a better world business cycle increases future default risk, which can be seen as a risk built-up process. Meanwhile, the proxy for the home country business cycle, $HGDP$, has a significantly negative contemporaneous effect on the full sample, non-renewable and mining panels; and significant lagged effects on the renewable ($-$), forestry and paper ($-$), and mining ($+$) panels. On the contrary with $WGDP$, these results strongly show that better home country business cycle conditions lower the failure risk. Considering these results, it could be inferred that the influence of the world and home country business cycles bring diverging effects on firms' failures. The control variable $INFL$, representing the home country's inflation rate, is generally significant and positive in the contemporaneous setting. This result suggests that higher inflation induces more firms' failures.

For firm-level variables, the lagged $CONCAP^{MFAIL}$ is significantly positive for all panels, indicating a bigger future failure risk once failure risk is already high. $PROFIT$ is a proxy of firms' performance and significantly negatively affects the full sample, non-renewable, and mining panels. This finding indicates that 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 $CONCAP^{MFAIL}$. $\sigma COMM$, in general, has a significantly positive contemporaneous effect for almost all panels except for the alternative energy and mining sectors. $GEPU$ is significantly positive for almost all panels in the contemporaneous

Table 4: Failure Analysis - $CONCAP^M$

Dep. Variable = $CONCAP^{MFAIL}_{i,t}$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$\sigma COMM_{i,t}$	0.3167***	0.2087**	0.3327***	-0.002	0.3267***	0.1274*	0.6250***
$GEPU_{i,t}$	0.1950***	0.4009***	0.1731**	0.2168	0.4900***	-0.0402	0.5069***
$GPR_{i,t}$	0.2675***	-0.2518	0.4305***	-0.7409*	-0.1144	0.3006***	0.6084***
$WGDP_{i,t}$	0.0083	-0.1131*	0.045	-0.2475	-0.0607	0.0023	0.1027*
$HGDP_{i,t}$	-0.0259**	-0.003	-0.0457***	-0.0047	-0.0088	-0.0676***	-0.0121
$INFL_{i,t}$	0.0132**	0.0861***	0.0002	0.1632***	0.0746***	-0.0127	0.0052
$\sigma COMM_{i,t-1}$	-0.074	-0.2336*	-0.0376	-0.457	-0.1433	-0.1057	0.0174
$GEPU_{i,t-1}$	0.3994**	-0.5731*	0.6267***	-0.6	-0.2967	0.3326	1.0108***
$GPR_{i,t-1}$	-0.2749***	-0.0549	-0.3072***	0.5249	-0.202	-0.2746**	-0.3477***
$WGDP_{i,t-1}$	0.0660***	0.0570*	0.0730***	0.0732	0.0641*	0.0609***	0.0868***
$HGDP_{i,t-1}$	-0.0032	-0.0540***	0.0155	-0.0821	-0.0562***	0.0501***	-0.0203
$INFL_{i,t-1}$	0.0056	-0.0223	0.0097	-0.0965*	-0.0177	0.0212**	0.0059
$CONCAP^{MFAIL}_{i,t-1}$	1.0784***	1.3824***	0.9704***	1.4659***	1.2945***	0.9903***	1.0026***
$PROFIT_{i,t-1}$	-0.0665***	-0.0183	-0.0655***	-0.1338	-0.0505	-0.0674***	-0.0658
$DEBT_{i,t-1}$	3.0100***	3.1702***	2.9963***	2.7513***	3.4745***	2.9416***	2.9911***
$CLTR_{i,t-1}$	0.0233	0.0471	0.0152	-0.4801	0.0271	0.0313	-0.0231
$SIZE_{i,t-1}$	-0.0399	0.0841	-0.0466	-0.1762	0.1028	-0.0900**	-0.0364
$SIZE^2_{i,t-1}$	0.0026**	-0.0017	0.0028**	0.0083	-0.0026	0.0045***	0.0017
$AGE_{i,t}$	0.0041	0.0046	0.0029	0.0601*	-0.016	0.0135*	-0.0125
$AGE^2_{i,t}$	0	0.0001	0	-0.0029*	0.0005	-0.0002	0.0003
$CONS$	-6.6099***	-0.8459	-8.4822***	4.2351	-3.7141	-3.8706*	-14.3575***
OBS	27,970	4,675	23,295	1,610	3,065	16,296	6,999
$Pseudo\ R^2$	0.3815	0.4455	0.3681	0.3199	0.4704	0.3811	0.3569
LL	-5480	-1170	-4240	-265	-884	-2550	-1640

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10% significance level.

