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The Information Effect of Sovereign Credit Ratings

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A B S T R A C T

This paper examines the quality of sovereign credit ratings of the Big Three rating agencies, including S&P, Moody's and Fitch and checks whether the information effect of sovereign credit ratings has improved after ESMA's regulatory reforms and increased competition. When considering the whole sample, the results show sovereign ratings of Big Three rating agencies can explain default probability and default amounts and bond yield spreads. However, the information effect of sovereign ratings of Big Three rating agencies does not change after regulatory reforms and increased competition from non-Big Three rating agencies. Second, when considering high-income countries sample, part of the results shows the information effect of sovereign ratings of Big Three rating agencies worsens after regulatory reforms and when facing the competition from non-Big Three rating agencies. Third, there is no significant information effect in middle-income countries. Our results echo some recent reports from the European Union, which found that the quality of credit ratings has not significantly improved following various reform measures and increased competition among credit rating agencies (ESMA, 2021; Karimov et al., 2024).

Keywords: sovereign credit rating; regulatory reform; competition; information effect
JEL Classification: G15; G21

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1. Introduction

Although credit ratings play a vital role in financial markets and the literature on credit ratings is voluminous, research which specifically investigates ratings quality is limited. Rating quality is important for international financial stability, because ratings are strongly embedded in many banking and investment regulations and therefore affect the welfare of both borrowers and investors (Bae et al., 2015). The quality of ratings rests on their ability to communicate information to market participants by maintaining a stable meaning of risk classification. Low quality ratings might harm the information diffusion of ratings unless all market participants are well informed. If investors are not able to extract reliable information from ratings, this lessens their value and reduces the benefits for the financial system (Bolton et al., 2012). Additionally, low quality ratings complicate regulations and make contracting with ratings more difficult. Finally, ratings quality is at the center of the policy agenda because it is closely related to banking regulation (capital adequacy requirements in particular).

Prompted by the increased demand for external borrowing by central governments, the sovereign rating market has grown sharply over the past two decades. As investment portfolios have become increasingly diversified across national boundaries, an understanding and assessment of sovereign credit risk has become increasingly important. The quality of sovereign ratings is highly important for practitioners and governments alike. Sovereign ratings reflect a country's willingness and ability to pay its obligations (Baum, Schafer, and Stephan, 2016; Cai, Kim, and Wu, 2019). They directly affect a country's cost of borrowing and foreign direct investment flows (Cai, Kim, and Wu, 2019), and indirectly affect the cost of firms' credit via the sovereign ceiling on bank and corporate ratings (Almeida, Ferreira, and Restrepo, 2017; Arezki, Candelon, and Sy, 2011; Borensztein, Cowan, and Valenzuela, 2013; Chen, Chen, Chang, and Yang, 2016; Huang and Shen, 2015).

During the financial crisis of 2008~2009, credit ratings have been accused as an inaccurate, coarse, and delayed indicator. Recently, there have been complaints from governments about the rating agencies exacerbating market panic during crisis times with excessive downgrades on sovereign ratings and changes in rating agencies regulation are in progress around the world.[4] They complained that the Standard & Poor's, Moody's, and Fitch Ratings were too slow to alert investors to the likely demise of Lehman Brothers in 2008. During the subsequent euro area debt crisis, certain countries were faced with abrupt bond sell-offs and higher borrowing costs following a downgrade of their credit ratings.

For the last decades, the list of critical arguments against the rating agencies has been lengthening. The most common accusations were lack of transparency, potential conflict of interest, low quality of ratings, pro-cyclical behaviour, unreliable methodology, promoting neoliberalism as the only alternative for political economy, etc.

In response, the European Commission made proposals to strengthen the regulatory and supervisory framework for rating agencies in the European Union (EU), to restore market confidence and increase investor protection. The new EU rules were introduced in three consecutive steps. The first set of rules, which entered into force at the end of 2009, established a regulatory framework for rating agencies and introduced a regulatory oversight regime, whereby rating agencies had to be registered and were supervised by national competent authorities. In addition, rating agencies were required to avoid conflicts of interest, and to have sound rating methodologies and transparent rating activities. In 2011, these rules were amended to take into account the creation of the European Securities and Markets Authority (ESMA), which supervised rating agencies registered in the EU. A further amendment was made in 2013 to reinforce the rules and address weaknesses related to sovereign debt credit ratings

In this paper, first, we want to examine the quality of sovereign credit ratings, one of the most

[1] In May 2010, after the downgrades of Greece, Spain, and Portugal's sovereign ratings, European leaders including President of the European Commission José Manuel Barroso, France's President Nicolas Sarkozy, and German's Chancellor Angela Merkel complained that the Standard & Poor's, Moody's, and Fitch Ratings were too slow to alert investors to the likely demise of Lehman Brothers in 2008.

common accusations to rating agencies. We include sovereign ratings of the Big Three rating agencies, i.e., Standard & Poor's (S&P), Moody's Investors Service (Moody's) and Fitch Ratings (Fitch), spans from 2000 to 2020. Empirically, we focus on the ability of ratings to transmit information to investors. In other words, we will check whether sovereign ratings can predict future defaults and correlate with current bond prices.

Second, this paper will investigate the effect of regulation reforms on sovereign rating quality. In the European Union, the financial crisis was followed by the deep sovereign debt crisis, so legislators and public opinion were more concerned about public finance sector. New rules were introduced in 2009 and subsequently revised in 2011 and 2013, after a series of sovereign ratings' downgrades. In 2012, the European Securities and Markets Authority (ESMA) introduced new regulations, stipulating that credit ratings must be accompanied by identifiers distinguishing between ratings issued by analysts within the EU, versus those issued in countries that qualify as endorsed jurisdictions. For the ratings to be classed as endorsed, the analyst must be located in a jurisdiction which has a comparably stringent regulatory regime to that of the EU (EC, 2011). Further, only ratings accompanied by these identifiers can be used for regulatory purposes after April 2012. This paper tries to investigate whether the new regulatory reform affects the sovereign rating quality.

Third, we investigate the effect of competition on sovereign rating quality. We try to examine whether the rating quality has changed when rating agencies face competition. Sovereign ratings category stands for 11% of revenue related to issuing ratings, which is more than 100,000,000 euro annually (EC, 2016). After the European debt crisis, the European Commission hopes to establish its own rating agency or a public rating agency. In fact, there are some rating agencies also publish sovereign ratings, including Dominion Bond Rating Services (DBRS), Scope Euro Rating Services (Scope), Japan Credit Rating Agency (JCR), Rating and Investment Information (R&I), and Dagong Global (Dagong). Amstad and Packer (2015) indicate the ratings of non-major agencies tend to correspond less with those of the major agencies. They find the rank order correlations of each of the non-major agencies with the average ratings of the Big Three are much lower than, for example, the rank-order correlation between Moody's and S&P. This paper tries to investigate whether the rating quality has changed when Big Three rating agencies face the competition from non-Big Three rating agencies. Prior literature mainly used non-sovereign ratings as sample and by considering the entry of a regulated rating agency and the corresponding effect of increased competition on the rest of the rating agencies industry (Bolton et al., 2012; Dimitrov et al., 2015; Flynn and Ghent, 2018; Behr et al., 2018). This paper uses sovereign ratings as sample and investigate whether rating quality can be improved when there are multiple agencies assign ratings to a sovereign.

Fourth, we discuss whether the sovereign rating quality differs in advanced and emerging countries. Rating studies have found that agencies apply different standards to issuers, depending on their country's development level (Cantor and Falkenstein 2001; Poon 2003; Vives 2006). Furthermore, the literature investigates the effect of the financial crisis on advanced and emerging market countries and sequentially obtains mixed results. Thus, the sovereign rating quality may also be affected by national income.

Prior literatures examine the determinants of sovereign credit ratings (Hu et al., 2002; Alexe et al., 2003; Bissoondoyal-Bheenick et al., 2005; Bennell et al., 2006; Afonso et al., 2012), the phenomena and determinants of split sovereign credit ratings (Cantor and Packer, 1996; Alsakka and ap Gwilym, 2013; Hill, Brooks and Faff, 2010; Vu, Alsakka and ap Gwilym, 2018). Some Literature indicated that sovereign ratings tend to be home bias (Özturk, 2014; Fuchs and Gehring, 2017; Yalta and Yalta, 2018). Some literature examines whether sovereign ratings of Big Three ratings agencies can explain government bond yield spread (Sy, 2004; Afonso et al., 2012; Gande and Parsley, 2005; Ferreira and Gama, 2007; Williams et al., 2013; Kim and Wu, 2011; Christopher et al., 2012).

Different with prior literature, this paper tries to investigate the quality of sovereign ratings of Big Three rating agencies and whether the quality of sovereign ratings has changed considering the ESMA's regulatory reforms and increased competition. Both American and European regulations were aimed at limiting the oligopolistic dominance of the "Big Three" in the credit rating market. They have been in a force for a few years now, so some conclusions can be already drawn and first assessment of their effectiveness can be done.

When considering the whole sample, the results show sovereign ratings of Big Three rating agencies can explain default probability and default amounts and bond yield spreads. However, the information effect of sovereign ratings of Big Three rating agencies does not change after regulatory reforms and increased competition from non-Big Three rating agencies. Second, when considering high-income countries sample, part of the results shows the information effect of sovereign ratings of Big Three rating agencies worsens after regulatory reforms and when facing the competition from non-Big Three rating agencies. Third, there is no significant information effect in middle-income countries. Our results echo some recent reports from the European Union, which found that the quality of credit ratings has not significantly improved following various reform measures and increased competition among credit rating agencies (ESMA, 2021; Karimov et al., 2024).

This paper tries to have some contributions to the academic literatures. First, this plan uses new sovereign defaults database to examine the rating quality, i.e., the database on government debt in default developed by the Credit Rating Assessment Group (CRAG) of the Bank of Canada. There is no literature uses this CRAG database to investigate the sovereign rating quality. [2] The database draws on previously published datasets compiled by various public and private sector sources. It combines elements of these, together with new information, to develop comprehensive estimates of stocks of government obligations in default. These include bonds and other marketable securities as well as bank loans and official loans, valued in US dollars, for the years 1960 to 2020 on both a country-by-country and a global basis. Previous studies identify a sovereign debt crisis when a country fails to meet its principals or interest payments on the due date, or when the country postpones its obligations by rescheduling debts with less favourable terms (De Bonis et al., 1999; Detragiache and Spilimbergo, 2001; Reinhart and Rogoff, 2014). However, due to the lack of data on worldwide sovereign defaults, existing studies face three problems. First, most studies have examined sovereign debt crises in a limited group of countries (De Bonis et al., 1999; Phillips & Shi, 2019). Second, some studies only focus on external debt crises or domestic debt crises (Balteanu and Erce, 2018; Detragiache and Spilimbergo, 2001; Ishihara, 2005). Third, most studies rely on a few sources of sovereign defaults, which undermines the real size of sovereign defaults and, consequently, provides false identifications of sovereign debt crises (Laeven and Valencia, 2013, 2020; Manasse and Roubini, 2009). Previous studies use CRAG database to investigate the role of IMF-supported programs in mitigating the likelihood of sovereign default (Balima and Sy, 2021)[3] and assess the role of the political environment in the timing of financial crises (Nguyen, Castro and Wood, 2020)[4].

Second, we include eight rating agencies to completely investigate the sovereign rating market and prior literature focuses on sovereign ratings of Big Three rating agencies. Prior literature uses multiple rating agencies to examine whether existing home bias of sovereign ratings (Özturk, 2014; Fuchs and Gehring, 2017; Yalta and Yalta, 2018) and this paper focuses on the sovereign rating quality.

[2] Reinhart (2002) examine the linkages between crises, default, and rating changes for anywhere between 46 to 62 countries. The results suggest that sovereign credit ratings systematically fail to anticipate currency crises-but do considerably better predicting defaults. Downgrades usually follow the currency crisis-possibly highlighting how currency instability increases default risk.

[3] Balima and Sy (2021) studies the role of IMF-supported programs in mitigating the likelihood of subsequent sovereign defaults in borrowing countries. Using a panel of 106 developing countries from 1970 to 2016 and an entropy balancing methodology, they find that IMF-supported programs significantly reduce the likelihood of subsequent sovereign defaults.

[4] Nguyen, Castro and Wood (2020) use the sovereign defaults database of the CRAG. They assess the role of the political environment in the timing of financial crises over a sample of 85 countries during the period 1975–2017. They consider systemic banking, currency and sovereign debt crises in addition to twin and triple crises. The results show time in office of incumbent chief executives reduces the likelihood of any type of financial crises. The incidence of twin and triple crises is lower when majority governments are in office.

Third, prior literature examines whether sovereign ratings of Big Three ratings agencies can explain government bond yield spread (Sy, 2004; Afonso et al., 2012; Gande and Parsley, 2005; Ferreira and Gama, 2007; Williams et al., 2013; Kim and Wu, 2011; Christopher et al., 2012). This paper checks whether the information effect has changed considering ESMA's regulatory reforms and increased competition. Besides, this paper considers sovereign defaults and bond yield spreads to measure the information effects of sovereign ratings.

The remainder of the current paper is organized into seven sections. Following the introduction, Section 2 describes the institutional background and regulatory reforms. Section 3 outlines the literature review. Section 4 presents the econometric model. Section 5 focuses on the data resources and the descriptive statistical analysis. This section also indicates the empirical results of the investigation. Section 6 concludes the paper.

2. Institutional background and regulatory reforms

2.1 Institutional background

Credit rating agencies are private companies that assess the default risk of bonds of all types. There are about 150 agencies operating in the rating business worldwide (White 2010; De Haan and Amtenbrink 2011). Of these, most agencies are active in a narrow national or regional market and focus solely on corporate ratings. Only a small number of agencies issue sovereign ratings. We are able to identify eight agencies that provide sovereign ratings for at least 25 sovereigns: Standard & Poor's (S&P), Moody's Investors Service (Moody's), Fitch Ratings (Fitch), Dominion Bond Rating Services (DBRS), Scope Euro Rating Services (Scope), Japan Credit Rating Agency (JCR), Rating and Investment Information (R&I) and Dagong Global (Dagong). These eight agencies are based in five countries and the company information is as shown in the Table below.

Big-Three and Non-Big-Three rating agencies

Agency	Short name	HQ locations	Founded	Sovereign ratings since	Registered in
Standard and Poor's	S&P	New York City, USA	1922	1922	EU, Japan, USA
Moody's Investors Service	Moody's	New York City, USA	1918	1918	EU, Japan, USA
Fitch Ratings	Fitch	New York City, USA; London, UK	1994	1994	EU, Japan, USA
Domninion Bond Rating Services	DBRS	Toronto, Canada	1998	1998	EU, USA
Scope Ratings	Scope	Berlin, Germany	1999	1999	EU
Japan Credit Rating Agency	JCR	Tokyo, Japan	1998	1998	EU, Japan, USA
Rating and Investment Information, Inc.	R&I	Tokyo, Japan	1998	1998	Japan
Dagong Global Credit Rating Co.	Dagong	Beijing, China	1994	2010	EU, China

2.2 Regulatory reforms

The most effective way of fighting oligopoly is to reduce barriers of entry.[5] The recent crises exposed all weaknesses related to the rating agencies position in the financial system and made clear that system-wide reforms were needed. In the US, it led to the introduction of Dodd-Frank Act Wall Street Reform and Consumer Protection Act in 2010, which brought significant changes to the financial services industry. Improvements to the regulations of credit rating agencies were among them. In 2017, there were 10 rating agencies registered as NRSROs in the US, eight of them were US-based, one from Mexico and one from Japan.

[5] In the US, an important barrier was removed in 2006, when the list of requirements for NRSRO designation was finally introduced. Further reforms – the Dodd-Frank Act and CRA3 in the EU – reduced any reference to the NRSRO or any other specific agencies and encouraged internal credit assessment. The main goal was to let other competitors to gain market share and reduce dominance of the "Big Three".

In the EU, the financial crisis was followed by the deep sovereign debt crisis, so legislators and public opinion were more concerned about public finance sector. New rules were introduced in 2009 and subsequently revised in 2011 and 2013, after a series of sovereign ratings' downgrades (Bayar, 2014). In Europe, only ESMA-accredited rating agencies can issue ratings. The supervisor, ESMA, is the guardian of the Regulation Framework and in particular Regulation (EC) 1060/2009 of the European Parliament and of the Council of 16 September 2009 on Credit Rating Agencies.

EU credit rating agency regulatory initiatives aim at reducing conflicts of interest, overreliance on ratings and spillover effects, while increasing independence and soundness of rating processes and improving quality of rating methodologies and ratings (ECB, 2012). When assessing the equivalence of non-EU countries, the rules incorporate all provisions of the EU credit rating agency Regulation. The equivalence in quality of ratings and methodologies (supported by the identifiers) should help to protect financial market stability. High quality ratings lead to improved efficiency of capital markets and improve transparency and competition (ESMA, 2011b). ESMA believe that endorsing ratings from non-EU countries enables supervisory integration of the rating agencies. Greater co-operation between outside supervisors benefits the functioning of financial markets and protects investors in the EU (ESMA, 2011a). According to the EC, a rating agency operating in a non-EU country needs to conform to the EU level of supervisory expectations. The usage of rating identifiers differentiates between ratings assigned inside/outside the EU. The regulators try to ensure that, in the current framework, "users of ratings in the EU would benefit from equivalent protections in terms of a credit rating agency's integrity, transparency, good governance and reliability" (ESMA, 2017a).

All ratings for EU registered and authorised rating agencies will be published on the central European Rating Platform which will improve the visibility and comparability of credit ratings from debt instruments. The Platform will also contribute to the visibility of small and medium-sized credit rating agencies operating in the EU

3. Literature reviews

3.1 The split and bias of sovereign ratings

Prior literature investigates the determinants of sovereign ratings (Hu et al., 2002; Alexe et al., 2003; Bissoondoyal-Bheenick et al., 2005; Bennell et al., 2006; Afonso et al., 2011) and whether existing the phenomenon of split sovereign ratings and the determinants of split sovereign ratings (Cantor and Packer, 1996; Alsakka and ap Gwilym, 2012; Hill, Brooks and Faff, 2010; Vu, Alsakka and ap Gwilym, 2018; Alsakka and ap Gwilym, 2010). However, they do not examine the sovereign rating quality and which rating agency has better sovereign rating quality.

For example, Cantor and Packer (1996) emphasize the prevalence of split sovereign ratings, but they do not investigate the causes. Alsakka and ap Gwilym (2012) examine some possible causes of split sovereign ratings and use emerging markets sample. They find that rating agencies use different quantitative factors and place different weights on these factors. Hill, Brooks and Faff (2010) find that rating agencies disagree more often than they agree about the rating of a sovereign obligor, however, disagreement tends to be within one or two notches on the finer scale. They find considerable divergence of opinion in respect of ratings at the time of documented sovereign defaults.

The second strand suggest that sovereign ratings are bias toward the home country of rating agencies.[6] For example, Fuchs and Gehring (2017) empirically investigate if
there is systematic evidence for a home bias in sovereign ratings. They conclude that rating agencies assign higher ratings not only to their respective home countries but also to those countries that are economically, geopolitically and culturally aligned with them. Yalta and Yalta (2018) investigate claims of regional bias in the sovereign ratings given by the rating agencies Fitch, Moody's and S&P's by considering 99 countries categorized into eight regions plus the United States. Empirical results indicate a strong home country bias towards the United States, while there seem to be no special

[6] The European Commission President (Reuters, 2011), the Russian Finance Minister (The Telegraph, 2015), the Chinese Finance Minister (Bloomberg, 2016), the Turkish President (Reuters, 2016) and India's chief economic advisor (The Times of India, 2017) have all alleged that the rating agencies were biased against their home countries.

biases against individual groups of countries. On the other hand, Özturk (2014) argues that the apparently biased behavior of rating agencies can be attributable to ignorance of institutional factors in the empirical analyses, suggesting that improved quality of institutions would greatly stimulate higher credit ratings. By contrast, Amstad and Packer (2015) compare sovereign credit ratings before and after the global financial crisis and do not find support for bias against emerging market economies.

3.2 Effects of regulation and competition on rating quality

Most previous studies assessing the impact of regulatory initiatives on the quality of ratings focus on US regulations. Also, the existing empirical evidence on the effects of regulation on rating agencies considers non-sovereign ratings and takes the perspective of changing competition between rating agencies. This plan uses sovereign ratings and consider the ESMA's regulatory reforms since the European debt crisis is highly related with sovereign credit ratings.

Prior studies assessing the impact of regulatory initiatives on the quality of ratings focus on US regulations (see Behr et al., 2018; Bongaerts, Cremers, and Goetzmann, 2012; Dimitrov et al., 2015; Doherty, Kartasheva, and Phillips, 2012). In addition, most prior research addresses time periods before the EU regulatory regime was introduced. For instance, Behr et al. (2018) use a data sample between 1973 and 1982, Bongaerts et al. (2012) utilize a sample for 2002 to 2008, and Doherty et al.'s (2012) sample is from 1989 to 2000. Becker and Milbourn (2011) apply a sample from 1995 to 2006 whereas Kisgen and Strahan (2010) use the period between 2001 and 2005.

The existing empirical evidence on the effects of regulation on rating agencies considers non-sovereign ratings and takes the perspective of changing competition between rating agencies (Bae et al., 2015; Behr et al., 2018). Bolton et al. (2012) and Dimitrov et al. (2015) suggest that the overall quality of ratings drops with increased competition. Bolton et al. (2012) conclude that increased competition between rating agencies might lead to increased rating shopping and a consequent reduced wealth effect. Studying the entry of new rating agencies into structured ratings, Flynn and Ghent (2018) find that entrant rating agencies issue higher ratings than the incumbent firms, a strategy used to win business. This results in rating shopping on the part of issuers. In contrast, Doherty et al. (2012) study insurance ratings and find that the new entrant rating agencies chooses higher standards than the incumbent companies. They conclude that increased competition results in improved precision of default rate estimates. Similarly, Bae et al. (2015) cast doubt on the view that competition leads to inflated ratings in the corporate bond market.