Table 5: Failure Analysis - $CONCAP^{C}$

Dep. Variable = $CONCAP_{i,t}^{CFAIL}$

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$\sigma COMM_{i,t}$	0.2676***	0.1686*	0.2953***	-0.1731	0.3332***	0.1063	0.5636***
$GEPU_{i,t}$	0.2107***	0.5932***	0.1842**	0.5522*	0.5940***	-0.0585	0.5664***
$GPR_{i,t}$	0.2150***	-0.5423***	0.4581***	-1.2514***	-0.3599**	0.3513***	0.6021***
$WGDP_{i,t}$	-0.013	-0.1217**	0.0306	-0.2026	-0.0816	-0.0176	0.0964
$HGDP_{i,t}$	-0.0267***	0.0061	-0.0485***	-0.0502	0.0059	-0.0643***	-0.0228
$INFL_{i,t}$	0.0139**	0.0342	0.0063	0.1385***	0.0259	-0.004	0.0096
$\sigma COMM_{i,t-1}$	-0.1163*	-0.2918**	-0.0572	-0.4227	-0.227	-0.14	0.0297
$GEPU_{i,t-1}$	0.265	-0.8271***	0.5291***	-0.9919	-0.4507	0.2635	0.8862***
$GPR_{i,t-1}$	-0.1905***	0.2513*	-0.3049***	0.9752**	0.0789	-0.2975***	-0.3002***
$WGDP_{i,t-1}$	0.0615***	0.0694**	0.0657***	0.036	0.0766**	0.0547**	0.0785***
$HGDP_{i,t-1}$	-0.0008	-0.0425**	0.0113	-0.0162	-0.0512***	0.0423**	-0.0198
$INFL_{i,t-1}$	0.0071	0.0216*	0.0055	-0.0679	0.0235**	0.0152*	0.0037
$CONCAP_{i,t-1}^{CFAIL}$	1.0615***	1.3802***	0.9631***	1.5187***	1.2839***	1.0028***	0.9402***
$PROFIT_{i,t-1}$	-0.0750***	-0.0266	-0.0728***	-0.215	0.0861	-0.0653***	-0.1077**
$DEBT_{i,t-1}$	3.0036***	3.1113***	2.9926***	2.8451***	3.3541***	2.8936***	3.1082***
$CLTR_{i,t-1}$	0.0291	0.1184	0.019	-0.4927	0.0875	0.0438**	-0.0468
$SIZE_{i,t-1}$	-0.0634**	0.0327	-0.0711**	-0.137	0.0265	-0.1234***	-0.0373
$SIZE_{i,t-1}^{2}$	0.0029**	-0.0009	0.0033***	0.0056	-0.0009	0.0053***	0.0014
$AGE_{i,t}$	0.0061	0.0168	0.0031	0.0730**	-0.0049	0.0125*	-0.0097
$AGE_{i,t}^{2}$	-0.0001	-0.0003	0	-0.0031**	0	-0.0002	0.0002
$CONS$	-5.3805***	0.3016	-7.5847***	5.2191	-2.5805	-2.8906	-13.8481***
OBS	27,975	4,679	23,296	1,610	3,069	16,296	7,000
$Pseudo\ R^2$	0.3731	0.4286	0.3639	0.3493	0.4479	0.3762	0.3494
LL	-5460	-1160	-4230	-242	-889	-2570	-1620

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10%.

Table 6: Failure Analysis by Country Group

Dep. Variable = $CONCAP^{MFAIL}_{i,t}$ and $CONCAP^{CFAIL}_{i,t}$

Variable	$CONCAP^{MFAIL}$			$CONCAP^{CFAIL}$		
	Developed	Emerging	Frontier	Developed	Emerging	Frontier
$\sigma COMM_{i,t}$	0.4488***	0.2530**	0.9255***	0.4221***	0.1636	0.3702
$GEPU_{i,t}$	0.3643***	0.1646	0.9468	0.4060***	0.0301	0.3283
$GPR_{i,t}$	0.3453***	-0.1507	-0.2575	0.3117***	-0.2585*	-0.2527
$WGDP_{i,t}$	0.0994***	-0.0692	0.5087**	0.0935***	-0.1430**	0.3515*
$HGDP_{i,t}$	-0.0751***	0.0163	-0.0156	-0.0789***	0.0145	-0.0135
$INFL_{i,t}$	-0.1140***	0.0288***	0.005	-0.1207***	0.0258***	0.0494**
$\sigma COMM_{i,t-1}$	-0.1103	-0.0797	0.8026	-0.1303*	-0.2360*	0.652
$GEPU_{i,t-1}$	0.5083***	0.2688	2.6011**	0.4329**	-0.0498	1.816
$GPR_{i,t-1}$	-0.3633***	-0.0811	-0.409	-0.3194***	0.0795	-0.1418
$WGDP_{i,t-1}$	0.0298	0.1147***	0.1456*	0.0337*	0.0970***	0.1226
$HGDP_{i,t-1}$	0.0504***	-0.0480***	0.004	0.0498***	-0.0403**	0.0234
$INFL_{i,t-1}$	0.0311*	-0.0111	0.0081	0.0239	-0.0051	-0.0102
$CONCAP^{FAIL}_{i,t-1}$	0.9319***	1.3244***	1.9675***	0.9653***	1.2301***	1.4916***
$PROFIT_{i,t-1}$	-0.0617***	-0.1255	-1.8186	-0.0663***	-0.35	-2.1347*
$DEBT_{i,t-1}$	3.0742***	3.1296***	2.0872***	3.0479***	3.0205***	2.5473***
$CLTR_{i,t-1}$	0.01	0.0446	-0.1915	0.0156	0.0386	-0.037
$SIZE_{i,t-1}$	-0.1594***	-0.3684***	0.2405	-0.1621***	-0.3426***	-0.1584
$SIZE^2_{i,t-1}$	0.0077***	0.0105***	-0.0058	0.0070***	0.0095***	0.0069
$AGE_{i,t}$	0.0059	0.0294*	0.001	0.0071	0.0392**	0.029
$AGE^2_{i,t}$	-0.0001	-0.0007	-0.0019	-0.0002	-0.0009*	-0.0031
$CONS$	-7.7101***	-1.5732	-29.5867**	-7.1722***	1.7601	-17.0068
OBS	23,068	4,345	557	23,068	4,348	559
$Pseudo\ R^2$	0.3783	0.4389	0.3259	0.3772	0.4162	0.2689
LL	-4190	-1010	-160	-4160	-1010	-167

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10%.

setting and relatively significant in the delayed setting. GPR is contemporaneously significant and positive for non-renewable related panels and significantly negative for renewable related panels, all with opposite signs in their delayed setting. This finding is particularly interesting and strengthens the notion that the renewable sector behaves divergently with the non-renewable. $WGDP$ is statistically significant in the delayed setting with positive signs. Meanwhile, $HGDP$ is contemporaneously significant and negative for the full sample, non-renewable, and mining panels; and significant for the renewable $(-)$, forestry and paper $(-)$, and mining $(+)$ panels in the lagged setting. Lagged $CONCAP^{CFAIL}$ is strongly positive. $DEBT$ is significant for all panels, all of which have positive signs. $PROFIT$ is significant for non-renewable related panels, with negative signs.

Table 6 presents estimation results based on country group for both $CONCAP^{MFAIL}$ and $CONCAP^{CFAIL}$. The three macro uncertainty variables ($\sigma COMM$, $GEPU$, GPR) are contemporaneously significant and positive, inducing firms' failure, especially for the developed groups. $WGDP$ is generally significant and positive in both contemporaneous and lagged settings. Meanwhile, $HGDP$ is contemporaneously negative and significant for developed groups, and in the lagged setting it is significant with mixed signs for developed and emerging groups. Firm-level variables are generally significant.

From the results in Tables 4-6, some general patterns can be inferred. $\sigma COMM$ and $GEPU$ have strong positive contemporaneous effects on firms' failure, emphasising the strong positive relationship between global macroeconomic uncertainties and firm failure. The contemporaneous effect

Table 7: Performance Analysis - $CONCAP^M$

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

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$CONCAP^{M+}_{i,t-1}$	-0.2531*	0.1921	-0.2636*	-0.0283	0.8645	-0.2631	-0.1327
$CONCAP^{M-}_{i,t-1}$	2.9946***	3.0836***	2.9680***	5.0039***	2.0194***	3.4259***	1.9948***
$SALES_{i,t-1}$	-0.0946**	0.0009	-0.1027**	-0.0422	0.1089	-0.1690**	0.0137
$DEBT_{i,t-1}$	-0.3211	-0.2815	-0.2902	-0.8456	0.4518	-0.5522*	0.3311
$SIZE_{i,t-1}$	-0.6459***	-0.5381***	-0.6555***	-0.6062***	-0.4767***	-0.6883***	-0.5660***
$RETURN_{i,t-1}$	0.0017**	-0.0009	0.0018**	-0.0024*	0.0009	0.0029*	0.0006
$\sigma COMM_{i,t-1}$	0.0977***	0.0353	0.1109***	0.0106	0.0193	0.1449***	0.1114***
$GEPU_{i,t-1}$	-0.1714***	-0.0165	-0.1885***	-0.4225*	0.0816	-0.2028***	-0.0134
$GPR_{i,t-1}$	0.0986***	0.1552***	0.0809**	0.2102	0.1472***	0.0802*	0.0285
$WGDP_{i,t-1}$	-0.0226*	-0.0631***	-0.0064	-0.0541	-0.0757***	0.0233	-0.0358
$HGDP_{i,t-1}$	-0.0698***	0.0292**	-0.1013***	0.0079	0.0341***	-0.1434***	-0.0343**
$INFL_{i,t-1}$	-0.0075	-0.0068	-0.0069	0.0651*	-0.0117*	-0.0488***	0.0182
$CONS$	8.1520***	6.7673***	8.1656***	8.8722***	5.6570***	8.2863***	6.8270***
OBS	27,379	4,457	22,922	1,506	2,951	16,103	6,819
R^2	0.1524	0.1216	0.1586	0.1333	0.1288	0.1682	0.1467
LL	-50500	-6900	-43200	-2660	-4050	-31000	-12000

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10%.

of GPR is, in general, significantly positive for the non-renewable sector and thus strengthens the general stream that global macro uncertainties have a positive influence on firm failure. Meanwhile, for business cycles, the lagged $WGDP$ has generally positive influences on firms' failures, indicating the risk built-up process, especially during the boom phase. $HGDP$ generally negatively influences firms' failure in the contemporaneous setting, 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 the 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). Furthermore, based on country group analysis, it could be inferred that the strong influence of macro uncertainties in inducing firms' failure is observed mainly for firms from developed countries. One explanation can be offered for this finding is that capital markets in developed countries are relatively efficient. This condition causes transmission of macro uncertainties to resource firms' financial condition becomes more straightforward.