Using a global dataset of sovereign ratings assigned by S&P, Moody's, Fitch and DBRS during 2000-2016, Vu, Alsakka, ap Gwilym (2018) find that S&P and Moody's inflate (deflate) their ratings in response to the increase in Fitch's (DBRS's) market share in the previous year. DBRS employs a generous rating policy to succeed in this market. Imposing a regulatory pressure on rating agencies weakens their motivation to inflate ratings to win market shares.

3.3 The information effect of sovereign credit ratings

Rating signals are treated as events which trigger responses from market participants. Prior literature examines whether sovereign ratings of Big Three ratings agencies can explain government bond yield spread. This plan checks whether the information effect has changed considering ESMA's regulatory reforms and increased competition and we consider sovereign defaults and bond yield spreads to measure the information effects of sovereign ratings.

Sovereign credit signals have an effect on various asset classes including credit derivatives, bonds, equity and foreign exchange. Many studies detect significant market reactions to negative signals, while the reactions to positive signals are either muted or negligible (e.g. Sy, 2004; Afonso et al., 2012). The information value of rating agencies' credit opinions is significant even after controlling for sovereign credit spreads and country fundamentals (Cavallo et al., 2013). In addition, the effect of sovereign rating events is transferred from country to country due to strengthening global market linkages (Gande and Parsley, 2005; Ferreira and Gama, 2007), as well as from sovereign issuers to sub-sovereign issuers due to the sovereign ceiling effect (Williams et al., 2013). Sovereign credit signals also affect the international bank flows to emerging countries and the stock and bond market correlations with their respective regional markets (Kim and Wu, 2011; Christopher et al., 2012).

The empirical results also suggested that the relative importance of capital market in terms of price discovery can vary substantially across entities. Cantor and Parker (1996) found that ratings changes give impact on bond return (yield) follow by Kaminsky and Schmukler (2002) that supported sovereign rating announcements have relationship with bond market returns. Pukthuanthong-Le et al. (2007) studies the relationship of sovereign rating changes and return of stock and bond market. They indicate that downgrades of ratings give negative impact on both bond and stock market, whereas positive returns only occur in bond market when there are upgrades announcements. Additionally, authors identified that downgrades of sovereign rating showed significant negative impact in countries which are high inflation and low current account.

4. Econometric model

This paper tries to investigate the sovereign rating quality of Big Three rating agencies and whether the sovereign rating quality has improved considering regulatory reforms and competition.

4.1 The sovereign rating quality

First, we investigate the sovereign rating quality of Big Three rating agencies. Following the empirical literature, the quality of ratings is captured by the information content of ratings (Bae et al., 2015; Becker and Milbourn, 2011; Behr et al., 2018; Dimitrov et al., 2015). The quality is examined by testing whether the market is more aligned with ratings through default prediction and bond yields.

4.1.1 Using defaults as the dependent variables

The dependent variable is the occurrence of a sovereign debt crisis. This variable is taken from the database on government debt in default developed by the Credit Rating Assessment Group (CRAG) of the Bank of Canada. Since 2014, the Bank of Canada has maintained a comprehensive database of sovereign defaults to systematically measure and aggregate the nominal value of the different types of sovereign government debt in default. The database draws on previously published datasets compiled by various public and private sector sources. It combines elements of these, together with new information, to develop comprehensive estimates of stocks of government obligations in default. These include bonds and other marketable securities as well as bank loans and official loans, valued in US dollars, for the years 1960 to 2020 on both a country-by-country and a global basis.

We include two default (*DEFAULT*) measures. First, consistent with previous literature on sovereign defaults (Reinhart and Rogoff, 2011; Cruces and Trebesch, 2013), a default (*Default*) is defined when a debt service is not paid on the due or within a specified grace period, or when payments are not made within the time frame specified under a guarantee or absent an outright payment default. However, given that the final resolution with creditors following a sovereign default can be very lengthy, we follow Reinhart and Rogoff (2011) and consider only the first year of default as a crisis year. Second, we also include the log of default amount of the country in that year (*LogAmount*) as the dependent variables.The default amount is obtained from CARG database. It combines elements of previously published data sets compiled by various public and private sector sources., together with new information, to develop estimates of stocks of government obligations in default, including bonds and other marketable securities, bank loans, and official loans in default, valued in US dollars. The model is specified as follows:

$$DEFAULT_{i,t+1} = \beta_0 + \beta_1 RATING_{Big3_{i,t}} + \beta_o Control\ Variables + \varepsilon_{i,t} \quad (1)$$

where subscripts *i* and *t* denote the default dummy variable in country *i* at time *t*. $RATING_{Big3}$ represents the average ratings assigned by Big Three rating agencies, including S&P, Moody's and Fitch. A larger rating indicates a better rating. If the coefficient of $RATING_{Big3}$ is negative and significant, suggesting that sovereign ratings of Big Three rating agencies can explain sovereign default and the better the sovereign ratings and the lower the default probability and lower default amounts.

Regarding the control variables, our baseline regressions include similar covariates as Jorra (2012). First, the macroeconomic variables are included. Real GDP growth (*GDPG*): Real GDP growth rate. External debt-to-GDP (*EDS/GNI*): Ratio of external debt stocks to GNI. Trade openness-to-GDP (*TRADE/GDP*): Sum of exports and imports of goods and services measured as a share of GDP. Current account balance-to-GDP: Sum of net exports of goods and services, net primary income, and net secondary income as a share of GDP. Inflation rate (*Inflation*): Annual percentage change of the consumer price index. Unemployment rate (Unemployment), Unemployment total (% of total labor force) (national estimate). Private credit-to-GDP (*DCPS/GDP*): Domestic credit to private sector as a share of GDP. Reserves-to-debts (Reserves/Debt): Ratio of total reserves minus gold to imports of goods and services (% of total external debt).

Besides, we include other country-specific control variables. *Rule of Law*: Rule of Law: Estimate. *LISTN*: Listed domestic companies, total. *INDV*: Industry (including construction), value added (current US$). *MC/GDP*: Market capitalization of listed domestic companies (% of GDP). *STV*: Stocks traded, total value (current US$). We also include year dummies (*YEAR*) and country dummies (*COUNTRY*) to control for the country and year fixed effects.

4.1.2 Using bond yield spreads as the dependent variables

Following Bae et al. (2015), Becker and Milbourn (2011) and Behr et al. (2018), we use the information content of ratings represented by linkages between ratings and bond yield spreads as a measure of rating quality. Bond yield spreads (*BSpread*), in basis points, are calculated by taking the difference between the yield to maturity of the sovereign bond subject to the rating and the yield to maturity of the comparable US benchmark bond. The selection criteria include publicly placed, unsecured, straight sovereign bonds with fixed coupon, remaining maturity between 1 and 30 years and issued in US dollars. We exclude structured notes, inflation-linked notes, hybrid or dual-currency bonds and restructured debt. Only bonds with the pricing information available are retained. We match each sovereign bond with the benchmark bond based on the closest remaining maturity and coupon amount. First, we measure government bond yield spread (*BSpread1*) by the differences between 10-year bond yield and three-month bond yield at the end of that year. Second, we measure government bond yield spread (*BSpread2*) by the differences between the average 10-year bond yields of that year and the average of three-month bond yields of that year. The model is specified as follow.

$$BSpread_{i,t+1} = \gamma_0 + \gamma_1 RATING_{Big3_{i,t}} + \gamma_o Control\ Variables + \varepsilon_{i,t} \quad (2)$$

If the coefficient of $RATING_{Big3}$ is negative and significant, suggesting that sovereign ratings of Big Three rating agencies can explain government bond yield spreads and the better the sovereign ratings and the lower the yield spreads, representing that investors ask for lower risk premium.

Regarding the control variables, our baseline regressions include similar covariates as Jorra (2012). First, the macroeconomic variables are included. Real GDP growth (*GDPG*): Real GDP growth rate. External debt-to-GDP (*EDS/GNI*): Ratio of external debt stocks to GNI. Trade openness-to-GDP (*TRADE/GDP*): Sum of exports and imports of goods and services measured as a share of GDP. Current account balance-to-GDP: Sum of net exports of goods and services, net primary income, and net secondary income as a share of GDP. Inflation rate (*Inflation*): Annual percentage change of the consumer price index. Unemployment rate (Unemployment), Unemployment total (% of total labor force) (national estimate). Private credit-to-GDP (*DCPS/GDP*): Domestic credit to private sector as a share of GDP. Reserves-to-debts (Reserves/Debt): Ratio of total reserves minus gold to imports of goods and services (% of total external debt).

Besides, we include other country-specific control variables. *Rule of Law*: Rule of Law: Estimate. *LISTN*: Listed domestic companies, total. *INDV*: Industry (including construction), value added (current US$). *MC/GDP*: Market capitalization of listed domestic companies (% of GDP). *STV*: Stocks traded, total value (current US$). We also include year dummies (*YEAR*) and country dummies (*COUNTRY*) to control for the country and year fixed effects.

4.2 Whether the regulation reform has improved sovereign rating quality?

Second, we investigate whether the ESMA's regulation reforms have improved sovereign rating quality of Big Three rating agencies?

4.2.1 Using defaults as the dependent variables

The dependent variable is a dummy (*Default*) indicating the occurrence of a sovereign debt crisis. Besides, we also include the log of default amount of the country in that year (*LogAmount*) as the dependent variables. The model is specified as follows.

$$DEFAULT_{i,t+1} = \beta_0 + \beta_1 RATING_{Big3_{i,t}} + \beta_2 RATING_{Big3_{i,t}} \times D_{RegRef}$$
$$+\beta_o Control\ Variables + \varepsilon_{i,t} \quad (3)$$

The D_{RegRef} indicator variable equals 1 after the ESMA endorsement rules took effect on 30 April 2012, and 0 otherwise. $RATING_{Big3} \times D_{RegRef}$, the key variable in this model, measures the linkage between ratings quality and ESMA's requirement for identifiers by observing the impact of rating actions upon defaults in the post-intervention period. The magnitude of rating events' impact on the default in the post-intervention period is calculated by summation of the coefficient values of $RATING_{Big3}$ and $RATING_{Big3} \times D_{RegRef}$. If the coefficient of β_1 and $\beta_1+\beta_2$ are both significantly negative and the absolute value of magnitude of $\beta_1+\beta_2$ is larger than β_1, suggesting that the sovereign rating quality of Big Three rating agencies has improved after ESMA's regulatory reforms.

4.2.2 Using bond yield spreads as the dependent variables

If ESMA's aims are to be achieved, we hypothesize that the link between rating changes and bond yield spreads should strengthen after the introduction of the ESMA's reforms in April 2012. The model is specified as follows.

$$BSpread_{i,t+1} = \gamma_0 + \gamma_1 RATING_{Big3_{i,t}} + \gamma_2 RATING_{Big3_{i,t}} \times D_{RegRef}$$
$$+\gamma_o Control\ Variables + \varepsilon_{i,t} \quad (4)$$

The coefficient γ_1 resembles the effect of comprehensive ratings of Big Three rating agencies ($RATING_{Big3}$) on yield spreads. The magnitude of rating impact of Big Three rating agencies on the bond spread in the post-identifier period is calculated by summation of the coefficient values of $RATING_{Big3}$ and $RATING_{Big3} \times D_{RegRef}$. If the coefficient of γ_1 and $\gamma_1+\gamma_2$ are both significantly negative and the absolute value of magnitude of $\gamma_1+\gamma_2$ is larger than γ_1, suggesting that the sovereign rating quality of Big Three rating agencies has improved after ESMA's regulatory reforms.

4.3 Whether competition has improved sovereign rating quality?

Third, we investigate whether competition has improved sovereign rating quality of Big Three rating agencies? We consider the competition from non-Big Three rating agencies.

4.3.1 Using default as the dependent variables

In this section, we test whether a rating agency facing peer pressure will assign a more accurate sovereign rating. If so, the rating can explain default better. The dependent variable is a dummy (*Default*) indicating the occurrence of a sovereign debt crisis. Besides, we also include the log of default amount of the country in that year (*LogAmount*) as the dependent variables. The model is specified as follows.

$$DEFAULT_{i,t+1} = \beta_0 + \beta_1 RATING_{Big3_{i,t}} + \beta_2 RATING_{Big3_{i,t}} \times D_{nonBig3_{i,t}}$$
$$+\beta_o Control\ Variables + \varepsilon_{i,t} \quad (5)$$

$D_{nonBig3}$ is a dummy and represents that the sovereign is also rated by another non-Big Three rating agency. When β2 (the coefficient of $RATING_{Big3} \times D_{nonBig3}$) is significantly negative, suggesting that the Big Three rating agency will improve its sovereign rating quality when it faces the other non-Big Three agencies' competition.

4.3.2 Using bond yield spreads as the dependent variables

This section uses government bond yield spreads to examine the effect of competition on rating quality. The model is specified as follow.

$$BSpread_{i,t+1} = \beta_0 + \beta_1 RATING_{Big3_{i,t}} + \beta_2 RATING_{Big3_{i,t}} \times D_{nonBig3_{i,t}} + \beta_o Control\ Variables + \varepsilon_{i,t} \quad (6)$$

When the coefficient of $RATING_{Big3} \times D_{nonBig3}$ is significantly negative, suggesting that the Big Three rating agency will improve its sovereign rating quality when it faces the other non-Big Three agency's competition.

5. Empirical results

5.1 Data and basic statistics

First, the data of default occurrences and default amounts is obtained from Credit Rating Assessment Group (CRAG) of the Bank of Canada. Next, the data of government bond yield to maturity is obtained from Datastream database. Third, we collect the long-term foreign-currency sovereign issuer ratings from each rating agency's website. Fourth, the macroeconomic variables are collected from the World Bank database and other country-specific variables are collected from the Datastream database. Table 1 presents the names, definitions, and sources of the variables.

Table 1 Variable definitions and data resources

Variable names	Definitions	Resources
Default	A default (*Default*) is defined when a debt service is not paid on the due or within a specified grace period, or when payments are not made within the time frame specified under a guarantee or absent an outright payment default. However, given that the final resolution with creditors following a sovereign default can be very lengthy, we follow Reinhart and Rogoff (2011) and consider only the first year of default as a crisis year.	Credit Rating Assessment Group (CRAG) of the Bank of Canada
Log Amount	The log of default amount of the country in that year (*LogAmount*).	
BSpread1	Bond yield spreads (*BSpread1*), in basis points, are calculated by taking the difference between the yield to maturity of the sovereign bond subject to the rating and the yield to maturity of the comparable US benchmark bond. we measure government bond yield spread by the differences between 10-year bond yield and three-month bond yield at the end of that year.	DataStream database
BSpread2	Bond yield spreads (*BSpread2*) measure government bond yield spread by the differences between the average 10-year bond yields of that year and the average of three-month bond yields of that year.	
$RATING_{Big3}$	We convert the long-term alphanumeric ratings into 22 numerical ratings. (AAA (Aaa) = 22, AA+ (Aa1) = 21, AA (Aa2) = 20,…, CC (Ca) =3, C = 2 and D(SD) = 1). We use the average numerical ratings of the big three rating agencies: Standard & Poor's (S&P), Moody's Investors Service (Moody's) and Fitch Ratings (Fitch).	Big three rating agencies' websites
$RATING_{nonBig3}$	We convert the long-term alphanumeric ratings into 22 numerical ratings. (AAA (Aaa) = 22, AA+ (Aa1) = 21, AA (Aa2) = 20,…, CC (Ca) =3, C = 2 and D(SD) = 1). We use the average numerical ratings of the five agencies are Dominion Bond Rating Services (DBRS), Scope Euro Rating Services (Scope), Japan Credit Rating Agency (JCR), Rating and Investment Information (R&I), and Dagong Global (Dagong).	Rating agencies' websites
GDPG	GDP growth (annual %)	
CAB/GDP	Current account balance (% of GDP)	World bank database
TRADE/GDP	Sum of exports and imports of goods and services measured as a share of GDP (% of GDP)	

EDS/GNI	External debt stocks (% of GNI)	
Inflation	Inflation, GDP deflator (annual %)	
Unemployment	Unemployment, total (% of total labor force) (national estimate)	
Reserves/Debt	Total reserves (% of total external debt)	
DCPS/GDP	Domestic credit to private sector (% of GDP)	
Rule of Law	Rule of Law: Estimate	
LISTN	Listed domestic companies, total	
INDV	Industry (including construction), value added (current US$)	DataStream database
MC/GDP	Market capitalization of listed domestic companies (% of GDP)	
STV	Stocks traded, total value (current US$)	

Table 2 illustrates the numbers of sovereign ratings of each rating agencies. Big Three rating agencies assign more sovereign ratings than non-Big Three rating agencies.

Table 2 The numbers of sovereign credit ratings of each rating agencies

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
S&P	83	86	89	95	101	103	107	111	115	114	117	119	119	119	118	119	118	119	121	122	120
Moody's	95	96	95	96	97	98	100	104	105	104	108	110	115	118	121	123	125	128	128	133	133
Fitch	68	70	77	82	86	91	96	100	100	100	103	104	100	101	103	108	109	104	104	106	106
DBRS	0	0	1	1	1	1	4	6	7	7	11	19	23	27	29	31	35	37	35	35	36
JCR	11	13	15	15	15	16	17	18	18	18	18	18	18	18	18	32	32	33	32	35	34
R&I	23	29	29	30	31	32	32	33	37	37	39	39	41	40	41	41	42	42	42	42	42
Dagong	0	0	0	0	0	0	0	0	0	0	0	2	38	92	93	94	94	91	91	0	0
Scope	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	34	30	16

Table 3 presents the average scores of sovereign ratings of each rating agencies at each year. The patterns are different between Big Three agencies and non-Big Three rating agencies. For Big Three rating agencies, using the univariate results, the year 2008 seems to be a watershed that divides the ratings into two groups. Prior to 2008, the average of sovereign ratings is stable and reaches its peak in 2007. Post−2008, the average ratings are decreasing. This range is consistent with the claim that a more stringent rating standard occurs after the crisis. However, the average ratings of non-Big Three agencies show a stable trend even post 2008.

Table 3 The average level of sovereign ratings of each rating agencies at each year

YEAR	S&P	Moody's	Fitch	Big Three	DBRS	JCR	R&I	Dagong	Scope	non-Big Three
2000	14.86	14.14	15.28	14.03		18.73	15.96			16.79
2001	14.72	14.22	15.03	14.13		19.23	16.86			17.26
2002	14.65	14.64	14.83	14.20	22.00	18.40	16.66			17.18
2003	14.58	14.85	14.65	14.16	22.00	18.60	16.57			17.11
2004	14.36	14.82	14.66	13.92	22.00	18.73	16.94			17.42
2005	14.54	14.85	14.55	13.96	22.00	18.50	17.25			17.61
2006	14.47	14.99	14.40	13.91	15.75	18.82	17.63			17.74
2007	14.60	14.91	14.52	13.97	14.00	18.67	18.00			17.63
2008	14.25	14.82	14.28	13.77	13.57	18.67	18.00			17.59
2009	14.29	14.80	14.34	13.87	13.71	18.72	17.92			17.50
2010	14.22	14.60	14.16	13.72	15.73	18.61	17.33			16.93
2011	13.94	14.17	13.91	13.46	17.95	18.67	17.18	15.00		16.96
2012	13.70	13.80	13.68	13.32	18.43	18.50	16.63	14.95		15.77
2013	13.61	13.56	13.55	13.18	17.44	18.56	17.00	14.39		14.57

2014	13.52	13.50	13.49	13.19	17.52	18.56	16.68	14.24		14.46
2015	13.36	13.36	13.30	12.98	17.45	18.44	16.56	14.14		14.45
2016	13.26	13.06	13.23	12.80	17.71	18.47	16.71	14.04		14.41
2017	13.24	12.85	13.53	12.89	17.86	18.52	16.76	14.07	17.28	14.54
2018	13.17	12.81	13.51	12.84	18.20	18.59	16.93	14.08	17.21	14.64
2019	13.22	12.64	13.40	12.72	18.17	18.63	17.19		17.13	16.95
2020	12.93	12.47	13.04	12.37	18.11	18.74	17.38		16.13	17.13
ALL	13.92	13.90	13.99	13.45	17.60	18.61	17.07	14.21	17.05	15.88

Table 4 is the mean test. The results show the Big Three agencies' average sovereign ratings are significantly lower than non-Big Three rating agencies, which are 15.68 and 16.00, respectively. The S&P average sovereign ratings are significantly lower than the other rating agencies, except Dagong. S&P's average rating is higher than Dagong for 0.247 notches. The average rating notch is lower than JCR for 0.83 notch, R&I for 0.43 notch,

DBRS for 0.282 notch and Scope for 0.17 notch. The notch gaps are smaller between S&P and another two Big Three rating agencies, i.e., Moody's and Fitch. However, the average rating notch is still lower than Moody's for 0.44 notch and Fitch for 0.61 notch, respectively. The results are similar for Moody's. Moody's average sovereign ratings are significantly lower than DBRS (0.419), JCR (0.753), R&I (0.467) and Scope (0.563). The exception is Dagong. Moody's average rating is higher than Dagong for 0.232 notches. The notch gap is insignificant between Moody's and Fitch, although Moody's average rating notch is still higher than Fitch for 0.019 notches. The results are similar for Fitch. Fitch's average sovereign ratings are significantly lower than DBRS (0.320), JCR (0.823), R&I (0.452) and Scope (0.205). The exception is Dagong. Fitch's average rating is higher than Dagong for 0.272 notches.