4.4 Performance and Conditional Capital Surplus/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 recent 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 7–9.

Table 7 presents results with $CONCAP^{M+}$ and $CONCAP^{M-}$ among independent variables. The dependent variable is $RTRN$, which is the annual growth of market capitalisation of each firm.

Table 8: Performance Analysis - $CONCAP^C$

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

Variable	Full Sample	Renewable	Non-Renewable	Alternative Energy	Forestry and Paper	Mining	Oil and Gas
$CONCAP^{C+}_{i,t-1}$	-0.2642*	-0.0108	-0.6261***	-0.037	0.8614	-0.7215***	-0.0684
$CONCAP^{C-}_{i,t-1}$	3.2697***	3.0249***	3.2319***	5.2966***	1.8309***	3.6557***	2.3358***
$SALES_{i,t-1}$	-0.0949**	0.0063	-0.1121**	-0.0323	0.135	-0.1820**	0.0147
$DEBT_{i,t-1}$	-0.4452**	-0.2378	-0.5646**	-0.7551	0.6792	-0.8400***	0.1706
$SIZE_{i,t-1}$	-0.6384***	-0.5328***	-0.6456***	-0.5992***	-0.4815***	-0.6780***	-0.5587***
$RETURN_{i,t-1}$	0.0016**	-0.0008	0.0018**	-0.0024*	0.001	0.0030*	0.0005
$\sigma COMM_{i,t-1}$	0.0938***	0.0359	0.1044***	0.006	0.0206	0.1391***	0.1058**
$GEPU_{i,t-1}$	-0.1837***	-0.0261	-0.2224***	-0.4485*	0.0848	-0.2406***	-0.0254
$GPR_{i,t-1}$	0.0970***	0.1672***	0.0748**	0.2384*	0.1525***	0.0698	0.0289
$WGDP_{i,t-1}$	-0.0221*	-0.0610***	-0.0074	-0.0524	-0.0740***	0.0229	-0.0363
$HGDP_{i,t-1}$	-0.0702***	0.0273**	-0.1008***	0.0073	0.0318***	-0.1434***	-0.0344**
$INFL_{i,t-1}$	-0.0074	-0.0068	-0.0067	0.0679*	-0.0125*	-0.0496***	0.0185
$CONS$	8.1784***	6.7369***	8.3799***	8.8199***	5.6479***	8.5653***	6.8286***
OBS	27,383	4,460	22,923	1,506	2,954	16,103	6,820
R^2	0.1544	0.1217	0.1615	0.1370	0.1286	0.1718	0.1486
LL	-50400	-6910	-43100	-2660	-4050	-30900	-12000

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10%.

Table 9: Performance Analysis by Country Group

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

Variable	$CONCAP^M$			$CONCAP^C$		
	Developed	Emerging	Frontier	Developed	Emerging	Frontier
$CONCAP^+_{i,t-1}$	-0.2325*	-1.5704***	1.0686	-0.2447*	-1.1144**	0.12
$CONCAP^-_{i,t-1}$	3.0207***	3.0668***	1.6621**	3.3231***	3.1279***	1.6576**
$SALES_{i,t-1}$	-0.1316***	-0.081	0.1474	-0.1326***	-0.0666	0.1477
$DEBT_{i,t-1}$	-0.2114	-0.9479**	0.6526	-0.3581	-0.8755*	0.5269
$SIZE_{i,t-1}$	-0.6826***	-0.4600***	-0.3046***	-0.6749***	-0.4488***	-0.2670***
$RETURN_{i,t-1}$	0.0019**	-0.003	-0.0302	0.0018**	-0.0031	-0.0255
$\sigma COMM_{i,t-1}$	0.0882***	0.1656***	-0.0579	0.0832***	0.1633***	-0.0402
$GEPU_{i,t-1}$	-0.2093***	0.11	-0.0813	-0.2239***	0.1055	-0.0487
$GPR_{i,t-1}$	0.0657*	0.1716***	-0.0453	0.0629*	0.1831***	-0.0626
$WGDP_{i,t-1}$	0.0498***	-0.1051***	-0.0460***	0.0490***	-0.1013***	-0.0461***
$HGDP_{i,t-1}$	-0.1499***	0.0613***	0.0085	-0.1490***	0.0581***	0.0057
$INFL_{i,t-1}$	-0.0298**	0.0197*	0.0073	-0.0295**	0.0195*	0.0063
$CONS$	8.3254***	5.5077***	5.4287***	8.3753***	5.3288***	4.7510***
OBS	22,540	4,337	502	22,540	4,340	503
R^2	0.1624	0.1549	0.1791	0.1642	0.1542	0.1749
LL	-42400	-6900	-491	-42400	-6910	-495

Note: The significance level is shown by ***, **, *, to denote respectively 1%, 5%, and 10%.

The results show that $CONCAP^{M+}$ is significant for the full sample and non-renewable 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 with positive signs, suggesting 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 a 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 returns.

The estimation results for $CONCAP^{C+}$ and $CONCAP^{C-}$ are listed in Table 8. In general, the results resemble Table 7. $CONCAP^{C+}$ 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.

Table 9 lists results from country group estimations. $CONCAP^{+}$ is significantly negative for developed and emerging groups. $CONCAP^{-}$ is strongly positive for all panels. These two variables are the main focus of the estimations, and these findings confirm the robustness of the relationship between conditional capital surplus/shortfall toward firms' future market performance. Other firm-level variables are in general significant with consistent results compared to sector-based analysis.

Furthermore, the results presented in Tables 7–9 suggest the strong influence of macro variables toward firms' future market performance, especially for non-renewable related sectors and developed and emerging country groups. Although these variables only serve as controls in this analysis, the findings strongly confirm the vital role of macro uncertainties, both economic and non-economic, on resource firms' financial condition.

The estimation results from this analysis provide two critical insights. First, a risk-return trade-off exists, as proven by the strong 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 consistent with 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 are 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. Analyses are also conducted by the country groups (developed, emerging, and frontier) to further examine the heterogeneity of the results between countries.

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 the conditional capital surplus/shortfalls of 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 tend to experience a conditional capital shortfall. These patterns are not unexpected, as can be explained by the pattern of $LIAB$ 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. Results from the country group analysis show that these findings are valid mainly for firms from developed countries, whose observations dominate the dataset used in this study. Some pattern variations are detected from emerging and frontier countries, where $LIAB$ stays relatively high, and $CONCAP$ generally is around zero for emerging countries and negative for frontier countries.

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 conditional capital shortfalls toward the world (home country) business cycle. Results from country group analysis show consistent and robust results aligned with the sector-based analysis.

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 the business cycle, the lagged $WGDP$ generally has a positive influence on firms' failure, indicating the risk built-up process, especially during the boom phase. $HGDP$ generally negatively influences firms' failure, supporting the theoretical model by Adrian and Shin (2014) which outline the negative relationship between the business cycle and default probability. Results from country group analysis show the strong influence of macro uncertainties, mainly for firms from developed countries.

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. Results from country group analysis show a consistent and robust pattern supporting results from the sector-based analysis.

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A Appendix

Table 10: List of Countries by Classification

Developed	Emerging	Frontier
Australia	Argentina	Bahrain
Austria	Brazil	Bangladesh
Belgium	Chile	Botswana
Canada	China	Bulgaria
Denmark	Egypt	Croatia
Finland	Ghana	Jordan
France	Hungary	Kazakhstan
Germany	India	Kenya
Hong Kong	Indonesia	Lithuania
Ireland	Malaysia	Morocco
Israel	Mexico	Nigeria
Italy	Pakistan	Romania
Japan	Peru	Slovenia
Netherlands	Philippines	Sri Lanka
New Zealand	Poland	Tunisia
Norway	Russia	Ukraine
Portugal	South Africa	Vietnam
Singapore	Taiwan	
Spain	Thailand	
Sweden	Turkey	
Switzerland	United Arab Emirates	
United Kingdom		
United States		

Note: Country classification follows MSCI.