Table 4 The mean test

Rating agency	Rating agency	Obs.	Mean	Mean	Diff	t-value
	Moody's	2054	14.25	14.30	-.044*	-1.874
	Fitch	1819	14.42	14.48	-.061***	-3.128
	DBRS	344	17.32	17.60	-.282***	-5.834
S&P	JCR	441	17.79	18.62	-.830***	-12.843
	R&I	752	16.71	17.14	-.430***	-9.885
	Dagong	534	14.60	14.36	.247***	2.664
	Scope	112	16.88	17.05	-.170*	-1.648
	Fitch	1775	14.58	14.57	.019	.749
	DBRS	341	17.18	17.60	-.419***	-6.815
Moody's	JCR	438	17.87	18.62	-.753***	-10.156
	R&I	745	16.63	17.10	-.467***	-10.033
	Dagong	556	14.75	14.52	.232***	2.686
	Scope	112	16.49	17.05	-.563***	-5.992
	DBRS	341	17.28	17.60	-.320***	-6.748
	JCR	429	17.81	18.63	-.823***	-12.431
Fitch	R&I	736	16.63	17.09	-.452***	-10.922
	Dagong	497	14.79	14.52	.272***	2.647
	Scope	112	16.85	17.05	-.205**	-2.221
Big Three	Non-Big Three	1194	15.68	16.00	-.314***	-7.090

Table 5 illustrates the summary statistics for all of the variables.

Table 5 The basic statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Default	4,557	0.452	0.498	0.000	1.000
LogAmount	4,557	0.897	1.280	0.000	5.495
BSpread1	854	3.236	3.666	-4.230	35.468
BSpread2	856	3.268	3.552	-4.210	23.956
$RATING_{Big3}$	2,723	13.449	5.287	1.000	22.000
$RATING_{nonBig3}$	1,224	15.866	5.002	1.000	22.000
GDPG	4,449	3.226	5.733	-62.076	123.140
CAB/GDP	3,791	-2.374	14.847	-73.047	311.761
DCPS/GDP	3,489	50.392	44.055	0.000	304.575
TRADE/GDP	3,967	90.800	58.708	0.785	863.195
Inflation	4,447	7.430	44.249	-30.200	2630.123
Unemployment	4,114	8.254	6.246	0.100	37.250
EDS/GNI	2,620	54.770	47.124	0.141	610.452
Reserve/Debt	2,354	71.256	228.646	0.009	3840.105
Rule of Law	4,036	-0.023	0.996	-2.606	2.130
LISTN	1,737	4.967	1.673	0.000	8.886
INDV	4,160	22.465	2.627	13.755	29.348
MC/GDP	1,581	67.454	120.476	0.009	1768.803
STV	1,658	22.894	3.841	10.309	31.486

Table 6 is the correlation coefficient matrix. The results show the correlation between sovereign ratings of Big Three and non-Big Three rating agencies and default probability (amounts) are significantly negative, suggesting that higher rating level and lower default probability (amounts). Besides, the correlation between sovereign ratings of Big Three and non-Big Three rating agencies and bond yield spreads are also significantly negative, suggesting that higher rating level and lower bond yield spread.

Table 6 Correlation coefficient matrix

		Default	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
LogAmount	(1)	0.692																	
BSpread1	(2)	0.492	0.426																
BSpread2	(3)	0.529	0.418	0.957															
$RATING_{Big3}$	(4)	-0.437	-0.371	-0.514	-0.590														
$RATING_{nonBig3}$	(5)	-0.460	-0.487	-0.517	-0.581	0.894													
GDPG	(6)	-0.188	-0.089	-0.399	-0.426	0.286	0.229												
CAB/GDP	(7)	-0.157	-0.277	-0.593	-0.548	0.340	0.421	0.392											
DCPS/GDP	(8)	-0.178	-0.178	-0.267	-0.293	0.624	0.669	0.193	0.147										
TRADE/GDP	(9)	-0.173	-0.284	-0.373	-0.380	0.110	0.097	-0.062	0.280	-0.044									
Inflation	(10)	0.264	0.258	0.483	0.532	-0.360	-0.332	-0.126	-0.239	-0.080	-0.183								
Rule of Law	(11)	-0.066	-0.149	0.025	0.038	-0.010	0.114	-0.132	-0.277	0.341	-0.080	0.149							
Unemployment	(12)	-0.012	-0.118	0.116	0.140	0.007	0.109	-0.318	-0.249	0.532	-0.054	0.231	0.606						
INDV	(13)	-0.282	-0.201	-0.234	-0.265	0.647	0.629	0.356	0.295	0.372	-0.416	-0.093	-0.114	-0.255					
MC/GDP	(14)	-0.054	-0.164	0.039	0.053	0.109	0.257	-0.095	-0.112	0.527	-0.063	0.120	0.554	0.818	-0.155				
STV	(15)	-0.151	-0.187	-0.137	-0.138	0.469	0.578	0.371	0.357	0.470	-0.421	0.114	0.165	0.083	0.777	0.253			
LISTN	(16)	-0.254	-0.263	-0.371	-0.376	0.343	0.500	0.493	0.405	0.366	-0.097	-0.073	0.347	-0.101	0.561	0.123	0.691		
EDS/GNI	(17)	0.132	-0.058	0.121	0.145	-0.356	-0.335	-0.408	-0.110	-0.200	0.658	0.025	0.059	0.103	-0.577	-0.132	-0.547	-0.331	
Reserves/Debt	(18)	-0.217	-0.139	-0.454	-0.489	0.634	0.599	0.603	0.620	0.472	-0.030	-0.213	-0.202	-0.264	0.586	-0.098	0.541	0.530	-0.462

5.2 Empirical results

5.2.1 Can sovereign ratings explain default probability and bond yield spread?

Table 7 reports the results of explanatory ability of sovereign ratings on default probability and amounts. In specifications (1) and (2) we use the dummy variable *Default* as the dependent variables and in specifications (3) and (4), we use the log of default amount of the country in that year (*LogAmount*) as the dependent variables. We consider the average sovereign rating levels of Big Three rating agencies, including S&P, Moody's and Fitch.

In Panel A, when considering the whole sample, the results show the coefficients of $RATING_{Big3}$ are significantly negative in specifications (1) and (2), suggesting that the better Big Three agencies' sovereign ratings and the lower default probability of that country. The coefficients of $RATING_{Big3}$ are also significantly negative in specifications (3) and (4), suggesting that the better Big Three agencies' sovereign ratings and the lower default amounts of that country.

In Panels B and C, we separate the sample into high-income and middle-income countries. The results are similar for high-income countries. The coefficients of $RATING_{Big3}$ are still significantly negative for all specifications, suggesting that sovereign ratings of Big Three rating agencies can explain government default probability and default amounts. However, the results are different for middle-income countries. The coefficients of $RATING_{Big3}$ are insignificant in specifications (1), (2) and (4) and only significantly negative in specification (3), suggesting that sovereign ratings of Big Three rating agencies cannot explain government default probability and default amounts in middle-income countries.

Table 8 reports the results of whether sovereign ratings can explain government bond yield spreads. In specifications (1) and (2), we measure government bond yield spreads by the differences between 10-year bond yield and three-month bond yield at the end of that year. In specifications (3) and (4), we measure government bond yield spreads by the differences between the average 10-year bond yields of that year and the average of three-month bond yields of that year.

In Panel A, when considering the whole sample, the results show the coefficients of $RATING_{Big3}$ are significantly negative in all specifications, suggesting that the better sovereign ratings of Big Three rating agencies and the lower bond yield spreads. In Panels B and C, when we separating the sample into high-income and middle-income countries, the results are similar for high-income countries. The coefficients of $RATING_{Big3}$ are still significantly negative in all specifications. The results suggest that sovereign ratings of Big Three rating agencies can explain government bond yield spreads. However, the results are different for middle-income countries. The coefficients of $RATING_{Big3}$ are insignificant in specifications (1), (2) and (4), suggesting that sovereign ratings of Big Three rating agencies cannot explain government bond yield spreads in middle-income countries.

Table 7 Can sovereign ratings explain government default?

	Panel A The whole sample				*Panel B High-income countries sample*				*Panel C Middle-income countries sample*			
	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*
$RATING_{Big3}$	**-0.416****	**-0.634***	**-0.099*****	**-0.088***	**-0.307*****	**-0.788*****	**-0.071****	**-0.116****	-0.199	-0.701	**-0.098****	0.012
	(-2.56)	**(-1.66)**	**(-3.97)**	**(-1.89)**	**(-4.86)**	**(-3.69)**	**(-2.03)**	**(-2.09)**	(-0.76)	(-1.40)	**(-2.54)**	(0.18)
GDPG	-0.037	-0.119	-0.014***	-0.004	0.032	0.163***	-0.018*	-0.025*	-0.009	-0.223	-0.005	0.014
	(-0.48)	(-1.44)	(-2.94)	(-0.39)	(0.48)	(3.19)	(-1.71)	(-1.86)	(-0.09)	(-1.61)	(-0.50)	(1.00)
CAB/GDP	-0.043	-0.155*	0.006	0.002	0.022	0.002	0.002	-0.004	-0.084*	0.065	0.004	-0.000
	(-0.91)	(-1.89)	(1.32)	(0.32)	(1.01)	(0.03)	(0.72)	(-0.68)	(-1.86)	(0.65)	(0.53)	(-0.00)
DCPS/GDP	0.053*	0.103**	0.005***	0.006**	0.019**	0.017**	0.002**	0.002*	0.034	0.188**	0.009**	0.011
	(1.96)	(2.43)	(2.94)	(2.47)	(2.21)	(2.07)	(2.16)	(1.93)	(1.09)	(2.45)	(2.39)	(1.52)
TRADE/GDP	0.013	-0.035	-0.000	-0.002	-0.013	0.043***	-0.000	0.001	0.025	-0.075	-0.005	-0.014***
	(0.61)	(-1.41)	(-0.01)	(-1.26)	(-1.43)	(2.78)	(-0.33)	(0.56)	(1.21)	(-1.38)	(-1.45)	(-2.70)
Inflation	0.021	0.016	0.000	-0.001	-0.062**	0.052	-0.001	0.002	0.017	-0.010	0.001	-0.004
	(0.58)	(0.24)	(0.06)	(-0.10)	(-2.41)	(0.48)	(-0.29)	(0.38)	(0.41)	(-0.15)	(0.27)	(-0.28)
Rule of Law	-1.117	-3.407	-0.101	-0.421*	-1.092	-0.270	0.129	0.038	-1.859	-4.110	-0.383*	-1.281***
	(-0.91)	(-1.13)	(-0.77)	(-1.86)	(-1.30)	(-0.12)	(1.55)	(0.30)	(-1.44)	(-1.32)	(-1.76)	(-3.21)
Unemployment	0.007	-0.067	-0.020*	-0.016	-0.143	-0.258**	0.006	0.003	0.029	-0.259	-0.054***	-0.077**
	(0.11)	(-0.38)	(-1.93)	(-1.11)	(-1.08)	(-2.02)	(0.52)	(0.18)	(0.28)	(-0.57)	(-2.78)	(-2.02)
INDV		-3.378		-0.164		-0.788		0.205		-3.208		-0.071
		(-1.26)		(-0.82)		(-0.58)		(1.09)		(-1.06)		(-0.26)
MC/GDP		-0.035**		0.000		-0.090***		0.000		-0.040*		0.001
		(-2.28)		(0.19)		(-3.23)		(0.22)		(-1.86)		(0.32)
STV		0.965		-0.055		1.331**		-0.081		1.429**		-0.032
		(1.51)		(-1.13)		(1.97)		(-1.54)		(2.14)		(-0.46)
LISTN		-5.261***		-0.078		2.309*		-0.051		-7.314***		-0.174
		(-3.87)		(-0.92)		(1.68)		(-0.96)		(-3.46)		(-0.94)
EDS/GNI									0.043**	0.018	0.003	0.007**
									(2.53)	(0.40)	(1.13)	(2.08)
Reserves/Debt									0.001	-0.038***	0.000***	-0.001
									(0.65)	(-2.97)	(2.58)	(-0.38)
Constant	1.601	94.985	1.423***	10.541**	4.279**	-15.171	1.121	-0.579	-4.708	96.164	2.147***	8.114
	(0.69)	(1.48)	(4.12)	(2.28)	(2.39)	(-0.91)	(1.40)	(-0.18)	(-1.33)	(1.23)	(3.21)	(1.28)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES	YES	YES
Observations	1883	996	1883	996	803	536	803	536	922	428	922	428
adj. R-square	0.344	0.302	0.303	0.242	0.098	0.087	0.072	0.164	0.303	0.305	0.292	0.305

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 8 Can sovereign ratings explain bond yield spread?

	Panel A The whole sample				***Panel B High-income countries sample***				***Panel C Middle-income countries sample***			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Spread1	*Spread1*	*Spread2*	*Spread2*	*Spread1*	*Spread1*	*Spread2*	*Spread2*	*Spread1*	*Spread1*	*Spread2*	*Spread2*
$RATING_{Big3}$	**-0.467****	**-0.744****	**-0.438*****	**-0.633*****	**-0.698****	**-1.086*****	**-0.571*****	**-0.826*****	-0.247	-0.019	**-0.409****	-0.291
	(-2.01)	**(-2.16)**	**(-3.04)**	**(-3.38)**	**(-2.21)**	**(-2.61)**	**(-3.08)**	**(-3.75)**	(-1.00)	(-0.06)	**(-2.22)**	(-1.25)
GDPG	-0.179**	-0.201**	-0.176***	-0.198***	-0.135	-0.156*	-0.107**	-0.117***	-0.121**	-0.167***	-0.225***	-0.268***
	(-2.11)	(-2.34)	(-3.26)	(-3.57)	(-1.33)	(-1.76)	(-1.97)	(-2.69)	(-2.32)	(-3.04)	(-4.36)	(-4.72)
CAB/GDP	-0.070**	-0.135***	-0.026	-0.075**	-0.033	-0.118**	0.009	-0.054**	-0.127*	-0.311**	-0.094	-0.251**
	(-2.14)	(-2.69)	(-0.99)	(-2.28)	(-0.81)	(-2.29)	(0.29)	(-2.12)	(-1.93)	(-2.37)	(-1.63)	(-2.16)
DCPS/GDP	0.016***	0.025***	0.014***	0.019**	0.017***	0.027***	0.016***	0.022***	0.033	0.001	0.020	-0.009
	(3.07)	(2.75)	(2.81)	(2.26)	(3.12)	(2.80)	(2.72)	(2.84)	(1.15)	(0.03)	(0.81)	(-0.31)
TRADE/GDP	-0.008	0.002	-0.009	-0.001	-0.008*	-0.001	-0.010**	-0.005	0.011	0.019	0.007	0.017
	(-1.11)	(0.25)	(-1.27)	(-0.16)	(-1.74)	(-0.18)	(-2.24)	(-1.24)	(0.40)	(0.67)	(0.27)	(0.55)
Inflation	0.005	0.081*	0.030	0.102*	-0.062	0.003	-0.003	0.046	0.093*	0.206***	0.100**	0.187**
	(0.15)	(1.77)	(0.73)	(1.88)	(-1.16)	(0.07)	(-0.07)	(1.00)	(1.94)	(3.60)	(1.97)	(2.47)
Rule of Law	1.428	0.878	1.295	0.770	2.883**	3.597**	1.896**	2.398***	-0.380	-3.331*	0.802	-2.083
	(1.25)	(0.69)	(1.22)	(0.70)	(2.39)	(2.77)	(2.49)	(3.29)	(-0.18)	(-1.84)	(0.33)	(-1.01)
Unemployment	-0.011	-0.046	0.057	0.054	-0.125	-0.179	-0.028	-0.047	0.139	0.200*	0.187	0.237**
	(-0.13)	(-0.44)	(1.18)	(1.09)	(-1.02)	(-1.20)	(-0.62)	(-0.81)	(1.00)	(1.96)	(1.15)	(2.20)
INDV		1.385		1.250		1.851*		1.362		0.849		1.346
		(1.30)		(1.39)		(1.74)		(1.45)		(0.83)		(1.28)
MC/GDP		0.001		0.000		-0.000		-0.000		-0.007		-0.007
		(1.24)		(0.16)		(-0.02)		(-0.65)		(-0.76)		(-0.55)
STV		-0.585**		-0.346		-0.428**		-0.239*		0.447		0.621
		(-2.06)		(-1.57)		(-2.10)		(-1.82)		(0.81)		(1.02)
LISTN		0.356		0.127		0.516		0.363		-1.147		-1.764
		(1.30)		(0.47)		(1.17)		(1.05)		(-1.00)		(-1.47)
Constant	7.578*	-9.538	7.370***	-12.227	10.860*	-23.767	9.701***	-18.275	8.116**	-20.447	10.332***	-30.481
	(1.75)	(-0.38)	(2.73)	(-0.49)	(1.88)	(-0.99)	(3.01)	(-0.76)	(2.60)	(-0.67)	(3.45)	(-1.03)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	738	578	739	578	509	373	510	373	229	205	229	205
adj. R-square	0.685	0.693	0.723	0.732	0.688	0.693	0.744	0.743	0.651	0.738	0.703	0.769

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively

5.2.2 Effect of regulatory reforms

Table 9 reports the effect of regulatory reforms on the relationship between sovereign ratings and defaults. In Panel A, when considering the whole sample, the coefficients of $RATING_{Big3}$ are significantly negative. The coefficients of $RATING_{Big3} \times D_{RegRef}$ are significantly positive in specifications (1) and (3). However, when we add more control variables, the coefficients of $RATING_{Big3} \times D_{RegRef}$ become insignificant in specifications (2) and (4), suggesting that explanatory ability of sovereign ratings of Big Three rating agencies on default probabilities and amounts does not significantly change after the regulatory reforms.

In Panel B, part of the results of high-income countries sample show the explanatory ability of sovereign ratings of Big Three rating agencies on default probabilities decreases after regulatory reforms. In Panel C, the results show the explanatory ability of sovereign ratings of Big Three rating agencies on default probability and default amounts does not significantly change after the regulatory reforms for middle-income countries.

Table 10 reports the effect of regulatory reforms on the relationship between sovereign ratings and bond yield spread. In Panel A, when considering the whole sample, the results show the effect of sovereign ratings on bond yield spread does not change after regulatory reforms for Big three rating agencies.

In Panel B, when considering high-income countries sample, the results are different with the whole sample. The coefficients of $RATING_{Big3} \times D_{RegRef}$ are significantly positive in *BSpread1* specifications, suggesting the information effect of sovereign ratings of Big Three rating agencies on bond yield spread decreases after regulatory reforms. In Panel C, when considering middle-income countries sample, the results suggest the effect of sovereign ratings on bond yield spread does not change after regulatory reforms.

5.2.3 Effect of competition

Table 11 reports the effect of non-Big Three agencies' competition on the relationship between sovereign ratings of Big Three rating agencies and default probability and amounts. Panel A considers the whole sample and find all the coefficients of $RATING_{Big3} \times D_{nonBig3}$ are insignificant, suggesting that explanatory ability of sovereign ratings of Big Three rating agencies on default probability and amount does not change when Big Three agencies face non-Big Three agencies' competition.

In Panel B and C, the results of high-income countries and middle-income countries sample are similar with the whole sample. The results suggest that the explanatory ability of sovereign ratings of Big Three rating agencies on default probabilities and amounts does not change when facing the competition from non-Big Three rating agencies.

Table 12 reports the effect of competition on the relationship between sovereign ratings of Big Three rating agencies and bond yield spreads. In Panel A, when considering the whole sample, the results show the coefficients of $RATING_{Big3} \times D_{nonBig3}$ are all insignificant, suggesting the effect of sovereign ratings of Big Three rating agencies on bond yield spreads does not change when Big Three rating agencies face the competition form non-Big Three rating agencies. In Panel B, when considering high-income countries sample, the results show the coefficients of $RATING_{Big3} \times D_{nonBig3}$ are significantly positive for all specifications, suggesting the effect of sovereign ratings of Big Three rating agencies on bond yield spread decreases when Big Three rating agencies face the competition form non-Big Three rating agencies. In Panel C, when considering middle-income countries sample, the results show the coefficients of $RATING_{Big3} \times D_{nonBig3}$ are significantly negative in specifications (2) and (4), suggesting the effect of sovereign ratings of Big Three rating agencies on bond yield spreads increases when Big Three rating agencies face the competition form non-Big Three rating agencies.

Table 9 Does the ability of sovereign ratings explaining default improve after regulatory reforms?