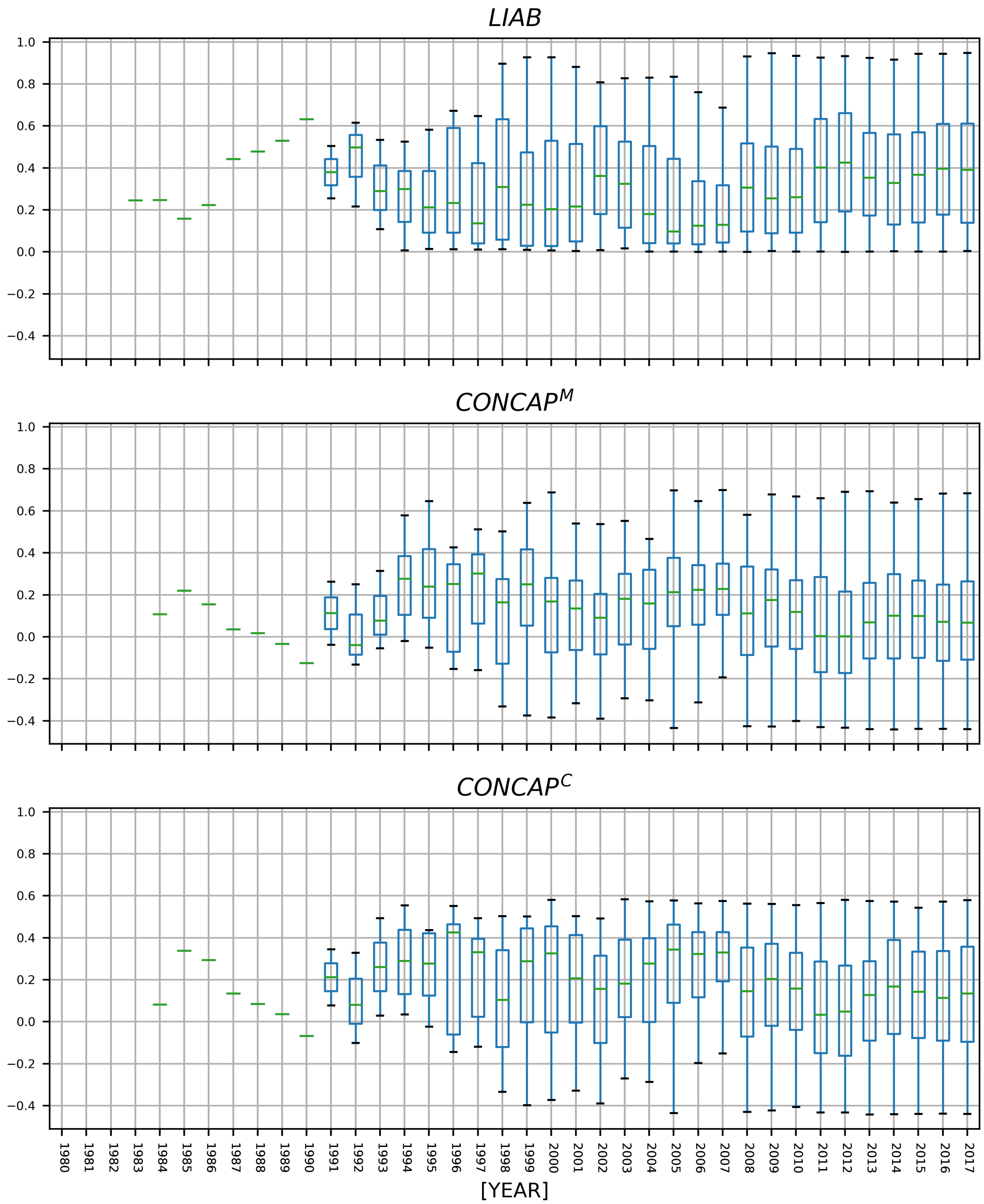

Figure 11: Distribution of LIAB, CSRISK, and MSRISK by Year - Alternative Energy

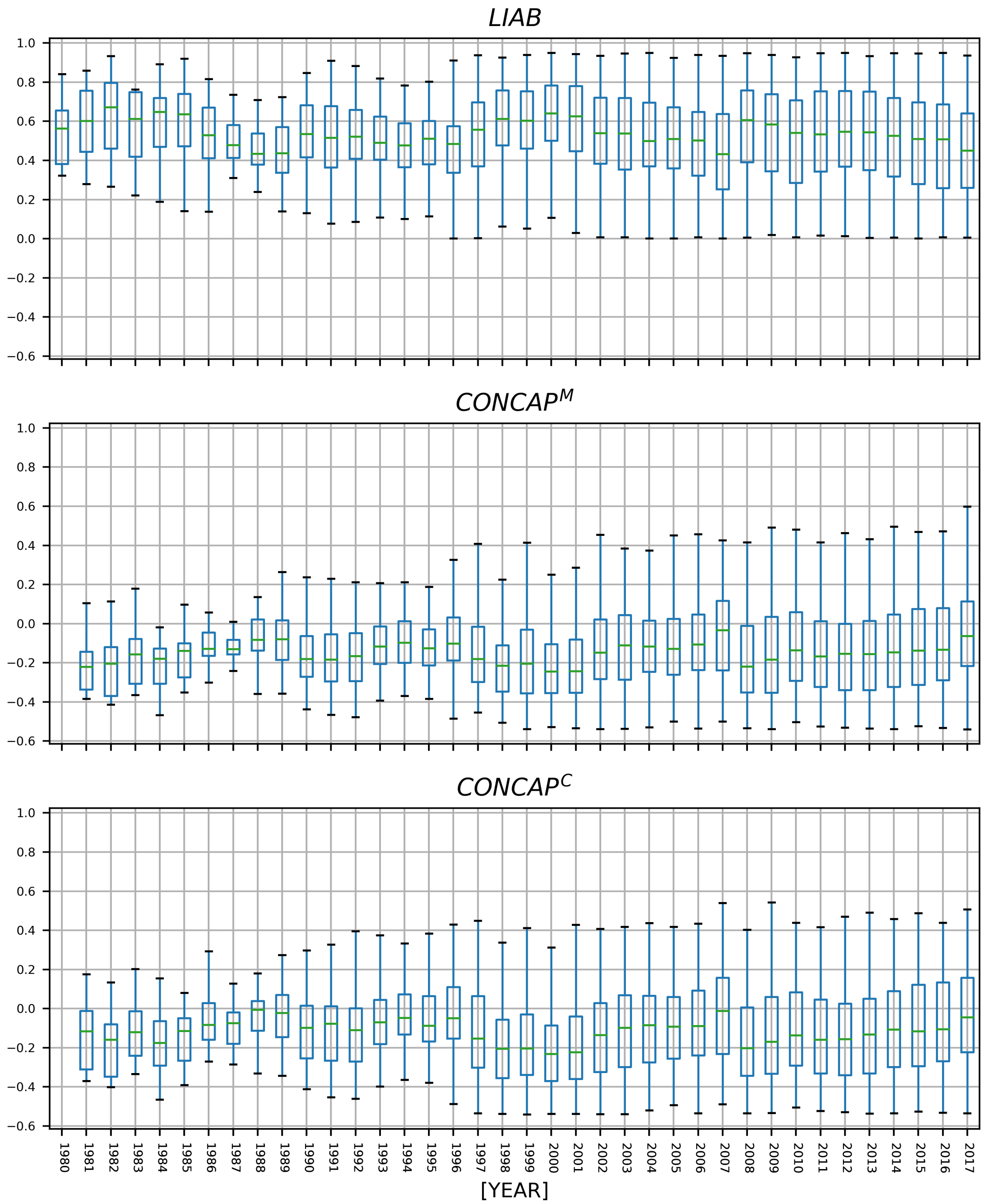

Figure 12: Distribution of LIAB, CSRISK, and MSRISK by Year - Forestry and Paper

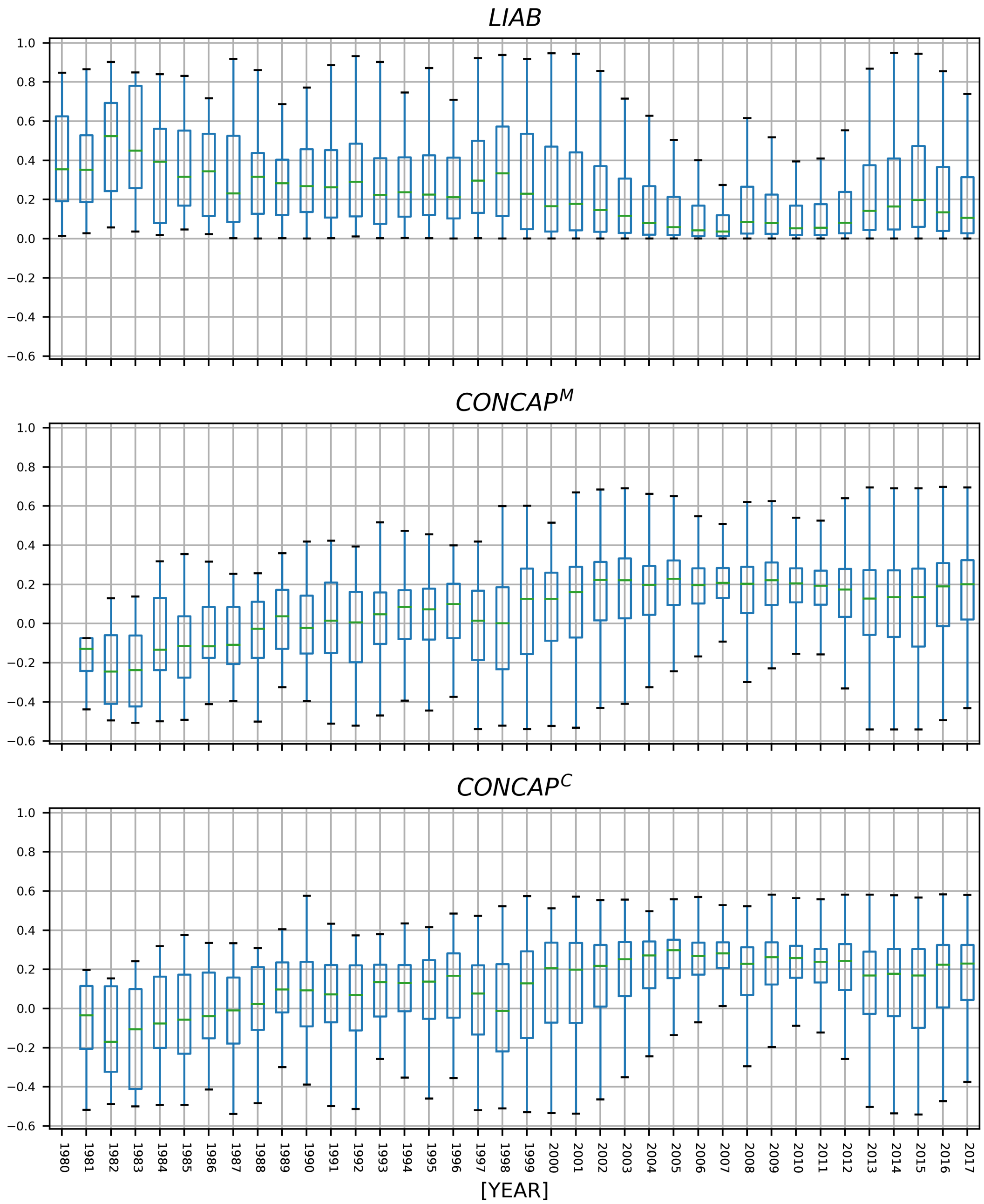

Figure 13: Distribution of