	Panel A The whole sample				*Panel B High-income countries sample*				*Panel C Middle-income countries sample*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Default	*Default*	*LogAmount*	*LogAmount*	*Default*	*Default*	*LogAmount*	*LogAmount*	*Default*	*Default*	*LogAmount*	*LogAmount*
$RATING_{Big3}$	**-0.565*****	-0.707	**-0.108*****	**-0.100****	**-0.427*****	**-1.329*****	**-0.072***	**-0.116***	-0.382	-0.699	**-0.102****	0.033
	(-2.92)	(-1.48)	**(-4.25)**	**(-2.13)**	**(-6.09)**	**(-6.21)**	**(-1.77)**	**(-1.65)**	(-1.28)	(-1.18)	**(-2.64)**	(0.58)
$RATING_{Big3} \times D_{RegRef}$	**0.293***	0.122	**0.020*****	0.022	**0.239*****	**0.721*****	0.001	-0.000	0.278	-0.003	0.007	-0.026
	(1.68)	(0.40)	**(2.65)**	(1.52)	**(3.06)**	**(2.94)**	(0.11)	(-0.01)	(1.37)	(-0.01)	(0.32)	(-0.66)
GDPG	-0.018	-0.121	-0.014***	-0.007	0.043	0.210***	-0.018*	-0.025*	-0.005	-0.223*	-0.005	0.016
	(-0.23)	(-1.45)	(-2.82)	(-0.66)	(0.63)	(2.92)	(-1.74)	(-2.02)	(-0.06)	(-1.65)	(-0.50)	(1.32)
CAB/GDP	-0.047	-0.159*	0.006	0.003	0.025	-0.007	0.003	-0.004	-0.092*	0.065	0.004	0.001
	(-0.96)	(-1.93)	(1.40)	(0.41)	(1.19)	(-0.07)	(0.68)	(-0.58)	(-1.89)	(0.64)	(0.51)	(0.10)
DCPS/GDP	0.053**	0.105**	0.005***	0.006***	0.023***	0.032***	0.002**	0.002*	0.032	0.188**	0.009**	0.011
	(2.04)	(2.41)	(3.17)	(2.61)	(2.62)	(2.78)	(2.08)	(1.70)	(1.05)	(2.46)	(2.34)	(1.57)
TRADE/GDP	0.011	-0.036	-0.000	-0.002	-0.011	0.052**	-0.000	0.001	0.027	-0.075	-0.005	-0.015***
	(0.53)	(-1.43)	(-0.39)	(-1.36)	(-1.42)	(2.48)	(-0.33)	(0.54)	(1.31)	(-1.27)	(-1.45)	(-2.82)
Inflation	0.021	0.007	-0.000	-0.001	-0.074***	0.016	-0.001	0.002	0.014	-0.010	0.001	-0.004
	(0.53)	(0.11)	(-0.10)	(-0.15)	(-2.82)	(0.09)	(-0.28)	(0.33)	(0.34)	(-0.13)	(0.27)	(-0.28)
Rule of Law	-0.912	-3.402	-0.128	-0.472**	-1.208	-1.477	0.125	0.038	-1.638	-4.113	-0.381*	-1.284***
	(-0.82)	(-1.12)	(-0.97)	(-2.05)	(-1.44)	(-0.64)	(1.30)	(0.26)	(-1.38)	(-1.30)	(-1.74)	(-3.19)
Unemployment	0.010	-0.045	-0.020**	-0.015	-0.111	-0.199*	0.005	0.003	0.036	-0.260	-0.055***	-0.079**
	(0.14)	(-0.22)	(-2.03)	(-1.02)	(-0.83)	(-1.67)	(0.48)	(0.18)	(0.34)	(-0.53)	(-2.80)	(-2.04)
INDV		-2.889		-0.084		-0.752		0.205		-3.221		-0.111
		(-1.10)		(-0.45)		(-0.56)		(1.02)		(-1.02)		(-0.46)
MC/GDP		-0.035**		0.000		-0.095***		0.000		-0.040*		0.001
		(-2.26)		(0.27)		(-2.64)		(0.22)		(-1.84)		(0.36)
STV		1.001		-0.051		1.585**		-0.081		1.429**		-0.042
		(1.61)		(-1.06)		(1.97)		(-1.63)		(2.15)		(-0.53)
LISTN		-5.272***		-0.080		2.109		-0.051		-7.315***		-0.185
		(-3.87)		(-0.98)		(1.55)		(-0.90)		(-3.33)		(-0.97)
EDS/GNI									0.040***	0.019	0.003	0.008**
									(2.83)	(0.40)	(1.15)	(2.11)
Reserves/Debt									0.002	-0.038***	0.000**	-0.001
									(1.03)	(-3.15)	(2.29)	(-0.58)
Constant	3.454	83.510	1.606***	8.614**	5.683***	-12.710	1.143	-0.577	-2.770	96.449	2.197***	9.183
	(1.36)	(1.35)	(4.66)	(1.96)	(2.72)	(-0.76)	(1.20)	(-0.16)	(-0.83)	(1.13)	(3.34)	(1.56)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES	YES	YES
Observations	1883	996	1883	996	803	536	803	536	922	428	922	428
adj. R-square	0.309	0.288	0.304	0.245	0.099	0.111	0.074	0.172	0.299	0.305	0.293	0.307

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 10 Does the ability of sovereign ratings explaining bond yield spread improve after regulatory reforms?

	Panel A The whole sample				*Panel B High-income countries sample*				*Panel C Middle-income countries sample*			
	(1) *Spread1*	(2) *Spread1*	(3) *Spread2*	(4) *Spread2*	(1) *Spread1*	(2) *Spread1*	(3) *Spread2*	(4) *Spread2*	(1) *Spread1*	(2) *Spread1*	(3) *Spread2*	(4) *Spread2*
$RATING_{Big3}$	**-0.465***	**-0.777****	**-0.411*****	**-0.629*****	**-1.053****	**-1.551*****	**-0.626*****	**-0.911*****	-0.218	-0.021	**-0.406*****	-0.295
	(-1.81)	**(-2.10)**	**(-2.76)**	**(-3.36)**	**(-2.35)**	**(-3.69)**	**(-3.16)**	**(-5.82)**	(-0.96)	(-0.07)	**(-2.91)**	(-1.30)
$RATING_{Big3} \times D_{RegRef}$	-0.005	0.102	-0.087	-0.015	**0.442****	**0.601*****	0.069	0.110	-0.071	0.011	-0.007	0.021
	(-0.06)	(1.06)	(-1.59)	(-0.32)	**(2.19)**	**(3.74)**	(1.11)	(1.48)	(-0.39)	(0.08)	(-0.03)	(0.14)
GDPG	-0.179**	-0.203**	-0.172***	-0.198***	-0.105	-0.098**	-0.102*	-0.106**	-0.121**	-0.167***	-0.225***	-0.267***
	(-2.05)	(-2.41)	(-3.13)	(-3.55)	(-1.54)	(-2.49)	(-2.01)	(-2.61)	(-2.37)	(-3.09)	(-4.42)	(-5.01)
CAB/GDP	-0.071**	-0.126***	-0.034	-0.077**	0.055	-0.023	0.023	-0.037	-0.125*	-0.310**	-0.094	-0.249*
	(-2.26)	(-2.76)	(-1.31)	(-2.30)	(1.44)	(-0.96)	(0.89)	(-1.51)	(-1.86)	(-2.31)	(-1.60)	(-2.14)
DCPS/GDP	0.016***	0.026**	0.014***	0.019**	0.025**	0.036***	0.017***	0.023***	0.037	0.001	0.020	-0.009
	(2.86)	(2.57)	(2.77)	(2.25)	(2.52)	(3.45)	(2.74)	(3.36)	(1.21)	(0.02)	(0.69)	(-0.31)
TRADE/GDP	-0.008	0.003	-0.009	-0.001	-0.000	0.007	-0.009	-0.004	0.008	0.019	0.007	0.017
	(-1.11)	(0.33)	(-1.25)	(-0.17)	(-0.04)	(0.94)	(-1.65)	(-1.00)	(0.27)	(0.67)	(0.24)	(0.57)
Inflation	0.006	0.067	0.048	0.104*	-0.079	0.025	-0.006	0.050	0.096**	0.206***	0.101**	0.186**
	(0.15)	(1.36)	(1.21)	(1.91)	(-1.25)	(0.79)	(-0.14)	(1.17)	(2.11)	(3.51)	(2.05)	(2.41)
Rule of Law	1.437	0.553	1.457	0.817	1.818**	1.807**	1.730**	2.071**	-0.623	-3.308*	0.780	-2.037
	(1.34)	(0.49)	(1.41)	(0.72)	(2.40)	(2.06)	(2.34)	(2.54)	(-0.29)	(-1.70)	(0.31)	(-0.91)
Unemployment	-0.012	-0.034	0.055	0.052	-0.181*	-0.219***	-0.037	-0.055	0.130	0.202*	0.186	0.241**
	(-0.13)	(-0.39)	(1.09)	(1.05)	(-1.81)	(-2.72)	(-0.91)	(-1.15)	(0.88)	(1.89)	(1.16)	(2.34)
INDV		1.551		1.226		1.420		1.284		0.844		1.337
		(1.34)		(1.41)		(1.65)		(1.35)		(0.80)		(1.21)
MC/GDP		0.001		0.000		-0.000		-0.000		-0.007		-0.007
		(1.41)		(0.12)		(-0.34)		(-0.71)		(-0.76)		(-0.55)
STV		-0.603**		-0.344		-0.099		-0.179		0.445		0.618
		(-2.09)		(-1.55)		(-0.46)		(-1.50)		(0.80)		(1.01)
LISTN		0.331		0.130		-0.039		0.262		-1.119		-1.710
		(1.27)		(0.48)		(-0.07)		(0.70)		(-0.90)		(-1.35)
Constant	7.534	-12.098	6.618**	-11.861	19.523**	-5.711	11.044***	-14.977	7.747**	-20.441	10.298***	-30.469
	(1.51)	(-0.46)	(2.36)	(-0.49)	(2.09)	(-0.23)	(3.02)	(-0.59)	(2.65)	(-0.67)	(3.81)	(-1.02)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	738	578	739	578	509	373	510	373	229	205	229	205
adj. R-square	0.685	0.693	0.726	0.732	0.727	0.761	0.746	0.750	0.655	0.739	0.705	0.769

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 11 Does the ability of sovereign ratings explaining default improve facing competition from non-Big three agencies?

	Panel A The whole sample				*Panel B High-income countries sample*				*Panel C Middle-income countries sample*			
	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*	(1) *Default*	(2) *Default*	(3) *LogAmount*	(4) *LogAmount*
$RATING_{Big3}$	**-0.495****	-0.716	**-0.103*****	**-0.092***	**-0.643*****	**-1.092*****	**-0.074****	**-0.121****	-0.285	-0.814	**-0.102****	0.012
	(-2.53)	(-1.62)	**(-4.04)**	**(-1.93)**	**(-4.46)**	**(-3.05)**	**(-2.02)**	**(-2.07)**	(-1.01)	(-1.57)	**(-2.55)**	(0.18)
$RATING_{Big3}\times D_{nonBig3}$	0.077	0.105	**0.007***	0.007	**0.351*****	0.430	0.003	0.005	0.087	0.141	0.009	-0.001
	(1.25)	(1.38)	**(1.92)**	(1.47)	**(2.98)**	(1.08)	(1.03)	(0.93)	(1.36)	(1.25)	(0.96)	(-0.09)
GDPG	-0.031	-0.109	-0.013***	-0.004	0.034	0.164**	-0.017*	-0.025*	-0.012	-0.228	-0.005	0.014
	(-0.39)	(-1.25)	(-2.80)	(-0.37)	(0.44)	(2.25)	(-1.69)	(-1.89)	(-0.12)	(-1.59)	(-0.49)	(0.99)
CAB/GDP	-0.047	-0.144*	0.006	0.003	0.031	0.085	0.003	-0.003	-0.095**	0.047	0.004	0.000
	(-0.99)	(-1.84)	(1.31)	(0.35)	(1.10)	(0.66)	(0.74)	(-0.55)	(-1.97)	(0.54)	(0.48)	(0.00)
DCPS/GDP	0.051**	0.099**	0.005***	0.006**	0.026**	0.027*	0.002**	0.002*	0.032	0.188**	0.009**	0.011
	(2.00)	(2.40)	(3.00)	(2.43)	(2.44)	(1.82)	(2.12)	(1.89)	(1.08)	(2.36)	(2.34)	(1.52)
TRADE/GDP	0.010	-0.035	-0.000	-0.002	-0.011*	0.034**	-0.000	0.001	0.022	-0.084	-0.005	-0.014***
	(0.48)	(-1.46)	(-0.15)	(-1.34)	(-1.72)	(2.05)	(-0.43)	(0.55)	(1.06)	(-1.33)	(-1.47)	(-2.69)
Inflation	0.022	0.014	0.001	-0.001	0.006	0.232	-0.000	0.003	0.018	-0.008	0.001	-0.004
	(0.59)	(0.19)	(0.15)	(-0.06)	(0.11)	(1.04)	(-0.11)	(0.44)	(0.42)	(-0.12)	(0.28)	(-0.28)
Rule of Law	-0.873	-2.584	-0.088	-0.396*	-1.115	-0.483	0.146*	0.072	-1.473	-2.216	-0.384*	-1.283***
	(-0.70)	(-0.83)	(-0.67)	(-1.80)	(-1.02)	(-0.25)	(1.94)	(0.65)	(-1.10)	(-0.65)	(-1.74)	(-3.13)
Unemployment	0.010	-0.060	-0.018*	-0.015	-0.174	-0.215*	0.006	0.003	0.038	-0.206	-0.053***	-0.078**
	(0.16)	(-0.33)	(-1.82)	(-1.04)	(-1.25)	(-1.80)	(0.60)	(0.23)	(0.38)	(-0.45)	(-2.73)	(-2.03)
INDV		-3.968		-0.166		-0.817		0.210		-3.971		-0.069
		(-1.49)		(-0.83)		(-0.56)		(1.12)		(-1.36)		(-0.26)
MC/GDP		-0.035**		0.000		-0.094***		0.000		-0.045**		0.001
		(-2.36)		(0.07)		(-3.61)		(0.10)		(-2.05)		(0.33)
STV		0.926		-0.058		1.182*		-0.085		1.416**		-0.032
		(1.45)		(-1.17)		(1.78)		(-1.57)		(2.12)		(-0.45)
LISTN		-5.169***		-0.085		2.088*		-0.056		-6.857***		-0.173
		(-3.84)		(-1.02)		(1.78)		(-1.07)		(-3.51)		(-0.93)
EDS/GNI									0.045***	0.027	0.003	0.007**
									(2.65)	(0.56)	(1.12)	(2.07)
Reserves/Debt									0.001	-0.037***	0.000**	-0.001
									(0.97)	(-2.73)	(2.50)	(-0.38)
Constant	2.849	110.365*	1.491***	10.710**	4.995***	-9.924	1.071	-0.602	-3.491	113.661	2.198***	8.056
	(0.98)	(1.71)	(4.18)	(2.34)	(2.86)	(-0.51)	(1.40)	(-0.19)	(-0.92)	(1.50)	(3.21)	(1.30)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES	YES	YES
Observations	1883	996	1883	996	803	536	803	536	922	428	922	428
adj. R-square	0.319	0.289	0.303	0.242	0.102	0.198	0.087	0.173	0.312	0.333	0.307	0.312

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 12 Does the ability of sovereign ratings explaining yield spread improve facing competition from non-Big three agencies?

	Panel A The whole sample				*Panel B High-income countries sample*				*Panel C Middle-income countries sample*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Spread1	*Spread1*	*Spread2*	*Spread2*	*Spread1*	*Spread1*	*Spread2*	*Spread2*	*Spread1*	*Spread1*	*Spread2*	*Spread2*
$RATING_{Big3}$	-0.473**	-0.754**	-0.446***	-0.648***	-0.717**	-1.137**	-0.592***	-0.879***	-0.247	0.043	-0.409**	-0.234
	(-2.05)	(-2.15)	(-3.10)	(-3.38)	(-2.28)	(-2.74)	(-3.23)	(-4.07)	(-0.99)	(0.15)	(-2.13)	(-1.07)
$RATING_{Big3}\times D_{nonBig3}$	0.021	0.015	0.024	0.021	0.033**	0.046*	0.037**	0.048**	-0.033	-0.166**	-0.052	-0.154*
	(1.00)	(0.56)	(1.15)	(0.80)	(1.98)	(1.76)	(2.23)	(1.96)	(-0.36)	(-2.23)	(-0.65)	(-1.88)
GDPG	-0.176**	-0.200**	-0.171***	-0.196***	-0.128	-0.150*	-0.099*	-0.110***	-0.120**	-0.167***	-0.224***	-0.267***
	(-2.08)	(-2.34)	(-3.22)	(-3.55)	(-1.29)	(-1.77)	(-1.93)	(-2.78)	(-2.29)	(-3.05)	(-4.31)	(-4.95)
CAB/GDP	-0.072**	-0.134***	-0.028	-0.075**	-0.032	-0.114**	0.010	-0.050*	-0.121	-0.306**	-0.084	-0.247*
	(-2.20)	(-2.71)	(-1.06)	(-2.30)	(-0.80)	(-2.28)	(0.32)	(-1.93)	(-1.61)	(-2.30)	(-1.22)	(-2.10)
DCPS/GDP	0.017***	0.026***	0.015***	0.019**	0.018***	0.028***	0.017***	0.024***	0.033	-0.002	0.019	-0.012
	(3.20)	(2.81)	(2.92)	(2.39)	(3.29)	(3.14)	(2.84)	(3.34)	(1.13)	(-0.08)	(0.79)	(-0.43)
TRADE/GDP	-0.008	0.002	-0.009	-0.001	-0.008	-0.000	-0.010**	-0.004	0.013	0.027	0.010	0.025
	(-1.16)	(0.24)	(-1.31)	(-0.18)	(-1.64)	(-0.03)	(-2.08)	(-1.04)	(0.50)	(0.95)	(0.41)	(0.80)
Inflation	0.010	0.082*	0.035	0.104*	-0.058	0.003	0.002	0.046	0.087*	0.198***	0.091*	0.179**
	(0.31)	(1.81)	(0.92)	(1.91)	(-1.14)	(0.07)	(0.05)	(0.93)	(1.69)	(3.61)	(1.69)	(2.34)
Rule of Law	1.434	0.862	1.302	0.747	3.093**	3.829***	2.131***	2.639***	-0.068	-2.249	1.305	-1.079
	(1.23)	(0.67)	(1.22)	(0.67)	(2.43)	(2.72)	(2.69)	(3.30)	(-0.03)	(-1.56)	(0.66)	(-0.73)
Unemployment	-0.005	-0.044	0.065	0.057	-0.116	-0.175	-0.018	-0.043	0.127	0.172*	0.167	0.212**
	(-0.06)	(-0.43)	(1.35)	(1.21)	(-0.95)	(-1.20)	(-0.40)	(-0.85)	(0.91)	(1.72)	(1.02)	(2.06)
INDV		1.422		1.302		2.081*		1.601		1.256		1.724*
		(1.31)		(1.43)		(1.83)		(1.64)		(1.27)		(1.71)
MC/GDP		0.001		0.000		-0.000		-0.000		-0.006		-0.005
		(1.24)		(0.18)		(-0.03)		(-0.63)		(-0.64)		(-0.45)
STV		-0.595**		-0.359		-0.422**		-0.234*		0.625		0.786
		(-2.04)		(-1.60)		(-2.08)		(-1.79)		(1.21)		(1.33)
LISTN		0.334		0.095		0.462		0.307		-0.933		-1.566
		(1.26)		(0.37)		(1.06)		(0.91)		(-0.99)		(-1.52)
Constant	7.241*	-10.148	6.983***	-13.090	10.186*	-29.705	8.945***	-24.437	8.647***	-35.351	11.187***	-44.314
	(1.70)	(-0.40)	(2.60)	(-0.52)	(1.84)	(-1.17)	(2.98)	(-1.00)	(2.70)	(-1.17)	(3.83)	(-1.50)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
COUNTRY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	738	578	739	578	509	373	510	373	229	205	229	205
adj. R-square	0.820	0.834	0.865	0.873	0.781	0.809	0.847	0.856	0.755	0.803	0.786	0.817

*, **, and *** denote significance at the 10%, 5%, and 1% levels respectively

6. Conclusion

Prior literature uses nine rating agencies to examine whether existing home bias of sovereign ratings (Özturk, 2014; Fuchs and Gehring, 2017; Yalta and Yalta, 2018) and this paper focuses on the sovereign rating quality. This paper uses new sovereign defaults database to examine the rating quality, i.e., the database on government debt in default developed by the Credit Rating Assessment Group (CRAG) of the Bank of Canada. This paper also examines whether sovereign ratings of Big Three ratings agencies can explain government bond yield spread. This paper checks whether the information effect has changed considering ESMA's regulatory reforms and increased competition. Besides, this paper considers sovereign defaults and bond yield spreads to measure the information effects of sovereign ratings.

When considering the whole sample, the results show sovereign ratings of Big Three rating agencies can explain default probability and default amounts and bond yield spreads. However, the information effect of sovereign ratings of Big Three rating agencies does not change after regulatory reforms and increased competition from non-Big Three rating agencies. Second, when considering high-income countries sample, part of the results shows the information effect of sovereign ratings of Big Three rating agencies worsens after regulatory reforms and when facing the competition from non-Big Three rating agencies. Third, there is no significant information effect in middle-income countries.

Our results echo some recent reports from the European Union, which found that the quality of credit ratings has not significantly improved following various reform measures and increased competition among credit rating agencies. Following the 2008 Global Financial Crisis, the European Union (EU) implemented regulatory reforms aimed at enhancing the quality of credit ratings and fostering competition among credit rating agencies. Despite these efforts, recent analyses suggest that significant challenges persist. A 2024 study by the European Central Bank examined asset-backed securities issued between 1998 and 2018. The findings indicated that while regulatory changes have mitigated certain conflicts of interest, the issue of rating shopping remains prevalent. This ongoing practice continues to undermine the reliability of credit ratings, particularly for higher-quality securities. Besides, ESMA also noted that the regulation's impact on enhancing competition and addressing conflicts of interest was limited. High fees and frequent increases imposed by some rating agencies suggest that effective competition is lacking in specific market segments. These developments suggest that, despite the EU's regulatory reforms, significant obstacles remain in improving the quality of credit ratings and fostering effective competition among rating agencies within the EU. Continuous efforts are underway to address these challenges and enhance the credibility of credit assessments within the EU.

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The Impact of Diversification and COVID-19 Pandemic on Financial Stability for Property-Liability Insurers: Quantile Regression Approach

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A B S T R A C T

This study examines the impact of the COVID-19 pandemic on the relationship between diversification and insurer financial stability in Taiwan. We use ordinary least squares (OLS) and quantile regression (QR) methods to explore the impact of diversification and the COVID-19 pandemic on insurer financial stability during 2010-2022, especially for the insurers at the different quantiles. The results show that product diversification presents a significantly negative impact on insurers' Z-scores using OLS and QR (all quantiles), and that higher quantiles insurer diversification is significantly and positively associated with the RBC ratio. In addition, The COVID-19 pandemic is negatively and significantly associated with insurer Z-score for the OLS regressions, whereas the COVID-19 pandemic is also negatively and significant associated with Z-scores for lower and median quantiles insurers. The findings suggest that managers must carefully evaluate and establish systems to control the degree of diversification to reduce solvency risk. The results also provide the regulatory authorities with a basis for supervision of diversification and financial stability.