LIAB, CSRISK, and MSRISK by Year - Mining

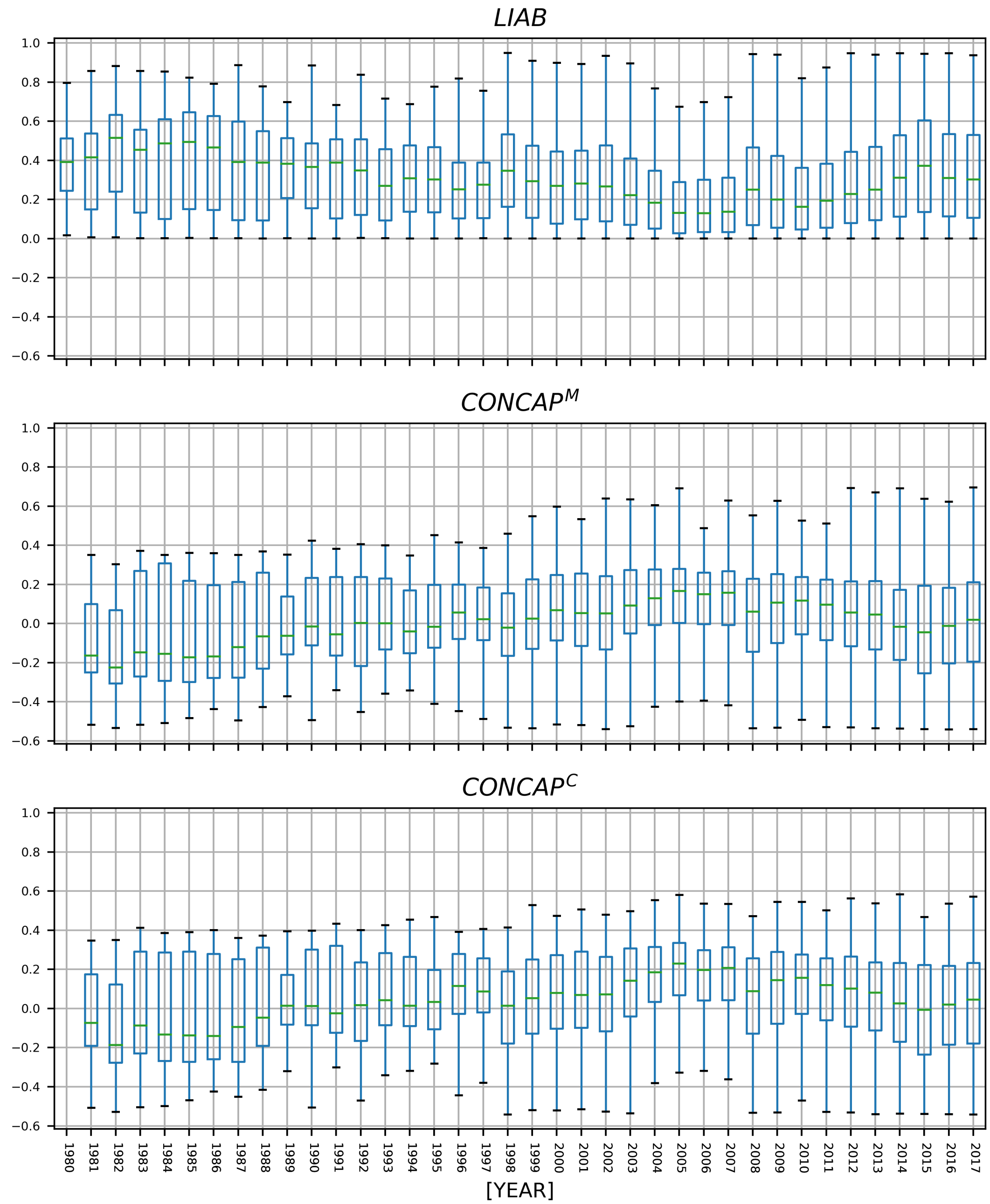

Figure 14: Distribution of LIAB, CSRISK, and MSRISK by Year - Oil and Gas Producers