Keywords: Diversification, Financial stability, Covid-19 pandemic, Quantile Regression
JEL Classification: G22, G33, L25

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1. Introduction

Cross-border operation of the financial industry has become an important trend. Therefore, at the end of 2000, under the trend of financial liberalization and internationalization, Taiwan's government passed the Financial Institution Merger Law to improve the economic efficiency of the financial industry, and passed the Financial Holding Company law in 2001, allowing banks, insurance, and securities to merge with each other, catalyzing the development of the financial industry. As a result, some insurers were acquired or merged, and financial holding companies began to develop. Many financial holding groups established insurance subsidiaries respectively or increased the scale of insurance operations through mergers and acquisitions, while some non-financial holding insurers cooperate with financial institutions to cross-market insurance products through various channels.

In view of the experience of advanced insurance countries and consumer awareness, there is still room for adjustment in the future business structure of the Taiwanese insurance industry. However, from the information disclosed by various insurers, we can also see the rapid growth and development of the insurers' scale and insurance product lines. As the market competition becomes more fiercer, business integration and cost structure reduction are very important for the sustainable operation of insurers. Therefore, insurers through business diversification may increase product categories or expand various business, produce and operate various products in different areas to promote operational scope and increase market share to improve firm performance to achieve economics of scope. However, diversified operations are like an asset pool, and companies can reduce the volatility of overall cash flow and, thus, minimize their financial risks (Amit & Livant,1988). Hann et al. (2013) indicate that diversified companies can generate internally the effect of coinsurance, compared to enterprises operating in a single industry, and can obtain lower equity capital costs and reduce the risk of earnings fluctuations. In contrast, when an enterprise crosses over to different market or industries through diversified operations, the greater the difference in the fields it crosses, the more it can reduce the correlation of cash flow of each operating department of the firms, but it will also increase the difficulty for the enterprise to master information and integrate resources, and increase the risk of business operation (Bettis & Hall,1982). Therefore, diversified enterprises may have increased their corporate operational risks due to the need for an increased management capacity and coordination requirement, as well as having large amounts of information that need to be mastered and processed when facing multiple products, (Hitt et al., 2006; Reeb et al., 1998). Previous studies point out that diversification strategy is an important factor affecting corporate value and risk (Bausch & Plis,2009; Wan et al.,2011). However, previous empirical literature has not obtained consistent evidence and conclusions on whether diversification can reduce corporate risk. Due to the small size of Taiwan's insurance market, the property-liability (P-L) insurers hope to expand the scale of insurance and obtain sufficient investment funds through a diversification strategy, but they must also pay attention to their business risk.

The COVID-19 pandemic had a major impact on the global economy, triggering an unexpected economic crisis. The insurance sector is one of the industries that suffered the most serious losses from the epidemic. Insurers must use their own funds to handle a larger number of claims, but at the same time they need to maintain sufficient solvency. Due to the product diversification strategy, the P-L insurers operate in both accident and health insurance. In 2022, Taiwan's local epidemic broke out again. Omicron, which is highly contagious and has a high infection rate, caused a peak in confirmed cases and led to a new high in epidemic prevention policy sales. At the same time, insurers' underwriting risk also increased, resulting in huge subsequent compensation payments, which in turn affects insurers' financial status. In Taiwan, the COVID-19 epidemic has also had an impact on the economy and industry, with the insurance sector bearing the brunt. According to statistics from the P-L Insurance Association, from 2022 to the end of March 2023, the total amount of epidemic prevention insurance claims was NT$264.983 billion, which is equivalent to the entire profit of P-L insurers for 20 years. In response to a new wave of epidemic prevention insurance claims, the top six insurers underwriting epidemic prevention insurance have completed a capital increase of nearly NT$1125 billion. Based on the above background, the purpose of this study is to explore the impact of diversification in the insurance sector on financial stability and further explore whether COVID-19 caused financial instability for P-L insurers. Consequently, understanding the relationship between diversification and insurance risks during times of economic uncertainty, such as the COVID-19 pandemic, is essential.

This paper has the following contributions: First, previous studies on diversification in the insurance sector mostly focus on performance (Liebenberg & Sommer,2008; Shim,2011; Lee,2017; Duijm & Van Beveren 2022) and risk-taking (Che & Liebenber,2017; Lee,2020), and bank diversification and financial stability (Al-Habashneh et al., 2023; Chowdhury et al., 2024); but less on insurers' financial stability. This study offers an in-dept analysis of P-L insurers' diversification strategies and the COVID-19 pandemic on financial stability, and attempts to bridge the gap in the literature on the insurance sectors. Second, different from previous literature, where most of the data analyzed was for developed countries such as Che and Liebenberg (2017); Shim (2017 b); Sheehan et al. (2023), this research focuses on developing economies, that is for the Taiwanese insurance sector, and can provide references for developing counties. Thirdly, the results of this study provide another perspective, analyzing whether the diversification of P-L insurers may have an adverse impact on financial stability. Managers must carefully evaluate these considerations when making diversification decisions. Finally, the findings will provide valuable insights for policymakers and insurers, aiding in the formulation of strategies to mitigate risks and ensure insurance and financial sector stability in times of economic uncertainty.

2. Literature Review

2.1 Theoretical Issues

The theories related to diversification and risk can be roughly divided into portfolio theory, coinsurance effect theory, and principal-agent theory. Portfolio diversification involves allocating wealth across various assets. Additionally, a balanced portfolio of various kinds of assets can successfully decrease investment risk while maintaining a minimal return (Li,2022). The benefit is risk reduction through multilateral insurance, minimizing the likelihood and severity of portfolio loss (Koumou,2020). The empirical research on diversification (whether industrial diversification or global diversification) and corporate risk in the literature has not found a consistent finding. For example, diversification strategies can reduce a firm's risk by reducing the cash flow dependencies among is various operation divisions (Berger & Ofek, 1995). Coinsurance effect theory is a theoretical hypothesis based on portfolio theory to explain the potential benefits of diversification. Hann et al. (2013) proposed that if a firm's cash flows from different business activities are not perfectly correlated, there will be a coinsurance effect that can stabilize the financial position of diversified institutions. On the other hand, the principal-agent theory denies the internal capital market of diversified enterprises market efficiency. The theory believes that the market is imperfect and has some insurmountable defects, such as low resource allocation efficiency under information asymmetry. Since diversification often has longer organizational levels and management chains, information may be blocked or distorted. Moreover, diversified operations bring principal-agent problems to enterprises, increasing opportunities for managers to obtain personal benefits, which may affect corporate strategy formulation and investment decisions and increases its business risks (Jensen,1986). And when a company crosses over to different markets or industries through diversified operations, the greater the difference in the cross-border fields, the more it can reduce the correlation of cash flow of each operating department of the company, but it will also increase the difficulty for the company to master information and integrate resources. It increases the risk of operating the company (Bettis & Hall,1982). Liang et al. (2020) finds that the increase of diversification will lead to more contributions to the risk of the banking system, which may be due to the higher similarity of activities. With the development of diversification, this may result in financial institutions facing common risks by holding similar investment portfolios (Wagner, 2010), resulting in financial instability. Adem (2022) states that diversification reduces risks and improve bank stability in emerging and developing economies during crisis and non-crisis periods, supporting portfolio theory.

2.2 Diversification on financial stability

Hoyt and Trieschmann (1991) studied insurers in the United States from 1973 to 1987 and found that insurers with diversified operations have higher risks than those with non-diversified operations. Cummins et al. (2010) considered that while diversification brings positive effects, it also amplifies the risks of insurance business operations, which is a new challenge for insurance supervision, and for the benefits derived from risk reduction. Ho et al. (2013) provided a different geographic view, finding that U.S. P-L insurance companies with lower geographic diversification had higher investment risks and financial stability. Che and Liebenberg (2017) find that diversified insurers take more asset risks than non-diversified insurers, and that the asset risk-taking is positively related to the degree of diversification. Shuang and Chan (2018) also dictated that the regulatory difficulties caused by diversification may lead to the rent-seeking behaviors of insurers and may increase the risks of insurers. The diversification of insurers may also lead to the different risk types and risk bearers, thereby increasing the operating difficulties of insurer. On the contrary, Che and Liebenberg (2017) argue that geographic diversification can reduce underwriting risk through cross-subsidies, allowing geographically diversified insurance companies to take on additional risks in the portfolios. Nguyen and Vo (2020) explore the relationship between corporate risk and solvency in listed insurers within the European Union, and highlight business diversification as a commonly regarded risk mitigation tool. Wu and Deng (2021) indicated that product diversification will improve the solvency of Chinese P-L insurers, but will reduce the solvency of foreign insurers. One possible reason for Chinese P-L insurers having improved solvency risk is the reduced volatility of its premium income and claims expenditure through a diversified portfolio of unrelated businesses and achieving a coinsurance effect. However, the information asymmetry caused by the principal-agent problem in foreign insurers makes external supervision and internal management become more difficult and expensive (Wei & Niu, 2006). Looking at the above literature, diversification is one the main growth factors for the insurers. This operation method brings benefits and lower costs to companies. For the question of whether diversified operations affect insurers' financial stability, there are positive and negative opinions, each with theoretical support. Nonetheless, there is still a divergence of opinion in the research and ideas regarding whether insurers diversification is beneficial. Therefore, the diversified strategy for insurers still needs to verified by more empirical research. This study considers that P-L insurers can reduce the possibility of portfolio losses and achieve financial stability through diversification strategies. Therefore, this study formulates the following hypothesis:

*H1**:** Diversification strategies have a positive impact on the P-L insurers' financial stability.*

2.3 COVID-19 pandemic and insurance stability

The COVID-19 pandemic was a major challenge for the global financial system following the 2008 to 2010 financial crisis and great recession. The pandemic caused a huge shock to the global economy, affecting various industries. However, this crisis is different from other previous types of crises-especially financial or banking crisis. COVID-19, as a major virus that spreads fast, had the widest impact, which is difficult to prevent and control, and caused the most serious damage to global economic development. Puławska (2021) confirmed that Covid-19 had a negative impact on the operation of the insurance sectors. In particular, any failure for an insurer could cause turmoil in the other business sectors. Wu et al. (2022) explores the impact of COVID-19 on China's insurers, showing that the return rate of listed insurers shows an "inverted N" curve of "declining, rising and falling again". The negative effects of the epidemic on insurers were mainly reflected in premium income and indemnity expenditure. Berry-Stölzle and Esson (2024) examine capital issuance and premium growth of U.S. P-L insurance during COVID-19 recessions, and their results showed that the business model of the P-L insurance is surprisingly resilient, even under the most different circumstances, and that P-L insurers can also provide financial stability services. The 2008-2009 crisis negatively impacted insurers, consumers, and business in Asia, compared with other regions. Taiwan's insurers underwrote a large number of epidemic prevention insurance policies, and its insurers were the most pessimistic about the impact of the COVID-19 pandemic on corporate finances (Teresiene et al., 2021). Based on the above, the following hypothesis is formulated:

H2: The COVID-19 pandemic has negatively impacted P-L insurers' financial stability.

3. Data, Methodology, and variables

3.1 Data Sources

The sample used in this research includes Taiwan's P-L insurance companies from 2010 to 2022, data collected from the Taiwan Insurance Institute (TII) website database, the Insurance Public Information Observatory website database, and *Taiwan Economic Journal* (TEJ). There are approximately 19 P-L insurers in Taiwan. Some foreign insurers are excluded from this study because they operate a special line of insurance and have a small market share. Therefore, this study chooses 15 insurers with relatively complete information. These 15 companies were selected as the research sample because their combined share in Taiwan's P-L insurance market is as high as up to 98.8 per cent, and the overall sample is representative.

3.2 Variables measuring in the research

3.2.1 Measuring financial stability

The key dependent variables in this study are the Z-score and the RBC ratio. The Z-score is a measure of risk that considers factors other than capitalization and events like bankruptcy. It is often used in financial stability literature as a proxy for the probability of corporate bankruptcy (Rauch & Wende, 2015; Turk-Ariss, 2010). Although the Z-score measure has traditionally been used as a proxy for individual risk in the banking sector (Baselga-Pascual et al., 2015; Khan et al., 2017), it may also be a useful tool when applied to the insurance sector (Cummins et al., 2017; Shim, 2017 a; Pavic et al., 2019; Moreno et al., 2022). This study uses the Z-score proposed by Rubio-Misas (2020), which indicates the probability of failure of a given insurer. Higher values of Z-scores imply lower probabilities of failure. Another indicator in this study is RBC ratio. RBC is a solvency ratio that indicates the assets and capital of insurers to be able to fulfill their obligations. However, Taiwan's insurers currently also use RBC ratio as a solvency indicator. The RBC regime requires insurers to maintain sufficient capital (own funds) determined by the risk that they assumed as a safety net for any unexpected investment and underwriting losses (Chen et al.,2021). The greater the RBC level of an insurers, the healthier the financial condition of that company (Hery et al., 2023). Therefore, we use RBC ratio proxy for insurers' capital adequacy is measured by their RBC ratio, that is, the ratio of owned capital divided by risk capital multiplied by 100%.

3.2.2 Measuring diversification and Covid-19 pandemic

Product diversification is one of dependent variables in this study. This study uses Herfindahl-Hirschman index (HHI) to measure the degree of diversification for each insurer. The product diversification (PD) is calculated as the sum of the squares of the percentages of direct premiums written across all product lines for each insurer in each year. In addition, the study measures the degree of geographical diversification using the number of branches of the company (Number of Branch Office; NBO), as a proxy variable for regional diversification, geographical diversification (GD) is the sum of the number of branches and the number of communications offices. Additionally, regarding measuring the COVID-19 pandemic's impact on P-L insurers, to analyze this effect, we follow Aqabna et al. (2023) by using a dummy variable, equal to 1 if firm is during COVID-19 period and 0 otherwise.

3.2.3 Factors affecting financial stability

1.Firm Size (FS)
Firm size is one of important factors affecting the solvency risk of insurers. Larger insurers bring low costs, richer cash flows and stronger solvency through economies of scale (Wu & Li,2021). Likewise, larger insurers are better able to spread portfolio risk through diversification than smaller insurers. However, Lopez-Valeiras et al. (2016) indicated firm size and financial performance had a negative impact on financial soundness. Al-Habashneh et al. (2023) also show that bank size adversely affects bank stability. Therefore, firm size factor presents the potential for a mixed result.

2.Firm age (FA)

Calantone et al. (2002) indicates that the older firms are able to respond to the market information more effectively and have higher good business performance than younger firms. In addition, Pottier (2007) pointed out that older firms have accumulated more experience through the learning effect and thus can better control the solvency risk.

3.Growth of premium (GP)

High premium growth is associated with an increase in a firm's corporate risk, as aggressive growth strategies may increase the risk of insolvency. (Lee & Urrutia,1996). When economies are bad, if an insurer increases its market share by increasing premiums coming through cash flow underwriting, it may not be able to bear the financial consequences of adverse circumstances.

4.Reinsurance (RE)

The use of reinsurance expands the insurer's underwriting capacity and allow insurers to hold less capital, reduce liabilities, and increase solvency without increasing its likelihood of its bankruptcy (Shim, 2017a). In addition, insurers transfer the risks through reinsurance to achieve risk diversification, reducing the potential for severe financial losses resulting from catastrophes.

5.Profitability (PRO)

Shim (2010) found that profitability plays an important role in determining an insurer's ability to increase capital. Moreno et al. (2020) also conclude that insurer solvency is positively related to profitability in Spain insurance sector.

6.Financial leverage (FL)

Colquitt and Hoyt (1997) indicated that leverage brings lower operational costs but also increases the likelihood of financial risks. Capital structure literature confirms that leverage increases, the value of the firm increases to optimum situation. Therefore, leverage about this optimum level may result in high risk of firm bankruptcy (Chen & Wong, 2004).

7.GDP growth (GDP)

The high growth of GDP during the rise of business capital creates good business opportunities for insurers (Tan,2016), and insurer may have good profits. Therefore, macroeconomic factors can affect the financial status of insurers; if insurers continue to be optimistic about the overall economic situation may be stimulated to engage in risky behavior, and vice versa. This study uses GDP growth rate as the macroeconomic environment variable (Hsieh et al., 2015).

8.COVID-19 pandemic (COVID)

The COVID-19 pandemic could lead to the beginning of another economic crisis (Oravský et al., 2020), since the P-L insurers face unique claims challenges due to the widespread disruption and uncertainty caused by the pandemic. As a result, the COVID-19 pandemic could have a serious impact on the insurers' capital.

9.Financial holdings (FH)

As far as the financial market is concerned, if an insurer belongs to one of the large groups, it can integrate and share the resources to improve efficiency and achieve good performance. Therefore, the chances of bankruptcy are lower. The definition of the variables is presented in table 1.

Table 1 Variables and Definitions

Variable	Definition
Dependent variables	
Z-score	(100+AverageROE) / (Standard deviation of ROE)
Risk-Based Capital (RBC)	(Owned capital /Risk-based capital) X100%
Explanatory	
Product diversification (PD)	Measured by 1-Herfindahl index (HHI) of product line
Geographic diversification (GD)	The number of branches of the company
Control variables	
Firm size (FS)	Natural logarithm of total assets
Firm age (FA)	Number of years since an insurer was established

Growth premium (GP)	Percentage growth in premiums from year t-1 to year
Reinsurance (RE)	It is calculated by dividing the reinsurance premium by the retained earned premium income.
Profitability (PRO)	Pre-tax income (losses) /average assets
Financial leverage (FL)	Total liabilities / total assets
GDP growth (GDP)	$(GDP_t\text{-}GDP_{t-1})/(GDP_{t-1})$, where GDP respects real gross domestic product
COVID-19 pandemic (Covid)	Dummy variable, during COVID-19 pandemic period then equal to 1, for the period before the COVID-19 pandemic to 0.
Financial holdings group (FH)	Dummy variable equals 1 if financial holding company; 0 otherwise.

3.3 Methodology

Traditional diversification determinants analysis adopts the ordinary least squares (OLS) approach (Liebenberg & Sommer, 2008; Che et al., 2017). The goal of the OLS approach is the minimum sum of the sum of squares of the error terms and emphasizes the average relationship between variables typically depends on an a priori distributional assumption of the dependent variable and the independent variable. Other parameters of conditional assignment of dependent variable are omitted, and different from the OLS, the quantile regression (QR) approach uses the minimum sum of the absolute values of the error terms in the target. Therefore, when the gap between samples is large or there are extreme values, the Quantile regression is more robust (Koenker & Hallock,2001). This approach details how the conditional distribution of the dependent variable depends on the covariates of independent variables at each quantile (Chang and Tsai,2014). In recent years, more of scholars have adopted QR models to analyze insurance data; for example, Shim (2017 b) used QR to examines diversification-performance relationship and Hung and Chang (2018) analysis of capital structure for P-L insurance.

Therefore, this study uses traditional OLS method and adds the QR approach for more detailed analysis. Through literature review, the regression model of insurers' financial stability can be predicted by the different following different factors:

$$\text{Z score}_{it}=\alpha+\beta_1\text{PD}_{it}+\beta_2\text{GD}_{it}+\beta_3\text{PRO}_{it}+\beta_4\text{GP}_{it}+\beta_5\text{RE}_{it}+\beta_6\text{FS}_{it}+\beta_7\text{FA}_{it}$$
$$+\beta_8 GDP_{it}+\beta_9 FL_{it}+\beta_{10} FH_{it}+\beta_{11} COVID-19_{it}+\varepsilon_{it}\cdots \quad (1)$$

$$\text{RBC}_{it}=\alpha+\beta_1\text{PD}_{it}+\beta_2\text{GD}_{it}+\beta_3\text{PRO}_{it}+\beta_4\text{GP}_{it}+\beta_5\text{RE}_{it}+\beta_6\text{FS}_{it}+\beta_7\text{FA}_{it}$$
$$+\beta_8 GDP_{it}+\beta_9 FL_{it}+\beta_{10} FH_{it}+\beta_{11} COVID-19_{it}+\varepsilon_{it}\dots\dots\dots \quad (2)$$

where i represents firms, t is years, and ε_{it} is the error term, α is the intercept; $\beta$is the estimated regression coefficient of independent variable; j = 1, 2, 3…11; assuming that is obeys the normal distribution.

4. Empirical results

4.1 Descriptive Statistics

Observing from the mean value of Z-score and RBC, P-L insurers are 8.4917 and 4.6445 respectively, among which RBC' maximum 10.8189 and minimum value of -16.8092, and the difference is extremely large, indicating that the solvency of this P-L insurers shows a wide range of extreme values. Further, the means of product and geographic diversification of P-L insurers are 0.6264 and 38.0972 respectively, show that P-L insurer has a high degree of product and geographic diversification strategy. In addition, P-L insurers' overall profitability (ROA) average -1.52% due to Covid-19 pandemic. Subsequently, this study uses the variance inflation factors (VIF) to test for multicollinearity among independent variables in the regression program. The VIF of all independent variables in the study were less than 5, which was lower than 10 of Cohen et al. (2003). Therefore, the regression results are not affected by multicollinearity. The descriptive statistics and the VIF values used in the regression analysis will be presented in Table 2.

Table 2 Descriptive Statistics of Variables

Variable	Mean	Std. dev.	Median	Min	Max	VIF
Z-score	8.4917	1.4892	8.7637	1.5995	10.8874	
Risk-Based Capital (RBC)	4.6645	3.0135	4.0186	-16.8092	10.8189	
Product diversification (PD)	0.6264	0.0683	0.6354	0.3618	0.7620	1.67
Geographic diversification (GD)	38.0972	17.8148	37.0000	1.0000	90.0000	2.60
COVID-19 pandemic (Covid)	0.1538	0.3617	0.0000	0.0000	1.0000	1.34
Profitability (PRO)	-0.0152	0.3489	0.0344	-4.0535	0.1684	3.62
Growth premium (GP)	0.0584	0.0773	0.0555	-0.1611	0.5392	1.10
Reinsurance (RE)	0.3195	0.1177	0.290	0.159	0.780	2.46
Firm size (FS)	16.6723	0.7323	16.6469	14.7983	18.6951	4.58
Firm age (FG)	48.2667	19.2796	53.0000	4.0000	91.0000	1.73
GDP growth (GDP)	0.0368	0.0226	0.0296	0.0147	0.1025	1.07
Financial leverage (FL)	0.7024	0.1401	0.6794	0.5068	1.8619	3.66
Financial holdings group (FH)	0.2769	0.4486	0.0000	0.0000	1.0000	1.51

4.2 Analysis of differences in variables before and during the COVID-19 Pandemic

Table 3 shows the differences in the mean values of each variable before and during the COVID-19 crisis. The table contains before and during the COVID-19 pandemic, as well as the differences, between the average value. Focusing on the statistically significant differences, this study can see that the mean values of Z-score and RBC before and during the COVID-19 pandemic periods were 8.7309, 7.1923, and 4.8782, 3.4894 respectively. It shows that during the COVID-19 pandemic period, the solvency of P-L insurers has shown a downward trend. The average of the profitability for the before and during of COVID-19 pandemic periods were 0.0320 and -0.2719, respectively, indicating that the profitability of P-L insurers has been greatly affected by the COVID-19 pandemic and has turned negative. Averages of premium growth, firm size, firm age and GDP growth during the COVID-19 pandemic have increased compared to before the COVID-19 crisis. Finally, before the COVID-19, financial leverage averaged 68.96%, and during the COVID-19 pandemic, financial leverage averaged 77.32%, indicating an increase on financial leverage during COVID-19 period. These figures show that the average Z-score and RBC have declined during the COVID-19 pandemic, compared to previous non COVID-19 pandemic period, demonstrating the impact of COVID-19 pandemic on P-L insurers' financial stability. Univariate analysis showed that most variables differed significantly during Covid-19 and before the COVID-19 pandemic. The results are detailed in Table 3.

Table 3 Analysis of Differences in Variables before and During the COVID-19 Pandemic

	Before-the COVID-19 pandemic average (2010– 2020)	During the COVID-19 pandemic average (2021– 2022)	Difference between before pandemic and pandemic average
Key variables			
Z-score	8.7309	7.1923	2.3488 ***
RBC	4.8782	3.4894	5.5955 ***
Product Diversification (PD)	0.6287	0.6141	1.0754
Geographic Diversification (GD)	37.8546	39.8667	-0.4267
Profitability (PRO)	0.0320	-0.2719	4.6126***
Growth premium (GP)	0.0535	0.0869	-2.2123**
Reinsurance (RE)	0.3319	0.2516	3.5369
Firm size (FS)	16.6203	16.9582	-2.3513***
Firm age (FA)	47.2667	53.7667	-1.7070**
GDP growth (GDP)	0.0355	0.0445	-2.0278**
Financial leverage (FL)	0.6896	0.7732	-3.0709***
Financial holdings (FH)	0.2667	0.3333	-0.7478

Notes: ***, **, and * indicate significant at the 0.01, 0.05 and 0.10 level, respectively.

4.3 Diversification and COVID-19 pandemic on financial stability

This study used both OLS and QR approaches, and the corresponding results are shown in Table 4. The product diversification coefficients in the OLS model have a significant negative correlation with Z-score (β=-6.961, p<0.01). In addition, the product diversification coefficients in the QR model are also significantly negatively related to the Z-score at the all quantiles, which is consistent with the principal-agent theory. Product diversification leads to information asymmetry among insurers, causing agency problems, increasing management costs and the risk of bankruptcy. The Geographic diversification coefficient has a positive impact on the Z-score but insignificant in OLS and QR model, indicating that if Taiwan's P-L insurers are diversified in regions, this may positively contribute to finances, but this may be due to the small size of the geographic area, so that there is no significant correlation. In addition, the coefficient of the COVID-19 pandemic dummy is negative significant with Z-score in OLS (β=-1.356, p<0.01), whereas the COVID-19 pandemic dummy coefficients in the QR are negative significant at the lower and median quantiles (**τ**=0.1, 0.25, 0.5, 0.75), which is consistent with Puławska (2021) that shows that the pandemic has had a negative impact on stability of the insurance sector, reducing insurers' average ROA and Solvency II ratio. Furthermore, for higher quantiles insurers, the Covid-19 pandemic dummy coefficients in are negative, but not significant. This shows that Covid-19 is not having a significant negative financial impact on all P-L insurers. In table 4, an insurer's financial leverage is negatively related to the Z-score for both OLS and the QR models. The result is consistent with the view proposed by Chen and Wong (2004) that insurers having greater financial leverage level could lead to high bankruptcy risk.

For other control variables, the coefficients of the RE variable are significantly positive for OLS model (β=1.899, p<0.1), which is consistent with Shim (2017 a), reinsurance is a substitute for capital that reduces the capital held by insurers without increasing insurers' probability of insolvency. The RE coefficients in the QR model are positive at median quantiles. The insurers at the median quantiles(τ =0.5, 0.75), show that insurers can reduce their capital burden and have higher financial stability by using reinsurance.The coefficients FS are positive and significant for the OLS model(β=0.564, p<0.05), consistent with the predictions of Wu and Li (2021). Larger insurers through economies of scale lead to low costs, with richer cash flows, whereas coefficients in the QR model are positive at lower and low and median quantiles(τ =0.1, 0.5), suggesting that insurers in the low and median quantiles may have more rigorous management and therefore have higher financial stability. The coefficients FH are positive and significant in the OLS and QR model, which is consistent with the views of Phillips et al. (1998), that an insurer that is a member of a group may be bailed out by the group to protect the group's reputation.

Table 4 Empirical Results of the OLS and QR Approach (Independ Variable: Z-score)

	OLS	Quantiles (τ =0.1, 0.25, 0.5, 0.75, and 0.90)				
		0.1	0.25	0.5	0.75	0.9
Intercept	7.1185*	5.2229	5.4740	1.2727	10.9503*	20.2250**
	(3.8889)	(5.5234)	(5.1841)	(6.3415)	(6.5098)	(10.1052_
PD	-6.9608***	-9.9570***	-5.7372***	-5.6530***	-6.1100***	-9.5462***
	(1.5560)	(2.8005)	(2.8201)	(2.2023)	(2.1587)	(2.7278)
GD	0.0030	-0.0075	0.0072	0.0102	0.0236	0.0303
	(0.0084)	(0.0113)	(0.0111)	(0.0101)	(0.1496)	(0.0240)
COVID-19	-1.3557***	-1.4574**	-1.0536***	-0.9887***	-0.7587**	-0.6691
	(0.2789)	(0.6589)	(2.0080)	(0.2702)	(0.3676)	(0.5439)
PRO	-0.5321	0.6724	1.1295	-0.9144	-0.4988	-0.5293
	(0.5515)	(2.9406)	(3.1188)	(3.0573)	(2.5920)	(2.8165)
GP	0.1525	0.8061	0.4135	-0.8381	-0.8602	-1.6623
	(0.7646)	(1.2448)	(0.9019)	(0.8986)	(1.8348)	(2.4795)
RE	1.8990*	2.5267	1.9825	2.8175**	3.6475**	3.2568
	(1.0932)	(1.9184)	(1.6336)	(1.2959)	(1.6414)	(2.4283)
FS	0.5636**	0.7341*	0.5883	0.8388**	0.2332	-0.1468
	(0.2388)	(0.3843)	(0.3698)	(0.3556)	(0.3886)	(0.6062)
FA	0.0071	0.0035	0.0046	0.0038	0.0057	0.0054
	(0.0053)	(0.0078)	(0.0062)	(0.0055)	(0.0094)	(0.0132)
GDP	-2.6468	0.7601	-1.8218	-2.8417	-7.6727*	-2.8383
	(3.4151)	(5.4584)	(5.1008)	(3.8507)	(4.3081)	(4.7195)
FL	-6.6349***	-6.8550***	-7.1396***	-6.2745***	-5.6658***	-6.4333**
	(1.3292)	(2.6380)	(2.0080)	(1.4402)	(1.6709)	(2.8443)
FH	0.7728***	1.2725***	0.8275***	0.3400	0.6204*	0.6421**
	(0.2088)	(0.3916)	(0.2542)	(0.2898)	(0.3439)	(0.4068)
N	195	195	195	195	195	195

This table presents the results of the OLS approach (column 2) and of the QR approach with quantiles t=0.1, 0.25, 0.5, 0.75 and 0.9 (column 3-7). The dependent variable is the insurers' Z-score. Standard errors are in parentheses. Note: ***, ** and * represent statistical significance at the 1 per cent, 5 per cent and 10 per cent levels, respectively.

Using the OLS and QR approaches as analysis tools, and the relevant results are listed in Table 5. The product diversification coefficients in the OLS model have a significant negative correlation with RBC (β=-6.413, $p<0.01$). It shows that the diversification of insurers may lead to differences in risk types and risk bearers, thereby increasing the operating difficulties of an insurer, whereas the product diversification coefficients in the QR model are significant at the lower and median quantiles(τ =0.25,0.5). In addition, the finding is that QR result provides insurers product diversification is significant and positive with the RBC ratio at the higher quantiles(τ =0.90) indicating higher quantiles insurers support coinsurance effect theory, insurers' cash flows from different business activities are not perfectly correlated, thus stabilizing the financial position of the diversified insurers (Hann et al., 2013). The P-L insurers product diversification reports a negative relationship with insurers' RBC ratio, which is same as the previous Z-score. The Geographic diversification coefficient shows a positive impact on Z-score, but is insignificant in OLS and QR model, indicating for Taiwan's P-L insurers that are diversified in regions, this may positively contribute to finances, but it may be that the small size of the geographic area results in no significant correlation. Furthermore, the coefficient of the COVID-19 pandemic dummy is insignificant with the RBC ratio in OLS, whereas the COVID-19 crisis pandemic coefficients in the QR are also insignificant at the all quantiles. The possible reason is that according to the Taiwan's financial supervision regulations, if the RBC ratio is between 150% and 200%, an insurer must increase capital with a time limit. Therefore, some insurers likely continuously increased capital during the period to raise or restore the RBC to the normal level, resulting in an insignificant relationship between the Covid-19 dummy and the RBC ratio.

For other control variables, we find that the coefficients of FS variable are insignificantly positive for the OLS model, whereas the FS coefficients in the QR model are negative at median and higher quantiles(τ =0.5,0.75), which is consistent with the argument of Lopez-Valeiras et al.(2016), that indicates that firm size has a negative impact on financial soundness. The coefficients FA are positive and significant in OLS model, whereas coefficients in the QR model are positive at median and higher quantiles(τ =0.5,0.75), consistent with the predictions of Pottier (2007). Older firms have accumulated more experience thus can better control the solvency risk. The coefficients GDP are negative and significant in the OLS and QR model, indicating that insurers have optimistic expectations about economic growth and are prone to engage in high-risk investment behaviors that affect their solvency.

Table 5 Empirical Results of the OLS and QR Approach (Independ Variable: RBC)

	OLS	Quantiles (τ =0.1, 0.25, 0.5, 0.75, and 0.90)				
		0.1	0.25	0.5	0.75	0.9
Intercept	26.7705***	15.1305**	22.5308***	30.7838***	29.4154***	19.4446**
	(5.5120)	(6.8140)	(8.3061)	(5.4512)	(5.6462)	(8.8167)
PD	-6.4132***	-4.0345	-7.3853**	-8.5485***	-1.7398	7.0887*
	(2.1611)	(3.4199)	(3.4739)	(2.7026)	(3.4704)	(3.6337)
GD	0.0109	0.0105	0.0164	0.0159	0.0175	-0.1625
	(0.0107)	(0.0099)	(0.0113)	(0.0116)	(0.0142)	(0.0273)
COVID-19	0.3117	0.4663	0.5269	-0.0475	-0.3109	-0.2009
	(0.3782)	(0.3391)	(0.3751)	(0.4232)	(0.3882)	(0.4478)
PRO	1.3488**	3.6541**	3.1733*	0.1555	-0.4756	-1.7378
	(0.6363)	(1.7448)	(1.9099)	(2.6326)	(2.9891)	(3.8140)
GP	-1.5470	2.7497	-1.0344	-0.5937	0.1295	-2.9652
	(1.6027)	(1.9562)	(2.8233)	(2.6367)	(2.5980)	(2.3497)
RE	-0.5532	0.1946	-0.9582	-0.0365	-1.6068	1.2603
	(1.5382)	(1.3939)	(2.0214)	(1.9476)	(2.4133)	(4.0008)
FS	-0.5306	-0.3906	-0.5766	-0.6178*	-0.7854**	-0.2650
	(0.3411)	(0.3403)	(0.4327)	(0.3468)	(0.3839)	(0.5322)
FA	0.0268***	0.0055	0.0111	0.0251***	0.0298***	0.0171
	(0.0082)	(0.0094)	(0.0121)	(0.0071)	(0.0092)	(0.0143)
GDP	-23.3945***	-3.2204	-12.9512**	-24.9123***	-12.3463**	-22.3512***
	(5.4284)	(5.1800)	(6.3920)	(6.4900)	(6.7030)	(7.8029)
FL	-13.9680***	-6.0407 *	-7.6613*	-16.4304***	-14.6798***	-17.1216***
	(1.6082)	(3.1183)	(4.4059)	(3.1329)	(3.5107)	(4.3628)
FH	-0.1355	0.3862	0.2245	0.5433	-0.4688	-1.1061*
	(0.3247)	(0.2611)	(0.4560)	(0.4465)	(0.3652)	(0.6025)
N	195	195	195	195	195	195

This table presents the results of the OLS approach (column 2) and of the QR approach with quantiles t=0.1, 0.25, 0.5, 0.75 and 0.9 (column 3-7). The dependent variable is the insurers' Z-score. Standard errors are in parentheses. Note: ***, ** and * represent statistical significance at the 1 per cent, 5 per cent and 10 per cent levels, respectively.

5. Conclusions and Policy Implications

The evidence shows that product diversification presents a significantly negative impact on insurers' Z-score at the OLS and QR (all quantiles). For insurers at all quantiles, the principal-agent argument is supported, indicating that product diversification makes information asymmetry in insurers, which increases management costs and the risk of bankruptcy. Some scholars (Berger & Ofek,1995; Borghesi et al., 2007; Volkov & Smith; 2015) have proposed that diversification discount due to such as opportunistic behavior, internal coordination and management costs and the failure of manager in product diversification decision-making. In this study, health insurance operations during COVID-19 brings high liquidation risks to Taiwan's P-L insurers due to high volatility of new activities resulting in higher loss than expected profits (Castro & Mej´ıa, 2019), show high product diversification leads to financial instability of insurers. However, product diversification has a significantly negative impact on insurers' RBC ratio at the lower and median quantiles which is same as previous Z-score, but higher quantiles insurer' diversification is significant and positive with RBC ratio, indicating insurers' cash flows from different business activities are not perfectly correlated, stabilizing the financial position of the diversified insurers. In addition, Geographic diversification coefficient is positive impact on Z-score and RBC but insignificant in OLS and QR model, indicates Taiwanese P-L insurers cannot effectively perform its diversification function due to small size geographic. There is a negative significant relationship between the COVID-19 pandemic with the Z-score in OLS, whereas there is also a negative significant relationship between the COVID-19 crisis with the Z-score for insurers in the lower and median quantiles in the QR model ($\boldsymbol{\tau}$=0.1, 0.25, 0.5, 0.75), indicating the COVID-19 pandemic on financial impact of Taiwan's P-L insurers. The COVID-19 crisis is insignificant with RBC ratio in OLS and QR models, possible reasons may be affected by the capital increase of the supervisory authority in the current year. These results contrast with those of the OLS approach.

Other major findings are summarized below. First, there is evidence that insurers with greater financial leverage have lower solvency and higher solvency risk. Second, reinsurance is generally considered as a risk transfer tool and higher and median quantile's insurers use reinsurance will help improve insurers' solvency risk. Third, insurers that belong to financial holding groups will be able to improve their solvency due to the financial support of the group. Finally, economic growth may lead to optimistic expectations among insurers and increase risk behavior that affect their finances.

Many literatures (Hann et al., 2013; Koumou, 2020; Adem,2023) believes that diversification is beneficial to financial stability. Different from previous studies. The findings highlight some policy implications for insurance regulation, policymakers and insurers. First, the result s of this study provides another perspective, the product diversification of P-L insurers may have an adverse impact on financial stability, insurers pay attention to diversification strategies, policymakers and/or regulators should understand the relationship between the product diversification and solvency of insurers, and managers must carefully evaluate and establish systems to control the degree of diversification to reduce potential risk. Second, The COVID-19 pandemic has indeed created financial instability for P-L insurers, which reflects the irresponsible risk-taking behaviors by insurers in order to profit. As a result, insurers face unbearable claims losses and financial risks, resulting in huge negative external impacts (Yeh & Lian,2024). Finally, this study proposes a QR method instead of using traditional OLS method to examine the impact of diversification and COVID-19 pandemic on financial stability for P-L insurers. Therefore, in terms of practice applications, we suggest not only considering the results of the OLS method, but also carefully studying the results of the QR approach, so that more complete information can be obtained. This study has some limitations, including the problem of insufficient sample size. In the future, it is suggested that life insurance or banks can be added for further comparative analysis. Additional, subsequent research suggests that different evaluation indicators such as net worth ratio can be added in terms of financial stability to obtain more complete results for reference. As a caveat, since Taiwan P-L insurers diversified into health insurance, entailing large payouts during the Covid pandemic, this type of diversification may have had a significant effect on the results for the negative relationship between diversification and an insurer's solvency risk.

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Evaluating the Choices of Strike Ranges for the Long Call Condor Strategy

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A B S T R A C T

This study proposes a new perspective on strike ranges to benefit long call condor strategy traders, enabling them to capture potential opportunities in response to market scenarios. We derive the analytical solutions for the long call condor strategy's fair value and risk sensitivity. We also explore how the choice of strike ranges influences the strategy's risk and rewards for traders. The findings suggest that a wider range of insider strikes lowers the profits of strategy traders, while a wider range for outsiders enlarges the profits. We recommend designing option portfolios with different strikes to enable strategy traders to capture potential interests more effectively if they expect specific market scenarios.

Keywords: Long call condor strategy, Option valuation, Strike ranges
JEL Classification: G12, G13

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1. Introduction

Investors enter the derivatives markets to pursue profits and manage potential risks by implementing appropriate strategies. Forming an options trading strategy is viable for traders to promote payoffs and mitigate risk, compared to holding plain vanilla options. Strategy traders attempt to select various options with different maturities, types, and strikes to respond effectively to market movements. In the context of these long-term and important issues, we examine how strategy traders select strike ranges based on their option positions to create value. Due to the difficulty in evaluating all trading strategies, we focus on one of the popular strategies, the long call condor (hereinafter, LCC) strategy, to examine how traders select appropriate option contracts with appropriate strike levels. Since little research has been conducted on the fair value and strike ranges of option trading strategies, deriving a formula for fair value, risk sensitivity, and options portfolio design is a challenging task that relies primarily on considering the valuation of the option strategies and analyzing the market scenarios.

The LCC strategy consists of one long in-the-money call, one short higher middle strike in-the-money call, one short middle out-of-the-money call, and one long highest strike out-of-the-money call, all with the same expiry date. The LCC strategy is implemented to achieve specific goals of stable returns in the face of market movement. Meanwhile, this strategy is profitable if the underlying price falls within the confines of the two breakeven points and is unprofitable when the underlying price exceeds either of the two breakeven points. The maximum possible profit is realized when the underlying security price falls somewhere between the strikes of the written options. A profit will also be made if the underlying security price moves slightly outside this range. However, a loss will be caused if it goes too far in either direction. Thus, the choice of strike prices in the LCC strategy is a matter for strategy traders to capture potential profits.

In this study, we re-examine the condor strategy to identify the impacts of strike ranges on the strategy value and risk management. We provide three remarkable viewpoints in the literature. First, the study aims to price the condor strategy by deriving the closed-form solution of the fair value for the long call condor strategy. The theoretical fair value of the condor strategy enables traders to assess accurately whether it is a better choice, considering the various components of call options based on their strike ranges. Specifically, we first derive the theoretical fair value of the condor strategy in the literature. Second, we derive the Greek letters to analyze the sensitivity of strategy values over risk exposures. The Greek letters benefit the analysis of strategy values in response to the various risk exposures. We believe this is the first work presenting the analytical risk measures of LCC trading strategies. Third, the strike ranges offer us an observation of how market movements influence the strategy values. A wider or narrower range of strike levels within the options portfolio significantly impacts the strategy's value and risks. Choosing a suitable structure of strike ranges in the condor strategy benefits traders by capturing relatively higher profits and mitigating potential risks. Combining the above three viewpoints to derive strategy value, acquire risk measures, and set strike range is crucial for the decision-making process of condor strategy traders.

This article proposes a new perspective, the strike range, to identify how options traders formulate an optimal condor strategy to create the value of their strategies. Our research results provide traders with a comprehensive understanding of the strategy, its potential outcomes, and practical guidance for implementing and managing trading situations. If the market scenario is correctly expected, we find that choosing a narrower strike range is preferred for traders who employ the LCC strategy. In that case, they can formulate the LCC strategy by planning an appropriate strike range in response to market movements.

We are concerned about the following issues, which we address through theoretical analysis to address the above considerations. First, this study answers the question of how we price the fair value of the LCC strategy. Evaluating fair value is crucial for assessing the strategy's performance under various scenarios. In our pricing task, the LCC strategy's fair value is the sum of the fair values of its option positions, as the strategy consists of four plain-vanilla options. The analytical solution of fair value can be carried out using a risk-neutral probability measure[2]. The estimated fair value results for

[1] Refer to Kwok (1998).

the LCC strategy vary with the market conditions, return volatility, and other factors.

Next, we explore how to implement risk management of the condor strategy. The traders of a condor strategy aim to reduce risk and increase the chances of success. However, that comes with reduced profit potential and increases the costs of trading several options legs. If the market conditions change, traders can adjust their LCC strategy by modifying the call options' strike prices by setting a stop-loss order at a predetermined price level. Zhong (2023) suggests that options trading is risky and challenging. It requires investors to conduct in-depth market analysis and develop effective trading strategies, while options traders must also understand risk management issues. Thus, we employ Greek letters to measure the degrees of risk exposure resulting from changes in underlying asset values, interests, return volatility, and contract maturity.

Finally, based on the results of the strategy value and Greek letters, this study examines how to choose appropriate strike ranges for condor traders. The LCC strategy is generally considered more suitable for traders in a range-bound market condition, where they believe the underlying security will experience minimal volatility and trade within a specified price range. The LCC strategy can be effective in a range-bound market because it is designed to generate profits when the underlying asset's price remains within a specific range. The strategy trader creates a profit zone within a specific price range, which can be profitable if the underlying asset's price remains within that range. According to the LCC strategy's portfolio of call options, the maximum potential profit occurs when the underlying price is within the range of the two middle strike prices. On the other hand, a possible loss occurs when the underlying price falls below the lowest strike price or rises above the highest strike price. Specifically, the study also discusses the special case of the long call butterfly strategy, a variant of the LCC strategy. The long call butterfly consists of two short calls at a middle strike and one long call at each lower and upper strikes. The upper and lower strikes are equidistant from the middle strike, and all options have the same expiration date. As the LCC strategy's two middle strikes are considered to approach each other, the LCC strategy gradually becomes the long call butterfly strategy.

Although the LCC is one of the rather complex options trading strategies, with four legs involved, it offers great flexibility in setting a strike range from which options traders can profit. Based on the above discussion, we examine potential interests in different ranges between four strikes in the LCC strategy. Therefore, to succeed in trading, traders should establish a policy for option portfolios with appropriate strike price choices to balance risk and reward when seeking potential opportunities in the financial markets.

Previous studies have demonstrated that the options portfolio strategy effectively generates profits while mitigating risks (Liu *et al*., 2021; Kang *et al*., 2022; Shivaprasad *et al*., 2022; Rustamov *et al*., 2024). We extend this stream of research by focusing on the strike ranges of condor strategy and analyzing how strategy traders capture potential interests from various market scenarios. We present our observations of strategy values across insider and outsider ranges of strike levels and recommend to traders how to select option contracts in the LCC strategy. Our findings suggest that wider or narrower strike ranges can directly impact strategy values. Traders should choose a narrower inside range to capture the maximum strategy interests and a wider outside range to gain more potential payoffs.

This study contributes to the literature on option trading strategies in the following ways. First, we derive and offer a fair value for the long condor strategy, enabling traders to evaluate its value more accurately and make better-informed decisions about whether to take this position. Previous studies do not provide concrete results of the strategy values of a condor. Second, the study also focuses on developing effective risk management for the condor strategy, helping traders better manage their risk exposure and potentially increase their returns. Third, we examine the strike ranges to explore how strategy traders determine an appropriate range of strikes for their options. Setting strike ranges is critical to capturing profits in response to market movements. Framing the closed-form solution of fair value for the LCC strategy, we can provide concrete recommendations for traders to incorporate into their option portfolios.

This study consists of five sections. Section 2 reviews the literature on the LCC strategy and risk management. Section 3 shows our research methodology, including given assumptions and derivations of closed-form solutions for fair value and Greek Letters based on the Black-Scholes model. Section 4 covers numerical analysis for our tasks, addressing the abovementioned issues and providing evident results, specifically in analyzing strike ranges across market scenarios. Section 5 concludes with a brief discussion of the managerial implications of this research.

2. Literature Review

The literature on options trading strategies has evolved from various perspectives, particularly in the context of spread trading. Practitioners and sophisticated traders employ various strategies in options markets, with a growing proportion of option spread trading (Chaput and Ederington, 2003; Falenbrach and Sandås, 2010; Stoltes and Rusnáková, 2012; Liu *et al*., 2021; Hemler *et al.*, 2024). Chaput and Ederington (2003) reveal that option spread trading totals 29% of Eurodollar options trading volume, while Falenbrach and Sandås (2010) show that vertical call and put option spread trading represents 16% of FTSE 100 index options trading volume. Hemler *et al*. (2024) examine the relative performance of four options-based investment strategies versus a buy-and-hold strategy in the underlying stock. Their results show that options-based strategies can improve the risk-return performance of market traders' portfolios. Overall, the literature on options trading strategies suggests that while they can generate substantial profits, they also involve significant risks and require a thorough understanding of the market and options trading.

Previous literature also discusses the characteristics of condor strategies and examines the relationships between risk and reward. McKeon (2016) supports that long call condor strategies are limited, directional, or non-directional risks constructed to generate a limited profit when seeking little or no movement in the underlying. Niblock (2017) demonstrates that the primary benefit of long call condors is that they can be set up to accommodate anticipated market conditions over the intended holding period, enabling investors to target investment goals tailored to their desired risk-return profiles. In addition, McKeon (2016) finds that the long volatility condor strategy adds value for traders and investors seeking positively skewed return distributions.

Risk management is a complex and crucial consideration when implementing the spread strategy (Chen *et al*., 2010; Jongadsayakul, 2018; Ewa, 2022; Shivaprasad *et al*., 2022; Jain, 2023), particularly for condor and butterfly strategies, as the strategies involve both limited risk and reward. Specifically, Ewa (2022) presents the structure of the iron condor strategy to examine the impact of the underlying instrument's price on the strategy's value and the value of the Greek letters. The author demonstrates that all risk measures associated with the iron condor strategy fluctuate significantly over time, indicating that the strategy's values are highly sensitive to changes in its underlying factors. Jain (2023) suggests that the iron condor strategy should ideally be initiated on stocks with higher implied volatility and advises traders to verify that stock options are relatively liquid, exercising caution when executing the trade. Shivaprasad *et al*. (2022) examine the risk-return trade-off of the long straddle, long strangle, and long call butterfly strategies. They suggested that strategy investors can improve excess returns relative to the risks by choosing the appropriate strategy and analyzing the impact of risk on the payoff.

Our work is related to the extensive theoretical literature investigating the spread strategies that use more options. Specifically, we have mentioned that strategy traders consider forming the LCC strategy by combining four options with different strike prices. Choosing the strike ranges between options will influence profits and losses. Based on this important issue, the present article aims to derive the closed-form solution for the LCC strategy's fair value and Greek letters and then analyze the impacts of strike ranges on the fair values in response to market movements.

3. Methodology

This section presents the derivation of the fair value of a long call condor, along with its associated Greek letters. We first describe the assumptions used to derive our formula and then outline the process used to obtain it based on the Black-Scholes (1973) formula.

3.1 Assumptions

This section presents the assumptions used to derive the closed-form solution for the fair value of the LCC strategy. The strategy is constructed by holding four options: buying one in-the-money (ITM) call (low strike), selling one ITM call (lower middle), selling one out-of-the-money (OTM) call (higher middle), and buying one OTM call (high strike), all with the same expiry date and underlying assets. We give the options' underlying is a representative stock[2], whose price (S_t) of the underlying stock follows a geometric *Brownian* motion[3] (*GBM*):

$$\frac{dS_t}{S_t} = (r - q)dt + \sigma dW_t \tag{1}$$

where St represents the underlying stock's price at time t, q represents the continuous dividend yield of the underlying stock, r represents the risk-free interest rate, and σ represents the underlying stock's volatility. The geometric *Brownian* motion process frames in a complete probability space (Ω, Σ, $\boldsymbol{Q}$) with filtration $\{\Sigma_t\}$, where $W^P(t)$ is *Wiener* process under a real-world probability $\boldsymbol{P}$-measure, in which $\Delta W(t) = W(t) - W(t-\Delta t) \sim N(0, \Delta t)$.

For simplicity's sake and without the loss of generality, we make some assumptions consistent with the works of Black and Scholes (1973), Merton (1974), Zhang and Zhou (2024), and other researchers. First, to derive a closed-form solution, the options contracts are European-style. Second, the transactions of stocks, risky assets, risk-free assets, and derivatives occur continuously. Third, we assume that trading has no transaction costs, taxes, or short-selling restrictions. Fourth, options traders can access a riskless asset with a risk-free interest rate in a financial market.

3.2 Pricing the LCC Strategy

The LCC strategy is constructed by buying one call option with a lower strike price (K_1), selling one call with a lower middle strike price (K_2), selling one call with a higher middle strike price (K_3), and buying one call with a higher strike price (K_4). All four option contracts have the same expiration date, *T*.

$$V_t = +C_t(K_1) - C_t(K_2) - C_t(K_3) + C_t(K_4) \tag{2}$$

where V_t represents the strategy value of the LCC at time *t*, and the terms $C_t(K_i)$ represent the prices of the European call options with strike prices K_i, at time t. Furthermore, under a risk-neutral probability measure $\boldsymbol{Q}$, the underlying stock price has the following formula at maturity *T*, where τ ($= T - t$) represents the time to expiration of the options involved in the strategy.

$$S(T) = S(t)e^{\sigma W^Q(T-t) + (r - \frac{1}{2}\sigma^2)(T-t)}$$

By a risk-neutral probability measure approach, the value of a financial asset should be equal to the discounted value of the expected future cash flows, where the risk-free interest rate (*r*) is used to discount the future value and a risk-neutral probability is used to average the possible outcomes. Thus, under a probability measure-$\boldsymbol{Q}$, the LCC strategy's value[4] (V_t) is written as.

$$V_t = e^{-r(T-t)}E(V_T)$$

Taking the Black and Scholes option pricing model's analytical solution of European-style plain vanilla call, we have the following formula.

[2] This strategy typically uses stocks or indexes as its underlying asset, and the choice of underlying asset depends on the investor's market outlook and preferences.
[3] Refer to Karatzas and Shreve (2000).
[4] Because the LCC strategy consists of four European plain vanilla call options, we can directly apply the results of Black and Scholes's option pricing model in its pricing process.

$$V_t = S_t e^{-q\tau}\left[N(d_{1,1}) - N(d_{2,1}) - N(d_{3,1}) + N(d_{4,1})\right]$$
$$-e^{-r\tau}\left[K_1 N(d_{1,2}) - K_2 N(d_{2,2}) - K_3 N(d_{3,2}) + K_4 N(d_{4,2})\right] \tag{3}$$

where,

$$d_{1,1} = \frac{\ln\left(\frac{S_t}{K_1}\right)+\left(r-q+\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{4}$$

$$d_{2,1} = \frac{\ln\left(\frac{S_t}{K_2}\right)+\left(r-q+\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{5}$$

$$d_{3,1} = \frac{\ln\left(\frac{S_t}{K_3}\right)+\left(r-q+\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{6}$$

$$d_{4,1} = \frac{\ln\left(\frac{S_t}{K_4}\right)+\left(r-q+\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{7}$$

$$d_{1,2} = \frac{\ln\left(\frac{S_t}{K_1}\right)+\left(r-q-\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{8}$$

$$d_{2,2} = \frac{\ln\left(\frac{S_t}{K_2}\right)+\left(r-q-\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{9}$$

$$d_{3,2} = \frac{\ln\left(\frac{S_t}{K_3}\right)+\left(r-q-\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{10}$$

$$d_{4,2} = \frac{\ln\left(\frac{S_t}{K_4}\right)+\left(r-q-\frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \tag{11}$$

where $N(d_i)$ represents the cumulative distribution function of the standard normal distribution based on the standard normal variables d_i. These equations are derived from the Black-Scholes option pricing model assumptions, which assume a continuous dividend yield and constant volatility.

3.3 Greek Letters

The main Greek letters associated with the LCC strategy include *Delta*, *Gamma*, *Rho*, *Theta*, and *Vega*. These Greek letters measure the sensitivities of strategy values over some strategy factors. Based on the closed-form solution (3) of the LCC strategy, we derive the following formulas:

$$Delta_t = e^{-q\tau}[N(d_{1,1}) - N(d_{2,1}) - N(d_{3,1}) + N(d_{4,1}) \tag{12}$$

$$Vega_t = S_t e^{-q\tau}[n(d_{1,1}) - n(d_{2,1}) - n(d_{3,1}) + n(d_{4,1}) \tag{13}$$

$$Gamma_t = \frac{e^{-q\tau}}{S_t\sigma\sqrt{\tau}}[n(d_{1,1}) - n(d_{2,1}) - n(d_{3,1}) + n(d_{4,1})] \tag{14}$$

$$Rho_t = \tau e^{-r\tau}[K_1 N(d_{1,2}) - K_2 N(d_{2,2}) - K_3 N(d_{3,2}) + K_4 N(d_{4,2})] \tag{15}$$

$$Theta_t = \frac{S_t \sigma e^{-q\tau}}{2\sqrt{\tau}}\left[n(d_{1,1}) - n(d_{2,1}) - n(d_{3,1}) + n(d_{4,1})\right] \quad (16)$$

$$-re^{r\tau}\left[K_1 N(d_{1,2}) - K_2 N(d_{2,2}) - K_3 N(d_{3,2}) + K_4 N(d_{4,1})\right]$$

$$+qS_t e^{-q\tau}\left[N(d_{1,1}) - N(d_{2,1}) - N(d_{3,1}) + N(d_{4,1})\right]$$

where $n(x)$ represents the probability density function of the standard normal distribution.

We have derived the closed-form solutions for these Greeks of long call condor strategy, in which these Greeks express several measures of risk exposures on the strategy values. Notably, the *Delta* value reflects the change in strategy values in response to movements in the underlying stock price (S_t). If the strategy's *Delta* approaches zero, the strategy is designed to neutralize small changes in the underlying asset's price. The *Gamma* reflects *Delta*'s movement, and the *Theta* indicates the change in strategy value over time. The *Vega* presents the sensitivity of strategy value over stock return volatility (σ). Finally, the *Rho* shows the strategy's interest rate risk. Due to the complexity of the Greek letters described above, we implement numerical calibrations for the strategy value, risk measurements, and the impact of the strike range.

4. Numerical Calibration

We implement a numerical procedure and perform comparative statics to examine how the strategy value changes in response to various factors. The results are generated using the 2023 version of the Matlab software. Specifically, we address several issues related to strategy values, sensitivity analyses, formulating an effective strategy of strike ranges in response to market fluctuations, and comparison issues with long call butterfly.

We specify a representative case to analyze the value and risk measures of the long-call condor strategy. That is a baseline case of the LCC strategy considered within the following scenario. The initial values of parameters in the LCC strategy pricing model (3) are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the middle lower strike K_2 of \$95, the middle higher strike K_3 of \$105, the highest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity $T-t$ of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%.

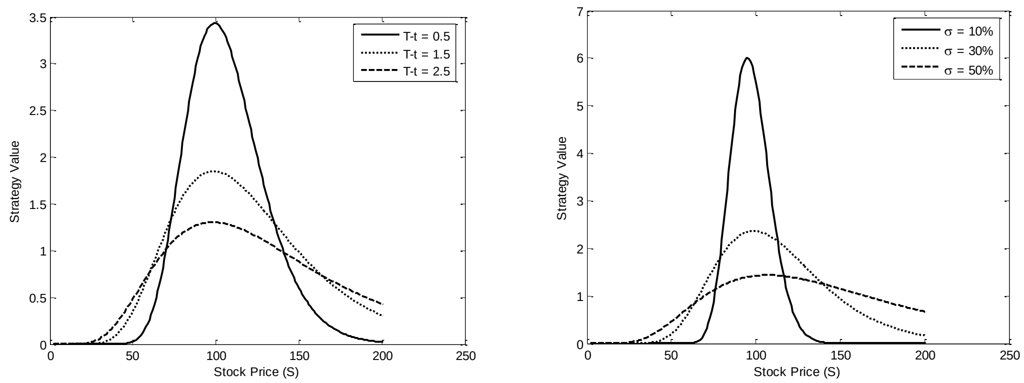
4.1 Strategy Values

Long call condor is an options trading strategy comprising four legs. These legs represent call options with different strike prices but the same expiration dates. We estimate the fair value of the representative long call condor strategy based on the determinants in pricing model (3). We show our results in Figure 1 and Table 1 and summarize our findings in the following descriptions.

Figure 1 illustrates the dynamics of the LCC strategy's fair value (V_t) about stock prices in a two-dimensional plot. First, the strategy values are relatively higher when the stock price is in a narrow range near two inside strikes (K_2, K_3). The results suggest that the LCC strategy traders seek maximum values by expecting invariant stock prices around the inside strikes. Strategy traders expect the underlying asset's price to remain stable, typically within the inside ranges (K_2, K_3) at expiry. Conversely, the strategy's value declines if the stock price deviates significantly from the inside range. Second, conversely to common recognition, a shorter-run LCC strategy has relatively greater strategy values, as shown in Panel A of Figure 1. As the time to maturity is shorter, the concrete terminal results tend to be identified, resulting in a higher value within the middle strike interval and a lower value outside the interval of the lowest and highest strike levels. Third, the strategy value is lower under these market conditions, which are characterized by higher return volatility. Panel B of Figure 1 shows that strategy values are relatively higher as the return volatility rate is 10%, and the fair value curve is depressed as the return volatility is 50%. The result implies that the LCC strategy is less feasible for creating value as the market varies highly. Higher return volatility disperses the stock price distribution, making it less likely for the stock price to remain within the range of middle strikes.

Therefore, the call condor strategy exhibits distinct values over time to maturity and return volatility compared to the plain vanilla call option[5].

Figure 1: Long Call Condor's Values



Panel A: Varying with maturity **Panel B: Varying with return volatility**

Note: The figure illustrates the fair value of the LCC strategy as it varies with the stock price, return volatility, and time to maturity. The initial values of parameters in the closed-form solution of long call condor strategy are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the second lower strike K_2 of \$95, the strike K_3 of \$105, the greatest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity T – t of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%

Table 1 presents the condor strategy (V_t) values as they vary with its determinants. First, the estimated value (V_t) decreases if the underlying stock price moves significantly to the downside or upside. The value increases as the underlying asset price approaches the range of two middle-strike prices. The maximum profits occur in the middle strikes (K_2 and K_3). This result notes that strategy traders should not expect the underlying stock price of the condor strategy to change significantly. Second, Panel B presents a negative relationship between the condor strategy values (V_t) and the lowest strike price (K_1). For example, if the K_1 gradually increases from \$66 to \$74, the strategy value (V_t) declines from \$15.6174 to \$7.6095. The reason for a declining trend for strategy values is that the profit is depressed as the lowest strike price increases. The feasible profit is reduced on narrower spans. Third, we see a negative impact of the riskless rate on the strategy values, as shown in Panel C of Table 1. Since the condor strategy trader receives a portfolio of call options with different strikes, the terminal values of the payoffs are thus reduced at the initial date, given a higher interest rate. The results are recommended to condor traders, who believe the strategy is more appropriate during a low market interest rate. Fourth, as shown in Panel D, the return volatility (σ) affects the condor values (V_t) inconsistently; however, the strategy value tends to be higher when return volatility is relatively lower. The reason for the inconsistent impacts is that the condor strategy is easily out-of-the-money, as the asset risk is higher, resulting in a lower possibility of receiving payoffs. Another reason is that the condor strategy offers higher payoffs at expiration if the terminal stock price is within the inner strikes; therefore, low-volatility underlying assets are preferred. However, as the time to maturity ($T - t$) increases, the maximum condor values (V_t) gradually shift to a location at a higher stock price.

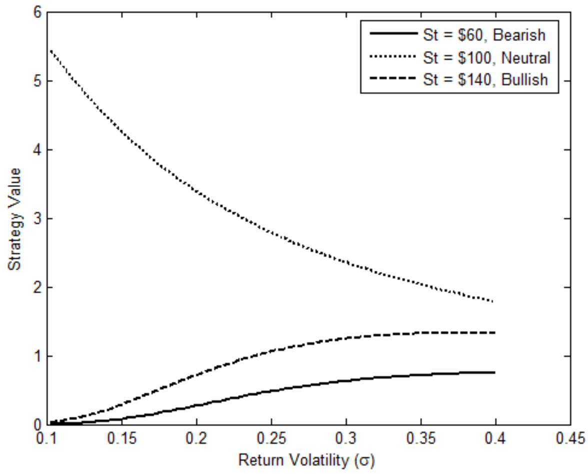
We have the following implications from the summary of the return volatility's impacts on the strategy values from Table 1 and Figure 1. The underlying stock's return volatility (σ) plays an important role in the LCC strategy under various market scenarios. If LCC traders expect the market to be neutral, they tend to choose the strategy that the current stock price falls within the insider range of strike prices. Given the neutral market, the lower return volatility benefits strategy traders since the strategy value of the options positions is expected to be higher. On the other hand, he thinks the current stock price is lower than K_1 or higher than K_4, which is a bullish or bearish market scenario. He prefers the stock price's more volatile dynamic since the underlying asset's terminal price is more likely in the insider ranges of two middle strikes, resulting in a high possibility of receiving payoffs[6].

[5] Note that the call option's value increases with the time to maturity and return volatility.

[6] We are thankful for the referee's recommendation to offer an analysis of strategy traders' choices under market scenarios.

Specifically, as shown in Panel B of Figure 1, the strategy value is relatively greater for the neutral market (the stock price falls in the insider range) and for the bullish and bearish markets (the stock price is lower than K_1 or higher than K_4, respectively).

Figure 2: Return Volatility and Market Condition



Note: The figure illustrates the fair value of the LCC strategy as it varies with return volatility under different market scenarios: bearish, neutral, and bullish. The initial values of parameters in the closed-form solution of long call condor strategy are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the second lower strike K_2 of \$95, the strike K_3 of \$105, the greatest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity T – t of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%.

Table 1. Fair Values of LCC Strategy

Panel A: Stock price (S_t)					
	S = \$60	S = \$80	S = \$100	S = \$120	S = \$140
T = 2	\$0.7870	1.3607	1.5272	1.3732	1.0904
T = 4	0.6447	0.8438	0.8891	0.8383	0.7429
T = 6	0.4847	0.5773	0.5953	0.5705	0.5246
Panel B: Lowest strike price (K_1)					
	K_1 = \$45	K_1 = \$55	K_1 = \$65	K_1 = \$75	K_1 = \$85
T = 2	28.9841	21.2051	13.9247	7.3281	1.5272
T = 4	21.5761	15.6628	10.2225	5.2963	0.8891
T = 6	16.7418	12.1467	7.9257	4.0799	0.5953
Panel C: Interest rate (r)					
	r = 3%	r = 6%	r = 9%	r = 12%	r = 15%
T = 2	1.6864	1.6374	1.5591	1.4558	1.3331
T = 4	1.0779	1.0190	0.9260	0.8089	0.6792
T = 6	0.7924	0.7294	0.6326	0.5169	0.3980
Panel D: Return volatility (σ)					
	σ = 3%	σ = 6%	σ = 9%	σ = 12%	σ = 15%
T = 2	3.0279	2.6269	2.2973	2.0297	1.8112
T = 4	1.6294	1.4694	1.3114	1.1715	1.0514
T = 6	0.9933	0.9368	0.8563	0.7752	0.7009

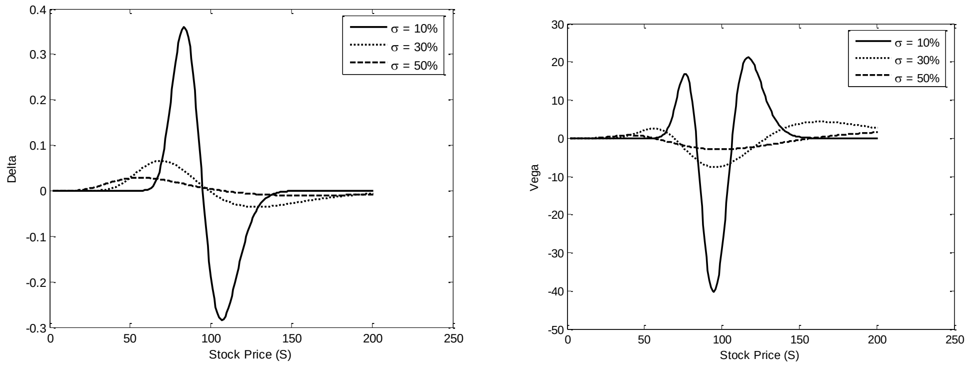
Note: The table presents the values of the LCC strategy, which vary with the stock price, return volatility, the lowest strike price, and the time to maturity. The initial values of parameters in the closed-form solution of long call condor strategy are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the second lower strike K_2 of \$95, the strike K_3 of \$105, the greatest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity T – t of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%.

4.2 Sensitivity Analyses

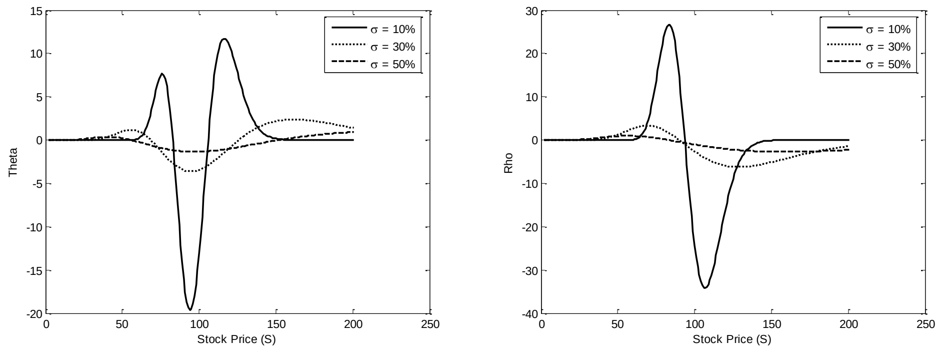
A sensitivity analysis of a long call condor strategy would involve evaluating the impacts of changes in the strategy's determinants. By understanding these sensitivities, traders can make more informed decisions about the strategy's potential risks and rewards and adjust their positions accordingly. The study examines the characteristics of Greek letters

Figure 3 presents the Greek letters associated with the condor strategy. In Panel A, the *Delta* changes dramatically over the stock price. Notably, the *Delta* gradually increases from zero to its maximum value before the strike on K_2. Sudden decreases occur within the inner range (K_2, K_3), and subsequently, it increases from its minimum to zero after the strike K_4. A reason for a positive *Delta* is that the condor strategy payoff increases if the stock price increases over the range (0, K_2). Otherwise, a negative strategy *Delta* shows a decreasing trend in strategy values (V_t) if the stock price increases, as shown in the ranges (K_2, K_3). Option strategy traders should recognize the changing process in strategy values (V_t) as the stock price falls within the range of ($K_2 < S_t < K_3$), and condor traders carefully respond to changes in the underlying stock price by taking hedging behaviors using other instruments.

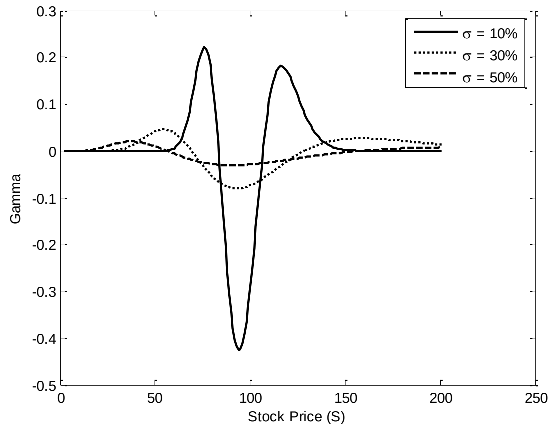
Figure 3: Greek Letters of Long Call Condor Strategy



Panel A: *Delta* **Panel B: *Vegas***



Panel C: *Theta* **Panel D: *Rho***



Panel E: *Gamma*

Note: The figure presents the values of the LCC strategy's Greek letters as the stock price and return volatility vary. The initial values of parameters are listed in Figure 1.

Next, note that the LCC strategy consisted of two long and two short calls, resulting in a strategy with complicated *Vega* dynamics. Panel B of Figure 3 shows that *Vegas* performs with positive, negative, or zero values, depending on the different strike ranges. First, focusing on the negative, *Vega* appears in the two middle strikes (K_2, K_3). The results indicate that the condor strategy trader benefits from lower-risk market scenarios. Second, the *Vega* shows a positive value when the stock price is within the ranges (K_1, K_2) and (K_3, K_4). Given other conditions, the underlying asset's price with a higher return volatility (σ) appears in the above strike ranges; the effect is positive for the condor strategy's values (V_t) since a higher return volatility (σ) is more likely to sway the stock prices enter the inside range at the expiration date. Third, the *Vega* values are susceptible to zero as the stock price exceeds the highest strike (K_4) or is lower than the lowest strike (K_1). It means that changes in return volatility (σ) affect the condor strategy's values (V_t) less significantly. To summarize the results above, we suggest that strategy traders may consider taking positions in other options or securities negatively correlated with *Vegas* if they intend to hedge against movements in stock return volatility by observing the strategy's *Vegas*.

Next, the *Theta* measures the rate of change for the strategy value over time. Panel C in Figure 3 indicates a plot of the condor strategy's *Theta* dynamics. The *Theta* remarkably declined as the stock price rose in the strike ranges (K_1, K_2) and (K_3, K_4). The condor value (V_t) decays over time if the stock price (S_t) is in the strike ranges (K_1, K_2) and (K_3, K_4). However, if the underlying stock's price falls within the inside range (K_2, K_3), the *Theta* immediately increases in value above the inside range. Besides, the strategy's *Theta* will reach zero as stock return volatility (σ) increases. The reason is that when stock return volatility (σ) is larger, the time value of the options involved in the strategy tends to be ignored. As time passes, the time value of the options becomes less remarkable. Hence, investors who employ a long call condor strategy should consider the impact of stock return volatility (σ) on the strategy's *Theta*. Higher return volatility may suggest a need for a more inactive position adjustment in response to the time decay.

Moving our discussion to the *Rho*, we measure the sensitivity of the strategy value in response to changes in interest rates. Panel D in Figure 3 illustrates the dynamics of the strategy's *Rho*, which varies significantly with the stock price. The strategy's *Rho* increases in the range (K_1, K_2), then declines in the range (K_2, K_3), and subsequently increases in the range (K_3, K_4) as the underlying stock's price rises gradually. Due to the LCC strategy comprising four call options, the explanation of *Rho*'s dynamics involves the combined effects of long and short calls. Besides, a higher stock return volatility (σ) implies greater uncertainty about the underlying asset's future price movements, which reduces the impacts of interest rates (r), making the strategy less sensitive to changes in interest rates.

The *Gamma* measures the rate of change of the strategy's *Delta* in response to changes in the underlying asset's price. In the case of a long call condor strategy, which consists of four options positions, the overall *Gamma* of the strategy will depend on the individual *Gamma* values of each position. As shown in Panel E in Figure 3, the condor strategy appears to have a maximum negative *Gamma* between the strikes (K_2, K_3). This implies that strategy traders should reduce their reaction to *Delta* management, as the condor strategy's payoff curve is more pronounced, making it more likely for option traders to profit. Over the ranges of (K_1, K_2) and (K_3, K_4), the condor's *Gammas* are positive, implying that the change rate of *Deltas* is apparent, suggesting that strategy traders are encouraged to take an aggressive attitude to adjust positions in response to the market movements. Outside of the lowest and largest strikes, the *Gammas* are lower. Also, a higher return volatility mitigates the movements of Greek letters.

4.3 Strike Ranges

The primary issue of this study is how strategy traders formulate a portfolio of call options with different strike prices to maximize the LCC traders' profit. As a result, the choice of strike ranges plays a notable role in forming the LCC strategy. A wider or narrower strike range influences the possibility of creating strategy values in response to market conditions.

We examine numerical results from our theoretical valuation formula by adjusting the widths of strike ranges to identify changes in fair value for the LCC strategy. To address the issues we have identified, this study sets stock prices at \$130, \$100, and \$70 for the scenarios of bullish, neutral, and bearish markets. A neutral market responds with stability and remains near the initial stock price. Additionally, the width ($K_3 - K_2$) of the inside range and the width ($K_4 - K_1$) of the outside range are centered around the initial stock price of \$100.

A wider range of outside strikes allows strategy traders to make more profits. Table 2 shows the strategy's fair values varying with the outside ranges and presents a growing trend for LCC strategy's fair values over the width of outside strikes. For example, the fair value (V_t) increases from \$2.3598 to \$6.8598 if we widen the strike ranges (K_1, K_4) from (\$85, \$115) to (\$75, \$125) around the underlying stock's initial price. A lower lowest strike price (K_1) or a rising highest strike price (K_4) can widen the outside ranges and capture more potential profits in the LCC strategy. The economic implication is that strategy traders shall buy the options with the lowest strike and the highest strike price to construct the strategy. Although the former has relatively high costs and the latter has relatively low costs, the sum of two long call options may maintain a cost level.

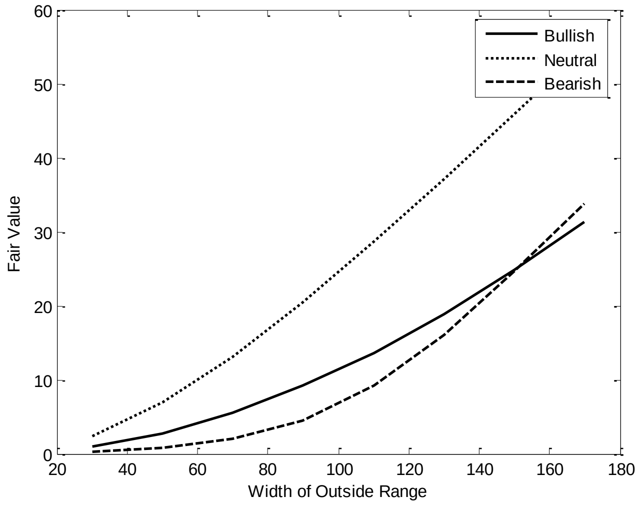
Table 2. LCC Strategy's Fair Values and the Width of Outside Ranges

(K_1, K_4)	V_t
(\$85, \$115)	\$2.3598
(\$75, \$125)	6.8598
(\$65, \$135)	13.0852
(\$55, \$145)	20.5073
(\$45, \$155)	28.6283

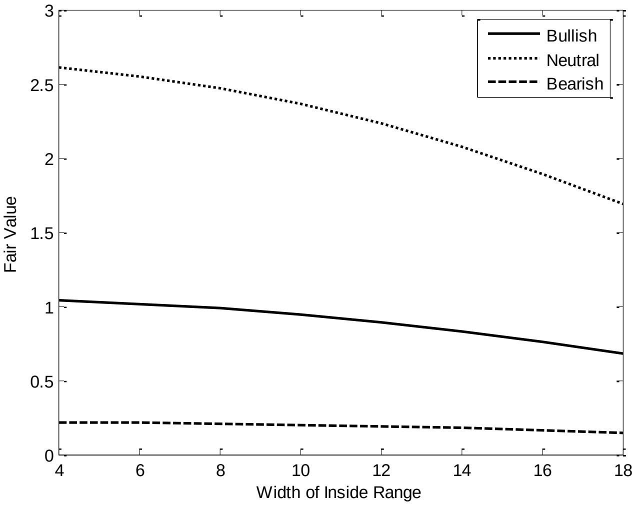
Note: The table presents the impacts of the width for outside ranges (K1, K4) of strike prices on the LCC strategy values. The initial values of parameters in the closed-form solution of long call condor strategy are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the second lower strike K_2 of \$95, the strike K_3 of \$105, the greatest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity T – t of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%.

Next, the study examines how market scenarios impact the results mentioned above. As shown in Pane A of Figure 4, widening outside ranges is more feasible for the neutral market than for the bullish and bearish markets. Three curves represent the dynamics of fair value for the LCC strategy over the widths of the outside ranges given three market scenarios. The fair values gradually increase over the widths of the outside ranges for all market scenarios. However, a wider range of outside strikes can boost profits more in the neutral market scenario because the future market price is more likely to fall in the range. Our findings suggest that a wider range of outside strikes is more appropriate for the neutral market.

Figure 4: Strike Ranges and Fair Value of LCC Strategy



Panel A: Outside ranges



Panel B: Inside ranges

Note: The figure illustrates the dynamics of fair value in response to changes in strike ranges. The sizes of the outside range ($K_4 - K_1$) and inside range ($K_3 - K_2$) are determined by adjusting the width of the strike ranges around the initial stock price. The initial setting of model parameters is listed in Figure 1. The setting of market scenarios is based on initial stock prices of \$130, \$100, and \$70 for bullish, neutral, and bearish markets.

Table 3 presents the numerical results of the strategy value as a function of the inside ranges of strike prices. A narrower width of the inside range (K_2, K_3) benefits the LCC strategy's values, given the market conditions of the stock price in the inside range. This implies that if the strategy traders set a narrower inside range of strike prices to capture the market conditions of a neutral scenario exactly, they tend to profit more. Conversely, strategy traders can easily capture the market conditions if the inside range is wider, but they will get lower profits. Note that a converse relationship appears between the inside range and strategy values.

Table 3. LCC Strategy's Fair and the Width of Inside Ranges

(K_2, K_3)	V_t
(\$98, \$102)	2.6119
(\$96, \$104)	2.4677
(\$94, \$106)	2.2281
(\$92, \$108)	1.8938
(\$90, \$110)	1.4662

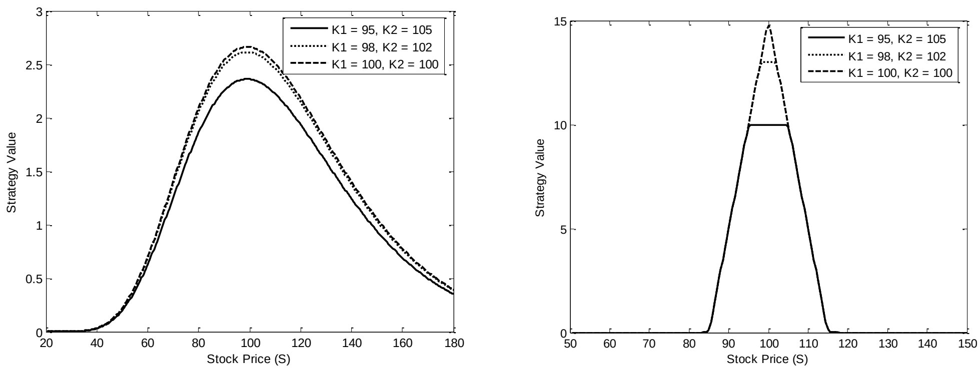
Note: The table presents the width impacts for the inside ranges (K_2, K_3) of strike prices on the LCC strategy values. The initial values of parameters in the closed-form solution of long call condor strategy are set as follows: the current stock price S_t of \$100, the lowest strike K_1 of \$85, the second lower strike K_2 of \$95, the strike K_3 of \$105, the greatest strike K_4 of \$115, the risk-free rate r of 10%, the time to maturity T – t of 1 year, the return volatility σ of 30%, and dividend yield rate q of 5%.

To identify the abovementioned issue, we further examine how market scenarios change the impact of the insider range's width ($K_3 - K_2$) on the strategy value. We implement a numerical analysis for a given case of market movements. There are three scenarios of market conditions: bullish (S_t = \$130), neutral (S_t = \$100), and bearish (S_t = \$70). We present our results using a 2-dimensional plot in Panel B of Figure 4. Although a wider inside range ($K_3 - K_2$) of strike prices can yield a lower fair value for the LCC strategy, the trader obtains relatively lower profits in both bearish and bullish markets and higher profits in the neutral market. The economic implication is that strategy traders can achieve greater profits by choosing an exact portfolio of options with a narrower range of strikes to capture specific market scenarios. Suppose the strategy traders remain in a bullish or bearish market. In that case, they should adjust their choice of inside ranges to align closer with the prevailing bullish or bearish market conditions, respectively.

4.4 Special Case: Long Call Butterfly Strategy

The study analyzes the effects of the strike range on the values of the LCC strategy. As the width ($K_3 – K_2$) of the insider range in the strike price gradually approaches zero, the LCC strategy's structure turns out to be the long call butterfly strategy[7]. The study thus examines and compares the two strategies mentioned above, displaying their results in a diagrammatic representation, as shown in Figure 5. Panels A and B present the strategy value over the underlying stock prices given three widths of insider range, i.e., (K_2, K_3) = (\$95, \$105), (\$98, \$102), and (\$100, \$100).

Figure 5: Comparison with Long Call Butterfly



Panel A: One year to maturity **Panel B: Appropriately maturity**

Note: The figure illustrates the dynamics of fair value when the inside range ($K_3 – K_2$) reduces to zero. The long call butterfly strategy is a special case of the LCC strategy, where $K_3 = K_2$. Panels A and B present the strategy values when $T – t = 1$ and 0.0001 years, respectively. The initial setting of model parameters is listed in Figure 1. The setting of market scenarios is based on initial stock prices of \$130, \$100, and \$70 for bullish, neutral, and bearish markets.

As the width of the insider range is zero, option traders exactly implement the long call butterfly strategy, in which they long a call with a relatively lower strike, long a call with a relatively higher strike, and short two calls with a middle strike. As shown in Panel A of Figure 5, far from one-year maturity ($T – t = 1$), the curves of strategy values exhibit similar trends to the underlying stock prices. However, the long call butterfly captures more values among the three cases, i.e., the width ($K_3 – K_2$) = 0. Panel B displays the strategy values at approximate maturity ($T – t = 0.0001$). With the reduction in the width of the insider strike range, the strategy value tends to be higher. The implication of the results suggests that LCC strategy traders can capture the highest payoffs if they can accurately predict the stock price's movement and choose the inner strike prices of the LCC strategy precisely. However, a wider insider range may be more appropriate for receiving potential interests if traders are unable to exactly estimate the terminal level of the underlying stock price, since a wider insider range is more likely to capture the interests of the LCC strategy, compared to the long call butterfly strategy that has a most narrow insider range.

5. Conclusions

In this article, we propose a new perspective, strike ranges, to examine the choices of option portfolios by strategy traders in the LCC strategy, aiming to capture potential strategy values. The study derives closed-form solutions for the fair value and Greeks of the LCC strategy, paving the way for further analysis of the strike range's impacts. We analyze the settings of strike ranges, how to influence strategy values, and how to respond to market scenarios appropriately.

Our study has the following main findings. First, the condor strategy values are relatively higher when the stock price is in a narrow range near two inside strike prices. If the underlying stock price deviates significantly from the two inside strike prices, the values of the profits turn out to be lower. Second, the strategy values vary according to several determinants in different ways. Our findings suggest that a long condor strategy trader benefits from the underlying asset, characterized by lower risk, interest rates, and short-run contracts. Third, the risk sensitivities, measured by the Greek letters,

[7] We thank the referees for suggesting that we examine the long call butterfly strategy, a special case of the LCC strategy, to enhance our statements.

show changes in appearance around the strikes. Strategy traders are susceptible to hedging behavior in response to various types of risk. Fourth, the strike range significantly impacts strategy values, where a wider insider range of strike prices lowers profits, and a wider outside range enlarges strategy traders' profits. Our findings suggest that selecting option portfolios with different strike prices can capture potential interests for strategy traders who expect precise market scenarios.

This paper provides a theoretical justification for strengthening strategy values and managing risks in the context of a specific options trading strategy analysis. The choice of strike ranges for holding the LCC strategy is critical to capturing the potential interests of practical strategy traders. Thus, this article contributes to identifying a strike issue framed in theoretical options trading strategy analysis.

While we have focused on the effects of the width of strike ranges on strategy values, this paper's analysis can be readily extended to other trading strategies that involve diverse options. More studies considering the effect of diverse maturities on option portfolios would be quite challenging and will be left to future work.

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